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CyanoHABs and CAPs: assessing community-based monitoring of $PM_{2.5}$ with regional sources of pollution in rural, northeastern North Carolina†

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Underserved rural communities in northeastern North Carolina (NC), surrounding the Albemarle Sound, have faced degraded environmental quality from various sources of air and water pollution. However, access to local air quality data is regionally scarce due to a lack of state-run monitoring stations, which has motivated local community science efforts. In January 2022, we co-developed a community-led study to investigate the relationship between fine particulate matter ($PM_{2.5}$) and sources of regional air pollution, with a specific focus on previously identified emissions from cyanobacterial harmful algal blooms (CyanoHABs). Using low-cost PurpleAir air quality sensors to quantify $PM_{2.5}$ mass, satellite-derived indicators of CyanoHABs, and other publicly available atmospheric and meteorological data, we assessed environmental drivers of $PM_{2.5}$ mass in the airshed of the Albemarle Sound estuary during 2022–2023. We found that bias-corrected PurpleAir $PM_{2.5}$ mass concentrations aligned with composite data from the three nearest federal reference equivalent measurements within 1 μg m^{-3} on average, and that the temporal variation in $PM_{2.5}$ was most closely associated with changes in criteria air pollutants. Ultimately, satellite-based indicators of CyanoHABs (*Microcystis* spp. equivalent cell counts and bloom spatial extent) were not strongly associated with ambient/episodic increases in PurpleAir $PM_{2.5}$ mass during our study period. For the first time, we provide local $PM_{2.5}$ measurements to rural communities in northeastern NC with an assessment of environmental drivers of $PM_{2.5}$ pollution events. Additional compositional analyses of $PM_{2.5}$ are warranted to further inform respiratory risk assessments for this region of NC. Despite the lack of correlation between CyanoHABs and $PM_{2.5}$ observed, this work serves to inform future studies that seek to employ widely available and low-cost approaches to monitor both CyanoHAB aerosol emissions and general air quality in rural coastal regions at high spatial and temporal resolutions.

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Environmental significance

Fine particulate matter ($PM_{2.5}$) is demonstrated to increase in the airshed of blue-green algae blooms occurring in polluted waterbodies. Working with community scientists in rural, coastal North Carolina, USA, we examined regional variation in $PM_{2.5}$ in association with localized air and water pollutants, with a focus on seasonal blue-green algae blooms. By leveraging publicly accessible databases with high spatial and temporal resolution, for the first time, we evaluated the use of low-cost air quality sensors (PurpleAir) and satellite-derived indicators of ocean color (CyAN) in the study of aerosol emissions from blue-green algae blooms. We also provide an assessment of PurpleAir derived $PM_{2.5}$ for its use by local communities in environmental health research and/or decision-making in coastal North Carolina.

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1. Introduction

Fine particulate matter < 2.5 μm in diameter ($PM_{2.5}$) is regulated as a criteria air pollutant (CAP) by the US-Environmental Protection Agency (EPA),[1,2] and the World Health Organization (WHO) has also set guidelines for limiting $PM_{2.5}$ exposures.[3] Exposure to high concentrations of $PM_{2.5}$ is associated with an increased risk of adverse child developmental outcomes, chronic respiratory illness, and cardiovascular related morbidity and mortality, especially in susceptible populations.[4–10] In North Carolina (NC), USA, $PM_{2.5}$ concentrations are primarily driven by industrial/vehicular sources in urban areas,[11] but agricultural emissions in rural areas pose their own suite of inhalation risks.[12,13] Moreover, sea spray in coastal zones can be a source of various aerosolized pathogens or biochemicals,[14–16] suggesting that varied sources of aerosol influence air quality in the coastal plain of northeastern NC.

The NC Department of Environmental Quality operates numerous environmental monitoring programs, including the maintenance of federal reference method air quality monitoring stations and a cyanobacterial harmful algal bloom (CyanoHAB) dashboard,[17] where citizen volunteers can report real-time water quality events. These programs routinely measure and track changes to health-relevant pollutants in various environmental media, but are generally more limited in the rural, eastern part of the state compared to more densely populated and urban areas.[18,19] Consequently, the data needed to inform localized environmental health-risk assessments and create adaptive policy in rural NC are often insufficient, as is true for many rural communities throughout the Southeastern (SE) United States.[20,21]

The Chowan River-Albemarle Sound is one such region in NC where historically poor water and air quality are compounded by a lack of resources allocated by research institutions. A key recreational, agricultural, fisheries, and residential region of coastal NC, the Albemarle Sound and its tributaries, span 5600 km^2 of coastal plain with a residential population of 180 000 in its surrounding towns and rural sprawl.[22,23] Communities residing in this watershed experience some of the poorest respiratory health outcomes in the state;[21,24,25] populations in Bertie, Chowan, and Hertford counties, which surround the Chowan River, experience among the highest asthma related emergency departments visits per year.[24] In the 1970's, the Chowan River was declared "dead" due uncontrolled discharges from upstream paper mill plants resulting in CyanoHABs, and in the 1990's, a ten-year fish consumption advisory was put in place due to dioxin contamination from the mills.[22,23] Targeted nutrient mitigation strategies successfully remediated CyanoHABs in the Albemarle Sound for the following decades, but in the late 2010's, toxin-producing CyanoHABs re-emerged seasonally with high occurrences of microcystin,[26,27] a well characterized liver toxin produced by cyanobacteria.[28]

In this study, conversations with community partners revealed a myriad of potential point sources of air and water pollutants in northeastern NC, but of particular concern were re-emergent CyanoHABs in the Chowan River and Albemarle Sound. While CyanoHABs have long been treated as a threat to water security across the globe,[29] aerosol emissions bearing CyanoHAB cells and their toxins have only recently been recognized as a respiratory health threat.[30,31] Many studies have quantified specific cyanobacterial biochemical compounds (*e.g.*, microcystin) in aerosol,[32–35] but such research relies on limited *in situ* monitoring campaigns with low spatiotemporal coverage.[31] To better inform respiratory risk assessments related to CyanoHABs, there is a pressing need to understand the relationship between adverse water quality events like CyanoHABs and air quality at a larger spatiotemporal scale.

To address observational gaps in the fate and transport of environmental pollutants, many environmental monitoring programs rely on crowd-sourcing approaches to generate *in situ* data.[36] Community-led research initiatives specifically utilize "community science" or "citizen science" participation not only to improve science literacy and outreach,[37] but also, importantly, to increase data availability and researcher access to local knowledge.[38–40] Since the early 2000s, community science efforts have gained reputability and expanded across multiple scientific disciplines.[41] For air quality measurements, the use of low-cost PurpleAir sensors is one popular approach to increase public access to real-time information and improve the spatiotemporal resolution of air quality monitoring.[42,43] In the past decade, numerous correction factors have been developed to improve the precision and accuracy of data provided by the PurpleAir network for use in scientific study and/or policymaking.[44–47]

Recent studies have demonstrated that CyanoHABs are correlated with increased $PM_{2.5}$ concentrations in the immediate airshed of ongoing blooms, which is attributed to the enrichment of cyanobacterial metabolites in spray aerosol and the potential formation of secondary aerosol derived from volatile compounds produced by CyanoHABs.[27,48–51] Given that real-time measurements of $PM_{2.5}$ are widely accessible through the PurpleAir network and using the Albemarle Sound region of northeastern NC as a case study, we hypothesized that the PurpleAir sensor network could be leveraged to improve understanding of the link between CyanoHABs, air quality, and additional drivers of aerosol in northeastern NC and beyond.

Working directly with community scientists, we installed 13 PurpleAir $PM_{2.5}$ sensors along the banks of the Albemarle Sound and in its surrounding townships. To understand regional variation in $PM_{2.5}$ in relation to local sources of air and water pollution, we (1) corrected PurpleAir-derived $PM_{2.5}$ data using established correction factors and compared the corrected-$PM_{2.5}$ data with the nearest federal reference $PM_{2.5}$ data, (2) examined $PM_{2.5}$ mass as a function of satellite ocean color-derived CyanoHAB cell count and spatial extent, (3) assessed confounding sources of $PM_{2.5}$ using CAP data from the nearest air quality system (AQS) station, and (4) placed the findings into environmental context using relevant meteorological data.

By leveraging publicly available air and water quality databases with high spatiotemporal resolution (*i.e.*, PurpleAir and satellite ocean color), our study provides novel insight into the use of PurpleAir sensors to monitor aerosol emissions during CyanoHABs with implications for respiratory exposure

guidelines. Our findings reveal previously unexplored connections between $PM_{2.5}$ mass and satellite-derived indicators of CyanoHABs. For the first time, we also highlight the primary drivers of episodic/ambient $PM_{2.5}$ mass in the airshed of the Albemarle Sound and evaluate PurpleAir derived $PM_{2.5}$ data for its use by local communities and public health practitioners in environmental health research and/or decision-making.

2. Methods

2.1. Community-driven study development

From the inception of this study (proposal development) to its completion (interpretation and dissemination of findings), this research was a community-led effort that spanned May 2022 to December 2023. In January of 2022, co-authors were approached by a representative of the Chowan Edenton Environmental Group (co-author Karl), a nonprofit organization that promotes environmental research and education in the Albemarle region of northeastern NC (Fig. 1). Their organization sought to develop a community-led study investigating the relationship between fine particulate matter (*i.e.*, $PM_{2.5}$) and sources of regional air pollution.

To actively engage community members from diverse backgrounds and lived experiences, new partnerships were developed and maintained between the Chowan Edenton Environmental Group and Albemarle Regional Health Services (local public health department), the Edenton Racial Reconciliation Group (local social injustice discussion group), Northampton First (regional environmental justice group), the town of Edenton (local government), and the Museum of the Albemarle (a local history museum). Community members raised concerns in various group forums that CyanoHABs, wood pellet plants, livestock and agricultural practices, and military operations are sources of CAPs of local concern. Based on these concerns, we identified the geographic location of CyanoHAB hotspots using the NC Department of Environmental Quality CyanoHAB dashboard,[17] livestock operations using the NC Department of Environmental Quality's animal feeding operation data for the year 2023 (**https://www.deq.nc.gov/water-resources/animalops/afo-permit-facilities-table-4-2023**), the density of nearby cotton fields based on the US Department of Agriculture's cotton production estimates by county (**https://www.nass.usda.gov/Statistics_by_State/North_Carolina/Publications/County_Estimates/Cotton.pdf**), and wood pellet plant and military bombing range locations, which are

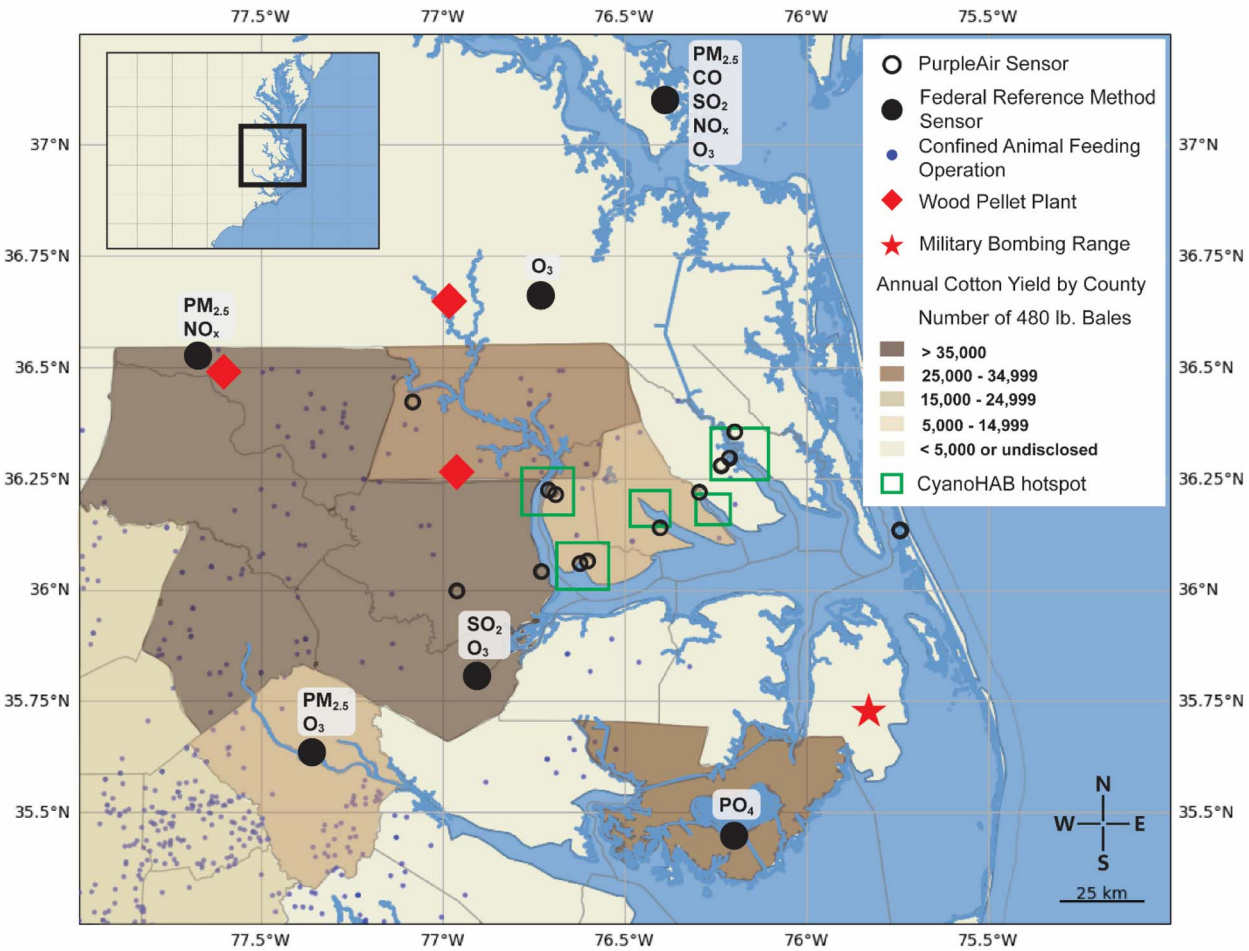

Fig. 1 A map of the study site showing PurpleAir sensor placements, potential point sources of pollution, and the nearest federal reference method (AQS) CAP monitoring instruments. For AQS sensors, the specific CAPs retrieved are listed.

publicly available (Fig. 1). Sites for air quality sensor placement were identified through community organizations, and regular email communications between co-authors and community partners were maintained to exchange research progress and findings. As such, two community members are included as co-authors on this study for their continued contributions (Karl and Stoops).

2.2. Particulate matter ($PM_{2.5}$) quantification

Localized sources of $PM_{2.5}$ in the Albemarle region are not currently represented in state and federal air quality monitoring networks, provided that the three nearest AQS $PM_{2.5}$ sensors operate approximately 50 miles from the central Albemarle Sound in Greenville, NC (35.641, −77.360), Roanoke Rapids, NC (36.512, −77.655), and Hampton, Virginia (37.104, −76.387) (Fig. 1). Therefore, to quantify $PM_{2.5}$, we installed 13 PurpleAir air quality sensors at the homes and workplaces of local volunteers between June 2022 and December 2023. PurpleAir sensors quantify $PM_{2.5}$ using dual operating optical particle counters (#PMS5006, Plantower), labeled channels A and B. An atmospheric pressure, temperature, and humidity sensor (#BME280, BOSCH) is also included with $PM_{2.5}$ readings. PurpleAir devices connect directly to WPA2 wifi networks and transmit air quality data to an open access map (**https://map.purpleair.com/?mylocation**) every 10 minutes.

PurpleAir sensor placements were dependent on the availability of volunteer hosts with appropriate wireless capacity, but general locations were selected based on proximity to known CyanoHAB hotspots within the estuary (Fig. 1)—with three key hotspots being Arrowhead Beach, Edenton, and Elizabeth City (Fig. 2). To examine the reduction of $PM_{2.5}$ with increasing distance from a CyanoHAB source, sensors were placed in approximate transects and categorized into sites <0.92 km and >0.92 km from the waterline. The value of 0.92 km was chosen to account for experimental observations of cyanotoxin degradation by atmospheric oxidants.[52,53] Two sensors were strategically placed to provide terrestrial "control" sites with limited nearby aquatic and/or CyanoHAB influence (*e.g.*, sensor 1562 and 1358; Fig. 2).

2.3. PurpleAir $PM_{2.5}$ data bias-correction

Daily average raw $PM_{2.5}$ data ('pm2.5_cf_1', for both channels A and B) were downloaded from **develop.purpleair.com**. While unprocessed PurpleAir $PM_{2.5}$ data generally track changes to air quality accurately enough for risk assessments by the general public, for scientific analyses and to improve precision of measurements, a series of quality controls addressing calibration biases and particle hygroscopicity must first be applied.[45,47] Published correction procedures generally follow the same steps to (1) remove values attributed to apparent measurement errors (*e.g.*, humidity < 0%, $PM_{2.5}$ < 0, extreme temperatures), (2) remove measurements where there is disagreement between dual channel readings, and (3) apply a correction factor based on humidity and/or temperature.

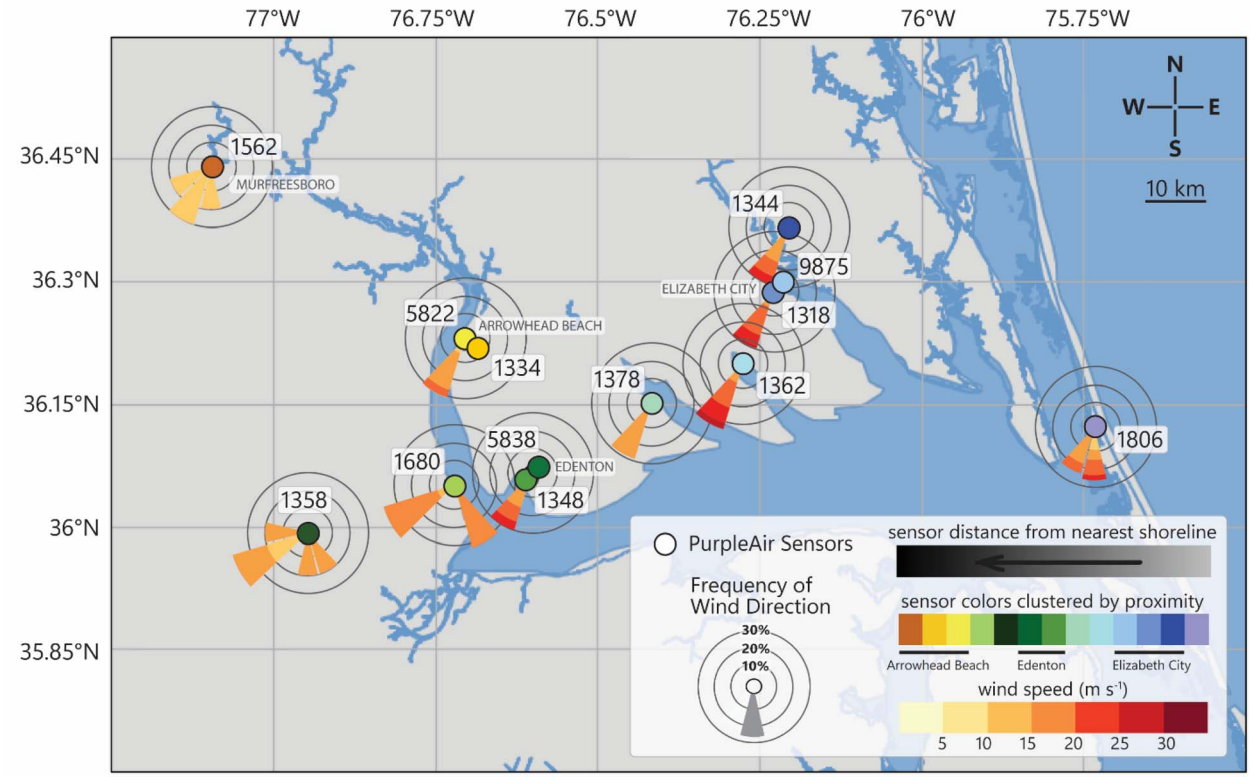

Fig. 2 A map of the PurpleAir sensor sites, labeled with the last four digits of each sensor's serial number and key residential areas. Sensors were assigned colors to indicate their relative proximity to other sensors and the nearest shoreline. Wind roses depicting the primary wind direction are provided for each sensor cluster.

The correction in step (3) is explicitly necessary for health-related research because dynamic mass concentrations of $PM_{2.5}$ vary with weather conditions (*i.e.*, condensation and evaporation of water vapor onto and off particle surfaces changes mass), but $PM_{2.5}$ monitors maintained by federal and state agencies measure dry mass of the pollutants to comply with the US EPA National Ambient Air Quality Standards.[1,2]

We tested two $PM_{2.5}$ mass correction approaches to increase confidence in the accuracy and precision of our PurpleAir data, the first determined by Barkjohn *et al.* 2021.[45] Their correction compared PurpleAir sensor $PM_{2.5}$ data from across the US (US-wide) to collocated federal reference sensor $PM_{2.5}$ data and adjusted $PM_{2.5}$ mass based only on humidity measurements. The second correction we applied was recently developed by Mathieu-Campbell *et al.*, 2024 (ref. 54) to address the high humidity conditions of southeastern US (SE-specific); their correction equation included adjustments for both humidity and temperature. The SE-specific correction also differed from the US-wide approach by applying a more stringent set of criteria for removing suspected erroneous readings.

To evaluate the efficacy of each correction factor, we used an identical input $PM_{2.5}$ dataset that adhered to the removal criteria outlined in the SE-specific approach. When A/B channels disagreed by >5 μg m^{-3} and by >1 standard deviation, or a $PM_{2.5}$ reading fell outside the range of 1.5–1000 μg m^{-3}, the daily value was removed from the final dataset ($n = 4257$). As an additional data cleaning step to limit the influence of extreme aerosol pollution events in this study, the Fourth of July and the following three days were completely removed from analyses due to potential firework contamination. When $PM_{2.5}$ measurements but internal PurpleAir data of temperature and relative humidity were not available for individual sensors, the temperature and relative humidity data were supplied from the next nearest PurpleAir device to apply the correction factor.

2.4. Water quality (CyanoHAB) measurements

CyanoHAB cell concentrations (bloom intensity) and spatial extent (bloom surface area) in the Albemarle Sound and its tributaries were retrieved from the multi-agency Cyanobacterial Assessment Network (CyAN) *via* the US National Aeronautics and Space Administration (NASA) ocean biology data archive center (**https://oceancolor.gsfc.nasa.gov/about/projects/cyan/**). We elected to utilize satellite-based estimates of CyanoHABs over *in situ* "grab" sampling methods due to their increased spatial and temporal coverage during our study period.

CyAN utilizes imagery captured by the Ocean Land Color Instrument (OLCI) sensors aboard the Sentinel-3A/3B satellites. A cyanobacterial index (CI_{cyano}) is calculated from three spectral bands using algorithms first developed by Wynne *et al.* in 2008 (ref. 55) and later updated by Matthews *et al.* in 2012 (ref. 56) and Lunetta *et al.* in 2015.[57] The final CI_{cyano} data product is corrected for upper atmospheric reflectance and is converted to *Microcystis* spp. equivalent cell counts as an indicator of CyanoHAB intensity.[56–58] The lower detection limit of the OLCI sensor is somewhere between 10 000 and 20 000 cells per mL. Individual files retrieved from CyAN are provided at a daily, 0.3 km spatial resolution, but we composited daily values into weekly maximums to account for missing data (*e.g.*, due to cloud cover preventing satellite images) and to average dynamic movements of CyanoHABs.[59] Compositing weekly averages for CI_{cyano} improved data availability for CyanoHAB indicators, with between 89 and 100% of satellite data pixels yielding a non-null value at the weekly level (Table S1†). Accordingly, all analyses involving CyanoHAB indicators were conducted at the weekly resolution.

CI_{cyano} values were retrieved within three distances from each PurpleAir sensor (~0.6 km, ~1.2 km, and ~2.4 km square pixel grid 'radius', with the distances extending at 90° [ESI Fig. S1†] from the center pixel). The three distances over which the CyanoHAB data were extracted were chosen to evaluate the extent of the 'localized' influence of CyanoHABs on $PM_{2.5}$ concentrations. The three pixel grid areas were selected based on the minimum accurate resolution capacities as recommended by Coffer *et al.* (2021) (ref. 60) and Clark *et al.* (2017) (ref. 61) and to test cyanobacterial toxin aerosol decay kinetics in the atmosphere. As revealed in Zorbas *et al.* 2023,[52] up to 25% of CyanoHAB derived microcystin is estimated to degrade within 0.92 km of its emission site, and therefore, we selected distances less than (0.6 km), just above (1.2 km), and significantly above (2.4 km) the 0.92 km threshold over which to extract CyanoHAB data.

2.5. Air quality system (AQS) criteria air pollutant (CAP) measurements

To contextualize $PM_{2.5}$ mass as a function of CyanoHABs, we examined trends in additional air pollutants, primarily gas-phase CAPs (ozone [O_3], carbon monoxide [CO], sulfur dioxide [SO_2], nitrogen oxides [NO_x]), and also particle-phase phosphate (PO_4), in association with $PM_{2.5}$. These data were accessed and downloaded from the US EPA's AQS Air Data network (**https://epa.maps.arcgis.com/**). Sensor locations with specific pollutant species accessed are provided in Fig. 1. Each pollutant was considered an approximate tracer (proxy) for community-identified key sources of $PM_{2.5}$ in the region, with CO serving as an indicator of combustion, including wildfires and open agricultural burning.[62] O_3 serves as a proxy for volatile organic compounds (VOCs), as it is a product of photochemistry with industrial and biogenic VOCs.[63] NO_x serves as an additional proxy for anthropogenic/industrial emissions closely aligned with O_3.[64,65] SO_2 acts as a proxy for fossil fuel burning and general combustion processes,[66,67] and PO_4 serves as a proxy for organophosphate pesticides common to this region and/or agricultural emissions. CO and O_3 were measured every eight hours but converted into daily averages. All others, including $PM_{2.5}$, are reported and retrieved as daily averages. For final analyses, data were composited into week-long averages to facilitate direct comparison with CyanoHAB data (Section 2.4).

2.6. Meteorological measurements

Daily weather data, including measurements of wind speed, wind direction, air temperature, relative humidity, and solar

radiation, were accessed using the Visual Crossing weather query builder (https://www.visualcrossing.com/weather/weather-data-services). The Visual Crossing platform collates and triangulates weather data for specific latitude and longitude coordinates using the nearest National Weather Service stations—closer stations are weighted most strongly in the calculation. Daily averages were collated into weekly averages for analyses.

To further assess potential point sources of $PM_{2.5}$, we simulated backward air mass trajectories using the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model by the National Oceanic and Atmospheric Administration (NOAA) (https://www.ready.noaa.gov/HYSPLIT_traj.php). Backward trajectories were utilized to evaluate whether the identified point sources of pollution (Fig. 1) fell within the air mass trajectory prior to $PM_{2.5}$ measurements by our PurpleAir sensor network. Using Edenton, NC or Arrowhead Beach, NC as a central reference point, we simulated 120-hour backward trajectories at the beginning and end of each week when average $PM_{2.5}$ mass exceeded the seasonal average. HYSPLIT images are reported in the ESI (Fig. S2†).

2.7. Statistical analyses

To determine which $PM_{2.5}$ correction factor best improved the accuracy and precision of our PurpleAir $PM_{2.5}$ measurement, we compared both corrected and uncorrected daily PurpleAir $PM_{2.5}$ to $PM_{2.5}$ triangulated from the three nearest AQS stations (Fig. 1). Using one goodness of fit (coefficient of determination [R^2]) and two error metric tests (restricted maximum likelihood [REML] and mean absolute error [MAE]), we evaluated the performance of each correction factor for PurpleAir $PM_{2.5}$ in coastal NC.

To evaluate variation in $PM_{2.5}$ mass with respect to each sensor's location within the Albemarle estuary system, we calculated averages of $PM_{2.5}$ for each sensor and compared means using a One-way Analysis of Variance (ANOVA) with Tukey multiple comparison to assess any systematic differences in measurements between sensors, which could have indicated sensor-bias or a local source of $PM_{2.5}$ (ESI Fig. S3†). Averages were calculated over various temporal scales (seasonal, annual, and grouped by CyanoHAB conditions) for individual sensors and after compositing multiple sensors together, categorizing based on sensor proximity to the nearest shoreline (*i.e.*, CyanoHAB aerosol source). To explicitly assess the impact of concentrated CyanoHAB events on localized $PM_{2.5}$ mass, we compared $PM_{2.5}$ concentrations measured by each sensor between bloom and non-bloom weeks, with a "bloom" week being defined by cell counts meeting the WHO's threshold for heightened health risk of 100 000 cells per mL.[68] A Wilcoxon rank-sum test was then used to compare $PM_{2.5}$ during bloom *versus* non-bloom per the imbalanced distribution of weeks when the bloom threshold was met.

Weekly changes in $PM_{2.5}$ mass were finally assessed as a function of multiple interacting environmental conditions using a series of multivariate generalized additive models (GAMs, R package 'mgcv'). $PM_{2.5}$ was modeled as the dependent variable with the following environmental variables as predictors: CyanoHAB indicators (spatial extent and cell counts), weather conditions (wind speed, wind direction, solar radiation, air temperature, and relative humidity), and CAP concentrations (CO, O_3, SO_2, PO_4, and NO_x).[69] Models were fitted with increasing complexity, initially examining $PM_{2.5}$ as a function of individual predictors (eqn (1)) and scaling up to multiple predictors assessing both additive and interactive effects (eqn (2)), where E indicates the modeled output value for $PM_{2.5}$, X_n is the value for the environmental variable, β_0 is the intercept, β_n is the coefficient for categorical variables (*e.g.*, sensor specific effects), s_n indicates that the variable is treated with a smooth term, and t_n indicates that the variables are treated with an interactive term. Specific combinations of interactions and additions between predictor variables are shown with model results in Table 1; further details on model configurations and results are found in the ESI.†

$$E[PM_{2.5}] = \beta_0 + s(X) \quad (1)$$

$$E[PM_{2.5}] = \beta_0 + \beta_1 X_1 + s_2(X_2) + t_{3,4}(X_3, X_4) + \ldots + \beta_n X_n + s_n(X_n) + t_n(X_n) \quad (2)$$

Models were fitted using the Gaussian link function. REML was used to estimate smoothing parameters due to its performance in the nested assessment of nonlinearity between interactive predictors. To account for the zero-inflated distribution of the CyanoHAB data, using the 'gamlss' package, CyanoHAB indicators were transformed into a composite index reflecting their relationship with $PM_{2.5}$ for use in the multivariate regressions.[70] The fit of each model was compared using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and residual plots.

3. Results and discussion

3.1. Bias-correction of PurpleAir $PM_{2.5}$

During the study period, daily averages for raw $PM_{2.5}$ mass concentrations ranged between 1.5 and 78.0 μg m^{-3} for PurpleAir sensors and 1.5–67.0 μg m^{-3} for AQS stations, with the lower concentrations being bounded by our data cleaning procedures. These findings suggest that while uncorrected PurpleAir data do overpredict $PM_{2.5}$ mass compared to gravimetric methods as frequently reported,[44,47] the sensors tracked temporal variability in $PM_{2.5}$ with nearest AQS sensor measurements as anticipated (Fig. 3).

When we applied the US-wide correction factor to our PurpleAir $PM_{2.5}$ data, daily $PM_{2.5}$ mass was reduced by 4.8 μg m^{-3} on average (Fig. 3). Following the correction, the difference in annual average between PurpleAir and AQS $PM_{2.5}$ fell below 1.0 μg m^{-3} (7.2 ± 6.7 and 7.9 ± 5.4 μg m^{-3}, respectively), with corrected PurpleAir slightly exceeding the AQS measured $PM_{2.5}$ mass. The SE-specific correction factor also increased the precision of the PurpleAir measurements when plotted as a function of AQS data, but in contrast to the US-wide correction, this approach resulted in $PM_{2.5}$ mass that was slightly

Table 1 Outline of the GAMs performed to examine $PM_{2.5}$ mass (dependent) as a function of environmental predictors (independent). Each row represents a model run with the predictor variables specified in each column. An '*s*' indicates that the variable was treated as an independent smooth term in the model equation—as shown in eqn (2). Multiple entries per row indicate that the variables were considered in a single equation for their additive effects. Paired *t*'s indicate covariates treated with an interactive term (eqn (2)). A dash indicates that the variable in that column was not included in the model equation. The AIC and BIC are provided for inter-model comparison, and models are listed in descending order from best to worst fit

Variable	CO	O_3	SO_2	PO_4	NO_x	CyanoHAB term	Wind speed	Solar radiation	Temp.	Relative humidity	AIC	BIC
$PM_{2.5}\sim$	t_1	s_1	t_1	s_2	s_3	t_2	t_2	s_4	t_3	t_3	664	985
$PM_{2.5}\sim$	t_1	s_1	t_1	s_2	s_3	—	s_4	s_5	t_2	t_2	728	992
$PM_{2.5}\sim$	t_1	s_1	t_1	s_2	s_3	t_2	t_2	s_4	t_3	t_3	731	998
$PM_{2.5}\sim$	t_1	s_1	t_1	s_2	s_3	s_4	—	—	—	—	787	1028
$PM_{2.5}\sim$	—	—	—	—	—	t_1	t_1	s_2	t_2	t_2	1395	1476

lower than the corresponding AQS data by ~1 μg m^{-3} on average (8.8 ± 5.5 μg m^{-3}) (Fig. 3).

We anticipated that the SE-specific correction factor would best improve the precision and accuracy of our PurpleAir $PM_{2.5}$ readings, given that our sensor network fell within the geographic boundary over which this correction factor was derived, and furthermore, the average relative humidity in the airshed of the Albemarle was 78 ± 10%, exceeding the average 'high' humidity conditions under which the SE-specific correction factor was determined. Regression analyses of each corrected dataset revealed that both correction methods were comparable (Fig. 3), but ultimately the SE-specific correction factor more effectively improved the fit of the PurpleAir $PM_{2.5}$ as a function of AQS measurements when compared to the US-wide correction factor (Fig. 3), as revealed by regression error metrics computed for daily measurements from each sensor (Fig. 3).

These findings suggested that the application of either correction factor would have been suitable for bias-correcting PurpleAir measured $PM_{2.5}$ in northeastern NC. However, based on the comparison of correlation error metrics, for subsequent analyses of spatiotemporal variation in $PM_{2.5}$ mass, we elected to utilize the SE-specific corrected $PM_{2.5}$ values.

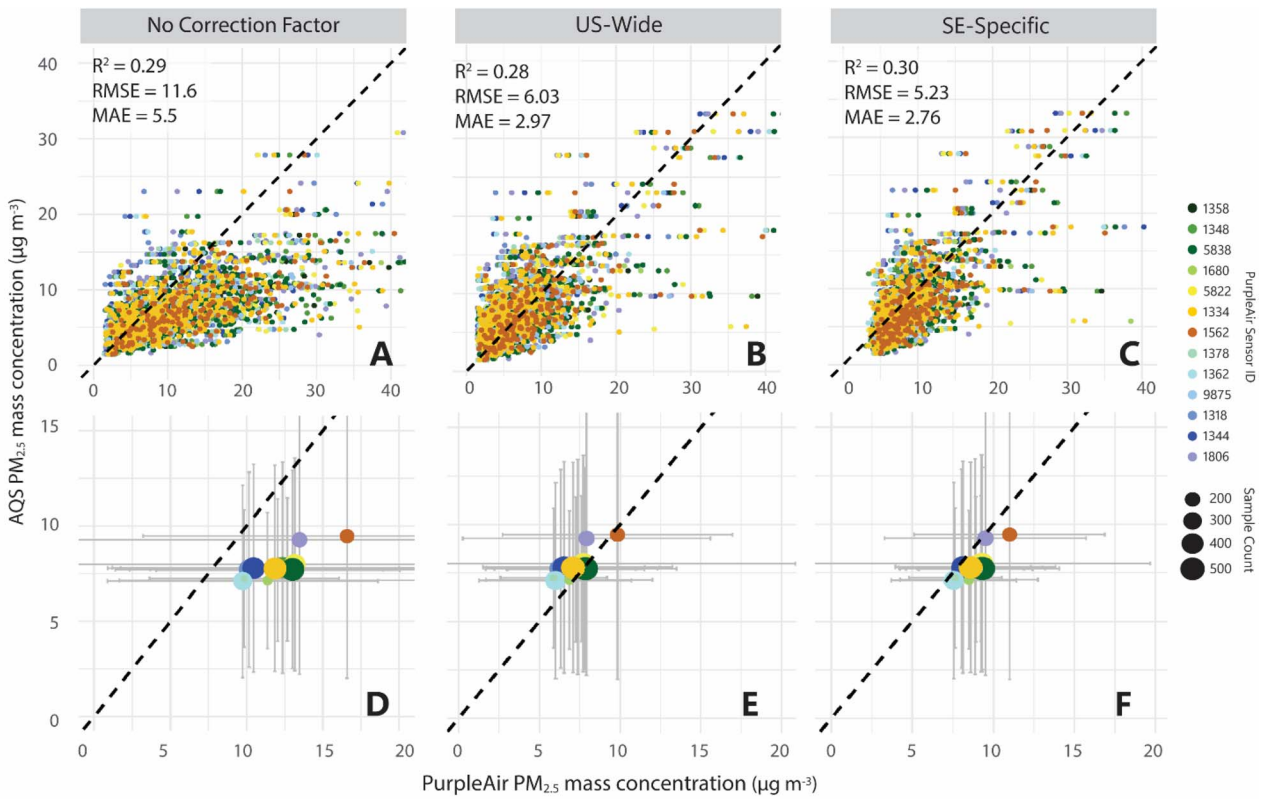

Fig. 3 (A–C) Daily $PM_{2.5}$ mass concentrations reported from 6-1-2022 to 12-31-2023. Regression error metrics (coefficient of determination [R^2], root mean squared error [RMSE], and mean absolute error [MAE]) are reported for daily comparisons. (D–F) Annual average $PM_{2.5}$ mass concentrations, grouped by sensor ID. Error bars reveal variation. Note difference in axes between top (A–C) and bottom (D–F) panels.

3.2. $PM_{2.5}$ as a function of sensor locality

Sensors 1562, 5838, and 9875 reported the highest $PM_{2.5}$ mass concentrations on average over the entire study (Fig. 3), but there was no apparent commonality between these sensors and nearby potential point-sources of pollution as identified by community scientists (Fig. 1 and 2). Generally, $PM_{2.5}$ mass was highest at the sites further inland (Fig. 4), likely due to the dilution of $PM_{2.5}$ at coastal sites from land-sea breezes, increasing coastal exchange at waterfront sites during diurnal cycles.[71] Sensor 1562, located in the town of Murfreesboro, was one of two terrestrial control sites (with sensor 1358), with little suspected influence from CyanoHABs and aquatic aerosol. However, this sensor was located amid several other community-identified potential point sources of pollution including wood pellet plants, cotton fields, and confined animal feeding operations, suggesting possible confounding signals from these sources (Fig. 1). Sensor 5838, located in a residential area of downtown Edenton, was installed ~1 km from the shoreline, and primary wind direction and speed indicated that aerosol formed in the northwestern basin of the Albemarle Sound likely influenced this site (Fig. 2). Similarly, sensor 9875 was located directly on the waterfront in Elizabeth City; however the primary wind direction did not flow across the river before reaching the sensor, suggesting that freshly emitted CyanoHAB aerosol did not consistently reach this sensor (Fig. 2).

3.3. $PM_{2.5}$ as a function of speciated CAPs

To isolate $PM_{2.5}$ signals that could be more directly linked to CyanoHAB indicators, we assessed ambient and episodic variation in $PM_{2.5}$ with AQS monitoring station CAPs as proxies for additional sources of $PM_{2.5}$. We flagged episodic air pollution events during seven separate weeks when $PM_{2.5}$ concentrations measured by two or more PurpleAir sensors exceeded the seasonal average by at least one standard deviation. All seven of these events occurred between April and November of 2023 (Fig. 4). In many cases, event-driven increases in $PM_{2.5}$ were correlated with spikes in specific AQS CAPs (Fig. 4). Consequently, these weeks were removed from specific CyanoHAB and $PM_{2.5}$ correlation analyses (as provided in Section 3.4).

During air pollution events, HYSPLIT backward trajectory analyses provided insights into the general direction from which the pollution was potentially sourced, with particular attention given to the point sources as mapped in Fig. 1. In mid-to-late April 2023, a slight but statistically significant increase in

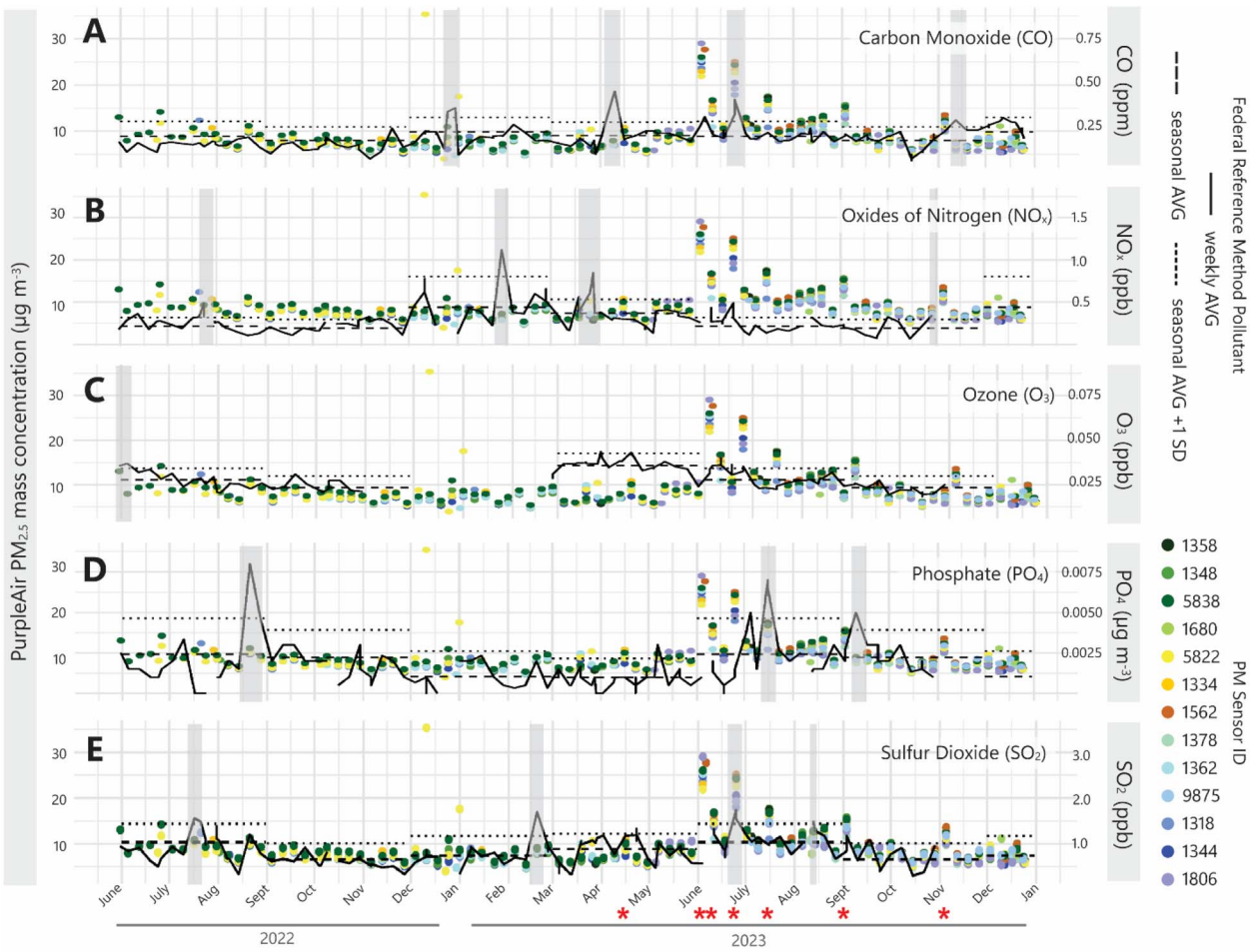

Fig. 4 A time-series of weekly averages for PurpleAir $PM_{2.5}$ mass and select CAPs quantified at nearby AQS stations. Weeks when each CAP exceeded its seasonal average (by +1 standard deviation) are shaded in gray. Weeks when $PM_{2.5}$ mass exceeded its seasonal average (by +1 standard deviation) are indicated with a red asterisk.

$PM_{2.5}$ was immediately preceded by a spike in CO levels. HYSPLIT analyses during this period suggested that $PM_{2.5}$ was transported from the south-to-southeast, where a wildfire was impacting the Croatan National Forest ~90 miles southeast of the Albemarle Sound (ESI Fig. S2†). Several weeks later, wildfire smoke again invaded the region and weekly averages for $PM_{2.5}$ mass reached concentrations as high as 28 μg m^{-3} (Fig. 4). A significant spike in both CO and SO_2 co-occurred with the $PM_{2.5}$ spike in late June. HYSPLIT analyses suggest that the sharp increase in $PM_{2.5}$ mass was likely driven by the extreme Canadian wildfires that burned 13 million acres in Quebec,[72] transporting smoke across the Eastern seaboard of the US.

During one $PM_{2.5}$ pollution event in late July of 2023, PO_4 also exceeded its seasonal average (Fig. 4). Given that no wildfires were reported in the southeastern US during this period, we suspect that this signal was derived from an alternate source, possibly nearby agricultural operations. Both $PM_{2.5}$ mass and O_3 were elevated during the summer months as expected across the US due to higher temperature, sunlight, and increased emissions of biogenic VOCs.[73,74]

3.4. $PM_{2.5}$ as a function of CyanoHABs

When examining $PM_{2.5}$ only as a function of sensor proximity to CyanoHAB hotspots, there was no evidence to suggest that $PM_{2.5}$ was elevated closer to the shoreline (ESI Fig. S3†). Apart from sensor 9875, $PM_{2.5}$ mass generally increased with distance from the shoreline and increasing terrestrial influence (Fig. 2 and 3); this trend remained consistent despite seasonal and interannual variability.

When both CyanoHAB indicators were treated as continuous variables, neither cell counts, nor bloom surface area were associated with changes in $PM_{2.5}$ mass concentrations for any

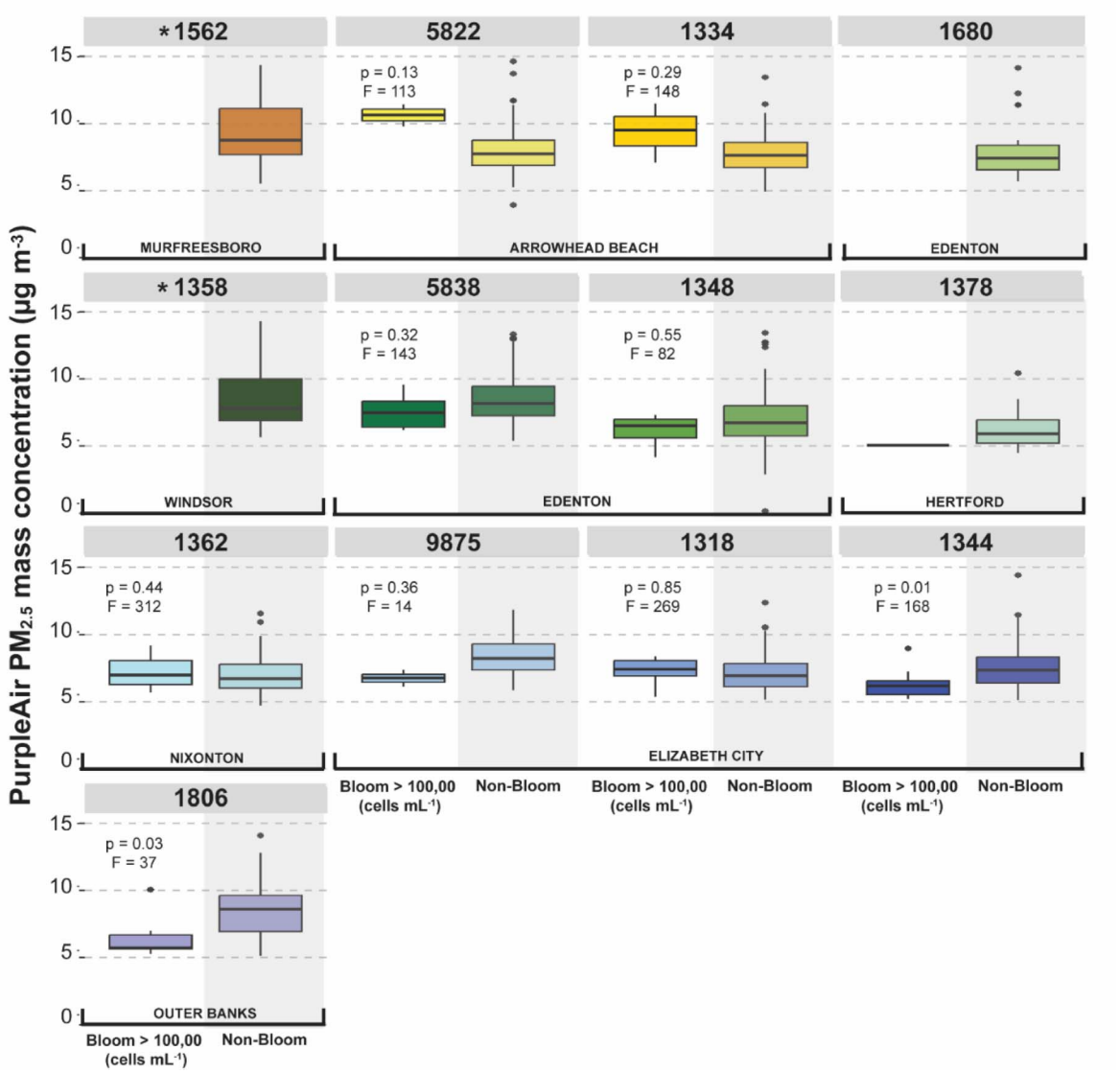

Fig. 5 Average $PM_{2.5}$ mass recorded by each sensor during conditions when the WHO high risk bloom threshold (100 000 cells per mL) was met and not met (shaded in gray). As indicated by asterisks, sensors 1562 and 1358 were terrestrial controls and therefore were not influenced by CyanoHABs, but sensor 1680 had no weeks where the bloom threshold was met. Wilcoxon nonparametric comparison of mean results for each sensor is shown on each plot.

individual sensor or sensor grouping. However, during weeks when average CyanoHAB intensity exceeded the WHO's threshold for heightened health risk of 100 000 cells per mL[68]—we observed higher $PM_{2.5}$ mass at sensors 5822 and 1334 compared to weeks when cell counts did not meet the WHO threshold (Fig. 5). However, this relationship was not statistically significant ($p = 0.13$, $F = 113$ and $p = 0.29$, $F = 148$, respectively). These two sensors were located on the northeast bank of the Chowan River near Arrowhead Beach, a known CyanoHAB hotspot and popular recreational area (Fig. 2). Satellite imagery identified a bloom occurring between July 2nd and July 16th, and HYSPLIT and wind direction analyses suggested that aerosol did blow onshore during this period. During the CyanoHAB, the median $PM_{2.5}$ rose to 10.6 μg m^{-3} and 9.50 μg m^{-3} as measured by sensors 5822 and 1334, respectively. These values were between 2.0 and 3.0 μg m^{-3} higher than the average $PM_{2.5}$ mass recorded at these locations when a high-risk bloom was not occurring (Fig. 5) as well as in the weeks immediately following the bloom.

It is important to note that multiple other sensor locations also experienced CyanoHAB events with cell counts that exceeded the WHO threshold during our study period, but there were no measurable increases in $PM_{2.5}$ in the immediate airshed of those blooms (Fig. 5). For example, sensor 1362 had the highest number of weeks when a nearby CyanoHAB exceeded the WHO threshold, but this site ultimately had the lowest average $PM_{2.5}$ mass average for any sensor location in the entire study (Fig. 5).

3.5. $PM_{2.5}$ as a function of interactive environmental conditions

Using GAMs to examine $PM_{2.5}$ as a function of multiple environmental factors revealed that ambient changes in CAP concentrations explained the majority (up to 88%) of the temporal variation in $PM_{2.5}$ mass. Out of all the AQS pollutants examined, SO_2 was the most predictive of $PM_{2.5}$ mass when considered individually, but the inclusion of more CAPs resulted in a model with the best fit. In this model, SO_2 and CO were treated with an interactive term due to their co-emissions during combustion (anthropogenic activity and wildfire).[67,75] Likewise, O_3 and NO_x were first tried as covariates due to their cyclic formation from VOCs,[76,77] but we found that treating these CAPs separately led to a better fitting model, suggesting that O_3 and NO_x have separate (or mixed) precursors/emission sources in the case of NO_x in this region. The inclusion of NO_x and PO_4 in the equation improved the fit but notably increased model complexity as indicated by the AIC and BIC (ESI Table S2†), suggesting that combustion aerosol and an atmospheric source of O_3 most significantly contributed to $PM_{2.5}$ mass in the Albemarle airshed during our study period.

When considered independently of other environmental conditions, CyanoHAB indicators were not strong predictors of $PM_{2.5}$ mass using GAMs. Treating CyanoHAB intensity and spatial extent individually, additively, and interactively within the model did not greatly change the model fit (ESI Table S4†). Furthermore, changes to the pixel-grid area (0.6, 1.2, and 2.4 km) over which CyanoHAB data were extracted did also not improve our ability to predict $PM_{2.5}$ using the GAM.

Meteorological conditions explained up to 28% of variation in $PM_{2.5}$ mass when treated independently from CAPs and CyanoHAB variables. Specifically, the model was best fitted only when temperature and humidity were treated with an interactive term. The inclusion of wind speed also improved the fit of the model, which suggests that wind-driven aerosolization of dust and river/sea spray is an important source of $PM_{2.5}$ in this region. Interestingly, wind direction, which could have suggested directional point sources, did not have a significant impact on the model fit.

Despite variation in $PM_{2.5}$ being mainly attributed to CAP concentrations, considering the additive effects of CAPs, weather, and CyanoHAB conditions ultimately resulted in the model with the best fit, explaining up to 98% of the variation in $PM_{2.5}$ (Table 1). Specifically, solar radiation, temperature × humidity, O_3, PO_4, NO_x, CO × SO_2, and CyanoHAB × wind speed when modeled together best predicted changes in $PM_{2.5}$ mass in the Albemarle airshed (with × indicating an interactive or covariate term; Table 1).

3.6. Discussion

By enhancing collaboration between local communities and scientific researchers, community science initiatives not only fill critical data gaps but also empower residents with the knowledge and tools to improve their own environmental health outcomes. Working with community scientist volunteers from nonprofit, healthcare, local government, and racial justice organizations, we sought to address and highlight this systemic issue in northeastern NC. *In lieu* of local, regulatory-grade air quality monitoring, we established a network of low-cost PurpleAir air quality sensors throughout the basin of the Chowan River-Albemarle Sound estuary for use by community members and researchers alike.

During our study period (May 2022 to December 2023), and following the application of a correction factor, we determined that $PM_{2.5}$ measured by our PurpleAir sensor network only deviated from the nearest regulatory-standard $PM_{2.5}$ readings by 0.7 μg m^{-3} on average. Although no established criteria for sensor performance currently exist to qualify low-cost sensor generated data for technical analyses and regulatory decision-making, the US EPA recommends that such data correlate with nearest AQS readings within a RMSE of ≤7 μg m^{-3}; our data met this criterion.[43] While the utility of community-based data for scientific reporting, policy development, and/or formal risk assessment is not universally agreed upon,[42] we argue that the <1 μg m^{-3} difference observed between our sensors and the nearest AQS sensors suggests that the bias-corrected PurpleAir $PM_{2.5}$ data generated in this region can be used to inform future environmental health research and/or policymaking with relatively high accuracy and precision.

Furthermore, these <1 μg m^{-3} differences could be explained by geographic differences between our study region and the nearest AQS stations, which were ~50 miles from our study region. As demonstrated by Mathieu-Campbell *et al.*, 2024,[54] the

correlation of $PM_{2.5}$ measurements from PurpleAir with AQS measurements decreases as a function of increasing distance between sensor locations. Our PurpleAir network was concentrated in a rural, coastal area with unique agricultural and aquatic aerosol sources. While specific correction factors for PurpleAir datasets affected by high humidity[54] and wildfire smoke[46] biases have been published, the systematic differences between PurpleAir and regulatory-standard measurements of $PM_{2.5}$ mass in rural and/or coastal sites with agricultural and/or sea spray aerosol sources, remain less explored.

GAM findings suggest that complex interactions between environmental factors promote $PM_{2.5}$ formation and atmospheric fate across the Albemarle Sound. PurpleAir sensors reveal local $PM_{2.5}$ mass but do not provide compositional information, preventing specific source-apportionment. To address this, we retrieved CAP concentrations from the nearest AQS stations to use as proxies for well-established sources of aerosol.[62,78,79] Proxies were assigned by referencing known relationships between emission sources and CAPs, but definitive tracing could not be achieved given that each air pollutant is associated with numerous emission sources.[62] This study ultimately aimed to empower local communities to participate in ambient $PM_{2.5}$ monitoring, with the high spatial and temporal resolution enabled by low-cost sensors being favored over compositional analyses.

Previous work by Plaas *et al.*, 2022 (ref. 27) determined that $PM_{2.5}$ mass increased by 3.6 $\mu g\ m^{-3}$ during a three week long CyanoHAB in the Chowan River in summer 2020. This was based on *in situ* water sampling and nephelometer $PM_{2.5}$ measurements from two waterfront locations. Herein, we examined satellite-derived indicators of CyanoHAB cell counts and spatial extent in association with $PM_{2.5}$ mass, providing higher spatiotemporal resolution of both CyanoHAB and $PM_{2.5}$ measurements than reported in previous work. However, we ultimately found that satellite-based indicators of CyanoHABs could not be associated with episodic increases in $PM_{2.5}$ mass. At one site (Arrowhead Beach), when CyanoHAB cell counts met the WHO high risk bloom threshold of 100 000 cells per mL, $PM_{2.5}$ mass was elevated. However, this difference in $PM_{2.5}$ as a function of WHO bloom conditions was not observed for any other site. We speculate that this signal was distinguished at this site due to the (1) primary wind direction favoring onshore transport and (2) the long residence time ($\sim$15 days) of the mid-upper Chowan River, leading to a persistent source of CyanoHAB aerosol. A combination of these conditions also likely concentrated the bloom along the coastline. Therefore, we conclude that regions with a fetch length that supports wave-driven aerosolization, and where wind and currents push blooms toward/onshore are the ones where CyanoHAB inhalation risks are the greatest.

Numerous studies have not found any apparent association between waterborne and airborne cyanotoxin concentrations in the field, suggesting that water conditions (*i.e.*, ecological and physicochemical parameters) are not strong predictors of CyanoHAB aerosol formation.[31,33] However, when we included a variable representing CyanoHAB–wind speed interactions, our multivariate regression model showed an improved fit, agreeing with previous findings that wind driven spray aerosol formation modulates CyanoHAB aerosol emissions.[33,80]

The area over which satellite-derived CyanoHAB data were composited did not significantly alter associated outcomes between CyanoHABs and $PM_{2.5}$ mass. Using a kinetic decay model, Zorbas *et al.*, 2023 estimated that up to 25% of microcystin in aerosol is degraded within 0.92 km of its point of emission during periods of high sunlight.[52] Accordingly, we anticipated a decay in signal with increasing distance from the shoreline. Conversely, our observations indicated that average $PM_{2.5}$ mass measured at our sensor locations increased with distance from the nearest shoreline. While microcystin suspended in spray aerosol may undergo chemically alteration over time and space in the atmosphere, particles with distinct physicochemical properties may persist over these distances and still pose an inhalation risk with unknown toxicological effects.

In this study, we did not explore the biochemical processes influencing CyanoHAB aerosol composition. Instead, we examined associations between indicators of CyanoHAB biomass and $PM_{2.5}$, a widely monitored CAP, at a previously untested spatial and temporal resolution. However, we found no strong correlation between satellite-derived measures of CyanoHABs and episodic increases to $PM_{2.5}$. A recent epidemiological study also reported no significant association between CyanoHABs and hospital visits pertaining to respiratory outcomes including asthma, wheezing, and allergic reactions.[81] Thus, our findings, when considered with such perspectives, suggest that future CyanoHAB aerosol work should continue to explore the direct health effects of exposure to CyanoHAB biochemical tracers (*e.g.*, cyanotoxins,[33,35,82] lipopolysaccharides,[34] and secondary aerosol from gas-phase CyanoHAB emissions[51]), as these studies may be more informative for inhalation risk assessments. Additional research examining chemical tracers associated with community-identified sources of air pollution, including CyanoHABs, is needed to better inform toxicological risk assessments for the Albemarle Sound region of northeastern NC.

4. Conclusion

To our knowledge, this community-led study provides the first spatiotemporal analysis of the drivers of $PM_{2.5}$ mass in the airshed of the Albemarle Sound estuary, with a particular focus on CyanoHABs. For the first time, we examined satellite-derived CyanoHAB cell counts and spatial extent in association with localized $PM_{2.5}$ mass. Neither was directly associated with episodic $PM_{2.5}$ pollution events, suggesting that despite high spatiotemporal resolution and wide accessibility, satellite data products and low-cost sensor PurpleAir $PM_{2.5}$ measurements are not likely to be useful indicators of aerosol emission rates from CyanoHABs when examined alone. Consideration of additional weather conditions, especially wind speed, is needed to accurately assess relative respiratory risks for those living near or recreating near CyanoHABs. We recommend that future research examining aerosol emissions from CyanoHABs prioritize assessing emission of and exposure to specific CyanoHAB

biochemical tracers over correlations between blooms and $PM_{2.5}$.

Data availability

The programming scripts written to perform data retrieval, cleaning, statistical analyses, and preliminary visualizations are found on the first author's Github repositories dedicated to the project (Python: **https://github.com/haleyplaas/CCRG**, R: **https://github.com/haleyplaas/CCRG_PurpleAir**). Python libraries and R packages utilized are reported within each repository. ChatGPT v3.5 and v4.0 were used to iteratively write and correct scripts for both Python and R.[83] Python code was primarily written and processed using Microsoft VScode v1.92.0 and R code was written using RStudio v2023.12.0. Cleaned data files are available in the Github repositories or are linked to in their README files. All data and programming scripts are labeled with Creative Commons Attribution 4.0 labeled for cited reuse.

Author contributions

Conceptualization: H. E. P. and C. K., formal analysis: H. E. P., M. E. M. C., and J. R. B., investigation: H. E. P., C. K., R. C., and N. R. G., resources: H. W. P. and D. S. H., writing – original draft: H. E. P., writing – review & editing: H. E. P., C. K., R. C., N. R. G., A. H. S., L. L. S., M. E. M. C., J. R. B., H. W. P., and D. S. H., supervision: H. W. P. and D. S. H., visualization: H. E. P., project administration: H. E. P. and H. W. P., funding acquisition: H. E. P., C. K., H. W. P., and D. S. H.

Conflicts of interest

The authors declare that they have no conflicts of interest related to this work to disclose.

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