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# Evaluation and Correction of PurpleAir Temperature and Relative Humidity Measurements

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**Abstract:** The PurpleAir PA-II sensor provides low-cost in situ measurements of meteorological variables including temperature and relative humidity (RH), as well as fine particulate matter ($PM_{2.5}$) in real time. The sensors have been used in several studies investigating intracity differences in temperature and $PM_{2.5}$. While the adoption and use of low-cost sensors has many benefits, care must be taken to ensure proper calibration and testing. This is true not only for $PM_{2.5}$ measurements but also for temperature and RH given the synergistic health impacts from extreme heat and air pollution exposure. Here, we compare continuous temperature and RH measurements from a PA-II sensor to measurements from a Campbell Scientific 107 temperature probe and Vaisala HMP45C RH probe. All three instruments were co-located from December 2021 to June 2023 in Asheville, North Carolina. We found that the PA-II has an overall high temperature bias of 2.6 °C and root mean square error (RMSE) of 2.8 °C. Applying a linear regression correction reduces RMSE to 1.0 °C, while applying the constant 4.4 °C correction suggested by PurpleAir reduces RMSE to only 2.2 °C. Our PA-II RH measurements have a low bias of −17.4% and uncorrected RMSE of 18.5%. A linear regression correction improves the RH RMSE to 4.5%. Applying the constant 4% RH correction suggested by PurpleAir reduces RMSE to only 14.8%. We present new correction factors that differ from those suggested by PurpleAir, which overcorrect the high temperature bias and undercorrect the low RH bias. We also show that our correction factors improve estimates of dewpoint temperature (RMSE of 0.6 °C and 0.9 °C) compared to the corrections suggested by PurpleAir.

**Keywords:** PurpleAir; low-cost sensor; air pollution; temperature; relative humidity

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## 1. Introduction

Air pollution monitoring has enjoyed a notable surge in the popularity of low-cost sensors, marking a shift in data availability and spatial coverage. The proliferation of these sensors has been driven by advancements in technology and a growing need for neighborhood-scale measurement data [1]. Characterized by affordability and ease of use, low-cost sensors are democratizing air quality data collection and empowering communities to actively participate in monitoring efforts [2,3]. Several studies have investigated possible uses from citizen science efforts to personal exposure monitoring [4–7], and sensor data can supplement existing monitoring networks [8]. This is of particular importance for pollutants—such as fine particulate matter ($PM_{2.5}$)—with high spatiotemporal variability [9–12].

Many low-cost sensors used for air pollution monitoring employ optical particle counters that estimate mass concentration based on how particulates in the sample scatter light. Several studies have described this technology in detail along with some of the drawbacks and potential sources of error when compared to federal reference method (FRM) or federal equivalent method (FEM) instruments [13–16]. The South Coast Air

Quality Management District's AQ-SPEC program has tested dozens of commercially available low-cost $PM_{2.5}$ sensors in laboratory and field settings [17]. Their results show a wide range of sensor quality with some sensors, including the PurpleAir PA-II sensor used in our study, exhibiting good precision and accuracy when compared to FRM and FEM monitors. The US EPA, through conversations with multiple stakeholders [18], developed guidance for testing $PM_{2.5}$ sensors in ambient, non-regulatory settings [19], and the agency also created an Air Sensor Toolbox [20] and Guidebook [21], which provides best practices for using low-cost sensors. Additionally, the US EPA incorporates adjusted data from over 10,000 PurpleAir sensors on the AirNow Fire and Smoke map in recognition of that sensor's usefulness and popularity [22].

While it is well known that exposure to air pollutants and extreme heat are individually hazardous, it is becoming clear that the negative health effects of poor air quality are magnified by high temperatures. A study of 17 cities in France found that the risk of mortality associated with a 10 $\mu g/m^3$ increase in $PM_{10}$ was 14.2% greater during a heat wave [23]. Other studies of European cities reported similar findings [24,25]. Rahman et al. [26], investigating the link between extreme heat and $PM_{2.5}$ in California, found that co-exposure had a greater effect on all-cause mortality (21.0% increase in risk) than the sum of the individual effects (6.1% increase in risk for high temperature days and 5.0% increase in risk for high $PM_{2.5}$ days). The effect was magnified when looking specifically at increased risk of cardiovascular mortality and respiratory mortality. Further, recent reviews of the literature on human population health studies found compelling evidence for synergistic effects of extreme heat and $PM_{2.5}$ [27–29].

Populations living in urban areas are particularly vulnerable to extreme heat and elevated $PM_{2.5}$ concentrations. Individual risk is communicated via the well-known heat index (HI), which integrates ambient temperature with relative humidity (RH), and air quality index (AQI), which relies on ambient concentrations of pollutants such as $PM_{2.5}$ and ozone. Yet, there is no consistent method to communicate the combined risk. Fever et al. [30] unified the HI and AQI for $PM_{2.5}$ and ozone in a combined index using several different models. They found that improved mortality predictions were possible with their combined indices in Monterrey, Mexico, but cautioned that their results might not be generalizable to regions with different air pollutant and weather patterns. Steeneveld et al. [31] developed an urban climate index that combined $PM_{10}$, ozone, and nitrogen dioxide concentrations with urban heat island effects. Of relevance to low-cost sensor networks, they highlight the importance of fine-scale measurement data when assessing the health risks of extreme heat and air pollution. A third study took a different approach to investigating the combined impact of extreme heat and $PM_{2.5}$ exposure on urban communities. Sabrin et al. [32] used neighborhood-scale data to assess the importance of underlying environmental and social parameters and to communicate the risk to vulnerable populations. Each of these investigations sought to integrate information about heat and air pollution exposure, which indicates the need for high-quality measurements of both.

Several studies have examined the performance of PurpleAir sensors with respect to $PM_{2.5}$ [33–37]. To date, these efforts have occurred in several countries and under a variety of ambient and laboratory conditions. Most often, $PM_{2.5}$ measurements from PurpleAir sensors are compared to nearby FRM or FEM instruments. While nearly all attempts to correct the $PM_{2.5}$ concentrations have recognized the importance of factoring in temperature and/or RH values, very few studies have investigated bias and error in these meteorological measurements from the PurpleAir sensors themselves. Holder et al. [38] found strong correlations to reference measurements ($r^2$ of 0.91 and 0.84 for temperature and RH) over a range of ambient conditions in North Carolina. They reported a mean temperature bias of 5.2 °C and a mean RH bias of −24.3%. Another study in Greece found excellent inter-sensor agreement between eight different PurpleAir sensors and strong correlations with reference temperature and RH [39]. Though specific values were not provided, this study also noted persistent high and low biases for temperature and RH, respectively. These biases are known by PurpleAir, and specific correction factors

(−4.4 °C and +4%) are provided on the company's community forum [40], though without information about how those correction factors were determined. PurpleAir attributes the measurement discrepancy to heat generated from the internal WiFi module and adds a disclaimer that the on-board temperature and RH readings are not meant to reflect actual ambient conditions. A third study reports yet another set of biases but blames the near-infrared laser counters for the elevated temperature and lower RH values [41]. They found a temperature difference of 4.4 °C and an RH difference of −15% without providing any explanation other than to mention a long period of comparison to an indoor monitor. Finally, Malings et al. [15] states that PurpleAir temperature and RH were 2.7 °C above and 9.7% below average, though again, without a description of how the reference values were obtained.

The current study provides the first long-term, systematic investigation of PurpleAir's on-board temperature and RH measurements. We compared data from the low-cost sensor to co-located research-grade meteorological instruments and provide correction factors to estimate ambient temperature and RH from values reported by PurpleAir. While it has been noted elsewhere that reasonably accurate PurpleAir $PM_{2.5}$ corrections are possible even without knowing actual ambient conditions [42], our results enhance the capability of the sensor by allowing the public health community to combine air quality information with temperature and RH data.

## 2. Materials and Methods

### *2.1. PurpleAir PA-II Sensor*

The PurpleAir PA-II sensor is a commercially available low-cost particulate matter and temperature/RH/pressure measurement platform. It is most often used to obtain ambient $PM_{2.5}$ levels using a pair of Plantower PMS-5003 optical particle counters. Mass concentrations are calculated using a proprietary algorithm. Descriptions of the PA-II's operating principles have been detailed elsewhere (for example, Ardon-Dryer et al. [33]). Meteorological measurements are provided by a Bosch BME280 sensor.

The PA-II's components are housed in a white plastic shell (85 mm × 85 mm × 125 mm) to protect the electronics from the elements. The plastic housing is open on the bottom to allow the sensors to measure ambient air. In addition to the two PMS-5003 particle counters and the BME280 sensor, the PA-II platform contains a wireless data transmitter, microSD card data logger, and programmable circuit board with a battery-powered real time clock. Figure 1 shows the PA-II sensor and its internal components.

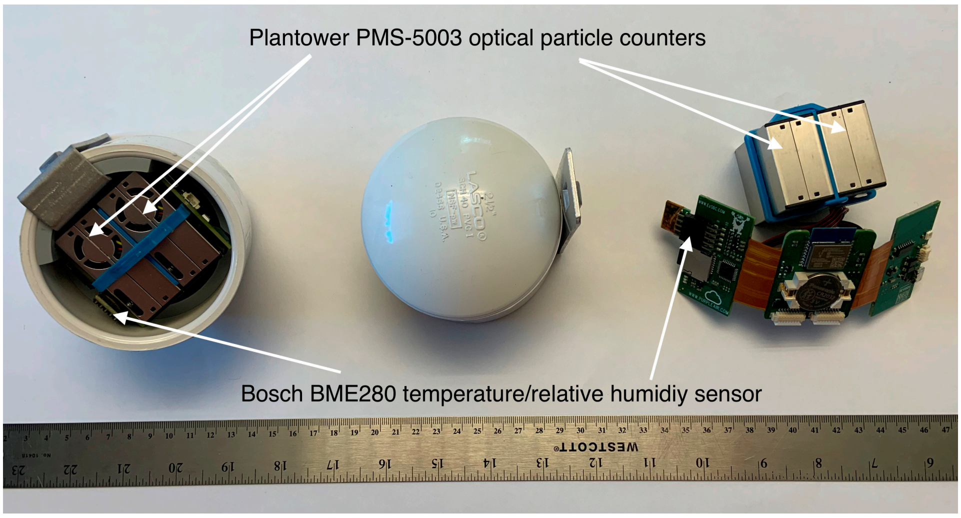


**Figure 1.** Images of the PurpleAir PA-II sensor labeled with the Plantower PMS-5003 optical particle counters and Bosch BME280 temperature/relative humidity sensor. The lefthand image shows the bottom of the PA-II, and the center image shows the top. The righthand image shows the internal electronic components.

A more recent version of the PurpleAir sensor, the PurpleAir Flex, is also available. The operating principles are identical, though the optical particle counters have been updated to the Plantower PMS-6003 model and the meteorological sensor was updated to the Bosch BME688.

### 2.2. Measurement Site

All measurements were taken in Asheville, North Carolina, at a weather station maintained by the Department of Atmospheric Sciences at the University of North Carolina Asheville (UNCA). The station, which is part of the North Carolina Environment and Climate Observing Network (ECONet) [43], is 2367 m above sea level and located at 35.62° N, 82.57° W. Temperature data were recorded using a Campbell Scientific 107 probe 2 m above the ground, and RH data were recorded using a Vaisala HMP45C probe also 2 m above the ground. All data are publicly available at https://atms.unca.edu/datarequest/ (accessed on 1 February 2024). North Carolina ECONet stations undergo rigorous quality control and maintenance procedures [44].

Continuous weather station measurements were taken at 1-min intervals for 553 days from 15 December 2021 to 30 June 2023. Both temperature and RH records were more than 99.9% complete. Upon inspection, some temperature data on 12 August 2022 had anomalously low readings and were removed from this analysis. The affected times were 11:12 through 13:14 (local time); RH data were also removed during this interval. After removing the anomalous data points, the 1-min data were aggregated to 5-min averages.

One PA-II sensor was installed on the UNCA weather tower at 3 m and measured temperature and RH. No adjustments were made to the data to account for the 1-m height difference between the PA-II sensor and the UNCA instruments. Continuous measurements were taken at 2-min intervals from 15 December 2021 through 26 July 2022. Measurements beginning on 27 July 2022 were taken at 5-min intervals. All data were aggregated to 5-min averages. Data completeness for the PA-II was 91.4%. Data were unavailable from 14:30 10 January 2023 through 08:35 23 January 2023 (local time), and several data points were removed on 29 October 2022 because the $PM_{2.5}$ measurements were greater than 500 $\mu g/m^3$, indicating a possible data logging malfunction.

### 2.3. Dewpoint

We used the Python package MetPy version 1.5.1 [45] to calculate dewpoint temperatures (DP) from temperature and RH measurements. While the Campbell scientific 107 probe was used to obtain reference temperatures for comparison to the PA-II's temperature measurements, we relied on temperature from the Vaisala HMP45C probe to calculate DP. It is recommended to use temperature and RH values from the same sensor when calculating DP. Values were calculated for both the UNCA and PA-II data sets using the metpy.calc.dewpoint_from_relative_humidity function.

### 2.4. Performance Metrics

To evaluate the reliability of the PA-II's meteorological measurements, we calculated mean bias (bias) and root mean square error (RMSE) to compare the UNCA and PA-II data sets. All comparisons were made on time-paired data, so we excluded records where only one data set had a valid measurement. Bias and RMSE were calculated using the following equations:

$$\text{Mean Bias} = \frac{1}{n}\sum_{1}^{n}(x(i) - y(i)) \tag{1}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{1}^{n}(x(i) - y(i))^2} \tag{2}$$

where x(i) and y(i) are time-paired measurements from PA-II and UNCA.

## 3. Results and Discussion

This study compared temperature and RH measurements from one PurpleAir PA-II low-cost sensor to UNCA's research-grade instruments during a 553-day period extending from 15 December 2021 through 30 June 2023. We performed a simple linear regression correction on the PA-II's values using the UNCA data as the reference. Our corrected measurements were then compared to corrections suggested by PurpleAir [40]. Results are presented separately for temperature, RH, and DP.

### *3.1. Temperature*

Measurements from the PA-II are strongly correlated with the UNCA temperature data. The Pearson correlation coefficient (r) between the two data sets is 0.99. Comparisons between the PA-II and UNCA temperatures reveal a consistent and systematic high bias, as shown in Figure 2. The uncorrected PA-II measurements, shown in blue, have a mean bias of 2.6 °C and RMSE of 2.8 °C. A total of 148,230 pairs of 5-min data were analyzed. The differences between the time-paired PA-II and UNCA values ranged from −2.7 °C to 9.1 °C, with 91.1% of the data points exhibiting a high bias. The maximum and minimum temperatures recorded during the study period were 33.8 °C and −19.3 °C for UNCA and 39.2 °C and −17.8 °C for PA-II.

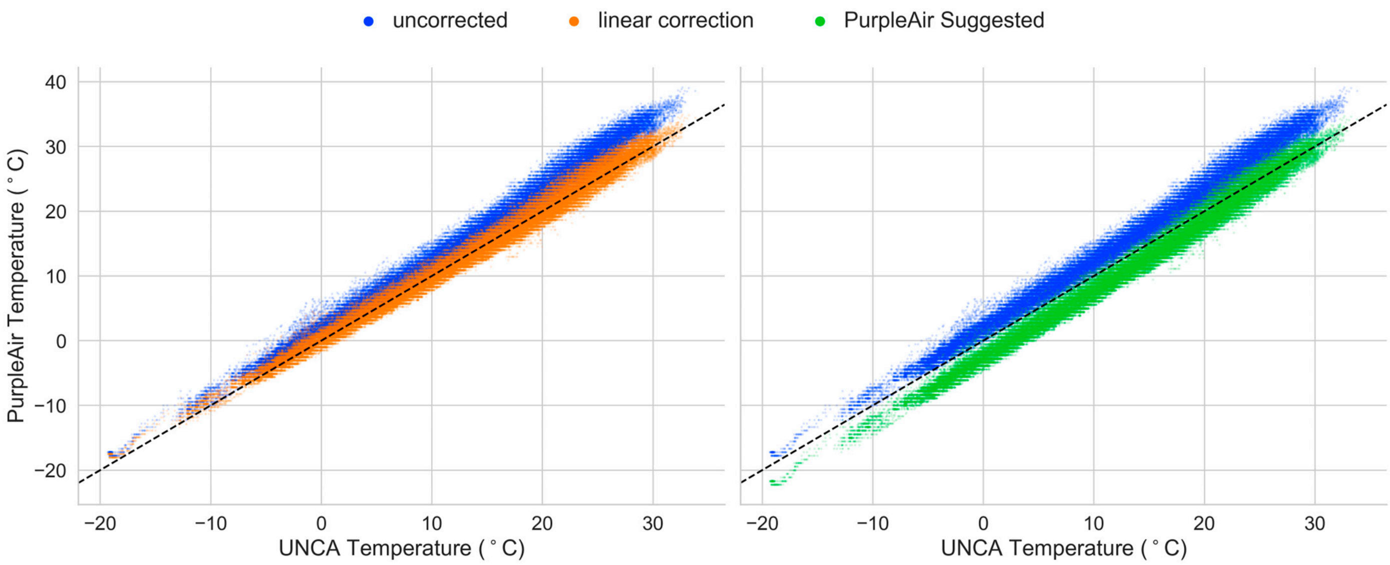


**Figure 2.** Comparisons of the time-paired 5-min PA-II and UNCA temperature measurements. In both plots, the blue markers show the uncorrected data. Orange markers in the left-hand plot show the PA-II data after applying a simple linear regression correction, and the green markers in the right-hand plot show the PA-II data after applying PurpleAir's suggested correction. The dotted line drawn across each plot is the 1:1 line.

We performed a simple linear regression on the uncorrected PA-II data to remove the high temperature bias. The left-hand side of Figure 2 compares the corrected data (orange) to the uncorrected data (blue). The linear regression correction (slope = 1.07, intercept = 1.60) reduces RMSE to 1.0 °C, and the range in differences between the data sets is now −5.4 °C to 5.3 °C. PurpleAir is aware of the high temperature bias in the PA-II, and they recommend a constant 4.4 °C correction to account for the heat generated by the sensor's WiFi module. We applied this suggestion to the uncorrected PA-II measurements, and the result is shown on the right-hand side of Figure 2 in green. The suggested correction introduces a readily apparent low bias especially for temperatures below 20 °C. Overall mean bias is −1.9 °C and RMSE is 2.2 °C, and the range in differences when comparing PurpleAir's suggested correction to the UNCA data set is −7.2 °C to 4.6 °C, with 84.1% of all data pairs exhibiting a low bias. Thus, while the suggested correction does reduce the magnitude of the bias and RMSE, it performs worse than a simple linear regression correction.

As a next step, we separated the measurement data into bins to determine whether the PA-II's bias is temperature-dependent. We chose five separate temperature bins using UNCA temperature as the reference, as shown in Table 1. Both the bias and RMSE increase monotonically with increasing temperature. Minimum bias (RMSE) is 1.8 °C (2.0 °C) when temperatures are −5 °C or below; maximum bias (RMSE) is 4.2 °C (4.4 °C) when temperatures are greater than 25 °C. Both conditions are rarely met occurring only about 8% of the time. The temperature dependence is reversed when considering the corrections suggested by PurpleAir, which are also provided in Table 1. Here, the bias and RMSE decreases from colder to warmer temperatures.

**Table 1.** Comparison of PA-II and UNCA temperature measurements.

| Correction Type | Temperature Bin (°C) | Mean Bias (°C) | RMSE (°C) | r | Slope | Intercept | n |
|---|---|---|---|---|---|---|---|
| uncorrected | All | 2.6 | 2.8 | 0.99 | 1.07 | 1.60 | 148,230 |
| | (−∞, −5] | 1.8 | 2.0 | 0.98 | 1.01 | 1.89 | 2239 |
| | (−5, 5] | 1.9 | 2.1 | 0.96 | 1.03 | 1.86 | 26,589 |
| | (5, 15] | 2.2 | 2.3 | 0.96 | 1.04 | 1.71 | 52,162 |
| | (15, 25] | 3.0 | 3.2 | 0.94 | 1.17 | −0.31 | 57,574 |
| | (25, ∞] | 4.2 | 4.4 | 0.80 | 1.07 | 2.36 | 9666 |
| simple linear regression correction | All | 0.0 | 1.0 | 0.99 | 1.00 | 0.00 | 148,230 |
| | (−∞, −5] | 0.8 | 1.1 | 0.98 | 0.94 | 0.27 | 2239 |
| | (−5, 5] | 0.2 | 0.8 | 0.96 | 0.96 | 0.24 | 26,589 |
| | (5, 15] | −0.2 | 0.8 | 0.96 | 0.97 | 0.11 | 52,162 |
| | (15, 25] | 0.0 | 1.0 | 0.94 | 1.09 | −1.78 | 57,574 |
| | (25, ∞] | 0.6 | 1.3 | 0.80 | 0.99 | 0.71 | 9666 |
| PurpleAir suggested correction | All | −1.9 | 2.2 | 0.99 | 1.07 | −2.85 | 148,230 |
| | (−∞, −5] | −2.6 | 2.8 | 0.98 | 1.01 | −2.55 | 2239 |
| | (−5, 5] | −2.6 | 2.7 | 0.96 | 1.03 | −2.59 | 26,589 |
| | (5, 15] | −2.3 | 2.4 | 0.96 | 1.04 | −2.73 | 52,162 |
| | (15, 25] | −1.4 | 1.9 | 0.94 | 1.17 | −4.76 | 57,574 |
| | (25, ∞] | −0.2 | 1.3 | 0.80 | 1.07 | −2.08 | 9666 |

The high temperature bias presented here is less than previously reported (Table 2). Holder et al. [38] found a bias of 5.2 °C. Their sensors were deployed for nine months in North Carolina. A lower bias of 2.7 °C was found during a March–June field measurement in Pennsylvania [15]. The third reported bias −4.4 °C, which is identical to the correction suggested by PurpleAir—is from an indoor sensor [41].

**Table 2.** Comparison of temperature and RH bias to previous studies.

| Study | T (°C) | RH (%) | Location | Dates |
|---|---|---|---|---|
| This study | 2.6 | −17.4 | Asheville, NC (USA) | 15 Dec 2021–30 June 2023 |
| Malings et al. [15] [1] | 2.7 | −9.7 | Pittsburgh, PA (USA) | 30 Mar 2018–4 June 2018 |
| Holder et al. [38] [1] | 5.2 | −24.3 | Research Triangle Park, NC (USA) | 10 Aug 2018–30 Apr 2019 |
| Wallace et al. [41] [1,2] | 4.4 | −15 | Santa Rosa, CA (USA) | unknown |
| PurpleAir [40] [1] | 4.4 | −4 | Unknown | unknown |

[1] These studies do not provide a clear methodology for determining the temperature and RH bias. [2] Temperature and RH were measured indoors.

### 3.2. Relative Humidity

PA-II RH, like temperature, has a consistent and systematic bias. Unlike temperature, however, the RH bias is low as shown in Figure 3. This bias is the result of the excess heat produced by the sensor's electronics. The excess heat increases the local temperature inside the sensor's enclosure thereby lowering RH. Despite the bias, the RH measurements from the PA-II are strongly correlated to the UNCA measurements illustrated by an r-value of 0.98. The overall RH bias and RMSE is −17.4% and 18.5%. The differences between the time-paired PA-II and UNCA measurements ranged from −45.4% to 2.7%, with nearly all measurements exhibiting a low bias (91.4% of all data points). The ranges of measured RH during the study period are 9.6% to 99.6% for UNCA and 8.0% to 90.0% for PA-II.

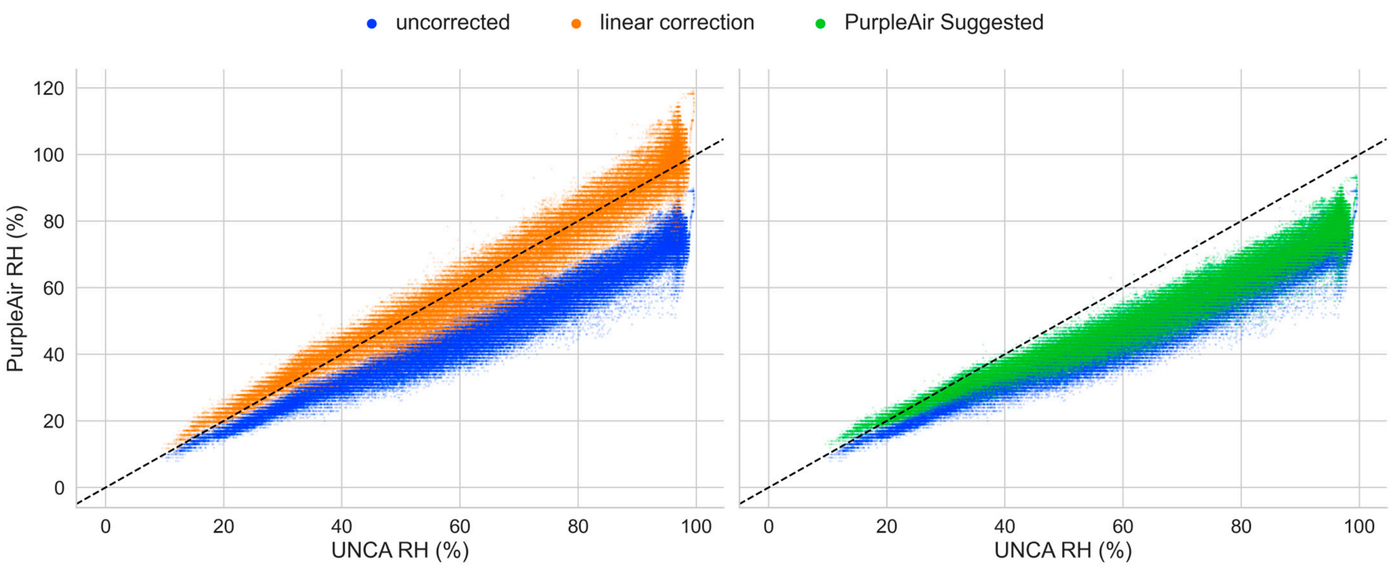


**Figure 3.** Comparisons of the time-paired 5-min PA-II and UNCA RH measurements. In both plots, the blue markers show the uncorrected data. Orange markers in the left-hand plot show the PA-II data after applying a simple linear regression correction, and the green markers in the right-hand plot show the PA-II data after applying PurpleAir's suggested correction. The dotted line drawn across each plot is the 1:1 line.

Applying a simple linear regression correction (slope = 0.75, intercept = 0.12) on the PA-II removes the high temperature bias. The left-hand side of Figure 3 compares the corrected data in orange to the uncorrected data in blue. RMSE decreases to 4.5% and the range in differences between the sets of measurements is now −28.7% to 20.5%. PurpleAir suggests a 4% correction to RH measurements from the sensor, and we applied this to the uncorrected PA-II data set. The right-hand side of Figure 3 illustrates that the suggested correction is not enough to overcome the persistent low RH bias; 89.0% of all PA-II measurements after the 4% correction are still less than the UNCA values. Overall bias and RMSE for the suggested correction are −13.4% and 14.8%, which is an improvement over the uncorrected data. But, as with temperature, PurpleAir's suggested RH correction has worse performance than the simple linear regression correction.

We partitioned the RH data into separate bins to investigate how the PA-II's bias depends on RH. Table 3 summarizes these results using UNCA RH values as the reference for determining each bin. Bias and RMSE are greater at higher RH. The largest bias (−22.0%) and RMSE (22.3%) was calculated for RH values between 80% and 100. Since nearly half of the data points come from this bin, the overall bias and RMSE are dominated by these values. The uncorrected data in Figure 3 shows a marked increase in data points with a lower bias starting around UNCA RH values of 40%. The picture is similar when considering the data after applying PurpleAir's suggested corrections. Worse RH performance occurs at higher RH values. Below 40% RH, however, the suggested correction has similar performance to the simple linear regression correction.

**Table 3.** Comparison of PA-II and UNCA RH measurements.

| Correction Type | RH Bin (%) | Mean Bias (%) | RMSE (%) | r | Slope | Intercept | n |
|---|---|---|---|---|---|---|---|
| uncorrected | All | −17.4 | 18.5 | 0.98 | 0.75 | 0.12 | 148,230 |
| | [0, 20] | −2.1 | 2.5 | 0.84 | 0.74 | 2.21 | 1323 |
| | (20, 40] | −6.0 | 6.4 | 0.92 | 0.74 | 2.01 | 16,506 |
| | (40, 60] | −13.0 | 13.4 | 0.79 | 0.63 | 6.10 | 29,269 |
| | (60, 80] | −18.6 | 19.0 | 0.79 | 0.78 | −2.95 | 39,682 |
| | (80, 100] | −22.0 | 22.3 | 0.82 | 0.92 | −14.56 | 61,450 |
| simple linear regression correction | All | 0.00 | 4.5 | 0.98 | 1.00 | 0.00 | 148,230 |
| | [0, 20] | 2.6 | 3.0 | 0.84 | 0.99 | 2.77 | 1323 |
| | (20, 40] | 2.2 | 3.1 | 0.92 | 0.99 | 2.51 | 16,506 |
| | (40, 60] | −0.6 | 3.8 | 0.79 | 0.83 | 7.96 | 29,269 |
| | (60, 80] | −1.7 | 4.9 | 0.79 | 1.03 | −4.09 | 39,682 |
| | (80, 100] | 0.7 | 4.8 | 0.82 | 1.22 | −19.5 | 61,450 |
| PurpleAir suggested correction | All | −13.4 | 14.8 | 0.98 | 0.75 | 4.12 | 148,230 |
| | [0, 20] | 1.9 | 2.3 | 0.84 | 0.74 | 6.21 | 1323 |
| | (20, 40] | −2.0 | 3.0 | 0.92 | 0.74 | 6.01 | 16,506 |
| | (40, 60] | −9.0 | 9.6 | 0.79 | 0.63 | 10.10 | 29,269 |
| | (60, 80] | −14.6 | 15.1 | 0.79 | 0.78 | 1.05 | 39,682 |
| | (80, 100] | −18.0 | 18.4 | 0.82 | 0.92 | −10.56 | 61,450 |

The low RH bias in our study is within the bounds of previous investigations (Table 2). Holder et al. [38] reported a bias of −24.3%, which is substantially lower than our overall bias of −17.4%. They also found a larger high temperature bias, which is consistent with a lower RH bias. Our RH bias is lower than the −9.7% bias reported by Malings et al. [15]. However, their temperature bias was slightly higher than ours, which would suggest a lower bias as found by [38]. Given the differences in data collection location, longevity, and time of year, however, some inconsistencies should be expected especially considering the nonlinear relationship between RH and temperature and the importance of local conditions in determining RH. Interestingly, our RH bias was close to the −15% reported by [41], which collected temperature and RH measurements indoors.

### *3.3. Dewpoint Temperature*

DP is a derived variable that is calculated from temperature and RH. It is arguably more relevant to predicting physical discomfort and dangerous heat conditions than the measurements reported by the PA-II. Because DP is determined from temperature and RH, it is subject to the same biases found in the previous sections, though it is not immediately obvious how the high temperature bias and low RH bias will affect bias in DP.

Figure 4 shows the uncorrected DP in blue. Correlation between the PA-II and UNCA values is strong with an r-value of 0.99. The overall DP bias is −1.6 °C and the RMSE is 1.7 °C. Differences between the time-paired PA-II and UNCA measurements ranged from −7.3 °C to 7.7 °C. Nearly all data points (88.9%) exhibited a low bias. The maximum and minimum DP were 24.5 °C and −23.1 °C for UNCA and 22.4 °C and −25.1 °C for PA-II.

Corrected DP values were calculated by using the corrected temperature and RH values obtained from the simple linear regression. The left-hand side of Figure 4 shows that the low bias is largely eliminated. The correction reduces the RMSE to 0.6 °C. The range in differences between the corrected PA-II and UNCA is −6.3 °C to 8.7 °C. We also calculated DP using the suggested PurpleAir corrections to temperature and RH, as shown on the right-hand side of Figure 4. The combination of these suggested corrections leads to a small high bias in DP. Overall bias is 0.6 °C and RMSE is 0.9 °C, and the range in differences when comparing PurpleAir's suggested correction to the UNCA data set is −5.1 °C to 9.9 °C. As with temperature and RH, the suggested PurpleAir corrections reduce the magnitude of DP bias and RMSE but not to the extent seen by applying the simple linear regression correction.

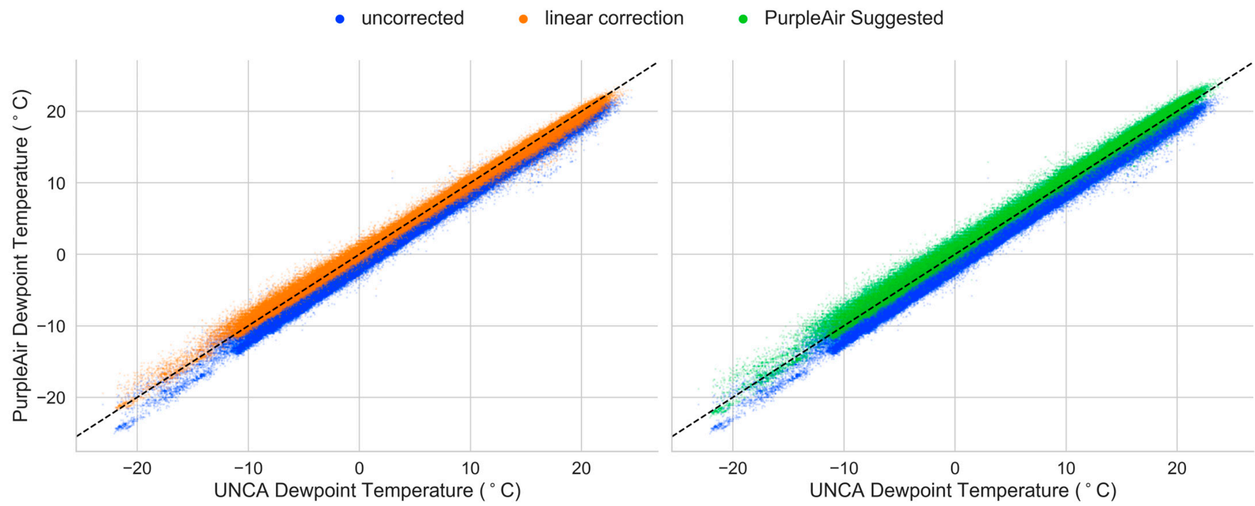


**Figure 4.** Comparisons of the time-paired 5-min PA-II and UNCA DP values. In both plots, the blue markers show the uncorrected data. Orange markers in the left-hand plot show the PA-II data after applying a simple linear regression correction, and the green markers in the right-hand plot show the PA-II data after applying PurpleAir's suggested correction. The dotted line drawn across each plot is the 1:1 line.

We then separated the DP data into bins (using UNCA DP as the reference) that roughly correspond to physical comfort levels. The results, compiled in Table 4, provide limited evidence for temperature dependence. As DP rises, the uncorrected bias becomes more negative with the lowest bias (−2.6 °C) observed when the DP is above 24 °C. This occurred rarely (n = 3), so care should be taken when considering this result. Temperature dependence is also observed with both corrected sets of DP values. However, the signs of the biases for the two corrected data sets are different. The low bias from the simple linear regression correction means that the actual DP is greater than would be expected for the higher DP bins, while the high bias from PurpleAir's suggested corrections means that the actual DP is lower than would be expected.

**Table 4.** Comparison of calculated PA-II and UNCA DP values.

| Correction Type | DP Bin (°C) | Mean Bias (°C) | RMSE (°C) | r | Slope | Intercept | n |
|---|---|---|---|---|---|---|---|
| uncorrected | All | −1.6 | 1.7 | 0.99 | 1.00 | −1.58 | 148,236 |
| | [−∞, 15] | −1.6 | 1.8 | 0.99 | 1.00 | −1.59 | 113,091 |
| | (15, 20] | −1.5 | 1.6 | 0.94 | 1.01 | −1.73 | 29,944 |
| | (20, 22] | −1.6 | 1.7 | 0.67 | 0.91 | 0.33 | 4813 |
| | (22, 24] | −1.9 | 2.0 | 0.43 | 0.68 | 5.26 | 385 |
| | (24, ∞] | −2.6 | 2.6 | 0.67 | 1.59 | −17.00 | 3 |
| simple linear regression correction | All | 0.1 | 0.6 | 0.99 | 0.98 | 0.27 | 148,236 |
| | [−∞, 15] | 0.2 | 0.7 | 0.99 | 0.97 | 0.27 | 113,091 |
| | (15, 20] | −0.1 | 0.6 | 0.93 | 0.98 | 0.23 | 29,944 |
| | (20, 22] | −0.3 | 0.7 | 0.60 | 0.83 | 3.16 | 4813 |
| | (22, 24] | −0.7 | 1.0 | 0.40 | 0.65 | 7.06 | 385 |
| | (24, ∞] | −1.5 | 1.6 | 0.73 | 1.48 | −13.22 | 3 |
| PurpleAir suggested correction | All | 0.6 | 0.9 | 0.99 | 1.00 | 0.64 | 148,236 |
| | [−∞, 15] | 0.6 | 1.0 | 0.99 | 1.00 | 0.63 | 113,091 |
| | (15, 20] | 0.7 | 0.8 | 0.94 | 1.01 | 0.49 | 29,944 |
| | (20, 22] | 0.6 | 0.8 | 0.67 | 0.91 | 2.55 | 4813 |
| | (22, 24] | 0.3 | 0.7 | 0.43 | 0.68 | 7.49 | 385 |
| | (24, ∞] | −0.4 | 0.5 | 0.67 | 1.59 | −14.78 | 3 |

## 4. Conclusions

While the qualitative results of our research were known previously (high temperature bias and low RH bias), this is the first *systematic* investigation of the sensor's bias in the scientific literature. Our study adds a missing piece to the literature in several ways. First, we conducted a long-term systematic investigation of the PurpleAir PA-II sensor's meteorological measurements spanning over 550 days across a variety of environmental conditions. Our results show that the PurpleAir PA-II has a persistent high temperature bias and low RH bias when compared to research-grade meteorological instrumentation. We quantified the correlation, bias, and RMSE between the low-cost sensor and reference measurements for several temperature and RH ranges and found that the biases persist across a wide range of values.

We used a simple linear regression model to calculate correction factors for temperature and RH and compared these to the corrections suggested by PurpleAir. Importantly, we found that PurpleAir's suggested corrections perform substantially worse than our corrections. Their suggested −4.4 °C adjustment over corrects temperature readings and introduces a low bias. Meanwhile, their suggested +4% adjustment to RH is not nearly enough to correct the negative bias. For all variables, we find that our linear regression corrections reduce error compared to the suggested PurpleAir corrections.

Finally, we extended our analysis to dew point calculations. Including corrections for this parameter enhances the usefulness of the PurpleAir PA-II sensor. Reliable correction factors for the sensor's meteorological measurements, provided here for the first time, coupled with reliable correction factors for the sensor's fine particulate matter measurements (provided elsewhere in literature) will allow researchers to investigate the synergistic health effects of exposure to extreme heat and particulate matter.

Other long-term studies of the meteorological capabilities of the PA-II in different climates will strengthen the scientific community's understanding of the sensor's bias and provide more confidence in its measurements. Future studies should also attempt to evaluate multiple PA-II sensors to validate our results. The PA-II sensor's well-documented ability to provide reliable $PM_{2.5}$ data has made it popular among the research, citizen-science, and emergency planning communities. As these sensors become more common for routine air quality monitoring applications, the temperature and RH measurements can also provide valuable information to an increasingly warming and urbanized world.

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**Conflicts of Interest:** The authors declare no conflicts of interest. The author affiliated with the company Sonoma Technology, Inc. declares that there is no conflict of interest associated with the content of this work.

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