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# Nephelometer-based air sensor networks systematically underestimate PM2.5 in dust-influenced West Africa

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# Abstract

Particulate matter air pollution is a major public health burden in West Africa, a region impacted by long-range transport of desert dust in addition to local combustion sources. While new data networks are emerging, most of the measurement growth has come in the form of optical air sensors, more specifically those that behave as imperfect nephelometers. We present an ongoing multi-year measurement campaign since 2024 of 16 monitoring sites across four major metropolitan regions in Ghana spanning the south coast, middle forested region, and the northern savannah, using the QuantAQ Modulair-PM. Results indicate a north-south geographic disparity, where coastal areas such as Sekondi-Takoradi, Accra, and Tema have lower concentrations and infrequent exceedance of EPA Ghana national ambient air quality standards (15% of days or less) while central and northern cities including Kumasi and Tamale have higher concentrations and frequent exceedance (30–49% of days). We find a strong seasonality in ambient $PM_{2.5}$ with dry Harmattan season $PM_{2.5}$ concentration double or triple wet season levels depending on the site and metropolitan area. Leveraging the Modulair-PM co-located nephelometer (Plantower PMS5003), optical particle counter (Alphasense OPC-N3), and locally calibrated product (which shows low bias and high correlation compared to Federal Equivalent Methods), we assess the bias in Plantower-only estimates of $PM_{2.5}$ against the calibrated estimates. We find that more than 30% of the actual $PM_{2.5}$ concentration is missed during dusty conditions in Plantower-only sensor approaches, which are the most commonly used in the current literature, while for $PM_{10}$ 91% of the mass is not accurately observed. This calls into question previous estimates of $PM_{2.5}$ and $PM_{10}$ in the region or potentially in other dusty environments that rely only on nephelometry, highlights the need for sensors that can accurately size particles, and emphasizes the importance of careful performance evaluation and calibration in deployment of air sensor networks.


# 1. Introduction

Exposure to ambient fine particulate matter, or $PM_{2.5}$ (particles with aerodynamic diameters less than 2.5 micrometers), is currently a major leading risk factor for premature mortality and morbidity, contributing to an estimated 4.9 million premature deaths annually and 124 million healthy years of life lost[1]. $PM_{2.5}$ exposure is also a critical equity concern, as it disproportionately burdens the most vulnerable segments of the population[2–6]. $PM_{2.5}$ is a subset of the ambient aerosol, which exert net cooling radiative effects on climate and impact clouds and the hydrologic cycle[7–12]. In Africa, air pollution exposure has been linked to 1.1 million premature deaths annually[13], but this is highly uncertain due to limited openly accessible data, which also hampers mitigative environmental policies[14]. The use of air sensor networks for $PM_{2.5}$ and gaseous pollutants, often referred to as “low cost sensors”, has rapidly proliferated across the African continent and around the world, and represents a possible path forward in closing a large air pollution data gap[15–25]. A key issue remains the reliability of this data, and the strengths and weaknesses of these devices are becoming better characterized, but gaps remain[26–30].

Optical particle sensors, when incorporated into integrated monitors, typically report particulate matter concentrations across a range of particle size bins, most commonly $PM_1$, $PM_{2.5}$, and $PM_{10}$. This implies that measurement principles enable sizing of particles. Several recent studies have presented evidence that certain classes of optical sensors, particularly the commonly used Plantower PMS5003, Sensirion SPS30, and others that operate similar to nephelometers, are not actually able to classify particles by size, effectively only measuring an ensemble of particles mostly below 1 μm in aerodynamic diameter, resulting in highly erroneous supermicron PM estimates[26,27,31]. Despite this, many crowd-sourced PM monitor vendors have historically reported size-resolved PM values (including the often coarse particle-dominated $PM_{10}$), and studies have investigated this potentially unphysical coarse PM data[32–36]. In environments where most of the aerosol is submicron, and the ratio of $PM_1$:$PM_{10}$ and $PM_1$:$PM_{2.5}$ is close to unity, accurate performance of $PM_{2.5}$ and $PM_{10}$ from nephelometer-based sensors compared to regulatory-grade monitors is possible, especially with rigorous bias correction[33]. However, in environments where supermicron ($PM_{1\text{-}10}$) or coarse mode aerosol ($PM_{2.5\text{-}10}$) dominates, both $PM_{2.5}$ and $PM_{10}$ sensor-reported values can be highly biased, and not easily corrected with post-hoc statistical methods since the coarse particles are not being detected, even indirectly[26,37,38]. On the other hand, integrated monitors that leverage optical particle counters, including the Alphasense OPC-N3, are thought to more accurately size individual particles because of a broader range of scattering detection angles made possible by an elliptical mirror[26,39–42].

Dusty environments are one such example where coarse mode aerosol can substantially impact both $PM_{10}$ and $PM_{2.5}$. Most dust aerosol mass with significant lifetime lies above 1 μm in aerodynamic diameter[43–45], resulting in possible high bias for air quality monitors that rely on nephelometry as the measurement principle[46–48]. Much of the African continent is impacted by dust aerosol, including in particular the densely populated West African coast along the Gulf of Guinea, which receives a heavy dust burden during the months of approximately November to March as part of the Harmattan season[17,49]. Transported Saharan dust measured near West Africa has been shown to have mass mean diameters much larger than 1 μm, typically around 2–6 μm, well beyond the physical measurement range of nephelometer-based air sensors[50–54]. The major influence of supermicron dust aerosol on air quality in this region represents a potential blind spot in past and current air quality monitoring, as studies that have leveraged nephelometer-based air monitors are likely underestimating both $PM_{2.5}$ and $PM_{10}$ during the dusty season[17,18,20,23,36,55,56].

Ghana, a major country in West Africa, encompasses several criteria for better understanding this problem. It is impacted by seasonal Harmattan dust and numerous anthropogenic sources and is also a canonical example of the boon in air quality monitoring leveraging simple, “low-cost”, air sensors[18,19,23,36]. Here we present a 16-node air monitoring network spanning 4 major Ghanaian metropolitan areas over a 2-year period to evaluate the bias in nephelometer-based air sensors especially during dusty seasons, leveraging co-located nephelometers, optical particle counters, and a calibrated, validated PM product. We present, for the first time, a survey of ground-based PM

measurements across a diverse range of locations in Ghana over the last 2–3 years. Leveraging our co-located equipment at each site, we then evaluate what fraction of $PM_{2.5}$ will go unobserved using a Plantower-only monitoring network by comparing it to a calibrated optical particle counter and nephelometer joint dataset. This work builds on a growing body of research characterizing the size limitations of nephelometer-based sensors. We go beyond previous studies by providing direct field quantification of nephelometer-based biases in $PM_{2.5}$ in an environment where they may actually fail and yet where past studies have relied almost exclusively on such sensors to characterize air quality, thereby underreporting $PM_{2.5}$ exposure. Additionally, while past studies have focused nearly exclusively on Accra[18,19,23,36,57–59], this work also expands into previously unmonitored smaller Ghanaian cities, providing novel data for future policy and public health relevance.

## 2. Methods

# 2.1 Monitoring network and sites

In collaboration with the Ghana Environmental Protection Authority, we deployed 16 QuantAQ Modulair-PM air monitors (hereafter referred to as MOD-PM) in four major Ghanaian metropolitan areas: Accra-Tema, Sekondi-Takoradi, Kumasi, and Tamale, spanning populated coastal cities, Ghanaian middle belt, and northern Ghana. Tamale, for instance, sits within the Guinea Savannah, Kumasi is located amidst a major tropical forest, and Accra-Tema and Sekondi-Takoradi are coastal environments. Each metropolitan area had 4 fixed locations for monitoring, selected based on representation of sources within a city, spanning near-roadway, urban background, solid-fuel burning impacted, and residential. Data collection began in January 2024 and is ongoing; for the purposes of this study, data was last retrieved in May 2026, resulting in nearly a 2.5-year data record. Further deployment details are available in Table 1, and a map of locations is shown in Fig. 1.

Table 1
Deployment locations, temporal coverage, and valid data availability

| Site Name | City | Lat | Lon | Start Date | End Date | Days of Data | Days > 75% Coverage |
|---|---|---|---|---|---|---|---|
| Asokwa New Road Shell | Kumasi | 6.6711 | -1.5975 | 2024-08-04 | 2025-03-08 | 216 | 84 |
| Guinness Ghana, Kaase | Kumasi | 6.6506 | -1.4400 | 2024-08-04 | 2025-10-27 | 449 | 256 |
| Sepe Dote | Kumasi | 6.7192 | -1.5772 | 2024-08-04 | 2024-08-26 | 21 | 8 |
| Adum Methodist Roundabout | Kumasi | 6.7189 | -1.6383 | 2024-08-07 | 2026-05-18 | 649 | 76 |
| Jakarayili | Tamale | 9.4067 | -0.8177 | 2024-01-11 | 2025-02-14 | 399 | 57 |
| Tamale Municipal Assembly | Tamale | 9.4017 | -0.8367 | 2024-08-04 | 2026-05-18 | 652 | 98 |
| Tamale Industrial Area | Tamale | 9.4053 | -0.8200 | 2024-08-04 | 2026-05-19 | 652 | 147 |
| Lamashegu Police Roundabout | Tamale | 9.3950 | -0.8481 | 2024-08-04 | 2025-05-06 | 275 | 104 |
| Secondi RCC Roundabout | Sekondi-Takoradi | 4.9402 | -1.7129 | 2024-08-04 | 2026-05-21 | 654 | 431 |
| Takoradi Market Circle | Sekondi-Takoradi | 4.8990 | -1.7618 | 2024-08-02 | 2026-05-21 | 656 | 191 |
| Takoradi Effia Pacific | Sekondi-Takoradi | 4.9340 | -1.7618 | 2024-08-04 | 2025-11-25 | 478 | 174 |
| Sekondi Kweikuma Zongo | Sekondi-Takoradi | 4.9334 | -1.7394 | 2024-01-11 | 2025-08-12 | 578 | 14 |
| Dansoman Police Station | Accra-Tema | 5.5438 | -0.2652 | 2024-01-12 | 2024-11-11 | 303 | 31 |
| Charlton Clinic Jamestown | Accra-Tema | 5.5400 | -0.2104 | 2024-01-12 | 2026-05-11 | 849 | 264 |
| Tema Metropolitan Assembly | Accra-Tema | 5.6480 | -0.0020 | 2024-01-11 | 2026-05-15 | 854 | 467 |
| Tema Freezone | Accra-Tema | 5.6930 | 0.0100 | 2024-01-11 | 2026-05-21 | 860 | 613 |

## 2.2 Equipment

The MOD-PM costs approximately $6000 USD at time of writing and measures $PM_1$, $PM_{2.5}$, and $PM_{10}$ at a 1-minute time resolution using both a Plantower PMS5003 and an Alphasense OPC-N3. The Alphasense OPC-N3 sizes individual particles in 24 size bins from 0.35 to 40 µm, while the Plantower PMS5003 measures the ensemble of particles[26]. Temperature and relative humidity are reported in each unit using a Bosch BME280 sensor. MOD-PM reports all three cumulative size classifications for Plantower-only, Alphasense-only, and a calibrated final MOD-PM product. The Plantower-only and Alphasense-only are reported as-is exactly as in the bare sensor output, including both the integrated mass concentrations but also the size-resolved particle number concentrations. In contrast, the calibrated final MOD-PM product combines the two raw data streams and includes several correction algorithms for density, aspiration efficiency, and environmental conditions (temperature and relative humidity). MOD-PM uses a κ-Köhler theory hygroscopicity correction based on the approaches by Crilley et al. (2018)[60] and Di Antonio et al. (2018)[61] which uses locally-measured temperature and relative humidity data to ensure that the correction is locally-relevant. Further information on this correction can be found in Hagan and Cross (2020)[62]. Additionally, the MOD-PM performed with high correlation ($r^2$ = 0.86) and low bias (RMSE = 3.85 µg $m^{-3}$) when compared over a 6-month period in Accra to independent reference-grade monitors including a Teledyne T640 at the University of Ghana as part of the Afri-SET project[19,23]. A related intercomparison in northern Ghana, specifically in Kintampo, comparing the MOD-PM to a GRIMM-EDM 180, is underway and showing similar performance as in Accra, and details on this will be presented in an upcoming manuscript. Additional statistically-based corrections on top of the MOD-PM κ-Köhler correction provided no correlation or bias improvements and thus were deemed unnecessary.

## 2.3 Data Processing and Quality Control

Minute-resolution data were pulled for every site over the entire deployment period using the QuantAQ v1 REST API. Quality control included removing physically impossible negative values for mass or number concentrations, and values above 2000 µg $m^{-3}$ which is above the manufacturer's stated range for $PM_1$, $PM_{2.5}$, and $PM_{10}$. Other than removal of values above this threshold, no other outlier filter was applied as instantaneous concentrations can reach high levels in this region.

Though the measurement time period spanned more than 2 calendar years, intermittent missing data was an issue, especially in the extreme heat environments of middle and northern Ghana where daily high temperatures exceed 37 ºC. Data completeness is shown in Table 1. Data coverage was first characterized by counting at every site the number of days containing at least 75% of hourly samples (i.e. more than 18 hours in a day of valid PM data). Only days that met these criteria were used for further analysis. Sites that had exceedingly few days within criteria, namely Sekondi Kweikuma Zondo (14 days, Sekondi-Takoradi), Dansoman Police Station (31 days, Accra-Tema), and Sepe Dote (8 days, Kumasi), were excluded from all further analysis, leaving 13 total sites. In the case of taking monthly

means, the same 75% criteria was applied at the day-level. Missing minute-level data were treated as NaN and propagated through rather than filled or imputed.

## 2.4 Dust-influenced classification

Each co-located minute resolution data point was classified as either dust-influenced or not using the manufacturer-calibrated fine-to-coarse PM ratios. We explored classifying dust influence using multiple ratios and settled on selecting dust-influenced data points as those with $PM_1$:$PM_{10}$ < 0.1. This aligns well with existing literature based on dust sampling in both the Sahara Desert and other regions[63,64,65]. Due to the more common availability of $PM_{2.5}$ measurements compared to $PM_1$, $PM_{2.5}$:$PM_{10}$ ratio is also sometimes used[66]. Since the size fraction alone cannot guarantee only dust particles make up the coarse aerosol, especially in coastal environments where sea salt is present, we cross-validate the ratio classifier by also classifying by time of year at two metropolitan areas: Accra-Tema and Tamale. We find that 67.4% and 66.9% of data points classified as “dust-influenced” occur during the November-March Harmattan window in Tamale and Accra-Tema, respectively, corroborating that the classifier is indeed likely segregating dusty conditions. We investigated the sensitivity of our results to using the $PM_{2.5}$:$PM_{10}$ ratio as well as multiple threshold values for both ratios ($PM_1$:$PM_{10}$ = 0.1, 0.2, 0.3, 0.4; $PM_{2.5}$:$PM_{10}$ = 0.1, 0.2, 0.3, 0.4, 0.5) to confirm that our results are not dependent on the chosen ratio type or cut point (see Supplementary Information).

## 2.5 Bias calculation

We employ some commonly-used bias and error metrics to evaluate the performance of the Plantower-only bare sensors against a calibrated product. Mean bias error (MBE) is the average signed difference between the sensor and the calibrated MOD-PM, following Eq. 1:

$$MBE = \frac{1}{N}\sum_{i=1}^{N}(\mathrm{sensor}_i - \mathrm{calibrated}_i) \quad \text{(Eq. 1)}$$

where *N* is the total number of co-located data points and *i* represents minute-level individual data points. To enable cross-site and cross-city comparisons, we also calculate the mean normalized bias (MNB), defined as:

$$MNB = \frac{1}{N}\sum_{i=1}^{N}\frac{(\mathrm{sensor}_i - \mathrm{calibrated}_i)}{\mathrm{calibrated}_i} \times 100\,\% \quad \text{(Eq. 2)}$$

with *N* and *i* as above.

Mean absolute error or MAE is the average magnitude of the error between the sensor against the calibrated product, not taking into account signs, following Eq. 3:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\mathrm{sensor}_i - \mathrm{calibrated}_i| \quad \text{(Eq. 3)}$$

with *N* and *i* as above.

Coefficient of variation of the mean absolute error expresses the MAE as a fraction of the mean calibrated concentration, as in Eq. 4:

$$CvMAE = \frac{\sum_{i=1}^{N} |\text{sensor}_i - \text{calibrated}_i|}{\sum_{i=1}^{N} \text{calibrated}_i} \times 100\,\% \quad \text{(Eq. 4)}$$

with *N* and *i* as above.

# 3. Results

# 3.1 Characterization of $PM_{2.5}$ in Ghana

We first present results on $PM_{2.5}$ concentrations between 2024 and 2026 across the national network of MOD-PMs. Figure 2 shows the daily mean $PM_{2.5}$ concentration at each of the sites, segregated by city. As expected, $PM_{2.5}$ concentrations peak in the dry Harmattan months of November – March, with daily mean concentrations reaching as high as 175 μg $m^{-3}$. Where overlapping data exists across cities, Harmattan peaks are generally higher in Tamale and Kumasi compared to Accra-Tema and Sekondi-Takoradi, which are further from the dust source and also impacted by coastal air sea breezes. In contrast, wet season $PM_{2.5}$ (roughly April – August) is lower, hovering around 20–30 μg $m^{-3}$ depending on the city and site. Variability in the intensity of the Harmattan season is also apparent, especially in Accra-Tema where the 2024 Harmattan results in much higher $PM_{2.5}$ concentrations than 2025 or 2026. Even the wet season concentrations can exceed healthy guidelines and standards, however. Figure S1 shows that, especially in Kumasi and Tamale, over 40% of the daily mean concentrations can exceed the Ghana EPA 24-hour $PM_{2.5}$ standard of 35 μg $m^{-3}$, though in the coastal cities this percentage can be as low as 3%. Using the WHO Air Quality Guideline of 15 μg $m^{-3}$ results in all sites having greater than 50% exceedance, with some sites in Kumasi exceeding 90%. The data missingness is also apparent in Fig. 2 at several sites, indicated by gaps in the time series. Though individual site records may not span at least one full year, the cumulative sum of data records at all sites in a given metropolitan area span at least a full year in each metropolitan area.

Figure 3 shows the daily mean $PM_{2.5}$ distributions in box plots (panel a), the diurnal profiles (panel b), and the seasonal patterns (panel c) over the entire campaign period. Daily mean concentrations over the entire period were highest in Kumasi (mean 37.1 μg $m^{-3}$, median 28.5 μg $m^{-3}$) and Tamale (mean 33.9 μg $m^{-3}$, median 21.1 μg $m^{-3}$) compared to the coastal cities of Sekondi-Takoradi (mean 20.6 μg $m^{-3}$, median 17.4 μg $m^{-3}$) and Accra-Tema (mean 22.8 μg $m^{-3}$, median 16.5 μg $m^{-3}$), indicating a north-south ambient air pollution disparity in Ghana. The distributions are also mostly right-skewed, with long whiskers as evidenced by the 95th percentile concentrations exceeding 100 μg $m^{-3}$ at sites in Kumasi and Tamale, indicating the presence of extreme air pollution events triggered by Harmattan dust and local anthropogenic sources.

Figure 3b shows the diurnal pattern across cities in the network. All cities show a similar pattern, with $PM_{2.5}$ peaking in the morning and the evening, coinciding with vehicular activity and cooking, which happens more frequently in the early evening. During the daytime, the lack of traffic and cooking emissions coupled with the deeper boundary layer driven by strong surface solar radiation leads to reduced building of particle pollution. The evening peaks are higher than the morning peaks in Kumasi and Tamale, while the opposite is the case in the coastal cities of Accra-Tema and Sekondi-Takoradi. The seasonal cycles in each city are shown in Fig. 3c in the form of monthly mean concentrations. As anticipated, there is a strong dry (November – March) and wet (April – October) season contrast, with dry season means 227%, 108%, 53%, and 25% higher than wet in Tamale, Kumasi, Accra-Tema, and Sekondi-Takoradi, respectively, as shown in Fig. S2.

# 3.2 Sensor bias under dusty conditions

We next leverage the co-located Plantower PMS5003, Alphasense OPC-N3, and MOD-PM calibrated PM measurements to analyze the bias and performance of the Plantower PMS5003. Figure 4 shows scatterplots of MOD-PM calibrated $PM_{2.5}$ (x-axis) against Plantower-only $PM_{2.5}$ estimates (y-axes) at each minute-level data point, colored by coarse PM concentration ($PM_{2.5-10}$) and segregated by $PM_1$:$PM_{10}$ = 0.1 threshold, where $PM_1$:$PM_{10} \leq 0.1$ (triangle shapes) is likely Harmattan dust influenced conditions. Sensitivity to different threshold values and different ratio identities (e.g. $PM_{2.5}$:$PM_{10}$) is minimal and shown in Fig. S3-S5. About 6% of all data points (n ~ 260,000) fall below the 0.1 ratio threshold. While there is some agreement between the Plantower-only and the calibrated MOD-PM product overall, there is a marked low bias in all three PM cumulative size classifications in the Plantower data at high coarse PM concentrations (~ 300 µg $m^{-3}$). The mean bias (MBE) in the Plantower $PM_{2.5}$ estimate is -13.1 µg $m^{-3}$ or -32.8% (mean normalized bias, MNB), and the slope of the regression line for the $PM_1$:$PM_{10} \leq 0.1$ data is 0.42, suggesting that using a Plantower-only $PM_{2.5}$ in such conditions can result in large underestimates of $PM_{2.5}$. Conversely, Plantower $PM_{2.5}$ is biased slightly high for data segregated by $PM_1$:$PM_{10} > 0.1$ (MBE = + 3.96 µg $m^{-3}$, MNB = + 27.9% slope = 0.83), resulting in some partial error cancellation in the merged dataset. For $PM_{10}$, $PM_{1-10}$, and $PM_{2.5-10}$, the Plantower-only estimates are even more biased (MNB = -91%, -95%, -99%, respectively) in dusty conditions. This is consistent with recent studies which highlight the inability of nephelometer-based sensor networks to accurately distinguish particle sizes[26], thereby severely underestimating $PM_{10}$ and $PM_{2.5}$, especially in dusty environments. When coarse particles are not present in high quantities, Plantower-only sensors exhibit far lower biases in all PM size classifications. Table 2 shows the bias and error statistics for each size class.

Table 2
Statistical summary of Plantower-only PM measurements versus MOD-PM calibrated. MAE is the mean absolute error, CvMAE is the coefficient of variation of mean absolute error, MBE is mean bias error (signed bias), and MNB is mean normalized bias.

| Particle Size | Regime | Slope | MAE (µg/m³) | CvMAE (%) | MBE (µg/m³) | MNB (%) |
|---|---|---|---|---|---|---|
| $PM_1$ | All | 0.594 | 4.86 | 22.9 | -3.93 | -11.4 |
| | $PM_1$:$PM_{10}$ > 0.1 | 0.592 | 4.93 | 22.8 | -3.96 | -10.6 |
| | $PM_1$:$PM_{10}$ < 0.1 | 0.599 | 3.85 | 26.6 | -3.36 | -23.2 |
| $PM_{2.5}$ | All | 0.778 | 7.99 | 31.3 | + 2.94 | + 24.2 |
| | $PM_1$:$PM_{10}$ > 0.1 | 0.833 | 7.57 | 30.3 | + 3.96 | + 27.9 |
| | $PM_1$:$PM_{10}$ < 0.1 | 0.417 | 14.47 | 43.8 | -13.08 | -32.8 |
| $PM_{10}$ | All | 0.073 | 42.47 | 62.3 | -36.64 | -17.0 |
| | $PM_1$:$PM_{10}$ > 0.1 | 0.236 | 27.28 | 51.3 | -21.07 | -12.3 |
| | $PM_1$:$PM_{10}$ < 0.1 | 0.033 | 280.76 | 92.6 | -280.76 | -90.8 |

# 4. Conclusion

We present results from a 2-year locally calibrated air quality monitoring network across four major metropolitan areas in Ghana, representing a large geographic diversity including measurements in cities where they have not previously existed. Despite some data missingness, a north-south geographic disparity emerges, where mean and extreme PM concentrations are generally higher by about 65% in the annual mean in more central and northern cities (Tamale, Kumasi) versus coastal metropolitan areas (Accra-Tema, Sekondi-Takoradi). Daily mean concentrations are more often than not below the EPA Ghana standard of 35 µg $m^{-3}$, with the highest exceedance rate happening in Tamale Jakarayili site (49% of days). The vast majority of these exceedance days occur during the dry Harmattan season, as mean and median wet season $PM_{2.5}$ concentrations are well below the standard. However, even the cleanest sites in the network are above the WHO Air Quality Guidelines on at least 50% of days. Diurnal profiles show typical morning and evening peaks associated with traffic and cooking.

Using the co-located raw Plantower PMS5003, Alphasense OPC-N3, and combined MOD-PM calibrated estimate, we quantify the bias in relying only on Plantower PMS5003 for PM concentrations in West Africa. Plantower-only $PM_{2.5}$ underestimates by 33% in dusty conditions, resulting in systemic undercounting of $PM_{2.5}$ in existing and planned networks that rely on nephelometry which may not be easily statistically bias corrected with post-hoc algorithms. The underestimation in dusty environments reaches to 91% for $PM_{10}$, suggesting that nephelometer-based sensors are missing nearly all of the coarse particles. We therefore recommend that air quality managers and researchers use caution when interpreting air quality readings from available nephelometry-only sensor networks, including many

public-facing crowdsourced open data portals, in order to ensure data accuracy and reliability in West African air quality management.

## Declarations

# Competing Interests

The authors declare no competing interests.

# Supplementary Information

See attachment.

# Author Contribution

DMW acquired the equipment, deployed the equipment, conceived the research idea, performed the analysis, and wrote the paper. AA performed analysis and reviewed and edited the paper. SA provided resources, deployed equipment, and reviewed and edited the paper. BE, CA, and MKA deployed equipment, maintained equipment, and reviewed and edited the paper. ENT and NABK provided supervision and reviewed and edited the paper.

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# Data Availability

Data in this study was used under license from QuantAQ, Inc. Data are available from the authors upon reasonable request and with the permission of QuantAQ, Inc.

# Code availability

The underlying code used for this study can be found here:
https://github.com/dmw2166/GhanaNationalNetworkPaper

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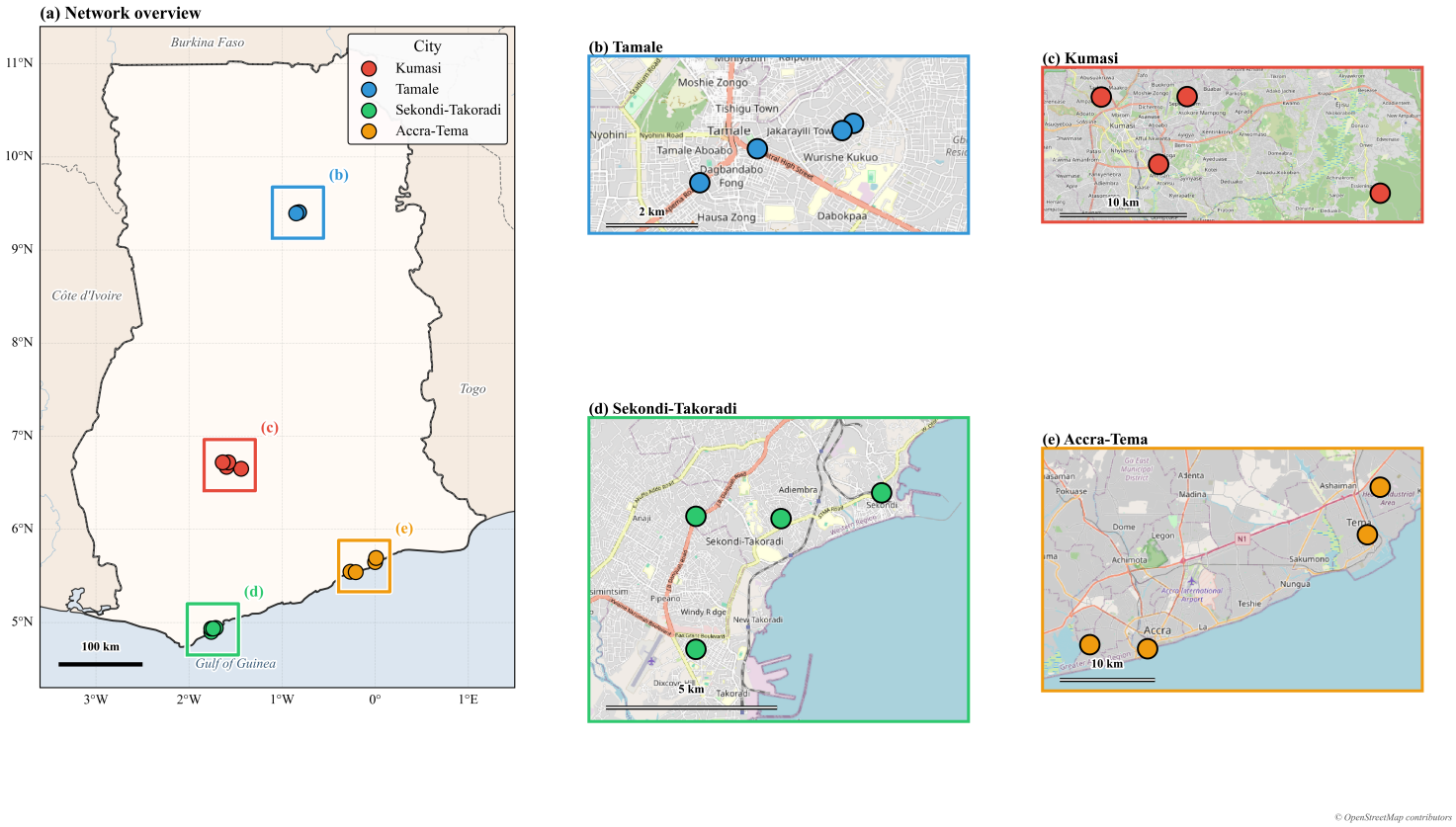

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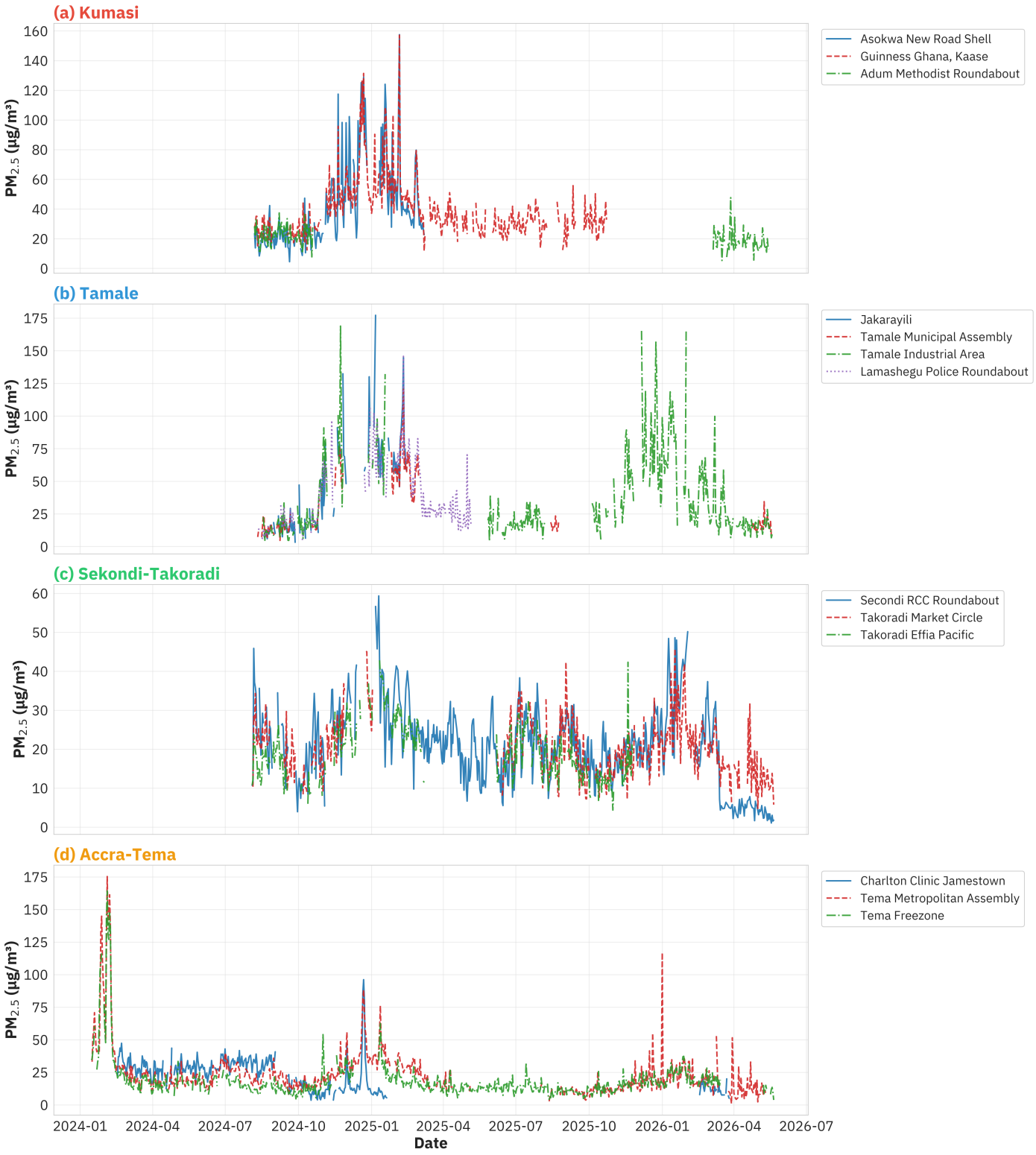
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# Figures



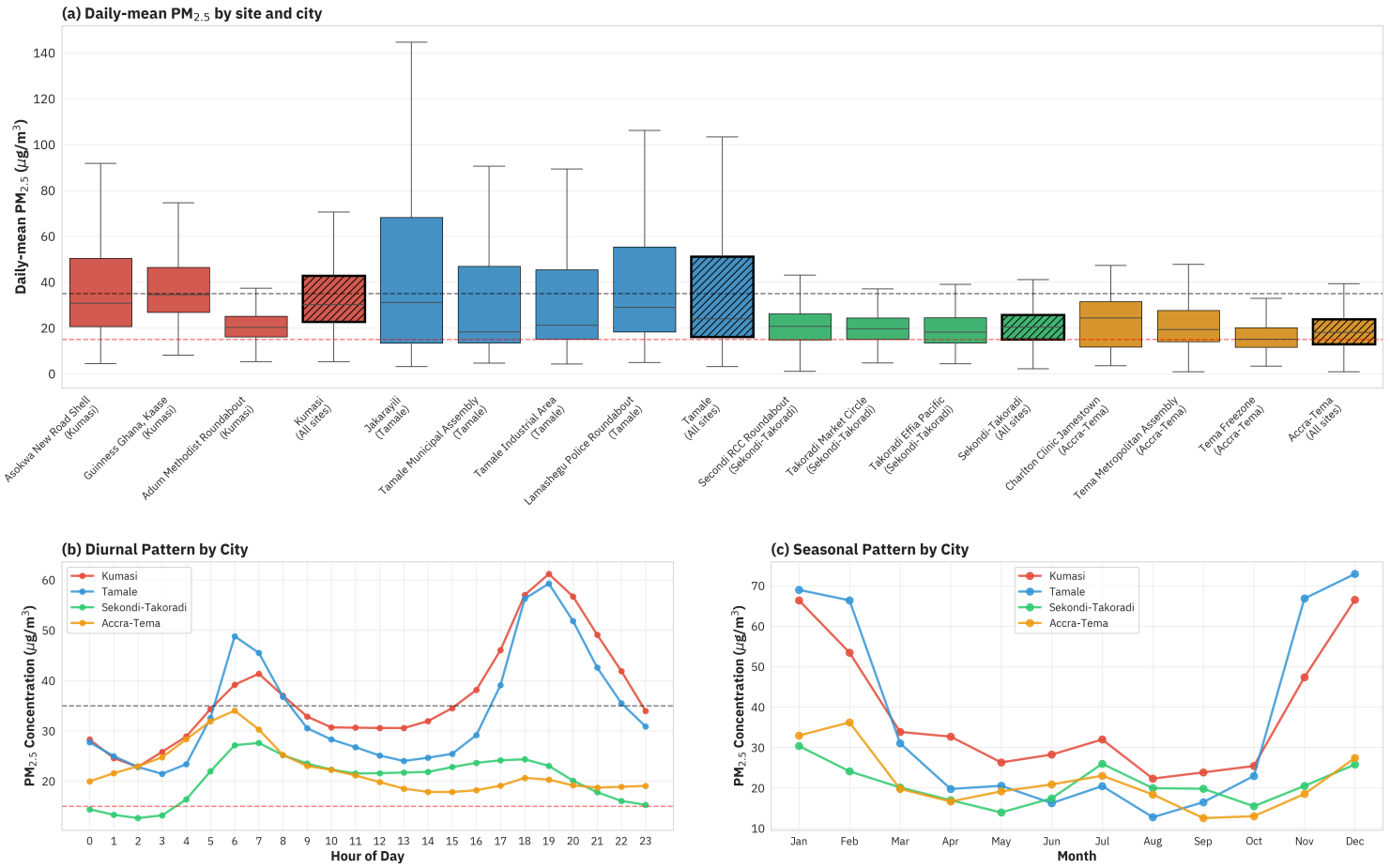

## Figure 1

Air quality monitoring network overview in Ghana. Map backgrounds courtesy of OpenStreetMap.




## Figure 2

Daily mean $PM_{2.5}$ concentrations at each site across 4 metropolitan areas: (a) Kumasi, (b) Tamale, (c) Sekondi-Takoradi, (d) Accra-Tema




## Figure 3

$PM_{2.5}$ analysis at each city in Ghana. (a) Box and whisker plot of daily mean $PM_{2.5}$ concentrations across each site and a city average (hatched box). The black horizontal dashed line represents that Ghana EPA 24-hour air quality standard, and the red horizontal dashed line represents the WHO 24-hour Air Quality Guideline. (b) Diurnal profiles aggregated by city with dashed lines the same as in panel a. (c) Monthly mean $PM_{2.5}$ at each city

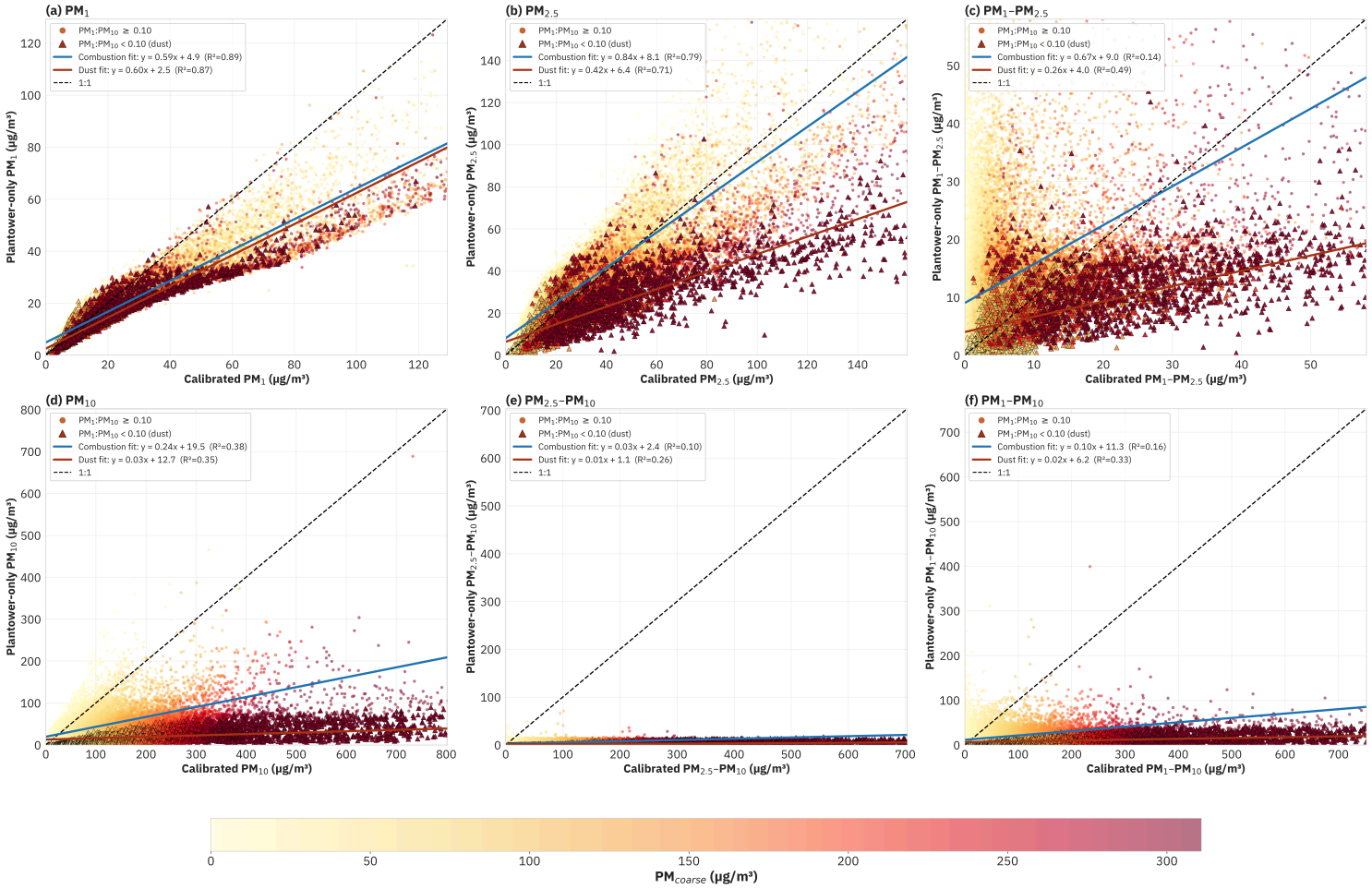



**Figure 4**

Scatterplots of minute-level Plantower-only versus calibrated MOD-PM calibrated for (a) $PM_1$, (b) $PM_{2.5}$, (c) $PM_{1\text{-}2.5}$, (d) $PM_{10}$, (e) $PM_{2.5\text{-}10}$, and (f) $PM_{1\text{-}10}$. Each data point is colored by coarse PM concentration and triangle shapes indicate $PM_1$:$PM_{10}$ < 0.1. The dashed black line is the 1:1 line, and regression lines for each regime ($PM_1$:$PM_{10}$ < 0.1, “dust” and $PM_1$:$PM_{10}$ ≥ 0.1, “combustion”) are shown.

# Supplementary Files

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