



Identifying and addressing long-term Alphasense OPC-N3 sensor degradation

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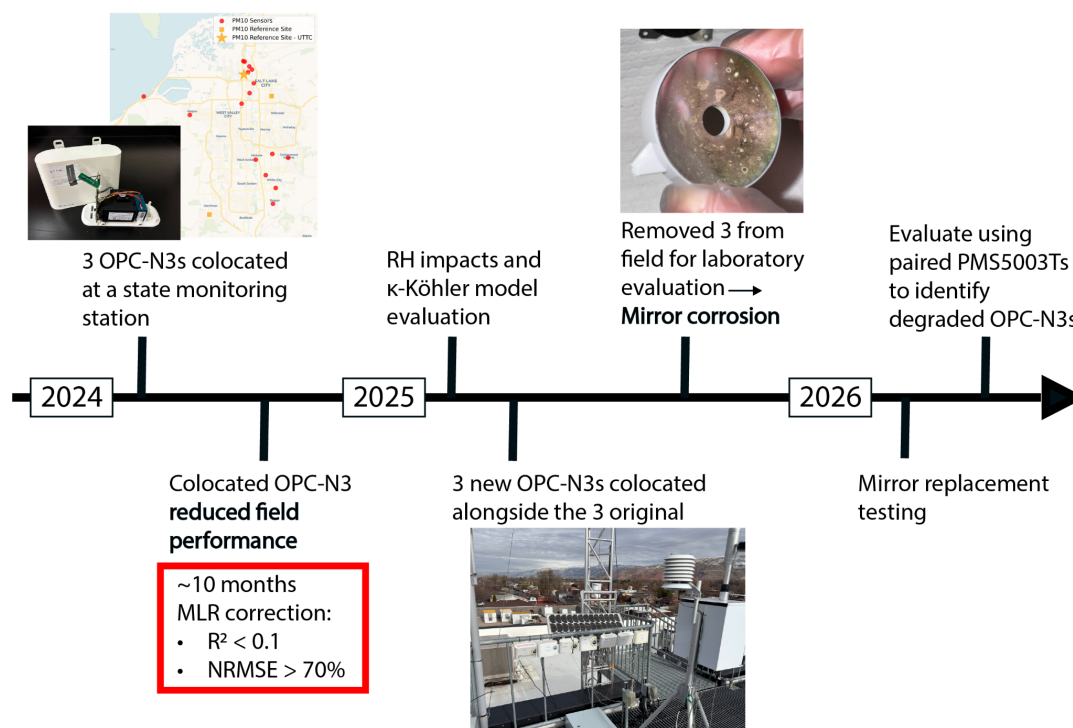
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Abstract. Low-cost optical particle counters are increasingly used for long-term particulate matter (PM) monitoring, but their long-term performance remains poorly understood. This study evaluates the field performance of six Alphasense OPC-N3 sensors colocated with Federal Equivalent Method (FEM) instruments in Salt Lake City, Utah, over deployment periods ranging from 5 to 24 months. It develops seasonal PM₁₀ correction models. However, the performance of the correction models for the three longest-deployed sensors exhibits progressive degradation after approximately 10–12 months, with correction model slopes increasing by up to sevenfold. In contrast, colocated Plantower PMS5003T sensors show no comparable long-term degradation in PM_{2.5} measurements. Comparison of OPC-N3s deployed for more than 12 months in the field with those for less than 3 months in the field reveals substantial differences in PM₁₀ response, with old-versus-new comparisons yielding an average slope of 0.18, compared with 0.72 for old-versus-old and new-versus-new comparisons. Post-deployment laboratory evaluations identify irreversible corrosion of the OPC-N3's internal elliptical mirror in the most degraded OPC-N3 sensor, with corresponding laboratory regression slope increases of more than an order of magnitude compared to pre-deployment evaluation. Mirror replacement substantially improves laboratory performance, suggesting that mirror replacement is a potential pathway to recover performance. Additionally, we observe a 56.3% decrease in the OPC-N3 PM_{2.5}-to-PMS5003T PM_{2.5} ratio within the first year for the three longest-deployed sensors, suggesting that this ratio may provide a practical indicator of OPC-N3 sensor degradation when FEM measurements are unavailable. These results provide the first evidence linking long-term OPC-N3 performance degradation to internal mirror corrosion and demonstrate that sensor performance can decline substantially after approximately one year of deployment.

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Graphical abstract



1 Introduction

PM₁₀ (particles with an aerodynamic diameter less than 10 μm) has been linked to adverse human health outcomes, including increased incidence of asthma, pneumonia, stroke, and adverse birth outcomes (Al-Hemoud, 2023; Herrera-Molina et al., 2024; James et al., 2018; Khaniabadi et al., 2017; Mahapatra et al., 2020; Sapkota et al., 2012; Scheers et al., 2015; Yaryfa and Burlaka, 2025; Zhang et al., 2018). The World Health Organization (WHO) has set guideline limits for outdoor PM₁₀ concentrations at 45 $\mu\text{g m}^{-3}$ (24-hour average) and 15 $\mu\text{g m}^{-3}$ (annual average) (WHO, 2026).

PM₁₀ concentrations can exceed these guidelines during dust storms, construction activities, and wildfires (Ardon-Dryer and Aziz, 2025; Gobbi et al., 2007; Krasnov et al., 2014, 2016; Tong et al., 2022). With increasing aridity and wildfires exposing large areas of bare soil, the occurrence of natural high-PM₁₀ events, such as dust storms, is expected to increase (Achakulwisut et al., 2019; Meng et al., 2025; Yu and Ginoux, 2022). Due to their larger size, PM₁₀ settles relatively quickly, causing elevated PM₁₀ episodes to be spatially heterogeneous and often short-lived (Ardon-Dryer et al., 2023; Vecchi et al., 2005, 2007). Regulatory monitoring networks aimed at capturing hourly PM₁₀ concentrations are generally sparser than those measuring PM_{2.5} (particles with an aerodynamic diameter less than 2.5 μm), with 672 sites reporting hourly PM₁₀ concentrations compared to 2141 sites reporting PM_{2.5} concentrations in the continental USA (EPA, 2024).



To address the gap in sparse regulatory measurements and to provide high-temporal-resolution particulate matter (PM) observations, low-cost sensors have gained increasing importance (Bagkis et al., 2025; Bi et al., 2020; Considine et al., 2023). The U.S. Environmental Protection Agency (EPA) has also begun deploying low-cost sensors at regulatory stations and other locations of interest to improve spatial coverage of PM measurements, primarily focusing on PM_{2.5} during wildfires (EPA, 2022). However, many low-cost sensors, including those that use Plantower PMS sensors, are ineffective at measuring PM₁₀ concentrations (Gautam et al., 2025; He et al., 2020; Kaur and Kelly, 2023b; Kosmopoulos et al., 2023; Kuula et al., 2020; Ouimette et al., 2024). A major reason for this limitation is scattering truncation error, which arises from the optical design of these sensors, where the photodiode is typically positioned at 90° to the laser beam (Kuula et al., 2020; Ouimette et al., 2024). This configuration limits the detection of light scattered at small angles, which is important for accurately measuring larger particles.

The Alphasense OPC-N3 sensor effectively detects coarse particles (particles with aerodynamic diameter between 2.5 and 10 µm) (Dubey et al., 2022; Dupont et al., 2025; Kaur and Kelly, 2023a; Nothhelfer et al., 2025; Sousan et al., 2016, 2021), and performs well during dust events (Kaur and Kelly, 2023b; Schön et al., 2024). The OPC-N3 uses a mirror to focus scattered light onto the photodiode, thereby increasing the efficiency of PM₁₀ measurements (Hagan and Kroll, 2020). Many studies have used the OPC-N3 in the lab or in the field to measure PM₁₀ concentrations and have reported good correlations between OPC-N3 PM₁₀ concentrations and research-grade or reference-grade instrument PM₁₀ concentrations ($R^2 > 0.8$) (Crilley et al., 2018; Dupont et al., 2025; Kaur and Kelly, 2023b; Penchala et al., 2025). A one-month field study in Salt Lake City, Utah, reports strong agreement between OPC-N3 and reference instruments (PM₁₀ $R^2 = 0.865\text{--}0.937$; RMSE = 12.4–17.7 µg m⁻³) (Kaur and Kelly, 2023b), and a study in India reports an $R^2 = 0.959\text{--}0.965$ using a linear correction for two OPC-N2 sensors compared with a GRIMM aerosol spectrometer (Dubey et al., 2022).

Field studies also find that Alphasense OPC sensors are influenced by relative humidity (RH) and hygroscopic growth, with overestimation at high RH (Crilley et al., 2018; Kaur and Kelly, 2023b; Nurowska and Markowicz, 2023). A five-week field collocation study in Birmingham, UK, evaluates 14 OPC-N2 sensors against a Tapered Element Oscillating Microbalance and a GRIMM aerosol spectrometer and reports a significant positive PM artifact when RH exceeds 85% (Crilley et al., 2018). Similarly, a two-year field study in Sweden using an OPC-N3 finds that RH, rather than temperature, dominates measurement error (Sarno et al., 2024). Both studies apply κ-Köhler corrections and correction improves performance compared to raw measurements. In the UK study, this correction reduces PM concentrations from approximately 250–400% times the reference measurements to within 33–52% of the reference (Crilley et al., 2018), while in the Sweden study it reduces PM₁₀ bias from approximately 5–5000 to -90–100 µg m⁻³ and decreases RMSE from 10–10,000 to 10–500 µg m⁻³ (Sarno et al., 2024).

Most of the field studies focusing on OPC sensors are short, with studies deploying sensors in the field for a few days to one year (Bauerová et al., 2020; Bittner et al., 2022; Correia et al., 2023; Crilley et al., 2018; deSouza et al., 2017, 2020, 2023b; Dupont et al., 2025; Kaur and Kelly, 2023b; Masic et al., 2020; Mukherjee et al., 2017; Nimo et al.,



2025; Nurowska and Markowicz, 2023; Pope et al., 2018; Vogt et al., 2021). One of the longest field deployments occurred in the Czech Republic, where OPC-N2 sensors operated for one year; however, only two sensors were colocated with reference instruments (an MP101M beta-ray absorption monitor and a Fidas200 optical particle counter), and the colocation period was limited to five months (Bauerová et al., 2020). During the colocation period, the two OPC-N2 sensors showed excellent agreement with each other (Spearman rank correlation = 0.99), while agreement with the reference instruments was moderate (Spearman rank correlation = 0.68–0.77; RMSE = 620.9–767.4 $\mu\text{g m}^{-3}$) (Bauerová et al., 2020). Previous studies generally report stable sensor performance over deployments ranging from several months to approximately one year and do not identify evidence of long-term degradation in OPC-N2 or OPC-N3 measurements (Bílek et al., 2021; Bittner et al., 2022; Sarno et al., 2024). However, long-term evaluations of OPC-N3 sensors colocated with reference instruments remain limited. In addition, no studies have examined how agreement between OPC-N3 sensors and reference monitors changes over time or directly compared the performance of old (≥ 12 months in the field) and new (< 12 months in the field) OPC-N3 sensors.

This study evaluates six OPC-N3 sensors colocated with Federal Equivalent Method (FEM) instruments at a state regulatory monitoring station in Salt Lake City, Utah. The sensors are deployed for 5 to 24 months. Performance of the three longest-deployed sensors declines after approximately 10–12 months in the field, prompting the deployment of three additional OPC-N3 sensors for comparison. Finally, we perform post-deployment laboratory evaluations to identify the mechanism responsible for the observed performance decline and assess whether mirror replacement can restore field performance.

2 Methods

This section details the laboratory testing and field evaluation of the OPC-N3 and Plantower PMS5003T sensors. We evaluate the PMS5003T sensors to assess their long-term field performance relative to the OPC-N3 sensors. In addition, we develop a correction model for PMS5003T-reported RH and use the corrected RH measurements in the OPC-N3 correction models. Using corrected PMS5003T-reported RH, rather than monitoring-station RH, improves the generalizability of the correction models to deployments where research-grade RH measurements are unavailable.

Before deployment of the OPC-N3 and PMS5003T sensors in the field, the sensors are initially laboratory precision tested. The sensors are then deployed in the field alongside FEM instruments at a state monitoring station. Following an extended period of field deployment, select OPC-N3 sensors are re-evaluated in the laboratory for precision and for size-binning efficiency. The elliptical mirrors of two field-retired OPC-N3 sensors and one never-deployed sensor are replaced, and the resulting changes in size-binning efficiency and precision performance are evaluated. The results from the laboratory and field evaluations are processed using Python 3.9 (Python Software Foundation) and R 4.4.0 (R Foundation for Statistical Computing, Vienna, Austria).



2.1 Sensors

This study evaluates six low-cost optical particle counters, the Alphasense OPC-N3 (Alphasense Ltd.; approximately
115 US\$ 500) (Table 1). The OPC-N3 uses a Class 1 laser (≈ 658 nm) to detect, size, and count particles from 0.35 to 40
 μm across 24 size bins. An embedded algorithm converts particle number counts to PM_{10} , $\text{PM}_{2.5}$, and PM_{10} mass
concentrations. This instrument uses an elliptical mirror to collect scattered light over a wide angular range and focus
it onto a photodiode (Kaur and Kelly, 2023a). An internal fan drives airflow; the manufacturer reports a typical sample
flow rate of 4.67 mL s^{-1} and a total flow rate of 91.7 mL s^{-1} (5.50 L min^{-1}). This study uses the manufacturer’s default
120 parameters for refractive index (real part = 1.5) and particle density (1.65 g cm^{-3}). The OPC-N3 measurements, used
in our field study, include particle counts in the 24 size bins, sample flow rate, laser wavelength, reject count
parameters (Table S15), and PM_{10} , $\text{PM}_{2.5}$, and PM_{10} concentrations.

This study also evaluates six PMS5003Ts (Plantower, Nanchang, China) (Table 1). The PMS5003T uses a fan to drive
flow ($\sim 1.67\text{ mL s}^{-1}$), a red laser ($\sim 680 \pm 10$ nm), a scattering angle of 90° , and a photo-diode detector to measure
125 total scattering from particles in the flow path (Kaur and Kelly, 2023a; Ouimette et al., 2022). The sensor converts the
total light scattering into several different metrics, including particle counts in six bins (> 0.3 , > 0.5 , > 1 , > 2.5 , > 5 ,
and $> 10\text{ }\mu\text{m}$; out of which only the first four bins are reported by the PMS5003T model), and PM_{10} , $\text{PM}_{2.5}$, and PM_{10}
using an embedded algorithm. The PMS5003T reports humidity, temperature, and pressure using the BME280 sensor
(Bosch Sensortec, Reutlingen, Germany). The PMS5003T measurements, used in our field study, include $\text{PM}_{2.5}$,
130 temperature, and relative humidity.

There are nine never-deployed OPC-N3 sensors that serve as control sensors throughout this study (Table 1, see
footnote). Sensors 716, 703, and 813 are used in the laboratory evaluations described in the main manuscript, whereas
the remaining six control sensors are used in the laboratory and field evaluations presented in Supplemental Material
Sect. S.5, S.6, S.8, and S.9.

135 **Table 1: Colocated OPC-N3 and PMS5003T serial numbers (SNs) and deployment timeframe at the Utah Division of Air
Quality (DAQ), Utah Technical Center (UTTC) reference station. We use the last three digits of the SNs to identify the
OPC-N3 and PMS5003T sensors throughout this manuscript, and we refer to these digits as the sensor number. Dates are
reported as MM/DD/YY.**

Unit	OPC-N3 SN (#) ^a	PMS5003T SN (#)	Deployment Dates	Total Time in Field (months)	Field Class
1	177380501 (501)	2023032500357 (357)	29 Jan 2024 - present	24+	Old
2	177111905 (905)	2023040600261 (261)	6 Feb 2024 - 16 Aug 2025	18	Old
3	177393605 (605)	2023040600155 (155)	6 Feb 2024 - 20 Feb 2025	12	Old
4	177112011 (011)	2023040600265 (265)	11 Mar 2025 - 16 Aug 2025	5	New
5	177400201 (201)	2023111100887 (887)	29 Apr 2025 - present	10+	New
6	177400216 (216)	2023111100792 (792)	29 Apr 2025 - present	10+	New



^aNine additional never-deployed OPC-N3 sensors are used as controls: 177520716 (716), 177560703 (703), 177312813 (813), 177400219 (219), 177400220 (220), 177290106 (106), 177292814 (814), 177560709 (709), and 177311320 (320).

140 2.2 Laboratory testing

2.2.1 PMS5003T PM_{2.5} laboratory precision testing

PMS5003T sensors undergo laboratory precision testing before field deployment using ammonium nitrate aerosol. We compare the sensor PM_{2.5} measurements with a DustTrak II Aerosol Monitor 8530 (TSI Inc., Shoreview, MN, USA), equipped with a PM_{2.5} impactor, using a four-point linear calibration at PM_{2.5} concentrations of approximately
 145 0, 50, 100, and 150 $\mu\text{g m}^{-3}$. We use the same experimental setup and PM chamber described in (Sayahi et al., 2019a).

Briefly, we dissolve approximately 50 mg of ammonium nitrate (ACS grade, $\geq 95\%$, granular; Alfa Aesar, Ward Hill, MA, USA) in 50 mL of deionized water, generate aerosol with an atomizer (Model 9302, TSI Inc., Shoreview, MN, USA), and dry the aerosol stream with a diffusion dryer (Model 3062, TSI Inc., Shoreview, MN, USA). We dilute the aerosol with 15 L min⁻¹ of filtered air before introducing it into the PM chamber containing the PMS5003T sensors.
 150 A sampling line from the PM chamber supplies the DustTrak. Custom printed circuit boards record PMS5003T PM_{2.5} measurements to an SD card at 15 s intervals, while the DustTrak records PM_{2.5} measurements every 5 s.

We determine the DustTrak ammonium nitrate correction factor annually after the instrument returns from manufacturer maintenance by collecting aerosol on 1 μm , 37 mm PTFE filters (SKC Inc., Eighty Four, PA, USA) following the instructions listed in DustTrak operation and service manual (TSI, 2023). The correction factor, ratio of
 155 DustTrak PM to gravimetric PM, is 1.85 for sensors tested in November 2023 and 1.94 for sensors tested in March 2025.

2.2.2 OPC-N3 PM₁₀ laboratory precision testing

OPC-N3 sensors undergo laboratory precision testing before field deployment using Arizona road dust (ISO 12103-1, A1 Ultrafine Test Dust; Powder Technology Inc. (PTI), Arden Hills, MN, USA). We compare the OPC-N3 PM₁₀
 160 measurements with those from the DustTrak equipped with a PM₁₀ impactor using a four-point linear calibration at PM₁₀ concentrations of approximately 0, 200, 500, and 700 $\mu\text{g m}^{-3}$. Figure S1 illustrates the laboratory test setup.

To generate the test aerosol, we suspend approximately 100 mg of Arizona road dust in 50 mL of deionized water and place the suspension in the atomizer reservoir. A magnetic stir plate continuously mixes the suspension throughout the experiment. The atomizer operates between 3 and 10 psig to generate the aerosol, which then passes through a
 165 diffusion dryer (Model DD-1100, Handix Scientific, Fort Collins, CO, USA), is diluted with 15 L min⁻¹ of filtered air, and is divided among four OPC-N3 sensors and the DustTrak sampling line using Y-connections (Fig. S1). The generated aerosol exits through custom 3D-printed outlets designed to provide free flow to the OPC-N3 sensors (Fig.



S2), thereby avoiding positive pressure at the OPC-N3 inlet and allowing each sensor to draw its required flow independently.

170 Custom printed circuit boards record OPC-N3 PM_{10} measurements to an SD card at 15 s intervals, while the DustTrak records PM_{10} measurements every 5 s. We do not determine a DustTrak correction factor for Arizona road dust, because the DustTrak is factory calibrated using Arizona road dust (ISO 12103-1, A1) (TSI, 2023).

2.2.3 Laboratory data analysis

We average the PMS5003T, OPC-N3, and DustTrak measurements to 1 min. For the PMS5003T laboratory tests, we
 175 correct the minute-averaged DustTrak $PM_{2.5}$ concentrations by dividing them by the corresponding ammonium nitrate correction factor. We then perform four-point simple linear regressions for both the PMS5003T and OPC-N3,

$$PM_{2.5_{DT}} = b_1 PM_{2.5_{PMS}} + b_0, \quad (1)$$

where $PM_{2.5_{DT}}$ is the corrected, minute averaged DustTrak $PM_{2.5}$ concentration ($\mu g m^{-3}$), and $PM_{2.5_{PMS}}$ is the minute averaged PMS5003T $PM_{2.5}$ concentration ($\mu g m^{-3}$), and

$$PM_{10_{DT}} = b_1 PM_{10_{OPC}} + b_0, \quad (2)$$

where $PM_{10_{DT}}$ is the minute-averaged DustTrak PM_{10} concentration ($\mu g m^{-3}$), and $PM_{10_{OPC}}$ is the minute-averaged
 180 OPC-N3 PM_{10} concentration ($\mu g m^{-3}$). We estimate the regression coefficients using ordinary least squares (OLS).

Laboratory precision for the PMS5003T sensors must satisfy two criteria to qualify for field deployment. First, all sensors within a batch must have regression slopes within $\pm 20\%$ of the mean slope for that batch (per-batch criterion) (Sousan et al., 2018). Second, we compile the slopes from all sensors that pass the per-batch criterion and require the
 185 coefficient of variation (CV) of the slopes across all batches to be less than 30% (across-batch criterion) (Schilt et al., 2023).

As with the PMS5003T sensors, the OPC-N3 sensors must satisfy two laboratory precision criteria before field deployment. However, the per-batch criterion is less stringent, because the OPC-N3 laboratory tests exhibit greater
 190 variability (Sect. S.6). Specifically, the regression slope for each sensor must fall within $\pm 30\%$ of the batch-average slope, and the CV across all batches must also be $\pm 30\%$.

2.3 Field evaluation

2.3.1 Colocation with FEM

We colocate the six OPC-N3 and six PMS5003T sensors at the Utah Division of Air Quality (DAQ), Utah Technical
 195 Center (UTTC) reference station (Station ID 49-035-3015; latitude 40.777028, longitude -111.94585 ; elevation 1284 m), located approximately 20 km from the Great Salt Lake (Fig. S3). The OPC-N3 and PMS5003T sensors are both connected to an AirU Pro board (TELLUS Networked Sensor Solutions, Inc., Salt Lake City, Utah, USA), which



records date and time, latitude, longitude, elevation, and sensor measurements at 1-min intervals. The sensors and AirU Pro board are housed in a weather-resistant white plastic enclosure with downward-facing sample inlets (Fig. S3). Table 1 summarizes the six AirU Pro units, the associated OPC-N3 and PMS5003T sensors, and the deployment dates. Throughout this manuscript, we will refer to the first three sets of OPC-N3 and PMS5003T sensors deployed in 2024 as the old sensors (Table 1), and the second three sets deployed in 2025 as the new sensors (Table 1).

The UTTC station operates a Met One E-BAM (Beta Attenuation Monitoring) PLUS (Met One Instrument, Grants Pass, OR, USA) as the PM_{10} reference instrument and a Thermo Scientific Model 5030 SHARP VSCC (Thermo Fisher Scientific, Waltham, MA, USA) as the $PM_{2.5}$ reference instrument. Ambient temperature and relative humidity are measured using a Campbell Scientific HMP60 probe. We obtain hourly UTTC PM measurements from the AirNow API (EPA, 2024), and hourly UTTC T and RH measurements from the Synoptic Data Mesowest API (Synoptic Data, 2024).

2.3.2 Correction model evaluation

Field measurements from the PMS5003T and OPC-N3 sensors are downsampled to hourly averages. We develop correction models for the following seven seasons: winter 2023 (February 2024), spring 2024 (March–May 2024), summer 2024 (June–October 2024), winter 2024 (November 2024–February 2025), spring 2025 (March–May 2025), summer 2025 (June–October 2025), and winter 2025 (November 2025–February 2026) (Sayahi et al., 2019b). All correction model coefficients are estimated using OLS. OLS regression results can be strongly influenced by a few outliers (Cook and Weisberg, 1980). Therefore, for each of the following correction models, we identify outliers in two steps. First, we fit each model using all hourly averaged measurements. Second, we refit the model after removing outliers, defined as observations with residuals exceeding $1.5 \times IQR$ (interquartile range), where the residual equals the prediction minus the corresponding reference measurement. The mean percentage of measurements removed is $3 \pm 1\%$ for the RH linear regression (Table S3), $5 \pm 3\%$ for the PMS5003T $PM_{2.5}$ linear regression (Table S4), $5 \pm 1\%$ for the OPC-N3 PM_{10} multiple linear regression (Table S6), and $6 \pm 2\%$ for the OPC-N3 PM_{10} κ -Köhler regression (Table S8). All subsequent correction model results are shown after the outliers have been removed.

2.3.3 PMS5003T relative humidity correction model

PMS5003T-reported RH measurements are corrected using a simple linear regression

$$RH_{corrected} \sim RH_{UTTC} = b_1 RH_{PMS} + b_0. \quad (3)$$

Where RH_{UTTC} is the hourly UTTC station RH measurement (%), and RH_{PMS} is the hourly PMS5003T-reported RH measurement (%). In the remainder of the manuscript, the corrected PMS5003T-reported relative humidity is referred to as RH.

2.3.4 PMS5003T $PM_{2.5}$ correction model

PMS5003T $PM_{2.5}$ measurements are corrected using a simple linear regression,



$$PM2.5_{corrected} \sim PM2.5_{FEM} = b_1 PM2.5_{PMS} + b_0. \quad (4)$$

Where $PM2.5_{FEM}$ is the hourly FEM $PM_{2.5}$ concentration ($\mu g m^{-3}$) and $PM2.5_{PMS}$ is the hourly PMS5003T $PM_{2.5}$ concentration ($\mu g m^{-3}$). PMS sensors show little dependence on RH in the Salt Lake Valley (Sayahi et al., 2019b).

2.3.5 OPC-N3 PM_{10} correction models

We evaluate two correction models for OPC-N3 PM_{10} measurements. The first is a multiple linear regression (MLR)

$$PM10_{corrected} \sim PM10_{FEM} = b_1 PM10_{OPC} + b_{RH} RH + b_0. \quad (5)$$

Where $PM10_{FEM}$ is the hourly FEM PM_{10} concentration ($\mu g m^{-3}$), $PM10_{OPC}$ is the hourly OPC-N3 PM_{10} concentration ($\mu g m^{-3}$), and RH is the hourly corrected PMS5003T-reported RH (%).

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The second correction model is based on the κ -Köhler model proposed by Crilley et al. (Crilley et al., 2018) and Nurowska and Markowicz (Nurowska and Markowicz, 2023). We first estimate the dry PM_{10} concentration by dividing the OPC-N3 wet PM_{10} measurement by the κ -Köhler hygroscopic growth factor. We then introduce a regression coefficient as a second parameter to account for seasonal differences in particle density and optical properties, which the OPC-N3 assumes to be constant. The resulting κ -Köhler correction model is

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$$PM10_{corrected} \sim PM10_{FEM} = b_1 \left(\frac{PM10_{OPC}}{1 + \left(\frac{1/1.65 \kappa}{-1 + 100/RH} \right)} \right). \quad (6)$$

Where $PM10_{FEM}$ is the hourly FEM PM_{10} concentration ($\mu g m^{-3}$), $PM10_{OPC}$ is the hourly OPC-N3 PM_{10} concentration ($\mu g m^{-3}$), and RH is the hourly corrected PMS5003T-reported RH measurement (%). The regression coefficient (b_1) and the aerosol hygroscopicity parameter (κ) are estimated simultaneously.

2.3.5 Performance metrics

245 We evaluate correction model performance using the coefficient of determination (R^2)

$$R^2 = 1 - \frac{\sum_1^n (y_i - \bar{y})^2}{\sum_1^n (y_i - \bar{y})^2}, \quad (7)$$

root mean square error (RMSE),

$$RMSE = \sqrt{\frac{1}{n} \sum_1^n (y_i - \hat{y}_i)^2}, \quad (8)$$

and the normalized root mean square error (NRMSE),

$$NRMSE = \frac{RMSE}{\max(y) - \min(y)}, \quad (9)$$

where n is the number of observations, y is the reference measurement, $\hat{y}$ is corrected low-cost sensor measurement, and $\bar{y}$ is the mean of the reference measurement. The U.S. EPA recommends performance targets of $R^2 \geq 0.70$ and $NRMSE \leq 30\%$ for $PM_{2.5}$ and PM_{10} low-cost sensors (Duvall et al., 2023, 2021).

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2.3.6 Long-term performance analysis

In addition to evaluating correction model performance over time, we assess inter-sensor variability and the effect of sensor aging by comparing uncorrected hourly averaged measurements between colocated sensors of the same type (OPC-N3 versus OPC-N3 and PMS5003T versus PMS5003T) and between each sensor and their corresponding FEM
 255 using scatter plot matrices and Bland-Altman plot matrices. We use the Bland-Altman method of differences to evaluate agreement between paired measurements (Bland and Altman, 1999; Ludbrook, 2010).

2.4 Post-field deployment laboratory evaluation

We reevaluate two old (905 and 605), one new (011), and two never-deployed (703 and 813) OPC-N3 sensors by repeating the laboratory precision tests (Sect. 2.2) after retrieval from the field and again after flushing the sensors
 260 with filtered air for approximately 24 h. We select three OPC-N3 sensors for disassembly and internal inspection: one old (905), one new (011), and one never-deployed (716). Before disassembly, we evaluate their size selectivity (Sect. 2.4.1). Internal inspection reveals visible corrosion on the elliptical mirror of old sensors. We then replace the mirrors in all three sensors following the procedure described in Sect. S.7 and repeat the size-selectivity (Sect. 2.4.1) and laboratory precision (Sect. 2.2) tests to evaluate whether mirror replacement restores sensor performance.

265 2.4.1 Size selectivity of selected OPC-N3s

We evaluate the size selectivity both before and after mirror replacement using a GRIMM 11-D aerosol spectrometer (DURAG, Muldestausee, Germany) and monodisperse aerosols generated by a Flow-Focusing Monodisperse Aerosol Generator (FMAG 1520, TSI Inc., Shoreview, MN, USA). The FMAG has been described in detail by Duan et al. (Duan et al., 2016) and Kaur et al. (Kaur and Kelly, 2023a). Briefly, it produces monodisperse aerosols by forcing a
 270 liquid solution, composed of a nonvolatile solute dissolved in a solvent, through a nozzle using coaxial flow-focusing air. Mechanical vibrations perturb the resulting jet, forming droplets with uniform diameters. These droplets can then be dried using particle-free air to generate solid or liquid particles of known size. The FMAG is commonly used to calibrate particle size distribution (PSD) instruments, such as the Aerodynamic Particle Sizer (APS) and GRIMM. According to the manufacturer, it can produce solid particles with diameters of 0.8–8.5 μm and liquid particles of
 275 0.85–12 μm , with a geometric standard deviation of < 1.05 (TSI, 2022).

In this study, liquid particles with target diameters of approximately 0.35, 0.7, 1.6, and 3.5 μm are generated using dioctyl sebacate (DOS; Sigma-Aldrich; density = 0.914 g cm^{-3}) dissolved in isopropyl alcohol (IPA; 99.99%, Sigma-Aldrich) at known concentrations. The spherical nature of FMAG-generated particles (Duan et al., 2016) makes them
 280 suitable for evaluating OPC-N3 size selectivity, as the OPC-N3 assumes spherical particles in its sizing algorithm (Alphasense, 2019). Target particle diameters are achieved by adjusting DOS concentration, vibration frequency, and injection flow rate (Table S1). For the smallest two target diameters, the FMAG should theoretically produce a diameter of 0.2 μm and 0.61 μm , but the low concentration of DOS and the DOS impurities cause the observed diameters to be $\sim 0.357 \mu\text{m}$ and $0.722 \mu\text{m}$, respectively, as measured by the GRIMM.



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The experimental setup for OPC-N3 size selectivity was adapted from the laboratory precision test configuration (Fig. S4). The FMAG output was diluted with particle-free air, then split into four lines using Y-connectors. For particles larger than 2.5 μm , a suction pump removed a portion of the FMAG outflow prior to dilution to maintain PM_{10} concentrations within the OPC-N3's operational range. The net flow rate, after accounting for suction-based flow removal and the addition of dilution air, was maintained at a minimum of 18 LPM. At any time, three OPC-N3 units are evaluated simultaneously, with the fourth line connected to GRIMM. Background measurements are performed with the syringe pump turned off. Under these conditions, the GRIMM registers zero particle counts (data not shown), confirming negligible background levels.

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295 The bin counts from the OPC-N3 are converted from $\# \text{ sec}^{-1}$ to $\# \text{ mL}^{-1}$ by dividing the counts by the sample flow rate (mL sec^{-1}). To compare the PSD between GRIMM and the OPC-N3, the number concentrations were converted to dN/dlogDp to accommodate the different bin sizes of OPC-N3 and GRIMM. The OPC-N3 and GRIMM number concentrations ($\# \text{ mL}^{-1}$) and mean diameter (μm) are compared using bias, calculated as:

$$\text{Bias}\% = \frac{1}{n} \sum_1^n \frac{y_{i,OPC} - y_{i,GRIMM}}{y_{i,OPC}} * 100, \quad (9)$$

where n represents the total number of 1 min-average runs, $y_{i,OPC}$ represent the OPC measurements, and $y_{i,GRIMM}$ represent the GRIMM measurements.

300

3 Results and discussion

This evaluation begins with precision testing, followed by seasonal correction model performance evaluations, and the identification of OPC-N3 performance degradation and a potential strategy for addressing the degradation.

3.1 Pre-deployment laboratory precision tests

305 When comparing results to previous work, we consistently report the regression slope and intercept for the low-cost sensor measurement as the independent variable (x) and the reference measurement as the dependent variable (y). In some cases, we convert what is reported in the prior work to facilitate comparison to our results (Eq. (1) and (2)).

3.1.1 PMS5003T $\text{PM}_{2.5}$

310 Four PMS5003T sensors (357, 261, 155, and 265) undergo laboratory precision testing in November 2023 using the laboratory PM chamber with ammonium nitrate particles (Sayahi et al., 2019a). These sensors overestimate $\text{PM}_{2.5}$ concentrations and produce an average: slope of 0.697 ± 0.090 , intercept of $3.06 \pm 0.86 \mu\text{g m}^{-3}$, and R^2 of 0.996 ± 0.004 (Eq. (1)). The additional two PMS5003T sensors (887 and 792) undergo laboratory precision testing in March 2025, and underestimate concentration with an average: slope of 1.28 ± 0.08 , intercept of $1.15 \pm 0.12 \mu\text{g m}^{-3}$, and R^2 of 0.991 ± 0.001 (Eq. (1)). To date, 248 PMS5003T sensors have passed the laboratory precision tests, and the



315 regression slopes from these passing sensors have an across-batch CV of 26.9%. Therefore, all six sensors satisfy both
 the per-batch criterion (within $\pm 20\%$ of the batch-average slope) and the across-batch criterion (CV of slopes $< 30\%$).

Although all sensors satisfy the pre-deployment laboratory precision criteria, the slopes and intercepts differ between
 the two test periods. These differences may result from changes in the equipment setup and potential differences in
 320 Plantower PMS sensor batches. A previous study evaluates 154 PMS3003 sensors from one manufacturing batch and
 88 sensors from a second batch and also identifies batch-to-batch differences in slopes (average slope of 0.86 for the
 154 sensors and 1.09 for the 88 sensors) along with strong correlations ($R^2 > 0.968$) (Sayahi et al., 2019a). Another
 previous study evaluates four PMS5003 sensors in a chamber using 11-point linear calibration with ammonium nitrate
 and finds a slope of 0.56 ± 0.14 , an average intercept of $0.21 \pm 0.20 \mu\text{g m}^{-3}$, and an average R^2 of 0.988 ± 0.004 (Searle
 325 et al., 2023).

3.1.2 OPC-N3 PM10

Like the PMS5003T sensors, four OPC-N3 sensors (501, 905, 605, and 011) are laboratory-precision tested in
 November 2023 using the y-split setup with Arizona road dust. These OPC-N3s underestimate concentration and
 produce an average: slope of 1.87 ± 0.12 , intercept of $-13.8 \pm 7.8 \mu\text{g m}^{-3}$, and R^2 of 0.989 ± 0.001 (Eq. (2)). The
 330 additional two OPC-N3 sensors (201 and 216) undergo precision testing in December 2024 and produce an average:
 slope of 1.95 ± 0.42 , intercept of $-10.8 \pm 3.3 \mu\text{g m}^{-3}$, and R^2 of 0.990 ± 0.004 (Eq. (2)). To date, 115 OPC-N3 sensors
 have passed the laboratory precision tests, and the regression slopes from these passing sensors have an across-batch
 CV of 27.3%. Therefore, all six sensors satisfy the pre-deployment laboratory precision criteria (per-batch: slopes
 within $\pm 30\%$ of the batch-average slope; across-batch: CV of slope $< 30\%$).

335 In this study, the OPC-N3 sensors underestimate Arizona road dust concentrations relative to the DustTrak. Although
 both instruments estimate particle mass from light scattering, they use different calibration materials and assumed
 particle densities. The OPC-N3 is size calibrated with monodisperse polystyrene latex spheres and assumes a particle
 density of 1.65 g cm^{-3} (Alphasense, 2019), whereas the DustTrak is factory calibrated with ultrafine Arizona road dust
 340 (TSI, 2023) and assumes a particle density of 2.65 g cm^{-3} (TSI, 2024). These differences likely contribute to the
 observed underestimation by the OPC-N3.

In two prior laboratory studies by Sousan et al. (Sousan et al., 2016, 2021), OPC-N3 sensors overestimate Arizona
 road dust concentrations relative to their research-grade instruments. In the first study, three OPC-N3 sensors are
 345 evaluated against measurements from an APS and a Scanning Mobility Particle Sizer (SMPS) over concentrations
 ranging from approximately 5 to $3500 \mu\text{g m}^{-3}$ (Sousan et al., 2016). The resulting regression produces a slope of 0.625
 and an intercept of $-65.6 \mu\text{g m}^{-3}$. However, the OPC-N3 measures light scattering while the APS and SMPS measure
 aerodynamic and mobility diameter, respectively. In the second study, three OPC-N3 sensors are compared with a
 GRIMM MiniWRAS spectrometer over a concentration range of approximately 0– $1600 \mu\text{g m}^{-3}$ and report a slope and
 350 intercept of 0.935 and $-12.3 \mu\text{g m}^{-3}$, respectively (Sousan et al., 2021). In this case, both the GRIMM and the OPC-



N3 measure light scattering. All evaluations reported strong linear agreement, with R^2 values of 0.99 (Sousan et al., 2016, 2021). The discrepancy between the results of this study and those reported by Sousan et al. likely arises, at least in part, from differences in the reference instruments and the large negative intercept in one of the studies. Regardless of the reference instrument used, laboratory precision testing in this study minimizes intersensor variability

355 by ensuring that only OPC-N3 sensors meeting the precision criteria are deployed in the field.

3.2 Field colocation correction models and impact of RH on OPC-N3 performance

Table S2 summarizes the seasonal descriptive statistics for PM, temperature, and relative humidity from the UTTC station measurements. We discuss the correction model results for PMS5003T reported RH and $PM_{2.5}$ for two reasons. First, PMS5003T reported RH is used in the correction models for the OPC-N3. Second, we compare the long-term performance of the OPC-N3 measurements to the PMS5003T $PM_{2.5}$ measurements to identify OPC-N3 degradation.

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3.2.1 PMS5003T RH correction model performance

Figure S5 presents an example scatter plot and linear regression results of PMS5003T-reported RH vs. UTTC RH measurements for the winter 2024 season (November 2024–February 2025). Table S3 reports the seasonal linear regression model parameters and performance metrics for the PMS5003T-reported RH. The tabulated PMS5003T RH results aggregate data across all sensors. This study finds that PMS5003T-reported RH underestimates ambient RH by approximately 20%, similar to the underestimation reported by Airgradient (AirGradient, 2023). The average seasonal linear regression correction model slope and intercept are 1.18 ± 0.05 and 0.36 ± 5.4 , respectively (Eq. (3); Table S3), with seasonal R^2 ranging from 0.73 to 0.93 and NRMSE ranging from 11% to 18% (Table S3). The underestimation in RH is attributed to heating within the sensor caused by its circuitry (Nurowska et al., 2023). For the remainder of the manuscript, RH refers to the corrected PMS5003T-reported RH.

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3.2.2 PMS5003T $PM_{2.5}$ correction model performance

Figure S6 presents an example scatter plot and linear regression results of PMS5003T $PM_{2.5}$ vs. UTTC $PM_{2.5}$ measurements for the winter 2024 season (November 2024–February 2025). Table S4 reports seasonal linear regression model parameters and performance metrics for PMS5003T $PM_{2.5}$. The tabulated PMS5003T $PM_{2.5}$ results are presented for each sensor. PMS5003T $PM_{2.5}$ results are presented for each sensor, because later sections look at individual sensor results to evaluate whether PMS5003T sensors show performance degradation.

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Similar to prior work (Barkjohn et al., 2021; Malings et al., 2020; Sayahi et al., 2019b; Tryner et al., 2020), the PMS5003T $PM_{2.5}$ field measurements overestimate FEM $PM_{2.5}$ concentrations (Eq. (4) average slope of 0.377 ± 0.081 across seasons; Table S4) with performance varying by season. The U.S. EPA recommends that low-cost $PM_{2.5}$ sensors achieve an $R^2 \geq 0.7$ and an $NRMSE \leq 30\%$ (Duvall et al., 2021). The PMS5003T $PM_{2.5}$ linear correction model demonstrates the strongest performance during the winter season with an average R^2 of 0.875 ± 0.067 and an average NRMSE of $28.9 \pm 3.9\%$ (Table S4), satisfying both EPA performance criteria. The summer season achieves an average

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385 R^2 of 0.662 ± 0.204 and an average NRMSE of $26.9 \pm 4.5\%$ (Table S4), which meets the EPA NRMSE criterion, but is slightly below the recommended R^2 of 0.7.

In contrast, the performance of the correction model during spring is worse with an R^2 of 0.355 ± 0.191 and an average NRMSE of $42.2 \pm 5.1\%$ (Table S4), and fails to meet either EPA guideline. This may be due to the lower central tendency of the spring measurements (IQR: $2.9\text{--}6.6 \mu\text{g m}^{-3}$) compared to the other seasons (IQR winter: $2.6\text{--}10.2 \mu\text{g m}^{-3}$ and IQR: summer: $5.3\text{--}10.6 \mu\text{g m}^{-3}$, Table S2). These spring concentrations are near the reported limit of detection of Plantower PMS sensors, estimated at approximately $1\text{--}5 \mu\text{g m}^{-3}$ (Bulut et al., 2019; Sayahi et al., 2019b), where measurement uncertainty represents a larger proportion of the observed signal. Additionally, prior work has found that the PMS5003 sensor $\text{PM}_{2.5}$ measurements underestimate dust and produce a bimodal pattern during time periods that include dust episodes (Kaur et al., 2026a), and this bimodal relationship can be seen in the PMS5003T scatter plot matrices compared to FEM (Fig. S27-S33), particularly during the spring and winter seasons.

395 Similar seasonal patterns and performance are observed during a 2017 evaluation of two colocated PMS5003 sensors at the Utah Division of Air Quality Hawthorne station in Salt Lake City (latitude 40.7343 , longitude -111.8721), located approximately 8 km from the UTTC station (Sayahi et al., 2019b). For winter, the R^2 values exceed 0.866, and for summer, the R^2 values range from 0.673 to 0.718. This previous study also shows that spring exhibits the poorest performance, with an R^2 of 0.324, which is also attributed to lower ambient $\text{PM}_{2.5}$ concentrations during spring (Sayahi et al., 2019b).

Barkjohn et al. (Barkjohn et al., 2021) evaluate 53 PurpleAir sensors, which use the Plantower PMS, from 16 different states across the U.S. using a variety of $\text{PM}_{2.5}$ correction models over two years. They recommend an MLR that includes PurpleAir $\text{PM}_{2.5}$ measurements, RH, and an intercept (Barkjohn et al., 2021). However, in this study, including RH as a predictor in the correction model provides little performance improvement for the PMS5003T sensors, similar to a prior study conducted in Salt Lake City (Sayahi et al., 2019b). Figure S8 contains the humidograms (PMS5003T to FEM $\text{PM}_{2.5}$ ratio vs RH) for aggregated PMS5003T sensor measurements for each season, and shows the PMS5003T to FEM $\text{PM}_{2.5}$ ratio having little dependency on RH. As an example, the humidograms for winter 2023, summer 2025, and winter 2025 each have PMS5003T to FEM $\text{PM}_{2.5}$ ratios > 10 (Fig. S8). However, the elevated ratios occur when RH is anywhere between 20% and 90% RH. Instead, we compare our results to the simple linear model evaluated in the Barkjohn et al. study, which uses only PurpleAir $\text{PM}_{2.5}$ measurements and an intercept, yielding a slope of 0.524, an intercept of 1.57, and an R^2 of 0.78 (Barkjohn et al., 2021). The average slope across all seasons for our study is 0.38 ± 0.08 (Eq. (4); Table S4), with the average slopes for winter and summer, 0.38 ± 0.08 and 0.45 ± 0.13 (Table S4), lower than the slope reported by Barkjohn, and the average slope for spring, 0.57 ± 0.46 (Table S4), slightly higher. The differences in slope are likely due to PM composition specific to the Salt Lake Valley since both studies compare to FEM measurements.

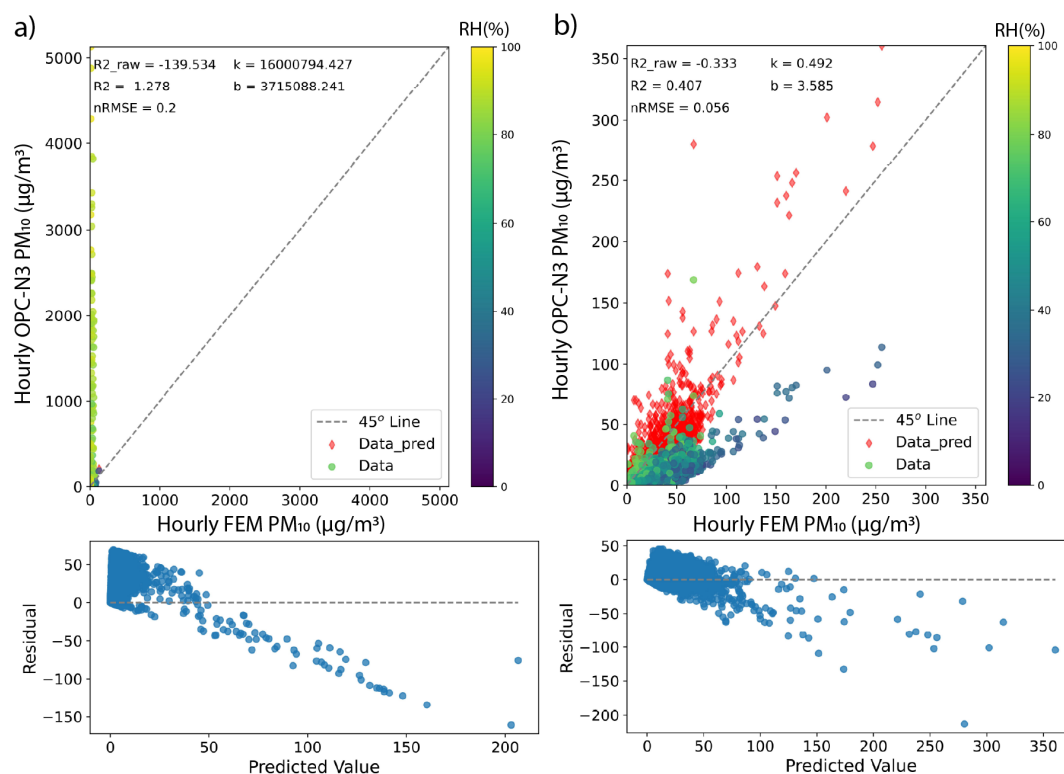


3.2.3 Screening OPC-N3 measurements for elevated RH

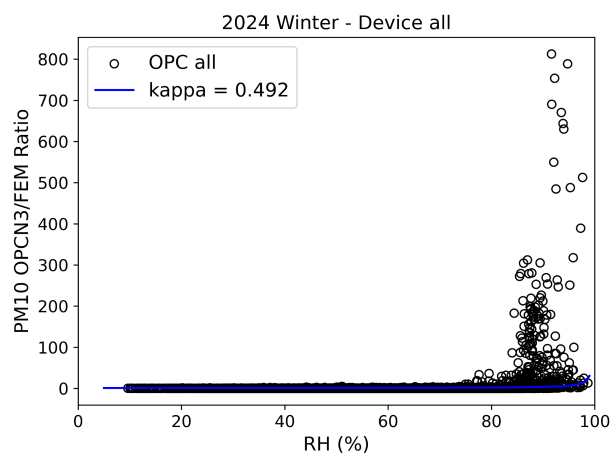
The OPC-N3 exhibits extremely high PM_{10} measurements (reaching $\sim 7500 \mu\text{g m}^{-3}$) when RH is above approximately 80% (Fig. S7a and Fig. 1a). Figure 2 presents the humidogram for the winter 2024 season and shows elevated OPC-N3 to FEM PM_{10} ratios (reaching ~ 800) at $RH > 80\%$ (Fig. S9 presents seasonal humidograms for each OPC-N3). Prior work reports that the OPC-N3 can overestimate mass concentrations at elevated RH (Bauerová et al., 2020; Crilley et al., 2018; Hagan and Kroll, 2020). For example, Crilley et al. (Crilley et al., 2018) found significant positive artifacts in PM mass measurements during times of high ambient RH ($> 85\%$), and Hagan and Kroll (Hagan and Kroll, 2020) report the OPC can overestimate $PM_{2.5}$ as much as 100-500% at humidities above 95%. A study using the OPC-N3 to measure fog reported PM_{10} measurements ranging from 6,897 to 14,960 $\mu\text{g m}^{-3}$, and concluded that these high values could not be explained by hygroscopic growth of aerosols (Nurowska et al., 2023). Figure 1a illustrates how applying the κ -Köhler correction model cannot account for the extreme hygroscopic growth seen in this study, with unreasonably high κ values (> 10 million) and slopes (> 1 million) estimated using Eq. (6). These estimates greatly exceed physically realistic values reported in the literature, where κ values for polluted continental aerosols typically range from 0.20 to 0.49, and sodium chloride, a highly hygroscopic aerosol, has a κ value of 1.31 (Carslaw, 2022).

We also evaluate the use of OPC-N3 reject count parameters to screen for exceptionally high PM_{10} measurements (Sect. S.3), but find that they are less effective than applying an RH threshold. Additionally, a one-month study in April 2022 of OPC-N3 sensors in Salt Lake City uses a similar RH threshold, where the authors drop measurements with $RH > 85\%$ ($< 2\%$ of measurements) (Kaur and Kelly, 2023b).

Tables S5 and S6 provide seasonal model parameters and performance metrics per sensor for the OPC-N3 PM_{10} MLR model (Eq. (5)) with and without the 80% RH threshold, respectively. Tables S7 and S8 provide the same for the OPC-N3 PM_{10} κ -Köhler model (Eq. (6)). Figures S7b and 1b present representative scatter plots for the winter 2024 season after excluding measurements with $RH > 80\%$ for the MLR and κ -Köhler models, respectively. On average, filtering measurements with $RH > 80\%$ removes 21% of winter observations, 7% of spring observations, and 1.3% of summer observations (Tables S5–S8). Filtering observations with $RH > 80\%$ substantially improves correction model performance during winter 2024. After removing these high-humidity observations, the average MLR model R^2 increases from 0.05 to 0.50, and the average NRMSE decreases from 75% to 50% (Fig. S7, Tables S5-S6). The κ -Köhler model exhibits an even larger improvement in winter 2024, with the average R^2 increasing from -1.25 to 0.59 and the average NRMSE decreasing from 29% to 5% (Fig. 1, Tables S7-S8). The rest of this manuscript focuses on measurements with $RH \leq 80\%$ to minimize the influence of this previously documented high-RH artifact.



450 **Figure 1: Collocated OPC-N3 PM₁₀ seasonal κ -Köhler correction model results for 2024 Winter (November 2024 to February 2025) for hourly measurements (a) and after dropping hourly measurements with relative humidity > 80% (b). Raw OPC-N3 measurements are denoted with circular scatter points colored by RH (Data), and corrected measurements are denoted with red diamonds (Data_{pred}). This illustration combines the measurements from the three collocated OPC-N3s.**



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Figure 2: PM₁₀ humidogram for the three colocated OPC-N3s for 2024 Winter (November 2024 to February 2025). Scatter points show the hourly OPC-N3 to FEM PM₁₀ ratio. OPC-N3 measurements are raw, hourly-averaged (no correction). The blue line shows the model fit using the κ (kappa) estimated from Eq. (2) using aggregated OPC-N3 PM₁₀ measurements from the three colocated sensors after dropping measurements with RH > 80% and removing outliers.

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3.2.4 OPC-N3 PM₁₀ MLR correction model performance

We initially compare the performance of the first three seasons (winter 2023, spring 2024, summer 2024) for the MLR and κ -Köhler correction models to prior work and EPA performance guidelines, because these seasons occurred before we colocated new OPC-N3 sensors to begin investigating sensor degradation. Table S2 also reports the number of
 465 hourly observations with a reference PM_{2.5}-to-PM₁₀ ratio less than 0.4. The U.S. EPA recommends at least one hour with a PM_{2.5}-to-PM₁₀ ratio less than 0.4 when evaluating colocated PM₁₀ sensors to confirm the presence of coarse particles during the evaluation period (Duvall et al., 2023). In this study, each season includes between 499 and 2472 hours with a PM_{2.5}-to-PM₁₀ ratio below 0.4 (Table S2).

470 Like low-cost PM_{2.5} sensors, low-cost PM₁₀ sensors have EPA performance guidelines of $R^2 \geq 0.7$ and $\text{NRMSE} \leq 30\%$ (Duvall et al., 2023). Table 2 presents the average values of the seasonal MLR parameters and performance metrics, grouped by old and new OPC-N3 sensors, whereas Table S6 presents the results for individual sensors. The MLR correction model passes EPA's guidelines for R^2 and NRMSE in winter 2023 and summer 2024, but in spring 2024 the model only passes the R^2 guideline and fails the NRMSE guideline with a value of 32% (Table 2). The
 475 decrease in performance in spring 2024 could be due to generally lower PM loading (average IQR: 7 to 20 $\mu\text{g m}^{-3}$) compared to winter 2023 and summer 2024 (average IQR: 6 to 24 $\mu\text{g m}^{-3}$ and 17 to 34 $\mu\text{g m}^{-3}$, respectively) (Table S2). In winter 2023, the OPC-N3 sensors underestimate PM₁₀ concentrations (Eq. (5) average slope of 1.66; Table 2 and Table S6), and corrected measurements show strong correlations with FEM PM₁₀ ($R^2 > 0.89$; Table 2 and Table S6). Two previous short-term studies also report strong correlations (R^2 0.865 to 0.956) and underestimations of PM₁₀
 480 (linear regression slopes of 1.09 - 2.09) (Dubey et al., 2022; Kaur and Kelly, 2023b).

Looking at longer deployment periods, an eight-month evaluation of an OPC-N3 sensor in Ostrava, Czech Republic, reports PM₁₀ underestimation (slope of 1.19) and an average R^2 of 0.61 between OPC-N3 and FIDAS 200 PM₁₀ measurements, with PM₁₀ concentrations ranging from approximately 5 to 90 $\mu\text{g m}^{-3}$ (Bílek et al., 2021). This study similarly finds underestimation and slightly reduced correlation (Eq. (5) slopes ranging from 1.57 to 2.26, and average
 485 R^2 of 0.79 and 0.74 during spring and summer 2024; Table 2 and Table S6). Additionally, a seven-month field study in Puerto Rico compares MLR-corrected OPC-N3 PM₁₀ measurements with 24 h filter-based FRM PM₁₀ measurements and reports an R^2 of 0.87 (Holder et al., 2026). Their MLR model includes an OPC-N3 PM₁₀ coefficient of 0.88 but includes Bin0 as an additional predictor, which may explain differences from the model coefficient developed here. The Puerto Rico study also reports a more negative RH coefficient (−0.49) than this study (−0.20 to
 490 −0.23 during spring and summer 2024; Table 2), likely because of its higher RH (77%–85% versus 30.4%–66.8%; Table S2) and coastal environment, where hygroscopic marine aerosols enhance RH effects (Holder et al., 2026).



After the summer of 2024, the MLR model performance for the old OPC-N3s declines substantially (average winter 2024 R^2 of 0.51 ± 0.02 and NRMSE of $52\% \pm 2\%$, Table 2). Consequently, we evaluate a κ -Köhler model for correction and whether it can account for the observed sensor response.

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Table 2: Seasonal average ($\pm$ standard deviation) correction model parameters and performance metrics for the old and new OPC-N3 sensors using the PM ₁₀ MLR, Eq. (1), and PM ₁₀ κ -Köhler, Eq. (2), correction models after removing outliers and observations with RH > 80%. Results for individual OPC-N3 sensors are in Tables S6 and S8.													
MLR (> 80% RH dropped)	Old OPC-N3 sensors (905, 605, 501)					New OPC-N3 sensors (011, 201, 216)							
	b ₀	b ₁	b _{RH}	R ²	NRMSE	b ₀	b ₁	b _{RH}	R ²	NRMSE			
2023 Winter	14.7 $\pm$ 4.3	1.66 $\pm$ 0.09	-0.23 $\pm$ 0.06	0.92 $\pm$ 0.03	0.30 $\pm$ 0.02								
2024 Spring	10.7 $\pm$ 0.7	1.66 $\pm$ 0.11	-0.20 $\pm$ 0.02	0.79 $\pm$ 0.05	0.32 $\pm$ 0.03								
2024 Summer	13.6 $\pm$ 2.9	2.09 $\pm$ 0.15	-0.22 $\pm$ 0.04	0.74 $\pm$ 0.03	0.27 $\pm$ 0.01								
2024 Winter	23.9 $\pm$ 3.8	2.28 $\pm$ 1.00	-0.27 $\pm$ 0.04	0.51 $\pm$ 0.02	0.52 $\pm$ 0.02								
2025 Spring	15.6 $\pm$ 1.2	7.68 $\pm$ 0.55	-0.41 $\pm$ 0.21	0.80 $\pm$ 0.06	0.39 $\pm$ 0.08	17.2 $\pm$ 1.9	1.64 $\pm$ 0.94	-0.25 $\pm$ 0.04	0.80 $\pm$ 0.15	0.42 $\pm$ 0.06			
2025 Summer	6.1 $\pm$ 9.6	10.7 $\pm$ 4.11	-0.15 $\pm$ 0.08	0.74 $\pm$ 0.07	0.31 $\pm$ 0.03	17.3 $\pm$ 10.5	1.47 $\pm$ 1.26	-0.14 $\pm$ 0.01	0.56 $\pm$ 0.42	0.36 $\pm$ 0.13			
2025 Winter ^a	23.4	11.7	-0.28	0.78	0.32	25.9 $\pm$ 8.9	4.56 $\pm$ 1.17	-0.22 $\pm$ 0.004	0.54 $\pm$ 0.53	0.43 $\pm$ 0.20			
κ -Köhler (> 80% RH dropped)	Old OPC-N3 sensors (905, 605, 501)					New OPC-N3 sensors (011, 201, 216)							
	b	κ	R ²	NRMSE		b	κ	R ²	NRMSE				
2023 Winter	2.22 $\pm$ 0.29	0.39 $\pm$ 0.46	0.92 $\pm$ 0.02	0.02 $\pm$ 0.002									
2024 Spring	2.71 $\pm$ 0.29	0.95 $\pm$ 0.22	0.81 $\pm$ 0.04	0.03 $\pm$ 0.001									
2024 Summer	3.90 $\pm$ 0.70	1.59 $\pm$ 0.86	0.75 $\pm$ 0.03	0.03 $\pm$ 0.003									
2024 Winter	5.37 $\pm$ 2.53	0.67 $\pm$ 0.20	0.59 $\pm$ 0.13	0.05 $\pm$ 0.01		3.83 $\pm$ 1.25	1.39 $\pm$ 0.16	0.84 $\pm$ 0.04	0.02 $\pm$ 0.01				
2025 Spring	16.0 $\pm$ 2.2	3.14 $\pm$ 0.69	0.79 $\pm$ 0.05	0.03 $\pm$ 0.01		2.24 $\pm$ 1.48	0.10 $\pm$ 0.43	-0.27 $\pm$ 1.78	0.14 $\pm$ 0.19				
2025 Summer ^b	12.2 $\pm$ 0.3	0.17 $\pm$ 0.10	0.72 $\pm$ 0.10	0.04 $\pm$ 0.02		2.57 $\pm$ 0.03	0.29 $\pm$ 0.38	0.14 $\pm$ 0.93	0.06 $\pm$ 0.04				
2025 Winter ^{a,c}	23.0	0.50	0.77	0.06									
^a Only one old sensor (501) was deployed during winter 2025.													
^b In summer 2025, new sensor 201 had different performance than the other two new sensors. The averages for b, κ , R ² , and NRMSE excluding sensor 201 are: 3.08 $\pm$ 0.33, 0.35 $\pm$ 0.06, 0.76 $\pm$ 0.07, and 0.04 $\pm$ 0.01.													
^c In winter 2025, new sensor 201 had different performance than new sensor 216. The values for b, κ , R ² , and NRMSE excluding sensor 201 are: 2.60, 0.024, 0.795, and 0.024.													

^aOnly one old sensor (501) was deployed during winter 2025.

^bIn summer 2025, new sensor 201 had different performance than the other two new sensors. The averages for b, κ , R², and NRMSE excluding sensor 201 are: 3.08 $\pm$ 0.33, 0.35 $\pm$ 0.06, 0.76 $\pm$ 0.07, and 0.04 $\pm$ 0.01.

^cIn winter 2025, new sensor 201 had different performance than new sensor 216. The values for b, κ , R², and NRMSE excluding sensor 201 are: 2.60, 0.024, 0.795, and 0.024.



3.2.5 OPC-N3 PM₁₀ κ -Köhler correction model performance

The κ -Köhler and MLR correction models produce similar R^2 values during winter 2023, spring 2024, and summer 2024, with the κ -Köhler model achieving average R^2 between 0.75 and 0.92 (Table 2). However, the κ -Köhler model produces substantially lower NRMSE values than the MLR model (average NRMSE between 2.0 to 3.0%, Table 2). Table S8 presents the individual sensor κ -Köhler parameters and performance metrics, and Fig. 1b shows an example of the κ -Köhler correction by plotting the hourly-averaged OPC-N3 PM₁₀ measurements alongside the κ -Köhler-corrected measurements for winter 2024.

The average seasonal κ values, estimated from Eq. (6), are 0.39 ± 0.46 for winter 2023, 0.95 ± 0.22 for spring 2024, and 1.59 ± 0.86 for summer 2024 (Table 2). The variation in κ values between seasons is expected because the hygroscopic behavior of aerosols depends on particle composition (particularly the inorganic fraction) (Crilley et al., 2018). The κ values in this study are larger than those reported in previous studies using OPC-N3 sensors. One study using two OPC-N3 sensors in Warsaw, Poland, during winter and spring, found a mean κ for PM₁₀ of 0.12 ± 0.17 in winter and 0.13 ± 0.13 in spring (Nurowska and Markowicz, 2023). Additionally, events with κ values > 0.5 occurred when the air mass was coming from the North Atlantic, carrying sea salt particles (Nurowska and Markowicz, 2023). Another study reports PM₁₀ κ values ranging from 0.41 to 0.51 for 14 OPC-N2 sensors over five weeks between August and October 2016 in Birmingham, United Kingdom (Crilley et al., 2018).

The κ values in this study are likely overestimated because Eq. (6) is fit to measurements with $RH < 80\%$ while the previous two studies did not exclude PM measurements with high RH, and fit the κ to PM measurements above the aerosol deliquescence relative humidity (DRH) of approximately 80% (Crilley et al., 2018; Nurowska and Markowicz, 2023). Fitting κ below the aerosol DRH can overestimate aerosol hygroscopic growth (Crilley et al., 2018; Nurowska and Markowicz, 2023). DRH is dependent on particle composition (e.g., sulfate DRH ranges from 78% to 87% and chloride DRH ranges from 11% to 86%) (Peng et al., 2022). The Salt Lake Valley shows elevated concentrations of sodium, magnesium, potassium, and chloride, similar to those in marine environments (Fig. S10) (EPA, 2025). The mean κ value for sodium chloride, sea salt, and clean marine aerosols ranges from 0.87 to 1.33 (Andreae and Rosenfeld, 2008; Petters and Kreidenweis, 2007; Zieger et al., 2017). The composition of aerosols in the Salt Lake Valley likely contributes to the elevated κ values found during spring and summer in this study (Table 2). While in winter, ammonium nitrate dominates particulate matter in the Salt Lake Valley (Kaur et al., 2026b; Kelly et al., 2013). Reported κ values for ammonium nitrate range from 0.58 to 0.75 (Petters and Kreidenweis, 2007), which fall within the mean $\pm$ one standard deviation of the winter κ values reported in this study (Table 2).

This study's growth factors range from 0.01 to 56 during winter 2023, 0.02 to 80 during spring 2024, and 0.3 to 11 during summer 2024, with a maximum range of 0.02 to 813 observed during winter 2024 (Fig. S9). Whereas the PM₁₀ growth factors in the Warsaw, Poland, study only ranged from 1.02 to 4.58 during winter, and from 1.32 to 2.80 during



spring (Nurowska and Markowicz, 2023). As discussed in Sect. 3.2.3, hygroscopic growth cannot explain these extremely high PM_{10} concentrations, which further supports excluding measurements with $\text{RH} > 80\%$.

The κ -Köhler performance during winter 2024 does not meet EPA guidelines, with an average R^2 of 0.59 ± 0.13 and an average NRMSE of $5\% \pm 1\%$ (Table 2). Therefore, we shift to investigate the degradation of the OPC-N3 sensors by colocating new OPC-N3 sensors alongside the old at the UTTC station (Table 1).

3.3 Long-term field performance

Unlike two previous field studies that report no evidence of OPC-N3 sensor performance degradation after approximately 12 months in the field (Bílek et al., 2021; Bittner et al., 2022), we identify sensor degradation after approximately 10 months in the field. The old OPC-N3 sensors (905, 501) show substantial increases in PM_{10} correction model slopes over time, where κ -Köhler slopes increase approximately sevenfold (Eq. (6); Fig. 3), and MLR slopes increase by approximately fivefold (Eq. (5); Fig. S11) from winter 2023 to spring 2025. Figure 4 illustrates this degradation by comparing OPC-N3 905 with the FEM, showing progressively lower OPC-N3 PM_{10} and $\text{PM}_{2.5}$ measurements relative to the FEM measurements throughout deployment. OPC-N3 501, the longest deployed sensor (Table 1), continues to show increasing PM_{10} correction model slopes after spring 2025 (Fig. 3 and Fig. S11). In contrast, the old PMS5003T sensors (261, 357) show no comparable changes in $\text{PM}_{2.5}$ correction model slopes, which range from 0.299 to 0.498 between winter 2023 and spring 2025 (Eq. (4); Fig. S12). Prior work reports that Plantower sensors installed in PurpleAir monitors require servicing after approximately 3 to 4 years in the field (deSouza et al., 2023a).

In March and April 2025, three new OPC-N3 and PMS5003T sensors are colocated at the UTTC station (Table 1), enabling comparisons between old and new sensors for spring, summer, and winter 2025. The new OPC-N3 sensors exhibit PM_{10} correction model slopes that differ from the older sensors' slopes (e.g., spring, summer, and winter 2025 mean κ -Köhler slopes of 2.92 ± 1.28 for new sensors, and 15.88 ± 4.53 for old sensors; Fig. 3) but match more closely to the slopes of the old sensors when first deployed (Fig. 3; Fig. S11). The new PMS5003T sensors also differ from the older sensors, although the changes in $\text{PM}_{2.5}$ correction model slopes are smaller (Fig. S12).

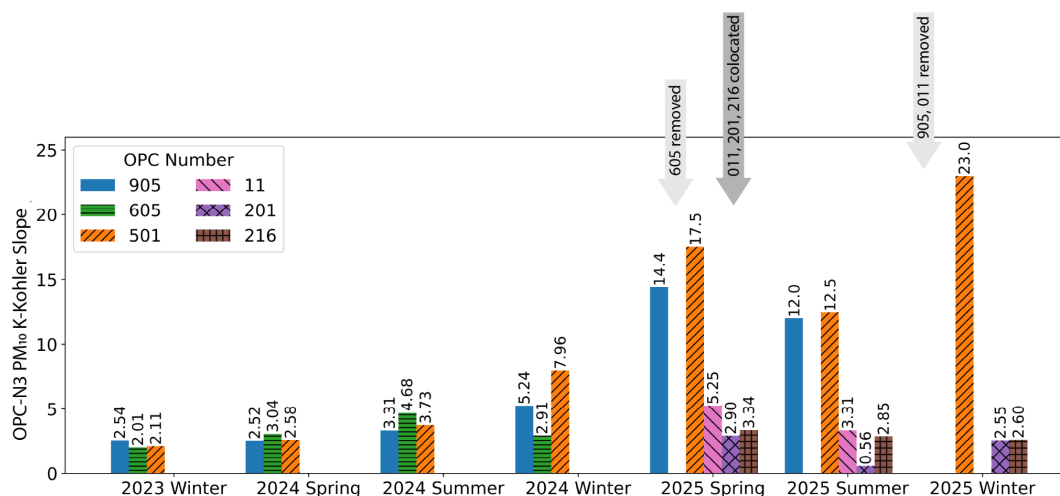


Figure 3: Slopes for collocated OPC-N3 PM₁₀ seasonal κ-Köhler correction models with RH > 80% dropped.

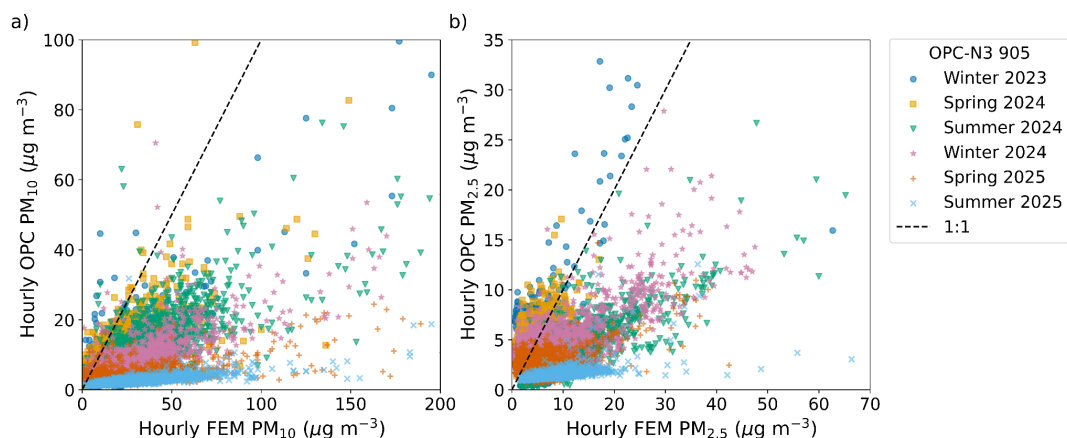


Figure 4: Hourly OPC-N3 sensor 905 measurements compared with FEM measurements for (a) PM₁₀ and (b) PM_{2.5}. Data points are colored by season. Measurements are uncorrected and RH < 80%. Axes are zoomed in for clarity; full seasonal scatter plots are provided in Fig. S13–S26.

3.3.1 Intersensor comparisons of old and new OPC-N3 sensors

Regardless of sensor age, OPC-N3-to-OPC-N3 PM₁₀ and PM_{2.5} comparisons yield high average R² values (> 0.66), reflecting their consistent response to changes in PM concentrations (Table 3 and Table S9; Fig. S13–S26). Previous studies similarly report strong intersensor correlation, including a Spearman correlation of 0.99 between two OPC-N3 PM₁₀ sensor measurements over five months (Bauerová et al., 2020), and R² > 0.9 among three OPC-N3 PM_{2.5} sensor measurements over one month (Bittner et al., 2022).



However, scatter plot slopes show high age-related intersensor variability, where the spring to winter 2025 old-versus-new OPC-N3 PM_{10} comparisons yield average slopes of 0.16–0.19, whereas old-versus-old and new-versus-new comparisons range from 0.52 to 0.87 (Table 3; Fig. S13-S19). Similar age-dependent differences appear in the slopes between OPC-N3 $\text{PM}_{2.5}$ measurements (Table S9; Fig. S20-S26). However, the PMS5003T $\text{PM}_{2.5}$ measurements show no consistent age-related trend, where the spring to winter 2025 old-versus-old and new-versus-new slopes range from 0.82 to 1.09, and old-versus-new slopes range from 0.52 to 1.43 (Table S10; Fig. S27-S33).

Bland-Altman analysis supports the conclusion that the old and new OPC-N3 sensors have differing responses to the same change in PM concentration. Table 4 summarizes OPC-N3 PM_{10} Bland-Altman results, with corresponding OPC-N3 $\text{PM}_{2.5}$ and PMS5003T $\text{PM}_{2.5}$ summaries provided in Tables S11 and S12. During spring 2025, old-versus-new OPC-N3 PM_{10} comparisons produce larger bias ($4.99 \pm 1.57 \mu\text{g m}^{-3}$) and LOA span ($121 \pm 63 \mu\text{g m}^{-3}$) than old-versus-old (bias = $-1.54 \mu\text{g m}^{-3}$; LOA span = $11.08 \mu\text{g m}^{-3}$) or new-versus-new (bias = $1.12 \pm 2.61 \mu\text{g m}^{-3}$; LOA span = $86 \pm 41 \mu\text{g m}^{-3}$) comparisons (Table 4). Although one study uses Bland-Altman analysis to compare OPC-N3 with reference $\text{PM}_{2.5}$ measurements (Nimo et al., 2025), to our knowledge, no prior study has used either Bland-Altman analysis or scatter plot comparisons to compare older and newer OPC-N3 sensors.



Table 3: Summary of seasonal scatter plot matrices for OPC-N3 PM ₁₀ showing the average ± standard deviation of R ² and slope for groups of new and old sensors. Fig. S13-S19 show seasonal scatter plot matrices and results for each sensor.				
OPC PM ₁₀ vs FEM PM ₁₀				
Season	Old (905, 605, 501) vs FEM	New (011, 201, 216) vs FEM		
	R ²	Slope	R ²	Slope
Winter 2023	0.86 ± 0.04	0.50 ± 0.03		
Spring 2024	0.61 ± 0.05	0.33 ± 0.04		
Summer 2024	0.61 ± 0.02	0.29 ± 0.02		
Winter 2024	0.61 ± 0.03	0.26 ± 0.16		
Spring 2025	0.70 ± 0.11	0.10 ± 0.04	0.70 ± 0.03	0.54 ± 0.20
Summer 2025	0.66 ± 0.00	0.07 ± 0.03	0.68 ± 0.05	0.37 ± 0.08
Winter 2025	0.58	0.07	0.64 ± 0.11	0.41 ± 0.04
OPC PM ₁₀ vs OPC PM ₁₀				
Season	Old vs Old (905, 605, 501)	New vs New (011, 201, 216)		
	R ²	Slope	R ²	Slope
Winter 2023	1.00 ± 0.00	0.94 ± 0.08		
Spring 2024	0.81 ± 0.04	0.83 ± 0.06		
Summer 2024	0.83 ± 0.04	0.85 ± 0.08		
Winter 2024	0.89 ± 0.05	1.62 ± 1.15		
Spring 2025	0.81	0.62	0.97 ± 0.03	0.72 ± 0.54
Summer 2025	0.93	0.52	0.75 ± 0.12	0.72 ± 0.33
Winter 2025			0.69	0.86
			New (011, 201, 216) vs Old (905, 605, 501)	
			R ²	Slope
			0.78 ± 0.15	0.18 ± 0.10
			0.87 ± 0.07	0.19 ± 0.09
			0.66 ± 0.37	0.16 ± 0.06



Table 4: Summary of seasonal OPC-N3 PM₁₀ Bland-Altman comparisons showing the average $\pm$ standard deviation for results based on groupings of new and old sensors. Fig. S34-S40 show seasonal Bland-Altman plots and results for each sensor. LOA - 95% limits of agreement. Bias and LOA units are $\mu\text{g m}^{-3}$.

OPC PM₁₀ vs FEM PM₁₀		Old (905, 605, 501) vs FEM			New (011, 201, 216) vs FEM		
Season		Bias	LOA Low	LOA High	LOA Low	LOA High	LOA Span
Winter 2023		-12.24 $\pm$ 1.77	-51.8 $\pm$ 0.3	27.4 $\pm$ 3.7			79.2 $\pm$ 4.0
Spring 2024		-8.22 $\pm$ 1.01	-30.0 $\pm$ 0.4	13.6 $\pm$ 2.0			43.6 $\pm$ 2.0
Summer 2024		-18.6 $\pm$ 0.3	-46.6 $\pm$ 0.3	9.48 $\pm$ 0.89			56.1 $\pm$ 1.2
Winter 2024		-17.8 $\pm$ 3.3	-69.7 $\pm$ 8.9	34.1 $\pm$ 13.4			103.8 $\pm$ 21.7
Spring 2025		-22.9 $\pm$ 1.0	-98.9 $\pm$ 2.0	53.1 $\pm$ 4.0			152.0 $\pm$ 5.9
Summer 2025 ^a		-27.5 $\pm$ 2.4	-74.1 $\pm$ 9.8	19.0 $\pm$ 5.0			93.2 $\pm$ 14.8
Winter 2025 ^a		-26.13	-69.6	17.3			86.9
OPC PM₁₀ vs OPC PM₁₀		Old vs Old (905, 605, 501)			New vs New (011, 201, 216)		
Season		Bias	LOA Low	LOA High	LOA Low	LOA High	LOA Span
Winter 2023		-0.74 $\pm$ 0.58	-16.9 $\pm$ 7.8	15.4 $\pm$ 6.6			32.2 $\pm$ 14.4
Spring 2024		-0.97 $\pm$ 1.17	-3.70 $\pm$ 7.55	5.14 $\pm$ 0.69			8.84 $\pm$ 6.92
Summer 2024		-0.30 $\pm$ 0.32	-6.33 $\pm$ 0.90	5.73 $\pm$ 0.35			12.1 $\pm$ 1.2
Winter 2024		-7.16 $\pm$ 2.93	-23.7 $\pm$ 19.7	17.1 $\pm$ 14.0			40.8 $\pm$ 33.2
Spring 2025		-1.54	-7.08	4.00			11.1
Summer 2025 ^a		0.10	-3.24	3.43			6.67
Winter 2025 ^a							
OPC PM₁₀ vs OPC PM₁₀		New (011, 201, 216) vs Old (905, 605, 501)			New vs Old (011, 201, 216)		
Season		Bias	LOA Low	LOA High	LOA Low	LOA High	LOA Span
...							
Spring 2025		4.99 $\pm$ 1.57	-55.5 $\pm$ 30.6	65.4 $\pm$ 32.9			120.9 $\pm$ 63.5
Summer 2025 ^a		11.2 $\pm$ 5.8	-66.5 $\pm$ 89.7	75.7 $\pm$ 81.0			142.2 $\pm$ 167.9
Winter 2025 ^a		9.34 $\pm$ 3.01	-45.5 $\pm$ 52.3	64.2 $\pm$ 58.3			109.8 $\pm$ 110.7

^aComparisons with OPC-N3 201 during summer and winter 2025 have differences reaching $\sim 1000 \mu\text{g m}^{-3}$, while other comparisons have differences within $\pm 400 \mu\text{g m}^{-3}$. Results with comparisons to OPC-N3 201 removed (bias; LOA span):
 Summer 2025 - new vs FEM (-20.0 $\pm$ 2.9; 71.2 $\pm$ 14.4), new vs new (2.16; 24.18), and new vs old (7.90 $\pm$ 1.04; 34.1 $\pm$ 10.1)
 Winter 2025 - new vs FEM (-19.1; 77.8), new vs new (-), and new vs old (7.21; 31.5)



3.4 Post-deployment laboratory investigation of selected OPC-N3s

To identify possible causes of OPC-N3 degradation, we evaluate the reported sample flow rate, the laser status, the Tellus custom printed circuit board, and the power supply (Sect. S.4 and S.5). However, none of these factors explains the observed performance decline. Next, we remove two old sensors (905 and 605) and one new sensor (011) from the UTTC station for laboratory evaluation. We also include two additional never-deployed OPC-N3 sensors as controls in this laboratory investigation to account for the inherent variability in laboratory testing discussed in Sect. S.6.

Before testing, we flush the removed sensors overnight with filtered air to remove residual dust from the sensing chamber. We then evaluate the PM_{10} response of all five sensors using Arizona road dust and the DustTrak. Figure 5 compares the laboratory regression slopes (Eq. (2)) measured before field deployment, after field retrieval, and after overnight flushing. OPC-N3 sensors 605 and 011 retain regression slopes similar to their pre-deployment values (Fig. 5). However, the post-deployment regression slopes for OPC-N3 sensor 905 are over ten times their pre-deployment value, indicating significant underestimation relative to the DustTrak, and flushing did not improve the result (Fig. 5).

To identify the cause of this underestimation, we disassemble and inspect OPC-N3 sensor 905. In addition to dust accumulation inside the sensing chamber, which has been reported as a mechanism for degradation for other low-cost light-scattering PM sensors (deSouza et al., 2023a; Kelly et al., 2017), visual inspection reveals a dandelion tuft and irreversible corrosion of the internal elliptical mirror (Fig. 6). The mirror corrosion is a likely contributor to the observed PM_{10} underestimation (Fig. 6). Figure 6 shows a photo of the corroded mirror removed from OPC-N3 sensor 905 and a photo of a new mirror purchased from Alphasense.

The OPC-N3 user manual does not describe the elliptical mirror or specify its material. Communication with Alphasense indicates that the mirror is a proprietary, custom-made component, and no additional design information is available. Based on its appearance and geometry, the mirror resembles commercially available protected aluminum mirrors. Metal mirrors, commonly aluminum-coated plastics (Alder et al., 2020; Arias and Jaramillo, 2020; Bielawny, 2019), are widely used because they are lightweight, inexpensive, and can achieve high optical accuracy (Zhang et al., 2021). In Sect. 3.2.5, we discuss that the airshed near the Great Salt Lake contains elevated chloride concentrations. Previous studies demonstrate that chloride-containing environments can corrode aluminum mirrors, even when dielectric protective coatings are present (Guenther, 1993; Guenther et al., 1990). More broadly, chloride is well known to promote corrosion of coated metals and reflective surfaces (Folgnier, 2019; Nguyen and Lin, 1991; Schütz et al., 1997). These findings suggest that chloride exposure is a plausible contributor to the mirror corrosion observed in the degraded OPC-N3 sensors.

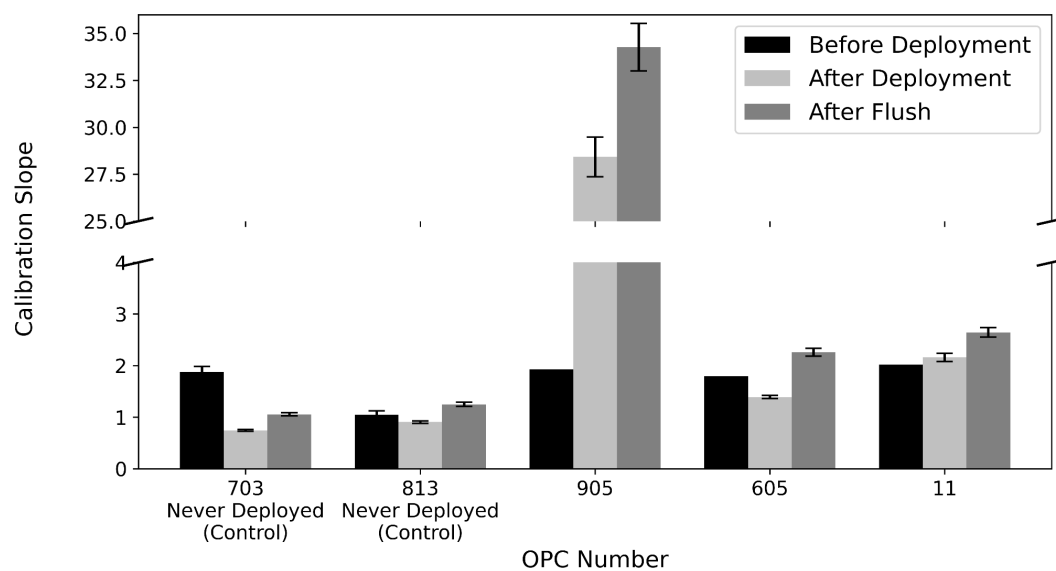


Figure 5: Laboratory regression slopes, from Eq. (2), using Arizona road dust against a DustTrak for three OPC sensors (905, 605, and 011) before and after colocation at UTTC, and after flushing with clean dry air. Two new/never-deployed OPCs (703 and 813) are included as controls. Error bars indicate the slope's 95% confidence interval (CI not calculated for 905, 605, and 011 before deployment calibration).

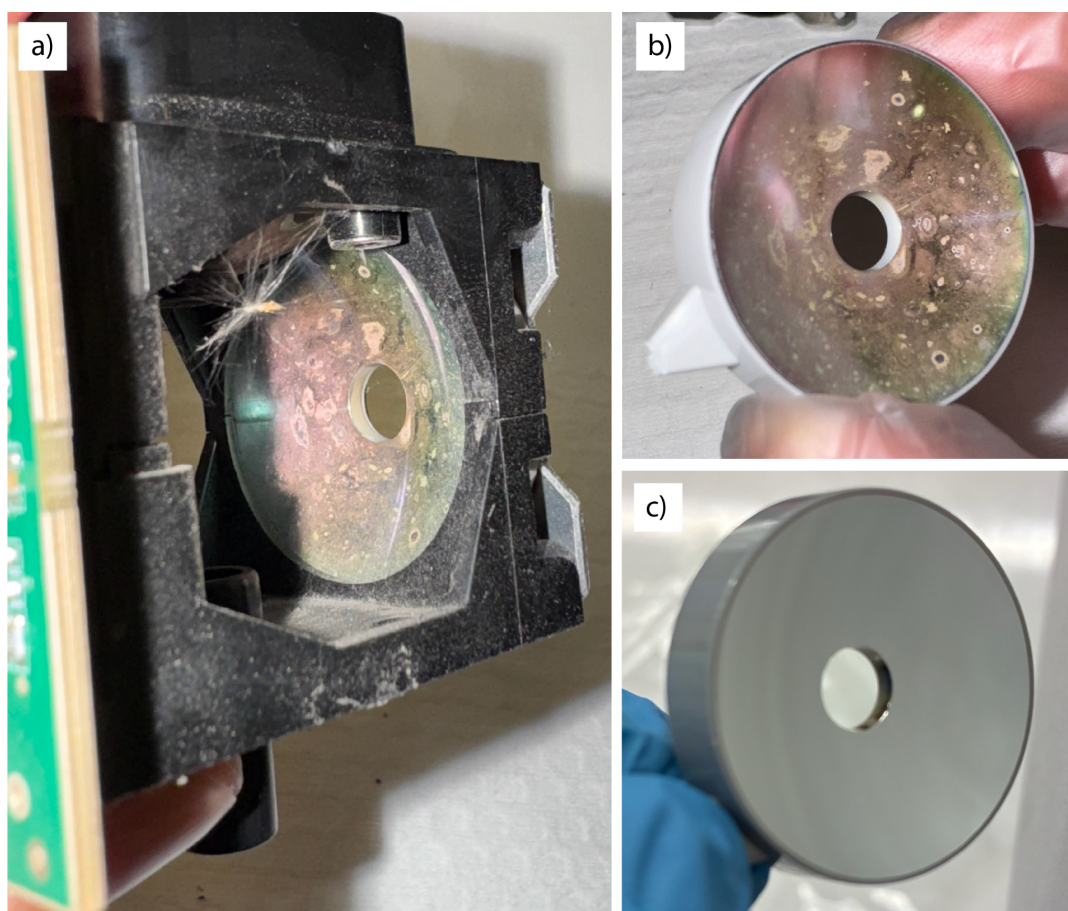


Figure 6: Corroded mirror from OPC-N3 from sensor 905 after 18 months in the field. a) The inside of the OPC-N3 chamber and mirror immediately after opening the sensor, including a dandelion tuft and dust residue inside the chamber. b) The mirror after removal from the OPC-N3 housing and gentle cleaning with a Kim wipe. c) A new mirror.

3.5 Improving the performance of OPC-N3s with a corroded mirror

Alphasense OPC-N3 sensors cost approximately US\$ 500, but the elliptical mirror from Alphasense only costs approximately US\$ 30 (per communication with Alphasense Ltd.). Therefore, we evaluate mirror replacement as an option to recover OPC-N3 performance on three sensors: one old (905), one new (011), and one never-deployed (716). The never-deployed sensor was included in the analysis to isolate the effect of mirror replacement on sensor performance, independent of prior sensor usage. Section S.7 is the standard operating procedure (SOP) to replace the mirror.



3.5.1 Size selectivity testing of OPC-N3 sensors with replaced mirror

First, the size selectivity of the OPC-N3 sensors before and after mirror replacement is evaluated with a GRIMM using particles generated by an FMAG (Fig. S4). Mirror alignment is critical, as even slight misalignment prevents the OPC-N3 from producing a response. Before the mirror change, old OPC-N3 sensor 905 (corroded mirror) reports ~0 counts for all target monodisperse particle diameters (Fig. 7), with a bias in total counts of ~100%, compared to the GRIMM (Fig. S55). New OPC-N3 sensor 011 (minor mirror corrosion compared to sensor 905) reports mean bias error in total number counts between -63.6% to 25.4% (negative bias for particle diameters $< 3.65 \mu\text{m}$; Fig. S55), a low mean bias in mean diameter for the smallest diameter (~2%, Fig. S56), and varying mean bias in mean diameter for the other four sizes (-17.3% to -29.4%, Fig. S56). Never-deployed OPC-N3 sensor 716 reports a similar PSD to the GRIMM (Fig. 7), with a mean bias error in mean diameter between -1% to 8% (Fig. S56), but the reported number concentration is generally higher than the GRIMM, with a mean bias error in total number of $\sim 50 \pm 24\%$ for diameters $> 0.5 \mu\text{m}$ (Fig. S55). The number concentration variation with respect to GRIMM is expected at larger diameters, but the never-deployed sensor shows higher number concentration bias even at the diameter of $0.7 \mu\text{m}$, indicating sensor-specific overestimation, rather than flow distribution issues.

After changing the mirror, OPC-N3 sensor 905 reports a similar total number concentration to the GRIMM for all sizes, with a mean bias error in total number between 5 to -5%, except the smallest size (mean bias error of -44%) (Fig. S55), while the bias in the mean diameter was less than 32% for all sizes (Fig. S56). For new OPC-N3 sensor 011 and never-deployed sensor 716, the bias in the mean diameter is somewhat similar to the results before changing the mirrors, especially for sizes $> 0.5 \mu\text{m}$, with mean bias in mean diameter between -7 to 2% and -24 to -30%, for sensor 011 and sensor 716, respectively (Fig. S56). New OPC-N3 sensor 011 reports slightly higher number concentration than the GRIMM, for sizes $> 5 \mu\text{m}$ (Fig. S55), while never-deployed sensor 716 reports higher total number concentrations than the GRIMM for all but the smallest size (Fig. S55), consistent with the results before mirror change. The improved performance observed after the replacement of the degraded mirror in OPC-N3 905, and the similar performance of the new sensor 716, suggest that these sensors can be used following a mirror change.

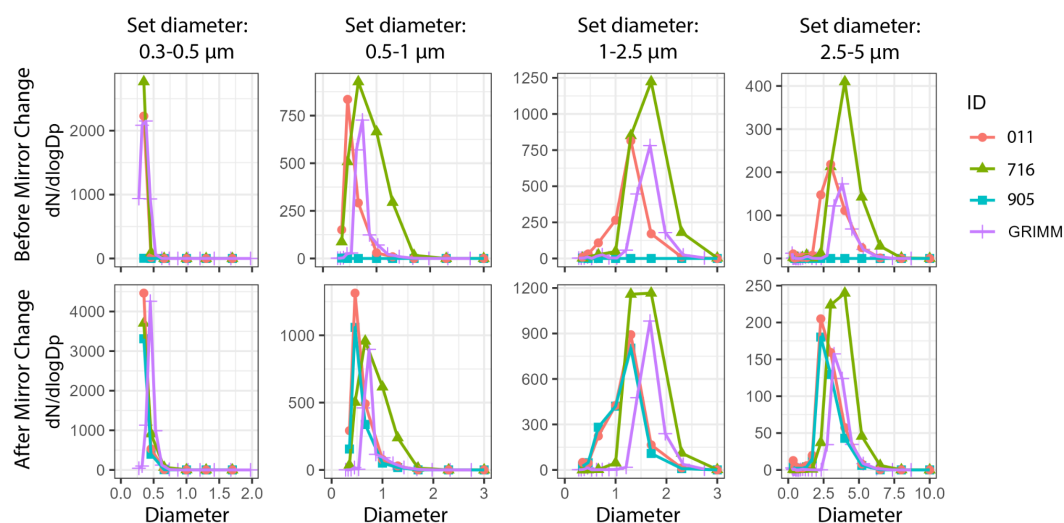


Figure 7: Particle size distribution of the OPC-N3 sensors and GRIMM at varying FMAG settings before (top row) and after (bottom row) replacing the mirror in the OPC-N3 sensors.

3.5.2 Evaluation of OPC-N3 mirror replacement using Arizona road dust

Evaluation of OPC-N3 mirror replacement using the laboratory precision test with Arizona road dust is faster and less expensive than size-selectivity testing with the FMAG. Thus, we assess the repeatability of different operators replacing a mirror and evaluate the replacement using the Arizona road dust setup (Fig. S1). Between each trial, the operator removes and reinstalls the replacement mirror following the SOP (Sect. S.7). Section S.8 describes the methods and results from the repeatability tests. Briefly, different operators can successfully perform the mirror replacement. Unfortunately, the laser mount on the never-deployed OPC-N3 sensor 716 was bumped in between one of the tests, and it subsequently failed every subsequent test, emphasizing the care that must be taken when replacing the mirror. Correcting the laser alignment requires manufacturer support.

After aligning the mirror such that the OPC-N3 sensor passes one precision test, we repeat the Arizona road dust precision test an additional four times. Never-deployed sensors pass the per-batch precision test four out of five times (Sect. S.6). Section S.9 presents the results of these repeated tests after mirror alignment. Only OPC-N3 sensor 011 passes all five of the Arizona road dust tests (Sect. S.9; Table S22). While mirror replacement substantially improves the performance of OPC-N3 sensor 905, reducing its Arizona road dust test regression slopes to 2.55–3.38 (Sect. S.9; Table S22) from post-deployment values greater than 27.5 (Fig. 5), the sensor only meets the per-batch precision criterion in two of the five tests. Therefore, even though size-selectivity tests using the FMAG and GRIMM for OPC-N3 905 show that mirror replacement improves bin assignment, the Arizona road dust test results indicate that this improvement may be insufficient for some applications or that the mirror replacement procedure may need refinement.



3.6 Screening OPC-N3s for degraded performance without FEMs

When FEM measurements are unavailable, the OPC-N3 $PM_{2.5}$ -to-PMS5003T $PM_{2.5}$ ratio may provide a practical indicator of OPC-N3 sensor degradation because the PMS5003T sensors do not exhibit the same decline in performance during the timeframe of this study. We use daily averaged ratios because the hourly ratios are autocorrelated (Figures S57-S59). We evaluate the ratios for the first 12 months of deployment for the old sensors, because AirU Pro Unit 3, containing old OPC-N3 605 and old PMS5003T 155, is only deployed for 12 months (Table 1). The analysis includes measurements with $RH \leq 80\%$, $PMS5003T PM_{2.5} \geq 1 \mu g m^{-3}$, and $OPC-N3 PM_{2.5} \geq 1 \mu g m^{-3}$. Where the second two criteria are applied to avoid unstable ratios caused by near-zero numerator or denominator values. For all three old AirU Pro units, the ratio distribution between the first three months and last three months of the first year decreases significantly (Mann–Whitney U test, $p < 0.05$; Fig. 8), with a $56.3 \pm 21.5\%$ decrease in the median averaged across the three units (Fig. 8). Because the first (February–April 2024) and last (December 2024–February 2025) three-month periods share only one month (February), this comparison may be influenced by seasonal differences in PM composition.

Figure 9 shows that the monthly OPC-N3 $PM_{2.5}$ -to-PMS5003T $PM_{2.5}$ ratio decreases steadily over time for the longest-deployed unit (AirU Pro Unit 1, containing OPC-N3 501 and PMS5003T 357; Table 1), with the median ratio declining from 0.48 in winter 2023 to 0.06 in winter 2025 (Table S13). To minimize the influence of seasonal variability, we also compare the same season across successive years. These comparisons show statistically significant decreases in the $PM_{2.5}$ ratio for all but two seasonal comparisons (Mann–Whitney U test or Kruskal–Wallis test with post hoc Dunn pairwise comparisons and Bonferroni correction, $p < 0.05$; Tables S13 and S14). Because statistical significance can be influenced by the large number of hourly measurements, we also report effect sizes. All comparisons exhibit medium to large effect sizes ($\epsilon^2 = 0.34$ or Cliff's $\delta \geq 0.17$; Table S14), where the thresholds for large effect sizes are $\epsilon^2 \geq 0.14$ and Cliff's $\delta \geq 0.43$ (Fiel Peres, 2025).

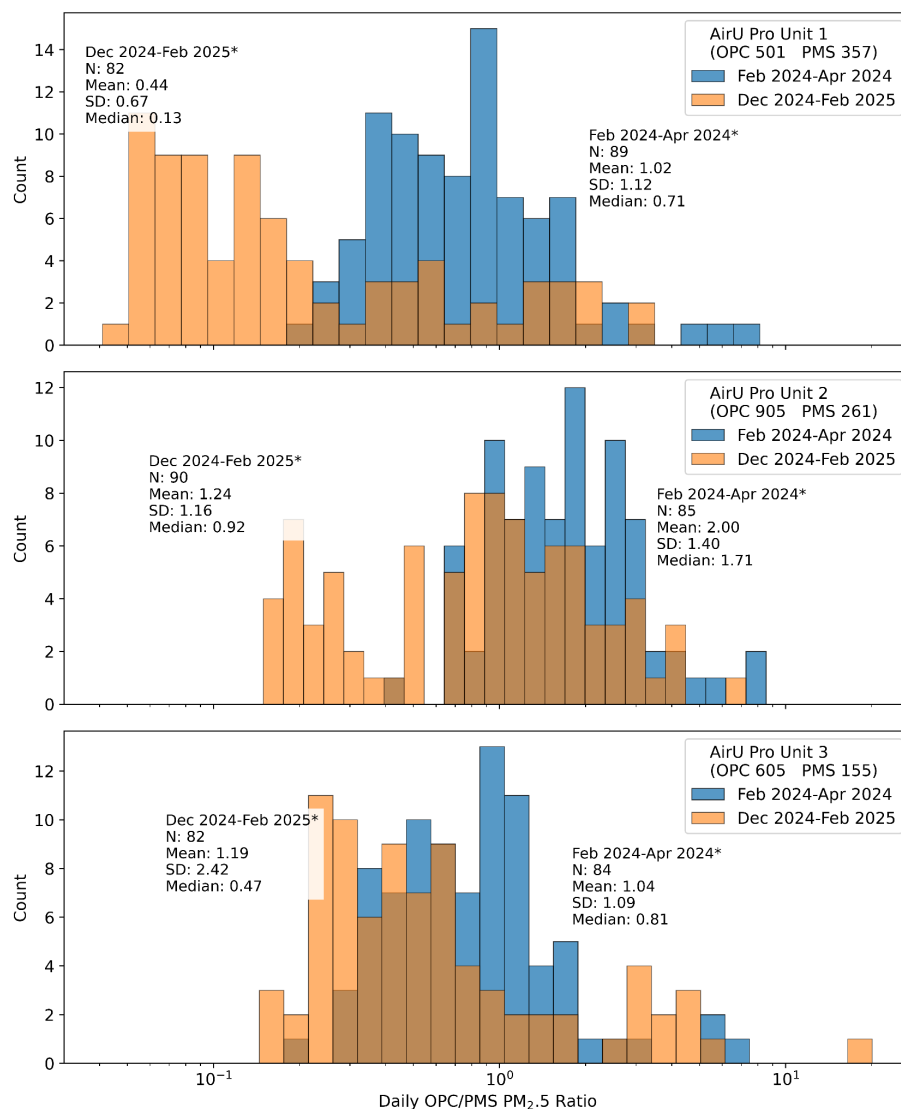


Figure 8: Daily averaged OPC-N3 PM_{2.5}-to-PMS5003T PM_{2.5} ratios for the three old sensors during the first (February–April 2024) and last (December 2024–February 2025) three months of the first 12 months of field deployment. Ratios are filtered for measurements with RH ≤ 80%, PMS5003T PM_{2.5} ≥ 1 µg m⁻³, and OPC-N3 PM_{2.5} ≥ 1 µg m⁻³. Asterisks indicate a statistically significant difference between the two periods (Mann–Whitney U test, $p < 0.05$; $p = 1.9 \times 10^{-12}$, 2.7×10^{-7} , and 6.5×10^{-4} for Units 1, 2, and 3, respectively).

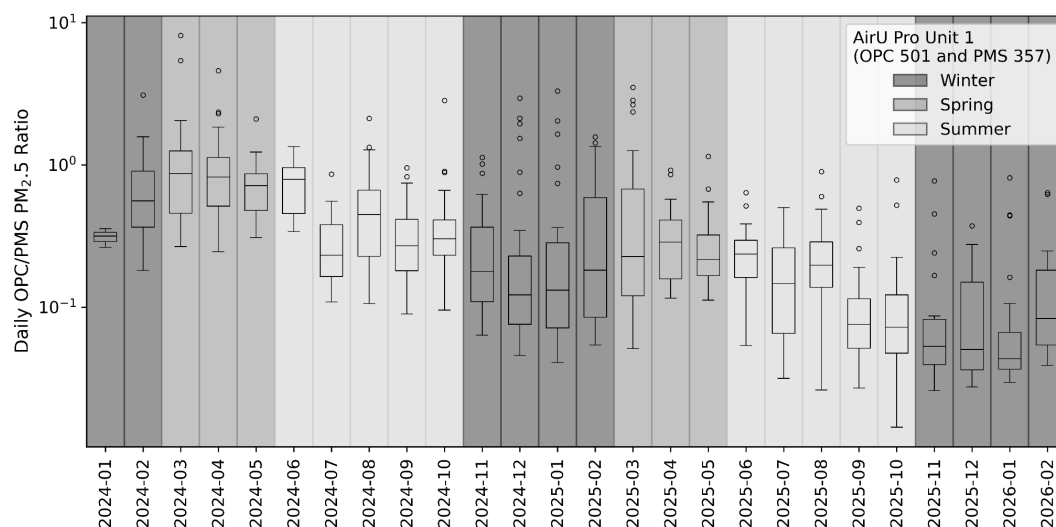


Figure 9: Daily averaged OPC-N3 $PM_{2.5}$ -to-PMS5003T $PM_{2.5}$ ratio boxplots for each month of the 24-month colocation period for AirU Pro Unit 1 (old OPC-N3 sensor 501 and old PMS5003T sensor 357; Table 1). Background shading indicates the winter, spring, and summer seasons. Statistical comparisons of the same season across successive years show statistically significant decreases in the OPC-N3 $PM_{2.5}$ -to-PMS5003T $PM_{2.5}$ ratio over time (Table S14). Measurements only include samples with $RH \leq 80\%$, PMS5003T $PM_{2.5} \geq 1 \mu g m^{-3}$, and OPC-N3 $PM_{2.5} \geq 1 \mu g m^{-3}$.

3.7 Limitations and future work

This study has several limitations in both the laboratory and field evaluations. First, the PM_{10} laboratory precision test exhibits inherent variability, as discussed in Sect. S.6. Second, we likely overestimate the κ value in the PM_{10} κ -Köhler correction model because we estimate κ and the regression coefficient (b_1) in Eq. (6) simultaneously using all measurements with $RH \leq 80\%$ (discussed in Sect. 2.3.5, 3.2.3, and 3.2.5), whereas previous studies (Crilley et al., 2018; Nurowska and Markowicz, 2023) determine κ from humidograms using measurements above the DRH. Third, the PM_{10} correction models use the corrected PMS5003T-reported RH rather than the regulatory monitoring station RH. Although this approach increases uncertainty, it enables the correction models to be applied in situations where research- or regulatory-grade RH measurements are unavailable. Fourth, using the OPC-N3 $PM_{2.5}$ -to-PMS5003T $PM_{2.5}$ ratio to identify degraded OPC-N3 sensors appears promising but requires validation under a broader range of aerosol compositions, meteorological conditions, and deployment environments before it can be adopted as a general screening approach. Finally, the geographic extent of the observed degradation remains unclear because this study evaluates sensors at a single monitoring site near the Great Salt Lake. Additional long-term deployments at diverse locations are needed to determine how widespread OPC-N3 degradation may be and how dependent it is on site conditions. Despite these limitations, this study suggests that the OPC-N3 may experience long-term performance degradation.



Future work should evaluate the long-term field performance of OPC-N3 sensors after elliptical mirror replacement by colocating repaired sensors with FEM instruments. Additional field deployments of OPC-N3 sensors with FEMs farther from the Great Salt Lake can determine whether sensor degradation varies with proximity to the lake and the associated chloride-rich environment. Further refinements to the mirror replacement may be possible. Additional work should evaluate the use of the OPC-N3 $PM_{2.5}$ -to-PMS5003T $PM_{2.5}$ ratio as a screening tool for identifying OPC-N3 sensor degradation. Finally, laboratory studies could identify the mechanism responsible for mirror corrosion. These efforts would improve understanding of the longevity of OPC-N3 sensors and inform maintenance strategies for long-term PM_{10} sensor networks.

4 Conclusions

This study evaluates the long-term performance of Alphasense OPC-N3 sensors and finds that OPC-N3 performance declines after approximately 10–12 months of field deployment, even after removing measurements with $RH > 80\%$ and applying a κ -Köhler model. In contrast, colocated Plantower PMS5003T sensors do not exhibit the same decline in performance. The OPC-N3 $PM_{2.5}$ -to-PMS5003T $PM_{2.5}$ ratio decreases by an average of 56.3% during the first year of deployment, suggesting that this ratio may provide a practical screening tool for identifying degraded OPC-N3 sensors when FEM measurements are unavailable. Post-deployment laboratory evaluation identifies irreversible corrosion of the OPC-N3 elliptical mirror, and mirror replacement is a potential pathway to recover OPC-N3 performance. The observed mirror corrosion may be associated with the composition of aerosols in the region (e.g., elevated chloride), which are similar to those found in coastal environments. Consequently, mirror corrosion could also affect OPC-N3 sensors deployed near the coast. Additional long-term field studies across diverse environments are needed to determine the prevalence of this degradation and the environmental factors that promote it, while further laboratory studies should verify the mechanism of mirror corrosion. Overall, these findings provide evidence that the long-term performance of OPC-N3 sensors can degrade substantially after approximately one year of field deployment. They also highlight the importance of routine quality assurance, periodic laboratory evaluation, and maintenance strategies for long-term PM_{10} sensor networks and provide practical guidance for identifying and managing degraded OPC-N3 sensors.

Code and data availability

The data presented in this study may be obtained from the authors upon reasonable request.

Supplement link

The supplement is available online.



Author contributions

TM, KK, and KEK conceptualized the research. TM and RR deployed devices in the field. TM, DR, and DT gathered field data. TM, KK, DT, and DR analyzed field data. TM, KK, RR, AH, AYM, and AM conducted laboratory experiments and analyzed data. TM and KK developed the original draft. TM, KK, ND, and KEK reviewed and edited the original draft. KEK and ND provided supervision and acquired funding.

Competing interest

Kerry E. Kelly has a financial interest in the company Tellus Networked Solutions, Inc., which commercializes solutions for environmental monitoring.

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