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

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## Abstract

**Background—**More frequent and intense wildfires will increase concentrations of smoke in schools and childcare settings. Low-cost sensors can assess fine particulate matter ($PM_{2.5}$) concentrations with high spatial and temporal resolution.

**Objective—**We sought to optimize the use of sensors for decision-making in schools and childcare settings during wildfire smoke to reduce children's exposure to $PM_{2.5}$.

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Ethical approval

Ethical approval was not required because this research did not involve human subjects.

Competing Interests

The authors declare no competing interests.

**Methods—**We measured $PM_{2.5}$ concentrations indoors and outdoors at four schools in Washington State during wildfire smoke in 2020-2021 using low-cost sensors and gravimetric samplers. We randomly sampled 5-minute segments of low-cost sensor data to create simulations of brief portable handheld measurements.

**Results—**During wildfire smoke episodes (lasting 4-19 days), median hourly $PM_{2.5}$ concentrations at different locations inside a single facility varied by up to 49.6 μg/m$^3$ (maximum difference) during school hours. Median hourly indoor/outdoor ratios across schools ranged from 0.22 to 0.91. Within-school differences in concentrations indicated that it is important to collect measurements throughout a facility. 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, $PM_{2.5}$ 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 (mean $R^2 = 0.60$), indicating that higher temporal resolution data is most informative for decisions about near-term activities indoors.

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

### Keywords

Low-cost Sensors; Wildfire Smoke; Particulate Matter; Schools; Indoor Air Quality

## 1. Introduction

Wildfires are increasing in severity and frequency with climate change.[1,2] Wildfire smoke contains many hazardous constituents,[3] including $PM_{2.5}$, carbon monoxide, volatile organic compounds, and polycyclic aromatic hydrocarbons.[4-7] Exposure to wildfire smoke causes respiratory morbidity, especially exacerbations of asthma and chronic obstructive pulmonary disease, with increasing evidence for respiratory infections, respiratory mortality, and all-cause mortality, mixed evidence for cardiovascular disease,[8-10] and emerging evidence of effects on cognition.[11]

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 particle deposition in the lower airways is greater than for adults.[12,13] Among children, exposure to PM is associated with respiratory diseases, neurodevelopmental issues, and prehypertension.[12,13] 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.[13,14] 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 outdoor sources.[15]

In schools and childcare settings, children are exposed outdoors during outdoor play, recess, and athletic events. Exposure also occurs indoors because wildfire smoke infiltrates into buildings.[13] There is substantial variability in the proportion of outdoor pollution that infiltrates indoors.[16-21] One study estimated that US indoor exposures account for 61% of the deaths attributed to $PM_{2.5}$ of outdoor origin.[22] In schools and childcare settings, guidance to have children stay inside during wildfire smoke may not be adequate, especially during high levels of physical activity indoors.

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). Several studies found average indoor/outdoor ratios of PM in naturally ventilated settings to range from 0.63 to 0.97,[23-26] and in mechanically ventilated settings from 0.10 to 0.69.[24,27,28] In non-smoking homes, infiltrated $PM_{2.5}$ accounts for most of the indoor $PM_{2.5}$.[29] 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.

At a federal level in the US, indoor air quality is not regulated beyond occupational settings. State and local agencies sometimes develop their own indoor air quality guidance. In Washington state (WA), USA building codes include ventilation and filtration standards applicable to new buildings, but there is no required ongoing indoor air quality monitoring. Currently, few schools and childcare facilities monitor indoor $PM_{2.5}$ at all, beyond sporadic spot sampling by government health agencies or school district staff in response to specific complaints and situations (one exception is Boston Public Schools, in Boston, Massachusetts, USA). In general, government health agencies and school districts do not have adequate funds, expertise, or staff time for ongoing indoor air quality sampling at all school and childcare facilities in their district. Spot sampling is often done with a handheld monitor that costs several thousand US dollars, or facilities hire outside consultants for air sampling and analysis. During wildfire smoke, some school and childcare facility staff check outdoor air quality measurements. Low-cost $PM_{2.5}$ sensors are increasingly being sited outside at schools across WA. Given the wide range of indoor/outdoor ratios across and within buildings, indoor air quality measurements are necessary. Approaches to measurement need to be relatively straight-forward and require little time commitment, while offering rigor in order to inform decisions.

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.[30] 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 handheld sensor. However, handheld sensor measurements only capture a snapshot in time. It is unclear how often and when one would need to collect handheld sensor measurements to approximate longer-term average concentrations.

In WA, the Department of Health developed guidance for school closures and school and childcare activities, which as of 2022 were based on both outdoor and indoor PM concentrations.[31,32] However, there is no established protocol or toolkit for assessing PM at schools. Outdoor regulatory monitors are not intended 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. There are various types of filtration used in ventilation systems. Filters are often rated according to their ability to filter different sized particles, denoted as a Minimum Efficiency Reporting Value (MERV).[33] A higher MERV indicates greater filtration.

In Montana, USA, the Missoula City-County Health Department found that two buildings with poor filtration had $PM_{2.5}$ similar to outdoors (i.e. an indoor/outdoor ratio close to 1), while in a building with 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 (i.e. an indoor/outdoor ratio <0.5).[34]

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 μg/m$^3$ (about 25%) during a wildfire smoke episode.[35] PM concentrations within a single school building may also vary considerably spatially[36,37] and temporally.[23,26]

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 with 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. Since wildfire smoke can be stable, or can fluctuate from hour-to-hour due to fire dynamics and meteorology,[38,39] this has implications for which averaging times would best support decision-making for near-term activities.

The ability to monitor variability of PM concentrations over space and time at schools and childcare facilities would inform classroom-level interventions, decisions about whether to hold outdoor activities, and facility 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.[40] Additionally, building-based models may overlook key variations in school and childcare facility rooms, 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) how the variation changed 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 $PM_{2.5}$ exposure during wildfires. The goal is a toolkit useful for immediate decision-making during wildfire smoke, and for decision-makers at 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 impacted by wildfire smoke. 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.

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 Environmental Protection Agency (EPA)'s Air Quality Index categories of "Moderate" and "Unhealthy for Sensitive Groups" at 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.

### 2.2 Air sampling equipment set-up

At each sampling location, we paired low-cost (~$279) Purple Air PM sensors (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 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.[41] 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 to calculate $PM_{2.5}$ concentrations.

The indoor sampling locations at each school were chosen in consultation with school staff. They included spaces where school staff expected the indoor air quality to vary due to location within the building, differences in ventilation and filtration, or differences in the use of the space. They also included spaces that were especially relevant to school staff during wildfire smoke; for example, the gym is especially relevant if that is the location for indoor recess.

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 reach of young children, and so that older students and staff would not accidentally touch them. However, they were placed such that the inlets were facing toward the middle of the room, and at a height relevant to the occupants' breathing zone. We assumed that the air in the room was generally well-mixed and the air around the sampling location was representative of what occupants were exposed to.

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 in locations where airflow would not be obstructed. Specific locations were chosen based on availability of power and Wi-Fi, and out of reach of young children. 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 pre-conditioned the filters used in gravimetric samplers 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 filters 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 $PM_{2.5}$ concentration over the time period that the impactor was running:

$$\begin{aligned} &Corrected\ Purple\ Air \\ &\quad = Purple\ Air \times (impactor\ concentration \\ &\quad \div mean\ Purple\ Air\ during\ impactor\ sampling) \end{aligned}$$

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 the two 2021 wildfire smoke periods at schools C and D, which did not include gravimetric sampling, we applied the US EPA correction equation (October 2021 equation)[42] 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 (so each 5-minute datapoint was the average of either two or three 2-minute datapoints) 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 shared 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 statistical model for an RBD analysis assumes that systematic differences between locations are constant across "blocks" (time). Ratios of concentrations (percentage differences) between locations were observed to be approximately constant over time. This corresponds to constant additive differences for log-transformed $PM_{2.5}$ as, comparing locations "$a$" and "$b$":

$$log(PM2.5_a) - log(PM2.5_b) = log(PM2.5_a \, / \, PM2.5_b) = log(k)$$

for some percentage location effect $k$. The log transformation is commonly found appropriate for analyses of pollutant concentration with the assumption of constant variance for the RBD model also being satisfied.

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 $PM_{2.5}$ peaks[43,44] to consider the influence of indoor sources.[16,23,24,28,43-46] Ultimately, we only detected two indoor generated peaks, and decided not to repeat the analysis with these peaks removed because we expected the impact of these two indoor peaks to be negligible.

We originally intended to repeat this analysis with the winter data. However, the winter sampling period occurred during a time with unusually low air pollution (maximum impactor $PM_{2.5}$ concentration was 7.5 $\mu g/m^3$ and maximum median Purple Air was 3.9 $\mu g/m^3$). It was not logistically feasible to arrange for another round of winter sampling to attempt to capture an inversion. This made differences between indoor/outdoor ratio measurements much more challenging to interpret, so 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 school 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 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 indoors vs outdoors and during 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 that we measured using the particle size analyzer at each school visit, as described in section 2.2. 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) (Supplementary Table 1). 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. Supplementary Table 1 shows gravimetric-corrected Purple Air data during the gravimetric sampling periods.

### 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.

During wildfire episode school hours, mean and median hourly within-school differences in $PM_{2.5}$ ranged from <1 μg/m$^3$ (school A portable, gym, and cafeteria) 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 2). 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 was 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.

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 3). This minimum percent difference corresponded to an untransformed difference of −11.1 μg/m$^3$ (mean $PM_{2.5}$ in the computer lab minus mean $PM_{2.5}$ in the classroom).

### 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.

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 given the length of the wildfire smoke episode, while 87% occurred over more than half of the possible days. For example, at least one walkaround per day over multiple days of the wildfire smoke episode resulted in lower error compared with multiple walkarounds on a single day.

### 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 (coefficient of determination) 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 smoke gravimetric sampling period, sources of smoke near schools A and B were dominated by local fires.[47] 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.[48] This plume continued through the entire wildfire smoke gravimetric sampling period at schools C and D.

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 2).

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 2).

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 2).

## 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 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 $PM_{2.5}$ in classrooms, gyms, and cafeterias would facilitate decisions around room use and air filtration needs to protect children from high $PM_{2.5}$ 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 $PM_{2.5}$.[26,36,37,49,50] 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 (Figure 1) showed that the rank ordering of differences within-school are generally consistent, but not always, and 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,[51] 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 $PM_{2.5}$ in every indoor space (though Boston Public Schools has done this).[30] It is likely more feasible for school and childcare facility decision-makers to measure $PM_{2.5}$ 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.

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 physical education class, or at the moment of deciding whether or not to open or close windows or relocate children 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 communicated 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[52-54] may be helpful to decision-makers with events that require advanced planning (such as a high-school sports game). However, models may not have sufficient 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.[55-59] However, quality control methods, such as calibration equations or correction factors and validation through co-location with reference instruments[58,60,61] 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.[62] Nevertheless, these underestimations may have little effect on decision-making given the very high $PM_{2.5}$ concentrations during many wildfires.

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 ratios of the uncorrected outdoor Purple Air mean $PM_{2.5}$ concentration to the impactor $PM_{2.5}$ concentration were similar across fresh and aged smoke. This suggests that a single outdoor Purple Air correction factor could be used for both fresh and aged smoke.

The ratios of the uncorrected indoor Purple Air mean $PM_{2.5}$ concentration to the impactor $PM_{2.5}$ concentration varied widely (Purple Airs more often underestimated indoor winter $PM_{2.5}$ and overestimated indoor 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 $PM_{2.5}$. 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 indoor 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 episode 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 $PM_{2.5}$ 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.

While this study focused on ways to optimize sampling, ultimately sampling is only useful if decision-makers know how to collect and interpret air quality measurements for decision-making. A toolkit for use in school and childcare settings must be informed not only by sensor utility and performance, but also by school and childcare decision-makers' experiences and perspectives on sensors. We interviewed school and childcare decision-makers to better understand their perspectives on using sensors for decision-making during wildfire smoke, described in a separate study.[63] Discussion topics included items in this study, such as the practicality of conducting six, or more, walkarounds with a handheld sensor, and the potential impacts of Purple Air measurement errors on decision making.

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 used 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 $PM_{2.5}$ during wildfires.

### 4.1 Conclusions

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. 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 $PM_{2.5}$. Sensor utility and limitations for assessing building ventilation and filtration are also needed areas of future research.

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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## Data availability statement

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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**Impact Statement:**

As wildfires continue to increase in frequency and severity, staff at schools and childcare facilities are increasingly faced with decisions around youth activities, building use, and air filtration needs during wildfire smoke episodes. Staff are increasingly using low-cost sensors for localized outdoor and indoor $PM_{2.5}$ measurements, but guidance in using and interpreting low-cost sensor data is lacking. This paper provides relevant information applicable for guidance in using low-cost sensors for wildfire smoke response.

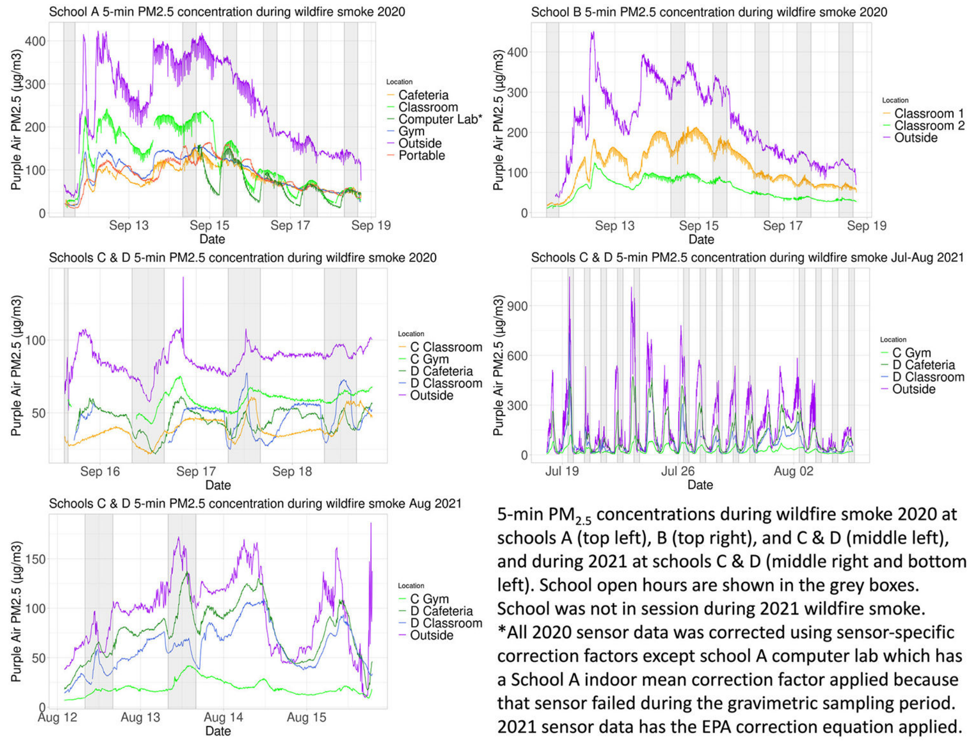


**Figure 1:**

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

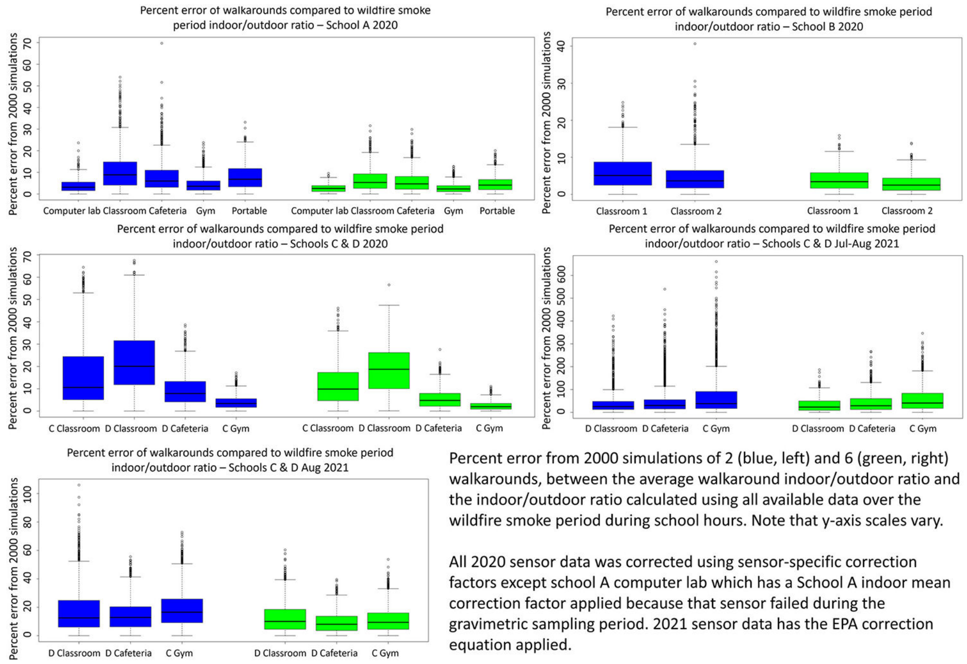


**Figure 2:**

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

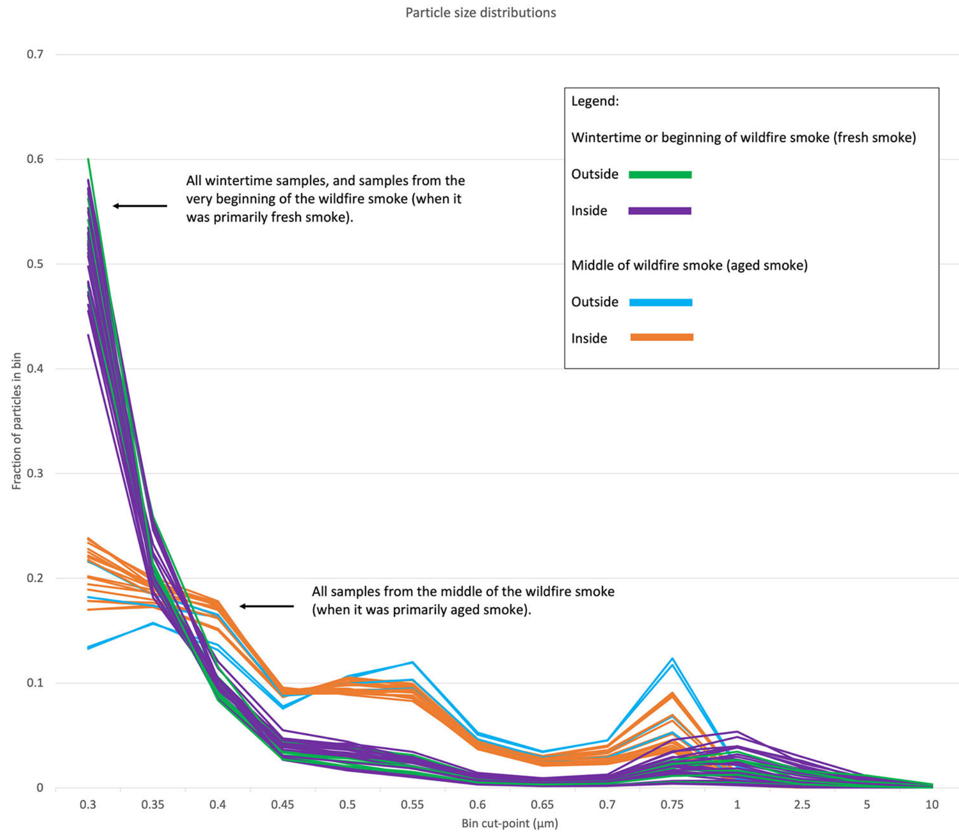


**Figure 3:**

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.

**Table 1:**

Summary of school sampling locations and timing

<table>
<tr><th>School</th><th>School type and description</th><th>Indoor locations sampled</th><th>Wildfire smoke impactor sampling dates</th><th>Wildfire smoke Purple Air sampling dates</th><th>Wintertime impactor & Purple Air sampling dates</th></tr>
<tr><td>A</td><td>High school: one main building plus portable classrooms</td><td>Portable, gym, classroom, cafeteria, computer lab</td><td rowspan="2">Sept 11-14, 2020</td><td rowspan="2">September 11-18, 2020</td><td rowspan="2">Mar 10-17, 2021</td></tr>
<tr><td>B</td><td>Preschool: one building with individual classrooms</td><td>Two classrooms</td></tr>
<tr><td>C</td><td>High school: one building</td><td>Hallway, classroom, gym</td><td rowspan="2">Sept 15-16, 2020</td><td rowspan="2">Sept 15-18, 2020; July 18 to Aug 5, 2021; Aug 12-15, 2021</td><td rowspan="2">Feb 24 to Mar 3, 2021</td></tr>
<tr><td>D</td><td>Elementary school: one building</td><td>Classroom, cafeteria</td></tr>
</table>

**Table 2:**

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

| | Mean (SD) Hourly Purple Air $PM_{2.5}$ Concentration (μg/m$^3$) | Median (IQR) Hourly Purple Air $PM_{2.5}$ Concentration (μg/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) |

| | Mean (SD) Hourly Purple Air $PM_{2.5}$ Concentration (μg/$m^3$) | Median (IQR) Hourly Purple Air $PM_{2.5}$ Concentration (μg/$m^3$) | Median (IQR) hourly Purple Air Indoor/Outdoor Ratio |
|---|---|---|---|
| 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.)

**Table 3:**

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