Title

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The value of adding black carbon to community monitoring of particulate matter

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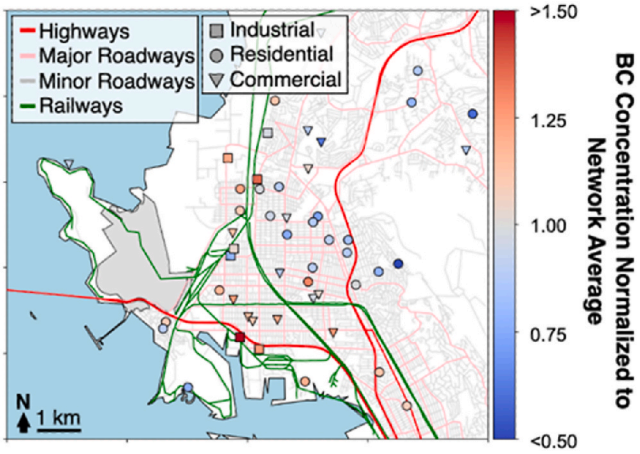
HIGHLIGHTS

- BC and PM sensors deployed 4 weeks in 2 seasons at 50 sites in an environmental justice community.
- Greater spatiotemporal heterogeneity and location persistence of BC compared to $PM_{2.5}$
- BC more informative than $PM_{2.5}$ of proximity and activity of local emission sources.
- Recommend measuring $PM_{2.5}$ plus BC for insights to community air protection plans.

GRAPHICAL ABSTRACT



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ABSTRACT

Low-cost particulate matter (PM) sensors are increasingly used by researchers, public health agencies, and the public to measure spatial and temporal variations in air pollution, which can inform strategies for community air pollution reduction. While low-cost PM sensors provide a valuable measure of harmful fine particulate matter ($PM_{2.5}$), a significant portion of ambient $PM_{2.5}$ is typically the secondary product of air pollution emitted by varied sources outside of community boundaries. In contrast, concentrations of black carbon (BC), a component of $PM_{2.5}$, are directly emitted by a few specific sources, such as diesel engines within communities. Motivated by

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community organizations seeking to understand persistent sources of local pollution, this study deployed a suite of custom-built BC sensors alongside a network of low-cost PM sensors for four weeks in two seasons at 50 stationary locations in the adjacent cities of Richmond, North Richmond, and San Pablo, California, east of the San Francisco Bay. Concentrations of BC varied more than $PM_{2.5}$ both temporally and spatially. Monthly network-average BC was 3 × higher in winter than late spring, while $PM_{2.5}$ was only 10% lower. In both seasons, average $PM_{2.5}$ concentrations at two-thirds of sites were *within* ±10% of the network average, whereas two-thirds of sites had BC levels *outside of* ±10% of the network-average concentration. The most and least polluted locations were more persistent across seasons for BC than $PM_{2.5}$, and the temporal dynamics of BC at these sites were similar, signifying that they are impacted by the same emission sources. Together, these spatiotemporal trends show that BC is a better indicator of the proximity and activity of local pollution sources than $PM_{2.5}$. Thus, including BC in addition to $PM_{2.5}$ in community monitoring networks can provide additional insights about local sources of air pollution.

1. Introduction

Low-cost sensors are widely used by researchers, public health agencies, and citizens alike to measure spatial and temporal variations in air pollution within communities (Barkjohn et al., 2021; Bi et al., 2020; Castell et al., 2017; Desouza, 2022; Kumar et al., 2015; Li et al., 2022; Lung et al., 2018; Mahajan et al., 2020; Morawska et al., 2018; Snyder et al., 2013). Air pollution monitoring with low-cost sensors has improved population exposure estimates, characterized local emission sources, and supported emission reduction planning, especially in communities that are disproportionately impacted by air pollution (California, 2019; Caubel et al., 2019; Connolly et al., 2022; Do et al., 2021; Hajat et al., 2015; Henneman et al., 2021; Weissert et al., 2020a). For example, California's Assembly Bill 617 created an air quality monitoring and pollution mitigation planning program in partnership with communities that experience elevated rates of asthma and cardiovascular disease due to inequitable exposure to pollution (California, 2019). Similarly, the government-sponsored Breathe London program is developing a hybrid network of reference-grade monitors and lower cost air quality sensors to provide more localized air pollution information to community members who are not represented by sparsely distributed regulatory monitors. (Breathe London Network Air Quality Monitoring Report (2021–2022)) The engagement of individual citizens has markedly changed the air monitoring landscape. For instance, the now massive-scale deployment of commercially available PurpleAir air quality monitors that estimate fine particulate matter ($PM_{2.5}$) concentrations has created an ad-hoc network of indoor and outdoor air pollution sensors that has increased the spatial density of pollution monitoring in some communities by two orders of magnitude compared to regulatory monitoring networks (Barkjohn et al., 2021; Bi et al., 2020; deSouza and Kinney, 2021; Liang et al., 2021; Mullen et al., 2022; Schulte et al., 2020; Wallace et al., 2022).

Numerous citizen science and government-funded low-cost sensor networks have primarily or exclusively included $PM_{2.5}$ monitoring, while a minority have incorporated other pollutants such as ozone (O_3) and nitrogen dioxide (NO_2) (Clark et al., 2017; Connolly et al., 2022; Jerrett, 2022; Kelly et al., 2021; Li et al., 2019; Lu et al., 2021; Mahajan et al., 2020; Miskell et al., 2018, 2019; Schulte et al., 2020; Wallace et al., 2021; Weissert et al., 2020b; Zimmerman et al., 2020). $PM_{2.5}$ is arguably the most commonly measured air pollutant in low-cost sensor networks because of its significant health impacts and the affordability and quality of the sensing technology. Additionally, $PM_{2.5}$ is a common target for emission reductions plans by these community organizations. It is critical to acknowledge that $PM_{2.5}$ is both formed in the atmosphere from precursor gases emitted by many biogenic, combustion, and non-combustion sources as well as directly emitted from sources such as traffic, residential wood burning, wildfires, and fossil fuel combustion in commercial and industrial applications. The existence of primary and secondary components of $PM_{2.5}$ together complicates community-informed emission reduction planning efforts, as a significant fraction of ambient $PM_{2.5}$ concentrations may be attributable to regional sources of pollution that are outside of a community and transported across municipal jurisdictions. While reducing all types of $PM_{2.5}$ would be beneficial, communities can more directly plan and advocate for the mitigation of local emission sources within their municipal jurisdiction, such as diesel particulate matter emissions from trucks operating on roads within their neighborhoods. By comparison, community air protection plans will be challenged to directly address other types of $PM_{2.5}$, such as ammonium nitrate $PM_{2.5}$ that is formed in the atmosphere from regionally distributed emissions of nitrogen oxides and ammonia. These precursor pollutants come from a range of sources, including trucks, power generating facilities, landfills and other waste management operations, and numerous agriculture activities, all of which are subject to more regional, state, or federal regulations beyond the reach of local community action (Bastien et al., 2015; Dedoussi and Barrett, 2014; Hagan et al., 2019; Maykut et al., 2003; Wang et al., 2022; Zhang et al., 2015).

Although BC is typically a small fraction of ambient $PM_{2.5}$ mass in the San Francisco Bay Area (~5–10%, based on unpublished analysis of publicly available data from regulatory monitoring sites), it is a primary particulate air pollutant that is directly produced by diesel engines, residential wood burning, and commercial cooking (Caubel et al., 2019; Kirchstetter et al., 2017; BAAQMD). The lowest cost BC sensors are an order of magnitude more expensive that widely available low-cost $PM_{2.5}$ sensors. The authors of this study previously developed, rigorously validated, and deployed 100 low-cost BC sensors in West Oakland, California (Caubel et al., 2018, 2019). The West Oakland study highlighted sharp block-by-block variations in BC concentrations that were dependent on proximity to emission sources, but it was limited to one season of the year and did not include measurements of $PM_{2.5}$ concentrations.

This current study took advantage of an opportunity to pair these low-cost BC sensors with a network of $PM_{2.5}$ sensors to compare spatiotemporal patterns of both pollutants in environmental justice communities. This study was part of a broader effort that involved community organizations seeking to identify persistent emission sources and develop emission reduction plans for improved air quality. This study sought to evaluate how monitoring BC in addition to $PM_{2.5}$ might be more insightful than measuring $PM_{2.5}$ alone for characterizing local source activity patterns and, in turn, provide potentially more actionable information for communities.

2. Materials and methods

This study took place in the cities of Richmond, North Richmond, and San Pablo, California, east of the San Francisco Bay. The study area covered 26 km^2, with a population of over 100,000 people composed primarily of racial and ethnic minority groups. This area includes numerous sources of air pollution, including heavy traffic from major highways and roadways (I-580, I-80, and the Richmond Parkway), one of the largest petroleum refinery in California, and locomotive rail yards and railways, as shown in Fig. 1 (California, 2019; August et al). It includes schools and homes in areas zoned for commercial and industrial activity.

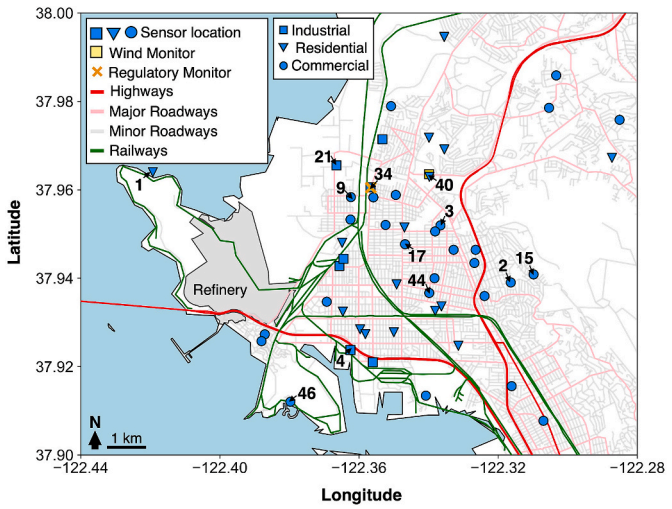

Fig. 1. Fifty locations where ABCDs and Aeroqual sensors were collocated in Richmond, California (blue symbols), where symbol shapes denote sensor locations in specific land-use designation areas: industrial (squares), residential (circles), and commercial (inverted triangles). The refinery is located on the west side of the study, as indicated by the gray polygon. A monitoring station operated by the regional air quality management agency is marked with an orange "X". The location of the wind monitor referenced in the text is marked as a yellow square. Highways, major and minor roadways, and railways are included as line segments and colored according to the legend. Sites with designated numbers are discussed in the Results section of the text.

At 50 locations in the study area, an Aerosol Black Carbon Detector (ABCD) was collocated with an Aeroqual AQY1 Micro Air Quality Monitoring System (hereafter referred to as an Aeroqual sensor). The ABCD is a custom-built, pre-commercial, filter-based absorption photometer that performs comparably to a commercially available aethalometer that is used by the regional air quality management agency. The sensor performance was rigorously evaluated and used for community monitoring, as described in two prior studies (Caubel et al., 2018, 2019). These sensors have a built-in algorithm to limit measurement bias associated with changes in temperature and relative humidity (Caubel et al., 2018). The Aeroqual sensors measured concentrations of $PM_{2.5}$ and NO_2. A proprietary real-time onboard correction for relative humidity and temperature was applied to the Aeroqual data, in addition to monthly calibration values provided by the manufacturer using Aeroqual's patent-pending mean-variance moment matching approach. Additional sensor details and quality assurance and control measures conducted for both the ABCDs and Aeroqual sensors are given in the Supporting Information (SI, Fig. S1).

This study covered two seasons in calendar year 2021: (1) four weeks in winter from January 14–February 10, and (2) four weeks in late spring from May 19–June 21. These periods were chosen to include the seasonal maxima and minima in BC concentrations that are predominantly driven by San Francisco Bay Area meteorology, in addition to seasonal differences in residential woodburning in some areas and temperatures (SI, Fig. S2). (Kirchstetter et al., 2008, 2017) The ABCD and Aeroqual sensors were placed outdoors, typically at a height of approximately 2 m and within 1–2 m of each other (Fig. S3). Of the 50 monitoring locations, 27 were outside of a host's home, 18 were in front of schools, and 5 were installed outside of a local business or organization.

3. Results

3.1. Temporal trends

Boxplot distributions of site-average BC and $PM_{2.5}$ concentrations measured at the 50 locations in winter and late spring 2021 are shown in Fig. 2. Each site-average is equal to the mean of all hourly concentrations measured at a monitoring location in the specified period. The network-average BC concentration was 3 × greater in winter than in late spring (0.52 ± 0.03 μg m^{-3} vs. 0.17 ± 0.01 μg m^{-3}; mean ± 95% confidence interval). In contrast, network-average $PM_{2.5}$ concentrations did not differ much between the two seasons and were instead only 1.2 × higher in the late spring than in the winter (8.9 ± 0.6 μg m^{-3} vs. 7.4 ± 0.3 μg m^{-3}). Dominated by the change in BC concentrations, the BC/$PM_{2.5}$ mass fraction was 2 × larger in winter than in late spring (9% vs. 4%, Fig. 2).

Lower wind speeds and lower atmospheric boundary layer heights in the winter are features of the San Francisco Bay Area meteorology that inhibit the dispersion of pollutants and contribute to higher concentrations of BC (a primary air pollutant), as reported previously based on decades-long historical datasets (Kirchstetter et al., 2017). While meteorological data was limited in the Richmond area, a weather station ~65 m from site 40 in San Pablo showed that wind tended to come from the south with higher speeds in the late spring (Fig. 1 and S4). The highest BC concentrations measured at this location corresponded with the slowest winds in the winter. In general, lower BC concentrations were measured across the study area at locations that were upwind and to the south of major roadways, while higher concentrations were typically measured downwind and north of these roadways. The pattern of moderately higher $PM_{2.5}$ concentrations in late spring than winter, despite increased atmospheric dispersion, suggests enhanced springtime secondary formation of $PM_{2.5}$ (Fig. 2) (Bastien et al., 2015; Gani et al., 2021; Saha et al., 2018).

In addition to exhibiting a greater seasonal difference, BC concentrations varied more throughout the day than $PM_{2.5}$. This difference in diurnal trends is highlighted in Fig. 3, which shows the typical concentrations of BC, NO_2, and $PM_{2.5}$ measured in each hour of the day on weekdays and weekends for each season. The diurnal cycle in BC was more prominent than that of $PM_{2.5}$, especially in the winter period where peak BC concentrations in the morning and evening were approximately 2 × larger than the minimum concentrations in the afternoon on both weekdays and weekends (Fig. 3 and S5). In contrast, the average daily mid-morning peak in wintertime $PM_{2.5}$ was only ~1.4 × larger than the afternoon minimum (Fig. S5). BC concentrations are also better correlated with NO_2 rather than $PM_{2.5}$, as further illustrated by the scatter plots presented in Fig. S6. The more modest diurnal patterns in $PM_{2.5}$ indicate that local activity patterns like traffic are not the main contributors of total $PM_{2.5}$ pollution in the community, which is instead driven more by regional-scale emissions and atmospheric formation. Together, these trends further support the argument that including measurements of BC in addition to $PM_{2.5}$ adds important value to community air pollution monitoring because it is a better indicator of local combustion activity, especially that of diesel engines.

The wintertime early morning peak in BC concentration coincided with peak concentrations of NO_2, which is the product of rapid oxidation of nitric oxide that is present in diesel exhaust (Kimbrough et al., 2017; Preble et al., 2019). These morning peaks were most likely due to diesel activity that is largely driven by on-road heavy-duty trucks, enhanced by a low atmospheric boundary layer in the morning when emissions are mixed vertically throughout a smaller volume of the atmosphere than later in the day. Historically, BC concentrations in the San Francisco Bay Area have been much higher on weekdays than weekends, following diesel truck activity patterns (Caubel et al., 2019; Kirchstetter et al., 2008; McDonald et al., 2014). This weekly cycle was not observed in the present study and the early morning peaks in BC persisted on the weekends during the four-week winter sampling period, indicating that diesel engine activity patterns in the region may be changing (Fig. 3, S5 and S7).

Unlike the wintertime morning peaks that were similar on all days, there were different pollutant patterns during wintertime evening peaks on weekends compared to weekdays. The weekday evening trends

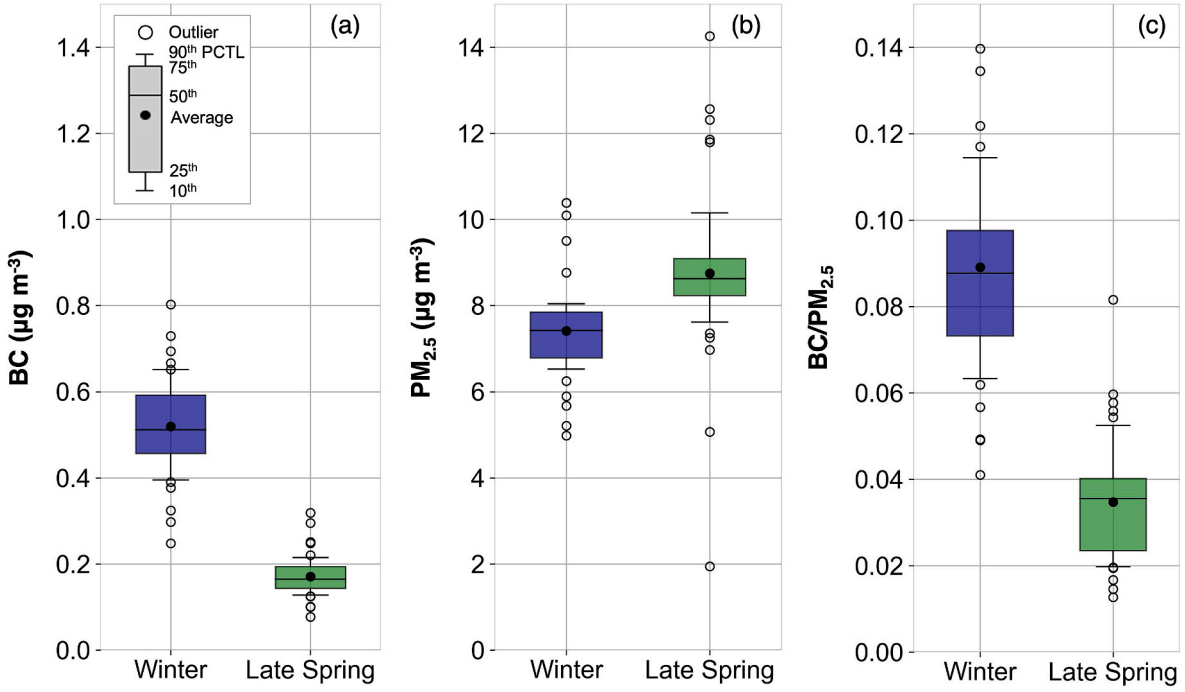

Fig. 2. Boxplot distributions of site-average (a) BC and (b) $PM_{2.5}$ concentrations and (c) BC/$PM_{2.5}$ ratios measured at the 50 monitoring locations in the winter (Jan/Feb) and late spring (May/Jun) of 2021. PCTL refers to percentile and outliers are defined as points ±1.5 × the interquartile range.

mirrored those of the morning, with a pronounced BC peak, a more muted NO_2 peak, and near-baseline $PM_{2.5}$ concentrations. Conversely, the weekend evening BC peak was more elevated than in the morning, persisted overnight, and corresponded in timing and shape to an NO_2 rise and notable $PM_{2.5}$ peak. This divergence indicates that a non-diesel emission source such as residential wood burning is likely an important contributor to wintertime pollution.

It is possible that the differences in temporal trends observed for BC and $PM_{2.5}$ may be also affected by the Aeroqual's $PM_{2.5}$ measurement method. Like other $PM_{2.5}$ sensors that use low-cost detection methods, the Aeroqual particle sensor is not fully quantitative for particles <300 nm in diameter (Wardoyo et al., 2020; Zou et al., 2021). As a result, the Aeroqual may understate the mass concentration of ultrafine particles emitted from certain combustion sources (Desouza, 2022; Hagan and Kroll, 2020; Kuula et al., 2020; Lung et al., 2018). For example, particles <300 nm in diameter comprise a majority of the $PM_{2.5}$ mass size distribution for on-road emissions by modern diesel trucks (Preble et al., 2015). Therefore, the combustion activity patterns that influence BC concentrations may not be equally well captured by the low-cost $PM_{2.5}$ sensor.

3.2. Spatial trends

Fig. 4 shows the distributions of site-average BC and $PM_{2.5}$ concentrations measured in winter and late spring, with the 50 sites categorized by land use designation. In the winter when BC concentrations were elevated across Richmond, the average BC concentration measured in industrial zones was 26% and 17% higher than the average levels measured in areas zoned as residential and commercial, respectively. Notably, a majority of monitoring sites were outside of homes and schools, even in industrial and commercial zones. In the late spring, the relative difference in average BC concentration measured in industrial zones compared to residential and commercial areas was even higher, 40% and 30%, respectively. However, as BC concentrations were lower across the network in late spring compared to winter, the absolute differences in average BC concentrations by land use designation were smaller compared to the wintertime differences. In contrast, $PM_{2.5}$ concentrations varied less than BC across sites in each of the three land use categories in both seasons, as shown in Fig. 4 by the differences in interquartile ranges.

The ranked order distributions of normalized BC and $PM_{2.5}$ concentrations presented in Fig. 5 further illustrate the extent to which BC and $PM_{2.5}$ varied across the monitoring sites. In both seasons, approximately two-thirds of the sites experienced $PM_{2.5}$ concentrations that were within ±10% of the network average, compared to only one-third of the sites for BC. This means that the majority of sites experienced comparable $PM_{2.5}$ concentrations, on average, while there was more spatial heterogeneity in BC concentrations across the community. As discussed above, this is further evidence that $PM_{2.5}$ pollution in the community is more driven by regional rather than local emissions and atmospheric formation.

To explore this idea more, we estimated primary $PM_{2.5}$ by calculating background-subtracted $PM_{2.5}$ at each location using the westernmost site in the network as the upwind regional background (Figs. S8a and b). When background-subtracted, $PM_{2.5}$ at a majority of locations decreases to near-zero concentrations (±2 µg m^{-3}). Whether background-subtracted or not, $PM_{2.5}$ is poorly correlated to BC, indicating that this estimate of primary $PM_{2.5}$ is not indicative of BC trends.

Fig. 6 shows another ranked order plot that evaluates the seasonal differences in sites that were the most and least polluted with BC and compared to those that were the most and least polluted with $PM_{2.5}$. Sites are ranked 1–50 from highest to lowest average BC concentration in each season. In the table presented below this plot, the specific location numbers corresponding to that ranked order are noted by season and pollutant. In the first row of this table, the 10 sites with the highest concentrations in the winter period are shaded in red and underlined, and the 10 locations with the lowest concentrations are shaded in green and italicized. The shading and font format for those 20 specific location numbers is repeated in the following rows for late spring BC and wintertime $PM_{2.5}$.

Five of the top ten sites most polluted with BC in winter were again among the top ten most polluted sites in late spring (Locations 4, 34, 21, 44, 9). Similarly, of the ten sites that had the lowest average BC levels in winter, half were again among the least polluted with BC in late spring

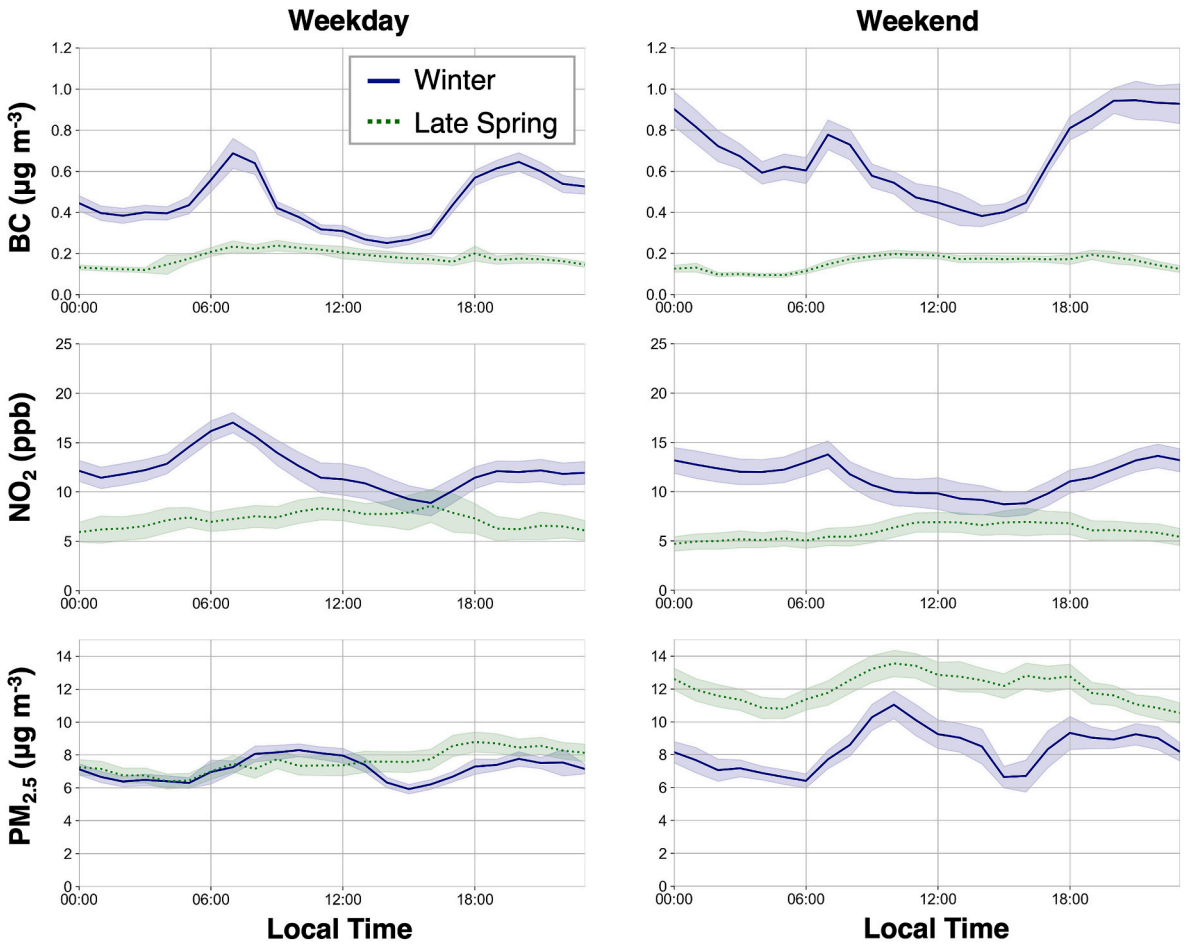

Fig. 3. Weekday (left panel) and weekend (right panel) diurnal trends of BC, NO_2, and $PM_{2.5}$ concentrations (top to bottom) in the winter (solid blue line) and late spring (dashed green line). The lines indicate the network-average, calculated as the mean of all data points in a given hour across the 50 sites in the specified period, and the shaded areas show the 95% confidence intervals that represent the temporal and spatial variability in the hourly concentrations.

(Locations 46, 2, 15, 17, 3). There is little commonality in the sites that experienced the highest concentrations of BC and $PM_{2.5}$—only one of the sites with the highest wintertime average BC concentration (Location 10) was among the sites in the top quintile for $PM_{2.5}$ in the winter, and the two most persistent wintertime BC hotspots (Locations 4 and 34) were in the lowest quintile for $PM_{2.5}$. Of the five sites that were consistent hotspots with elevated BC in both seasons, three are zoned for industrial activity (Locations 4, 34, 21). The other two (Locations 9 and 44) are adjacent to diesel activity: Location 9 is a home in North Richmond that is approximately 250 m from a railway and less than 0.5 km from Location 34, while Location 44 is a home 200 m from a designated truck route. These five locations and the five persistently lowest concentration sites are noted in Fig. 1 and also highlighted in the monitoring network map in Fig. S9. All of the persistently least polluted sites are in residential zones.

While the five most polluted sites in the winter had an average BC concentration 2.2 × the average concentration of the five least polluted sites (0.71 µg m^{-3} vs. 0.33 µg m^{-3}), the temporal dynamics of the BC pollution at each of the sites were similar. For example, as shown in Fig. 7a, 25% of the hours over the winter study period accounted for approximately 50% of the BC pollution at both the most and least polluted locations. The same was true when considering the distribution of pollution over 10- and 1-min averaging times (Fig. S10). This indicates that the BC concentrations at each site were dominated by persistent emission sources rather than highly episodic extreme pollution events; if periods of highest BC pollution were very short-lived (e.g., 1-min or less), then the distribution of 1-min average concentrations shown in Fig. S10 would be more skewed than that of 1-hr values. Normalized BC diurnal time series of the top five most and least polluted locations (Fig. 7b) further illustrate that the temporal dynamics of BC pollution are similar despite the large differences in absolute BC concentrations. Together, these trends suggest that the same source activity governs pollution at sites that are among the most and least polluted with BC. In other words, we conclude that the dominant emission sources affecting the most and least BC-polluted sites are the same and the proximity to the sources determines the BC pollution levels. For example, the most polluted Location 4 that is 0.1 km from a freeway is perhaps expectedly impacted by traffic-related pollution, and the BC pollution at Location 15 that is 1.2 km from a freeway, while much lower in concentration, also appears to be attributable mainly to traffic.

4. Conclusions

While deploying low-cost sensors to better characterize neighborhood-scale air pollution trends, it is important to recognize their limitations and take steps to ensure data quality. As described above and in the SI, we implemented a number of quality assurance and control measures, but there may be some additional uncertainties that require further investigation. For instance, it is possible that the spatial variability in $PM_{2.5}$ reported here may be inadvertently affected by Aeroqual's MOment-MAtching (MOMA) calibration. Like other low-cost $PM_{2.5}$ sensor data that requires corrections to better match regulatory methods, the MOMA calibration attempts to reduce erroneous sensor-to-sensor variability. In this study, there were two nearby regulatory

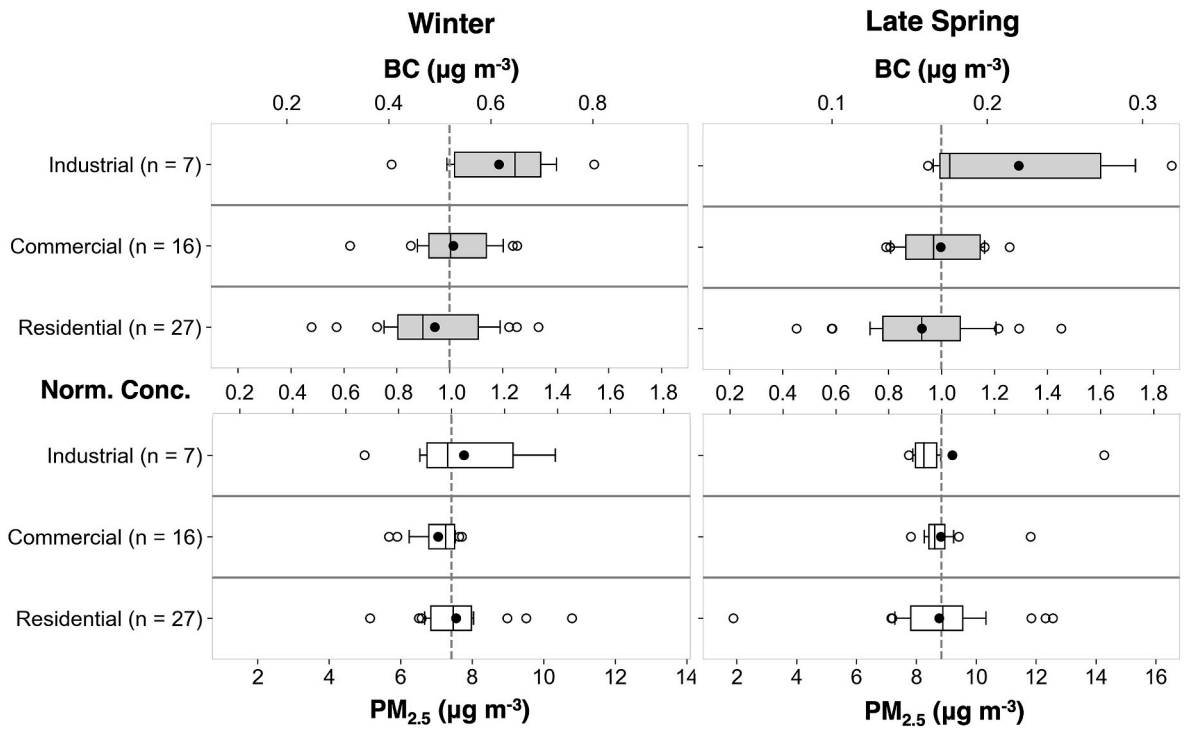

Fig. 4. Distributions of site-average BC (top panels in gray) and $PM_{2.5}$ (bottom panels in white) concentrations measured in the winter and late spring, categorized by land-use area designation. Absolute concentration scales for BC and $PM_{2.5}$ are on the top and bottom axes, respectively. The shared middle axis gives the normalized concentration scale relative to each pollutant's network-average value. The number of locations per land use category is noted in parenthesis. The box plot tails represent the 10th and 90th percentiles while the vertical lines on the box represent the 25th, 50th, and 75th percentiles. The mean for each distribution is represented by a black circle, while outliers are open circles.

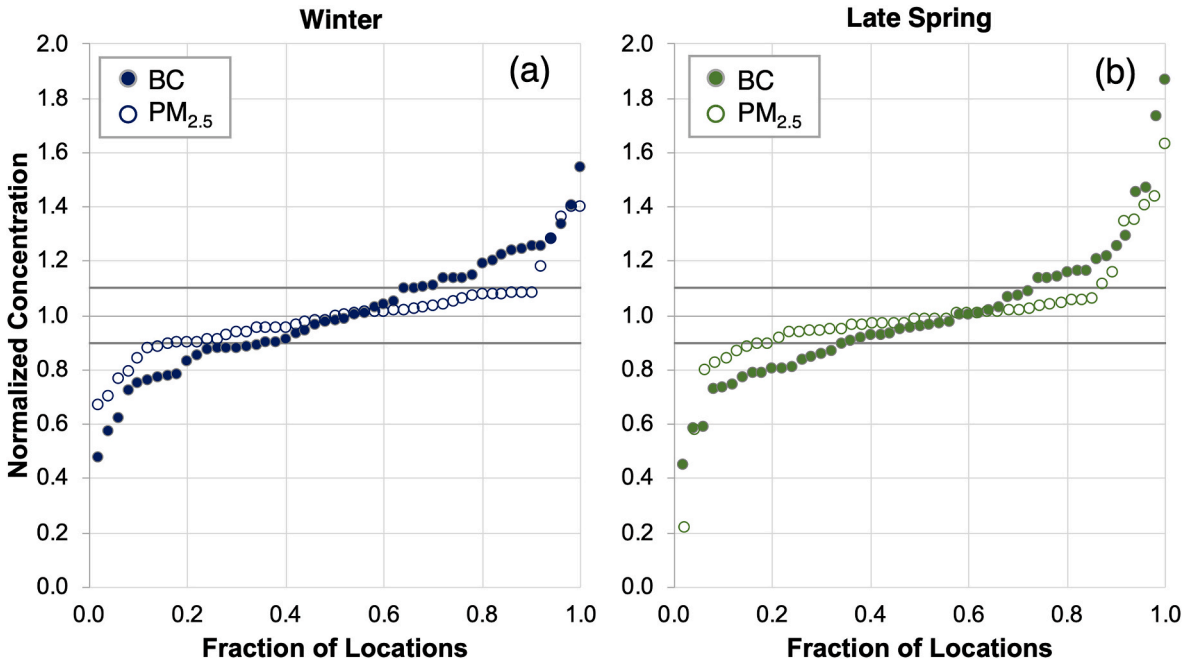

Fig. 5. Ranked order distributions of normalized concentrations of BC (closed circles) and $PM_{2.5}$ (open circles) for the (a) winter and (b) late spring sampling periods. Locations are ordered from lowest to highest average concentration left-to-right on the x-axis, and the corresponding site-average concentration normalized to the network-average value is plotted on the y-axis for each season. Dark gray horizontal lines mark ±10% of the network average that is denoted by the normalized value of 1.

monitoring stations that were used as the proxy measurements for comparison, as described in the SI. To evaluate the extent to which this calibration may have dampened sensor response and site-to-site variability, we compared $PM_{2.5}$ concentrations with and without the MOMA correction. As shown in Figs. S8c and d, there is more variability in network $PM_{2.5}$ concentrations when this calibration is not applied,

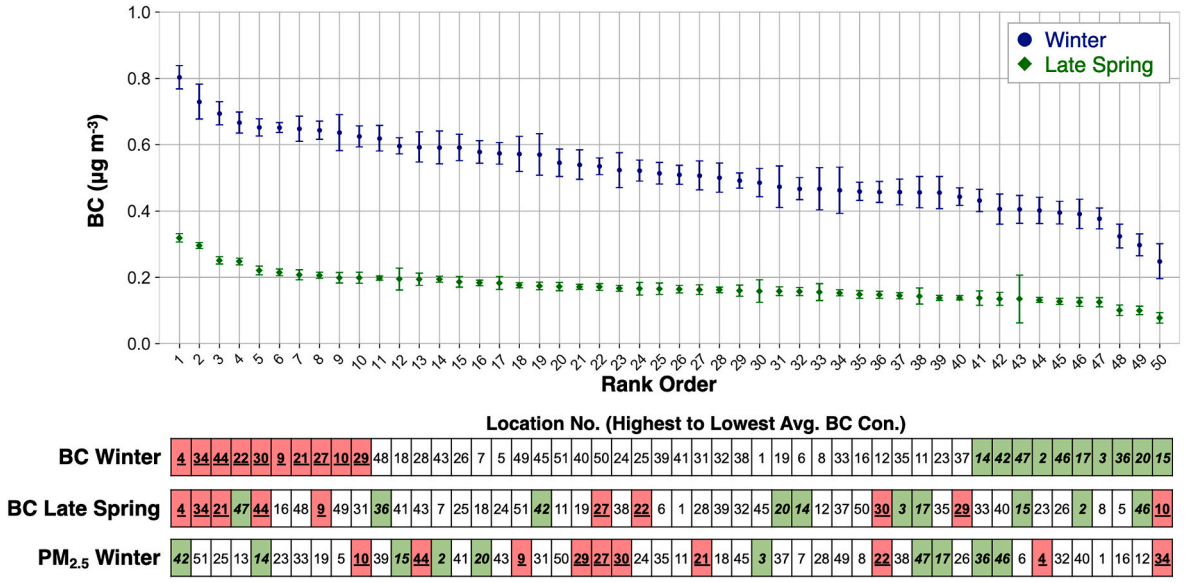

Fig. 6. Site-average BC concentrations for winter (blue circles) and late spring (green diamonds), with sites ranked 1–50 from highest to lowest concentration on the x-axis from left to right. Error bars represent the 95% confidence interval for each site. The table below the plot notes the specific location numbers corresponding to that ranked order by season and pollutant. In the first row of this table, the 10 sites with the highest concentrations in the winter period are shaded in red and underlined and the 10 least polluted locations are shaded in green and italicized. The denotation for those 20 specific location numbers is repeated in the following rows for late spring BC and winter $PM_{2.5}$.

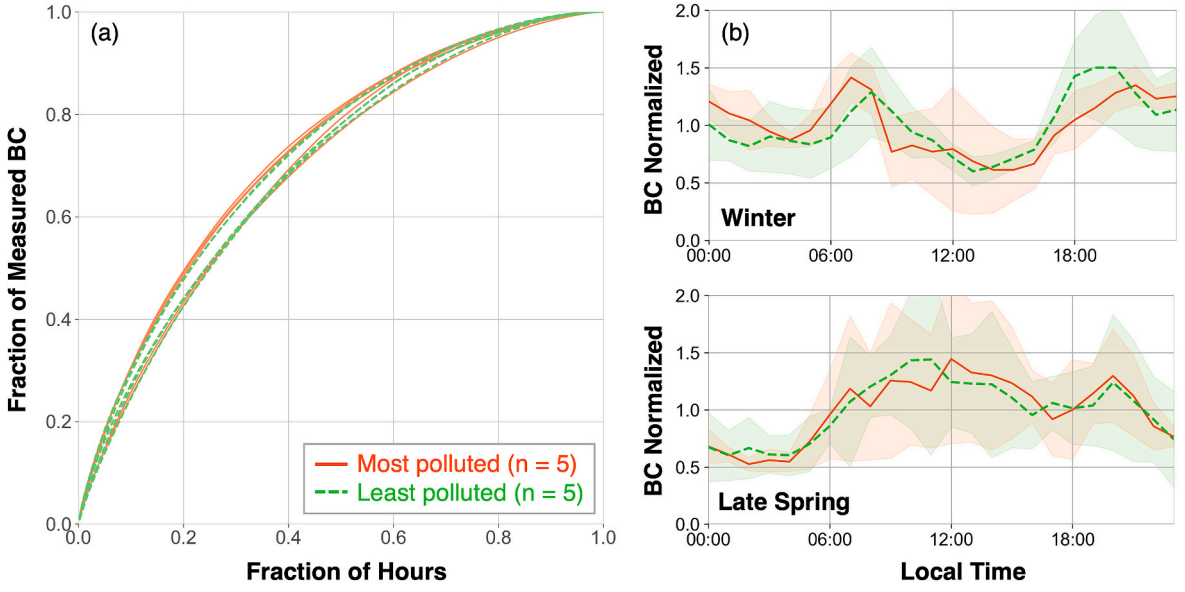

Fig. 7. For the five most polluted (solid red lines) and five least polluted (dashed green lines) sites: (a) the cumulative distributions of hourly BC concentrations measured in the winter sampling period; and (b) average BC concentration measured during the winter (top) and late spring (bottom) sampling periods, normalized to the seasonal network average and with 95% confidence intervals indicated by the shaded areas about each line.

and it is unclear if this increased variability is real or a measurement artifact. Even so, consistent with the results discussed above and shown in Fig. S8, uncalibrated $PM_{2.5}$ data with and without background-subtraction are poorly correlated with BC concentrations across the network and are thus not indicative of local primary emissions.

The results presented above highlight the importance of including primary pollutants like BC, an indicator of diesel engine activity, in community monitoring networks, in addition to other criteria pollutants like $PM_{2.5}$, NO_2, and O_3, that are partially or entirely formed in the atmosphere rather than emitted locally. The greater spatial and temporal heterogeneity and location persistence of BC compared to $PM_{2.5}$ is more informative of the proximity and activity of emission sources that are within the boundaries of the community, which public health agencies and communities can try to mitigate through air protection plans. Moreover, these findings illustrate that our research community needs to advance the state and use of low-cost air pollution sensing technology to better serve communities in their development of air pollution mitigation strategies.

CRediT authorship contribution statement

Rebecca A. Sugrue: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Validation, Visualization, Writing – original draft, Writing – review & editing. **Chelsea V.**

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.atmosenv.2024.120434.

References

August, L.; Komal Bangia, ·; Plummer, L.; Prasad, S.; Ranjbar, K.; Slocombe, A.; Wieland, W. CalEnviroScreen 4.0.

BAAQMD - Air Quality Data. https://www.baaqmd.gov/about-air-quality/current-air-quality/air-monitoring-data/#/airp?date=2023-05-13&id=59&view=hourly&style=chart (accessed 2023-May-13).

Barkjohn, K.K., Gantt, B., Clements, A.L., 2021. Development and Application of a United States-wide correction for PM_{2.5} data collected with the PurpleAir sensor. Atmos. Meas. Tech. 14 (6), 4617–4637. https://doi.org/10.5194/amt-14-4617-2021.

Bastien, L.A.J., McDonald, B.C., Brown, N.J., Harley, R.A., 2015. High-resolution mapping of sources contributing to urban air pollution using adjoint sensitivity analysis: benzene and diesel black carbon. Environ. Sci. Technol. 49 (12), 7276–7284. https://doi.org/10.1021/acs.est.5b00686.

Bi, J., Wildani, A., Chang, H.H., Liu, Y., 2020. Incorporating low-cost sensor measurements into high-resolution PM2.5 modeling at a large spatial scale. Environ. Sci. Technol. 54 (4), 2152–2162. https://doi.org/10.1021/acs.est.9b06046.

Breathe London Network Air Quality Monitoring Report, 2021-2022. BREATHE+LONDON+NETWORK+AIR+QUALITY+MONITORING+REPORT+2021-2022.pdf (2024, January). https://static1.squarespace.com/static/6033f57839d79800143f9e20/t/65a7e446f317843cc2b5e456/1705501769435/BREATHE+LONDON+NETWORK+AIR+QUALITY+MONITORING+REPORT+2021-2022.pdf.

California, S., 2019. of. Assembly Bill No. 617, 1–10.

Castell, N., Dauge, F.R., Schneider, P., Vogt, M., Lerner, U., Fishbain, B., Broday, D., Bartonova, A., 2017. Can commercial low-cost sensor platforms contribute to air quality monitoring and exposure estimates? Environ. Int. 99, 293–302. https://doi.org/10.1016/j.envint.2016.12.007.

Caubel, J.J., Cados, T.E., Kirchstetter, T.W., 2018. A New black carbon sensor for dense air quality monitoring networks. Sens. Switz. 18 (3), 1–18. https://doi.org/10.3390/s18030738.

Caubel, J.J., Cados, T.E., Preble, C.V., Kirchstetter, T.W., 2019. A distributed network of 100 black carbon sensors for 100 Days of air quality monitoring in West Oakland, California. Environ. Sci. Technol. 53 (13), 7564–7573. https://doi.org/10.1021/acs.est.9b00282.

Clark, L.P., Millet, D.B., Marshall, J.D., 2017. Changes in transportation-related air pollution exposures by race-ethnicity and socioeconomic status: outdoor nitrogen dioxide in the United States in 2000 and 2010. Environ. Health Perspect. 125 (9), 1–10. https://doi.org/10.1289/EHP959.

Connolly, R.E., Yu, Q., Wang, Z., Chen, Y.H., Liu, J.Z., Collier-Oxandale, A., Papapostolou, V., Polidori, A., Zhu, Y., 2022. Long-term evaluation of a low-cost air sensor network for monitoring indoor and outdoor air quality at the community scale. Sci. Total Environ. 807, 150797 https://doi.org/10.1016/j.scitotenv.2021.150797.

Dedoussi, I.C., Barrett, S.R.H., 2014. Air pollution and early deaths in the United States. Part II: attribution of PM2.5 exposure to emissions species, time, location and sector. Atmos. Environ. 99, 610–617. https://doi.org/10.1016/j.atmosenv.2014.10.033.

Desouza, P.N., 2022. Key concerns and drivers of low-cost air quality sensor use. Sustain. Switz. 14 (1) https://doi.org/10.3390/su14010584.

deSouza, P., Kinney, P.L., 2021. On the distribution of low-cost PM2.5 sensors in the US: demographic and air quality associations. J. Expo. Sci. Environ. Epidemiol. 31 (3), 514–524. https://doi.org/10.1038/s41370-021-00328-2.

Do, K., Yu, H., Velasquez, J., Grell-Brisk, M., Smith, H., Ivey, C.E., 2021. A data-driven approach for characterizing community scale air pollution exposure disparities in inland southern California. J. Aerosol Sci. 152 (October 2020), 105704 https://doi.org/10.1016/j.jaerosci.2020.105704.

Gani, S., Chambliss, S.E., Messier, K.P., Lunden, M.M., Apte, J.S., 2021. Spatiotemporal profiles of ultrafine particles differ from other traffic-related air pollutants: lessons from long-term measurements at fixed sites and mobile monitoring. Environ. Sci. Atmospheres 1 (7), 558–568. https://doi.org/10.1039/d1ea00058f.

Hagan, D., Kroll, J., 2020. Assessing the accuracy of low-cost optical particle sensors using a physics-based approach. Atmospheric Meas. Tech. Discuss. 1–36. https://doi.org/10.5194/amt-2020-188.

Hagan, D.H., Gani, S., Bhandari, S., Patel, K., Habib, G., Apte, J.S., Hildebrandt Ruiz, L., Kroll, J.H., 2019. Inferring Aerosol sources from low-cost air quality sensor measurements: a case study in Delhi, India. Environ. Sci. Technol. Lett. 6 (8), 467–472. https://doi.org/10.1021/acs.estlett.9b00393.

Hajat, A., Hsia, C., O'Neill, M.S., 2015. Socioeconomic disparities and air pollution exposure: a global review. Curr. Environ. Health Rep. 2 (4), 440–450. https://doi.org/10.1007/s40572-015-0069-5.

Henneman, L.R.F., Shen, H., Hogrefe, C., Russell, A.G., Zigler, C.M., 2021. Four decades of United States mobile source pollutants: spatial-temporal trends assessed by ground-based monitors, air quality models, and satellites. Environ. Sci. Technol. 55 (2), 882–892. https://doi.org/10.1021/acs.est.0c07128.

Jerrett, M., 2022. Air pollution as a risk for death from infectious respiratory disease. Am. J. Respir. Crit. Care Med. 205 (12), 1374–1375. https://doi.org/10.1164/rccm.202202-0351ED.

Kelly, K.E., Xing, W.W., Sayahi, T., Mitchell, L., Becnel, T., Gaillardon, P.E., Meyer, M., Whitaker, R.T., 2021. Community-based measurements reveal unseen differences during air pollution episodes. Environ. Sci. Technol. 55 (1), 120–128. https://doi.org/10.1021/acs.est.0c02341.

Kimbrough, S., Chris Owen, R., Snyder, M., Richmond-Bryant, J., 2017. NO to NO2 conversion rate analysis and implications for dispersion model chemistry methods using Las Vegas, Nevada near-road field measurements. Atmos. Environ. 165 (1994), 23–34. https://doi.org/10.1016/j.atmosenv.2017.06.027.

Kirchstetter, T.W., Aguiar, J., Tonse, S., Fairley, D., Novakov, T., 2008. Black carbon concentrations and diesel vehicle emission factors derived from coefficient of haze measurements in California: 1967–2003. Atmos. Environ. 42 (3), 480–491. https://doi.org/10.1016/j.atmosenv.2007.09.063.

Kirchstetter, T.W., Preble, C.V., Hadley, O.L., Bond, T.C., Apte, J.S., 2017. Large reductions in urban black carbon concentrations in the United States between 1965 and 2000. Atmos. Environ. 151, 17–23. https://doi.org/10.1016/j.atmosenv.2016.11.001.

Kumar, P., Morawska, L., Martani, C., Biskos, G., Neophytou, M., Di Sabatino, S., Bell, M., Norford, L., Britter, R., 2015. The rise of low-cost sensing for managing air pollution in cities. Environ. Int. 75, 199–205. https://doi.org/10.1016/j.envint.2014.11.019.

Kuula, J., Mäkelä, T., Aurela, M., Teinilä, K., Varjonen, S., González, Ó., Timonen, H., 2020. Laboratory evaluation of particle-size selectivity of optical low-cost particulate matter sensors. Atmos. Meas. Tech. 13 (5), 2413–2423. https://doi.org/10.5194/amt-13-2413-2020.

Li, H.Z., Gu, P., Ye, Q., Zimmerman, N., Robinson, E.S., Subramanian, R., Apte, J.S., Robinson, A.L., Presto, A.A., 2019. Spatially dense air pollutant sampling: implications of spatial variability on the representativeness of stationary air pollutant monitors. Atmos. Environ. X 2 (November 2018), 100012. https://doi.org/10.1016/j.aeaoa.2019.100012.

Li, Y., Yuan, Z., Chen, L.W.A., Pillarisetti, A., Yadav, V., Wu, M., Cui, H., Zhao, C., 2022. From air quality sensors to sensor networks: things we need to learn. Sens. Actuators B Chem. 351 (January 2021), 1–9. https://doi.org/10.1016/j.snb.2021.130958.

Liang, Y., Sengupta, D., Campmier, M.J., Lunderberg, D.M., Apte, J.S., Goldstein, A.H., 2021. Wildfire smoke impacts on indoor air quality assessed using crowdsourced data in California. Proc. Natl. Acad. Sci. 118 (36), e2106478118 https://doi.org/10.1073/pnas.2106478118.

Lu, Y., Giuliano, G., Habre, R., 2021. Estimating hourly PM2.5 concentrations at the neighborhood scale using a low-cost air sensor network: A Los Angeles case study.

Environ. Res. 195 (November 2020), 110653 https://doi.org/10.1016/j.envres.2020.110653.

Lung, S.C.C., Jones, R., Zellweger, C., Karppinen, A., Penza, M., Dye, T., Hüglin, C., Ning, Z., Leigh, R., Hagan, D., Laurent, O., Carmichael, G., Beig, G., Cohen, R., Cross, E., Gentner, D., Gerboles, M., Khan, S., Mudu, P., Carceller, X.Q., Ruggeri, G., Smith, K., Tarasova, O., 2018. Low-Cost Sensors for the Measurement of Atmospheric Composition: Overview of Topic and Future Applications. https://doi.org/10.1016/j.biopsych.2014.07.012.

Mahajan, S., Kumar, P., Pinto, J.A., Riccetti, A., Schaaf, K., Camprodon, G., Smári, V., Passani, A., Forino, G., 2020. A citizen science approach for enhancing public understanding of air pollution. Sustain. Cities Soc. 52, 101800 https://doi.org/10.1016/j.scs.2019.101800.

Maykut, N.N., Lewtas, J., Kim, E., Larson, T.V., 2003. Source apportionment of PM $_{2.5}$ at an urban IMPROVE site in Seattle, Washington. Environ. Sci. Technol. 37 (22), 5135–5142. https://doi.org/10.1021/es030370y.

McDonald, B.C., McBride, Z., Martin, E., Harley, R., 2014. High-resolution mapping of motor vehicle carbon dioxide emissions. J. Geophys. Res. Atmospheres (May), 5283–5298. https://doi.org/10.1002/2013JD021219.Received.

Miskell, G., Salmond, J.A., Williams, D.E., 2018. Solution to the problem of calibration of low-cost air quality measurement sensors in networks. ACS Sens. 3 (4), 832–843. https://doi.org/10.1021/acssensors.8b00074.

Miskell, G., Alberti, K., Feenstra, B., Henshaw, G.S., Papapostolou, V., Patel, H., Polidori, A., Salmond, J.A., Weissert, L., Williams, D.E., 2019. Reliable data from low cost ozone sensors in a hierarchical network. Atmos. Environ. 214 (July), 116870 https://doi.org/10.1016/j.atmosenv.2019.116870.

Morawska, L., Thai, P.K., Liu, X., Asumadu-Sakyi, A., Ayoko, G., Bartonova, A., Bedini, A., Chai, F., Christensen, B., Dunbabin, M., Gao, J., Hagler, G.S.W., Jayaratne, R., Kumar, P., Lau, A.K.H., Louie, P.K.K., Mazaheri, M., Ning, Z., Motta, N., Mullins, B., Rahman, M.M., Ristovski, Z., Shafiei, M., Tjondronegoro, D., Westerdahl, D., Williams, R., 2018. Applications of low-cost sensing technologies for air quality monitoring and exposure assessment: how far have they gone? Environ. Int. 116 (February), 286–299. https://doi.org/10.1016/j.envint.2018.04.018.

Mullen, C., Flores, A., Grineski, S., Collins, T., 2022. Exploring the distributional environmental justice implications of an air quality monitoring network in Los Angeles county. Environ. Res. 206 (June 2021), 112612 https://doi.org/10.1016/j.envres.2021.112612.

Preble, C.V., Dallmann, T.R., Kreisberg, N.M., Hering, S.V., Harley, R.A., Kirchstetter, T. W., 2015. Effects of particle filters and selective catalytic reduction on heavy-duty diesel drayage truck emissions at the port of Oakland. Environ. Sci. Technol. 49 (14), 8864–8871. https://doi.org/10.1021/acs.est.5b01117.

Preble, C.V., Harley, R.A., Kirchstetter, T.W., 2019. Control technology-driven changes to in-use heavy-duty diesel truck emissions of nitrogenous species and related environmental impacts. Environ. Sci. Technol. 53 (24), 14568–14576. https://doi.org/10.1021/acs.est.9b04763.

Saha, P.K., Reece, S.M., Grieshop, A.P., 2018. Seasonally varying secondary organic Aerosol formation from in-situ oxidation of near-highway air. Environ. Sci. Technol. 52 (13), 7192–7202. https://doi.org/10.1021/acs.est.8b01134.

Schulte, N., Li, X., Ghosh, J.K., Fine, P.M., Epstein, S.A., 2020. Responsive high-resolution air quality index mapping using model, regulatory monitor, and sensor data in real-time. Environ. Res. Lett. 15 (10) https://doi.org/10.1088/1748-9326/abb62b.

Snyder, E.G., Watkins, T.H., Solomon, P.A., Thoma, E.D., Williams, R.W., Hagler, G.S.W., Shelow, D., Hindin, D.A., Kilaru, V.J., Preuss, P.W., 2013. The changing paradigm of air pollution monitoring. Environ. Sci. Technol. 47 (20), 11369–11377. https://doi.org/10.1021/es4022602.

Wallace, L., Bi, J., Ott, W.R., Sarnat, J., Liu, Y., 2021. Calibration of low-cost PurpleAir outdoor monitors using an improved method of calculating PM2.5. Atmos. Environ. 256 (May), 118432 https://doi.org/10.1016/j.atmosenv.2021.118432.

Wallace, L., Zhao, T., Klepeis, N.E., 2022. Calibration of PurpleAir PA-I and PA-II monitors using daily mean PM2.5 concentrations measured in California, Washington, and Oregon from 2017 to 2021. Sensors 22 (13), 4741. https://doi.org/10.3390/s22134741.

Wang, Y., Bastien, L., Jin, L., Harley, R.A., 2022. Responses of photochemical air pollution in California's san joaquin valley to spatially and temporally resolved changes in precursor emissions. Environ. Sci. Technol. 56 (11), 7074–7082. https://doi.org/10.1021/acs.est.1c07011.

Wardoyo, A.Y.P., Dharmawan, H.A., Nurhuda, M., Adi, E.T.P., 2020. Optimization of PM2.5 measurement System using NOVA SDS011 sensor. J. Phys. Conf. Ser. 1428 (1), 012053 https://doi.org/10.1088/1742-6596/1428/1/012053.

Weissert, L., Alberti, K., Miles, E., Miskell, G., Feenstra, B., Henshaw, G.S., Papapostolou, V., Patel, H., Polidori, A., Salmond, J.A., Williams, D.E., 2020a. Low-cost sensor networks and land-use regression: interpolating nitrogen dioxide concentration at high temporal and spatial resolution in southern California. Atmos. Environ. 223 https://doi.org/10.1016/j.atmosenv.2020.117287.

Weissert, L., Miles, E., Miskell, G., Alberti, K., Feenstra, B., Henshaw, G.S., Papapostolou, V., Patel, H., Polidori, A., Salmond, J.A., Williams, D.E., 2020b. Hierarchical network design for nitrogen dioxide measurement in urban environments. Atmos. Environ. 228 (November 2019), 117428 https://doi.org/10.1016/j.atmosenv.2020.117428.

Zhang, L., Liu, L., Zhao, Y., Gong, S., Zhang, X., Henze, D.K., Capps, S.L., Fu, T.-M., Zhang, Q., Wang, Y., 2015. Source attribution of particulate matter pollution over north China with the adjoint method. Environ. Res. Lett. 10 (8), 084011 https://doi.org/10.1088/1748-9326/10/8/084011.

Zimmerman, N., Li, H.Z., Ellis, A., Hauryliuk, A., Robinson, E.S., Gu, P., Shah, R.U., Ye, Q., Snell, L., Subramanian, R., Robinson, A.L., Apte, J.S., Presto, A.A., 2020. Improving correlations between land use and air pollutant concentrations using wavelet analysis: insights from a low-cost sensor network. Aerosol Air Qual. Res. 20 (2), 314–328. https://doi.org/10.4209/aaqr.2019.03.0124.

Zou, Y., Clark, J.D., May, A.A., 2021. Laboratory evaluation of the effects of particle size and composition on the performance of integrated devices containing plantower particle sensors. Aerosol Sci. Technol. 55 (7), 848–858. https://doi.org/10.1080/02786826.2021.1905148.