Wintertime and wildfire smoke $PM_{2.5}$: Community-engaged research and use of low-cost sensors to characterize $PM_{2.5}$ and mitigate exposures

Orly Stampfer

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Reading Committee:

Catherine J. Karr, Chair

Edmund Seto, Chair

Ryan Allen

Stephanie Farquhar

Program Authorized to Offer Degree:

Environmental and Occupational Health Sciences

University of Washington

Abstract

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Orly Stampfer

Chairs of the Supervisory Committee:

Catherine J. Karr

Department of Environmental and Occupational Health Sciences

Edmund Seto

Department of Environmental and Occupational Health Sciences

Background

The two main seasons with highest concentrations of fine particulate matter ($PM_{2.5}$) in the state of Washington (WA) are wintertime and periods of wildfire smoke. We examined wintertime $PM_{2.5}$ through a research partnership with the Yakama Nation Air Quality Section, and wildfire smoke $PM_{2.5}$ through research with schools in two different regions of WA, as well as school and childcare facility air quality decision-makers.

Our research sought to address the following aims: 1) Characterize wintertime $PM_{2.5}$ concentrations and chemical composition in the Yakama Nation reservation based on paired indoor and outdoor air sampling, 2) Examine application of low-cost sensors to understand indoor $PM_{2.5}$ concentrations in four WA schools in areas impacted by wildfire smoke, and 3) Understand perspectives on feasibility, data-interpretability, and decision-making in using low-cost sensors for wildfire smoke response in schools and childcare facilities.

Methods

For Aim 1, we collected $PM_{2.5}$ onto filters during three 1-week periods indoors and outdoors at five locations. We quantified $PM_{2.5}$ concentrations gravimetrically and analyzed the samples for levoglucosan – a biomass burning tracer compound – as well as select elements, ions, and polycyclic aromatic hydrocarbons (PAHs). We also measured continuous $PM_{2.5}$ concentration using low-cost sensors. We quantified spatial variation in $PM_{2.5}$ and analytes. $PM_{2.5}$ temporal variation was observed by plotting diurnal patterns.

For Aim 2, we measured $PM_{2.5}$ concentrations indoors and outdoors at four schools in WA during wildfire smoke in 2020. This involved monitoring continuously using a low-cost sensor and gravimetrically. We randomly sampled 5-minute segments of low-cost sensor data to create hypothetical simulations of brief portable handheld measurements.

For Aim 3, we conducted 15 semi-structured interviews with school, childcare, local health jurisdiction, air quality, and school district personnel regarding sensor use for wildfire smoke response. Interviews included sharing $PM_{2.5}$ data collected at schools during wildfire smoke. Interviews were transcribed and transcripts were coded.

Results

In the wintertime data, the $PM_{2.5}$ concentration at one site was generally about half of the concentration measured at the closest regulatory monitor. While $PM_{2.5}$ concentrations at other sites were similar, greater between-site variation was evident for analytes. Percent differences in PAHs relative to the median for at least one site within the same week were more than twice as high in 22 cases, and in two cases were more than 10 times as high. Gravimetric indoor/outdoor ratios varied overall from 0.3 to 2.6. Sites had varied diurnal patterns of peak $PM_{2.5}$ concentrations which did not strongly resemble diurnal patterns typically associated with residential wood burning.

During wildfire smoke events (lasting 4-19 days), median hourly $PM_{2.5}$ concentrations at different locations inside a single facility varied by up to 50 μg/m^3 during school hours over the same time period. Median hourly indoor/outdoor ratios during school hours ranged from 0.22 to 0.91. Within-school differences indicated that it is important to collect measurements throughout a facility. The simulation results suggested that making handheld measurements more often and over multiple days better approximates indoor/outdoor ratios for wildfire smoke.

Three major themes were identified in the interview responses: 1) Low-cost sensors are useful despite data quality limitations, 2) Low-cost sensor data can inform decision-making to protect children in school and childcare settings, and 3) There are feasibility and public perception related barriers to using low-cost sensors.

Conclusion

Spatial and temporal variation of $PM_{2.5}$ in a rural area suggests that sparse regulatory monitors may misrepresent the range of $PM_{2.5}$ exposures that people experience, as well as the multiplicity of $PM_{2.5}$ sources.

We found useful, practical information applicable for optimized sampling with low-cost sensors for wildfire smoke response in schools. Interview responses provided practical implications, including demonstrating a need for guidance that allows a variety of sensor preferences and addresses sensor uses outside of activity decisions, especially assessment of ventilation and filtration.

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Table of Contents

Introduction

Fine particulate matter ($PM_{2.5}$) is a component of air pollution that causes respiratory and cardiovascular morbidity and mortality.[1,2] Early deaths are associated with $PM_{2.5}$ exposure even at low concentrations, with no safe threshold level.[3] The two main seasons with highest concentrations of $PM_{2.5}$ in the state of Washington (WA) are wintertime and periods of wildfire smoke.

In the wintertime, wood burning for heat is suspected to be a major source of $PM_{2.5}$ in several communities in WA, including some of the rural communities of study for this dissertation. However, in rural, agricultural areas there are a variety of $PM_{2.5}$ sources in addition to wood burning for heat. Rural regulatory air monitoring is typically sparse, and spatial variability in wintertime $PM_{2.5}$ concentrations and constituent species is unclear. Further, the indoor burden of $PM_{2.5}$ concentrations and constituent species is also unclear. Understanding sources and spatial variation of wintertime $PM_{2.5}$ is crucial to develop targeted mitigation efforts.

For wildfire smoke season, the source of $PM_{2.5}$ is known, whether from local fires or plumes of smoke from farther fires. However, exposure mitigation strategies are complex. Reducing emissions at the source relies on improved forest management, such as using prescribed burning, and reversing climate change. Reducing exposures requires improved air filtration indoors and modifying behaviors. Activity and building related decisions during wildfire smoke to protect building occupants are best informed by locally relevant data. One particularly impactful group of buildings to focus on is schools and childcare facilities, as children and youth are more vulnerable to $PM_{2.5}$ compared with adults[4,5] and spend a significant amount of time at schools and childcare facilities.

In both of these cases, community-engaged research is essential. For wintertime $PM_{2.5}$, community experiences with spatial variation and hypotheses on potential sources of $PM_{2.5}$ provide insight on appropriate monitoring site selection and $PM_{2.5}$ constituent selection for analysis. We partnered with staff from the Yakama Nation Environmental Management Program and community members at five sites to collect $PM_{2.5}$ data throughout the Yakama Nation reservation. For wildfire smoke $PM_{2.5}$, designing effective and feasible mitigation efforts requires engagement with staff from schools, childcare facilities, and those who assist with activity and building related decisions during wildfire smoke. We partnered with agency and school staff to collect $PM_{2.5}$ data during wildfire smoke at four schools, and interviewed 15 people involved in school and childcare facility building and activity decisions.

Low-cost $PM_{2.5}$ sensors have great potential to be useful for both wintertime and wildfire smoke $PM_{2.5}$ monitoring goals. For wintertime $PM_{2.5}$, low-cost sensors allow for more spatial coverage, and both indoor and outdoor monitoring. Further, the high temporal resolution of low-cost sensors allows for detection of temporal patterns in $PM_{2.5}$ concentration, which can help indicate sources. For wildfire smoke, when making timely activity decisions, it is also helpful to have higher temporal resolution. Making activity decisions indoors and identifying locations within school and childcare facilities that need supplemental air filtration relies on indoor $PM_{2.5}$ monitoring, which is most accessible with low-cost sensors. Outdoor $PM_{2.5}$ can also vary spatially during wildfire smoke, so low-cost sensors can help support tailored decision-making based on localized information.

In this study, we used community engagement, a combination of low-cost sensors and robust $PM_{2.5}$ monitoring, and qualitative methods to address the following aims: 1) Characterize wintertime $PM_{2.5}$ concentrations and chemical composition in the Yakama Nation reservation based on paired indoor and outdoor air sampling, 2) Examine application of low-cost sensors to understand indoor $PM_{2.5}$ concentrations in four WA schools in areas impacted by wildfire smoke, and 3) Understand perspectives on feasibility, data-interpretability, and decision-making in using low-cost sensors for wildfire smoke response in schools and childcare facilities. Results from Aims 2 and 3 will be used to develop toolkits to guide school and childcare facility decision-makers in using low-cost sensors for wildfire smoke response.

Chapter 1: Variation in wintertime $PM_{2.5}$ composition in a rural agricultural valley, characterized through a Tribal-academic research partnership

Summary

Community air pollution monitoring is essential for understanding general population exposures and elucidating major sources of pollutants. In the United States, regulatory air monitoring for fine particulate matter ($PM_{2.5}$) is sparse in rural communities, and monitoring of $PM_{2.5}$ composition is even less common. Through a partnership between the Yakama Nation Air Quality Section and University of Washington, we sought to characterize wintertime variability in concentrations of $PM_{2.5}$ and select constituents in a rural, agricultural valley prone to cold-weather inversions. Specifically, we sought to characterize indoor and outdoor variability between sites across the reservation where people regularly spend time, and outdoor variability between our sampling sites and the closest regulatory sites (one Yakama Nation monitor located on the reservation, and one located within approximately 6.5 km of the reservation).

In the winter of 2019/2020, we collected $PM_{2.5}$ onto filters during three 1-week periods indoors and outdoors at five locations. We quantified $PM_{2.5}$ concentrations gravimetrically and analyzed the samples for levoglucosan – a biomass burning tracer compound – as well as select elements, ions, and polycyclic aromatic hydrocarbons (PAHs). We also measured continuous $PM_{2.5}$ concentration using low-cost sensors. We quantified spatial variation in $PM_{2.5}$ by calculating the median ratio of each site’s concentration to the Yakama Nation monitor. We quantified spatial variation in analytes by 1) calculating which decile of the distribution of annual measurements from the closest speciation monitor corresponded with each analyte concentration, and 2) calculating the percent difference of

each sample's concentration to the overall median across all sites and weeks. $PM_{2.5}$ temporal variation patterns were observed by plotting diurnal patterns of peaks in $PM_{2.5}$ concentration using the continuous data.

The $PM_{2.5}$ concentration at one site was generally about half of the concentration measured at the closest regulatory monitor. While $PM_{2.5}$ concentrations at other sites were similar, greater between-site variation was evident for analytes. For example, differences in analytes between at least one pair of sites within the same week were at least three deciles 60% of the time. Percent differences in PAHs relative to the median for at least one site within the same week were more than twice as high in 22 cases, and in two cases were more than ten times as high. Gravimetric indoor/outdoor ratios varied overall from 0.3 to 2.6. Ratios for some analytes were >2 at two sites, suggesting significant indoor emissions. Sites had varied diurnal patterns of $PM_{2.5}$ which did not strongly resemble diurnal patterns typically associated with residential wood burning.

Spatial and temporal variation in a rural area suggests that sparse regulatory monitors may misrepresent the range of $PM_{2.5}$ exposures that people experience, as well as the multiplicity of $PM_{2.5}$ sources.

1. Background

Exposure to fine particulate matter ($PM_{2.5}$) causes respiratory and cardiovascular morbidity and mortality, and is increasingly associated with impaired neurodevelopment.[4,6–11] Both the concentration and composition of $PM_{2.5}$ are relevant to health,[12–15] and composition can provide information on sources.[16–19] $PM_{2.5}$ concentration and composition measurements inform communities and air quality agencies about managing sources of $PM_{2.5}$.

In the United States, outdoor concentrations of $PM_{2.5}$ are regulated by the Environmental Protection Agency (EPA), which works with federally recognized Tribal

Nations and states to site air quality monitors. PM composition is measured at few of these sites. Indoor air quality in non-occupational settings is not currently regulated or monitored by government agencies.

Regulatory air quality monitors tend to be concentrated in densely populated areas. Despite air quality issues associated with agriculture, the air quality in rural communities is monitored at fewer locations.[20] As of 2023, 68% of the $PM_{2.5}$ monitors on the Washington Department of Ecology Air Monitoring Map[21,22] and 100% of the PM speciation monitors in Washington state (WA) were in urban areas.[23] Therefore, without additional monitoring, community health assessments and epidemiologic studies must rely on spatially sparse measurements to estimate exposures to pollution of outdoor origin in rural communities.

Studies in urban areas have reported spatial and temporal variation in outdoor $PM_{2.5}$ on scales not captured by agency regulatory monitors, and concentrations vary considerably between indoor and outdoor locations.[24–31] Few studies of spatial and temporal concentration variations were conducted in rural areas.[32–34] Variation in PM composition on a regional scale is not as well understood, as PM species measurements are resource intensive.[18,35]

The importance of community-based air monitoring has recently been highlighted through the EPA funded American Rescue Plan enhanced air quality monitoring for communities grants, recognizing the important environmental and health outcomes disparities that can be addressed through enhanced air quality monitoring.[36] The EPA has also developed an Air Sensor Toolbox for a wide audience including community scientists.[37,38]

This chapter presents a Tribal and community-based project to describe spatial and temporal variation in $PM_{2.5}$ concentration and composition in the Yakama Nation reservation. The Confederated Tribes and Bands of the Yakama Nation is a sovereign nation pursuant to the Treaty of 1855. The reservation land area is over one million acres and, as of 2022, has one permanent Yakama Nation agency $PM_{2.5}$ monitor. The reservation is in a rural, agricultural valley prone to wintertime weather inversions marked by elevated $PM_{2.5}$ concentrations.[39,40]

Our study team comprises a partnership between the Yakama Nation Air Quality Section (AQS) and the University of Washington (UW) Department of Environmental and Occupational Health Sciences (DEOHS). While various definitions of community air monitoring exist,[36,41] in this project, we defined community air monitoring as 1) building accountable relationships with people rooted in the local community to jointly address their air quality concerns, priorities, and ideas, 2) creating hypotheses based on their expertise about pollution sources and people at risk for exposure, 3) matching air monitoring methods to community aims, not limited to low-cost sensors, and 4) returning sampling results and jointly working towards understanding of important sources and findings.

A key interest of the Yakama Nation AQS was whether the nearest regulatory monitors were adequately capturing area-wide impacts and emissions. To begin to inform the potential limitations of relying on sparse regulatory monitoring, the team sought to use low-cost and conventional monitoring equipment to examine spatial variability of $PM_{2.5}$ concentrations and composition within the large reservation community, focused on places where community members gathered.

Spatial variation is relevant to potential exposure misclassifications. Often health studies are interested in exposure to PM of outdoor origin, but in this instance we were interested in total PM exposure (including PM of both indoor and outdoor origin). Indoor PM includes PM of outdoor origin, as well as PM emitted indoors from sources such as cooking, cleaning, and burning biomass for heat. This research focused on wintertime $PM_{2.5}$, which is the main season for high PM concentrations in this area outside of wildfire smoke.

2. Methods

2.1 Partnership formation and roles

UW DEOHS and Yakama Nation AQS began relationship-building in 2016 through NextGenSS, a 3-year US EPA STAR grant (#RD83618501, Air Pollution Monitoring for Communities). The project had two main components: 1) a partnership with local Heritage University to support high school student-led air quality research projects using low-cost sensors,[42] and 2) a partnership with Yakama Nation AQS to better understand community $PM_{2.5}$ concentrations and composition. Yakama Nation AQS participated in the NextGenSS advisory board, supported high school student projects, and partnered with UW DEOHS to explore the utility of a multi-wavelength aethalometer in characterizing local $PM_{2.5}$.[43]

UW DEOHS and Yakama Nation AQS collaborated on a successful proposal (National Institute of Environmental Health Sciences #P30ES007033) to fund further $PM_{2.5}$ characterization activities in conjunction with the NextGenSS project. First, over a series of in-person and phone meetings, Yakama Nation AQS led the selection of sampling sites, and UW DEOHS suggested $PM_{2.5}$ analytes for Yakama Nation AQS consideration. Next, Yakama Nation AQS initiated and oversaw engagement with partners at each sampling site. This was followed by data collection site visits, during which UW DEOHS led the sampling procedures with Yakama Nation AQS support. After data collection, UW DEOHS managed sample logistics for laboratory analyses and conducted data analysis. UW DEOHS then presented results to Yakama Nation AQS and results were interpreted jointly during in-person meetings. Yakama Nation AQS and UW DEOHS then collaborated to return results to partners at each sampling site.

Finally, UW DEOHS wrote this dissertation chapter, which Yakama Nation AQS reviewed. The discussion section of this chapter contains joint interpretations of the findings. Yakama Nation AQS were compensated for their time spent on the project through the grant funding. Our collaboration was rooted in years of trust-building, with partners demonstrating accountability to each other. We used and honored verbal agreements in conducting this research together.

2.2 Community air sampling sites and times

There are three fixed-site air pollution monitors within about 10 km of the Yakama Nation reservation. The Yakama Nation operates a beta-attenuation monitor (BAM) in the city of Toppenish (near Site C in Figure 1). $PM_{2.5}$ and PM_{10} concentrations and $PM_{2.5}$ species are measured in the city of Yakima (north of Site E), which is about 6.5 km north of the reservation on the other side of a ridge that divides the upper Yakima Valley from the lower Yakima valley. $PM_{2.5}$ concentrations are also measured in the city of Sunnyside (east of Site C), about 10 km east of the reservation in a heavily agricultural area.[23]

Yakama Nation AQS selected five sampling sites to represent the main population centers of the reservation, with a focus on child and youth exposures (Figure 1). The sites were expected to vary by amount of $PM_{2.5}$ pollution and by proximity to different potential $PM_{2.5}$ sources, based on conversations with Yakama Nation AQS and people at the sites, as well as observations of site locations and indoor characteristics (Table 1).

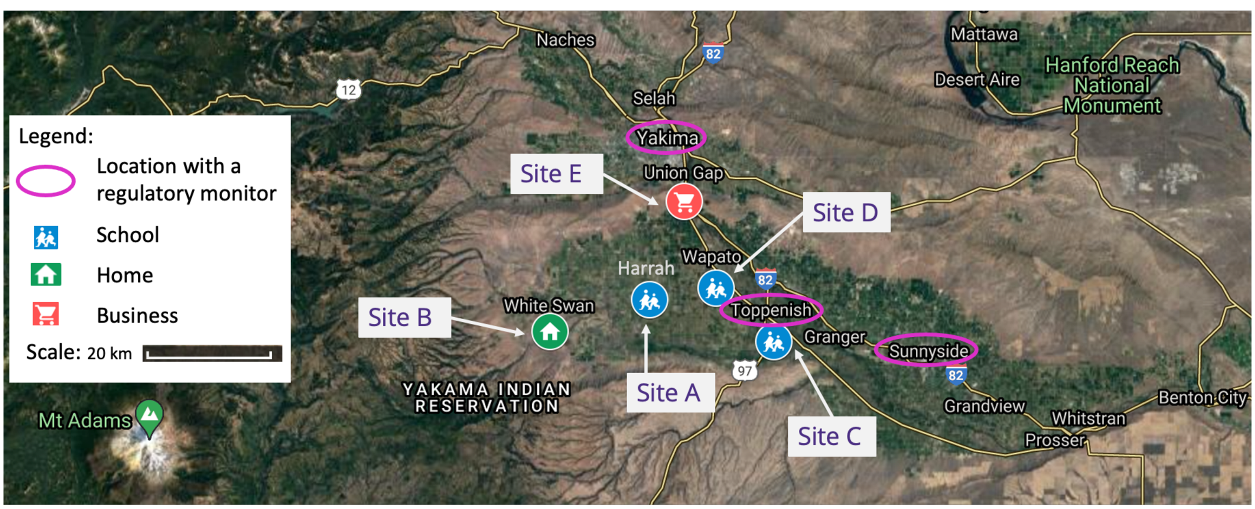

Figure 1: Locations of sampling sites (base map from Google Maps 2022).

Table 1: Description of sampling sites.

Site ID	Site type	General regional location	Indoor setting	Outdoor setting	Expected sources of outdoor-generated $PM_{2.5}$	Expected sources of indoor-generated $PM_{2.5}$	Sampling dates
A	School	Central (Harrah)	Classroom, window often open, carpet present	Next to play-ground	Agricultural activity, truck traffic, backyard burning	Dust from carpet, cleaning	Week 1.1: 12/4/19 to 12/11/19 Week 2: 1/16/20 to 1/23/20 Week 3: 2/27/20 to 3/5/20
B	Home	West (White Swan)	Living room, open to kitchen and hallways	Front porch	Residential wood burning	Cooking, cleaning, wood stove	Week 1.1: 12/4/19 to 12/11/19 Week 2: 1/16/20 to 1/23/20 Week 3: 2/27/20 to 3/5/20
C	School	East (Toppenish)	Classroom, window often open	Back of school	Industrial activity, highway traffic, backyard burning	Cleaning	Week 1.2: 12/12/19 to 12/19/19 Week 2: 1/17/20 to 1/23/20 Week 3: 2/28/20 to 3/6/20
D	School	North-east (Wapato)	Classroom	Back of school	Agricultural activity, truck traffic, backyard burning	Cleaning, cooking	Week 1.2: 12/12/19 to 12/19/19 Week 2: 1/17/20 to 1/24/20 Week 3: 2/27/20 to 3/5/20
E	Business	North (Wapato, near Union Gap)	Commercial work area, low activity	Front porch facing/ on highway	Agricultural activity, highway traffic	None expected	Week 1: N/A Week 2: 1/17/20 to 1/24/20 Week 3: 2/28/20 to 3/6/20

We intended to sample indoors and outdoors at each site concurrently over three 1-week sampling periods during the winter season 2019-2020. Due to logistical issues, site E business near Union Gap was not included in the first round of sampling. The first round was split into two adjacent weeks, with two sites sampled concurrently each week. The next two rounds of sampling were nearly concurrent, offset by one day (Table 1).

2.3 Gravimetric and low-cost $PM_{2.5}$ sampling procedure

We used Harvard personal environmental monitors (HPEMs, Thermo Environmental Instruments, Franklin, MA, USA) to collect two indoor and two outdoor gravimetric $PM_{2.5}$ samples at each site (except site D school in Wapato, which had only one gravimetric sampler outdoors due to site limitations). Outdoor samplers were placed under a rain shield without obstructing air flow on either a front porch or on the exterior wall of a shed or portable classroom. We attached indoor samplers to walls, sides of cabinets, or in one case a non-operable window, so samplers were out of the way of children but still capturing concentrations relevant to occupants' exposures.

We used Sidepak air pumps (TSI SP530, Shoreview, MN, USA) indoors and MEDO VP0125 pumps (Medo, Hanover Park, IL, USA) outdoors, calibrated to a flow rate of 1.8 L/min[44] (± 2.5%). We placed outdoor pumps inside an insulated box with a thermostat-controlled lightbulb to stabilize pump conditions. We measured the flowrate at the beginning and end of the sampling period using a DryCal (MesaLabs DCL-M, Lakewood, CO, USA) (see Supplementary Methods for more details).

Impactor samples were collected on PTFE filters with 2.0 μm pore size, one set with a PMP support ring (SKC, Eighty Four, PA, USA) and one set without (Pall, Port Washington, NY, USA) (site D school in Wapato outdoors only had the set without a support ring). We used the set with the support ring for measuring mass of $PM_{2.5}$, elements, and ions. We used the set without the support ring for measuring levoglucosan, PAHs, and nitropyrenes. Filters used to measure $PM_{2.5}$ mass were pre-conditioned in a climate-controlled chamber for at least six weeks prior to pre-weighing using a microbalance (Mettler-Toledo UMT-2, Columbus, OH, USA), and post-conditioned in the same chamber for three days prior to post-measurement weighing.

We co-located each set of gravimetric samplers with one low-cost (~$279 USD) Purple Air monitor (Purple Air PA-II-SD 2018, Draper, UT, USA). Each site had two gravimetric samplers and one Purple Air indoors, and two gravimetric samplers and one Purple Air outdoors. We placed the three instruments as close together as possible while still allowing for airflow to each. One outdoor site per sampling round had a duplicate gravimetric set-up (i.e. four gravimetric samplers outdoors) to estimate measurement precision. In addition, at one outdoor site per round we deployed two field blanks, where impactors were briefly exposed to the air, then wrapped in aluminum foil and never connected to a pump.

The Purple Airs remained in place over the entire study period. At the end of the study, the Purple Airs were moved to be co-located with the BAM in Toppenish for 6 weeks (3/16/21 to 4/28/21). Additional information about Purple Airs is available in the Supplementary Methods.

2.4 Gravimetric $PM_{2.5}$ composition analyses

Selected analytes were analyzed to provide insights into $PM_{2.5}$ sources and compositions. Trace elements and ions are frequently used in $PM_{2.5}$ source apportionment studies. Additional source specific analyte tracers that were selected for analysis include 1-nitropyrene (1-NP) which is primarily associated with diesel emissions,[45] 2-Nitropyrene (2-NP) and 2-Nitrofluorene (2-NFL) which are tracers for secondary organic aerosol,[45] levoglucosan which is primarily formed from wood combustion,[46] and a variety of polycyclic aromatic hydrocarbons (PAHs) that are markers for a variety of combustion sources.[47,48]

X-ray Fluorescence was used to determine concentrations of 48 elements and ion chromatography was used to determine the concentrations of anions and cations (fluoride, chloride, nitrate, phosphate, sulfate, sodium, ammonium, potassium, magnesium, and calcium). Liquid chromatography with tandem mass spectrometry was used to measure concentrations of 2-Nitropyrene (2-NP), 2-Nitrofluorene (2-NFL), and 1-Nitropyrene (1-NP), gas chromatography-mass spectrometry was used to measure concentrations of levoglucosan, and gas chromatography with tandem mass spectrometry was used to measure concentrations of Fluoranthene, Pyrene, Benzo[a]anthracene, Chrysene, Benzo[b]fluoranthene, Benzo[k]fluoranthene, Benzo[a]pyrene, Indeno[1,2,3-cd]pyrene, Dibenzo[ah]anthracene, and Benzo[g,h,i]perylene. Additional details on these methods are available in the Supplementary Methods.

2.5 Data processing

Details on Purple Air data processing are available in the Supplementary Methods. Unless otherwise noted, we averaged 2-minute Purple Air $PM_{2.5}$ data by hour. Where corrected Purple Air data is noted in the results, we used the gravimetric sampler $PM_{2.5}$ concentrations to calibrate the hourly Purple Air data by dividing each $PM_{2.5}$ data point by a correction factor specific to that Purple Air (see the Supplementary Methods for more details).

For the gravimetric sampling weeks, we also calculated the Purple Air $PM_{2.5}$ hourly mean using the US EPA Purple Air correction equation from October 2021, which was developed for smoke.[49] $PM_{2.5}$ concentration data for Yakima was available every three days (from gravimetric samplers) and hourly (from the BAM).

We obtained Toppenish, WA weather and $PM_{2.5}$ concentration data from the Washington State Department of Ecology Air Monitoring Network.[21] We obtained Yakima city, WA $PM_{2.5}$ speciation data from Dr. Kotchenruther,[50] who obtained the data from the EPA Air Quality System, AMP350 data report.[51]

2.6 Data analysis

2.6a Spatial variation

To evaluate spatial variation in $PM_{2.5}$ concentration, we plotted the ratio of 24-hr corrected Purple Air $PM_{2.5}$ at each outdoor community sampling site to the 24-hr $PM_{2.5}$

measured by the Toppenish BAM. We also plotted the ratio of 24-hr $PM_{2.5}$ measured by the Yakima BAM to the Toppenish BAM.

To inform variations in source contributions and potential exposures between the sampling sites and the nearest regulatory monitor that measures PM species, we examined analytes we measured that are also included in the Yakima speciation database. We calculated the distribution of air concentrations of each analyte in Yakima for all samples during the year 3/10/2019 to 3/4/2020. $PM_{2.5}$ concentrations were available approximately every three days, for a total of 120 samples. Analyte concentrations were available approximately every six days, for a total of 61 samples. We determined which decile of the distribution of those 120 or 61 samples corresponded to each of the ambient analyte measurements that we collected, as well as the measurements collected in Yakima on the days overlapping our sampling periods.

To characterize spatial variation in levoglucosan and PAHs (not measured in Yakima), we calculated the percent differences between ambient analyte concentrations for each site for each week with respect to the overall median across all sites and all three weeks.

The small sample size in this study precludes statistical testing for the significance of variation. Given these limitations, the duplicate gravimetric measurements can still be used to calculate precision. Hyslop & White (2009) present several ways to calculate precision in gravimetric samples, including by using mean absolute difference (MAD).[52] In the calculation below, n denotes the number of sets of duplicates, and C_i is each set of duplicates:

$$MAD\ precision = \sqrt{\pi/2}\ (1/n)\ \sum_{i=1}^{n} |D_i\,| \times\ 100\% \quad \text{where } D_i =\ [(C_{i1} -\ C_{i2})/\sqrt{2}\,]/\bar{C}_i$$

In presentation of the results, we interpret only those differences that are larger than the MAD precision to be meaningful.

2.6b Temporal variation

We calculated the frequency of 5-minute corrected $PM_{2.5}$ measurements above or equal to 23 µg/m^3 by hour of the day over the entire study period to display diurnal patterns in $PM_{2.5}$ peaks. We used 23 µg/m^3 because this is the 95th percentile of all indoor and outdoor community site 5-minute measurements. Site C school in Toppenish outdoors was excluded because it only contained nine days of data. Two locations had zero peaks and one only had 17 peaks; these three locations were also excluded.

2.6c Indoor/outdoor relationships

To evaluate indoor/outdoor relationships, we calculated indoor/outdoor ratios of the hourly averaged particle number concentrations (for particle sizes >0.3 µm) measured by the Purple Airs over the entire study period, which were visually compared between sites using boxplots. For site C school in Toppenish, where the outdoor Purple Air failed for most of the study period, we used corrected hourly Purple Air $PM_{2.5}$ mass concentration indoors, and the Toppenish BAM mass concentration outdoors. We excluded hourly BAM concentrations less than or equal to zero, which amounted to 153 hours (7.7%).

To describe variation between indoor and outdoor measurements of $PM_{2.5}$ and analytes at the same site, we calculated the indoor/outdoor ratios for each site for each week. Where the outdoor concentration was zero, we did not calculate a ratio.

3. Results

3.1 Sensor calibration

The agreement between Purple Air and gravimetric monitors varied. The mean Purple Air $PM_{2.5}$ divided by the mass concentration measured with the gravimetric sampler provided a simple correction factor for the Purple Air data. During gravimetric sampling weeks 1 and 2, all but one correction factor was between 1.21 and 2.23 (Figure 2 and

Supplementary Table 1). During week 3, correction factors were between 0.13 and 0.88. Outdoor correction factors tended to be higher than indoor correction factors. Correction factors appeared to be associated with concentration except for indoors week 3 (Figure 2).

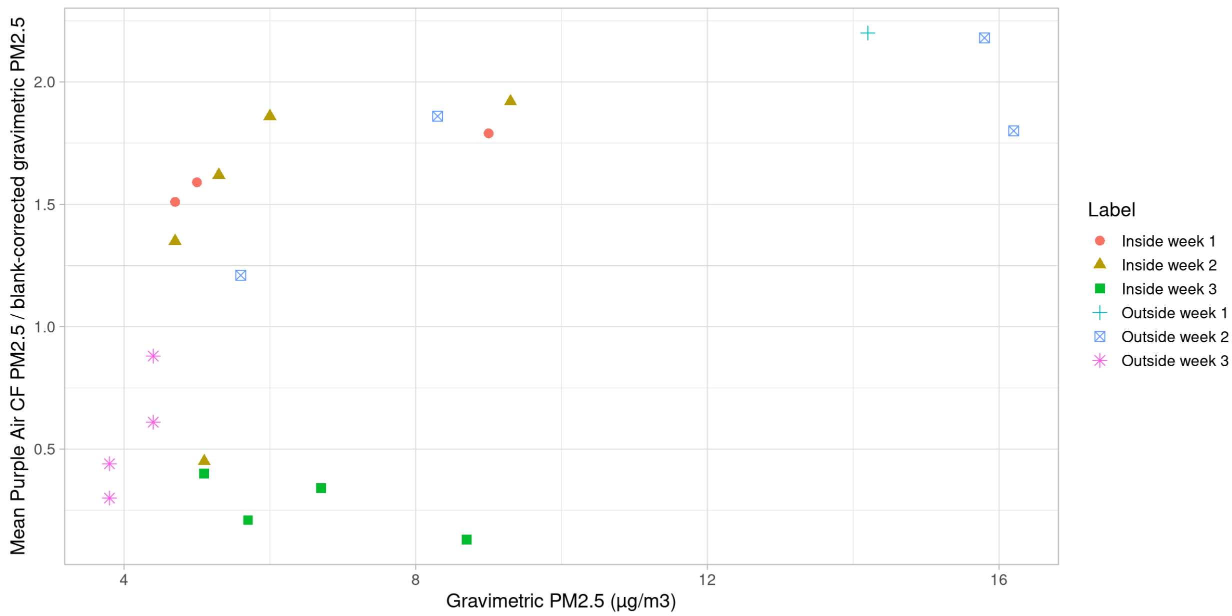

Figure 2: Mean Purple Air $PM_{2.5}$ divided by the mass concentration measured with the gravimetric sampler, by gravimetric $PM_{2.5}$ mass concentration. Data points are grouped by sampling week and location (indoors vs. outdoors). Site D school in Wapato outdoors is included in "Outside week 2" even though it occurred during an adjacent week.

Using the correction factors from week 2 as described in the Supplementary Methods had variable impacts on outdoor Purple Air $PM_{2.5}$ estimates during weeks 1 and 3. The mean of the hourly Purple Air $PM_{2.5}$ averaged over the gravimetric sampling period at site A school in Harrah was 3.3 (23%) µg/m^3 higher than the gravimetric $PM_{2.5}$ during week 1, and 2.2-3.2 µg/m^3 (50-84%) lower across all sites during week 3 (Supplementary Table 1).

Using the EPA correction equation, outdoor Purple Air $PM_{2.5}$ was overestimated more than with the gravimetric-based correction factor during weeks 1 and 2. During week 3, the EPA-corrected $PM_{2.5}$ was just slightly underestimated for three of four sites, while the gravimetric-based correction factor greatly underestimated $PM_{2.5}$ (Supplementary Table 1).

The week 2 correction factor also impacted Purple Air $PM_{2.5}$ estimates indoors. During week 1, the mean of the hourly Purple Air $PM_{2.5}$ averaged over the gravimetric sampling period at site B home in White Swan was 2.1 μg/m^3 (23%) higher than the gravimetric $PM_{2.5}$, at site C school in Toppenish was 0.9 (19%) μg/m^3 lower, and at site D school in Wapato was 0.1 μg/m^3 lower. During week 3, the mean of the hourly Purple Air $PM_{2.5}$ averaged over the gravimetric sampling period was 1.7-8.1 μg/m^3 (25-93%) lower than the gravimetric $PM_{2.5}$ (Supplementary Table 1).

Using the EPA correction equation, indoor Purple Air $PM_{2.5}$ was overestimated during weeks 1 and 2. During week 3, the EPA corrected $PM_{2.5}$ was slightly underestimated for three of four sites, while the gravimetric-based correction factor greatly underestimated $PM_{2.5}$ for three of four sites (Supplementary Table 1).

Missing Purple Air data was due to interruptions in power to the monitors or logistical issues, which occurred for site A school in Harrah indoors during week 1, site B home in White Swan outdoors during week 1 and indoors during week 3, site C school in Toppenish outdoors for most of the study period, and site D school in Wapato outdoors during week 3.

3.2 Spatiotemporal variability in $PM_{2.5}$ concentration

We observed substantial variability in $PM_{2.5}$ concentrations between the two government sites and between the government and community sites. Mean hourly $PM_{2.5}$ measured at the regulatory monitor in Yakima was greater than at Toppenish across weeks 1 and 2. $PM_{2.5}$ at the Toppenish BAM was similar to the gravimetric $PM_{2.5}$ measurements at community sites C in Toppenish and A in Harrah during weeks 1 and 2. Site E business near Union Gap was similar to site A school in Harrah in week 2. Site B home in White Swan was 39% lower than Toppenish in week 1, and 54% lower in week 2. Gravimetric samples were not collected outdoors at site D school in Wapato during the three sampling periods, but the corrected Purple Air measurements suggest that site D school in Wapato was similar to Yakima during weeks 1 and 2 (Table 2). During week 3, all sites were similar. The third gravimetric sampling week occurred during a time of particularly low $PM_{2.5}$ concentrations outdoors relative to the other two weeks (Table 2). MAD precision for $PM_{2.5}$ based on gravimetric sample duplicates was 2.9%.

We also observed considerable between-site variability in indoor $PM_{2.5}$ concentrations. Indoor $PM_{2.5}$ concentrations were similar across sites A school in Harrah, C school in Toppenish, and D school in Wapato during weeks 1 and 2. During week 1, concentrations at site B home in White Swan were 1.8-2.1x higher than the other sites, and during week 2, concentrations at site E business near Union Gap were 1.6-2.0x higher than the other sites (Table 2). Week 3 was more variable.

Weeks 1 and 2 had similar weather, while week 3 was different. The first two sampling weeks had similar mean temperatures (-1.7-1.7°C) and wind speeds (1.3-1.6 km/hour), while the third sampling week was warmer (8.9°C) and windier (9.7 km/hour). Wind directions were similar (S-SSW) across all sampling weeks.

Table 2: Outdoor $PM_{2.5}$ measured by agency monitors, and indoor and outdoor $PM_{2.5}$ measured at community sites with Purple Airs and gravimetric samples.

Site	Date	Outdoor PM2.5 concentration		Indoor PM2.5 concentration	
		Hourly $PM_{2.5}$* mean, median (SD) ($\mu g/m^3$)	Gravimetric $PM_{2.5}$ (µg/m3)	Hourly $PM_{2.5}$* mean, median (SD) ($\mu g/m^3$)	Gravimetric $PM_{2.5}$ (µg/m3)
Sampling week 1.1					
Government Sites					
Toppenish	12/4-12/11	15.5, 15.0 (9.1)	--	--	--
Yakima	12/4-12/11	18.0, 15.0 (12.1)	18.5	--	--
Community Sites					
A	12/4-12/11	17.5, 16.6 (10.4)	14.2	--	4.3
B	12/4-12/11	--	9.5	11.1, 4.8 (30.3)	9.0
Sampling week 1.2					
Government Sites					
Toppenish	12/12-12/19	12.1, 11.0 (5.0)	--	--	--
Yakima	12/12-12/19	16.4, 16.0 (5.8)	11.4	--	--
Community Sites					
C	12/12-12/19	--	10.6	3.8, 2.9 (2.6)	4.7
D	12/12-12/19	16.3, 15.0 (8.4)	--	4.9, 3.9 (6.7)	5.0
E	--	--	--	--	--
Sampling week 2					
Government Sites					
Toppenish	1/16-1/24	18.0, 17.0 (9.3)	--	--	--
Yakima	1/16-1/24	21.1, 21.0 (8.9)	19.3	--	--
Community Sites					
A	1/16-1/23	16.2, 14.6 (9.2)	16.2	5.1, 3.1 (7.7)	5.2
B	1/16-1/23	8.2, 5.1 (7.7)	8.3	4.7, 2.2 (8.3)	4.7
C	1/17-1/23	--	19.0	6.2, 4.4 (4.8)	6.0
D	1/17-1/24	21.6, 20.0 (11.9)	--	5.3, 4.8 (2.9)	5.3
E	1/17-1/24	15.9, 16.5 (5.5)	15.8	9.3, 9.8 (3.7)	9.3
Sampling week 2 alt**					
Government Sites					
Toppenish	1/24-1/29	7.9, 7.0 (4.9)	--	--	--
Yakima	1/24-1/29	8.1, 7.0 (4.7)	--	--	--
Community Sites					
D	1/24-1/29	5.6, 3.6 (5.8)	5.6	--	--
Sampling week 3					
Government Sites					
Toppenish	2/27-3/6	5.0, 3.0 (5.3)	--	--	--
Yakima	2/27-3/6	5.5, 5.0 (4.6)	4.2	--	--
Community Sites					
A	2/27-3/5	1.5, 0.5 (2.2)	4.4	5.0, 0.2 (15.4)	6.7
B	2/27-3/5	0.6, 0.2 (1.7)	3.8	--	9.8
C	2/28-3/6	2.2, 0.6 (3.4)	4.4	0.6, 0.1 (0.9)	8.7
D	2/27-3/5	--	--	1.2, 0.5 (2.0)	5.1
E	2/28-3/6	0.8, 0.2 (1.2)	3.8	0.6, 0.3 (0.7)	5.7

*BAM in the case of government sites and corrected Purple Air in the case of the community monitoring sites.
**Week 2 alt. refers to the week when we collected a gravimetric $PM_{2.5}$ sample outside at site D school in Wapato. This was the measurement used for the site D Purple Air correction.

The gravimetric sampling weeks included the range of outdoor $PM_{2.5}$ concentrations that occurred over the winter season, capturing weeks of high and low concentrations (Figure 3). Site B home in White Swan (red) tended to have lower concentrations compared to other sites. While there are some differences in the heights of the peaks, the timing of the peaks seems temporally correlated, suggesting that there may be periods of regional $PM_{2.5}$ that affect most sites. Yet differences in the heights of the peaks and site to site variations can be clearly observed over the study period. The Yakima regulatory site (yellow), tended to measure the highest $PM_{2.5}$ concentrations among the sites in the study, but not always. On some occasions, the peaks measured at the study's community sites (notably site D school in Wapato in green) are higher.

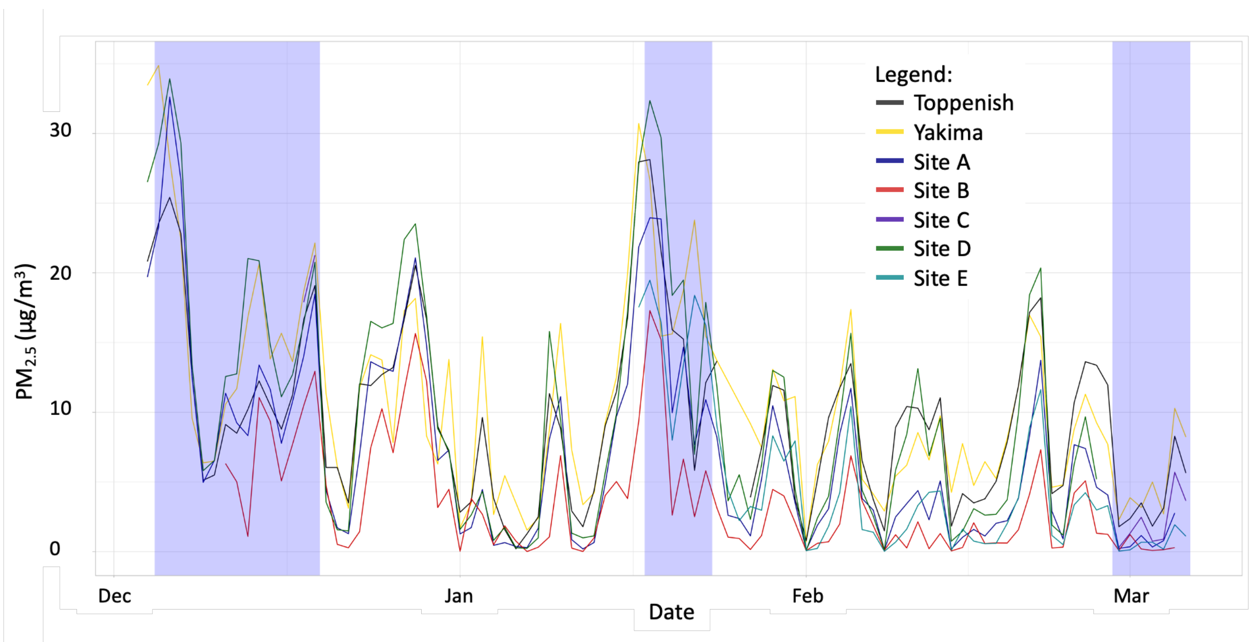

Figure 3: 24-hr average outdoor $PM_{2.5}$ concentrations over the study duration at sampling sites (corrected Purple Air data) and agency sites (BAM data). Blue boxes denote the weeks when gravimetric sampling was also conducted.

To more clearly visualize the relationships between outdoor concentrations measured at the regulatory sites versus those at the community sites during the study period, we plotted the concentration ratios as a time series (Figure 4). Using the BAM for regulatory sites and corrected Purple Airs for community sites, $PM_{2.5}$ concentrations were generally highest for measurements at the Yakima regulatory monitor (median ratio with Toppenish = 1.1), followed by the Toppenish Yakama Nation monitor and study community sampling site D school in Wapato (median ratio with Toppenish = 1.0) (Figure 4). Sites A school in Harrah (median ratio = 0.7), E business near Union Gap (median ratio = 0.3), and B home in White Swan (median ratio = 0.2) tended to be lower (Figure 4). Site C school in Toppenish was missing all but 9 days of data.

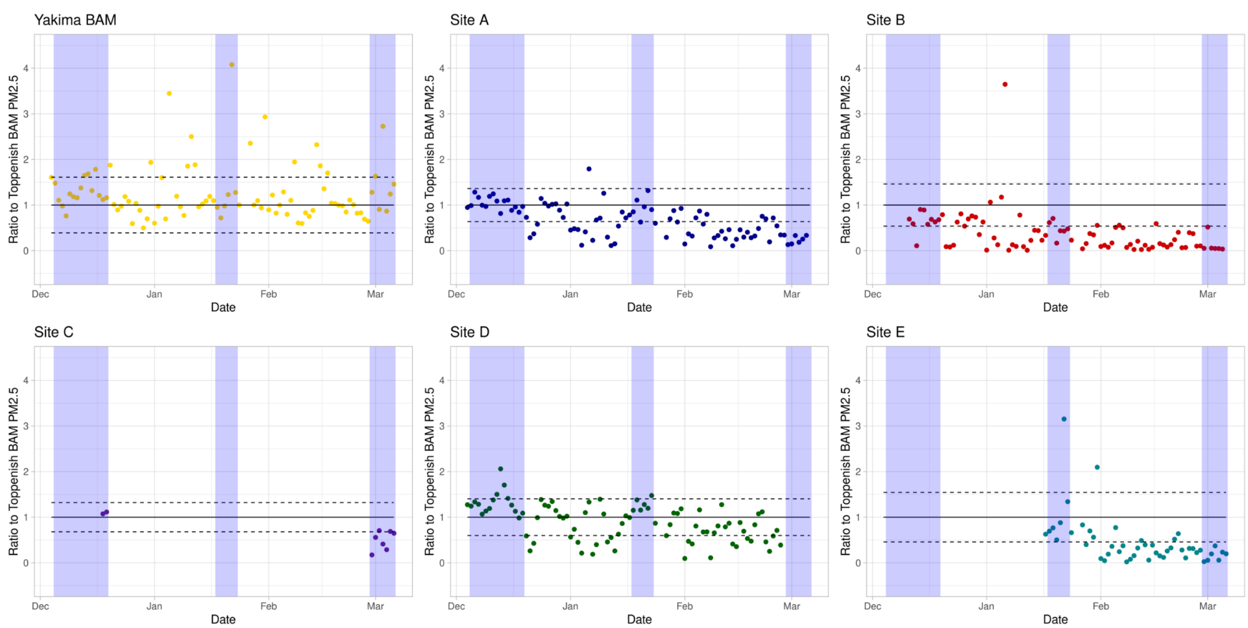

Figure 4: Ratio of 24-hr average outdoor $PM_{2.5}$ concentrations at each site relative to the Toppenish site over the study duration. The solid line indicates a ratio of 1. Dotted lines indicate +/- 1 SD of the ratio for each site. $PM_{2.5}$ concentrations at community sites are from corrected Purple Air data, and concentrations at agency sites are from BAM data. Blue boxes denote weeks when gravimetric sampling was also done. For figure clarity, we excluded one datapoint where the ratio of the Yakima to Toppenish BAM $PM_{2.5}$ was >30.

3.3 Spatiotemporal variability in analyte concentrations

$PM_{2.5}$ constituents were more variable from site to site than $PM_{2.5}$ concentrations. For analytes measured at our sampling sites and in Yakima, we compared ambient air concentrations to deciles of the annual distribution of concentrations in Yakima (Figure 5). Within each sampling week, at least one pair of analyte concentrations differed by at least three deciles over 60% of the time (differences between at least 1 pair of duplicates corresponded to a difference of three deciles for Ca only). Concentrations of $PM_{2.5}$ overall differed at most by two deciles within each week. The $PM_{2.5}$ concentrations in Toppenish (BAM data, not shown) fell into the same deciles as the concentrations in Yakima (gravimetric data). Deciles were identical across sites for only one instance, sodium ion during week 3. 38% of the time, concentrations of analytes in Yakima differed from all other sites more than the maximum duplicate differences.

Patterns in temporal variation from week to week varied by analyte and did not always follow the temporal pattern of $PM_{2.5}$. Within the first two sampling weeks in December and January, site B home in White Swan $PM_{2.5}$ concentrations were consistently lower, and Yakima, site C school in Toppenish, and site A school in Harrah were generally higher. We observed less variation in week 3.

Figure 5: Ambient air concentrations of $PM_{2.5}$ and PM analytes at sampling sites and at Yakima city, with respect to deciles of annual (3/2019-3/2020) Yakima City measurements. Each pixel represents one sample. Darker purple/blue represents higher deciles (i.e. higher concentrations), and lighter purple/white represents lower deciles. Grey denotes missing data. W refers to the sampling week, as noted in Table 2. Analytes are ordered from least overall variation on the left to most overall variation on the right. Differences between at least one pair of duplicates corresponded to at most a difference of: one decile for Al, Si, Cl^-, NH_4^+, and SO_4^{-2}; two deciles for Fe and NO_3^-; three deciles for Ca; no difference for all other analytes.

For levoglucosan and PAHs, which are not measured by the regulatory monitor in Yakima, we present the percent difference of ambient air concentrations by site with respect to the overall median measurement for that analyte across all sites and weeks (Figure 6). Percent differences relative to the analyte median were greater than 200% for at least one site 19% of the time. Site C school in Toppenish and especially site D school in Wapato had particularly high concentrations of several PAHs (>250% different from the median concentration). Maximum MAD precision was 131%. Patterns in variation in analyte concentrations by site did not always match variation in $PM_{2.5}$.

The percent differences of Toppenish (BAM data) and Yakima (gravimetric data) measurements for $PM_{2.5}$ are not included in Figure 6, but ranged from -44% in week 3 to 100% in week 2 for Toppenish, and from -53% in week 3 to 114% in week 2 for Yakima.

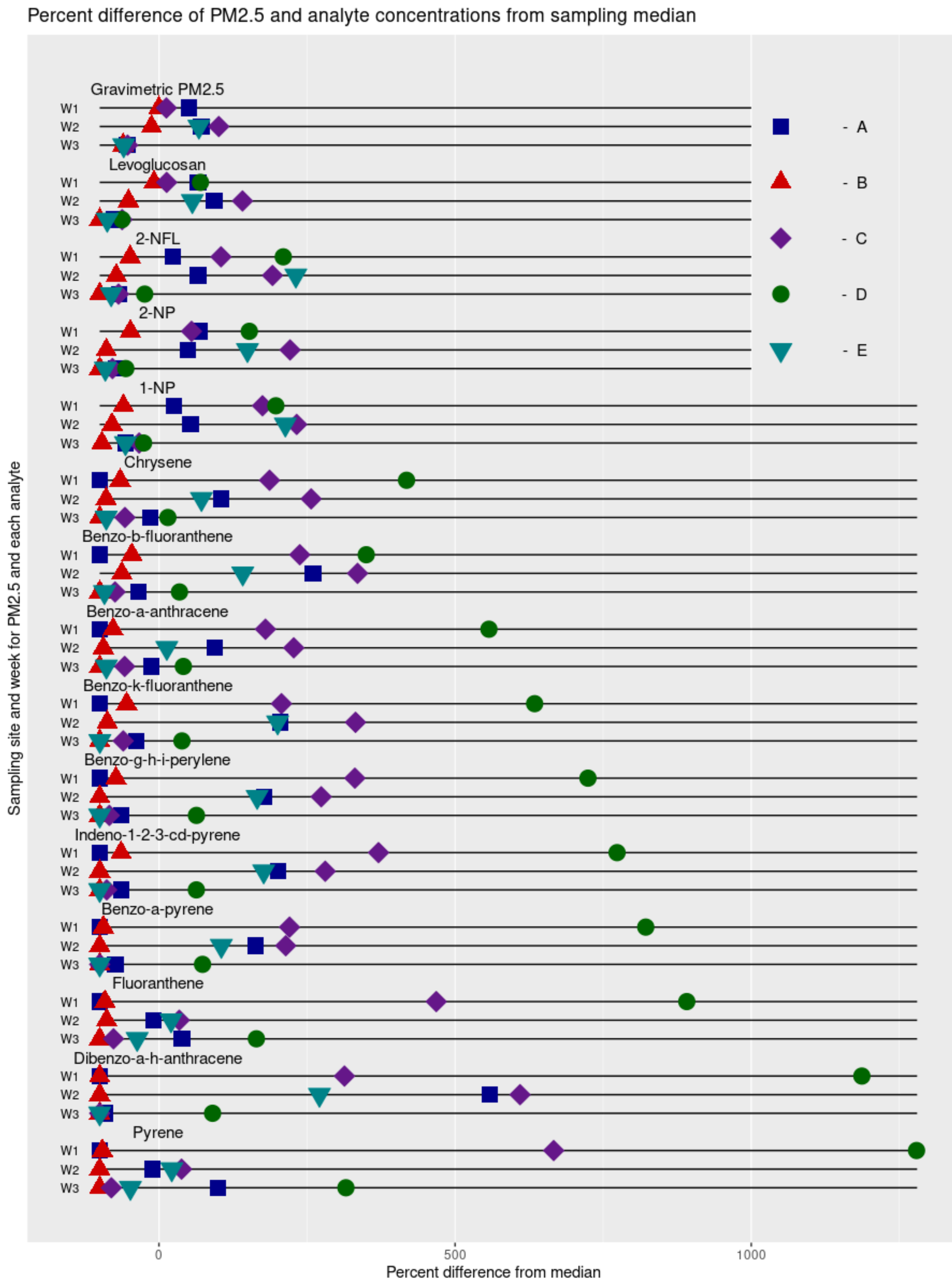

Figure 6: Percent difference of ambient air concentrations of $PM_{2.5}$ and PM analytes with respect to the overall median measurement for that analyte. Each sampling site is

represented by a different shape and color. W refers to the sampling week. Analytes are arranged in order of the maximum percent difference, with the highest maximum at the bottom. MAD precision for duplicate sample concentrations of levoglucosan, 1-NP, 2-NP, and 2-NFL = 9-20%. MAD precision for the remaining analytes = 60-131%.

3.4 Temporal variation

Diurnal patterns of outdoor 5-minute peaks in corrected $PM_{2.5} \geq 23$ μg/m^3 varied by site. Peaks occurred most in the mid-morning and late evening at site A school in Harrah and site D school in Wapato (Figure 7). Outdoors at site B home in White Swan peaks occurred in the early morning and late morning, and at site E business near Union Gap in the late morning and early afternoon. Indoor peaks occurred most in the middle of the day at site A school in Harrah, and evening and early morning at site B home in White Swan. Site C school in Toppenish outdoors was excluded due to high missingness, and indoors had zero peaks. Site E business near Union Gap indoors had no peaks, and site D school in Wapato indoors only had 17 peaks (not displayed).

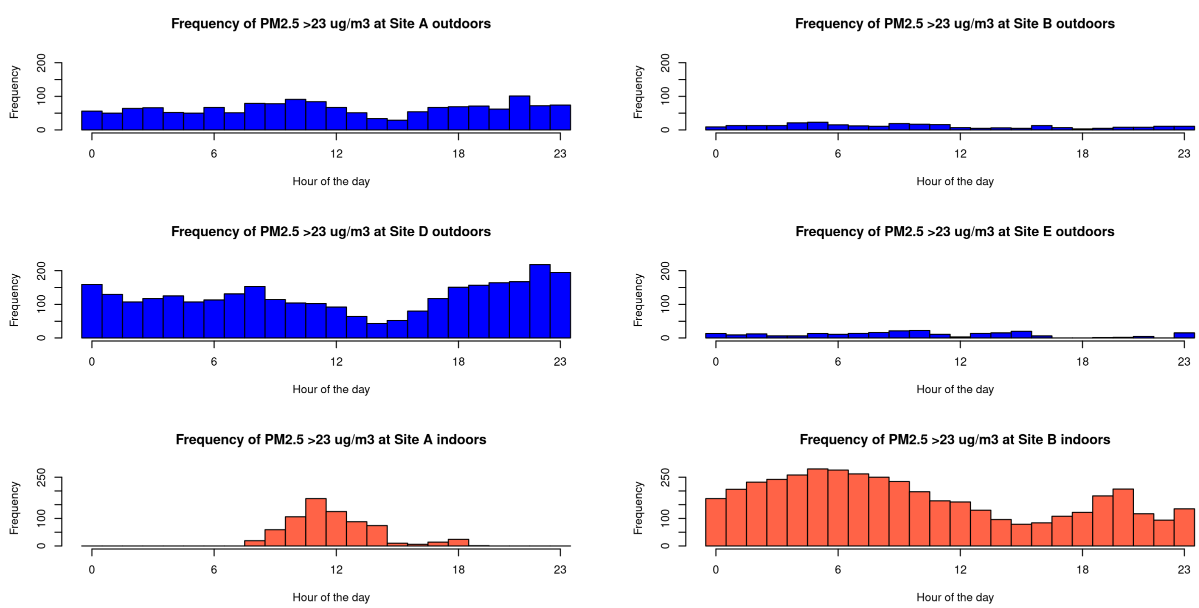

Figure 7: Diurnal patterns of corrected 5-minute $PM_{2.5}$ peaks $\geq$23 μg/m^3 over the entire study period. Site C school in Toppenish outdoors was excluded due to high missingness, site C indoors and site E indoors had zero peaks, and site D indoors had only 17 peaks. Blue bars are outdoor $PM_{2.5}$ and red bars are indoor. Y-axes for outdoor data are identical, and for indoor data are identical.

3.5 Indoor/outdoor comparisons

Hourly indoor/outdoor ratios of particle number concentrations also varied by site. Ratios were generally less than 1 at site A school in Harrah (median = 0.2) and site C school in Toppenish (median = 0.2), generally less than 2 at site D school in Wapato (median = 0.7) and site E business near Union Gap (median = 0.8), and had a much larger range at site B home in White Swan (Figure 8). The median indoor/outdoor ratio at site B home in White Swan was 1.4, and 75th percentile was 9.9.

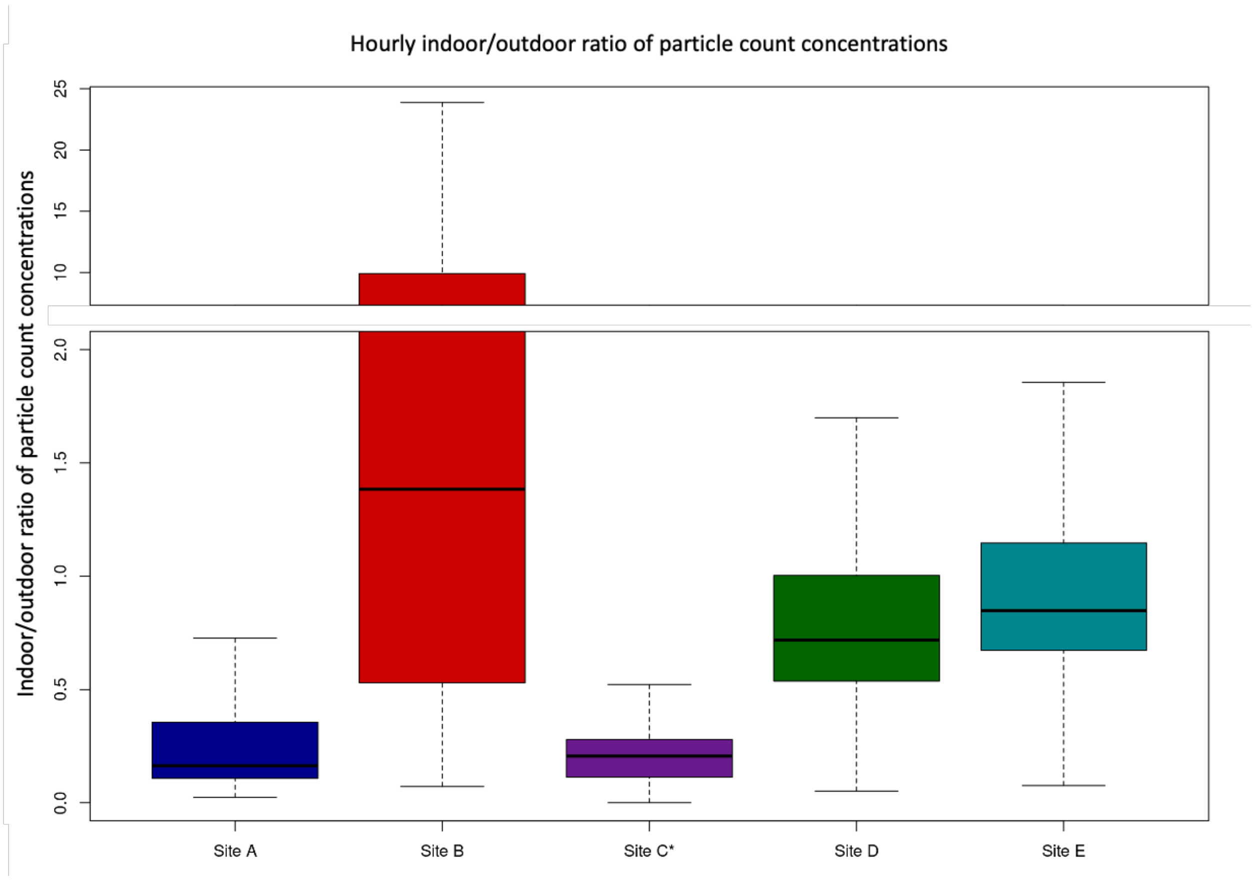

Figure 8: Boxplots of hourly indoor/outdoor ratios of the concentration of particles >0.3 μm measured by the Purple Airs over the entire study period. Site A school in Harrah excludes week 1 due to missing data. Solid line indicates the median. Boxes range from 25th to 75th percentile. Whiskers indicate 75th percentile + 1.5 times the inter-quartile range (IQR) and 25th percentile - 1.5*IQR. Data points outside of the whiskers are not shown. Note that the y-axis is broken to allow for greater detail at lower ratios. *Site C school in Toppenish data is from corrected Purple Air $PM_{2.5}$ mass concentration indoors and the Toppenish BAM mass concentration outdoors (BAM $PM_{2.5} \leq 0$ excluded), not particle count concentrations.

The particle count concentration ratios are consistent with the gravimetric indoor/outdoor ratios. The gravimetric ratios for Site B home in White Swan (mean of the three ratios = 1.4) were greater than the other sites (mean ratios of 0.7 at site A school in Harrah, 0.9 at site C school in Toppenish, and 1.0 at site E business near Union Gap). Gravimetric indoor/outdoor ratios also varied temporally: from 0.3 to 0.9 in week 1, 0.3 to 0.6 in week 2, and 1.5 to 2.6 in week 3 (Supplementary Table 2).

Indoor/outdoor ratios of $PM_{2.5}$ and analytes varied by analyte, spatially, and sometimes temporally from week to week (Figure 9). Site E business near Union Gap had generally higher ratios across all analytes. Site A school in Harrah and B home in White Swan had high ratios among analytes typically associated with soil and dust, and site B home in White Swan also had high ratios among several PAHs.

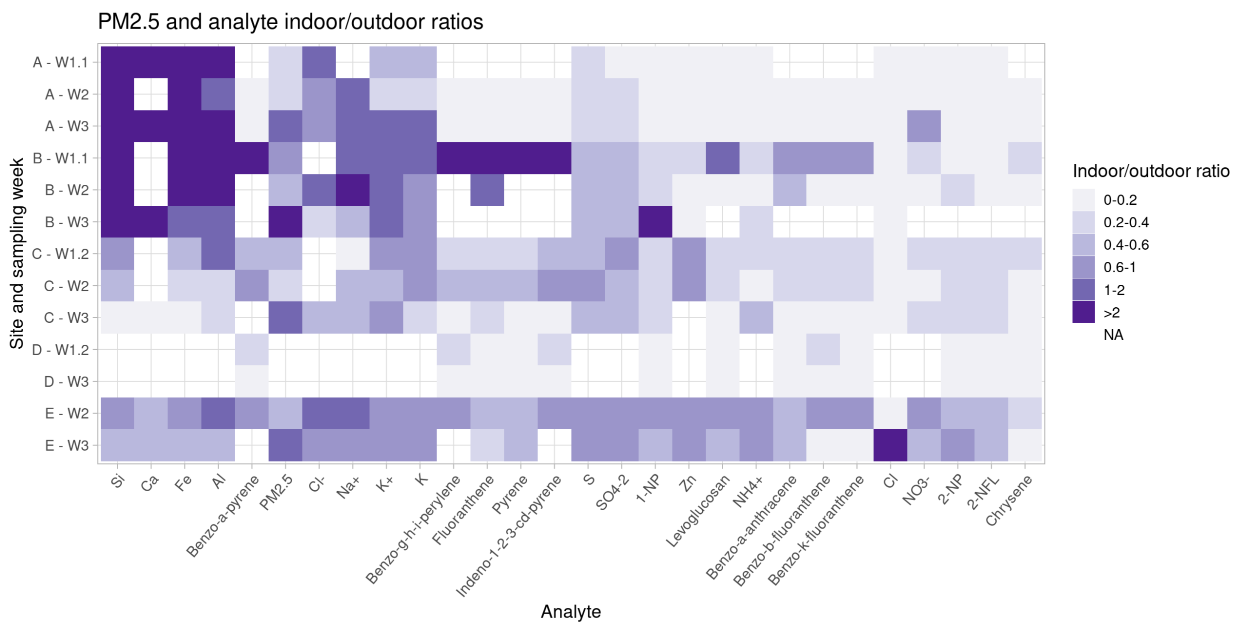

Figure 9: Indoor/outdoor ratios of $PM_{2.5}$ and analytes at each site during each week. In the case of outdoor concentrations of zero, the indoor/outdoor ratio is not presented. Analytes are ordered from most overall variation in ratios on the left to least variation on the right.

3.6 Examples of potential misclassification

For the analytes also measured in Yakima, differences between at least one pair of sites within the same week were frequently at least three deciles. For levoglucosan and

PAHs, percent differences relative to the median for at least one site within the same week were greater than 200% in 22 cases, and in two cases were greater than 1000%. This spatial variation could lead to important risk estimate differences.

For example, during week 1, the concentration of benzo[a]pyrene measured outside at site B home in White Swan corresponds to the level, which if continued over a lifetime, is estimated to have a lifetime cancer risk of 0.4 in 100 million, whereas the risk corresponding to the outside measurement at site D school in Wapato is 50 in 100 million.

As another example, concentrations of zinc were noticeably higher near site E, in Wapato close to Union Gap, compared to other sites, even while $PM_{2.5}$ overall at site E was not highest. Combining this spatial variation with variations in indoor/outdoor ratios, if one were to use the Yakima monitor and an average indoor/outdoor ratio of 0.6 to estimate indoor exposures of zinc during week 2, the result would be 40 ng/m^3. Indoor concentrations that week were <1 ng/m^3 at sites A school in Harrah and B home in White Swan, 12 ng/m^3 at site C school in Toppenish, 7 ng/m^3 at site D school in Wapato, and 27 ng/m^3 at site E business near Union Gap. This means that indoor exposures to zinc would be slightly overestimated at site E, but highly overestimated at sites A and B.

4. Discussion

$PM_{2.5}$ concentration and composition varied between sites on the Yakama Nation reservation and between the reservation and Yakima city. Diurnal patterns in $PM_{2.5}$ concentration peaks also varied by site. Further, we observed considerable between-site and temporal variability in indoor $PM_{2.5}$ concentrations, indoor/outdoor ratios of $PM_{2.5}$, and indoor/outdoor ratios of analyte concentrations. This spatial variation could lead to important risk estimate differences. The examples of potential misclassification provided demonstrate differences in exposure by site of orders of magnitude.

Patterns in analyte concentrations often did not follow patterns in $PM_{2.5}$ concentration, suggesting that $PM_{2.5}$ composition is different between sites. Additionally, we observed temporal variation in $PM_{2.5}$ and analyte concentrations across sampling weeks within the same winter season. Rural areas such as this often have sparse monitoring data to characterize spatial and temporal variations in $PM_{2.5}$, as well as specific pollution species. Moreover, diverse sources may be present, especially in agricultural areas.[39,40,53,54] Using sparse and/or short-term regulatory monitoring to inform mitigation efforts and exposure estimates may lead to less relevant interventions and misclassification of exposures. This research included a wide range of analytes relevant to health[48] and emissions sources.

The spatial variation in $PM_{2.5}$ composition likely indicates a different mix of emissions sources, which has implications for mitigation of $PM_{2.5}$. For example, concentrations of multiple PAHs were noticeably higher outside of site D school in Wapato compared with other sites, while levoglucosan, which is associated with biomass burning,[55] was similar to other sites. This suggests that there are emissions sources near site D school in Wapato that generate more PAHs relative to levoglucosan compared to emissions sources near other sites. The Yakama Nation AQS hypothesized that greater concentrations of PAHs may be present at site D due to increased backyard garbage burning relative to biomass burning. This idea is supported by a study that found increased emissions of PAHs from burning garbage compared to wood,[56] as well as a study that found increased emissions of PAHs from open burning of garbage relative to controlled combustion.[57] Concentrations of zinc were higher at site E business near Union Gap compared to other sites, while $PM_{2.5}$ overall at site E was more similar to other sites, suggesting a source mix near site E that generates more zinc compared to source mixes near the other sites. This is consistent with site E being most impacted by traffic emissions, which are sometimes associated with zinc.[58–60] Lower outdoor $PM_{2.5}$ concentrations at site B home in White Swan was consistent with expectations because White Swan is a more rural area compared to the other sampling sites, and less impacted by agricultural or industrial emissions.

Variation in diurnal patterns of 5-minute peaks in $PM_{2.5}$ could also point to potential differences in emissions sources by site. Notably, only the diurnal pattern at site B home in White Swan indoors strongly resembled diurnal patterns typically associated with residential wood burning for heat, which is usually late night and early morning.[32] It is unclear what emissions sources would be associated with the varied diurnal patters outdoors at site A school in Harrah and D school in Wapato. However, greater late afternoon and evening emissions at site D is consistent with backyard burning, as this type of burning often takes place after business hours to avoid detection.

The timing of indoor peaks at site A school in Harrah corresponded well with the school day. It is not surprising that 5-minute peaks were most prevalent indoors at site B, because this site is a non-smoking home but has other indoor sources of $PM_{2.5}$ (cooking, cleaning, wood stove). Site B is expected to have more indoor-generated PM compared to the other sites which are not homes. These spatial differences in diurnal patterns of short-term concentrations would be more difficult to see if one were relying on just regional monitors because regulatory data is typically available at most hourly.

Indoor $PM_{2.5}$ concentrations were similar across sites A school in Harrah, C school in Toppenish, and D school in Wapato during weeks 1 and 2. During week 1, site B was 1.8-2.1x higher than the other sites. During week 2, site E business near Union Gap was 1.6-2.0x higher than the other sites. This business site has few expected indoor sources of $PM_{2.5}$, but when in use may have high penetration of outdoor $PM_{2.5}$ due to large garage-door style openings to the space.

Indoor/outdoor ratios varied substantially by site and week to week. Site B home in White Swan had a much wider range of indoor/outdoor ratios compared to the other sites, which is consistent with site B having more expected indoor $PM_{2.5}$ emissions. This variation in both gravimetric and particle count indoor/outdoor ratios suggests that using an average indoor/outdoor ratio estimate for $PM_{2.5}$ might lead to misclassification of exposures. This misclassification could be compounded if exposures to specific analytes are of interest, as indoor/outdoor ratios varied by analyte and often did not follow the same pattern as $PM_{2.5}$. Indoor exposures are a major component of a person's overall exposures,[61] so reliably estimating indoor exposures is necessary to reliably estimate overall exposure. In the US, 61% of deaths associated with outdoor $PM_{2.5}$ are due to exposure to indoor $PM_{2.5}$, which is made up of $PM_{2.5}$ of both indoor and outdoor origin.[62]

Generally both the Purple Air raw data and corrected with the EPA equation,[49] which is designed for smoke, overestimated $PM_{2.5}$ during weeks 1 and 2, and underestimated during week 3. Outdoor correction factors were generally greater than indoor, suggesting differences between indoor and outdoor aerosols. This suggests that different correction factors are needed for different aerosols, which is consistent with what others have found.[63–65] Week 1 and 2 correction factors in this study were generally similar to those found for wildfire smoke,[63] incense burning,[64] and heating oil.[64] Week 3 correction factors in this study were similar to those found for dust, humidifiers, candles and cigarettes, and various types of cooking.[64] It is possible that week 3 $PM_{2.5}$ was more dominated by dust compared to weeks 1 and 2, because week 3 was much windier than weeks 1 and 2. An increased proportion of dust relative to emissions from combustion may have led to lower correction factors in week 3. This may also explain the one low week 2 correction factor, which was indoors at site A school in Harrah. This site had a carpet nearby the monitor, which was frequently used by children playing, likely kicking up dust. It may be challenging to use low-cost sensors in settings with varied aerosols without periodic co-locations with more accurate instruments.

The small sample size in this project precluded formal source apportionment. Additionally, there were inconsistencies in sampling: week 1 was offset between sites and was missing site E business near Union Gap, and we were only able to collect one gravimetric sample outdoors each week at site D school in Wapato. Nevertheless, we found important variation in $PM_{2.5}$ concentration and composition spatially, temporally, and indoors vs. outdoors. We verified our suspicion that enriched monitoring would reveal the limitations of sparse rural regulatory monitors to capture spatial variability and $PM_{2.5}$ source information in a setting such as the Yakama Nation reservation. Additional regulatory monitoring would improve exposure estimation in rural areas. In the absence of sufficient regulatory monitoring, community-based measurements can provide important information on spatial and temporal variations, but measurements should be designed carefully and results from low-cost monitors should be interpreted carefully, especially in conditions with varied aerosols.

We illustrated in this study how community air monitoring using a combination of calibrated low-cost sensors, gravimetric samplers, and PM speciation analyses could help address the challenges of sparse monitoring in rural areas. In general, community site participants were not surprised by the findings, offered ideas of possible PM sources near their site, and expressed interest in both indoor and outdoor air quality. Community science can combine many different methods, including costly analyses; it does not need to be limited to low-cost sensors.

The Yakama Nation AQS had previously hypothesized that the air pollution in the reservation would be different from the air pollution measured by the Yakima city monitor in the upper valley. This hypothesis is supported by comparisons between the Yakima city BAM and the Toppenish BAM. This study further corroborates this hypothesis by demonstrating that the $PM_{2.5}$ concentration and composition vary spatially between community sites, and that $PM_{2.5}$ species concentrations vary between Yakima city and community sites. This study also points to the potential importance of increased PM monitoring and mitigation efforts in Wapato. This research project was greatly enriched and strengthened by the participation of the Yakama Nation AQS, and the opportunity to combine Tribal and community air quality expertise with $PM_{2.5}$ speciation resources for exposure assessment.

Supplementary Materials

Supplementary Methods

Gravimetric and low-cost $PM_{2.5}$ sampling procedure

Additional details on flow rates: At the end of the gravimetric sampling periods, 42 of 60 pumps were still running within our target ± 5% of 1.8 L/min. Upon review of a duplicate measure where one pump end flowrate was 13% from 1.8 L/min and the duplicate concentrations were within 0.2% of each other, we decided to include the other samples with flowrates within 13% of 1.8 L/min. This resulted in removing 1 non-duplicate filter sample (week 2 site D outdoors).

Additional details on Purple Air: The Purple Air contains temperature and humidity sensors, and two Plantower optical particle counters. Two mass concentrations are provided using two different correction factors: CF=1 and CF=ATM (discussed further below).[66] The Purple Air PA-II-SD logs data on an internal microSD card either every 80 seconds or every 2-minutes, depending on the firmware version.

Gravimetric $PM_{2.5}$ composition analyses

After post-weighing the filters, we stored them in the freezer (-18°C) until laboratory analyses, and shipping was done overnight in a cooler with icepacks. We shipped the filters with support rings to Cooper Environmental Services, LLC (now Sailbri Cooper, Inc, Tigard, OR, USA) to determine the concentrations of 48 elements. Analyses were conducted under vacuum with Energy Dispersive X-ray Fluorescence (XRF) using a Spectrace Quanx (ThermoFisher Scientific, Waltham, MA, USA) ED-XRF spectrometer with a 50 watt rhodium target tube as an excitation source and a SiLi detector.[67] The machine operation, data acquisition, and spectral processing were handled by Thermo Scientific's software program.[67] Analyses followed EPA compendium IO 3.3.[67,68]

We subsequently delivered these same filters to the UW DEOHS Environmental Health Laboratory, who used ion chromatography (IC) to determine the concentrations of anions and cations (fluoride, chloride, nitrate, phosphate, sulfate, sodium, ammonium, potassium, magnesium, and calcium). The method was based on a modified version of CARB Method MLD064,[69] using a Dionex ICS-1000 with an AS-40 autosampler (ThermoFisher Scientific, Waltham, MA, USA) equipped with AS9-HC RFIC (4 x 250mm) and AS16 (4 x 250mm) analytical separation columns for anion and cations, respectively.

The other set of filters were analyzed at UW DEOHS with liquid chromatography with tandem mass spectrometry (LC/MS/MS) to measure concentrations of 2-Nitropyrene (2-NP), 2-Nitrofluorene (2-NFL), and 1-Nitropyrene (1-NP) as described in Miller-Schultze et al., 2010;[45] gas chromatography-mass spectrometry (GC/MS) to measure concentrations of levoglucosan as described in Simpson et al., 2004[46] and Simpson et al., 2005;[70] and gas chromatography with tandem mass spectrometry (GC/MS/MS) to measure concentrations of Fluoranthene, Pyrene, Benzo[a]anthracene, Chrysene, Benzo[b]fluoranthene, Benzo[k]fluoranthene, Benzo[a]pyrene, Indeno[1,2,3-cd]pyrene, Dibenzo[ah]anthracene, and Benzo[g,h,i]perylene, as described in Sarver et al., 2019.[71]

<u>Purple Air data processing</u>

For each Purple Air monitor, we assessed whether both Plantower sensors were functioning (not reading all zeros). If only one was functioning we used the data from that sensor. When both sensors were functioning, we calculated daily Pearson's correlations between the two sensor measurements, and used the average of the two as long as the correlation was >0.7, or the correlation was <0.7 but the $PM_{2.5}$ concentration measured by both sensors concurrently was <10 μg/m^3. If the correlation was <0.7 and the concentration was >10 μg/m^3, then those data points were excluded from analysis. Tryner et al., 2020 reported that early Purple Air monitors switched the Plantower output for CF=1 with CF=ATM,[66] so we reassigned those data labels as needed (so that CF=1 was greater than CF=ATM when they differed).

We used the dataset from the six-weeks after the study when the Purple Airs were co-located with the Toppenish BAM to confirm that the Purple Airs we used performed similarly to each other, specifically that the Pearson's correlation between each Purple Air and the overall mean hourly $PM_{2.5}$ concentrations were >0.7 and the mean absolute error was <5 μg/m^3 (this was the case for all of the Purple Airs).

Unless otherwise noted, we averaged Purple Air $PM_{2.5}$ data by hour. Where corrected Purple Air data is noted in the results, we used the gravimetric sampler $PM_{2.5}$ concentrations to calibrate the hourly Purple Air data by dividing each $PM_{2.5}$ CF=1 data point by a correction factor specific to that Purple Air. Correction factors were obtained by dividing each mean $PM_{2.5}$ CF=1 over the week 2 period of gravimetric sampling by the field blank-corrected gravimetric $PM_{2.5}$ from that period. For site D outdoors, where we did not have gravimetric samples during the sampling periods, we used Purple Air data and a gravimetric sample collected during an alternative week (1/24/20-1/29/20). For site C outdoors, where the Purple Air failed during sampling week 2, we used the mean of the other week 2 correction factors.

Gravimetric sample data processing

All filter results were evaluated against lab and field blanks. To calculate $PM_{2.5}$ concentrations from the gravimetric samplers, we subtracted the mean mass collected on the field blanks (post-sampling mass – pre-sampling mass) from the sample mass. We then divided the sample mass by the total volume of air drawn through the impactor, using the average of the pre- and post-sampling flowrates. Analytes (elements, anions, cations, levoglucosan, nitropyrenes, and PAHs) were field blank subtracted and normalized by sampling volume to report air concentrations. In the case of elements determined by XRF, we only included elements with any air concentrations higher than two times the EPA method detection limit (EPA method 811).[72]

Supplementary Table 1: Purple Air $PM_{2.5}$ correction factors

Site	Outdoor			Indoor		
	Hourly mean raw $PM_{2.5}$ (CF=1) / gravimetric $PM_{2.5}$	Hourly mean $PM_{2.5}$ with week 2 correction factor / gravimetric $PM_{2.5}$	Hourly mean $PM_{2.5}$ with EPA correction equation / gravimetric $PM_{2.5}$	Hourly mean raw $PM_{2.5}$ (CF=1) / gravimetric $PM_{2.5}$	Hourly mean $PM_{2.5}$ with week 2 correction factor / gravimetric $PM_{2.5}$	Hourly mean $PM_{2.5}$ with EPA correction equation / gravimetric $PM_{2.5}$
Sampling week 1.1						
A	2.2	1.2	1.4	--	--	--
B	--	--	--	1.8	1.2	1.2
Sampling week 1.2						
C	--	--	--	1.5	0.8	1.7
D	--	--	--	1.6	1.0	1.7
E	--	--	--	--	--	--
Sampling week 2						
A	1.8	1.0	1.1	0.5	1.0	1.0
B	1.9	1.0	1.1	1.4	1.0	1.5
C	--	--	--	1.9	1.0	1.7
D	--	--	--	1.6	1.0	1.6
E	2.2	1.0	1.3	1.9	1.0	1.3
Sampling week 2 alt**						
D	1.2	1.0	0.9	--	--	--
Sampling week 3						
A	0.6	0.3	0.9	0.3	0.7	0.8
B	0.3	0.2	0.8	--	--	--
C	0.9	0.5	1.1	0.1	0.1	0.6
D	--	--	--	0.4	0.2	1.0
E	0.4	0.2	0.9	0.2	0.1	0.7

**Week 2 alt. refers to the week when we collected a gravimetric $PM_{2.5}$ sample outside at site D school in Wapato. This was the measurement used for the site D Purple Air correction.

Supplementary Table 2: Gravimetric $PM_{2.5}$ indoor/outdoor ratios

Site	Gravimetric PM2.5 concentration indoor/outdoor ratio
Sampling week 1.1	
A	0.3
B	0.9
Sampling week 1.2	
C	0.4
D	--
E	--
Sampling week 2	
A	0.3
B	0.6
C	0.3
D	--
E	0.6
Sampling week 3	
A	1.5
B	2.6
C	2.0
D	--
E	1.5

Chapter 2: Practical considerations for using low-cost sensors to assess wildfire smoke exposure in school and childcare settings

Summary

Climate change related increases in wildfires will increase concentrations of smoke in schools and childcare settings. Low-cost $PM_{2.5}$ sensors can be useful for assessing fine particulate matter ($PM_{2.5}$) concentrations with high spatial and temporal resolution, and are increasingly being used for indoor air quality measurements. We sought to optimize the use of sensors for decision-making in schools and childcare settings during wildfire smoke.

We measured $PM_{2.5}$ concentrations indoors and outdoors at four schools in Washington State during wildfire smoke in 2020, and two schools in 2021. This involved monitoring continuously using a low-cost sensor and gravimetrically. We randomly sampled 5-minute segments of low-cost sensor data to create hypothetical simulations of brief portable handheld measurements.

During wildfire smoke events (lasting 4-19 days), median hourly $PM_{2.5}$ concentrations at different locations inside a single facility varied by up to 50 μg/m^3 during school hours over the same time period. Median hourly indoor/outdoor ratios during school hours ranged from 0.22 to 0.91. Within schools we observed a maximum difference in median ratios of 0.52. Within-school differences indicated that it is important to collect measurements throughout a facility. The simulation results suggested that making handheld measurements more often and over multiple days better approximates indoor/outdoor ratios for wildfire smoke. During a period of unstable air quality conditions, $PM_{2.5}$ over the next hour indoors was more highly correlated with the last 10-minutes of data (mean R^2 = 0.94) compared with the last 3-hours of data (mean R^2 = 0.60), indicating that higher temporal resolution data is most informative for decisions about near-term activities indoors.

We found useful, practical information applicable for optimized sampling with low-cost sensors for wildfire smoke response in schools. This information can be directly applied to schools and childcare settings to mitigate children's exposure to $PM_{2.5}$ from wildfire smoke.

1. Background

Wildfires are increasing in severity and frequency with climate change.[73,74] Wildfire smoke contains many hazardous constituents,[75] including $PM_{2.5}$, carbon monoxide, volatile organic compounds, and polycyclic aromatic hydrocarbons.[76–79] Exposure to wildfire smoke causes respiratory morbidity, especially exacerbations of asthma and chronic obstructive pulmonary disease (COPD), with increasing evidence for respiratory infections, respiratory mortality, and all-cause mortality, and mixed evidence for cardiovascular disease.[80–82]

Children are particularly sensitive to health effects of air pollutants present in wildfire smoke because their lungs are still developing, their air intake per body mass is greater than for adults, and particles and particle deposition in the lower airways is greater than for adults.[4,5] Among children, exposure to PM is associated with respiratory diseases, neurodevelopmental issues, and prehypertension.[4,5] Wildfire smoke exposure specifically has been investigated less than overall $PM_{2.5}$ in children, and is associated with eye irritation, respiratory issues, medication use, and physician visits.[5,83] A study investigating the association between $PM_{2.5}$ exposure and pediatric emergency and urgent care visits for respiratory issues found that wildfire smoke $PM_{2.5}$ was more harmful than $PM_{2.5}$ from other general outdoor sources.[15]

In schools and childcare settings, child exposure occurs outdoors during outdoor play, recess, and athletic events. Exposure also occurs indoors because wildfire smoke infiltrates into buildings.[5] While there is substantial variability in the proportion of outdoor pollution that infiltrates indoors,[84–89] one study estimated that US indoor exposures account for 61% of the deaths attributed to $PM_{2.5}$ of outdoor origin.[61] In schools and childcare settings, guidance to have children simply stay inside during wildfire smoke may not be adequate, especially with high levels of physical activity. Furthermore, variation in $PM_{2.5}$ concentrations inside a building reflect variable infiltration and indoor sources of pollution.

One way to assess variation in indoor air quality within a building is to measure the indoor/outdoor ratio of $PM_{2.5}$ in each room. The indoor concentration includes $PM_{2.5}$ that originates indoors (e.g. from cooking or cleaning) and $PM_{2.5}$ that originates outdoors and infiltrates indoors (e.g. wildfire smoke, traffic emissions). In non-smoking homes, infiltrated $PM_{2.5}$ accounts for most of the indoor $PM_{2.5}$.[90] During wildfire smoke periods, in spaces with few indoor sources of $PM_{2.5}$, we expect that the indoor $PM_{2.5}$ is predominantly infiltrated wildfire smoke. This means that differences in indoor/outdoor ratios better reflect differences in infiltration compared to a situation where indoor-generated PM is a main contributor to indoor PM concentrations.

Continuously measuring the indoor/outdoor ratio in each room could be accomplished by having a fixed site sensor in every room and outdoors, as Boston Public Schools has done in their classrooms.[91] However, though low-cost sensors are more affordable than conventional air monitoring instruments, scaling up to every classroom and indoor space is not feasible for most schools and childcare settings. Another option to measure within-building variability in $PM_{2.5}$ is to walk from room to room holding a portable sensor. However, handheld sensor measurements only capture a snapshot in time. It is unclear how often and when one would need to collect portable handheld sensor measurements to approximate longer-term average variability.

In Washington state (WA), USA the Department of Health developed guidance for school closures and school and childcare activities based on both outdoor and indoor PM concentrations.[92,93] However, there is no established protocol or toolkit for assessing PM at schools. Outdoor regulatory monitors are inadequate for assessing concentrations in indoor spaces. Variability in school and childcare building features, such as ventilation and filtration, presents challenges in generalizing and providing guidance. In Montana, USA, the Missoula City-County Health Department found that two buildings with poor filtration had $PM_{2.5}$ similar to outdoors, while in a building with Minimum Efficiency Reporting Values (MERV) 8 filtration and in a room with a portable air cleaner the indoor $PM_{2.5}$ concentration was less than half the outdoor concentration.[94] The spatial distribution of smoke also presents challenges. One study with sensors at two buildings separated by only 3.5 km found that median outdoor levels over the entire 13-day smoke period differed by 17 $\mu g/m^3$ (about 25%) during a wildfire smoke episode.[95] PM concentrations within a single school building may also vary considerably spatially[96,97] and temporally.[98,99]

Low-cost sensors allow users to view concentrations averaged over different time periods, while publicly available US government $PM_{2.5}$ data is typically displayed using the NowCast which uses variable averaging times according to air quality stability. The NowCast is similar to a 3-hour historical average when air quality is unstable over the previous hours and represents a 12-hour average when air quality is stable. Guidance thresholds for activities are often based on Air Quality Index categories, which are intended to be used with either 24-hour averages or a NowCast value. However, it is possible that a historical average shorter than the NowCast could better approximate short-term future conditions during rapidly changing wildfire smoke conditions. This has implications for which averaging times would best support decision-making for near-term activities.

The ability to monitor variability of PM concentrations at schools would inform classroom-level interventions, decisions about whether to hold outdoor activities, and school closure decisions. While models exist to predict PM infiltration based on building ventilation and filtration characteristics, high variability in maintenance practices, such as frequency of ventilation system filter replacement, and occupant behavior, such as opening of windows and doors, presents challenges in applying these models.[100] Additionally, building-based models may overlook key variations in school classrooms, such as differences between main building classrooms and modular portable classrooms, or use of portable air cleaners.

In this study, we sought to identify: 1) within-school variation in $PM_{2.5}$ indoor/outdoor ratios during wildfire smoke, 2) variation differences during a non-wildfire smoke period, 3) how many short-term (e.g. 5-minute) handheld sensor measurements are required to approximate the average indoor/outdoor ratio over the course of the wildfire smoke period, 4) whether handheld sensor measurements during specific times or days provide a better approximation of the average indoor/outdoor ratio during a wildfire smoke episode, and 5) how two different averaging times of $PM_{2.5}$ measurements reflect short-term future conditions. The results from this study provide evidence for a planned toolkit for schools and childcare settings to reduce high $PM_{2.5}$ exposure during wildfires. The goal is a toolkit useful for immediate decision-making during wildfire smoke, and for schools and childcare settings to have a better understanding of indoor concentrations throughout the wildfire smoke period.

2. Methods

2.1 School sampling locations and times

We had established relationships with the four schools involved in this study through previous research partnerships and through the Wildfire Smoke Impacts Advisory Group of WA, an expert/stakeholder consortium led by the WA State Department of Health. The four schools are located in two regions of central WA that are both frequently wildfire smoke-impacted. We prepared all equipment for deployment in anticipation of a wildfire smoke episode. We worked with each school to identify two to five indoor sampling locations (Table 1) and one outdoor location.

Table 1: Description of school sampling locations and timing

School	Type of school	Indoor locations sampled	Wildfire smoke impactor sampling dates	Wildfire smoke Purple Air sampling dates	Wintertime impactor & Purple Air sampling dates
A	High school: one main building plus portable classrooms	Portable, gym, classroom, cafeteria, computer lab	9/11/20 to 9/14/20	9/11/20 to 9/18/20	3/10/21 to 3/17/21
B	Preschool: one building with individual classrooms	Two classrooms			3/10/21 to 3/17/21
C	High school: one building	Hallway, classroom, gym	9/15/20 to 9/16/20	9/15/20 to 9/18/20; 7/18/21 to 8/5/21; 8/12/21 to 8/15/21	2/24/21 to 3/3/21
D	Elementary school: one building	Classroom, cafeteria			2/24/21 to 3/3/21

Wildfire smoke periods were identified as days when the closest regulatory agency monitor measured a 24-hour average $PM_{2.5}$ concentration greater than 35.5 $\mu g/m^3$, which is the threshold between the US EPA's Air Quality Index categories of "Moderate" and "Unhealthy for Sensitive Groups" as of the time of this writing.

We also sampled during the wintertime, aiming to capture winter air pollution, as both regions are impacted by cold weather inversions leading to stagnant air conditions.

2.2 Air sampling equipment set-up

At each sampling location, we paired low-cost (~$279) Purple Air PM monitors (Purple Air PA-II-SD 2018, Draper, UT, USA) with gravimetric samplers to enable correction of the Purple Airs. Purple Airs contain temperature and humidity sensors, and two optical particle counters. The Purple Air PA-II-SD logs data on an internal microSD card every two minutes. We measured $PM_{2.5}$ gravimetrically using Harvard impactors (Harvard personal environmental monitors (HPEMs), Thermo Environmental Instruments, Franklin, MA, USA). Each impactor contained a PTFE filter with 2.0 μm pore size (SKC, Eighty Four, PA, USA). We placed Purple Airs as close as possible to impactors while still allowing airflow to each.

Indoor Purple Airs and gravimetric samplers were attached to walls or sides of cabinets or bookshelves, out of the way of students but at a height relevant to the occupants' breathing zone.

Since schools C and D are within 200 meters of one another, we set up a single outdoor Purple Air and impactor between them. At school A, the outdoor Purple Air and impactor were outside of a portable classroom, and at schools B, C, and D the outdoor Purple Air and impactor were outside of a shed. Outdoor set-ups were on school grounds within 100 meters of school buildings. We placed outdoor impactors under a rain shield without obstructing air flow.

During each visit to the schools to set up and take down the impactors, we operated a research-grade particle size analyzer (Optical Particle Sizer 3330, TSI, Shoreview, MN, USA) for 5-45 minutes per room and outdoors. This instrument provides a particle count in different size bins for particles with a diameter of 0.3-10 µm. We used the following bin lower cut-points: 0.3, 0.35, 0.4, 0.45, 0.5, 0.55, 0.6, 0.65, 0.7, 0.75, 1, 2.5, and 5 µm.

Two outdoor sites and two indoor sites per sampling season had duplicate set-ups, and in each season there were at least two field blanks. We used Sidepak air pumps (TSI SP530, Shoreview, MN, USA) indoors and MEDO VP0125 pumps (Medo, Hanover Park, IL, USA) outdoors, calibrated to a flow rate of 1.8 L/min.[44] We measured the flowrate at the beginning and end of the sampling period using a DryCal (MesaLabs DCL-M, Lakewood, CO, USA) and used the average of the two flow measurements. We pre-conditioned the filters for at least six weeks in a temperature and humidity-controlled chamber prior to pre-sample weighing using a microbalance (Mettler-Toledo UMT-2, Columbus, OH, USA). We post-conditioned in the same chamber for three days prior to post-sample weighing.

2.3 Purple Air correction with impactor data

We calculated sensor-specific correction factors for each Purple Air during wildfire smoke and wintertime sampling. We divided the field blank-corrected impactor concentration by the mean Purple Air $PM_{2.5}$ concentrations over the time period that the impactor was running:

$$Corrected\ Purple\ Air = Purple\ Air \times (impactor\ concentration \div mean\ Purple\ Air\ during\ impactor\ sampling)$$

The Purple Air provides two options of $PM_{2.5}$ measurements: one is called "CF=1" and one is called "CF=ATM". To calculate the gravimetric-based correction factors, we used the "CF=1" Purple Air $PM_{2.5}$ output. More details on Purple Air data processing are available in the Supplementary Methods.

The Purple Air in the school A computer lab failed during the wildfire smoke gravimetric sampling period, so in this case we used the mean of the other school A indoor correction factors.

For the Purple Air data from two 2021 wildfire smoke periods at schools C and D, which did not include gravimetric sampling, we applied the US Environmental Protection Agency (EPA) correction equation (October 2021 equation)[49] which was developed for smoke.

2.4 Simulations of walkaround sampling with a handheld sensor

We averaged the 2-minute Purple Air data to 5-minute data, and used the corrected 5-minute Purple Air data to simulate "walkaround" sampling at each school. In each simulation we selected five minutes of data from each location at the school in a random consecutive order with a 5-minute break between locations. Specifically, this simulates scenarios in which a person made 5-minute measurements in different rooms and outdoors with a low-cost handheld sensor to assess variation of $PM_{2.5}$ concentrations within the school, and variation between indoor and outdoor concentrations. We created a dataset of 2,000 simulations for each school for each wildfire smoke period. The simulations were restricted to typical building usage days and hours (Monday to Friday, 8am to 4pm) to reflect the times when personnel would be on site. Because schools C and D are adjacent and share an outdoor Purple Air and impactor, we combined schools C and D for the simulation analyses and treated them as one school.

2.4a Assessment of within-school variation using simulation data

From each dataset of 2,000 simulations, we randomly selected one simulation per hour to create tables for a Randomized Blocks Design (RBD) analysis. In this analysis the "treatment" was the location, and the "blocks" were 1-hour periods where each location was sampled only once in each hour in a random order. The RBD analysis assumes that differences between locations are constant across "blocks" of time. Therefore, we used log-transformed $PM_{2.5}$ concentration data, as differences between locations expressed as ratios were, in general, approximately constant over time.

We conducted the RBD analysis with corresponding two-way ANOVA and Tukey multiple comparison procedure. This tested whether the differences in log $PM_{2.5}$ between indoor spaces within the same school were statistically significantly different from zero, while accounting for the shared temporal trend represented in the 1-hour block effects.

2.4b Analysis of simulated walkaround sampling

In addition to the RBD analysis above, we quantified how well simulated walkaround monitoring captures average indoor/outdoor ratios over several days of wildfire smoke and variability between indoor spaces at each school. We calculated the percent error of the indoor/outdoor ratio that would be observed in each location from walkaround sampling as compared to the median hourly indoor/outdoor ratio observed using all available data over the course of the wildfire smoke period, limited to school hours and days only. We calculated this percent error from 2,000 samples of either two or six walkarounds. A priori we considered two to be the minimum useful number of walkarounds, and six to be the maximum feasible number of walkarounds.

We checked the data during wildfire smoke school hours for indoor-generated PM peaks[101,102] to consider the influence of indoor sources.[84,98,101–106] Ultimately, we only detected two indoor generated peaks, and decided not to repeat the analysis with these peaks removed.

We originally intended to repeat this analysis with the winter data, but we happened to capture a period of very low $PM_{2.5}$ concentrations. This made differences between indoor/outdoor ratio measurements much more challenging to interpret, so ultimately we did not conduct the wintertime analysis.

2.4c Analysis of characteristics of simulations with lowest percent error

Of the samples of two or six walkarounds, we identified characteristics of the "best" walkarounds (those with <10% error in all spaces) by quantifying the proportion of each day of the wildfire smoke period and each hour of the day represented among the "best" walkarounds. The goal was to understand whether sampling on certain days or hours resulted in walkarounds with lower error. We also quantified the proportion of "best" walkarounds that contained multiple days of the wildfire smoke period, to understand whether sampling over more days is advantageous compared to fewer days.

For this analysis of the "best" walkarounds, when needed, we used initial datasets with more than 2,000 simulations (up to 20,000) to achieve complete datasets (data available from each indoor space and outdoors for each simulation time) of at least 1,000 simulations. We normalized the proportion of each day and hour represented among the "best" walkarounds by the proportion of each day and hour possible given the set of simulations with complete data. We used 8am as a reference hour of the day to represent a decision being made based on measurements collected at the beginning of the day.

2.5 Analysis to examine the relationship of historical data with short-term upcoming conditions

To determine the most informative averaging interval for short-term decision making about activities in schools and childcare settings, we examined the relationship between 10-minute historical data and 1-hour future data, as well as between 3-hour historical data and 1-hour future data. The 3-hour historical average is meant to approximate the NowCast during unstable air quality conditions, and the 10-minute time interval was chosen because it is the default averaging time displayed by Purple Air.

We used the full 5-minute datasets during the 2021 July-August wildfire smoke period at schools C and D. This smoke period was chosen because it contained the largest sample size of $PM_{2.5}$ measurements. It was also a period of unstable air quality conditions which is most relevant to this analysis. Each indoor location and outdoors were in separate datasets. Each row contained the average $PM_{2.5}$ concentration of the last three hours (last 36 5-minute data points), the average of the last 10 minutes (last two 5-minute data points), and the average of the following one hour (following 12 data points).

We selected out one row during the 8am hour and one row during the 3pm hour from each location. These hours were chosen because we wanted to examine two times during the school day where the four-hour window (3-hour lag data plus 1-hour future data) would not overlap. These hours are also relevant because they represent plausible decision-making times for morning and afternoon activities.

Using the selected 8am and 3pm hour data, we used linear regression to model the relationship between 10-minute historical data and 1-hour future data, as well as between 3-hour historical data and 1-hour future data. We reported indoor and outdoor R^2 values from the regressions.

2.6 Analysis of particle size distributions

Variation in particle size distribution could indicate a need for different Purple Air correction factors for indoors vs outdoors and wildfire smoke vs wintertime pollution. To qualitatively assess whether particle size distribution differed between indoors and outdoors and between wildfire smoke and wintertime, we plotted the particle size distribution from each school visit. For each particle size distribution dataset, we plotted the fraction of the total particle count detected in each bin over the five to 45-minute period.

3. Results

3.1 Within school variability in $PM_{2.5}$ during wildfire smoke and wintertime seasons

Using data from the gravimetric sampling periods, during wildfire smoke mean indoor gravimetric $PM_{2.5}$ concentrations varied within schools by 1.4 μg/m^3 (difference between the school D cafeteria and classroom) to 134.2 μg/m^3 (difference between the school A classroom and computer lab) (Table 2). Gravimetric indoor/outdoor $PM_{2.5}$ ratios ranged from 0.11 to 0.67 during wildfire smoke. In the winter, within-school differences in mean gravimetric $PM_{2.5}$ were <3 μg/m^3 and indoor/outdoor ratios ranged from 0.17 to 0.96.

Table 2 shows gravimetric-corrected Purple Air data during the gravimetric sampling periods. Missing Purple Air data is due to: a failed Purple Air in the school A computer lab during the wildfire smoke gravimetric sampling period, and a failed Purple Air in the school C hallway for the whole study period.

Table 2: Impactor and median Purple Air $PM_{2.5}$ during wildfire smoke and wintertime periods.

	Wildfire smoke period			Winter		
	Impactor $PM_{2.5}$ (μg/m^3)	Corrected Purple Air Median (IQR) $PM_{2.5}$ concentration (μg/m^3)	Impactor Indoor/outdoor ratio	Impactor $PM_{2.5}$ (μg/m^3)	Corrected Purple Air Median (IQR) $PM_{2.5}$ concentration (μg/m^3)	Impactor Indoor/outdoor ratio
School A[1]						
Portable	87.3	93.7 (75.6, 112.6)	0.30	1.3	0.9 (0.1, 2.3)	0.17
Gym	103.3	114.5 (83.6, 135.4)	0.36	3.6	2.2 (0.4, 6.3)	0.48
Classroom	166.8	182.3 (140.6, 217.0)	0.58	3.0	2.3 (0.4, 5.2)	0.40
Cafeteria	82.0	86.4 (67.2, 102.4)	0.28	4.3	2.7 (0.5, 7.3)	0.57
Computer Lab	32.6	--	0.11	1.8	1.1 (0.3, 3.4)	0.24
Outdoors	290.0	308.7 (246.3, 370.4)	--	7.5	3.9 (0.8, 12.9)	--
School B[1]						
Classroom 1	123.7	136.3 (93.0, 159.4)	0.47	3.3	1.8 (0.3, 5.3)	0.46
Classroom 2	70.5	72.6 (60.4, 90.0)	0.27	2.3	1.4 (0.2, 3.8)	0.32
Outdoors	263.4	268.5 (217.7, 333.7)	--	7.1	3.8 (0.4, 11.4)	--
School C[2]						
Hallway	39.0	--	0.47	1.4	--	0.54
Classroom	34.6	35.0 (31.0, 38.0)	0.41	0.6	0.1 (0.0, 0.9)	0.23
Gym	56.4	55.8 (54.8, 57.9)	0.67	0.7	0.5 (0.0, 1.2)	0.27
School D[2]						
Classroom	46.6	47.9 (44.5, 50.2)	0.56	1.2	0.7 (0.0, 2.0)	0.46
Cafeteria	48.0	49.1 (46.0, 51.9)	0.57	2.5	2.0 (0.5, 3.7)	0.96
Outdoors	83.6	81.9 (75.5, 89.2)	--	2.6	2.1 (0.8, 3.9)	--

[1] Wildfire smoke period was September 11 to 14, 2020; winter period was March 10 to 17, 2021.
[2] Wildfire smoke period was September 15 to 16, 2020; winter period was February 24 to March 3, 2021.

3.2 Within school variability in $PM_{2.5}$ during wildfire smoke during school hours

During wildfire smoke episodes, trends in indoor $PM_{2.5}$ often followed trends in outdoor $PM_{2.5}$ during school hours (Figure 1). Relative differences between rooms within each school were generally consistent in terms of rank ordering. In two school A rooms, $PM_{2.5}$ decreased after the school day, increased shortly before the school day, and then followed outdoor trends during the school day.

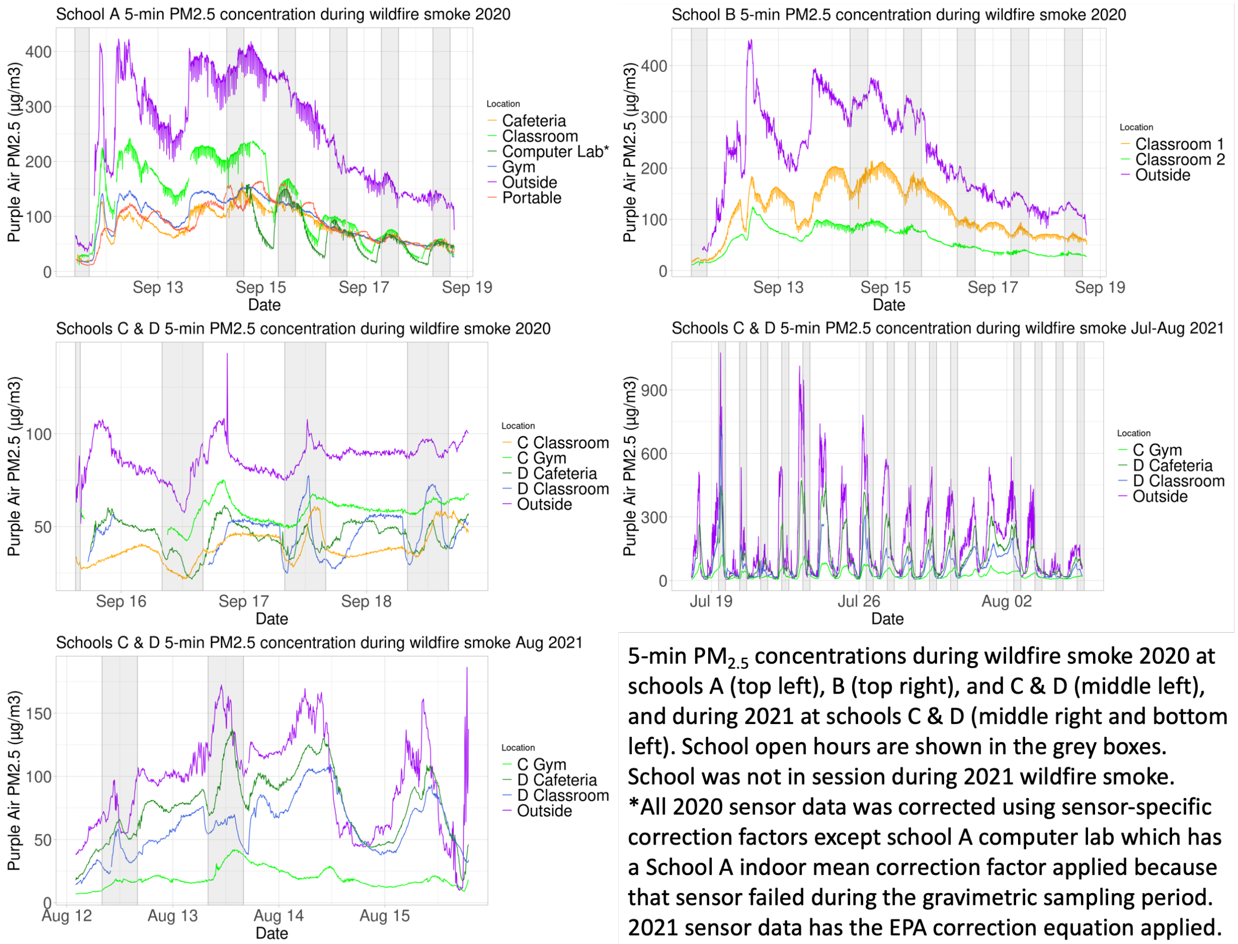

Figure 1: Time series of 5-minute $PM_{2.5}$ concentrations at schools during wildfire smoke.

During wildfire episode school hours, mean and median hourly within-school differences in $PM_{2.5}$ ranged from $\leq$1 µg/m^3 (school A portable, gym, cafeteria, and computer lab) to mean difference of 57.4 µg/m^3 and median difference of 49.6 µg/m^3 (difference between school D classroom and cafeteria during July-August 2021) (Table 3). Median hourly indoor/outdoor ratios ranged from 0.22 to 0.91 overall; the maximum within-school difference in indoor/outdoor ratios was 0.52 (difference between school D classroom and cafeteria during July-August 2021). Missing Purple Air data is due to: a failed Purple Air in the school C hallway for the whole study period, and a failed Purple Air in the school C classroom during the last two wildfire smoke periods.

Table 3: Hourly wildfire smoke $PM_{2.5}$ concentrations and indoor/outdoor ratios during school hours.

	Mean (SD) Hourly Purple Air $PM_{2.5}$ Concentration ($\mu g/m^3$)	Median (IQR) Hourly Purple Air $PM_{2.5}$ Concentration ($\mu g/m^3$)	Median (IQR) hourly Purple Air Indoor/Outdoor Ratio
School A[1]			
Portable	82.2 (45.5)	72.1 (55.0, 123.2)	0.37 (0.33, 0.41)
Gym	81.4 (40.1)	72.3 (52.7, 122.9)	0.37 (0.36, 0.39)
Classroom	111.3 (64.5)	93.1 (59.3, 161.8)	0.48 (0.42, 0.56)
Cafeteria	81.5 (36.6)	72.9 (54.5, 117.4)	0.36 (0.35, 0.40)
Computer Lab	86.5 (35.3)	73.1 (57.1, 124.5)	0.40 (0.38, 0.41)
Outdoors	219.3 (114.7)	184.8 (137.8, 349.2)	--
School B[1]			
Classroom 1	99.9 (53.5)	89.1 (65.6, 155.9)	0.55 (0.50, 0.57)
Classroom 2	50.9 (25.4)	45.2 (32.3, 77.9)	0.27 (0.25, 0.28)
Outdoors	206.1 (94.7)	164.2 (130.5, 309.4)	--
School C[2]			
Hallway	--	--	--
Classroom	38.3 (12.0)	34.8 (29.6, 47.4)	0.41 (0.38, 0.50)
Gym	56.5 (7.3)	57.0 (50.1, 62.7)	0.66 (0.64, 0.70)
School D[2]			
Classroom	49.0 (15.9)	45.5 (36.1, 63.8)	0.48 (0.40, 0.71)
Cafeteria	37.4 (7.2)	37.1 (34.36, 40.81)	0.44 (0.42, 0.49)
Outdoors	83.9 (11.2)	88.1 (73.8, 92.1)	--
School C[3]			
Hallway	--	--	--
Classroom	--	--	--
Gym	39.5 (24.1)	38.4 (19.1, 51.5)	0.27 (0.15, 0.41)
School D[3]			
Classroom	78.0 (95.4)	52.3 (23.0, 97.8)	0.39 (0.33, 0.58)
Cafeteria	135.4 (94.8)	101.9 (65.1, 184.8)	0.91 (0.60, 1.25)
Outdoors	186.9 (186.3)	107.7 (54.8, 320.5)	--
School C[4]			
Hallway	--	--	--
Classroom	--	--	--
Gym	24.0 (10.6)	17.9 (16.5, 33.5)	0.22 (0.18, 0.29)
School D[4]			
Classroom	48.5 (14.7)	51.2 (35.5, 61.4)	0.45 (0.40, 0.49)
Cafeteria	77.7 (29.7)	67.0 (54.2, 95.9)	0.72 (0.62, 0.86)
Outdoors	105.4 (38.3)	98.3 (71.1, 142.2)	--

[1] Wildfire smoke period: September 11 to 18, 2020 (47 school hours).
[2] Wildfire smoke period: September 15 to 18, 2020 (25 school hours)
[3] Wildfire smoke period: July 18 to August 5, 2021 (110 school hours, but school was not in session during this time. Schools C and D were being used as a base for firefighters.)
[4] Wildfire smoke period: August 12 to 15, 2021 (16 school hours but school was not in session during this time. Schools C and D were being used as a base for firefighters.)

The RBD analyses in each school used one randomly selected 5-minute $PM_{2.5}$ data point per hour per location during wildfire smoke school hours. The smallest exponentiated log $PM_{2.5}$ difference between location-pairs flagged as statistically significant ($p<0.01$) was 0.89 for the contrast between school A computer lab and classroom (Table 4). This minimum percent difference corresponded to an untransformed difference of -11.1 $\mu g/m^3$ (mean $PM_{2.5}$ in the computer lab minus mean $PM_{2.5}$ in the classroom)

Table 4: Exponentiated log $PM_{2.5}$ difference (95% confidence interval) of location pairs (column location minus row location) from complete dataset of one randomly selected 5-minute measurement per location per hour. Differences with $p<0.01$ are denoted with asterisks. Exponentiated log differences are expressed as ratios (column location/row location). Mean $PM_{2.5}$ at each location is shown next to the location name.

PM2.5 concentration ratios (95% confidence interval) of column location/row location

School A[1]	Computer lab (85.3 µg/m3)	Classroom (96.4 µg/m3)	Cafeteria (78.9 µg/m3)	Gym (78.3 µg/m3)	Portable (84.9 µg/m3)
Classroom (96.4 µg/m3)	0.89 (0.84, 0.95)*	--	--	--	--
Cafeteria (78.9 µg/m3)	1.05 (0.99, 1.12)	1.17 (1.11, 1.26)*	--	--	--
Gym (78.3 µg/m3)	1.06 (1.00, 1.13)	1.19 (1.12, 1.27)*	1.01 (0.95, 1.07)	--	--
Portable (84.9 µg/m3)	1.01 (0.95, 1.07)	1.14 (1.06, 1.21)*	0.96 (0.90, 1.02)	0.95 (0.90, 1.01)	--
Outside (216.4 µg/m3)	0.39 (0.36, 0.41)*	0.44 (0.41, 0.46)*	0.37 (0.35, 0.39)*	0.36 (0.36, 0.41)*	0.38 (0.36, 0.41)*

School B[1]	Classroom 1 (109.5 µg/m3)	Classroom 2 (54.1 µg/m3)
Classroom 2 (54.1 µg/m3)	1.99 (1.92, 2.10)*	--
Outside (206.2 µg/m3)	0.53 (0.51, 0.56)*	0.27 (0.26, 0.28)*

Schools C & D[2]	School C Classroom (45.3 µg/m3)	School C Gym (60.1 µg/m3)	School D Classroom (50.1 µg/m3)	School D Cafeteria (41.3 µg/m3)
School C Classroom (45.3 µg/m3)	--	--	--	--
School C Gym (60.1 µg/m3)	0.73 (0.62, 0.87)*	--	--	--
School D Classroom (50.1 µg/m3)	0.91 (0.78, 1.08)	1.25 (1.05, 1.48)*	--	--
School D Cafeteria (41.3 µg/m3)	1.07 (0.91, 1.27)	1.46 (1.25, 1.73)*	1.17 (1.00, 1.39)	--
Outside (90.0 µg/m3)	0.49 (0.41, 0.58)*	0.66 (0.57, 0.79)*	0.53 (0.45, 0.63)*	0.45 (0.39, 0.54)*

Schools C & D[3]	School C Gym (39.9 µg/m3)	School D Classroom (83.7 µg/m3)	School D Cafeteria (141.1 µg/m3)
School C Gym (39.9 µg/m3)	--	--	--
School D Classroom (83.7 µg/m3)	0.59 (0.50, 0.70)*	--	--
School D Cafeteria (141.1 µg/m3)	0.28 (0.24, 0.34)*	0.48 (0.40, 0.57)*	--
Outside (189.9 µg/m3)	0.27 (0.23, 0.32)*	0.45 (0.38, 0.53)*	0.94 (0.79, 1.12)

Schools C & D[4]	School C Gym (23.9 µg/m3)	School D Classroom (49.3 µg/m3)	School D Cafeteria (79.3 µg/m3)
School C Gym (23.9 µg/m3)	--	--	--
School D Classroom (49.3 µg/m3)	0.47 (0.39, 0.55)*	--	--
School D Cafeteria (79.3 µg/m3)	0.30 (0.25, 0.35)*	0.64 (0.53, 0.76)*	--
Outside (107.7 µg/m3)	0.22 (0.18, 0.26)*	0.47 (0.39, 0.56)*	0.74 (0.63, 0.89)*

$^*p<0.01$

[1] Wildfire smoke period: September 11 to 18, 2020 (47 school hours).

[2] Wildfire smoke period: September 15 to 18, 2020 (25 school hours)

[3] Wildfire smoke period: July 18 to August 5, 2021 (110 school hours, but school was not in session during this time. Schools C and D were being used as a base for firefighters.)

[4] Wildfire smoke period: August 12 to 15, 2021 (16 school hours but school was not in session during this time. Schools C and D were being used as a base for firefighters.)

3.3 Percent error of indoor/outdoor ratios from sampling with a handheld sensor

We simulated indoor/outdoor ratios obtained from sampling with a handheld sensor during two or six walkarounds, and calculated the percent error of the simulated measurements compared to the median hourly ratio during school hours over the wildfire smoke period. The maximum percent error was consistently lower with six walkarounds vs two walkarounds (Figure 2). Maximum percent error during the 2020 wildfire smoke was 70%, while during 2021 wildfire smoke it was over 650%. Median percent error during 2020 was 3-20% with two walkarounds and 2-19% with six walkarounds. In 2021 the median percent error was 13-38% with two walkarounds and 8-41% with six walkarounds. Maximum error including both 2020 and 2021 was reduced by 16-66% with six vs two walkarounds.

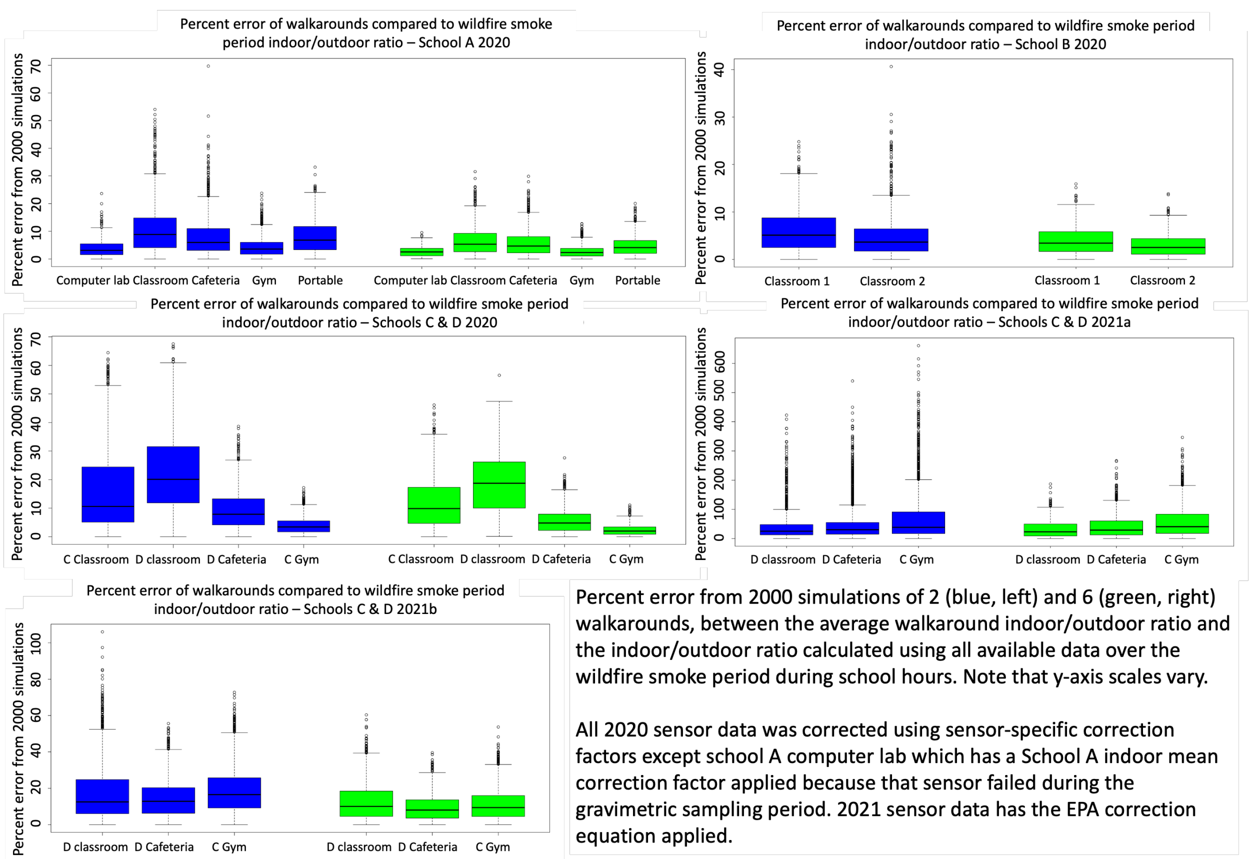

Figure 2: Boxplots of percent error in indoor/outdoor ratios from walkaround sampling.

Among the set of two and six walkarounds with <10% error in every space, starting hours were evenly represented; representation relative to 8am ranged from 0.7 to 1.2. Walkarounds on more days had less error than walkarounds on fewer days. Among the set of two walkarounds with error <10%, on average 29% occurred on a single day, while 71% occurred over two days. Among the set of six walkarounds with error <10%, on average 11% occurred on less than half of the possible days, while 87% occurred over more than half of the possible days.

3.4 Relationship of historical data with next hour data

We examined the relationship of historical data with next hour data during a period of unstable air quality conditions (wildfire smoke 2021 July-August). Using the wildfire smoke 8am and 3pm data, 10-minute historical data approximated the next hour closer than 3-hour historical data indoors. Outdoors, the two historical averaging times were similarly correlated with the next hour.

The R^2 value for the linear relationship between the last 3-hours of data and the next hour of data was 0.53 in the school D classroom, 0.75 in the school D cafeteria, 0.52 in the school C gym, and 0.91 outdoors. The R^2 value for the linear relationship between the last 10-minutes of data and the next hour of data was 0.87 in the school D classroom, 0.99 in the school D cafeteria, 0.96 in the school C gym, and 0.94 outdoors.

3.5 Particle size distributions and Purple Air correction factors

The particle size distributions measured briefly during set up and take down of the impactors fell into two general categories: one with 40-60% of particles <0.35 μm, and another with 10-25% of particles <0.35 μm (Figure 3). The category with a larger proportion of particles <0.35 μm contained all of the wintertime samples and the wildfire smoke samples from set-up only at schools A and B. The category with a smaller proportion of particles <0.35 μm contained the rest of the wildfire smoke samples.

During the beginning of the wildfire gravimetric sampling period, sources of smoke near schools A and B were dominated by local fires.[107] By the end of the gravimetric sampling period at schools A and B, sources of smoke were dominated by a plume that formed off of the coast and drifted inland.[108] This plume continued through the entire wildfire gravimetric sampling period at schools C and D.

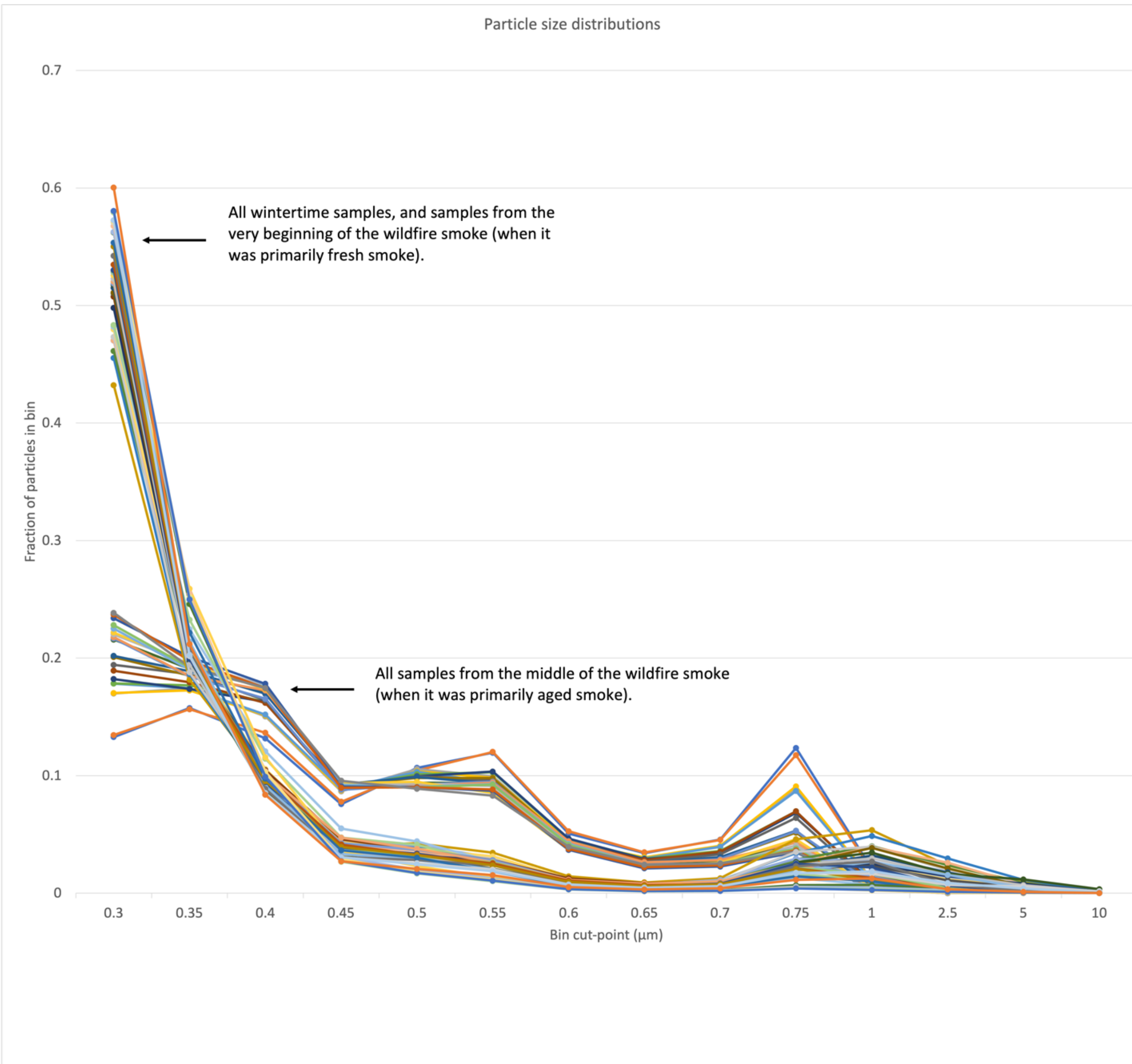

Figure 3: Particle size distributions of $PM_{2.5}$ samples collected at the time of set up and take down of the impactors during wildfire smoke and wintertime.

While these two groups of datasets display markedly different particle size distributions, the ratio of the outdoor uncorrected Purple Air $PM_{2.5}$ concentrations to the outdoor impactor $PM_{2.5}$ concentrations during wintertime and wildfire smoke gravimetric sampling periods were all between 0.98 to 1.31 (Supplementary Table 1).

During the wildfire smoke gravimetric sampling period, the mean uncorrected Purple Air $PM_{2.5}$ concentrations ranged from 1.20 to 2.11 times higher than the impactor $PM_{2.5}$ indoors, and 1.00 to 1.21 times higher outdoors. During the wintertime gravimetric sampling period, the mean uncorrected Purple Air $PM_{2.5}$ concentrations ranged from 0.56 of the impactor $PM_{2.5}$ to 1.21 times higher than the impactor $PM_{2.5}$ indoors, and 0.98 to 1.31 outdoors (Supplementary Table 1).

Using the EPA correction factor, the mean Purple Air $PM_{2.5}$ concentrations were generally lower than the impactor $PM_{2.5}$ during the wildfire smoke gravimetric sampling period, and generally higher during the wintertime gravimetric sampling period (Supplementary Table 1).

4. Discussion

We assessed how low-cost sensor data could be useful for wildfire smoke response. Our findings have implications for sampling strategies to inform decision-making at schools and childcare settings to reduce children's exposure to wildfire smoke. We found that within-school differences in $PM_{2.5}$ during wildfire smoke can be substantial. Simulated handheld sampling in each space was more likely to approximate the average indoor/outdoor ratio when conducted more often and over multiple days. Indoors, $PM_{2.5}$ over the next hour was more highly correlated with the last 10-minutes of data compared to the last three hours of data.

Wildfire smoke can occur at any time of year in highly wildfire smoke prone regions. Nationwide, many children attend school and childcare facilities in regions impacted by air pollution from other sources. Low-cost, reliable, and practical methods to estimate indoor PM in classrooms, gyms, and cafeterias would facilitate decisions around room use and air filtration needs to protect children from high PM exposure.

$PM_{2.5}$ concentrations varied considerably within schools, suggesting that $PM_{2.5}$ measurements taken in one room may not be representative of the whole school. This highlights the importance of measuring $PM_{2.5}$ in multiple rooms. This is consistent with other studies, which have found within-building spatial variation in $PM_{2.5}$.[96,97,99,109,110] This is especially relevant for rooms where children may go for indoor recess and/or be more active, such as the gym, and in rooms where children with health conditions may spend more time. Exposure may be mitigated by avoiding certain areas of the facility, if possible, or prioritizing certain areas of the facility for supplemental air filtration.

The time series data showed that while the rank ordering of differences within-school are generally consistent, the relative sizes of the differences change. This suggests that measurements should be taken either continuously via stationary monitoring or periodically via handheld monitoring to capture temporal changes. Additionally, the trends in some locations displayed diurnal patterns while others did not. The diurnal patterns in two rooms in school A were likely due to the ventilation systems in those rooms. If this is the case, the decreases in $PM_{2.5}$ concentrations after school might have been due to the ventilation system being shut down, and the increases shortly before school started were perhaps due to the ventilation system turning on prior to building occupancy. As many schools have their ventilation systems on a set schedule to conserve energy,[111] measurements should be taken during school hours to better understand exposures to children while they are in the building.

We simulated measurements from handheld sensors because it is impractical for most school and childcare settings to continuously measure PM in every indoor space (though Boston Public Schools has done this).[91] It is more feasible for school and childcare facility decision-makers to measure PM in multiple indoor spaces using a low-cost, handheld instrument.

Our comparison of two vs six walkarounds suggests that for school and childcare facility decision-makers who are interested in better understanding their average within-school differences over the course of the wildfire smoke period, six or more walkarounds would be recommended. The practicality of conducting six, or more, walkarounds will be a topic of our planned interviews with decision-makers.

Walkarounds with <10% error were more likely to occur over multiple days (i.e. one walkaround per day over multiple days as opposed to multiple walkarounds on the same day). This suggests that decision-makers should repeat walkarounds on different days during a wildfire smoke period. While we only observed two periods of indoor-generated $PM_{2.5}$ during wildfire smoke school hours, it is probably still important to avoid conducting walkarounds during times of known indoor $PM_{2.5}$ emissions if the primary concern is outdoor-generated $PM_{2.5}$.

For decision-makers who are interested in using walkaround data to inform short-term decision-making, we recommend repeating walkarounds prior to decision points (e.g. just prior to the start of activities such as recess and PE class, or at the moment of deciding whether or not to open or close windows or relocate students from a particular room) due to the rapid changes in $PM_{2.5}$ concentrations. This variability was particularly evident during the July-August 2021 wildfire, where the maximum error from walkaround sampling was over 650%.

Changes in $PM_{2.5}$ concentrations from hour to hour over the course of a school day also have implications for concentration averaging times used for decision-making. Outdoors, US government agency $PM_{2.5}$ data is typically displayed using the NowCast estimate, which approximates to a 3-hour average during unstable air quality. The NowCast is not designed for indoor use. Low-cost sensors have a variety of $PM_{2.5}$ information displays; in some cases only "real-time" data is available. The Purple Air default is to display

10-minute data, but the user can choose different averaging time options. We found that during unstable air quality, the following 1-hour average $PM_{2.5}$ concentration was more highly correlated with the 10-minute historical data rather than the longer 3-hour historical data indoors. Outdoors, the 10-minute data and 3-hour data were similarly correlated. This suggests that for short-term decision-making indoors, such as for activities occurring in the next hour, recent 10-minute data provides valuable information for forecasting. We expect that this would be less relevant during stable air quality conditions.

Wildfire smoke prediction models and forecasts[112–114] may be helpful to decision-makers with events that require advanced planning (such as a high-school sports game). However, models may not have high enough time resolution to inform short-term decision-making (such as recess). Further, predicted changes in outdoor air may not immediately translate to changes in indoor air, so models and forecasts are likely more useful to inform outdoor activities than indoor activities.

Newer low-cost (~$300/ea) $PM_{2.5}$ sensors may provide a cost-effective approach for measuring short-term fluctuations in $PM_{2.5}$ concentrations with greater spatial resolution.[24–28] However, quality control methods, such as calibration equations or correction factors and validation through co-location with reference instruments[27,115,116] are needed. Typically, users cannot change or calibrate low-cost sensor instrument settings directly. Instead, the concentration data itself needs to be adjusted.

In this study we determined sensor-specific gravimetric-based Purple Air correction factors, but this would be impractical for most schools. Using the EPA correction equation, which was designed for outdoor use, during wildfire smoke underestimated the true $PM_{2.5}$ concentrations in most locations, consistent with what others have found.[65] Nevertheless, these underestimations may have little effect on decision-making given the very high $PM_{2.5}$ concentrations during many wildfires. In a future study we plan to interview school decision-makers to better understand the potential impacts of Purple Air measurement errors on decision making.

The particle size distribution findings may be relevant to Purple Air correction factors. We found that the particle size distributions differed between wintertime and fresh wildfire smoke samples vs aged wildfire smoke samples. However, the outdoor Purple Air correction factors were similar. This suggests that a single outdoor Purple Air correction factor could be used for both fresh and aged smoke.

The indoor Purple Air correction factors varied widely (Purple Airs generally underestimated winter $PM_{2.5}$ and overestimated wildfire smoke) despite the similarities between the indoor and outdoor particle size distributions. This is perhaps because we collected particle size data when indoor spaces were unoccupied, so there was relatively little resuspension of indoor dust or other indoor-generated PM. If there had been dust impacts during the particle sizer sampling period, they likely would have changed the particle size distributions. Dust impacts occurring during the gravimetric sampling period likely contributed to the low correction factors in the wintertime. This suggests that using the same Purple Air correction factor indoors and outdoors may be reasonable during a high air pollution event such as wildfire smoke, where the indoor $PM_{2.5}$ is dominated by infiltrated outdoor $PM_{2.5}$. It may be more challenging during low outdoor air pollution (such as the wintertime period in this study), when the concentrations are low enough that indoor sources are a larger fraction of the total indoor $PM_{2.5}$.

Differences between indoor and outdoor PM composition and sensor response during non-wildfire smoke periods make it challenging to compare indoor/outdoor ratios across seasons. Additionally, it is difficult to interpret indoor/outdoor ratios when concentrations are very low, as the ratio would be highly variable. Therefore, it is probably not feasible to extrapolate indoor/outdoor measurements collected during low air pollution to estimate expected conditions during wildfire smoke. Instead, to estimate conditions during wildfire smoke, measurements should be collected during wildfire smoke.

This study was limited by a small number of schools sampled, and only having gravimetric samples for the 2020 wildfire smoke period. Additionally, the handheld sensor simulations use 5-minute averages, while most handheld sensors display data closer to "real-time." However, this study provided important and novel data from monitoring of school indoor PM during wildfires.

We found useful, practical information applicable for optimized sampling with low-cost sensors for wildfire smoke response in schools and childcare settings. This research identified the importance of measuring $PM_{2.5}$ throughout a facility and repeating handheld measurement collection to capture temporal changes. Measurements and indoor/outdoor comparisons will be most informative when collected during building occupancy hours and during a wildfire smoke period. This information can be directly applied to schools and childcare settings to mitigate children's exposure to $PM_{2.5}$ from wildfire smoke.

Supplementary Materials

Supplementary Methods

Post-data collection, we co-located Purple Airs with each other and with air quality agency monitors (a different co-location from the impactors) to confirm that the Purple Airs continued to perform similarly to each other (Pearson's correlation >0.7 and mean absolute error <5 $\mu g/m^3$). One Purple Air was missing from the co-location analysis because the data card was corrupted, and another was missing because it never worked properly throughout the study period. Two Purple Airs were co-located with a nephelometer local to one school area from 8/31/21 to 12/23/21, two Purple Airs were co-located with a different nephelometer local to the same school area from 8/31/21 to 9/5/21, and the remaining nine Purple Airs were co-located with a beta-attenuation monitor local to the other school area from 3/15/21 to 4/28/21.

For each Purple Air, we assessed whether both Plantower sensors were functioning (not reading all zeros). If only one was functioning we used the data from that sensor. When both sensors were functioning, we calculated daily Pearson's correlations between the two sensor measurements, and used the average of the two as long as the correlation was >0.7, or the correlation was <0.7 but the $PM_{2.5}$ concentration measured by both sensors concurrently was <10 μg/m^3. If the correlation was <0.7 and the $PM_{2.5}$ concentration was >10 μg/m^3, those data were excluded from analysis. Tryner et al (2020) reported that early Purple Airs switched the Plantower output for the two PM mass concentration estimates, CF=1 and CF=ATM,[66] so we reassigned those data labels as needed (so that CF=1 was greater than CF=ATM when they differed).

Supplementary Table 1: Ratio of uncorrected and EPA-corrected Purple Air $PM_{2.5}$ concentration to impactor $PM_{2.5}$ concentration

	Wildfire smoke period			Winter		
	Impactor $PM_{2.5}$ (μg/m^3)	EPA-corrected Purple Air / impactor	Uncorrected Purple Air $PM_{2.5}$ CF=1 / impactor	Impactor $PM_{2.5}$ (μg/m^3)	EPA-corrected Purple Air / impactor	Uncorrected Purple Air $PM_{2.5}$ CF=1 / impactor
School A[1]						
Portable	87.3	0.88	1.61	1.3	3.94	1.13
Gym	103.3	1.13	2.11	3.6	1.65	0.85
Classroom	166.8	0.80	1.48	3.0	2.07	1.10
Cafeteria	82.0	0.86	1.61	4.3	1.47	0.88
Computer Lab	32.6	--	--	1.8	2.97	1.08
Outdoors	290.0	0.73	1.21	7.5	1.09	1.31
School B[1]						
Classroom 1	123.7	0.80	1.49	3.3	1.88	0.91
Classroom 2	70.5	1.02	1.88	2.3	2.58	1.21
Outdoors	263.4	0.55	1.00	7.1	0.96	0.98
School C[2]						
Hallway	39.0	--	--	1.4	--	--
Classroom	34.6	0.81	1.42	0.6	8.30	0.84
Gym	56.4	0.73	1.20	0.7	7.19	0.88
School D[2]						
Classroom	46.6	0.71	1.24	1.2	3.96	0.66
Cafeteria	48.0	0.92	1.64	2.5	2.04	0.56
Outdoors	83.6	0.64	1.17	2.6	1.41	1.26

[1] Wildfire smoke period was September 11 to 14, 2020; winter period was March 10 to 17, 2021.

[2] Wildfire smoke period was September 15 to 16, 2020; winter period was February 24 to March 3, 2021.

Chapter 3: School and childcare facility air quality decision-makers' perspectives on using low-cost sensors for wildfire smoke response

Summary

During wildfire smoke, school and childcare facility staff and those who support them need air quality data to inform activity decisions. Where ambient regulatory monitor data is sparse, low-cost sensors can help inform local outdoor activity decisions, and provide indoor air quality data. However, there is no established protocol for air quality decision-makers to use sensor data. To develop practical, effective toolkits to guide the use of sensors in school and childcare settings, it is essential to understand the perspectives of the potential end-users of such toolkit materials.

We conducted 15 semi-structured interviews with school, childcare, local health jurisdiction, air quality, and school district personnel regarding sensor use for wildfire smoke response. Interviews included sharing $PM_{2.5}$ data collected at schools during wildfire smoke. Interviews were transcribed and transcripts were coded using a codebook developed both a priori and amended as additional themes emerged.

Three major themes were identified by organizing complementary codes together: 1) Low-cost sensors are useful despite data quality limitations, 2) Low-cost sensor data can inform decision-making to protect children in school and childcare settings, and 3) There are feasibility and public perception related barriers to using low-cost sensors.

Interview responses provided practical implications for toolkit development, including demonstrating a need for toolkits that allow a variety of sensor preferences. In addition, participants expected to have a wide range of available time for monitoring, budget for sensors, and decision-making types. Finally, interview responses revealed a need for

toolkits to address sensor uses outside of activity decisions, especially assessment of ventilation and filtration.

1. Background

Wildfire smoke is increasing in frequency and severity and impacts health.[73,74,80–82] Children are particularly vulnerable to air pollution because they are still developing and their physiology results in a higher dose of air pollution compared to adults with a similar concentration of ambient exposure.[4,5] Wildfire smoke can occur during the school year, and summertime smoke impacts childcare facilities and summer school. Decision-makers at school and childcare facilities, and those who provide guidance and recommendations to decision-makers, need air quality information to support their decisions and recommendations in the face of poor air quality resulting from wildfire smoke. Regulatory agency monitor data can be spatially sparse, especially in rural areas, and typically updates hourly at most. There is no regulatory air monitoring indoors.

Washington state (WA) provides guidance for school and childcare facility activity decisions during wildfire smoke. This guidance references agency monitor derived Air Quality Index (AQI) levels for outdoor air quality information, and suggests using low-cost fine particulate matter ($PM_{2.5}$) sensors for indoor air quality information. Individuals are increasingly using low-cost sensors for more personally relevant indoor and outdoor air quality information. Personalized sensor data can be helpful for personal knowledge and behavior change,[117–121] but its utility for decision-making at a facility level has not been established to our knowledge. Further, sensors have data quality limitations and many utilize optical particle counters which require different adjustment factors for different sources of $PM_{2.5}$ pollution.[63,64]

There is no established protocol for using sensor data to inform school and childcare facility decision-making. Our objective is to develop toolkits that provide guidance on using sensors to inform decision-making for school and childcare settings. School, childcare, local health jurisdiction (LHJ), and air quality agency personnel feedback on sensor data use and interpretation is key to effective toolkit development. We aim to better understand how low-cost sensors can support decision-making in schools and childcare facilities to respond to poor air quality, especially wildfire smoke, through the following questions: 1) How do features of data accuracy influence end-user interest in low-cost sensors as tools for decision-making? 2) What information do people hope to gain from low-cost sensors? 3) What actions do or would people take that are informed by low-cost sensor measurements?

In this study, we sought to address these questions through interviews with people who are involved in school and childcare facility air quality decision-making. These include either school or childcare staff, who make the decisions themselves, or air quality agencies, LHJs, or school and educational service districts, who provide suggestions or guidance to school and childcare facility staff. The two accuracy issues discussed are: 1) often low-cost sensors overestimate wildfire smoke pollution, and 2) when someone uses a handheld sensor, they are only capturing conditions at a particular moment in time, which could be different from the average exposure experience over time. These two data quality issue examples were established with $PM_{2.5}$ data collected at four schools during wildfire smoke, and described in a separate study.[122]

Participant perspectives on qualities that impact toolkit feasibility, data interpretability, and support for decision-making from the interviews will be incorporated into the development of the toolkits. The range of perspectives will be used to establish the different types of guidance that would be useful for different situations. Feasibility and the generation of interpretable data useful for decision-making will be prioritized to mitigate children's exposures to air pollution.

2. Methods

2.1 Theoretical framework

Qualitative interviews were useful for this study because the goal was to understand how people think about air sensor data and what impacts their decision-making or recommendations. This research was guided by a Data-Driven Decision Making theoretical framework.[123,124] Data-driven decision making consists of *"systematic collection, analysis, examination, and interpretation of data to inform practice and policy in educational settings."*[123] A generalized framework (Figure 1) informed by data literacy research consists of data (raw numbers) transformed into information (data within context) and summarized into knowledge (meaningful information that can guide action).[123–125]

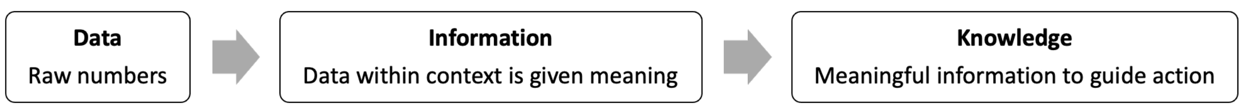

Figure 1: Data-Driven Decision Making theoretical framework. Not shown: implementation and iterative connection back to data collection via monitoring and evaluation of the action/change.[123–125]

This theoretical framework is a good fit for this research because it is specifically relevant to collecting and using data for decision-making in educational settings. While air pollution data is not directly related to education, the context for decision-making remains in the educational setting and involves the school or childcare facility and school district, with support from local agencies. The processes for decision-making in the facility and school district, and the relationships between local agency staff and educational facility staff and parents are highly relevant.

The interview procedures were guided by feminist theory, including an emphasis on self-reflexivity, recognizing that the researcher cannot be separated from study design, questions, and theme identification.[126–130] These interviews included a mutual exchange of information, as participants were asked to react to air sensor data and information. Therefore, the interviews were conversational, which can help respondents think things through[126] and is a way to generate knowledge.[130] Using open-ended questions and being flexible allows for participants to describe their experiences in their own words[129] and for the research to be rooted in participants' experiences and interpretations.[130,131]

2.2 Interviewer positionality

The interviewer is a white, femme-presenting doctoral student with a masters degree conducting air quality research at a large, public university in a large city. The interviewer had prior training in qualitative research methods, and experience conducting interviews and focus groups and qualitative data analysis. The interviewer recruited participants, conducted the interviews, transcribed the interviews, and was the lead researcher on developing the interview guide and conducting data analysis. The interviewer had prior research connections and/or collaborations with many of the interview participants.

2.3 Participant recruitment

This study occurred following preliminary data analysis of air pollution data collected during wildfire smoke at four schools, described in a separate study.[122] The interviews included questions asking participants to respond to air pollution data summaries derived from the study. We sought to use a case-study approach and recruit eight specific people affiliated with the schools or school areas where we collected wildfire smoke data based on their school and agency roles, with the original intention to use snowball sampling to recruit additional participants to reach 17 people. Three people agreed to participate, two refused because their participation in the interview was out of the scope of their job responsibilities, and three did not respond.

We broadened our recruitment to 12 people at air quality agencies, LHJs, and school and educational service districts unaffiliated with the schools in the study, who either had previous research connections with the interviewer or were suggested by the WA Wildfire Smoke Impacts Advisory Group. Eight agreed to participate and four did not respond. We used snowball sampling to recruit five more people, and four participated (one did not respond). We concluded that 15 was an adequate sample size compared to our original goal of 17. In total, 15 people participated, two did not wish to participate, and eight did not respond. Respondent and non-respondent groups were similar in terms of occupation and location; the non-respondent group had slightly fewer prior connections with the interviewer.

Of the 15 participants, nine had prior research connections with the interviewer, and were aware of the interviewer's research interests. All participants were aware of the motivations for the study. All recruitment occurred over email, and participants received and returned signed consent forms over email. The study protocol was submitted to the UW IRB and was determined to be exempt on 4/8/21 (STUDY00013077).

2.4 Interview procedure and setting

All interviews were conducted via Zoom video conferencing between July and November 2022, and lasted from 16 to 57 minutes. To our knowledge, all participants were in private offices or rooms at the time of the interviews without other people present. Interviews were semi-structured with an interview guide containing questions and prompts, but allowing for open dialogue and follow-up questions. The interview also contained slides with background information on air pollution data and guidance so that participant responses could be more equally informed on relevant background to the topic. The slides included: 1) background on $PM_{2.5}$ health impacts and monitoring using low-cost sensors, 2) the WA Air Quality Guide for School & Child Care Activities and explanation of how the guide motivated the study, 3) $PM_{2.5}$ data results demonstrating how low-cost sensor estimates differed from more expensive, "gold standard" methods of determining air concentrations of $PM_{2.5}$, and 4) simulated $PM_{2.5}$ data results demonstrating how estimates of $PM_{2.5}$ derived from short momentary assessment via handheld sampling differed from average results over the wildfire smoke period.

Prior to the interview, 14 participants completed a survey through Google Forms with short-answer and multiple-choice questions. 12 participants completed a similar post-interview survey with some identical questions. The survey included questions related to the first component of the theoretical framework, Data: raw numbers (Figure 1). These questions focused on the feasibility of data collection with low-cost sensors during wildfire smoke, including considerations of time, cost, staff availability, and preferred sensor characteristics.

The interview guide questions were organized around the other two components of the theoretical framework: Information and Knowledge (Figure 1). Questions focused on interpretations of low-cost sensor data and use for decision-making. Interview guide questions and prompts, organized by the theoretical framework, are available in Supplementary Table 1. All interviews were recorded with participant permission. Repeat interviews were not conducted.

2.5 Data analysis

Interviews were transcribed using Microsoft Word. Transcripts were not returned to participants for review. Transcripts were coded using Dedoose[132] qualitative software (Los Angeles, CA, USA). Deductive coding was used first; a draft codebook was developed prior to coding based on expected decisions and recommendations. New codes were added inductively as they emerged during coding. The codebook contained groups of codes organized into the following categories: Actions that people do or would take during wildfire smoke informed by low-cost sensor data, Type of decision-making, Perspectives on guidance, Types of information people hope to gain from low-cost sensor data, Barriers to using low-cost sensors, and Ways that low-cost sensors are useful. Additionally, there were several stand-alone codes: Perspectives on health impacts, Preferred data averaging time for decision-making, Mention of who would be mostly likely to take measurements, and Sensor preferences.

Five of the 15 transcripts were independently co-coded by the interviewer and a graduate student with qualitative research training not otherwise affiliated with the study. Co-coders were provided with background on the study, the research goals, general background on the participant roles, and a list of definitions of common abbreviations and jargon that appeared in the transcripts. The interviewer reviewed the codebook with co-coders during a meeting and answered clarifying questions.

After co-coding was complete, coding discrepancies were discussed, and mainly stemmed from lack of clarity in code definitions, differing knowledge of interview content context, and forgetting about codes due to the high number of codes. After modifying the codebook to clarify code definitions and providing additional context, co-coder agreement ranged from 81% to 93%. Agreement was calculated by the number of concurrent code applications divided by the total code applications. After co-coding, two new codes were added to track additional barriers to using low-cost sensor data and making action recommendations.

Minor themes were identified by documenting the general range of responses contained in excerpts by code. The discussion includes responses represented by a small minority of the participants, or even just one participant. Major themes were identified by organizing complementary codes together. Where themes were dominated by one category of interview participant (school/childcare, school district, LHJ, or air quality agency) this was noted. The interviewer sought to identify themes beyond those that were expected prior to the start of the study by practicing self-reflexivity and keeping an open mind as they reviewed the transcripts and organized codes into themes. Participants did not provide feedback on the findings.

3. Results

The interview participants were somewhat evenly affiliated with school or childcare facilities, local health jurisdictions, air quality agencies/organizations, and school districts/educational service districts (Table 1). These workplaces were located in various Tribal Nations, rural WA counties, or urban WA counties (Table 1). One workplace did not fall into one of those location categories.

Table 1: Description of participants

Place of work	Number of participants (% out of 15)
School or childcare facility	3 (20%)
Local health jurisdiction	5 (33%)
Air quality agency/organization	4 (27%)
School district/Educational service district	3 (20%)
Location of work	Number of different Nations or Counties
Tribal Nation	3
Rural WA county	3
Urban WA county	2

14 people filled out the pre-interview survey that gathered information on time and budget capacity for air monitoring, and sensor preferences. 12 people filled out the post-interview survey, which was very similar. Time and budget capacity for air monitoring varied widely among respondents (Supplementary Table 2).

Only three respondents said they checked indoor air quality multiple times per day, but 11 said they would want to check indoor air quality readings multiple times per day based on the WA Air Quality Guide for School & Child Care Activities. Less than half of respondents thought they could use a handheld sensor to collect and document measurements from six walk-throughs of a facility. All post-interview survey respondents noted that lack of funding was a barrier in implementing air quality interventions.

The most popular responses for where people looked up outdoor air quality information were: AirNow (5 people), local clean air agency website (5), the WA Smoke Blog (4), Purple Air website (4), and WA Department of Ecology website (2).

At least two respondents were interested in every sensor characteristic listed. More than 60% of respondents on either the pre- or post-interview survey were interested in these sensor characteristics: stationary, handheld, connects to the internet to view real time data online, battery powered, plugs into wall outlet, option to view past data, option to apply a correction factor, and able to leave outside.

There were four knowledge questions about $PM_{2.5}$. All respondents answered correctly on three of the questions; 11 of 14 answered correctly on the last question.

Three major themes emerged from the interviews: 1) Low-cost sensors are useful despite data quality limitations, 2) Low-cost sensor data can inform decision-making to protect children in school and childcare settings, and 3) There are feasibility and public perception related barriers to using low-cost sensors (Figure 2).

Major themes represent general categories of perspectives on sensor use. Minor themes, listed below each major theme in Figure 2, represent the general range of responses relevant to each theme. Generally, minor themes are associated with specific codes, while major themes are associated with groups of related codes.

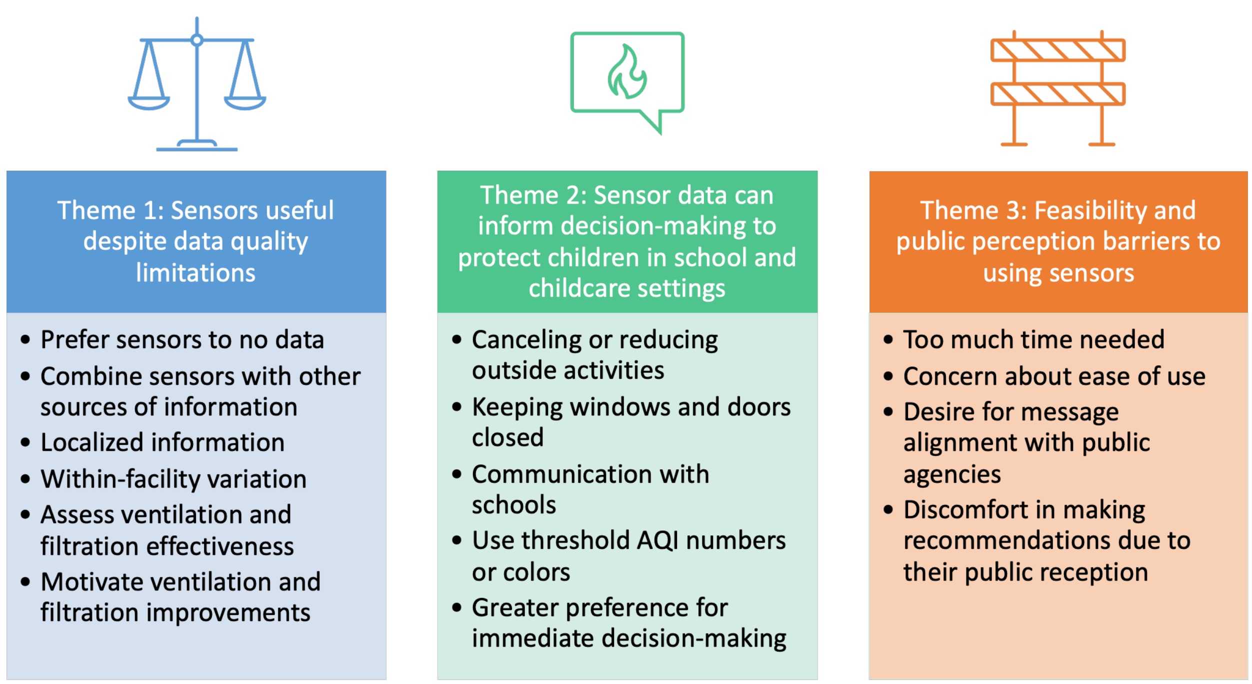

Figure 2: Major and minor themes from interviews.

3.1 Theme 1: Low-cost sensors are useful despite data quality limitations

3.1a Sensors are useful despite accuracy issues

All but one of the interview participants expressed that they would use low-cost sensors despite being shown discrepancies of sensor data from more accurate data. Most participants explicitly stated that they would prefer low-cost sensors to no data. However, the participants had accuracy concerns even while agreeing that they would use the low-cost sensors. Some participants shared that at very high concentrations accuracy becomes less important because the actions would be the same at these high concentrations. Participant 6 said:

> *"So if we have something where it's – and I'm looking at the chart you had up – we know that the – it's in one of the worst categories, we know regardless of plus or minus ten or twenty points, it still means the data we're getting is showing that it's unhealthy, at some level."*

Some expressed that issues with accuracy would not impact the sensors' usefulness in identifying relative comparisons.

Because of concerns about accuracy, about half of the participants expressed that they would use the low-cost sensor data in combination with their own ideas about correction factors, comparisons to outdoor conditions, visual smoke indicators, or other sources of air quality information. Several participants noted that the sensors tend to overestimate during wildfire smoke, and shared that they preferred to overestimate than underestimate to encourage protective behavior change earlier.

3.1b Sensors are useful for localized information

In addition to using low-cost sensors for decision-making during wildfire smoke, which is covered in the next theme, participants shared other ways that low-cost sensor data are useful to them. About half of the participants noted that local conditions do not always reflect the Air Quality Index available for the area, and that sensors could help them get more localized information. Participant 15 said:

> *"Depending again on the direction of the wind, it doesn't take much wind coming from the north, north-east, to really clear out the eastern part of our district. And then you have the southwest part of the district that is more difficult. So more [sensors] would certainly be an advantage."*

Most of the participants mentioned that handheld low-cost sensors would be useful in assessing within-school variation in air quality. Much of this interest was in identifying ventilation and filtration differences, or variation in individual behaviors from room to room, such as keeping windows and doors open.

3.1c Sensors are useful for assessing filtration

Most participants were interested in using sensor data to check ventilation and filtration effectiveness in general, not just how it varied throughout the school. Further, about half of the participants mentioned using sensor data to motivate ventilation and filtration improvements by sharing the data with building administrators or facilities managers. Participant 1 said:

> *"So they [facilities] might not think of air filters as something that's high on the priority list, but if we're telling them our air quality indoors is really low - or really high - we really need our filters changed, and maybe even give them numbers, then maybe that'll motivate them to put us more at the top of the priority list."*

3.2 Theme 2: Low-cost sensor data can inform decision-making to protect children in school and childcare settings

Participants mentioned a variety of actions they would or already do take or recommend during wildfire smoke that are informed by low-cost sensor data (Table 2). Some actions were noted to be easier or more difficult due to logistics or public perception.

Table 2: Actions informed by low-cost sensor data

Action	Number of participants	Exemplary quote
Canceling outdoor recess or lunch	4	Participant 4: *"I don't think I could make any sort of big asks from a school based off of Purple Air. ...maybe just possibly switching recess to indoors or making some other little changes that aren't as demanding as closing school..."*
Keeping windows and doors closed	6	Participant 10: *"If I'm trying to make a determination of, am I going to spend 3 million dollars correcting this? Then I'd probably want some research-grade meters to guide me. But if I'm talking about things like opening and closing windows, running HEPA filters, opening and closing outside air vents, that kind of stuff, I feel like those are relatively low-cost, low-risk kinds of things. So the precision and accuracy isn't my priority at that point."*
Reducing the rigor of indoor activities	3	Participant 3: *"With PE you could have the PE teacher try to think of a game activity that is less physically active."*
Reducing the rigor of outdoor activities	1	Participant 2: *"I've encouraged coaches to restrict athletic activity, like athletic aerobic activity, you know, so maybe do drills but don't run wind sprints."*
Communicating with schools (relevant to non-school or childcare participants)	6	Participant 9: *"If one [sensor] inside is really off the charts compared to outside, I'm like 'Ok what are they doing inside?' And if it's really bad outside and I see that reflected inside then I'm like 'Ok so they got infiltration and what's going on, what can I do to help with that?'"*
Avoiding areas of the school that have worse air quality	4	Participant 3: *"The actual logistics of moving a classroom for a day – logistically, 1) there's not another spot to put them. We don't have an extra classroom. I would certainly consider it, I'm just not sure logistically how that would work."*
Canceling sports practices or games	3	Participant 11: *"If they are going to use Purple Air data, we want them to use corrected data if at all possible to make decisions on keeping kids inside and outside, and then sports in particular — that's the real hot button topic, is when to cancel baseball or football or those kinds of things."*

A few participants noted that although sensor data was useful for some actions, it would not be adequate for school closures decisions. Participant 12 said:

> *"I would say with Purple Air is, it is a good detection and reference data point, but I don't think that—when it comes into play for cost allocations, especially for public instruction, because there's millions of dollars involved when you start closing*

hundreds of schools, let alone lost instruction time—you need to have something a little bit more validated to the general public, and so when it comes to validating those decisions or generating a solid recommendation, I only point to the websites that Department of Health recommends, just because they can be validated."

Most of the participants expressed that they used threshold Air Quality Index numbers or colors for most decisions, usually following guidance from a health or air quality agency. However, a few participants also mentioned broader, non-threshold-based decision-making.

Few participants preferred making one decision for the rest of the day's activities based on the air quality at the beginning of the day, mainly for practical reasons, while more participants mentioned that they prefer immediate decision-making. Participant 15 (first quote) and participant 3 (second quote) offer opposing perspectives:

> *"I think that's just a practical matter. It's much more difficult to change that up midday than it is in the morning when a principal can pull their staff together and communicate with parents that are dropping of their kids.... So we tend to make those decisions early in the morning."*

> *"I'm a firm believer that it's best to be outside, balanced with – we don't want to be outside if it's unhealthy. So I will wait until the last possible moment, so multiple times a day.... I think there was one day this year that we were inside all morning through several recesses. Our last lunch-time recess starts at 12, at 11:45 I looked at the air quality and it was below 150, I said we're going outside."*

Several participants noted that their ability to make immediate decisions was important because of how air quality conditions can change throughout the day. Participant 10 said:

"We need better tools other than the AirNow broad predictions for regions, and what I expressed in that discussion was that every school needs a Purple Air so that they can make more immediate decisions about what kids are going to do or not do on any particular day, because we need them outside and moving as much as we can do."

These participants also noted that the high temporal resolution of low-cost sensors was helpful for interpreting data and deciding when to open and close windows, doors, or dampers. In response to questions about preferences for air quality data averaging time, two participants preferred the NowCast over a shorter-term average, two were unsure, and four preferred a shorter-term average.

3.3 Theme 3: There are feasibility and public perception related barriers to using low-cost sensors

Most of the difficulty in using low-cost sensors was related to practical issues (Table 3).

Table 3: Logistical and time constraint-related barriers to using low-cost sensors

Barriers	Number of participants	Exemplary quote
Handheld sampling would take too much time	6	Participant 14: *"I think it's unfeasible, to start with, just thinking about what I've witnessed the last week and half and being out in our facilities. And looking at our staffing, staffing models, and what's going on with our building level administrators, they wouldn't ever have time to do this, nor would I have the staffing for it."*
Ease of use/user-friendliness	5	Participant 1: *"So like say I wasn't here one day, or say I had meetings or something, could I hand that [taking handheld sensor measurements] off to somebody else to do? If I couldn't do it."*

Few participants (all from workplaces outside of a school or childcare facility) shared that low-cost sensor data would be difficult to use because they want to defer to regulatory agency authority for the sake of their reputation and public perception of their recommendations. Participant 14, who was the only participant who preferred no data to low-cost sensor data, said:

> *"I would really rather not use data with erroneous information or questionable information, I would rather just not have it at all and continue to use quite frankly what a lion's share of the people use, which would be [local] regional clean air's website. Because that's what most other people use, I can stand there and say: I'm doing what everybody else is using, the exact same tool, I didn't have to go out on my own and use some slide-rule corrections and you start feeling a little isolated which is uncomfortable."*

Several participants, again all from workplaces outside of a school or childcare facility, expressed discomfort and aversions to making recommendations to schools because of how they might be received by the public.

4. Discussion

This study identified ways that people use or would like to use low-cost air sensors to inform decision-making in schools and childcare facilities during wildfire smoke, and identified barriers to sensor use. Overall, our interviews found a lot of interest in using sensors to guide activity decisions/recommendations and to gather information on ventilation and filtration system effectiveness. While we anticipated sensor accuracy issues to be a major barrier to their perceived utility, almost everyone expressed that they would still find sensor data useful despite data quality issues. Instead, time required to collect measurements, ease of use, and discomfort with public perception of making activity decisions/recommendations based on sensor data were the main barriers to sensor use. Time constraints were especially relevant for handheld sensor use.

4.1 Implications for toolkit development

The survey and interview responses offered a range of perspectives on qualities that impact toolkit usefulness for gathering meaningful information to support decision-making. Responses suggested that multiple toolkits are needed to cover different options (Figure 3). Additionally, responses indicated areas where further explanation and clarity are needed (Figure 4).

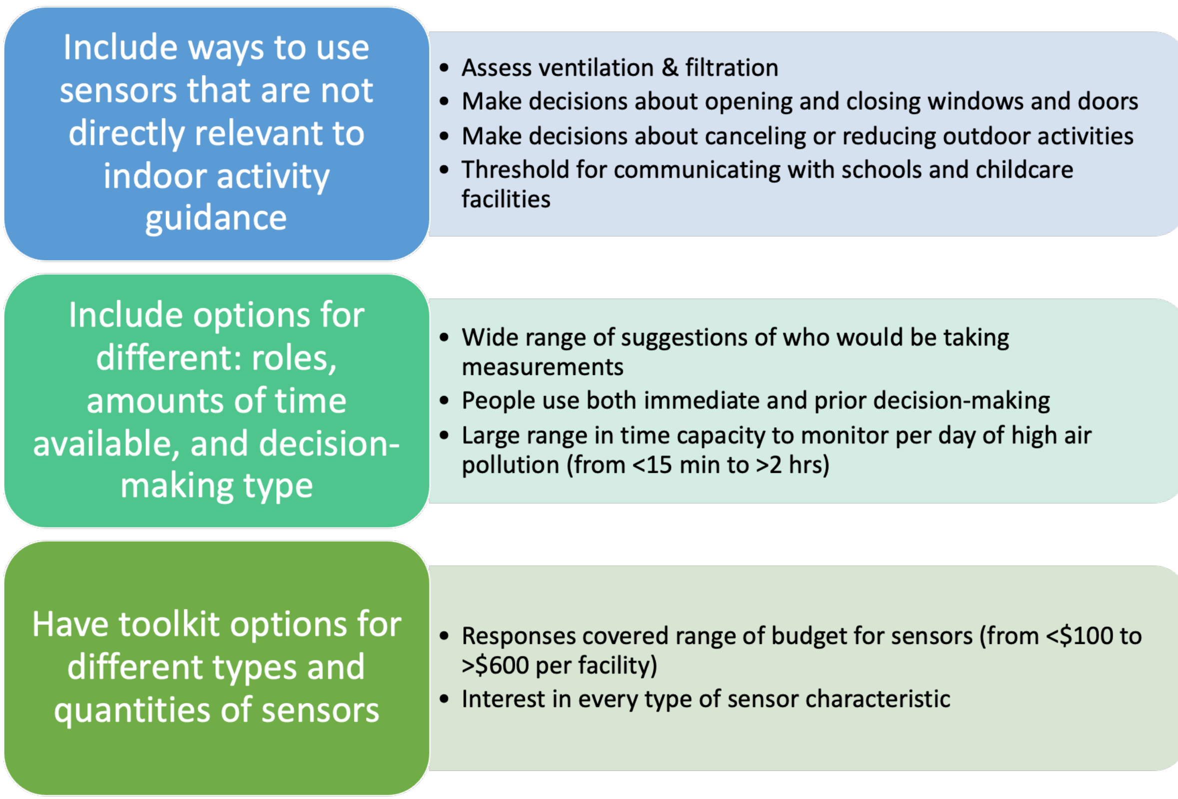

Figure 3: Survey and interview responses suggested that multiple toolkits are needed.

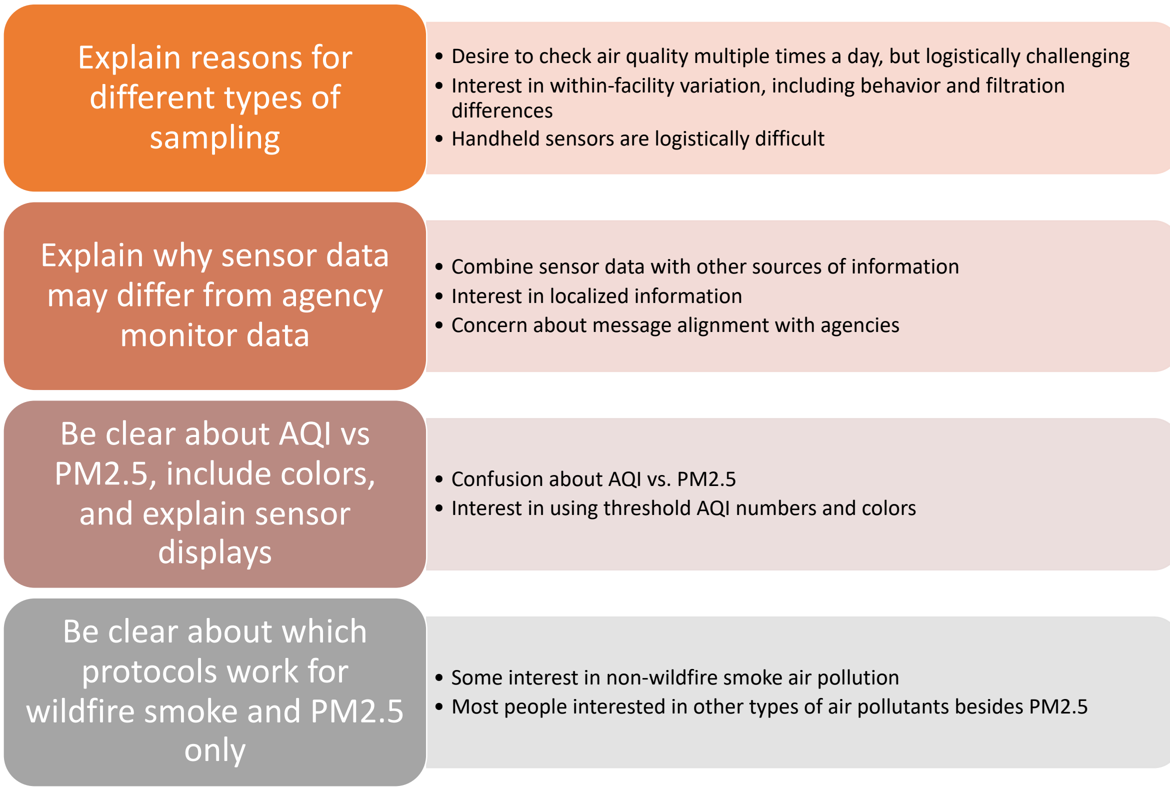

Figure 4: Areas of further explanation and clarity needed, as indicated during interviews.

4.2 Connections to other sensor studies

Other studies that have focused on personal behavior change rather than school or childcare facility activity decisions reflect some overlap with participant responses in this study. Multiple studies found that sensor data influences behavior change, including changes relevant to short-term exposures[117–120] which implies that the sensor data was useful at high temporal resolution. Sensor data was also desirable because it allowed for greater spatial coverage,[118,121] ability to check multiple times per day,[117] addressing multiple seasonal air quality issues,[117] and complementing agency monitor data.[121] The same sensor benefits were identified by interview responses in this study.

In one study of sensor use during wildfire smoke, participants used sensor data to decide whether to wear N95 respirators, whether to exercise, and when to go outside.[117] They also used sensors to identify places nearby with better air quality where they might be able to spend time.[117] This aligns well with school and childcare activity decisions discussed in this study; while interview participants did not discuss mask or respirator use, deciding whether to exercise and when to go outside are analogous to decisions on activity rigor and holding indoor vs. outdoor activities. Using sensors to identify places nearby with better air quality could be applicable to school athletics, if it is logistically feasible to hold practices or events in different locations. However, this type of decision was not raised in the interviews.

In another study using personalized monitoring, participants changed behaviors in response to sensor readings, such as avoiding walking on busier streets and doing projects outside if they emitted air pollution.[118] Other studies were focused on indoor air quality, and based on sensor readings participants increased ventilation[119,120] and reduced incense burning.[119] In these examples, sensor use helped promote air quality awareness and people taking action to protect the health of themselves and their households and workplaces.

While these types of decisions are less relevant to school and childcare facility activity decisions in response to wildfire smoke, they speak to concerns raised by interview participants about the impact of occupant behaviors. Several interviewees discussed different occupant behaviors that impact air quality, such as art classes, wood shop, and chemistry labs. More relevant to wildfire smoke, they raised concerns about opening windows and doors, and noted that sensors could be useful to raise awareness about these actions.

Interview responses also emphasized using sensors to assess building ventilation and filtration, which is not represented in these other studies of sensor use. This is likely because the other studies were focused on individual behavior changes, rather than facility-level changes. While many studies have examined school air quality,[133,134] they have not investigated the use of low-cost sensors by school and childcare facility decision-makers in assessing their own air quality.

4.3 Limitations and strengths

Participants selected for this study were interested in or knowledgeable about air quality issues. It is possible that the areas of further explanation identified by the interview responses do not adequately capture the range of explanations that would be helpful in general. For example, it may be helpful to provide explanations in the toolkits about air quality health impacts, to motivate the use of the toolkits by decision-makers who were previously unaware of air quality health concerns.

The established connection that many of the participants had with the interviewer could be a limitation or a strength. It is possible that prior connections would lead the participants to respond in a way that they thought the interviewer wanted to hear due to social desirability bias. However, this seems unlikely to have impacted interview responses because they covered a wide range of opinions. Connection between interviewer and participant could be viewed as a strength as rapport was already present. This rapport likely led to more candid responses, as participants may have been less concerned about judgmental reactions from the interviewer.

This study provides new information on the ways people may use sensor data to inform decision-making in school and childcare settings, and builds on studies of how sensor data informs personal behavior change. Participants were from a range of workplaces and locations, including Tribal Nations, urban areas, and rural areas, potentially increasing the generalizability of this study in the Northwest. Having a greater understanding of how people think about using sensors for decision-making in schools and childcare facilities can improve guidance for school and childcare settings, facilitating behavior and building changes that reduce child and youth exposures to wildfire smoke.

Supplementary Materials

Supplementary Table 1: Interview guide questions and prompts, organized by the theoretical framework

Information: Data within context is given meaning	Knowledge: Meaningful information to guide action
What does this [low-cost sensor accuracy data] information mean to you? • Show where numbers fall with respect to the school activity guidance. • Are you surprised by the differences between the rooms? Why/why not? • What questions do you have about this data? • What is more meaningful to you – the numbers or the AQI colors?	If you did feel comfortable making decisions, what types of decisions would you make based on these results? How would you use these findings? • Refer to the school activity guide • Avoid certain rooms? • Supplement air filtration in certain rooms?
If you could only have a low-cost sensor to collect $PM_{2.5}$ measurements, would you feel comfortable making decisions about school activities based on the low-cost sensor data? • Does the difference of __$\mu g/m^3$ seem important to you? Why/why not? • Would it make a difference in your decision-making? • Refer to the school activity guide • If you knew of a way to get more accurate readings (using a correction factor), would that increase your confidence in the low-cost sensor data?	How do you use outdoor air quality information?
Are the differences between the results you get from different [sampling] methods meaningful to you? • Does the difference of __$\mu g/m^3$ seem important to you? Why/why not? • Would it make a difference in your decision-making? • Refer to the school activity guide	What kind of monitor do you use for indoor air quality measurements? • What do you like/dislike about it?
Do you feel confident in the low-cost sensor data from the walk-throughs [handheld sampling] enough to guide your decision-making? Why/why not? • Do you feel confident in data from two walk-throughs? Why/why not? • Do you feel confident in data from six walk-throughs? Why/why not?	How do you use indoor air quality information?

Supplementary Table 2: Pre-interview survey responses (only the last row has a post-interview survey question).

Question	Response	Number of people
Do you or another staff member at your agency or facility collect air quality measurements indoors and/or outdoors at any schools or daycares?		
	Yes	9
	No, but this could fall under my job description or another staff person's job description	4
	No, and this could not fall under my or someone else's job description	1*
How much time do you (or another staff person) spend on air quality monitoring during a wildfire smoke event or other bad air quality period? If you don't currently collect measurements, how much time do you think you (or another staff person) could spend?		
	More than 2 hours per day	3
	Less than 15 minutes per day	5
	15 minutes to 1 hour per day	4
	1 to 2 hours per day	2
How often do you (or another staff person) check outdoor air quality at any schools or daycares, including by looking at publicly available information?		
	Regularly	6
	Only during wildfire smoke or bad air quality	7
	Other	1
How often do you (or another staff person) check indoor air quality at any schools or daycares during wildfire smoke or another bad air quality period?		
	Never	2
	Once at the beginning of the day	1
	Multiple times per day in addition to before outdoor activities	3
	Other	8
Please review the table below, which is from the Washington Air Quality Guide for School & Child Care Activities. Given this table, how often would you (or another staff person) WANT to check indoor air quality at schools or daycares during wildfire smoke or another bad air quality period?		
	Never	0
	Once at the beginning of the day	0
	Multiple times per day in addition to before outdoor activities	11
	Other	3
What budget do you think your agency or facility has to spend on air monitors PER SCHOOL? Please make your best guess.		
	More than $600	2
	$300 to $600	3
	$100 to $300	6
	Less than $100	3
Are you interested in measuring other air pollutants besides PM2.5?		
	No	3
	Yes - VOCs	5
	Yes - CO2	3
	Yes - other	6
If you had a portable air monitor, would you (or another staff person) have time to walk through any school or daycare to take air monitoring measurements throughout the school or daycare at least 6 times (total) during a wildfire smoke period?		
	Yes	6
	No	2
	Don't know	6
During a wildfire smoke period, would you (or another staff person) have time to record 6 air monitoring measurements on paper per room and use a calculator to determine measurement averages?		
	Yes	4
	No	5
	Don't know	5
POST INTERVIEW ONLY: 12 total respondents		
What do you think are barriers to making changes at schools and daycares in your area regarding air quality? Check all that apply.		
	Not enough funding	12
	Need to document health benefits to justify implementing interventions	5
	Not enough time to learn about interventions and implement them	3
	Additional staff training is needed	7

*note that during the interview this person said they do check the air sensor at their school

Conclusion

This dissertation research was greatly enriched and strengthened by the participation of the Yakama Nation Environmental Management Program (EMP), and staff who support school and childcare building and activity decisions. Using community-engaged research made this work more robust and relevant to exposure mitigation efforts.

The study of wintertime $PM_{2.5}$ in the Yakama Nation reservation relied on combining Tribal air quality expertise with $PM_{2.5}$ speciation resources for exposure assessment. We found spatial and temporal variation in wintertime $PM_{2.5}$ concentration and composition, suggesting that sparse regulatory monitors may misrepresent the range of $PM_{2.5}$ exposures that people experience, as well as the multiplicity of $PM_{2.5}$ sources. This variation in $PM_{2.5}$ concentration and composition has implications for effective source reduction and exposure mitigation efforts, as well as exposure classification in epidemiologic health studies. This study contributed to Yakama Nation EMP plans to augment their regulatory air monitoring network and conduct additional PM speciation efforts.

The study of wildfire smoke $PM_{2.5}$ in schools indicated that there can be health-relevant differences in $PM_{2.5}$ concentration within the same building during wildfire smoke, and that low-cost sensors can identify these differences. The interview responses revealed a strong interest in using low-cost sensor data to guide activity decisions/recommendations and to gather information on ventilation and filtration system effectiveness. Both the $PM_{2.5}$ data collected at schools during wildfire smoke and the interview responses provided practical information applicable for feasible, optimized sampling with low-cost sensors that is relevant to decision-making during wildfire smoke. This information can be directly applied to guidance for schools and childcare facilities to mitigate children's exposure to $PM_{2.5}$ from wildfire smoke. The within-building variation in $PM_{2.5}$ and perspectives on low-cost sensor use also have broader implications for decision-making and identifying air filtration needs in other types of buildings and settings for wildfire smoke as well as other high air pollution events.

Further community-engaged research on spatial and temporal variation in $PM_{2.5}$, especially on scales not captured by regulatory air monitoring, would help inform exposure measurements and information about PM sources. Additional research on low-cost sensor calibrations indoors and for different aerosols would inform the utility and limitations of sensors in identifying indoor exposures to PM. Sensor utility and limitations for assessing building ventilation and filtration is a needed area of future research. The ultimate goal of improved exposure measurement is to reduce exposures and improve health outcomes. Community-engaged research on the health impacts of source reductions, building changes, and activity decisions that are informed by air monitoring would be useful to assess intervention effectiveness and generate ideas of new interventions.

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