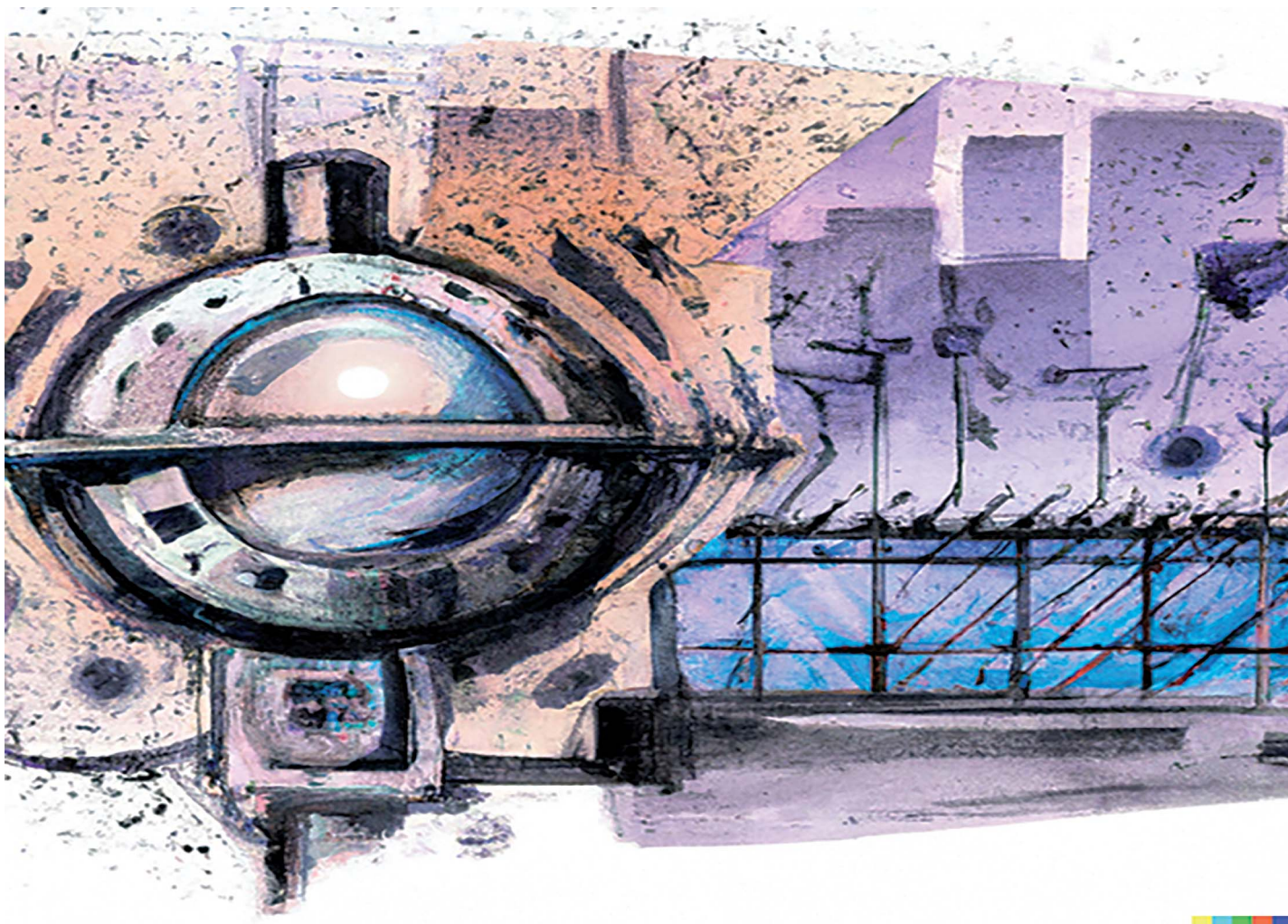


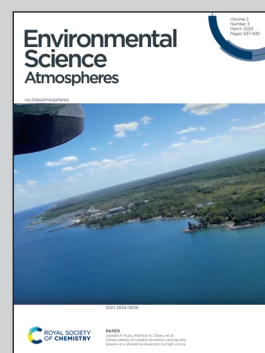


Showcasing research from Professor Priyanka deSouza's group, Department of Urban and Regional Planning, University of Colorado Denver.

An analysis of degradation in low-cost particulate matter sensors

Low-cost air quality sensors are widely used to fill in data gaps. However, little is known about the performance of these sensors over time. We evaluate degradation patterns across a network of widely-used low-cost particulate matter sensors, the PurpleAir. Overall, we find that 4% of measurements from PurpleAir sensors are degraded after 4 years of operation. Rates of degradation vary by climate zone. We also identify permanently degraded PurpleAir sensors that should be removed from operation. Our work provides a framework to quantify degradation in other low-cost air quality sensors.

As featured in:



See Priyanka deSouza *et al.*, *Environ. Sci.: Atmos.*, 2023, **3**, 521.

PAPER

View Article Online
View Journal | View Issue



Cite this: *Environ. Sci.: Atmos.*, 2023, 3, 521

An analysis of degradation in low-cost particulate matter sensors†

Priyanka deSouza,^a *^{ab} Karoline Barkjohn,^c Andrea Clements,^c Jenny Lee,^d Ralph Kahn,^e Ben Crawford^f and Patrick Kinney^g

Low-cost sensors (LCSs) are increasingly being used to measure fine particulate matter (PM_{2.5}) concentrations in cities around the world. One of the most commonly deployed LCSs is PurpleAir with ~15 000 sensors deployed in the United States, alone. PurpleAir measurements are widely used by the public to evaluate PM_{2.5} levels in their neighborhoods. PurpleAir measurements are also increasingly being integrated into models by researchers to develop large-scale estimates of PM_{2.5}. However, the change in sensor performance over time has not been well studied. It is important to understand the lifespan of these sensors to determine when they should be serviced or replaced, and when measurements from these devices should or should not be used for various applications. This paper fills this gap by leveraging the fact that: (1) each PurpleAir sensor is composed of two identical sensors and the divergence between their measurements can be observed, and (2) there are numerous PurpleAir sensors within 50 meters of regulatory monitors allowing for the comparison of measurements between these instruments. We propose empirically-derived degradation outcomes for the PurpleAir sensors and evaluate how these outcomes change over time. On average, we find that the number of 'flagged' measurements, where the two sensors within each PurpleAir sensor disagree, increases with time to ~4% after 4 years of operation. Approximately, 2 percent of all PurpleAir sensors were permanently degraded. The largest fraction of permanently degraded PurpleAir sensors appeared to be in the hot and humid climate zone, suggesting that sensors in these locations may need to be replaced more frequently. We also find that the bias of PurpleAir sensors, or the difference between corrected PM_{2.5} levels and the corresponding reference measurements, changed over time by $-0.12 \mu\text{g m}^{-3}$ (95% CI: $-0.13 \mu\text{g m}^{-3}$, $-0.10 \mu\text{g m}^{-3}$) per year. The average bias increases dramatically after 3.5 years. Further, climate zone is a significant modifier of the association between degradation outcomes and time.

Received 27th October 2022
Accepted 29th January 2023

DOI: 10.1039/d2ea00142j

rsc.li/esatmospheres

Environmental significance

Low-cost air quality sensors are widely used to fill in air quality monitoring gaps. However, little is known about the performance of these sensors over time. We evaluate degradation patterns across a network of widely-used low-cost particulate matter sensors, the PurpleAir. Overall, we find that 4% of measurements from PurpleAir sensors are degraded after 4 years of operation. Rates of degradation vary by climate zone. We also identify permanently degraded PurpleAir sensors that should be removed from operation. Our work provides a framework to quantify degradation in other low-cost air quality sensors.

1 Introduction

Poor air quality is currently the single largest environmental risk factor to human health in the world,^{1–5} with ambient air pollution responsible for 6.7 million premature deaths every year.⁶ Accurate air quality data are crucial for tracking long-term trends in air quality levels, and for the development of effective pollution management plans. Levels of fine particulate matter (PM_{2.5}), a criteria pollutant that poses more danger to human health than other widespread pollutants,⁷ can vary over distances as small as ~10's of meters in complex urban environments.^{8–12} Therefore, dense monitoring networks are often needed to capture relevant spatial variations. U.S EPA air

^aDepartment of Urban and Regional Planning, University of Colorado Denver, Denver, CO, 80202, USA. E-mail: priyanka.desouza@ucdenver.edu

^bCU Population Center, University of Colorado Boulder, Boulder, CO, 80302, USA

^cOffice of Research and Development, US Environmental Protection Agency, 109 T.W. Alexander Drive, Research Triangle Park, NC, 27711, USA

^dDepartment of Biostatistics, Harvard T.H. Chan School of Public Health, Boston, MA, 02115, USA

^eNASA Goddard Space Flight Center, Greenbelt, MD, 20771, USA

^fDepartment of Geography and Environmental Sciences, University of Colorado Denver, 80202, USA

^gBoston University School of Public Health, Boston, MA, 02118, USA

† Electronic supplementary information (ESI) available. See DOI: <https://doi.org/10.1039/d2ea00142j>



(3) Several studies have evaluated the short-term performance of the PurpleAir sensors at many different locations, under a variety of conditions around the world.^{31,32} However, none of these studies has evaluated the performance of the PurpleAir sensors over time. We aim to fill this gap.

For this study, data from 14 927 PurpleAir sensors operating in the United States (excluding US territories) between 1 January 2017 to 20 July 2021 were downloaded from the API at 15-minute time resolution. A small number of PurpleAir sensors were operational before 2017. However, given that the number of PurpleAir sensors increased dramatically from 2017 onwards, we choose January 1 2017 as the start date of our analysis. Overall, 26.2% of dates had missing measurements, likely due to power outages or loss of WiFi that prevented the PurpleAir sensors from transmitting data. Of the sensors in our dataset, 2989 were missing channel B data, leaving us with 483 511 216 measurements from 11 938 sensors with both channel A and B data. We removed all records with missing $\text{PM}_{2.5}$ measurements in cf_1 channels A and B ($\sim 0.9\%$ of the data). We then removed all records with missing T and RH data ($\sim 2.6\%$ of all data). Of the non-missing records, all measurements where $\text{PM}_{2.5}$ in cf_1 channels A and B were both $>1500 \mu\text{g m}^{-3}$ were removed, as they correspond to conditions beyond the operating range of the PurpleAir sensor.²⁵ We also removed measurements where T was $\leq -50 \text{ }^{\circ}\text{C}$ or $\geq 100 \text{ }^{\circ}\text{C}$, or where RH was $>99\%$, as these

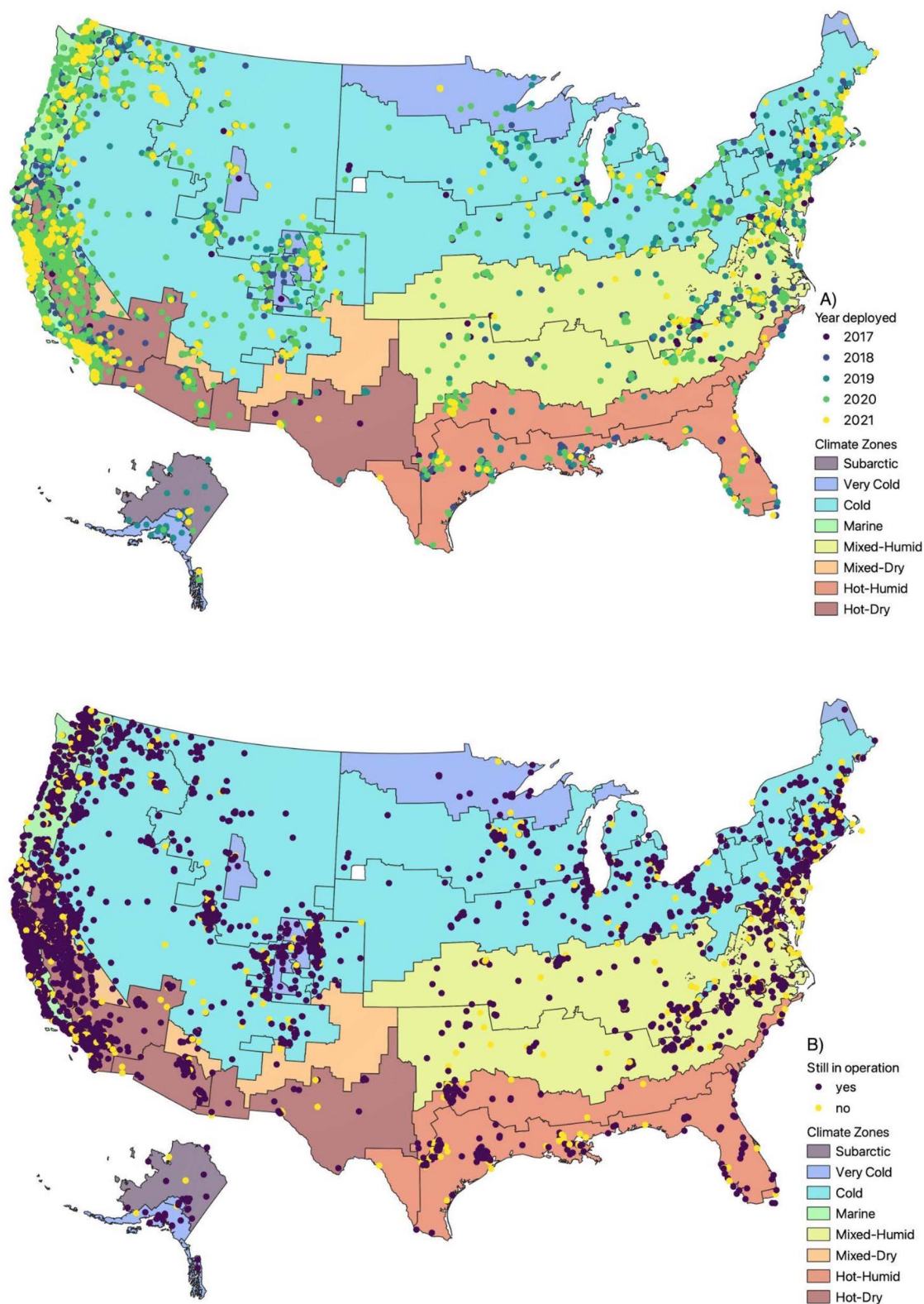
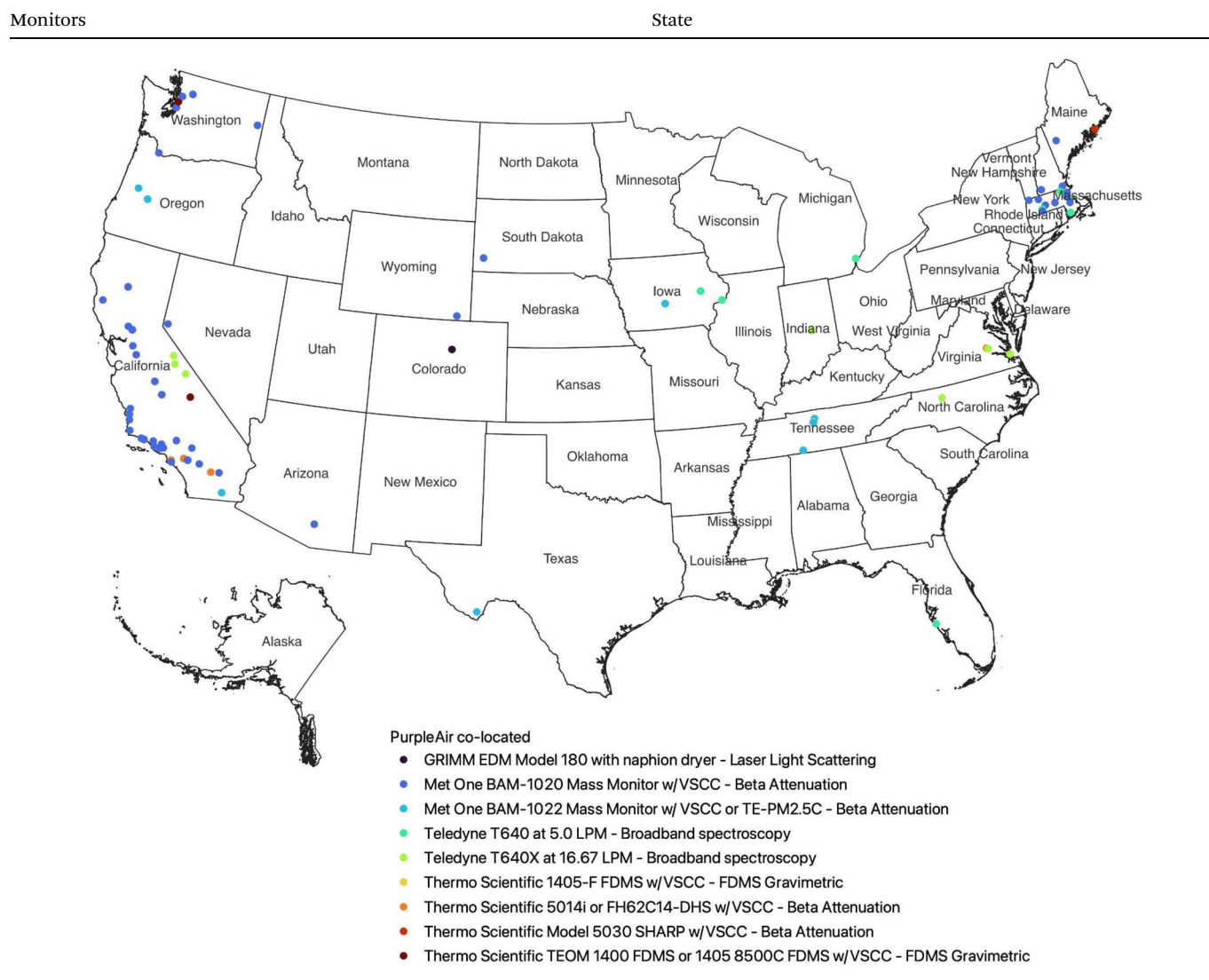


Fig. 1 The distribution of PurpleAir sensors considered in this analysis (Hawaii is not displayed) depicting (A) the year each sensor was deployed, and (B) if the sensor was removed before 20 July 2021. Climate zones displayed are from the International Energy Conservation Code (IECC) climate zones (<https://codes.iccsafe.org/content/IECC2021P1/chapter-3-ce-general-requirements>, last accessed August 31, 2022).



© 2023 The Author(s). Published by the Royal Society of Chemistry

Table 1 Location and type of the 88 reference PM_{2.5} monitors within 50 meters of a PurpleAir sensor included in the current work. The number of merged PurpleAir and EPA measurements in each category is also listed



48 of the monitors in our sample were Met One BAM-1020 Mass Monitor w/VSCC - Beta Attenuation (1 002 533 merged measurements)

9 were Met One BAM-1022 Mass Monitor w/VSCC or TE-PM2.5C - Beta Attenuation (218 084 merged measurements)

10 were Teledyne T640 at 5.0 LPM - broadband spectroscopy (97 706 merged measurements)

8 were Teledyne T640X at 16.67 LPM - broadband spectroscopy (88 040 merged measurements)

6 were Thermo Scientific 5014i or FH62C14-DHS w/VSCC - Beta Attenuation (52 116 merged measurements)

3 were Thermo Scientific TEOM 1400 FDMS or 1405 8500C FDMS w/VSCC - FDMS Gravimetric (21 591 merged measurements)

2 were Thermo Scientific 1405-F FDMS w/VSCC - FDMS Gravimetric (15 872 merged measurements)

1 was GRIMM EDM Model 180 with Nafion dryer - Laser Light Scattering (1000 merged measurements)

33 reference monitors were in California (866 197 merged measurements)

16 in Massachusetts (26 930 merged measurements)

9 in Washington (102 382 merged measurements)

5 in Tennessee (88 505 merged measurements)

4 in Virginia (33 353 merged measurements)

4 in Iowa (199 138 merged measurements)

2 in Maine (8575 merged measurements)

2 in Oregon (33 554 merged measurements)



Table 1 (Contd.)

Monitors	State
1 Was a Thermo Scientific Model 5030 SHARP w/VSCC – Beta Attenuation monitor (3199 merged measurements)	2 in Indiana (26 499 merged measurements) 2 in Michigan (13 678 merged measurements) 1 each in Arizona (6045 merged measurements), Colorado (1000 merged measurements), Florida (15 434 merged measurements), Nevada (17 146 merged measurements), New Hampshire (30 591 merged measurements), North Carolina (27 253 merged measurements), South Dakota (1879 merged measurements), Texas (364 merged measurements), Wyoming (1618 merged measurements)

sensor as permanently degraded if more than 40% of the current and subsequent hourly averages were flagged and the sensor operated for at least 100 hours after the current hour (Fig. 4; Fig. S4†). In sensitivity analyses, we evaluated the number of PurpleAir sensors that would be considered 'degraded' for different thresholds (Fig. S5†). We also examined where such sensors were deployed.

A limitation of using the percentage of flagged measurements as a degradation metric is that it does not account for the possibility that channels A and B might both degrade in a similar manner. Therefore, we rely on a second approach, using collocated reference monitoring measurements, to evaluate this aspect of possible degradation.

2.4.2 Method 2: evaluating the time-dependence of the error between corrected PurpleAir and reference measurements. PurpleAir data are often corrected using an algorithm to predict, as accurately as possible, the 'true' $\text{PM}_{2.5}$ concentrations based on reported PurpleAir concentrations. At the collocated sites, the reference $\text{PM}_{2.5}$ measurements, which are considered the true $\text{PM}_{2.5}$ concentrations, are the dependent variable in the models. Flagged PurpleAir measurements were first removed in the merged dataset (~2.5% of all measurements: ~151 PurpleAir sensors) leaving 1 463 156 measurements (Table S2†). We then used the following eqn (1), as proposed in Barkjohn *et al.* (2021),³³ to correct the PurpleAir sensors with the corresponding reference measurement:

$$\text{PM}_{2.5, \text{ reference}} = \text{PM}_{2.5} \times s_1 + \text{RH} \times s_2 + b + \varepsilon \quad (1)$$

Here, $\text{PM}_{2.5, \text{ reference}}$ is the reference monitor measurement; $\text{PM}_{2.5}$ is the PurpleAir measurement calculated by averaging concentrations reported by channels A and B; RH is the relative humidity reported by the PurpleAir sensor. We empirically derived coefficients: s_1 , s_2 , and b by regressing uncorrected PurpleAir $\text{PM}_{2.5}$ measurements on reference measurements of $\text{PM}_{2.5}$. ε denotes error from a standard normal distribution. We evaluated one correction model for all PurpleAir sensors in our dataset in a similar manner to Barkjohn *et al.* (2021). We evaluated and plotted the correction error, which is defined as the difference between the corrected measurement and the corresponding reference $\text{PM}_{2.5}$ measurement in $\mu\text{g m}^{-3}$. In supplementary analyses, we repeat this process using nine additional correction functions ranging from simple linear regressions to

more complex machine learning algorithms, some of which additionally correct for T and D , in addition to RH (Table S3†), to evaluate the sensitivity of our results to the correction model used. A key concern is that some part of the correction error observed might not be due to degradation but to inadequate correction of RH or other environmental parameters. We plot correction error *versus* RH to visually assess if such a dependence exists. Some of the supplementary correction models used to rely on non-linear corrections for RH. Research has shown that a non-linear correction equation might be more suitable to correct for PurpleAir measurements above $\sim 500 \mu\text{g m}^{-3}$ of $\text{PM}_{2.5}$ levels.³⁷ The machine learning models that we used in the supplement can identify such patterns using statistical learning. A full description of these additional models can be found in deSouza *et al.* (2022).²⁵

2.5 Evaluating associations between the degradation outcomes and time

We evaluated the association between the degradation outcomes under consideration on time of operation using a simple linear regression (Fig. 5):

$$\text{Degradation outcome} = f + d \times \text{hour of operation} + \varepsilon \quad (2)$$

where f denotes a constant intercept; d denotes the association between operational time (number of hours since each sensor was deployed) and the degradation outcome as the percentage of (cumulative) flagged measurements over all PurpleAir sensors at a given operational time; and ε denotes error from a standard normal distribution.

For the degradation outcomes under consideration, we evaluated whether the associations were different in subgroups stratified by IECC Climate Zones that represent different T and RH conditions (Table S2† contains information on the number of PurpleAir measurements and reported $\text{PM}_{2.5}$ concentrations by climate zone.) When evaluating the impact of climate zone on the percentage of flagged measurements, we examined the impact on outside devices alone, as indoor environments may not always reflect outside conditions due to heating, cooling, general sheltering, *etc.* Note that when joining climate zones with the complete dataset of PurpleAir IDs, there were a handful of sensors which did not fall within a climate zone. (This was



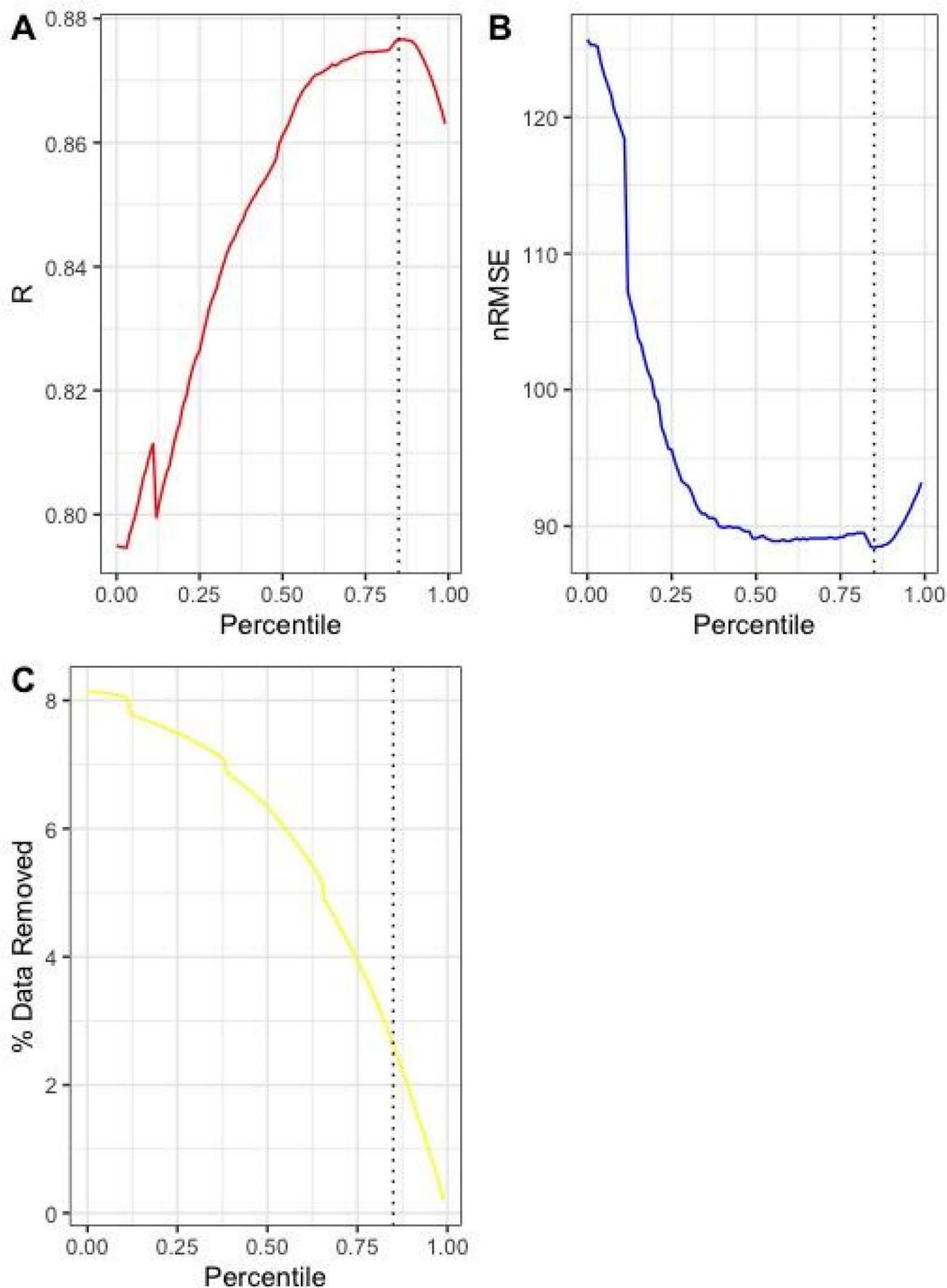


Fig. 2 : Agreement between the hourly PurpleAir measurements and the corresponding reference measurements, where measurements are flagged and removed based on the criterion: $|\text{channel A} - \text{channel B}| > 5 \mu\text{g m}^{-3}$ and the % difference between channels A and B: $\frac{\text{abs}(A - B) \times 2}{(A + B)} > x\text{th percentile of the percentage difference between A and B for each PurpleAir sensor}$, where we vary x between 0–0.99, captured by: (A) Pearson correlation coefficient (R), and (B) normalized root mean square error (nRMSE) metrics comparing unflagged measurements and the corresponding reference data based on different threshold percentile values. (C) The % of measurements that were removed (because they were flagged) when evaluating R and nRMSE, for different percentile thresholds applied to the data are also displayed. The dotted vertical line represents the 85th percentile which corresponds to the lowest nRMSE and the highest R .



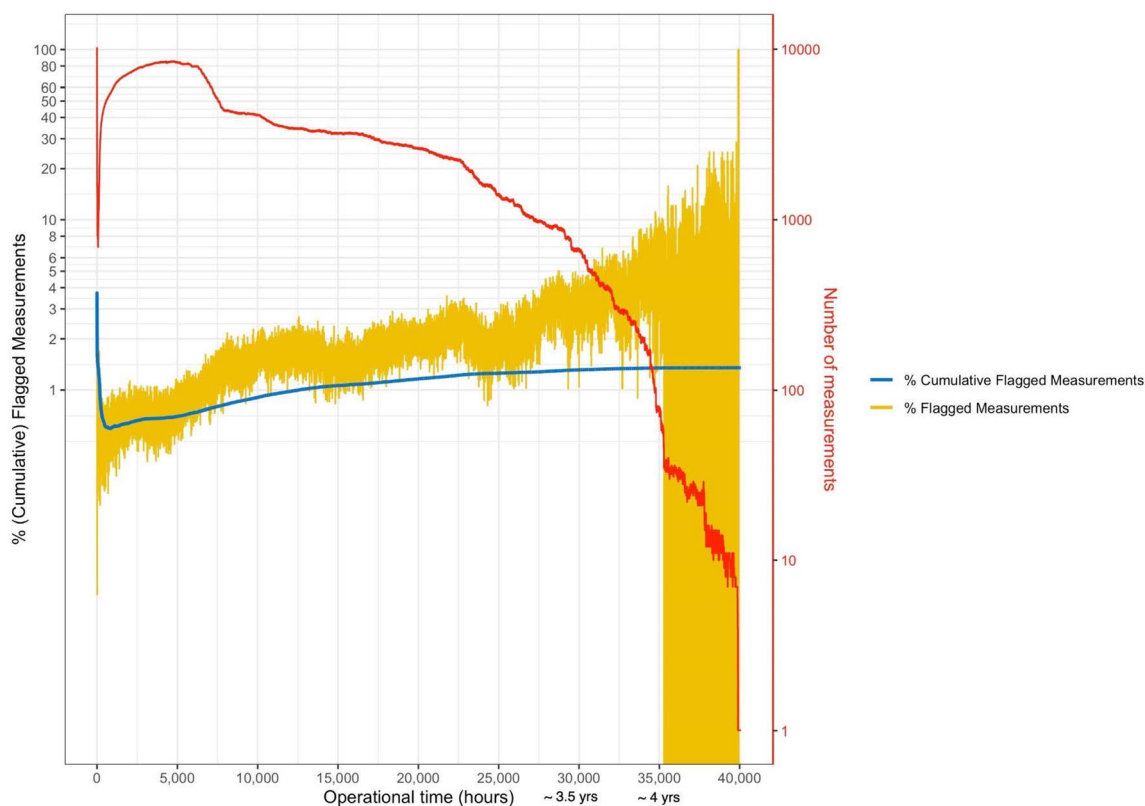
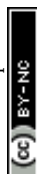


Fig. 3 Percentage of flagged PurpleAir measurements (yellow) and percentage of cumulative flagged (blue) measurements at a given operational time (time since each sensor started operation in hours) as well as the number of measurements recorded (red) plotted on the secondary y-axis on the right over all the PurpleAir sensors considered in this analysis.

Table 2 PM_{2.5}, temperature, and RH values, and months corresponding to flagged and unflagged measurements

	Unflagged data ($n = 112\,716\,535$, 99%)	Flagged data ($n = 1\,543\,405$, 1%)
Raw mean PM _{2.5} (mean of channel a and channel B) ($\mu\text{g m}^{-3}$)	Min/max: 0/1459 Mean: 10 Median: 5 1st Quartile: 2 3rd Quartile: 11	Min/max: 2.5/1339 Mean: 26 Median: 14 1st Quartile: 7 3rd Quartile: 27
RH (%)	Min/max: 0/99 Mean: 46 Median: 48 1st Quartile: 34 3rd Quartile: 59	Min/max: 0/99 Mean: 43 Median: 44 1st Quartile: 30 3rd Quartile: 57
Temperature ($^{\circ}\text{C}$)	Min/max: -42/68 Mean: 18 Median: 18 1st Quartile: 11 3rd Quartile: 24	Min/max: -46/89 Mean: 19 Median: 19 1st Quartile: 13 3rd Quartile: 26
Month	Jan: 10 233 928 (98.5%) Feb: 9 650 954 (98.4%) March: 10 979 861 (98.7%) April: 10 989 824 (98.9%) May: 11 671 186 (98.8%) June: 11 674 808 (98.6%) July: 9 555 217 (98.6%) Aug: 5 246 854 (98.7%) Sep: 6 248 360 (98.6%) Oct: 8 025 096 (98.8%) Nov: 8 759 251 (98.6%) Dec: 9 681 196 (98.5%)	Jan: 157 728 (1.5%) Feb: 156 615 (1.6%) March: 141 003 (1.3%) April: 125 060 (1.1%) May: 143 421 (1.2%) June: 160 317 (1.4%) July: 140 255 (1.4%) Aug: 67 196 (1.3%) Sep: 86 200 (1.4%) Oct: 99 753 (1.2%) Nov: 120 721 (1.4%) Dec: 145 136 (1.5%)



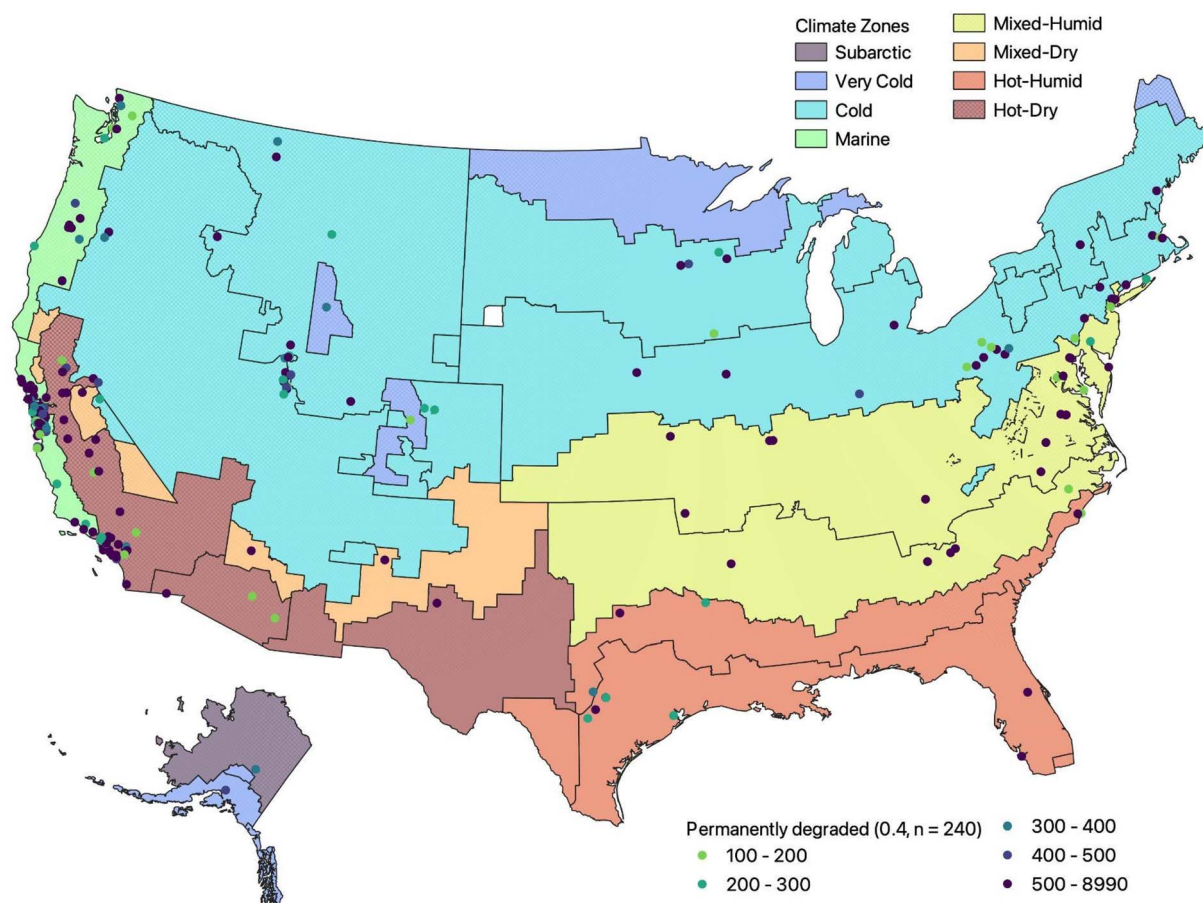


Fig. 4 Map of permanently degraded PurpleAir sensors with at least 100 measurements for which the cumulative mean of the flagged indicator ≥ 0.4 . The number of hours of operation for which the cumulative mean of the flag indicator is ≥ 0.4 is indicated by point color.

not the case for our subset of collocated PurpleAir sensors.) We removed data corresponding to these sensors when evaluating climate zone-specific associations, corresponding to 2.9% of all data records Fig. S2 in the ESI† shows where these sensors were located.

We also tested whether the cumulative number of $\text{PM}_{2.5}$ measurements recorded over 50, 100, and 500 $\mu\text{g m}^{-3}$ by individual PurpleAir sensors significantly modifies the association between operational time and the correction error, as previous work has found that low-cost optical PM sensors can degrade after exposure to high PM concentrations.²⁸ As the correction error will be larger at higher $\text{PM}_{2.5}$ concentrations,^{25,38} we also evaluated this association after normalizing the correction error by $(\text{PM}_{2.5,\text{corrected}} + \text{PM}_{2.5,\text{reference}})/2$ to make it easier to interpret how cumulative exposure to high $\text{PM}_{2.5}$ measurements can affect the association between degradation and hour of operation.

The merged PurpleAir and reference measurements dataset only included measurements from outdoor PurpleAir sensors. We also evaluated the indoor/outdoor-specific associations between the percentage of flagged measurements and hours of operation.

Finally, we tested for potential non-linearities between the degradation outcomes under consideration and the time of

operation. Penalized splines (p-splines) were used to flexibly model the associations between the error and time of operation using a generalized additive model [GAM; degradation outcome $\sim s(\text{hour})$]. We used a generalized cross-validation (GCV) criterion to select the optimal number of degrees of freedom (df) and plotted the relationships observed. Ninety-five percent confidence intervals (CIs) were evaluated by m-out-n bootstrap, which creates non-parametric CIs by randomly resampling the data. Briefly, we selected a bootstrapped sample of monitors, performed the correction, and then fit GAMs in each bootstrap sample using sensor ID clusters (100 replicates; Fig. 6).

All analyses were conducted using the software R. In all analyses, p -values < 0.05 were taken to represent statistical significance.

3 Results

3.1 Defining a 'flagged' PurpleAir measurement

Fig. 2a and b display agreement between the unflagged hourly PurpleAir measurements and the corresponding regulatory measurements using the R and nRMSE metrics, for different percentile thresholds to define a 'flag'. The lowest nRMSE and highest R were observed for the following definition of a flagged PurpleAir measurement: the absolute difference between $\text{PM}_{2.5}$



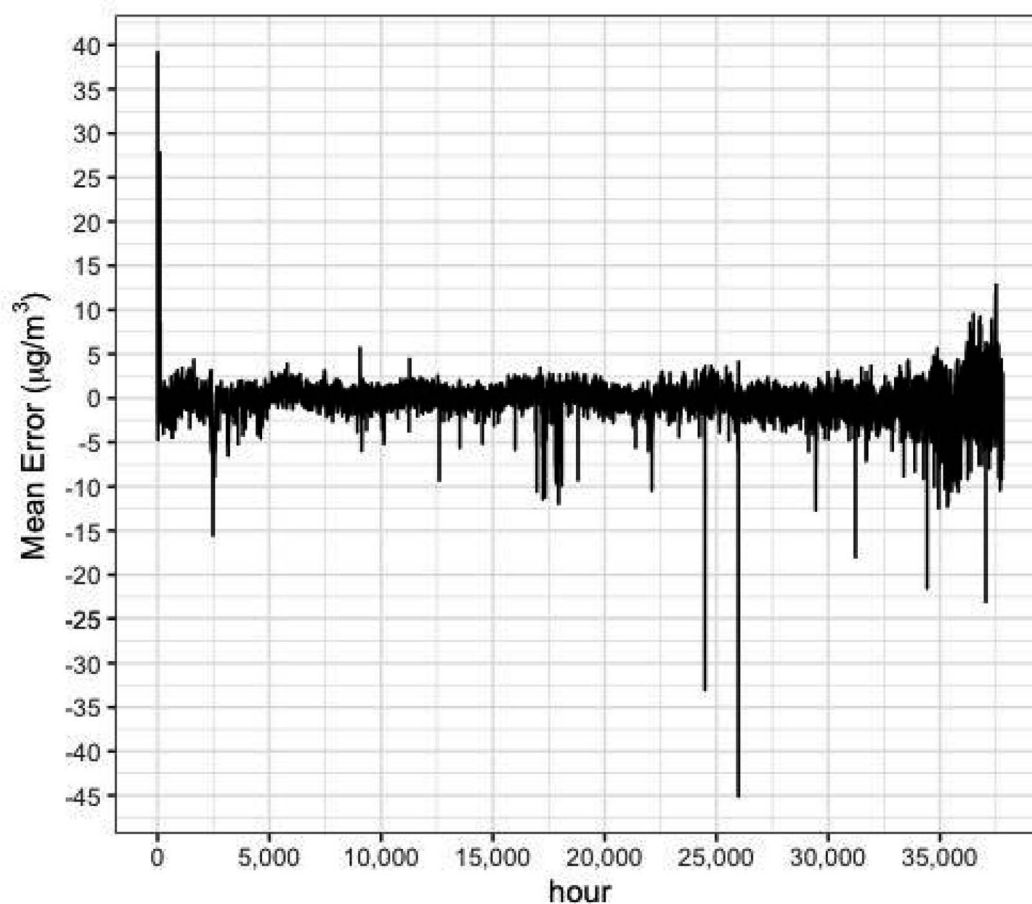


Fig. 5 Mean error ($\mu\text{g m}^{-3}$) calculated as the difference between the corrected $\text{PM}_{2.5}$ measurements from the PurpleAir sensors and the corresponding reference $\text{PM}_{2.5}$ measurements across all sensors as a function of hour of operation.

from channels A and B $> 5 \mu\text{g m}^{-3}$ and the % difference between channels A and B: $\frac{\text{abs}(A - B) \times 2}{(A + B)} > 85\text{th percentile of the percentage difference between channels A and B for each PurpleAir sensor}$. The 85th percentile of the percentage difference between channels A and B of each PurpleAir varies, with a mean of 38%. This definition resulted in about $\sim 2\%$ of the PurpleAir data being flagged (Fig. 2c).

When we repeated this analysis excluding measurements from reference monitors that relied on light scattering techniques, using the 86th percentile yielded marginally better results (the metrics differed by $< 1\%$) than using the 85th percentile (Fig. S3 in the ESI†). Given the small difference in results, the 85th percentile is used as the threshold in this study to define a flagged PurpleAir measurement.

3.2 Visualizing the degradation outcomes: percentage of flagged measurements over time

Using the empirically derived definition of flagged measurements, the percentage of flagged measurements, as well as the percentage of cumulative flagged measurements across the 11 932 PurpleAir sensors for every hour of operation, is plotted in Fig. 3. The total number of measurements made at every hour of

operation is also displayed using the right axis. The percentage of flagged measurements increases over time. At 4 years ($\sim 35\,000$ hours) of operation, the percentage of flagged measurements every hour is $\sim 4\%$. After 4 years of operation, we observe a steep increase in the average percentage of flagged measurements, likely due at least in part to the small number of PurpleAir sensors operational for such long periods of time in our dataset. Note that as we rely on a crowd-sourced dataset of PurpleAir measurements, we do not have information on why users removed sensors from operation. Users might have removed PurpleAir sensors that displayed indications of degradation. The removal of such sensors would bias our results, leading to us reporting lower degradation rates than appropriate. We also observe a high percentage of flagged measurements during the first 20 hours of the operation of all sensors.

Using t -tests, we find that the mean of $\text{PM}_{2.5}$, T , and RH measurements were statistically different ($p < 0.05$) for flagged PurpleAir measurements compared to unflagged measurements (Table 2). $\text{PM}_{2.5}$ and T measurements recorded when a measurement was flagged were higher than for unflagged measurements, whereas RH tended to be lower. The differences between RH and T values for flagged *versus* non-flagged measurements are small. The difference in $\text{PM}_{2.5}$ distribution



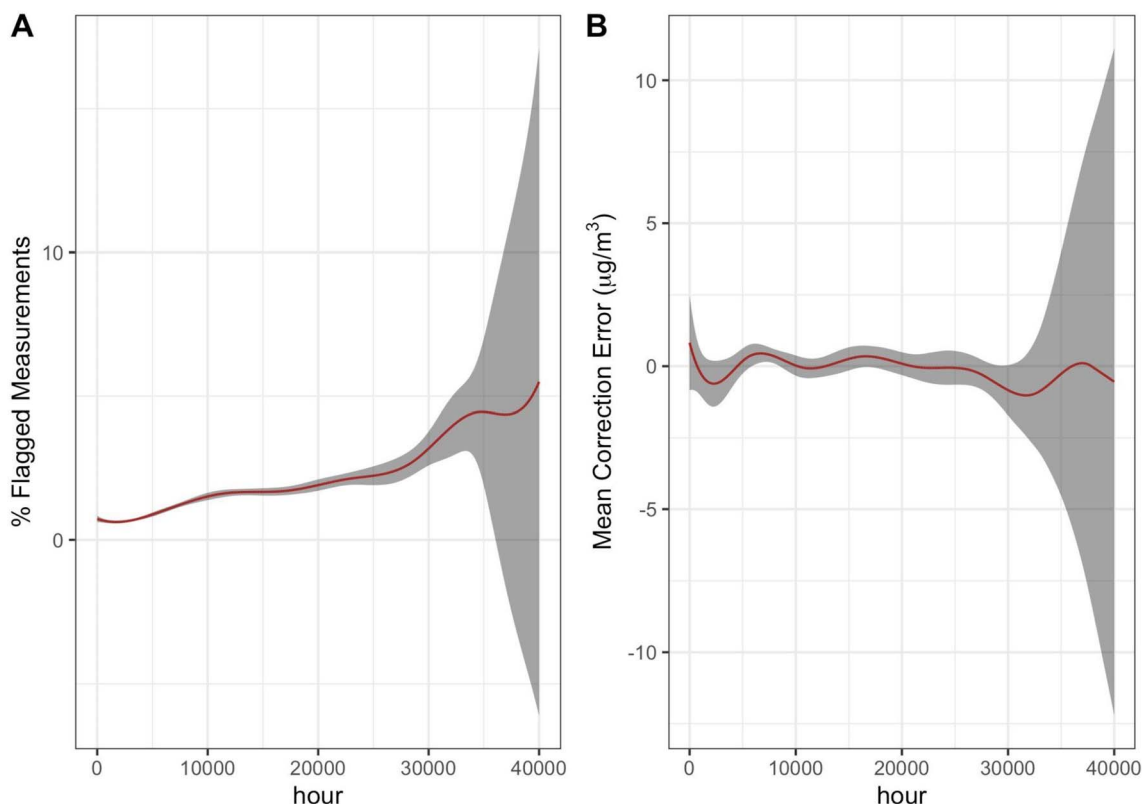


Fig. 6 Response plot and 95% confidence intervals (shaded region) for the association between the degradation outcomes of (A) percentage (%) of flagged measurements and (B) correction error with respect to operational time in hours generated using GAMs.

was due in part to the way flags have been defined. As data are flagged only if concentrations differ by at least $5 \mu\text{g m}^{-3}$ different, the minimum average flagged concentration is $2.5 \mu\text{g m}^{-3}$ (e.g., $A = 0$, $B = 5$). There are no notable differences between the percentage of flagged measurements made every month.

We next evaluated the number of PurpleAir measurements that were permanently degraded, or that had a cumulative mean of flags over subsequent hours of operation ≥ 0.4 for at least 100 hours of operation (i.e., at least 40% of measurements flagged) (Fig. 4). Table 3 displays the fraction of permanently degraded sensors in different climate zones and different locations (inside/outside). It appears that the largest fraction of degraded sensors occurred in the south-east United States, a hot and humid climate. Fig. S4† displays the cumulative mean of flag for each 'permanently degraded' sensor (the title of each plot corresponds to the sensor ID as provided on the PurpleAir website) at each instance of time. Fig. S4† also depicts the starting year of each permanently degraded sensor. The sensor age varied widely over the set of permanently degraded sensors, indicating that permanent degradation is not dictated by time dependence.

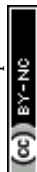
Note that from Fig. S4† some of the 240 sensors identified appear to recover or behave normally after a long interval (>100 hours) of degradation (cumulative mean of flag decreases). This could be an artifact of the way the cumulative mean of the flagged indicator is calculated. If the final few measurements of the sensor are not flagged, then the cumulative mean for the

final hours of operation of the PurpleAir sensors might be low. It is also possible that some of the sensors could have been temporarily impacted by dust or insects. The owner of the PurpleAir sensors might have cleaned the instruments or replaced the internal Plantower sensors or cleaned out the sensors which could have caused the sensors to recover.

Fig. S5A and S5B† are maps showing locations of PurpleAir sensors that had a cumulative mean of 'flag' over subsequent

Table 3 Fraction of permanently degraded PurpleAir sensors in climate zones and locations

	Percentage of permanently degraded sensors
All	240 out of 11 932 (2.0%)
Device location	
Inside	2 out of 935 (0.21%)
Outside	238 out of 10 997 (2.2%)
Climate zone	
Cold	51 out of 2458 (2.1%)
Hot-dry	54 out of 2680 (2.0%)
Hot-humid	11 out of 281 (3.9%)
Marine	84 out of 4842 (1.7%)
Mixed-dry	3 out of 361 (0.8%)
Mixed-humid	24 out of 750 (3.2%)
Subarctic	1 out of 58 (1.7%)
Very cold	3 of 108 (2.8%)
No information	9 of 394 (2.3%)



hours of operation of ≥ 0.3 (number of sensors = 323) and 0.5 (number of sensors = 182), respectively, for at least 100 hours of operation.

3.3 Visualization of the error in the corrected PurpleAir $\text{PM}_{2.5}$ measurements over time

The correction derived using a regression analysis yielded the following function to derive corrected $\text{PM}_{2.5}$ concentrations from the raw PurpleAir data: $\text{PM}_{2.5,\text{corrected}} = 5.92 + 0.57\text{PM}_{2.5,\text{raw}} - 0.091\text{RH}$. After correction, the Pearson correlation coefficient (R) improved slightly, from 0.88 to 0.89, whereas the RMSE improved significantly, from 12.5 to 6.6 $\mu\text{g m}^{-3}$. The mean, median, and maximum errors observed were 3.3, 2.2, and 792.3 $\mu\text{g m}^{-3}$, respectively (Table S3†). Fig. 5 displays the mean correction error across all sensors for every hour in operation. The mean error past 35 000 hours (3 years) becomes larger, reaching $-0.45 \mu\text{g m}^{-3}$, compared to $-0.13 \mu\text{g m}^{-3}$ before. A plot of correction error *versus* RH did not reveal any associations between the two variables Fig. S6†. We note that similar time dependence of the correction errors was observed when using a wide array of correction models, including models that contain both RH and T as variables, as well as more complex machine learning models that yielded the best correction results (Random Forest: $R = 0.99$, $\text{RMSE} = 2.4 \mu\text{g m}^{-3}$) (Table S3†).

3.4 Associations between degradation outcomes and operational times

We assessed the association between degradation outcomes and operational time based on eqn (2). We observed that the percentage of flagged measurements increased on average by 0.93% (95% CI: 0.91%, 0.94%) for every year of operation of a PurpleAir sensor. Device location and climate zone were significant effect modifiers of the impact of time-of-operation on this degradation outcome. PurpleAir sensors located

outside had an increased percentage of flagged measurements every year corresponding to 1.06% (95% CI 1.05%, 1.08%), whereas those located inside saw the percentage of flagged measurements decrease over time. Outdoor PurpleAir sensors in hot-dry climates appeared to degrade the fastest with the percentage of flagged measurements increasing by 2.09% (95% CI 2.07%, 2.12%) every year in this climate zone (Table 3). Hot-dry places are dustier. Dust can degrade fan performance and accumulate in the air-flow path and optical components which would lead to potentially more disagreement between channels A and B of the PurpleAir sensors.

The correction error ($\text{PM}_{2.5,\text{corrected}} - \text{PM}_{2.5,\text{reference}}$) appeared to become negatively biased over time: -0.12 (95% CI -0.13 , -0.10) $\mu\text{g m}^{-3}$ per year of operation, except for sensors in hot and dry environments where the error was positively biased and increased over time by 0.08 (95% CI: 0.06, 0.09) $\mu\text{g m}^{-3}$ per year of operation. Wildfires often occur in hot-dry environments. Research has shown that the correction approach could over-correct the PurpleAir measurements at very high smoke concentrations, potentially explaining the disagreement between the corrected PurpleAir and reference measurements in these environments.³⁹ We note that mean $\text{PM}_{2.5}$ concentrations were highest in hot-dry environments (Table S2†). In addition, the number of $\text{PM}_{2.5}$ concentrations $>100 \mu\text{g m}^{-3}$ recorded was the highest in hot-dry environments. The magnitude of the correction error bias over time appears to be highest in hot and humid environments corresponding to -0.92 (95% CI -1.10 , -0.75) $\mu\text{g m}^{-3}$ per year. RH has an impact on PurpleAir performance and can also cause the electronic components inside the sensors to degrade quickly, so it is not altogether surprising that degradation appears to be highest in hot and humid environments. We observed similar results when regressing the correction errors derived using other correction model forms (Table S4†). Climate zone is a significant modifier of the association between both degradation outcomes and time (Table 4).

Table 4 Associations between the degradation outcomes (% of flagged measurements and correction error) and year of operation of the PurpleAir sensors. Note that we did not have any PurpleAir sensors collocated with a regulatory monitor in Sub Arctic and Cold Climates. In addition, all PurpleAir monitors collocated with regulatory monitors were outdoor^a

Dataset	Associations (95% confidence interval)	
	Percentage of flagged measurements	Correction error
All	0.93* (0.91, 0.94)	-0.12^* (-0.13 , -0.10)
Device location		
Inside	-0.10^* (-0.12 , -0.09)	—
Outside	1.06* (1.05, 1.08)	—
Climate zone (outside devices only)		
Cold	0.74* (0.71, 0.76)	-0.27^* (-0.29 , -0.25)
Hot-dry	2.09* (2.07, 2.12)	0.08* (0.06, 0.09)
Hot-humid	0.34* (0.32, 0.37)	-0.92^* (-1.10 , -0.75)
Marine	0.41* (0.39, 0.44)	-0.13^* (-0.15 , -0.10)
Mixed-dry	-0.05^* (-0.07 , -0.02)	-0.31^* (-0.40 , -0.21)
Mixed-humid	0.54* (0.51, 0.57)	-0.28^* (-0.33 , -0.23)
Sub arctic	-0.18^* (-0.22 , -0.14)	—
Very cold	0.13* (0.10, 0.16)	—

^a (* $p < 0.05$).



Environ. Sci.: Atmos., 2023, 3, 521-536 | 533

consequence to the operation of PurpleAir sensors. Climate zone was a significant effect modifier of the association between bias and time. The highest associations were observed in hot and humid regions corresponding to -0.92 (95% CI $-1.10, -0.75$) $\mu\text{g m}^{-3}$ per year. Exposure to a cumulative number of high $\text{PM}_{2.5}$ measurements did not significantly affect the association between the normalized correction error over time.

It is not altogether surprising that the correction error increases most rapidly in hot and humid climate zones, as past evidence suggests that the performance of PurpleAir is greatly impacted by RH. It is surprising that this is not the case for the other degradation outcomes considered in this study: % of flagged measurements. It is likely that the percentage of flagged measurements increases most rapidly over time in hot and dry environments because such environments tend to be dusty and dust can degrade fan performance and accumulate in the air flow path and optical components of the PurpleAir sensors which can lead to disagreement between the two Plantower sensors. We note that under conditions of wildfire smoke, also prevalent in hot and dry climates, the calibration error could also be magnified due to under-correction of the PurpleAir data. Future work is needed to evaluate the impact of wildfire-smoke on the performance of PurpleAir sensors.

When accounting for non-linearities in the relationship between the correction error and time, Fig. 6a indicates that the bias in the correction error is not linear with time; rather it increases significantly after 30 000 hours or 3.5 years. Overall, we found that more work is needed to evaluate degradation in PurpleAir sensors after 3.5 years of operation, due to a paucity of longer-running sensors in the database. Importantly, the degradation outcomes derived in this paper can be used to remove ‘degraded’ PurpleAir measurements in other analyses. We also show that concerns about degradation are more important in some climate zones than others, which may necessitate appropriate cleaning or other maintenance procedures for sensors in different locations.

Disclaimer

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

Conflicts of interest

There are no conflicts to declare.

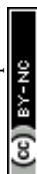
Acknowledgements

The authors are grateful to Mike Bergin and John Volckens for several useful discussions. Thanks to PurpleAir (<https://www2.purpleair.com/>) for providing publicly the data that made this paper possible.

References

- 1 P. deSouza, D. Braun, R. M. Parks, J. Schwartz, F. Dominici and M.-A. Kioumourtzoglou, Nationwide Study of Short-Term Exposure to Fine Particulate Matter and Cardiovascular Hospitalizations Among Medicaid Enrollees, *Epidemiology*, 2020, 32(1), 6–13, DOI: [10.1097/EDE.0000000000001265](https://doi.org/10.1097/EDE.0000000000001265).
- 2 P. N. deSouza, M. Hammer, P. Anthamatten, P. L. Kinney, R. Kim, S. V. Subramanian, M. L. Bell and K. M. Mwenda, Impact of Air Pollution on Stunting among Children in Africa, *Environ. Health*, 2022, 21(1), 128, DOI: [10.1186/s12940-022-00943-y](https://doi.org/10.1186/s12940-022-00943-y).
- 3 P. N. deSouza, S. Dey, K. M. Mwenda, R. Kim, S. V. Subramanian and P. L. Kinney, Robust Relationship between Ambient Air Pollution and Infant Mortality in India, *Sci. Total Environ.*, 2022, 815, 152755, DOI: [10.1016/j.scitotenv.2021.152755](https://doi.org/10.1016/j.scitotenv.2021.152755).
- 4 A. F. Boing, P. deSouza, A. C. Boing, R. Kim and S. V. Subramanian, Air Pollution, Socioeconomic Status, and Age-Specific Mortality Risk in the United States, *JAMA Netw. Open*, 2022, 5(5), e2213540, DOI: [10.1001/jamanetworkopen.2022.13540](https://doi.org/10.1001/jamanetworkopen.2022.13540).
- 5 P. deSouza, A. F. Boing, R. Kim and S. Subramanian, Associations between Ambient PM_{2.5} – Components and Age-Specific Mortality Risk in the United States, *Environ. Adv.*, 2022, 9, 100289, DOI: [10.1016/j.envadv.2022.100289](https://doi.org/10.1016/j.envadv.2022.100289).
- 6 H. E. Institute. *State of Global Air 2019*. Health Effects Institute Boston, MA, 2019.
- 7 K.-H. Kim, E. Kabir and S. Kabir, A Review on the Human Health Impact of Airborne Particulate Matter, *Environ. Int.*, 2015, 74, 136–143, DOI: [10.1016/j.envint.2014.10.005](https://doi.org/10.1016/j.envint.2014.10.005).
- 8 H. L. Brantley, G. S. W. Hagler, S. C. Herndon, P. Massoli, M. H. Bergin and A. G. Russell, Characterization of Spatial Air Pollution Patterns Near a Large Railyard Area in Atlanta, Georgia, *Int. J. Environ. Res. Public Health*, 2019, 16(4), 535, DOI: [10.3390/ijerph16040535](https://doi.org/10.3390/ijerph16040535).
- 9 P. deSouza, A. Anjomshoa, F. Duarte, R. Kahn, P. Kumar and C. Ratti, Air Quality Monitoring Using Mobile Low-Cost Sensors Mounted on Trash-Trucks: Methods Development and Lessons Learned, *Sustain. Cities Soc.*, 2020, 60, 102239, DOI: [10.1016/j.scs.2020.102239](https://doi.org/10.1016/j.scs.2020.102239).
- 10 P. deSouza, A. Wang, Y. Machida, T. Duhl, S. Mora, P. Kumar, R. Kahn, C. Ratti, J. L. Durant and N. Hudda, Evaluating the Performance of Low-Cost PM_{2.5} Sensors in Mobile Settings. *arXiv* January 10, 2023, preprint, 10.48550/arXiv.2301.03847.
- 11 P. deSouza, R. Lu, P. Kinney and S. Zheng, Exposures to Multiple Air Pollutants While Commuting: Evidence from Zhengzhou, China, *Atmos. Environ.*, 2020, 118168, DOI: [10.1016/j.atmosenv.2020.118168](https://doi.org/10.1016/j.atmosenv.2020.118168).
- 12 P. N. deSouza, P. A. Oriama, P. P. Pedersen, S. Horstmann, L. Gordillo-Dagallier, C. N. Christensen, C. O. Franck, R. Ayah, R. A. Kahn, J. M. Klopp, K. P. Messier and P. L. Kinney, Spatial Variation of Fine Particulate Matter Levels in Nairobi before and during the COVID-19 Curfew:

- Implications for Environmental Justice, *Environ. Res. Commun.*, 2021, 3(7), 071003, DOI: [10.1088/2515-7620/ac1214](https://doi.org/10.1088/2515-7620/ac1214).
- 13 P. deSouza and P. L. Kinney, On the Distribution of Low-Cost PM 2.5 Sensors in the US: Demographic and Air Quality Associations, *J. Exposure Sci. Environ. Epidemiol.*, 2021, 31(3), 514–524, DOI: [10.1038/s41370-021-00328-2](https://doi.org/10.1038/s41370-021-00328-2).
 - 14 G. Anderson and R. Peng, *Weathermetrics: Functions to Convert between Weather Metrics (R Package)*, 2012.
 - 15 R. Williams, V. Kilaru, E. Snyder, A. Kaufman, T. Dye, A. Rutter, A. Russel and H. Hafner, *Air Sensor Guidebook*, US Environmental Protection Agency, Washington, DC, EPA/600/R-14/159 NTIS PB2015-100610, 2014.
 - 16 N. Castell, F. R. Dauge, P. Schneider, M. Vogt, U. Lerner, B. Fishbain, D. Broday and A. Bartonova, Can Commercial Low-Cost Sensor Platforms Contribute to Air Quality Monitoring and Exposure Estimates?, *Environ. Int.*, 2017, 99, 293–302, DOI: [10.1016/j.envint.2016.12.007](https://doi.org/10.1016/j.envint.2016.12.007).
 - 17 P. Kumar, L. Morawska, C. Martani, G. Biskos, M. Neophytou, S. Di Sabatino, M. Bell, L. Norford and R. Britter, The Rise of Low-Cost Sensing for Managing Air Pollution in Cities, *Environ. Int.*, 2015, 75, 199–205, DOI: [10.1016/j.envint.2014.11.019](https://doi.org/10.1016/j.envint.2014.11.019).
 - 18 L. Morawska, P. K. Thai, X. Liu, A. Asumadu-Sakyi, G. Ayoko, A. Bartonova, A. Bedini, F. Chai, B. Christensen, M. Dunbabin, J. Gao, G. S. W. Hagler, R. Jayaratne, P. Kumar, A. K. H. Lau, P. K. K. Louie, M. Mazaheri, Z. Ning, N. Motta, B. Mullins, M. M. Rahman, Z. Ristovski, M. Shafiei, D. Tjondronegoro, D. Westerdahl and R. Williams, Applications of Low-Cost Sensing Technologies for Air Quality Monitoring and Exposure Assessment: How Far Have They Gone?, *Environ. Int.*, 2018, 116, 286–299, DOI: [10.1016/j.envint.2018.04.018](https://doi.org/10.1016/j.envint.2018.04.018).
 - 19 E. G. Snyder, T. H. Watkins, P. A. Solomon, E. D. Thoma, R. W. Williams, G. S. W. Hagler, D. Shelow, D. A. Hindin, V. J. Kilaru and P. W. Preuss, The Changing Paradigm of Air Pollution Monitoring, *Environ. Sci. Technol.*, 2013, 47(20), 11369–11377, DOI: [10.1021/es4022602](https://doi.org/10.1021/es4022602).
 - 20 P. N. deSouza, Key Concerns and Drivers of Low-Cost Air Quality Sensor Use, *Sustainability*, 2022, 14(1), 584, DOI: [10.3390/su14010584](https://doi.org/10.3390/su14010584).
 - 21 P. deSouza, V. Nthusi, J. M. Klopp, B. E. Shaw, W. O. Ho, J. Saffell, R. Jones and C. Ratti, A Nairobi Experiment in Using Low Cost Air Quality Monitors, *Clean Air J.*, 2017, 27(2), 12–42.
 - 22 T. Lu, M. J. Bechle, Y. Wan, A. A. Presto and S. Hankey, Using Crowd-Sourced Low-Cost Sensors in a Land Use Regression of PM_{2.5} in 6 US Cities, *Air Qual., Atmos. Health*, 2022, 15(4), 667–678, DOI: [10.1007/s11869-022-01162-7](https://doi.org/10.1007/s11869-022-01162-7).
 - 23 J. Bi, A. Wildani, H. H. Chang and Y. Liu, Incorporating Low-Cost Sensor Measurements into High-Resolution PM_{2.5} Modeling at a Large Spatial Scale, *Environ. Sci. Technol.*, 2020, 54(4), 2152–2162, DOI: [10.1021/acs.est.9b06046](https://doi.org/10.1021/acs.est.9b06046).
 - 24 P. deSouza, R. A. Kahn, J. A. Limbacher, E. A. Marais, F. Duarte and C. Ratti, Combining Low-Cost, Surface-Based Aerosol Monitors with Size-Resolved Satellite Data for Air Quality Applications, *Atmos. Meas. Tech. Discuss.*, 2020, 1–30, DOI: [10.5194/amt-2020-136](https://doi.org/10.5194/amt-2020-136).
 - 25 P. deSouza, R. Kahn, T. Stockman, W. Obermann, B. Crawford, A. Wang, J. Crooks, J. Li and P. Kinney, Calibrating Networks of Low-Cost Air Quality Sensors, *Atmos. Meas. Tech. Discuss.*, 2022, 1–34, DOI: [10.5194/amt-2022-65](https://doi.org/10.5194/amt-2022-65).
 - 26 M. R. Giordano, C. Malings, S. N. Pandis, A. A. Presto, V. F. McNeill, D. M. Westervelt, M. Beekmann and R. Subramanian, From Low-Cost Sensors to High-Quality Data: A Summary of Challenges and Best Practices for Effectively Calibrating Low-Cost Particulate Matter Mass Sensors, *J. Aerosol Sci.*, 2021, 158, 105833, DOI: [10.1016/j.jaerosci.2021.105833](https://doi.org/10.1016/j.jaerosci.2021.105833).
 - 27 C. Malings, D. M. Westervelt, A. Haurlyliuk, A. A. Presto, A. Grieshop, A. Bittner, M. Beekmann and R. Subramanian, Application of Low-Cost Fine Particulate Mass Monitors to Convert Satellite Aerosol Optical Depth to Surface Concentrations in North America and Africa, *Atmos. Meas. Tech.*, 2020, 13, 3873–3892, DOI: [10.5194/amt-13-3873-2020](https://doi.org/10.5194/amt-13-3873-2020).
 - 28 J. Tryner, J. Mehaffy, D. Miller-Lionberg and J. Volckens, Effects of Aerosol Type and Simulated Aging on Performance of Low-Cost PM Sensors, *J. Aerosol Sci.*, 2020, 150, 105654, DOI: [10.1016/j.jaerosci.2020.105654](https://doi.org/10.1016/j.jaerosci.2020.105654).
 - 29 L. Sun, D. Westerdahl and Z. Ning, Development and Evaluation of A Novel and Cost-Effective Approach for Low-Cost NO₂ Sensor Drift Correction, *Sensors*, 2017, 17(8), 1916, DOI: [10.3390/s17081916](https://doi.org/10.3390/s17081916).
 - 30 G. Tancev, Relevance of Drift Components and Unit-to-Unit Variability in the Predictive Maintenance of Low-Cost Electrochemical Sensor Systems in Air Quality Monitoring, *Sensors*, 2021, 21(9), 3298, DOI: [10.3390/s21093298](https://doi.org/10.3390/s21093298).
 - 31 K. Ardon-Dryer, Y. Dryer, J. N. Williams and N. Moghimi, Measurements of PM_{2.5} with PurpleAir under Atmospheric Conditions, *Atmos. Meas. Tech. Discuss.*, 2019, 1–33, DOI: [10.5194/amt-2019-396](https://doi.org/10.5194/amt-2019-396).
 - 32 K. E. Kelly, J. Whitaker, A. Petty, C. Widmer, A. Dybwad, D. Sleeth, R. Martin and A. Butterfield, Ambient and Laboratory Evaluation of a Low-Cost Particulate Matter Sensor, *Environ. Pollut.*, 2017, 221, 491–500, DOI: [10.1016/j.envpol.2016.12.039](https://doi.org/10.1016/j.envpol.2016.12.039).
 - 33 K. K. Barkjohn, B. Gantt and A. L. Clements, Development and Application of a United States-Wide Correction for PM_{2.5} Data Collected with the PurpleAir Sensor, *Atmos. Meas. Tech.*, 2021, 14(6), 4617–4637, DOI: [10.5194/amt-14-4617-2021](https://doi.org/10.5194/amt-14-4617-2021).
 - 34 T. Sayahi, D. Kaufman, T. Becnel, K. Kaur, A. E. Butterfield, S. Collingwood, Y. Zhang, P.-E. Gaillardon and K. E. Kelly, Development of a Calibration Chamber to Evaluate the Performance of Low-Cost Particulate Matter Sensors, *Environ. Pollut.*, 2019, 255, 113131, DOI: [10.1016/j.envpol.2019.113131](https://doi.org/10.1016/j.envpol.2019.113131).
 - 35 G. Hagler, T. Hanley, B. Hassett-Sipple, R. Vanderpool, M. Smith, J. Wilbur, T. Wilbur, T. Oliver, D. Shand, V. Vidacek, C. Johnson, R. Allen and C. D'Angelo, Evaluation of Two Collocated Federal Equivalent Method



- PM2.5 Instruments over a Wide Range of Concentrations in Sarajevo, Bosnia and Herzegovina, *Atmos. Pollut. Res.*, 2022, **13**(4), 101374, DOI: [10.1016/j.apr.2022.101374](https://doi.org/10.1016/j.apr.2022.101374).
- 36 M. Kushwaha, V. Sreekanth, A. R. Upadhy, P. Agrawal, J. S. Apte and J. D. Marshall, Bias in PM2.5 Measurements Using Collocated Reference-Grade and Optical Instruments, *Environ. Monit. Assess.*, 2022, **194**(9), 610, DOI: [10.1007/s10661-022-10293-4](https://doi.org/10.1007/s10661-022-10293-4).
- 37 L. Wallace, J. Bi, W. R. Ott, J. Sarnat and Y. Liu, Calibration of Low-Cost PurpleAir Outdoor Monitors Using an Improved Method of Calculating PM2.5, *Atmos. Environ.*, 2021, **256**, 118432, DOI: [10.1016/j.atmosenv.2021.118432](https://doi.org/10.1016/j.atmosenv.2021.118432).
- 38 E. M. Considine, D. Braun, L. Kamareddine, R. C. Nethery and P. deSouza, Investigating Use of Low-Cost Sensors to Increase Accuracy and Equity of Real-Time Air Quality Information, *Environ. Sci. Technol.*, 2023, DOI: [10.1021/acs.est.2c06626](https://doi.org/10.1021/acs.est.2c06626).
- 39 K. K. Barkjohn, A. L. Holder, S. G. Frederick and A. L. Clements, Correction and Accuracy of PurpleAir PM2.5 Measurements for Extreme Wildfire Smoke, *Sensors*, 2022, **22**(24), 9669, DOI: [10.3390/s22249669](https://doi.org/10.3390/s22249669).

