# Air Pollution in the Puget Sound: Environmental Health Disparities and Brain Health

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## Abstract

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Ambient air pollution such as fine particulate matter ($PM_{2.5}$) has been demonstrated to have respiratory and cardiovascular effects and is hypothesized to be associated with the Alzheimer's disease processes. Community-engaged research provides an opportunity for the public to learn about their neighborhood level exposures to ambient air pollution, health effects, and mitigation strategies. Cumulative impact mapping tools have been used to inform state and local environmental policy, funding priorities, environmental justice advocacy and regulation enforcement to reduce health inequities across communities. However, it is not clear how much work has been done to evaluate the sensitivity of the mapping tools using different data sets. Furthermore, as new methods improve our ability to map and estimate exposures to ambient air pollution there are opportunities to improve health effects research, such as environmental epidemiological studies of $PM_{2.5}$ and brain health in older adults. The goal of the following studies were to advance our understanding of air pollution health effects through an

environmental justice lens as well a deeper understanding of the relationship between air pollution and cognitive function.

In the first aim, I evaluated the importance of fit-for-purpose communication strategies for community-engaged research and identified elements of an overarching framework for tailoring communications for target public audiences. I present examples from two case studies of community-engaged air pollution research in the Puget Sound region. *CAMPS* was a community air monitoring study in the Puget Sound investigating neighborhood level ambient air pollution. *Healthy Air, Healthy Schools* was a collaborative study with the cities of Burien, Des Moines, Normandy Park, SeaTac and five schools in the Puget Sound region investigating infiltration of ambient air pollution into classrooms and the intervention of portable air cleaners in the classroom environment. Our case studies provide a framework that prioritizes developing partnerships, determining community needs, developing culturally relevant content, developing accessible educational materials, disseminating results in multiple approaches, and evaluation.

In the second aim, I conducted a sensitivity analysis approach to illustrate the influence that different air pollution data sources have on Environmental Health Disparities (EHD) ranking. In addition, I developed novel NAAQS based ranking methodology to develop a new health informed map layer. The sensitivity analyses illuminated that overburdened communities could be at risk of not being prioritized for pivotal funding if alternate $PM_{2.5}$ datasets are used in cumulative impact tools. The new health informed map layers can educate the public on the potential health risk from exposure to ambient air pollution in their communities.

In the third aim, I tested the hypothesis that higher individual-level mid- to late-life long-term average exposure to fine particulate matter is associated with lower cognitive ability in later life. Cognitive Abilities Screening Instrument (CASI) data from ACT study was paired with individual-level exposure estimates of $PM_{2.5}$ to determine the association between $PM_{2.5}$ exposure and cognitive ability. We found that each additional 1 $\mu g/m^3$ (5-year average) $PM_{2.5}$ exposure at baseline was comparable to cognition of cohort members who were 0.62 (95% Confidence Interval (CI): -0.15, 1.28) years older. Similarly, we found that for every additional 1900 $pt/cm^3$ of UFP at baseline was comparable to cognition of cohort members who were 0.73 (95% CI: 0.26, 1.13) years older.

This broad innovative work developed a framework for communicating environmental health data and capitalized on novel air pollution data and ACT cohort data to investigate the effect of $PM_{2.5}$ and UFP on cognitive function. Overall, these studies present novel findings in the areas of report-back and risk communication, environmental health disparities mapping and brain health.

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# Chapter 1. Introduction

Ambient air pollution including fine particulate matter ($PM_{2.5}$) has been demonstrated to have respiratory and cardiovascular effects[1], impact birth weight and infant mortality[2,3] and is hypothesized to be associated with the Alzheimer's disease processes.[4,5,6] Regulatory monitoring does not capture exposure variation within communities particularly well; within-community exposures can be impacted by local sources such as highways, major roadways, construction, or industrial facilities. Exposures may also be disproportionate with black and Hispanic minorities experiencing more air pollution than non-Hispanic whites. [7] Community-engaged research provides an opportunity for the public to learn about their neighborhood level exposures to ambient air pollution, health effects, and mitigation strategies. [8,9] The goal of the following studies were to advance our understanding of air pollution health effects through an environmental justice lens, as well as to gain a deeper understanding of the association of ambient air pollutants and cognition.

## Aim 1 (Chapter 2): Communication in community-engaged research

Community-engaged research applies features of community based participatory research (CBPR) that emphasize equal engagement of all partners throughout the research process; from defining the problem, collecting data, analyzing data, disseminating data, and uses those findings to promote change. [10] The first aim applies a community-engaged framework to two studies. The first study, *Healthy Air, Healthy Schools* included engaging community members in determining what pollutants to measure and the return of results. This study was a collaborative study with the cities of Burien, Des Moines, Normandy Park, SeaTac and five schools in the Puget Sound region investigating infiltration of ambient air pollution into classrooms and the intervention of portable air cleaners in the classroom environment. The second study, Community Air Monitoring in Puget Sound (*CAMPS*), included engaging community members to select monitoring locations using community air monitors used in the Adult Changes in Thought – Air Pollution (ACT-AP) study presented in Aim 3 (Chapter 4).

I evaluated the importance of fit-for-purpose communication strategies for community-engaged research and identify elements of an overarching framework for tailoring communications for target public audiences. To identify common elements for communicating ambient air pollution results to a public audience, I present examples from two case studies of community-engaged air pollution research in the Puget Sound region. In the chapter supplement I include two subsections (Supplemental Material: Chapter 2A and 2B) derived from the *Healthy Air, Healthy Schools* study. The first being a previously published manuscript for the exposure assessment component of the *Healthy Air, Healthy Schools* study and the second being a manuscript for a qualitative component of the *Healthy Air*, *Healthy Schools* study.

### Aim 2 (Chapter 3): Environmental Health Disparities Mapping

Moreover, as communities and regulatory agencies work to address ambient air pollution concerns, there is a question of inequities with respect to air pollution exposures, and how air pollution data are utilized in environmental justice (EJ) tools and policy. Mapping tools have been used to inform state and local environmental policy, funding priorities, environmental justice advocacy and regulation enforcement to reduce health inequities across communities.[11,12,2] Although these tools integrate vulnerability factors and illustrate environmental inequities, it is not clear how much work has been done to evaluate the sensitivity of the mapping tools using different data sets. There is an opportunity to build upon current health disparities mapping tools and evaluate whether exposure estimates developed using different methods will illuminate the same disparities.

I learned how much Environmental Health Disparities (EHD) ranking changes when using different datasets. A sensitivity analysis approach can illustrate influence the different air pollution data sources. To accomplish this, I conducted a sensitivity analysis of the Washington EHD map using four unique $PM_{2.5}$ dataset sources. The data sources include the Washington State Department of Ecology (WA ECY) exposure estimates which leverage data from the Air Indicator Report for Public Awareness and Community Tracking (AIRPACT) project [13], the Center for Air, Climate, and Energy Solutions (CACES) [14] exposure predictions, the University of Colorado's Reid Lab exposure estimates [15] and spatiotemporal predictions developed for the ACT–AP study.

### Aim 3 (Chapter 4): Air pollution and cognitive function in older adults

Furthermore, as new methods improve our ability to map and estimate exposures to ambient air pollution there are opportunities to improve health effects research, such as environmental epidemiological studies of $PM_{2.5}$ and brain health in older adults. Past studies have found an association between exposure to air pollution and reduced global cognition.[16] However, these studies contain several limitations including using exposure assessment methods that are based on regional data instead of individual level exposures which may result in exposure misclassification, short exposure windows that do not capture long-term historical exposures which may be of clinical relevance, and absence of APOE gene data which is an important effect modifier.[17,18,16] While recent short-term exposures are of immediate concern to residents, understanding the effect of long-term and past exposures of $PM_{2.5}$ is also of concern in older populations. In addition, we leverage an innovative exposure layer of ultrafine particle (UFP) to learn more about this emerging air pollutant of concern. Currently, air pollution exposures in mid-to late-adulthood and cognition have not been investigated in many community-based cohorts of older adults living in a low exposure area.

I learned what the cognitive impacts of $PM_{2.5}$ exposures are in a community-based based cohort of older adults in the Puget Sound. To test the hypothesis that higher individual-level mid- to late-life long-term average exposure to fine particulate matter is associated with lower cognitive ability in later life, I used Cognitive Abilities Screening Instrument (CASI) data from ACT study, paired with individual-level exposure estimates of $PM_{2.5}$ to determine the association between $PM_{2.5}$ exposure and cognitive ability.

The proposed studies established new guidance for reporting air monitoring results and provide greater insight into engaging the public in science activities. We learned how sensitive EHD scoring on a census tract level is to using alternate exposure datasets. Our final study provides knowledge that is currently lacking to yield novel insights into the cognitive impact of air pollution exposures. The proposed work is innovative as it develops a framework for communicating environmental health data and capitalizes on decades of air pollution data and ACT cohort data to investigate the effect of $PM_{2.5}$ and UFP on cognition. These studies present novel findings in the areas of report-back and risk communication, environmental health disparities mapping and the association between fine particulate air pollution exposures and cognition.

# Chapter 2. Communication of exposure assessment data in community-engaged research

## 2.1 ABSTRACT

Although community-engaged air pollution studies are becoming more common there is an absence of established frameworks to communicate results with the public.[8,19] Current report back in community-based participatory research (CBPR) studies have implemented culturally appropriate collaborative methods [9,19] with reports that are customized for individuals or communities.[20] To effectively communicate environmental exposure data to a public audience I developed an overarching framework for engaging with community members and reporting back air monitoring results leveraging two case studies employing community-engaged research in the Puget Sound region. To identify common elements for communicating ambient air pollution results to a public audience, I present the methodologies of two case studies of community-engaged air pollution research in the Puget Sound region. The first case study is *Healthy Air, Healthy Schools,* was a collaborative study with the cities of Burien, Des Moines, Normandy Park, SeaTac and five schools in the Puget Sound region investigating infiltration of ambient air pollution into classrooms. I will also conclude the chapter with two manuscripts (Supplemental Material: Chapter 2A and Chapter 2B) motivated by the *Healthy Air, Healthy Schools* study activities, including exposure assessment of ultra-fine particles (UFPs) and key informant interviews developed to learn about the barriers of using portable air cleaners in schools. The second case study included in the methodology section is the Community Air Monitoring in Puget Sound (*CAMPS*) study, which was a community air monitoring study in the Puget Sound investigating neighborhood level ambient air pollution and was funded by the National Institute

of Environmental Health Sciences (NIEHS) to expand and enhance the exposure assessment activities of the Adult Changes in Thought –Air Pollution (ACT-AP) study (presented in Chapter 4) by complementing the efforts of academic research with citizen science in efforts of improving the health among residents.

## 2.2 INTRODUCTION

Community-engaged research applies features of community-based participatory research (CBPR) that emphasize equal engagement of all partners throughout the research process; from defining the problem, collecting data, analyzing data, disseminating data, and uses those findings to promote change.[10] Since 2002, the National Institute of Environmental Health Sciences (NIEHS) has endorsed six principles of CBPR including 1) promoting active collaboration and participation at every step of research, 2) fostering co-learning, 3) ensuring projects are community-driven, 4) disseminating results in useful terms, 5) ensuring research and intervention strategies are culturally appropriate, and 6) define community as a unity of identity.[21] O'Fallon and Dearry (2002) indicate that communication should be constant throughout the entire project.[21] Overall, planning the communication aspects of report back from the onset of a community-engaged exposure assessment study is vital to implementing a successful communication strategy.

Additionally, environmental health literacy (EHL) is an important component of presenting environmental exposure data to the public. The NIEHS defines EHL as "an emerging and evolving concept that bridges shared theories from the fields of risk communication, environmental health science, behavioral science, evaluation, communications, public health, and the social sciences".[22] This process includes raising scientific literacy, environmental literacy, and numeracy among the general public while increasing awareness of specific exposures and their potential health effects.[22] Kollmuss and Agyeman (2010) have identified gaps regarding environmental knowledge which include demographic factors, external factors (e.g., economic, social, cultural), and internal factors (e.g., motivation, awareness, priorities).[23] Improving EHL provides individuals the opportunity to have agency of their own health, and be aware of how their actions may affect the environment around them.[24]

Furthermore, community-engaged exposure assessment studies can integrate report back to provide a new informal learning education setting and encourage free-choice learning that is driven by individuals interests.[25] Previous research has suggested that almost half of the public's science understanding and learning drives from free-choice learning.[26] Community-engaged exposure assessment studies can be thought of as informal education settings because there is no framework for EHL, especially for topics such as exposure assessment and the challenges of establishing a relationship between exposure and health outcomes.[25] Community members have partnered with universities to learn about their environmental health determinants and are establishing new informal education frameworks to support and promote free-choice learning.[25] For example, community-engaged biomonitoring studies can provide scientific evidence to promote prevention of environmental exposures and motivate action.[27] Community members in communities that are disproportionately exposed to environmental pollution may want additional information about their health risks due to this gap in EHL.[25]

Notably, biomonitoring studies have led the field in report back practices and methodologies.[8,27–30] In these studies, reporting back data reinforces free-choice learning and can lead to improvements in EHL.[25] However, report back has several challenges including the uncertainty of the clinical significance of health effects associated with environmental exposures and receiving exposure measurements may result in legal obligation under related laws.[9] If researchers themselves cannot confidently interpret the exposure measurements it will be much more difficult to communicate the results clearly to participants.[31] Information that is difficult to understand may lead to anxiety in participants.[31] Conversely, not reporting results due to fear of causing anxiety may violate participants right to make a personal choice.[32] This is important in environmental exposures where exposure risks can be modifiable by individual actions to avoid sources of exposure.[32]

However, previous community-engaged studies have identified barriers to report back. Communicating with low socio-economic status populations and racial/ethnic minorities can be challenging when there is an overwhelming quantity of information, use of complicated language, and presentation of contradictory health information.[33] Public health practitioners identify health literacy as a factor in health disparities, because poor reading and math skills hinder access and understanding of scientific information.[8] Community partners in a community-engaged metal exposure study in homes reported that challenges in EHL goals included access to and the ability to network with other participants, face-to-face engagement with the research team and, additional information to metals analyzed and spatial representation of the data.[34] An additional challenge is that researchers may fail to acknowledge that lived experience of exposure can contribute to better understanding environmental exposures. A community members' experience can draw on firsthand knowledge that is important, relevant and can challenge scientific expertise.[35] Community members often rely on visible evidence such as visible soot from nearly point sources.[36] Previous studies in medical research have found that Black and Latinos report higher level of distrust in research even if they are as likely to participate in research as other groups.[37]

In contrast, there are a plethora of recommendations to improve communication in community-engaged studies. First, it is important to provide for flexibility in the role of communities in research. Depending on the nature of research and existing community capacity, different modes of engagement may be appropriate. Options for disseminating results include mail, telephone, drop-off, face-to-face, internet, or a combination of approaches.[38] Consulting with community members will help teams determine a suitable process.[38] Lessons learned from the EPA's Science To Achieve Results (STAR) cumulative risk community engaged studies have noted the importance of flexibility in the role of communities in studies based on the community capacity allowing for different types of engagement.[39] In addition, given the iterative projects of reporting back, the translation, communication, and dissemination may occur after a studies funding period and published results.[39] Moreover, consideration should be given to the sensitive, complex, and stress associated with environmental justice (EJ) studies.[39] Participant stress may stem from trying to comprehend data that does not provide a clear picture of health implication of clear guidance on how to reduce exposures.[27] Participants in biomonitoring studies have noted that that they would not understand the results without discussing their results packet with the research team.[8] However, some participants felt the terminology did not speak to their experience if they don't understand what it means.[8] Importantly, guidance from a community leaders in the form of a community advisory board (CAB) can be critical in understanding how to effectively communicate with the study participants and the community.[9] Previous environmental health studies have suggested providing group exposure results with companions to similar groups allow participant to better understand their exposure and to have context to wider studies.[9,30] Prior biomonitoring studies have found that communicating group study results is also an effective manner in facilitating behavioral changes to reduce environmental exposure.[9] In addition, they recommend pilot testing to evaluate whether report-back materials are responsive, understandable, appealing, and appropriate.[38] Finally, community engagement and evaluation metrics should be developed prior to start of a study.[39] However, there is a lack of structured evaluation processes and metrics in community-engaged projects.

Nevertheless, there is limited knowledge of how to evaluate communication strategies in community-engaged research. Measuring who, when and where learning is occurring can be challenging and new methods are needed to improve and evaluate EHL.[25] Methods for evaluating report-back include interviews with participants after they receive results, surveys conducted at community meetings, and focus groups.[38] The Silent Spring Institute recommends evaluating community meetings with anonymous five-question surveys at the community meetings that asked attendees why they attended, what they hoped to learn, and what follow-up questions they may have.[38] Similarly, the Home-based Observation and Monitoring Exposure (HOME) study also employed a mixed-methods evaluation framework which included a questionnaire mailed with the report-back packets, a sign-in table and qualitative note taking at the in-person community meeting, a post-meeting questionnaire, and an optional voicemail line for feedback.[40] Tomsho et al. (2019) proposed that future report-back evaluations should include a follow-up component to assess whether participants later took action.[40] Evaluating community concerns over time can test if the changes in concern and inquiry over time demonstrates a progression in the community environmental health understanding and as a result the community involvement of engaged research efforts.[41] For example, the Gardentroots and Metal Exposures Study in Homes (MESH) found that community concerns can change over time as a result of US EPA outreach and university community-engaged research activities.[41]

Furthermore, having an effective method in dissemination information is important for eliciting the desired outcomes, whether that is increased awareness, attitudes, or behavioral change.[42] A 2010 systematic review aimed to identify the effectiveness of communication strategies and factors that impact communication uptake related to environmental health risks.[43] The review found that a combination of information types such as text and diagrams is more effective than just a single type.[43] The review also found that factors which influence the response to risk communication is impacted by personal risk perception, previous personal experience with risk, and sources of information and trust in those sources.[43] These include ensuring that communication comes from a trusted source, tailor communication for the audience, build the content messages with the strongest scientific evidence, incorporate text with visuals with qualitative and quantitative data for print materials, disseminate information in the media through multiple sources.[43] Trust in communication can be enhanced when it is presented to all the affected people in a timely manner, consistent, easy to understand, and comes from a trusted source.[43] Furthermore, we can implement empirically based recommendations from the field of risk communication in public health to disseminating results in community-engaged research.

Lastly, to have a successful study, researchers need to establish trust in all stages of research, from the planning to reporting back.[8] Previous research in report back found that people who participate in communication evaluation are more interested in learning about the study and environmental health compared to those who do not participate.[9] Evaluating report back efforts methods can be useful in illuminating new to assess EHL.[25] In our work I examine barriers to engagement, notably with populations exposed to higher concentrations of ultra-fine particles (UFPs) in the *Healthy Air, Healthy Schools* study.

## 2.3 METHODS & RESULTS

In **Figure 2.1** we present an overarching framework for community-engagement incorporating lessons learned from both the *Healthy Air, Healthy Schools,* and *CAMPS* studies. We first describe the studies and follow with presenting examples of community-engagement activities from each study. We end each sub-section summarizing what was learned from applying each engagement method.

The *Healthy Air, Healthy Schools* study was developed to measure and identify the sources of UFPs in indoor air in schools to inform future recommendations in schools and potentially other public buildings. Monitoring sites within the Federal Way and Highline school districts were selected by the University of Washington (UW) with guidance from the Federal Way and Highline Public Schools. Schools in the Seattle-Tacoma International Airport flight path were selected to understand the impact of airport traffic. The schools represented a variety of air handling designs and building ages. We measured infiltration of outdoor air pollution into classroom spaces under normal operating conditions and after deploying high-efficiency particulate air (HEPA) filters as a classroom level intervention. Although school buildings already actively filter outdoor air, we were able to measure the effectiveness of existing filtration. We identified any additional benefit and potential cost of implementing room specific filtration. Communicating study results to partners was also an integral part of our study.

We developed the *CAMPS* study to address community member concerns of ambient air pollution in their neighborhoods. Our study goals were to engage community members, educate the public on air pollution and health effects, learn about community concerns, collect monitoring data and report back. We recruited community groups that were concerned about air pollution in their neighborhoods, mostly in Southern Seattle closer to industrial sources than

Northern Seattle. The organizations we recruited included childcare centers, community centers and senior centers. We held informational meetings for each organization and presented information about air pollution, known health effects, community air monitors and the goals of study. We installed a community air monitor at each community location or a proxy location if monitoring was not possible for technical siting issues. Siting required being plugged into an electrical outlet and being at least 10 away from dirt or gravel roadways and driveways, gas grills, firepits, charcoal grills, smoking areas, woodworking, construction or other dust sources, engines and exhaust pipe or vent from home or buildings. We deployed monitors during warm and cold months for 6-8 weeks at each location during 2017-2019. Our community air monitors were constructed by the Seto Lab at the UW and used low-cost sensors for $PM_{2.5}$, nitrogen dioxide, carbon monoxide and ozone. Low-cost sensor data was calibrated against regulatory monitors using methods described by Zusman et al. (2020).[44] Data were transmitted wirelessly to a database on a UW server. Real time data was available to community members online through a public website dashboard hosted by the UW. We asked participants to log unusual air quality events to later examine if they were picked up by our community monitors. We summarized and discussed air monitoring data with our community steering committee (CSC). We developed report back materials with guidance from our CSC and additional community members.

### 2.3.1 Forming Community Partnerships and Advisory Boards

Receiving guidance from a community is critical in understanding how to effectively communicate with the study participants and the community.[9,45,46] Ongoing communication and rapport building is essential to the success of receiving consultation.[47] Community advising was employed in both case studies presented. I first describe the UFP advisory board in *Healthy Air*, *Healthy Schools*. I also describe the community steering committee utilized in *CAMPS*. Both studies utilized partnerships in different ways due to differences in the study's conception.

The *Healthy Air, Healthy Schools* study was prompted by the cities SeaTac, Burien, Federal Way, Normandy Park and Des Moines, and Washington State legislators concerns about air pollution exposures due to their proximity to Sea-Tac Airport. The development of report back materials was advised by the UW UFP Advisory Group and Federal Way and Highline School Districts. The Advisory Group consisted of state legislators, domestic and international researchers, community coalitions, and local government officials. School administrators included Directors of Communication, Directors of Facilities, and Superintendents.

In contrast to the first case study, *CAMPS* was funded to expand and enhance the exposure assessment activities of the ACT-AP Study. Our research team began this study by recruiting community groups that were concerned about air pollution in their neighborhoods, mostly in Southern Seattle closer to industrial sources than Northern Seattle. We recruited childcare centers, community centers and senior centers. To form a formal partnership a Memorandum of Understanding (MOU) was reviewed and signed by participating organizations.

A CSC was formed with representatives from each organization. Committee members attended regular meetings to discuss results of needs assessment survey, placement of additional community monitors and report back activities. We summarized and discussed air monitoring data with the CSC. The community report back was developed with guidance from the CSC and additional community members. Development of the report back content included determining what types of figures or tables to present monitoring results.

Furthermore, the use of advisory boards can be utilized in future studies. Community advisory boards are a proven strategy for increasing community engagement in research.[47] The level of activity by partners occurs on a continuum with titles such as community informed, community consultation, community participation, community initiated, or community driven.[48] Future studies can determine the level of engagement appropriate for a study. Giving community members and researchers a like the opportunity to discuss their level of engagement can benefit the study development and success of a study.

### 2.3.2 Conducting Needs Assessment

Community needs assessments have been traditionally used in the development of health programs or interventions.[49,50] Successful efforts in translation research include bidirectional learning and the identification of community needs.[46] Understanding community health needs and the depth of researchers addressing those areas may help to focus priorities for a studies success.[46] Previous community-engaged studies have used needs assessments using surveys and focus groups to identify a continued need to improve upon the information that families are receiving regarding daily asthma management, including symptoms, triggers, and medications.[49]

Employing a needs assessment survey was especially important in the *CAMPS* study given that the study was funded first and instead of being motivated by the concerns of community members. We developed a needs assessment based on the knowledge, attitude, and behavior (KAB) survey model.[51] The goal of the survey was to learn about community members general health concerns, air pollution knowledge, perception of air pollution and protective behaviors against air pollution (instrument located in **Appendix A**). Some needs assessment surveys were completed following an informational meeting, while others were taken home and later returned.

Moreover, the use of needs assessment can be utilized in future community-engaged studies. Future research should develop validated survey instruments that can be applied in environmental health monitoring studies to learn about the priorities of community members, including community priorities, exposures of concern and environmental health literacy gaps.

### 2.3.3 Content Development

Empirically based recommendations from the field of risk communication in public health can be employed to content development in community-engaged research. These recommendations include building the content messages with the strongest scientific evidence and incorporating text with visuals with qualitative and quantitative data for print materials.[43] The underlying goal in risk communication is to provide useful, relevant and accurate information in understandable language and format for that particular audience or risk group.[43] Previous community-engaged air monitoring research has recommended that report back materials should decrease the amount of text, increase the use of visuals, and simplify tables and figures to reduce literacy and numeracy demands on participants.[52]

In the *Healthy Air, Healthy Schools* study, we presented a variety of visualizations to all participants, allowing them to discuss which visualizations and language they preferred. We developed three separate reports with varying amounts of content for each target audience. First, we developed a detailed technical report for school district administrators and Washington State legislators. Second, we developed a school specific report for each participating school (**Appendix B**). Third, we created a two-page executive summary with a straightforward visualization of the HEPA effectiveness for mass distribution (**Appendix C**). We designed report back materials through a conscientious iterative process allowing us to adjust and align the methods to suit the community’s needs. During this iterative process we found the two participating school districts were uneasy about different terminology and content, thus the language used in each school districts report was tailored to their specific concerns.

School specific report back materials included information about the study objectives, summary of the results, sampling description including total air exchange rate and particle movement, air quality, and why indoor air quality is important. The PDF report also links to more information on the study’s technical webpage. The linked report allows community members who want to learn more to find that information, but those who do not want too much information can look at the straightforward report. Having detailed information as an option was informed from the *CAMPS* study where through focus groups and advice from the community advisory committee, we found that about half of the audience wanted the basic information, such as bar plots, while the other half wanted more detailed information.

Seeing that bar plots may not be easy to understand for those with limited scientific literacy, we developed visuals that were designed to convey the results of the study in a simplified manner. In **Figure 2.2**, the left panel (**a**) shows that half of the outdoor UFP pollution was measured inside classrooms without the use of a HEPA air purifier. On the right panel (**b**) we see that UFP pollution in classrooms was only one tenth of outdoor levels when using a HEPA air purifier.

Similarly, in the *CAMPS* study we summarized and discussed air monitoring data with the CSC. We developed the community report back with guidance from the CSC and additional community members. Development of the report back content included determining what types of figures or tables to present monitoring results. We used focus groups to gather recommendations on the most useful visualizations to include in report back materials for a public audience. We showed participants simple bar graphs, bar graphs with error bars, time series plots, hourly average plots, and tables. Exposure concentrations were compared to the National Ambient Air Quality Standards (NAAQS) to determine whether a community location exceeded a safe level. Other comparative values considered were background air pollution concentrations monitored by the Puget Sound Clean Air Agency (PSCAA). Participants voted on their preferred visualizations and provided their feedback on why they preferred some over others.

Moreover, report back content customization methods can be improved in future community-engaged studies. Potential methods include meeting with community advisory boards, focus groups with all stakeholders including community members, and highlighting priorities identified in a community needs assessment surveys. In addition, pilot testing can be used to learn if the content is understandable and comprehensive.

### 2.3.4 Educational Resources

Report back has several challenges including the uncertainty of the clinical significance of health effects of environmental exposures and receiving exposure measure.[9] This is especially true when measuring emerging air pollutants, such as UFPs, which have not been thoroughly studied. Given that previous research has suggested that almost half of the public's science understanding and learning drives from free-choice learning[31], it is vital to provide educational resources to improving community members understanding of their exposure measure results.

Technical information sources were developed for the *Healthy Air, Healthy Schools* study. Notably, we found that we needed to meet the EHL needs of the community. Considering our participants EHL was important in determining what language, content, figures, and educational materials were necessary for the development of successful report back materials. Consulting with school district administration, we learned of the gap of knowledge about sources of UFPs, infiltration, and potential health effects. To meet the needs of the community we developed a web page with in-depth information about these topics using lay language (**Appendix D**). We developed a variety of figures to illustrate concepts such as infiltration. This web page was also used to provide information in conjunction with the PDF report. The community partner report included hyperlinks to specific portions of the webpage to provide more information to community members who wanted to learn more about a particular topic. Using the linked webpage, we were able to provide different quantities of information, as some community members may want more details about a topic while others are interested in straightforward results.

Moreover, developing educational materials for future community-engaged studies can also be improved. Similar to the development of tailored materials, the content of educational materials can be informed by community advisory boards, focus groups with community members, and knowledge gaps identified in a community needs assessment surveys.

### 2.3.5 Dissemination of Results

Empirically based recommendations from the field of risk communication in public health can also be employed to disseminating results in community-engaged research. These recommendations include ensuring that communication comes from a trusted source and disseminating information in the media through multiple sources.[43] Previous community-engaged air monitoring research has recommended that studies should provide more opportunities for participants to interact with study team members such as hosting multiple meetings in different community locations and times of day.[52] Recommendations for in person meetings included having more time for participants to review results while having study team members available, encouraging notetaking, peer learning, and discussion.[52]

Due to COVID-19 concerns during the *Healthy Air*, *Healthy Schools* study, we held virtual report back meetings over Zoom to present the study findings. We held separate meetings to address the specific goals of our different audiences, including school districts and the UW UFP Advisory Group. Information on air pollution, health effects and mitigation strategies were presented along with study results. Due to the mixed engagement of online meetings, we pivoted to embedding our KAB survey questions into our report back presentation. Survey questions were presented in three languages, English, Spanish and Vietnamese. We found limited attendance of online meetings, which were mostly attended by school administration and teachers. Furthermore, we used a multi-media approach because previous studies have found that using multiple forms of media is more effective than using any single media approach.[43] The report back approach included online report back meetings, PDF reports, and a technical web page.

The report back process for *CAMPS* also entailed holding in-person meetings to present the study findings. We provided community members with copies of the report and reviewed the results as a group. We presented the air monitoring results with a comparison to the NAAQS. The report back letter included information to address knowledge gaps identified in the needs assessment survey results as well as information on air quality standards, air pollution sources, related health effects, guidance on where to find more information, and actionable recommendations to reduce personal exposures. Community members were given the opportunity to ask questions about the results at each in-person report-back meeting. After reviewing the study findings, some participants still had concerns about air pollution in their neighborhoods. Contact information was also included for participants to contact researchers for additional information or to report additional environmental concerns.

Furthermore, the lessons learned in our dissemination activities can be used to improve future community-engaged studies. Guidance from community advisory boards can be utilized to learn about the best ways to effectively communicate with a specific community.

### 2.3.6 Report Back Evaluation

Establishing a causal relationship between community engagement and reduced air pollution or improved health is difficult [53], community-engaged research should include evaluation methods from the beginning planning stages of a study. A mixed-methods evaluation framework can include surveys, focus groups, and interviews. Specific methods can include interviews and focus groups with local stakeholders to learn about the perceptions of community members.[54]

The *Healthy Air, Healthy Schools* study employed report back evaluation methods. We designed the evaluation of report back in consultation with the UW's Interdisciplinary Center for Exposure, Diseases, Genomics, and Environment (EDGE) Community Engagement Core (CEC). The CEC fosters community-engaged research and promotes best practices for meaningful involvement with communities in environmental health research.[55] The evaluation survey (instrument located in **Appendix E**) was developed following a KAB model to determine if participation in the study improved community members knowledge about air pollution, awareness of air pollution in their communities, and promoted actions to reduce exposures. The model theorizes that people acquire information about a behavior, which leads to the development of an attitude (intention) to respond that leads to behavior that is in line with the attitude.[51]

To increase engagement with parents, we adapted the KAB survey questions to an online REDCap survey (**Figure 2.4** shows selected questions). The survey questions included if they have learned about air pollution and if they feel they need to know more information about indoor air pollution, what types of air pollution sources they are concerned about, strategies they use to protect themselves from air pollution, attitudes towards preventing outdoor air pollution from entering their homes or schools, attitude towards improving indoor air quality at schools, attitude and concerns towards using portable air cleaners in schools, and how they would prefer to receive information about the study. The REDCap survey was also available in English, Spanish, and Vietnamese. School administrators distributed the school specific report and evaluation survey via email to all parents, teachers, and staff. We found that repeated outreach by school administration was necessary to increase parent involvement in the study.

In addition, we used Google Analytics Data to examine page views and help us learn if more outreach was necessary and verified that administration was following through with its outreach component. Furthermore, semi-structured interviews were conducted to evaluate the content of the executive summary and to learn more about the barriers and facilitators to using portable air cleaners with HEPA filters in schools. We present the results of these semi-structured interviews in Supplemental Material: Chapter 2B manuscript.

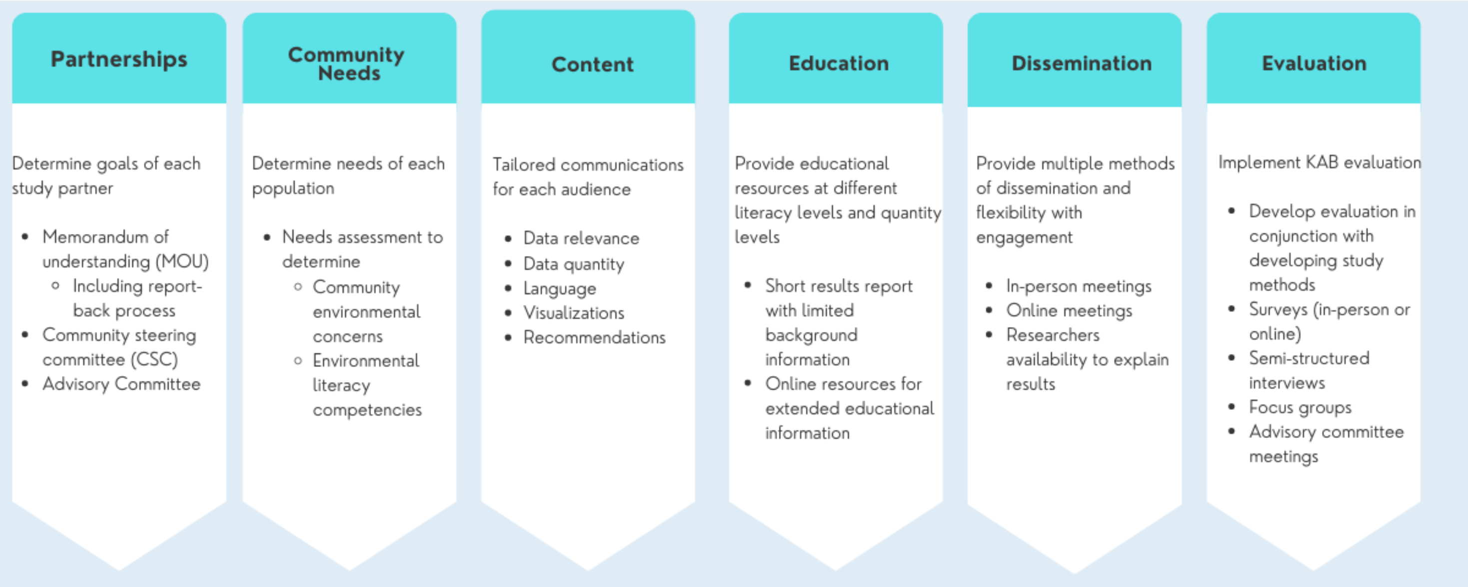
Furthermore, we encountered various challenges in disseminating the results of our pilot study. Given challenges in engagement with our community members we pivoted to using an online survey to understand where community members air pollution knowledge, attitudes on portable air cleaners, and protective behaviors. In **figure 2.5** we present the examples of the survey's knowledge questions. We found that participants did not learn about air pollution from researchers or government websites, indicating that outreach needs to be done through other methods such as community groups or television. We also found there was no clear consensus on needing more information about air pollution. In **figure 2.6** we present the examples of the survey's attitude questions. We found that participants believed portable air cleaners with HEPA filters are effective, but they are concerned with the cost of these instruments.

The findings of the evaluation survey led the research team to develop a study of semi-structured interviews (**Appendix F**) to learn about the barriers of implementing the demonstrated effective intervention of portable air cleaners. The following two papers emerged from this process of community-engaged work. The first paper (Supplemental Material: Chapter 2A) presents the exposure assessment component of the *Healthy Air, Healthy Schools* study. The second paper (Supplemental Material: Chapter 2B) emerged from the engagement process of the *Healthy Air*, *Healthy Schools* study. We used community feedback to determine what to measure in the exposure assessment component of the study and what questions to ask in the interview analysis.

## 2.4 CONCLUSION

The methods discussed in this chapter summarize existing community-engaged research context, processes, and outcomes. Future studies can address limitations encountered in our two case studies to further improve community-engaged methods.

## 2.5 TABLES & FIGURES



**Partnerships**

Determine goals of each study partner

- Memorandum of understanding (MOU)
  - Including report-back process
- Community steering committee (CSC)
- Advisory Committee

**Community Needs**

Determine needs of each population

- Needs assessment to determine
  - Community environmental concerns
  - Environmental literacy competencies

**Content**

Tailored communications for each audience

- Data relevance
- Data quantity
- Language
- Visualizations
- Recommendations

**Education**

Provide educational resources at different literacy levels and quantity levels

- Short results report with limited background information
- Online resources for extended educational information

**Dissemination**

Provide multiple methods of dissemination and flexibility with engagement

- In-person meetings
- Online meetings
- Researchers availability to explain results

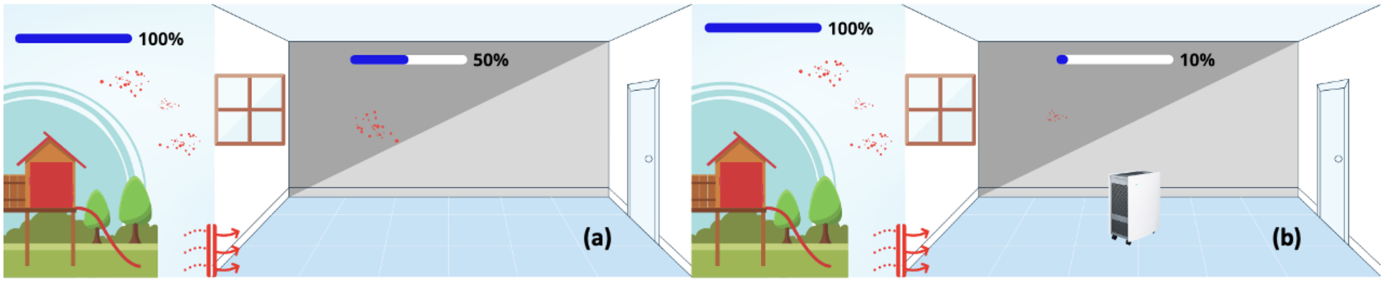
**Evaluation**

Implement KAB evaluation

- Develop evaluation in conjunction with developing study methods
- Surveys (in-person or online)
- Semi-structured interviews
- Focus groups
- Advisory committee meetings

Figure 2.1 Overarching Community-Engagement and Report Back Framework

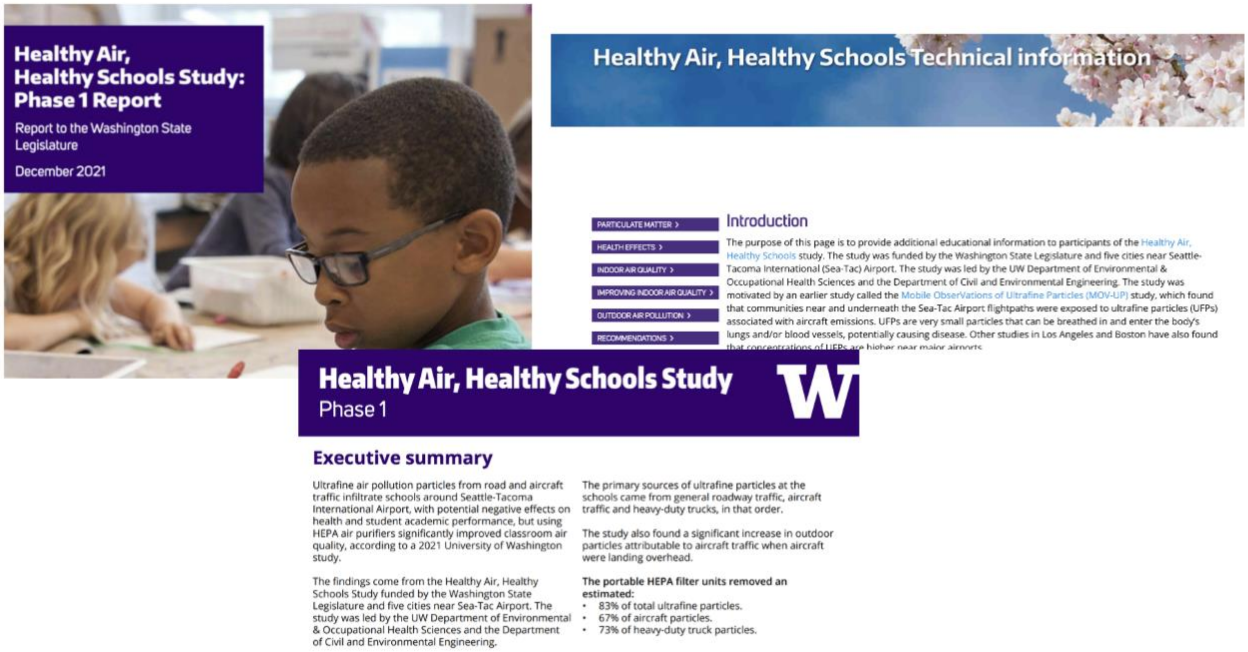
Can indoor air quality improve using a portable HEPA filter?



- About **one-half of all outdoor ultrafine pollution was measured inside classrooms** in five schools near the airport before HEPA air purifiers were installed.

- Measurements after the HEPA units were deployed found that **ultrafine pollution in classrooms dropped to about one-tenth of outdoor levels.**

Figure 2.2 Simplified visualization of *Healthy Air, Healthy Schools* pilot study results



**Healthy Air, Healthy Schools Study: Phase 1 Report**

Report to the Washington State Legislature

December 2021

**Healthy Air, Healthy Schools Technical information**

Introduction

The purpose of this page is to provide additional educational information to participants of the Healthy Air, Healthy Schools study. The study was funded by the Washington State Legislature and five cities near Seattle-Tacoma International (Sea-Tac) Airport. The study was led by the UW Department of Environmental & Occupational Health Sciences and the Department of Civil and Environmental Engineering. The study was motivated by an earlier study called the Mobile ObserVations of Ultrafine Particles (MOV-UP) study, which found that communities near and underneath the Sea-Tac Airport flightpaths were exposed to ultrafine particles (UFPs) associated with aircraft emissions. UFPs are very small particles that can be breathed in and enter the body's lungs and/or blood vessels, potentially causing disease. Other studies in Los Angeles and Boston have also found that concentrations of UFPs are higher near major airports.

**Healthy Air, Healthy Schools Study**

Phase 1

**Executive summary**

Ultrafine air pollution particles from road and aircraft traffic infiltrate schools around Seattle-Tacoma International Airport, with potential negative effects on health and student academic performance, but using HEPA air purifiers significantly improved classroom air quality, according to a 2021 University of Washington study.

The findings come from the Healthy Air, Healthy Schools Study funded by the Washington State Legislature and five cities near Sea-Tac Airport. The study was led by the UW Department of Environmental & Occupational Health Sciences and the Department of Civil and Environmental Engineering.

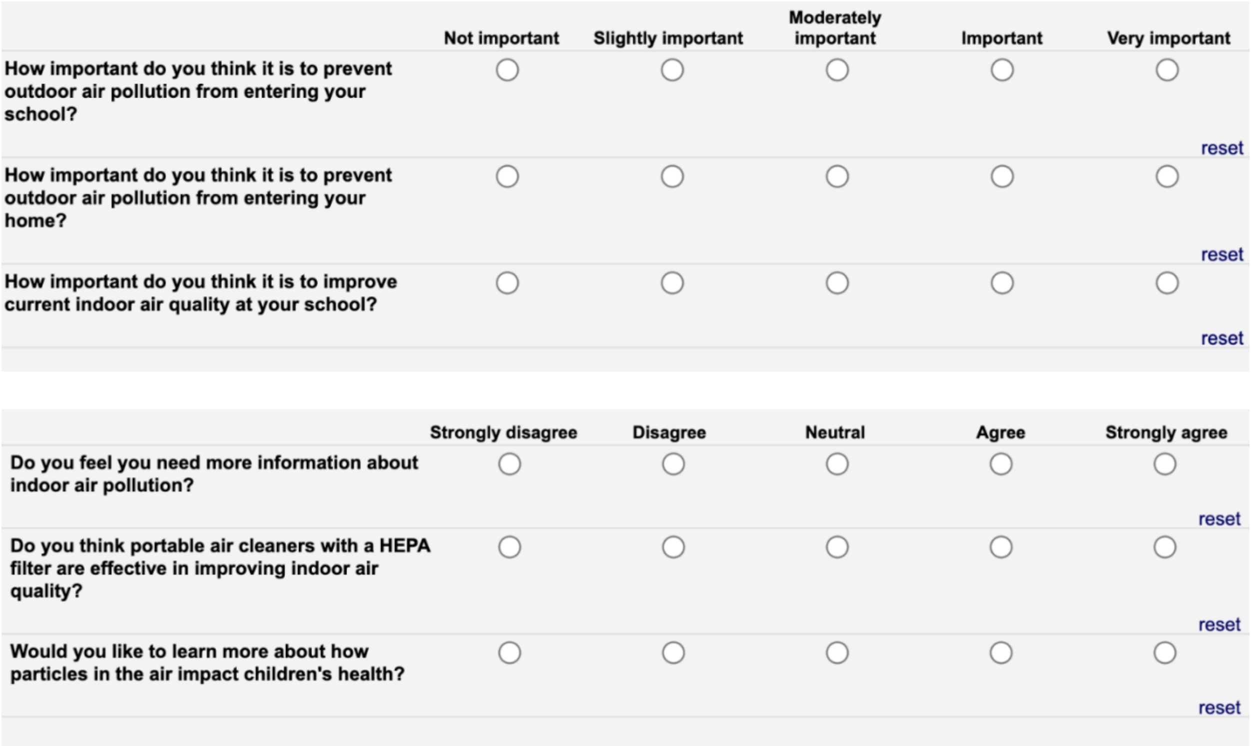
The primary sources of ultrafine particles at the schools came from general roadway traffic, aircraft traffic and heavy-duty trucks, in that order.

The study also found a significant increase in outdoor particles attributable to aircraft traffic when aircraft were landing overhead.

**The portable HEPA filter units removed an estimated:**

- 83% of total ultrafine particles.
- 67% of aircraft particles.
- 73% of heavy-duty truck particles.

Figure 2.3 Tailored report back materials for *Healthy Air, Healthy Schools* study



| | Not important | Slightly important | Moderately important | Important | Very important |
|---|---|---|---|---|---|
| **How important do you think it is to prevent outdoor air pollution from entering your school?** | ○ | ○ | ○ | ○ | ○<br>reset |
| **How important do you think it is to prevent outdoor air pollution from entering your home?** | ○ | ○ | ○ | ○ | ○<br>reset |
| **How important do you think it is to improve current indoor air quality at your school?** | ○ | ○ | ○ | ○ | ○<br>reset |

| | Strongly disagree | Disagree | Neutral | Agree | Strongly agree |
|---|---|---|---|---|---|
| **Do you feel you need more information about indoor air pollution?** | ○ | ○ | ○ | ○ | ○<br>reset |
| **Do you think portable air cleaners with a HEPA filter are effective in improving indoor air quality?** | ○ | ○ | ○ | ○ | ○<br>reset |
| **Would you like to learn more about how particles in the air impact children's health?** | ○ | ○ | ○ | ○ | ○<br>reset |

Figure 2.4 Selected *Healthy Air, Healthy Schools* report back REDCap survey questions

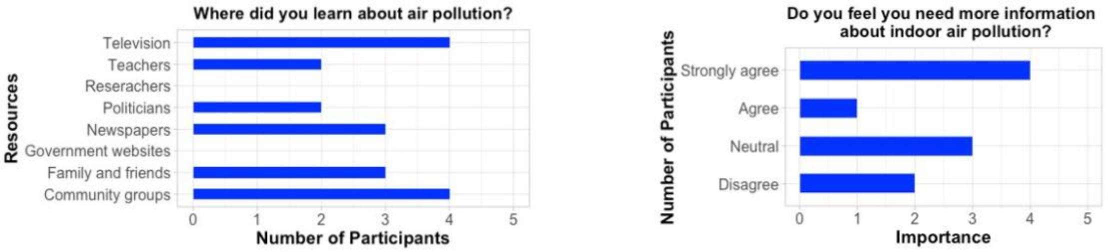


Figure 2.5 Evaluation of air pollution knowledge in *Healthy Air, Healthy Schools* study

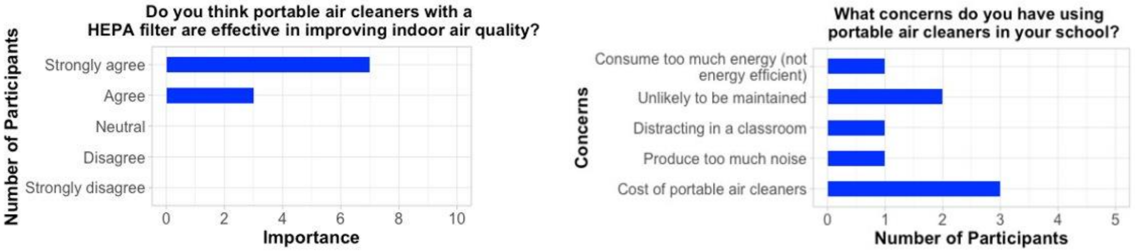


Figure 2.6 Evaluation of portable air cleaner attitudes in *Healthy Air, Healthy Schools* study

## 2.6 Supplemental Material

# Chapter 2A. Indoor Air Quality Intervention in Schools: Effectiveness of a Portable HEPA Filter Deployment in Five Schools Impacted by Roadway and Aircraft Pollution Sources

This chapter was published in the journal *Atmosphere* and is licensed under a CC-BY license.

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## 2A.1 ABSTRACT

The Healthy Air, Healthy Schools Study was established to better understand the impact of ultrafine particles (UFPs) on indoor air quality in communities surrounding Seattle-Tacoma (Sea-Tac) International Airport. The study team took multipollutant measurements of indoor and outdoor air pollution at five participating school locations to estimate infiltration indoors. The schools participating in this project were located within a 7-mile radius of Sea-Tac International

Airport and within 0.5 mile of an active flight path. Based on experimental measures in an unoccupied classroom, infiltration rates of a) UFPs of aircraft origin, b) UFPs of traffic origin, and c) wildfire smoke or other outdoor pollutants were characterized before and after the introduction of a portable high-efficiency particulate air (HEPA) filter intervention. The portable HEPA cleaners were an effective short-term intervention to improve the air quality in classroom environments, reducing the UFP count concentration from one-half to approximately one-tenth of that measured outside. This study is unique in focusing on UFPs in schools and demonstrating that UFPs measured in classroom spaces are primarily of outdoor origin. Although existing research suggests that reducing particulate matter in homes can significantly improve asthma outcomes, further investigation is necessary to establish the benefits to student health and academic performance of reducing UFP exposures in schools.

**Keywords:** indoor air quality; schools; portable air cleaners; aircraft pollution sources

## 2A.2 INTRODUCTION

Given that people spend 85% to 90% of their time indoors, the quality of indoor air is likely to have a significant impact on health, even though it is outdoor air that is regulated.[56] Increasing evidence has highlighted the health impacts of traffic-related outdoor air pollutants, including ultrafine particles (UFPs), on communities living in proximity to aircraft descent paths within the United States and internationally. The recently completed Mobile Observations of Ultrafine Particles (MOV-UP) study in King County, Washington, identified a clear, aircraft-associated footprint of UFPs under flight paths. Monitoring campaigns conducted in communities near airports in Seattle,[57,58] Los Angeles,[59–62] Atlanta,[63] Boston,[62] New York,[64] and Amsterdam[65] have all identified elevated levels of total UFPs in proximity to international airports. This work has also highlighted differences in the pollutant mixtures between aircraft and roadway traffic sources, [61,64,66,67] as well as differences in fuel-based emissions of UFPs from aircraft and roadway traffic sources.[57,68]

Even though the spatial distribution of UFPs is still relatively unknown, minority and low socioeconomic status (SES) communities are often located closer to many UFP sources. A recent study in Boston, MA found that block group-level indicators of race/ethnicity and SES were related to the distribution of outdoor UFP concentrations.[69] Children are thought to be especially vulnerable to exposure to air pollution due to their higher ventilation rate and pulmonary surface area to body mass ratios, and relatively immature immune and respiratory systems.[70,71] A European review of UFP exposures in children suggests that the greatest predictors of high exposure in children were proximity to heavy traffic or proximity to cooking and cleaning activities.[72] School settings have been identified as priority environments for interventions to improve air quality, particularly in response to extreme events such as wildfires.[73] Portable air cleaners with HEPA filters may improve indoor air quality by removing particulates from the air. [74] Previous efforts to evaluate the impact of interventions to remove air pollutants in indoor spaces are limited and generally focused on residential environments.[75,76]

The purpose of this proof-of-concept study is to assess the potential effectiveness of a portable HEPA intervention in reducing aircraft, traffic, and diesel-related exposures in highly impacted schools. We hypothesized that HEPA air cleaners would significantly reduce UFP and black carbon (BC) concentrations in classrooms and could provide solutions to reduce disparities in exposure within a metropolitan region. The present work is the first effort to examine the concentrations of indoor and outdoor UFP levels and the UFP removal efficiency of HEPA filters in schools located in airport communities.

## 2A.3 MATERIALS AND METHODS

### 2A.3.1 Study Area and Study Design

Seattle-Tacoma International (Sea-Tac) Airport lies about 13 miles (~21 km) south of downtown Seattle, but several smaller cities such as SeaTac, Burien, Des Moines, and Normandy Park surround the airport. UFP levels have been found to be elevated near large airports and have different compositions and sizes than those from road traffic.[77] Puget Sound's high population density makes this an important public health concern, particularly for sensitive populations such as children.

Monitoring sites within the Federal Way and Highline School Districts were selected by the University of Washington research team with guidance from the Federal Way and Highline Public Schools partners. These school districts are particularly impacted by roadway and aircraft traffic. Five schools in the Sea-Tac Airport flight path were selected to evaluate the impact of airport traffic. Figure 1 shows the locations of participating schools with an overlay of Sea-Tac Airport 10-mile radius. The participating school buildings represent a variety of air handling designs and building ages. Infiltration of outdoor air pollution into classrooms was measured under normal operating conditions before and after deploying HEPA filters. Air monitoring took take place in spring and summer of 2021.

For each school, we computed the total count of 2019 flights that flew overhead within a one-mile radius of the school. The 2019 flight tracking data were used as a representative of normal conditions not impacted by COVID-19 pandemic flight reductions and were obtained from the Federal Aviation Administration through a Freedom of Information Request. School coordinates were obtained from the Washington Geospatial Open Data Portal from which the dataset contained all Washington State public schools for schools listed in 2021–2022 on the

Washington State Office of Superintendent of Public Instruction (OSPI) School Directory. Data on flight counts per school were computed individually for the arrivals and departures of Sea-Tac Airport, Boeing Field (BFI), and Renton Municipal Airport (RNT) as well as the total overall flight counts from all three airports. Flights were counted if they were less than 750 meters in altitude and within one mile of the school location. We performed the graphical representation of the data using the leaflet library in R and presented the flight counts as values of radius in logarithmic scale.[78]

### 2A.3.2 Portable Air Cleaner Selection

The portable air cleaner used in this study was the Blueair model 605 portable air cleaner with a HEPA-rated filter. Each device is evaluated by the Association of Home Appliance Manufacturers (AHAM) Institute to ensure it can provide a clean air delivery rate (CADR) for smoke and dust and supply adequate filtration for large spaces (~800 square feet). This device is expected to provide adequate filtration over a six-month period before a filter change is necessary and a HEPA filter with 99.9% efficiency at capturing ultrafine and fine particles, including those originating from wildfire smoke. The noise level is between 33 and 62 dB(A), depending on the fan speed setting. The portable air cleaner was placed in the center of the classroom away from walls and corners. The upright HEPA filter was placed on the floor of each classroom where its filtered air outlet was approximately 24” above the floor. Figure 2a shows the portable air cleaner placement in the center of an unoccupied classroom. The HEPA filter was set to “3” its highest flow rate at 500 cubic feet per minute (CFM).

### 2A.3.3 School Site Selection

Sites were selected in consultation with school district partners to represent a range of building ages as well as proximity to flight paths and roadway traffic. All school sites selected were within 0.5 mile of an active flight path serving Sea-Tac Airport and within a 7-mile radius of the airport (see Figure 1). The classrooms where monitoring occurred were selected by school staff to be representative of the school or a particular part of the building in addition to being vacant of students at the time of our sampling. Characteristics of the monitored classrooms are shown in Table 1. Classroom ventilation varied by building, with some having central ventilation and other using room-specific ventilation units. All school classrooms, except School A 2nd floor, were located on the ground floor.

### 2A.3.4. Outdoor Air Exchange Rate

The outdoor air exchange rate (AER) was measured in the first 2 to 3 hours of each 48-hour site visit. This measure of air exchange reflects the exchange of air between the indoor and outdoor space and is a component of total air exchange rate that also includes recirculation through the HVAC filter system. Since our primary interest was in the movement of outdoor air into indoor spaces, we focused on the measurement of outdoor AER in this project. We followed the protocol developed by the Harvard University T.H. Chan School of Public Health's Healthy Buildings Program.[79] Since we were able to conduct our measurements in unoccupied buildings, we used the $CO_2$ decay method to determine the air exchange rate from among the options presented in the Harvard Healthy Buildings Program guide. The Harvard Healthy Buildings Program method involves elevating the $CO_2$ concentration in the test classroom and then measuring the declining $CO_2$ concentration over time to enable determination of the decay rate.

Dry ice was used to elevate the inside concentration of $CO_2$. A tray was filled with dry ice and two box fans operated in the room to thoroughly mix the $CO_2$ as the concentration increased. With $CO_2$ elevated to four times or more the background level, the dry ice was removed from the room and the mixing fans shut off to begin the decay of $CO_2$ concentration while the field technician exited the classroom. Figure 2b shows the air exchange experimental setup in a classroom.

Two $CO_2$ analyzers were used to characterize $CO_2$ concentration, one inlet near the center of the room and the other close to the windows along an outside wall of the classroom. Uniformity of $CO_2$ concentration within the room was tracked over time, and with equivalent or very similar levels determined from the two monitors, we could then average the concurrent results as being representative for the entire room. The rate of decay without $CO_2$ sources in the room is based on air exchange from (1) infiltration of air from the outside, and (2) the active ventilation system in the building. An adequate time series of $CO_2$ decay is attained once the concentration drops to about one-third of the starting elevated level. The $CO_2$ data from the time at which sources are removed and the decline begins, through the time at which ventilation characteristics are altered by opening doors or people reentering the room, define the decay rate of $CO_2$, used to determine the air exchange rate. The measured in-room $CO_2$ minus the ambient outdoor $CO_2$ concentration is the quantity of interest to use in determining the air exchange rate. We used a dynamic mass balance model (Equation (1)) to calculate the outdoor exchange rate:

$$(C_{classroom})_t = C_{indoor_{background}} + A_0 * \exp(-\mathrm{k} * \Delta \mathrm{t}) \qquad (1)$$

where $C_{classroom}$ is the concentration within the classroom at time $t$; $C_{indoor_{background}}$ is the initial indoor concentration; $k$ is the deposition rate; and $\Delta t$ is the study sample period. $A_0$ is defined as $C_{peak} - C_{indoor_{background}}$. The dynamic model accounts for $CO_2$ moving in and out of an indoor microenvironment. The model assumed that there were no indoor sources, perfect mixing and no mass loss or gain due to differences in gas-phase concentrations or temperature and relative humidity conditions between indoors and outdoors.[79]

### 2A.3.5. Air Quality Sampling and Analysis Methods

Indoor and outdoor concentrations of selected air pollutants were measured over two consecutive 24-hour time intervals concurrent with the outdoor air exchange rate measurements. The air pollutant measurements conducted for this pilot scale study were designed to accomplish three inter-related objectives: (1) determine the outdoor air exchange rate, (2) characterize the indoor pollutant concentrations and the outdoor ambient air pollutant concentrations and (3) assess the effectiveness of installing a portable air cleaner in the test classroom. The instruments used to measure the pollutants of interest are presented in Table 2. The UFP instruments provide a number count concentration, not a mass concentration measurement. The BC devices use a light absorption method to estimate the mass concentration of BC particles captured on an internal filter material. Figure 2c shows a picture of the instruments arranged in a classroom.

Classrooms were assessed twice with this research-grade sampling methodology. For most visits, a solenoid timer valve was set to alternate 5-minute indoor and outdoor measurements with results stored with a 10-second time resolution. We trimmed the first two minutes of each 5-minute NanoScan sample to account for potential mixing of indoor and outdoor air within the same one-minute scan, following the switch of the valve position between the two inlet locations.

An inlet line to sample ambient air outside the classroom was installed using a slightly open window that was then backfilled with shim material and sealed with duct tape, or by use of an available conduit to the outside from within the classroom. At the first three classroom deployments, separate instruments were used for the indoor and outdoor air sampling, but from the fourth site visit starting in June 2021, a timer and valve switch mechanism was used to alternate the inlet to the monitoring instruments between an indoor and outdoor location every 5 minutes (e.g., timer switched the valve at hh:00:00, hh:05:00, hh:10:00, etc.). Figure 3 illustrates the configuration of instruments for indoor and outdoor air sampling using the switch valve.

### 2A.3.6. Estimating Average Infiltration

Each school site was visited on two occasions over the measurement period of this project. At each visit, indoor and outdoor air quality was measured for 24 hours prior to a portable HEPA intervention and 24 hours after a HEPA filter intervention. These data provided the basis for estimating the average infiltration rate of particles into the indoor space. Average infiltration (see Equation (2)) was calculated from 30-minute averages of indoor and outdoor count concentrations and the ratio was defined as infiltration. This required an assumption that the pollutants measured indoors were attributable to outdoor sources [80].

$$\text{Infiltration} = \frac{\text{Pollutant}_{\text{indoor}}}{\text{Pollutant}_{\text{outdoor}}} \tag{2}$$

Removal effectiveness for the HEPA filter was calculated according to Equation (3) across the mean observations of our study [81].

$$\text{Effectiveness} = 1 - \frac{\text{Infiltration}_{\text{HEPA}}}{\text{Infiltration}_{\text{noHEPA}}} \tag{3}$$

### 2A.3.7. Statistical Analysis

We also estimated the percent removal of the HEPA cleaner using a regression approach. A log-log multivariate linear model regressed the indoor concentration of particles to a 30-minute outdoor lagged concentration (see Equation (4)).

$$\log(\mathrm{Pollutant}_{\mathrm{indoor}}) = \log\,(\mathrm{Pollutant}_{\mathrm{lagged\ outdoor}}) + \mathrm{HEPA} + \mathrm{School} \qquad (4)$$

A 30-minute lag was selected based on time series data indicating a lag between outdoor peaks and subsequent indoor peaks. A school-specific adjustment was used to account for differences between schools, and a term indicating the presence of HEPA filter or not was included. Based on the coefficient estimated for the HEPA term, the removal effectiveness for the HEPA filter was calculated (according to Equation (3) above) across the mean observations of our study. The log-log model (see Equation (4)) was used to predict the concentration of particles in indoor air when outdoor concentrations were assumed to be 5000 particles/cc which was the median in our dataset. Confidence intervals were generated based on propagating the error terms from the regression output.

We conducted a two-sample Wilcoxon Rank Sum test to determine if the infiltration before the HEPA filter intervention was significantly higher than after the intervention ($p < 0.5$). We also calculated Pearson's Correlation Coefficient to better understand the relationship between infiltration with and without the HEPA filter.

All analyses were conducted in R version 4.1.1. Packages used for analysis and output of results included data.table [82], ggplot2 [83], emmeans [84], zoo [85], psych [86], GPArotation [87] and dplyr.[88]

## 2A.4. RESULTS

The dates of sampling in the Federal Way and Highline schools are presented in Table 3, along with the flight direction of aircraft at Sea-Tac Airport relative to the school location.

Over the course of these deployments, 10-second data were collected both inside and outside the school using the instruments and measurement protocols described in the Methods section. This allowed for detailed information on $CO_2$, BC, and particle size to be characterized. The TSI NanoScan instrument occasionally would develop operating errors over the course of the sampling. Table 4 presents a summary of the percentage of time the NanoScan instrument produced errors during the school deployments. For time periods when the NanoScan data were not available, the TSI condensation particle counter (CPC) instrument measurements were substituted for the total concentration of particles (CPC does not measure multiple size ranges like the NanoScan). CPC data were not used to determine pollutant source.

Outdoor exchange rates were calculated using the $CO_2$ decay method described above. Overall, the outdoor air exchange rates ranged from 0.6/h to 4.4/h, highlighting the variability in direct exchange of air with the outdoors at the different school sites (Table 5).

### 2A.4.1. Outdoor Concentration

The outdoor concentration observed at each of the five schools represents only four days of non-concurrent sampling. It is therefore difficult to directly compare the concentration of particles across the locations. Although there were distinct differences in total pollutant concentration at the different sites, these differences are likely not representative of the year-round average differences at these sites. However, the indoor and outdoor monitoring allowed for the comparison of the infiltration dynamics over time (Figure 4).

### 2A.4.2. Observed Impact of HEPA Filter

The impact of the HEPA filter was evaluated by analyzing the relationship between the indoor and outdoor concentrations of pollutants measured over the course of deployment. In

Figure 4, visual inspection suggests an effect from the use of the portable HEPA filter for both UFP and BC. The ratio of indoor-to-outdoor air pollution was calculated for each pollutant in order to assess the impact of the HEPA filter. The HEPA filter removed many of the pollutants that caused a spike due to infiltration when the HEPA filter was not present. Figure S1 (Supplementary Information) shows the change in the indoor-to-outdoor ratio of UFP measured at each visit, before and after the portable HEPA filter deployment.

Combining the data across all school locations, we found a significant reduction in pollutants after the HEPA filter deployment. Table 6 presents the estimated infiltration rates with and without portable HEPA filter deployment as well as the associated confidence intervals for all estimated values.

The total particle number (general traffic), particles of aircraft origin (d = 15.4 nm), and BC all decreased substantially after the HEPA filter deployment. Before the HEPA filter deployment, approximately half of all outdoor particles were measured indoors. After the HEPA filter deployment, approximately 1/10th of all outdoor UFP were measured indoors. The removal of outdoor particles infiltrating into the indoor space attributed to the portable HEPA filter is estimated to be 83% removal for UFP, 67% removal for aircraft particles, and 73% removal for heavy-duty traffic particles. This represents a removal percent of 83% for particles of outdoor origin (Equation (3)). The estimated median removal indoors is moderately significant among particle types, suggesting that the HEPA filter intervention is effective for all outdoor particle air pollutants, including those of aircraft, wildfire, and roadway origin.

We conducted a two-sample Wilcoxon Rank Sum test to better understand the relationship between infiltration and the HEPA filter intervention. A two-sample Wilcoxon Rank Sum test confirmed that the infiltration before the HEPA filter intervention was significantly higher than after the intervention ($p < 0.5$), for each of the three particle sources (Figure 5).

We also calculated Pearson's Correlation Coefficient to better understand the relationship between infiltration with and without the HEPA filter. We found that, without the HEPA filter, there was a 40% correlation (moderate) between the indoor and outdoor measures. When the HEPA filter was deployed, there was a 9% correlation (weak) between the indoor and outdoor measures. We also found that this relationship between indoor and outdoor air quality persisted for up to 60 minutes after the HEPA filter was turned off, but that there was no observable correlation between indoor and outdoor when the HEPA filter was deployed. This can be observed in Figure 4 where the indoor concentration closely follows the change in outdoor concentration before the introduction of the HEPA filter (moderate correlation). After the introduction of the HEPA filter, there is no obvious relationship between the change in outdoor concentration and the change in indoor concentration.

### 2A.4.3. Modeled Impact of HEPA Filter

In order to better understand the overall impact of HEPA filtration, we developed a regression model to predict indoor concentration based on the school location, use of a HEPA filter, and average outdoor concentration over the previous 30 minutes (Equation (4)). This model assumed that the indoor concentration represented a fraction of the outdoor concentration (log-log model). We then predicted the average indoor air quality concentration at each school, for a fixed outdoor concentration of 5000 #/cc with and without the HEPA filter intervention. We saw a statistically significant decrease in indoor air quality in all the schools, with School A having the highest infiltration rates with and without the HEPA filter intervention (Figure 6).

School E was not included in the model as there were multiple indoor concentration values of zero observed after the HEPA filter deployment, making it impossible to include this location in the log-log model.

Overall, we estimated that the HEPA filter effectiveness was 71% [95% CI: 70–72%] across the measurement conditions, after accounting for school-specific differences. This regression result is consistent with the result observed when calculating HEPA filter effectiveness using the ratio of indoor-to-outdoor pollutants (Figure 6). We found that the prevention of infiltration varied between schools. In the next phase this model will be further expanded to include information on building age and ventilation type.

### 2A.4.4. Overall Distribution of Pollutants

We found that prior to HEPA filter deployment, outdoor concentrations of UFPs, ultra-UFs, and BC are substantially higher than those measured indoors. This is consistent for all measured particulate pollutants. We consistently find that the total indoor concentrations are lower after the HEPA filter deployment, as shown below. Consistent with the findings of this paper that the portable HEPA filter has a significant impact on indoor air quality, we observed a reduction in the pollution from outdoor sources persisting in the classroom environment (Figure 7). The indoor/outdoor ratio also varied by school location. In Figure 8, we present the results of the observed 30-minute indoor/outdoor ratios at each school location. Consistently, there are lower ratios after the HEPA filter deployment, but the magnitude of this change varies by school.

### 2A.4.5. Spatial Distribution of Flightpaths

This study team was particularly interested in determining the potential removal of UFPs in airport communities. King County schools had a median of 154.5 nearby flights, with 102.5 nearby arrivals and 35 nearby departures (Table 7). Nearby flights were defined as flights below 750 meters and within a one-mile radius of a school.

Schools participating in the present study had significantly more nearby flights, nearly all of them associated with Sea-Tac Airport. Participating schools had a median of 61,240 nearby arrivals and 53,547 nearby departures in 2019 (Table 8). We found that the schools participating in the study were substantially impacted by aircraft emissions from overhead flights when compared to the average school in King County.

Figure 9 illustrates the number of arrivals and departures from Sea-Tac Airport and regional airports. The spatial distribution of departures is more closely centered south of SeaTac while arrivals extend north of SeaTac.

## 2A.5 DISCUSSION

This pilot study aimed to determine whether HEPA units are a feasible intervention to reduce aircraft UFP exposures in a school setting. Measurements in the present study were only conducted over a total of four days in each classroom, it would be informative to continue longer-term monitoring to better understand the impact of UFPs across this area. UFPs are not routinely measured in the outdoor environment by air quality agencies across the United States. Because of the lack of health-based regulatory standards as well as limited long-term monitoring data, it is difficult to compare the magnitude of the outdoor concentrations observed in this study to typical outdoor concentrations.

However, in recent years, there have been special studies in Pittsburgh, the Netherlands, New York, Montreal, Seattle, and Los Angeles that confirm UFPs are elevated near roadways, near industrial sites, in urban cores, and in proximity to flight paths.[57,89–91] There are strong gradients of exposure to UFPs observed in these studies, with UFPs decreasing to background levels within 100 meters of sources.

To inventory available regulatory UFP monitoring data, we searched the EPA Air Quality System (AQS) database and contacted select local air quality agencies across the US. We found some form of UFP monitoring data near Baltimore, Miami, New York, Saint Paul, Pittsburgh, Los Angeles, and Seattle. In general, these special studies were either designed as short-term mobile monitoring studies or snapshot designs, where monitors were rotated among fixed sites for a year or less.[57,92–95] The New York State Department of Environmental Conservation (DEC) collected one-minute UFP count data across seven sites in New York State over the year 2017 at near-road, urban, suburban, and state park locations. The dataset clearly demonstrates UFP gradients away from roadways, with a site located directly next to a freeway in Queens, NY, reporting 1.5 to 2 times greater concentrations of UFPs than a site located only 300 m downwind of the road.

A study in Boston, MA, looked at the infiltration of aircraft related UFP into residential buildings in proximity to flight paths.[60] Hudda et al. found that median outdoor concentrations of UFP were 19,000 #/cc when the residence was downwind of the flight path and 10,000 #/cc during other wind conditions. The authors also found significant infiltration of aircraft particles into local residences and calculated a 33% decrease in indoor concentration after a portable HEPA filter was installed. A decrease in aircraft particles is consistent with the findings of this study, although HEPA filter effectiveness and infiltration rates were not calculated in the Boston project.

### 2A.5.1 UFP Infiltration

Few studies have examined UFP levels in the classroom environment. Unlike our present study which measured UFPs in an unoccupied classroom, Mullen et al. measured UFPs during normal occupancy. Mullen et al. measured particle number (PN) concentrations inside and outside six classrooms in northern California and found that exposures appeared to be primarily attributed to outdoor sources.[96] Weichenthal et al. characterized UFP counts in 37 occupied classrooms in rural Ontario during winter and developed a model to predict exposures based on ambient weather conditions, classroom characteristics, and outdoor UFPs.[97] The study found that windspeed and outdoor UFPs were important determinants of classroom UFP levels. Weichenthal et al. found that predictive models based on outdoor UFP data perform reasonably well in estimating classroom UFP counts when indoor UFP sources were not present.[97]

There are also a limited number of studies examining the infiltration of outdoor particles into the indoor environment of schools. Infiltration of outdoor particles into the indoor environment has been assessed in Barcelona schools. Rivas et al. assessed infiltration of traffic related emissions including UFPs and found that the median indoor/outdoor ratio $\leq 1$ indicating that the outdoor traffic related sources contributed to indoor concentrations.[98] Infiltration factors have also been found to be different based on sources, with traffic components having indoor/outdoor ratios of 0.31–0.75 in the cold season and 0.50–0.92 in the warm season. However, building age and window material were not found to be a major determinant of indoor pollutant concentrations.

### 2A.5.2 HEPA Filtration Intervention

In the Healthy Air, Healthy Schools Phase 1 project, we estimated that HEPA filtration resulted in 70% to 80% lower UFPs as compared to no additional filtration. This result is consistent with the findings from Boston. Recent controlled interventions have established improvements in symptoms of children with asthma after a HEPA filter intervention in their homes.[99–102] These studies also show consistent improvement in the indoor air quality of these homes after HEPA filter intervention. However, none of these studies directly evaluated UFPs, the primary pollutant of interest in this study, instead focusing on the $PM_{2.5}$ fraction of air pollution.

Studies evaluating the impact of HEPA filtration in school settings are limited. Nine studies were identified that assessed portable air filters in a classroom environment. However, these studies investigating the potential benefit of portable air cleaners with HEPA filters in classrooms have not measured infiltration of UFPs[103,103–112]. Yang et al. conducted a double-blind crossover study investigating the pulmonary benefits of a HEPA air purifier intervention in 125 school children in China.[104] The study found that the intervention was associated with a decrease in runny nose, FeNO, and markers of systemic inflammation.[104]

A randomized crossover study of HEPA filtration, without a washout period, in 23 homes of low-income Puerto Ricans in Boston and Chelsea, MA, concluded that a portable HEPA filter intervention significantly improved of indoor air quality.[113] Median UFP concentration when using HEPA filtration was 50% to 85% lower compared to no filtration in most homes.

Existing literature supports the notion that in-class performance of students is directly impacted by the air pollution level at their school. In Los Angeles, researchers studied how changes in ambient air pollution concentrations affected the performance of second- through sixth-grade students on standardized tests between 2002 and 2008.[114] Comparisons were made between different cohorts within the same school to account for differences between schools, including differences in outdoor pollution, socioeconomic status of students and other factors that vary between schools. Researchers found that lower concentrations of daily outdoor particulate matter significantly increased mathematics and reading test scores. Similar associations between test scores and short-term air pollution concentrations have been observed nationally and internationally.

The findings of Phase 1 of the Healthy Air, Healthy Schools Project are consistent with existing literature demonstrating that HEPA filter interventions reduce exposure to outdoor pollutants in indoor spaces. This study is unique in focusing on UFPs in school settings and demonstrating through multivariate methods that the UFPs measured in the classroom space are primarily of outdoor origin. Although existing research suggests that improvements to indoor air quality in homes can significantly improve asthma outcomes, further investigation is necessary to establish the benefits to student health and academic performance of improved air quality in schools.

## 2A.6. CONCLUSIONS

Indoor air quality in schools is significantly impacted by outdoor sources of UFPs. Portable HEPA filters can substantially reduce the concentration of outdoor pollution in the classroom. Using portable HEPA filter units reduced indoor concentrations of UFPs by approximately 70%. Schools that are near truck routes, aircraft flight paths, and high-traffic roadways are at higher risk of indoor air pollution. Landing aircraft contribute significantly to indoor and outdoor UFP concentrations in this study region. Portable HEPA filter units can be effectively used in the short term to decrease air pollution in classrooms by removing particles. Ventilation changes and building-level remediations such as sealing gaps and managing doorways should be investigated as an approach to reduce infiltration of outdoor particles indoors. The next phase of the project will evaluate the (1) optimal usage of HEPA filter units to balance energy usage and air quality management, (2) health and well-being benefits of reduced UFP concentrations indoors, and (3) methodologies to identify schools at higher risk UFP impacts.

**Supplementary Materials:** The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/atmos13101623/s1, Figure S1: Ratio of indoor to outdoor particle count concentration at all school visits.

**Author Contributions:** Conceptualization, E.A.; methodology, E.A.; software, N.C., E.R. and E.A.; validation, E.A.; formal analysis, N.C., E.R. and E.A.; investigation, T.R.G.; resources, J.H.S.; data curation, N.C., T.R.G., E.R. and E.A.; writing—original draft preparation, N.C., E.R. and E.A.; writing—review and editing, N.C., E.S., T.R.G., J.H.S., B.C., L.H., T.V.L. and E.A.; visualization, N.C., E.R. and E.A.; supervision, E.A.; project administration, J.H.S.; funding acquisition, E.A. All authors have read and agreed to the published version of the manuscript.

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**Data Availability Statement:** All data produced in the present study are available upon reasonable request from the authors.

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**Conflicts of Interest:** The authors declare no conflict of interest.

| Abbreviations | |
|---|---|
| AER | Air exchange rate |
| AHAM | Association of Home Appliance Manufacturers |
| AQS | Air Quality System |
| BC | Black carbon |
| BFI | Boeing Field |
| CADR | Clean air delivery rate |
| CFM | Cubic feet per minute |
| CPC | Condensation particle counter |
| FeNO | Fractional exhaled nitric oxide |
| HEPA | High-efficiency particulate air filter |
| MOV-UP | Mobile Observations of Ultrafine Particles |
| OSPI | Office of Superintendent of Public Instruction |
| RNT | Renton Municipal Airport |
| Sea-Tac | Seattle-Tacoma International Airport |
| SES | Socioeconomic |
| UFPs | Ultrafine particles |
| Ultra-UFPs | Ultra-ultrafine particles |

## 2A. TABLES & FIGURES

**Table 1.** School classroom dimension and volume.

| School | Distance From Airport | Room Area, Full Dimensions (ft) † | Ceiling Height (ft) | Room Volume (ft$^3$) | Room Volume (m$^3$) |
|---|---|---|---|---|---|
| **School A 1st flr.** | 1.5 miles | 30.2 × 29.2 | 9.9 | 8725.3 | 247.1 |
| **School A 2nd flr.** | 1.5 miles | 35.0 × 28.0 | 9.9 | 9227.5 | 261.3 |
| **School B** | 2.1 miles | 32.0 × 28.7 | 9.3 to 12.9 ‡ | 10,053.7 | 284.7 |
| **School C** | 7.2 miles | 31.8 × 26.5 | 10.4 | 8750.3 | 247.8 |
| **School D** | 0.5 miles | 31.7 × 23.1 | 9.1 | 6574.7 | 186.2 |
| **School E** | 5.3 miles | 32.0 × 30.0 | 8.2 | 7840 | 222.0 |

† Some classrooms have walled-off corner sections so are not fully rectangular. ‡ Sloping ceiling, minimum height near windows and maximum by interior hallway.

**Table 2.** Air quality instruments used to measure conditions in classroom and ambient air.

| Parameter | Instrument | Manufacturer | Averaging Time |
|---|---|---|---|
| $CO_2$ | LI-850 $CO_2$ | Li-Cor Biosciences | 10 s |
| Ultra-fine particle size distribution | NanoScan | TSI, Inc. | 1 min (full scan) |
| Particles > 10 nm count | CPC | TSI, Inc. | 10 s |
| Particles > 20 nm count | P-Trak | TSI, Inc. | 10 s |
| Black carbon | MA200 | AethLabs | 10 s |
| Black carbon | AE51 | AethLabs | 10 s |
| Temperature, RH | Hobo sensor | Onset Computer Corp. | 10 s |

**Table 3.** School classroom visit dates and aircraft operations at school location.

| School and Room | First Visit | Sea-Tac Flight Operations | Second Visit | Sea-Tac Flight Operations |
|---|---|---|---|---|
| School A 1st flr. | June 9–11 | Landing | July 26–28 | Takeoff |
| School A 2nd flr. | June 14–16 | Landing 14th and 15th<br>Takeoff 16th | July 28–30 | Take off |
| School B | April 14–16 | Takeoff | July 20–22 | Landing 20th and 21st<br>Takeoff 22nd |
| School C | April 7–9 | Takeoff | July 13–15 | Takeoff |
| School D | June 22–24 | Takeoff | August 10–12 | Landing |
| School E | March 24–26 | Takeoff 24th and 26th<br>Landing 25th | July 7–9 | Takeoff |

**Table 4.** Percentage of missing or error flagged data.

| Location | Percent Instrument Error (%) |
|---|---|
| School A Classroom 1, Visit 1 | 0 |
| School A Classroom 1, Visit 2 | 43 |
| School A Classroom 2, Visit 1 | 0 |
| School A Classroom 2, Visit 2 | 33 |
| School B Visit 1 | 0 |
| School B Visit 2 | 27 |
| School C Visit 1 | 0 |
| School C Visit 2 | 0 |
| School D Visit 1 | 0 |
| School D Visit 2 | 0 |
| School E Visit 1 | 19 |
| School E Visit 2 | 0 |

**Table 5.** Outdoor air exchange rate (AER Outdoor).

| School | AER Visit 1 | AER Visit 2 |
|---|---|---|
| School A | | |
| Room # 1 | 2.1/h | 1.3/h |
| Room # 2 | 4.4/h | 1.1/h |
| School B | 0.6/h | 0.9/h |
| School C | 2.2/h | 2.6/h |
| School D | 2.9/h | 0.4/h |
| School E | 1.1/h | 1.1/h |

**Table 6.** Infiltration (%) with and without the portable HEPA filter unit.

| Pollutant Type | Infiltration before HEPA | Confidence Range (%) | Infiltration After HEPA | Confidence Range (%) | Removal by HEPA (%) | Confidence Range |
|---|---|---|---|---|---|---|
| Total UFP | 54% | 47–59 | 9% | 8–9 | 83% | 82–84 |
| Aircraft Particles | 41% | 38–56 | 14% | 12–15 | 67% | 67–73 |
| Black Carbon | 74% | 71–79 | 20% | 18–21 | 73% | 73–74 |

**Table 7.** Number of arrivals and departures below 750 meters and within a one-mile radius of King County Schools in 2019. Flight information including the median and 25th-75th percentiles are provided for the three airports in the region.

| Airport | # Arrivals | | # Departures | |
|---|---|---|---|---|
| | **Median** | **(25th–75th Percentile)** | **Median** | **(25th–75th Percentile)** |
| **Sea-Tac Airport** | 3 | (0–36) | 10 | (3–24.75) |
| **Boeing Field** | 44.5 | (7–232) | 11 | (0–60) |
| **Renton Municipal Airport** | 0 | (0–1) | 0 | (0–0) |
| **All Airports** | 102.5 | (18–589) | 35 | (5204.75) |

**Table 8.** Number of arrivals and departures below 750 meters and within a one-mile radius of study schools in 2019. Flight information including the median and 25th-75th percentiles are provided for the three airports in the region.

| Airport | # Arrivals | | # Departures | |
|---|---|---|---|---|
| | **Median** | **(25th–75th Percentile)** | **Median** | **(25th–75th Percentile)** |
| **Sea-Tac Airport** | 61,234 | (59,529 –154,962) | 53,313 | (6157–55,589) |
| **Boeing Field** | 18 | (8–89) | 26 | (25–104) |
| **Renton Municipal Airport** | 0 | (0–0) | 0 | (0–0) |
| **All Airports** | 61,240 | (59,537–155,094) | 53,547 | (6183–55,693) |

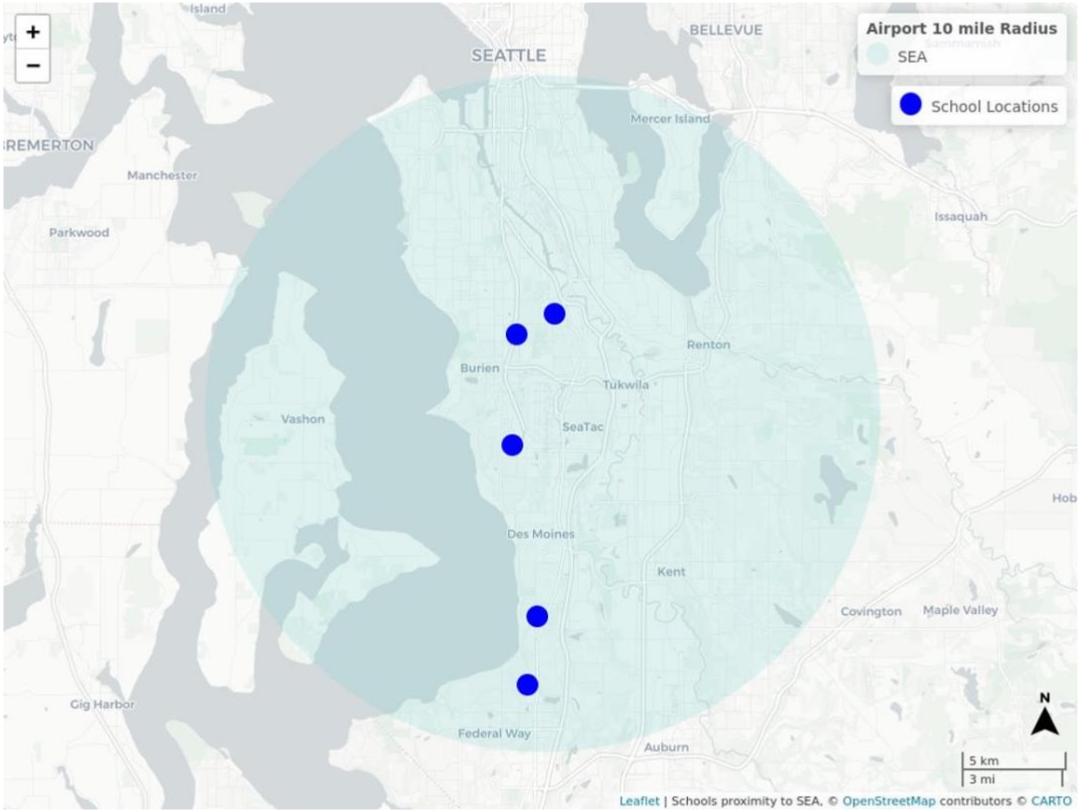
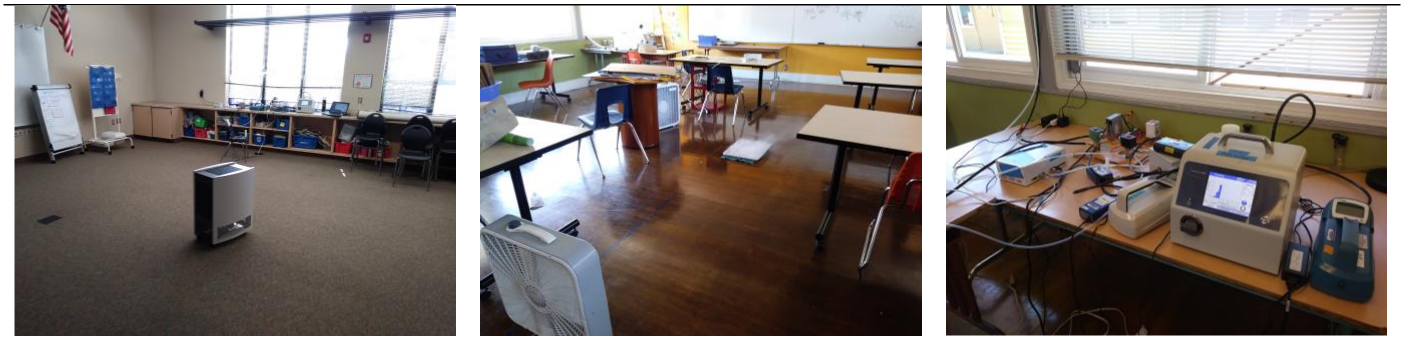


**Figure 1.** Map of school locations with an overlay of Sea-Tac Airport 10-mile radius. An interactive version of this map is available https://deohs.washington.edu/sites/default/files/mu/flights_near_schools.html (accessed on 3 October 2022). The interactive map also includes a layer illustrating the number of flights below 750 meters in altitude and within one mile of schools in the year 2019. Map data were made available under the Open Database License: http://opendatacommons.org/licenses/odbl/1.0/. Any rights in individual contents of the database are licensed under the Database Contents License: http://opendatacommons.org/licenses/dbcl/1.0/



(**a**) (**b**) (**c**)

**Figure 2** Instrument arrangement for indoor/outdoor air sampling. (**a**) Portable air cleaner placement in the center of unoccupied classroom. (**b**) Air exchange $CO_2$ experiment. (**c**) Sampling instruments.

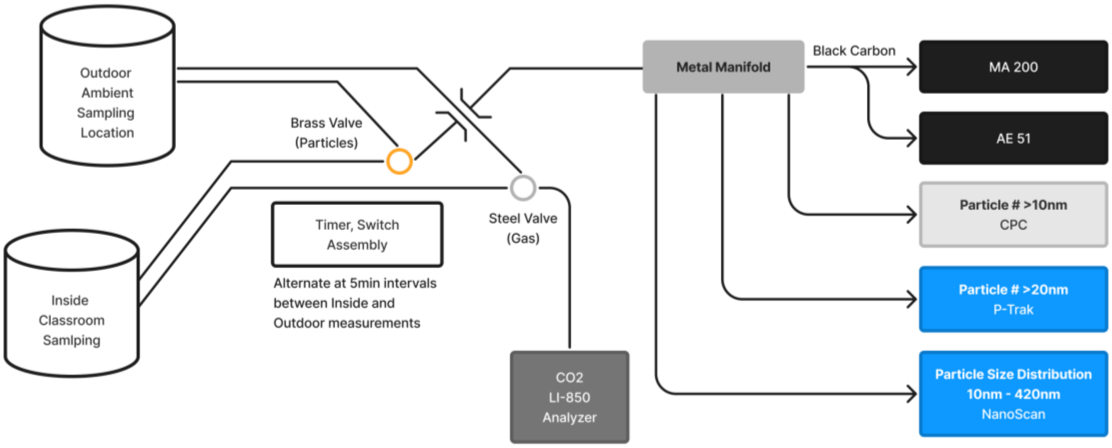
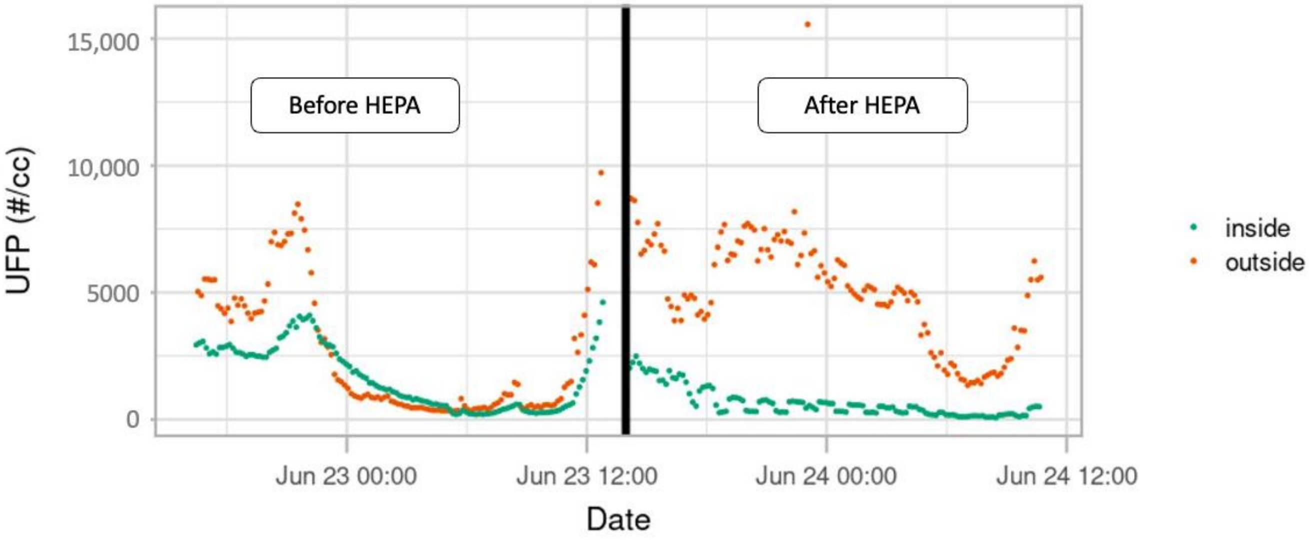
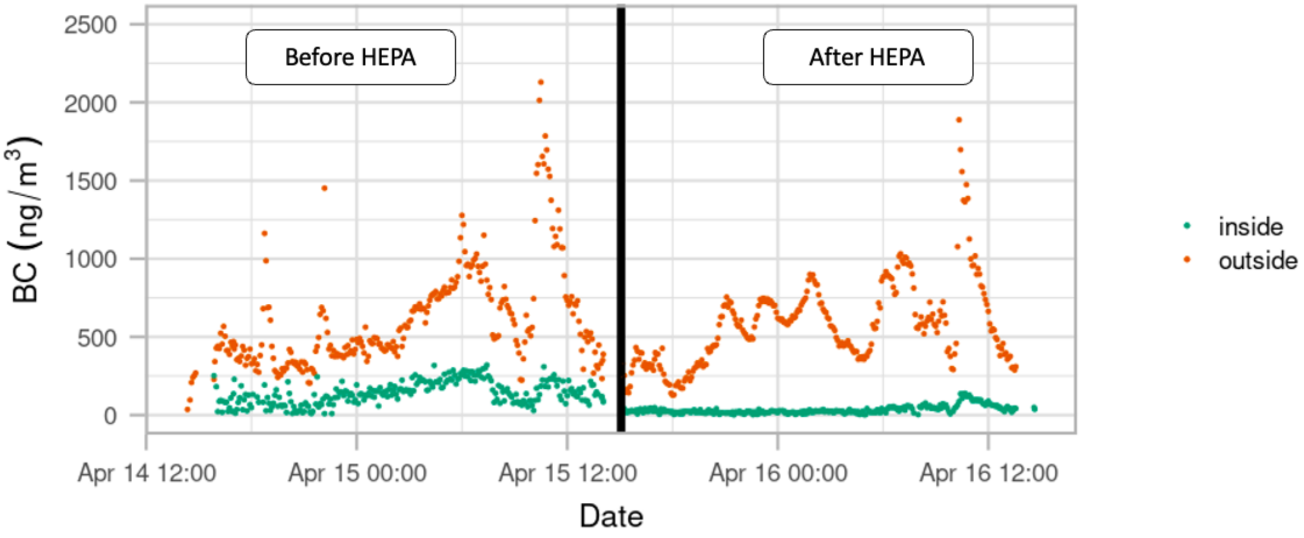


**Figure 3.** Pneumatic configuration of sampling instruments.



(**a**)



(**b**)

**Figure 4.** Indoor and Outdoor concentration of UFP Count and Black Carbon Particles at example schools. (**a**) Indoor and Outdoor concentration of total particle count before and after portable HEPA filter deployment. (**b**) Indoor and Outdoor concentration of Black Carbon before and after portable filter deployment.

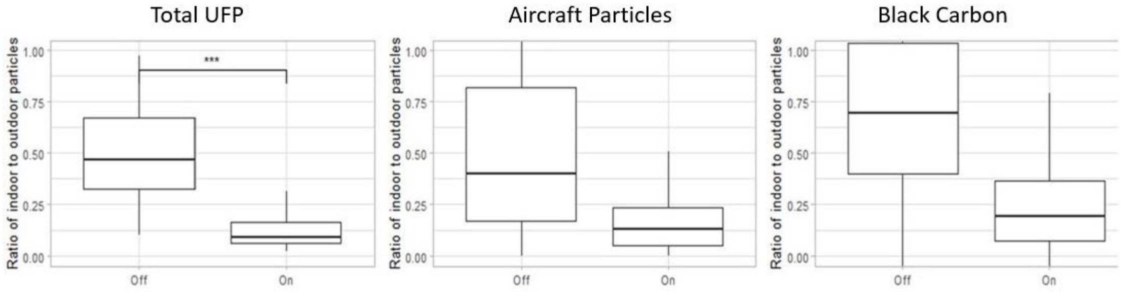


**Figure 5.** Infiltration ratio of different particle types before and after the portable HEPA filter intervention. This data represents the range of indoor/outdoor ratio of pollutants across all five schools. In the boxplots, the upper whisker represents the maximum, the top of the box represents the 75th percentile, the middle line represents the median or 50th percentile, the bottom of the box presents the 25th percentile, and the lower whisker represents the minimum. A two-sample Wilcoxon Rank Sum test confirms that the infiltration before the HEPA filter intervention is significantly higher than after the intervention ($p < 0.5$), for each of the three particle sources. *** indicates the results are statistically significant.

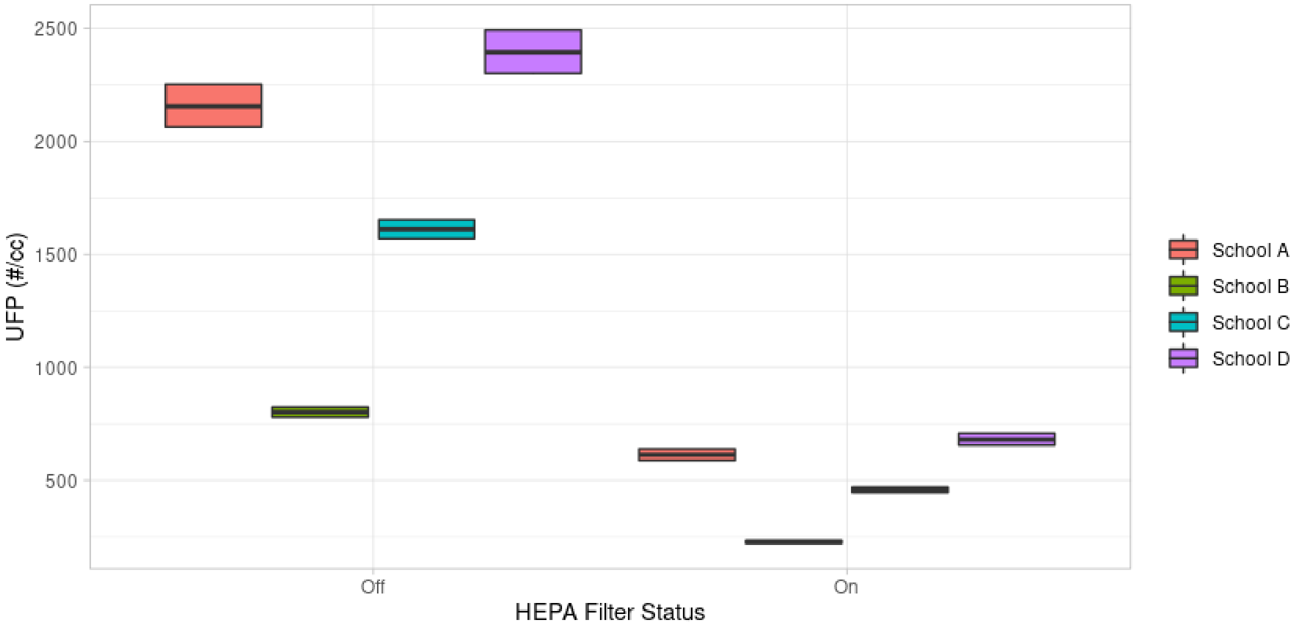


**Figure 6.** Prediction of indoor concentrations with and without a portable HEPA filter deployed in the classroom. The middle bar represents the mean, and the top and bottom bars represent the upper and lower 95% confidence interval. We assumed an outdoor concentration of 5000 #/cc to predict the indoor concentrations. School E was not included in this model due to multiple 0 values for the indoor air quality measurement.

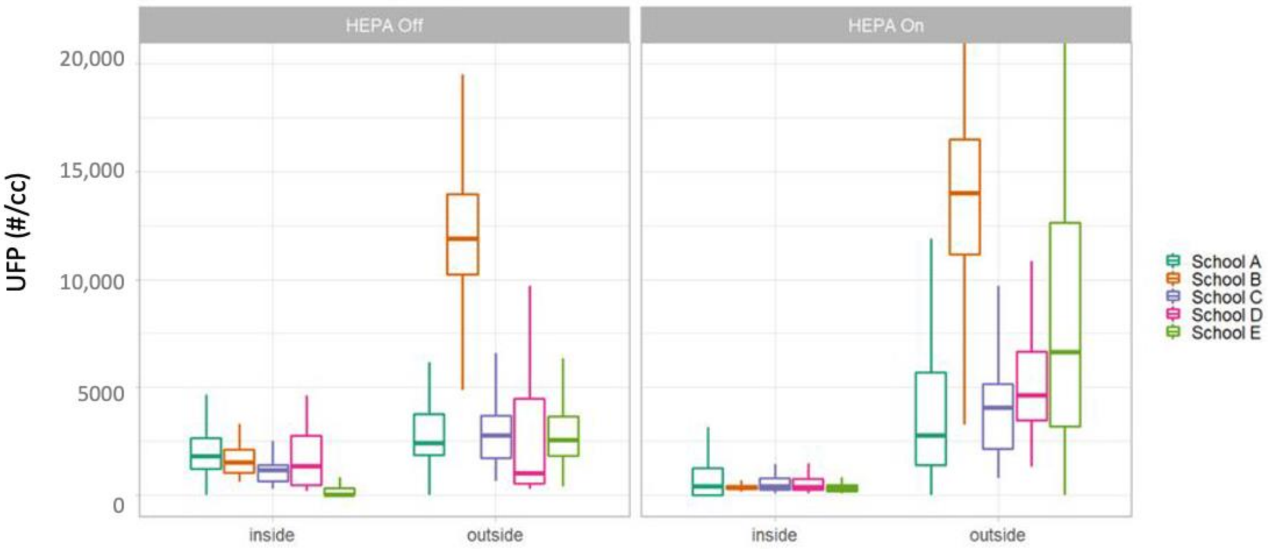


**Figure 7.** Distribution of UFPs before and after HEPA filter deployment at all five school locations. In the boxplots, the upper whisker represents the maximum; the top of the box represents the 75th percentile; the middle line represents the median or 50th percentile; the bottom of the box presents the 25th percentile; and the lower whisker represents the minimum.

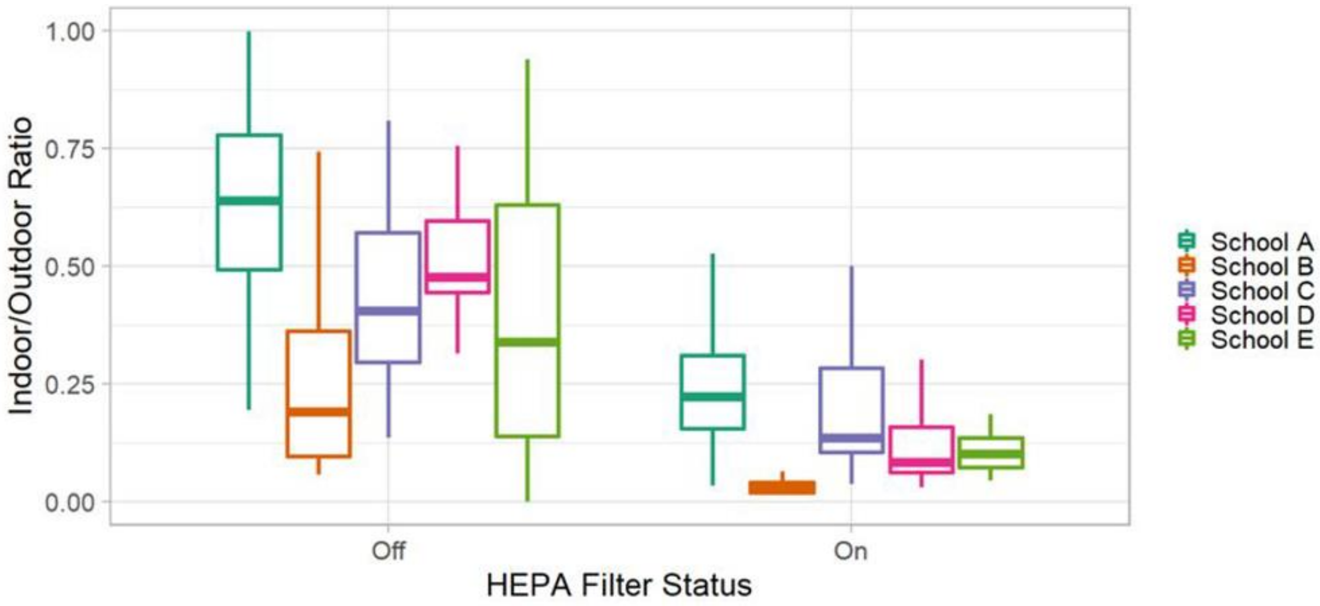
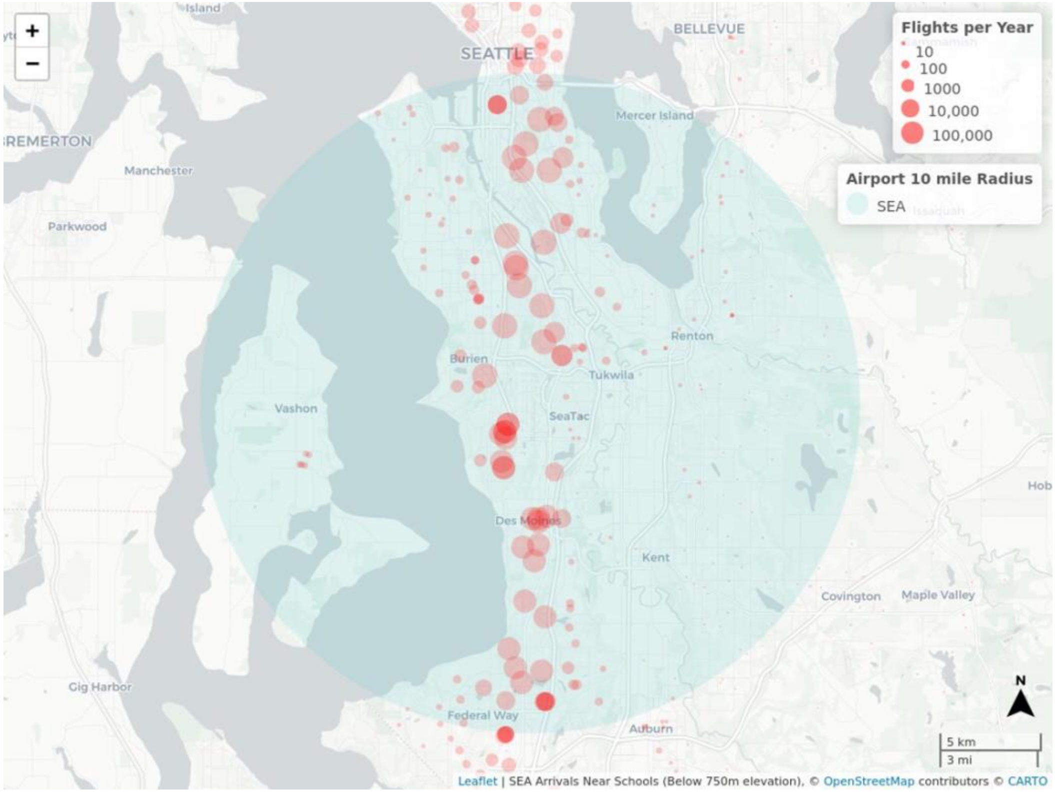
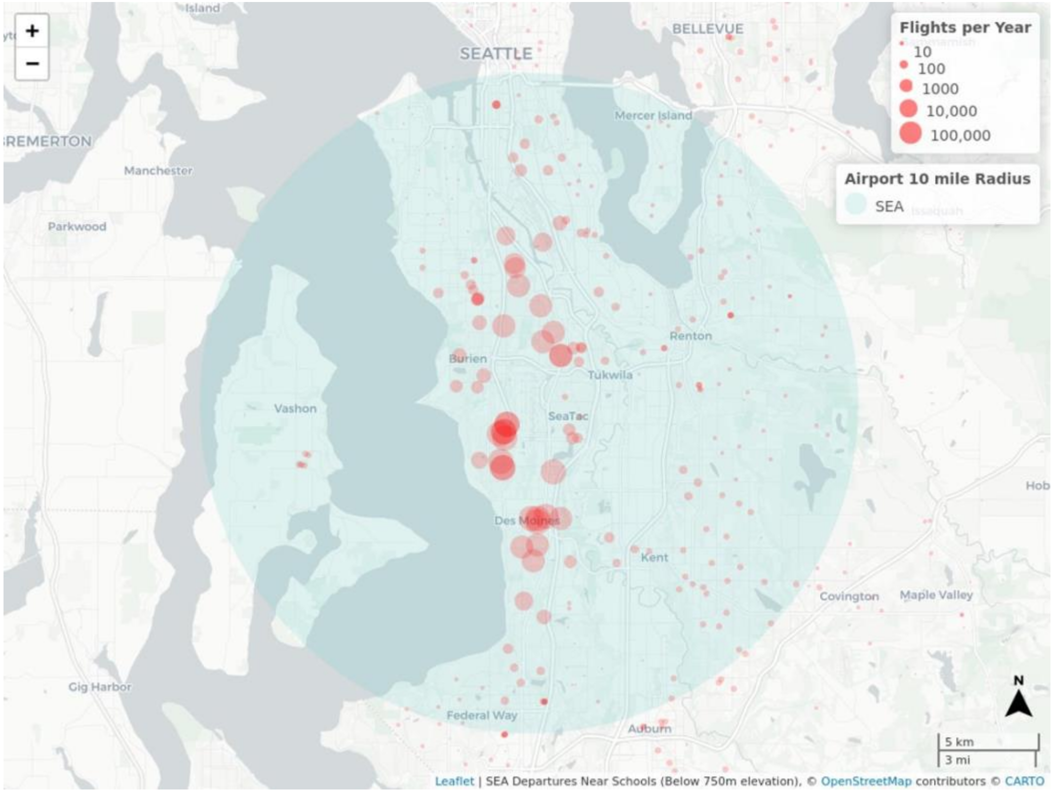


**Figure 8.** Distribution of indoor/outdoor ratio values for UFPs at each school location. Values were computed on the 30-minute timescale. In the boxplots, the upper whisker represents the maximum, the top of the box represents the 75th percentile, the middle line represents the median or 50th percentile, the bottom of the box presents the 25th percentile, and the lower whisker represents the minimum.


Flights per Year
10
100
1000
10,000
100,000
Airport 10 mile Radius
SEA
SEATTLE
BELLEVUE
Mercer Island
BREMERTON
Manchester
Parkwood
Burien
Tukwila
Renton
Vashon
SeaTac
Des Moines
Kent
Covington
Maple Valley
Gig Harbor
Federal Way
Auburn
N
5 km
3 mi
Leaflet | SEA Arrivals Near Schools (Below 750m elevation), © OpenStreetMap contributors © CARTO

(**a**)


Flights per Year
10
100
1000
10,000
100,000
Airport 10 mile Radius
SEA
SEATTLE
BELLEVUE
Mercer Island
BREMERTON
Manchester
Parkwood
Burien
Tukwila
Renton
Vashon
SeaTac
Des Moines
Kent
Covington
Maple Valley
Gig Harbor
Federal Way
Auburn
N
5 km
3 mi
Leaflet | SEA Departures Near Schools (Below 750m elevation), © OpenStreetMap contributors © CARTO

(**b**)

**Figure 9.** Number of flights in 2019 below 750 meters and within a one-mile radius of a school. (**a**) Number of Sea-Tac Airport arrivals with overlay of the 10-mile radius for Sea-Tac Airport. (**b**) Number of Sea-Tac airport departures with overlay of the 10-mile radius for Sea-Tac Airport. An interactive version of this map can be found at https://deohs.washington.edu/sites/default/files/mu/flights_near_schools.html (accessed on 3 October 2022). Map data were made available under the Open Database License: http://opendatacommons.org/licenses/odbl/1.0/. Any rights in individual contents of the database are licensed under the Database Contents License: http://opendatacommons.org/licenses/dbcl/1.0/

# Chapter 2B. Indoor Air Quality in Washington State Schools: Qualitative Investigation of Factors that Influence Use of Portable Air Cleaners

This chapter is a manuscript in preparation. The authors of the manuscript are:

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## 2B.1 ABSTRACT

**Background**: The United States government provided schools "Elementary and Secondary School Emergency Relief (ESSER)" funds, including over $2.5 billion in Washington State for the COVID-19 response, which partially funded ventilation improvements. Although funding mechanisms have been made available, a gap remains in supporting schools to successfully use portable air cleaners (PACs) to achieve healthy air in schools. We characterized factors influencing schools' purchase and use of PACs.

**Methods**: Semi-structured interviews (N=13) based on the technology acceptance model (TAM) were conducted with school personnel from administration, facilities, maintenance, and operations. A thematic analysis was conducted using inductive and deductive coding. Logistic regression models were used to examine the predictive capability of the TAM.

**Results**: Facilitators included: positive attitude about PACs, knowledge about PACs or similar instruments, and beliefs that they are easy to use and effective at improving air quality. Barriers included: a lack of training or education on how to use PACs, a lack of education about PACs, and concerns about the maintenance and sustainability of PACs. TAM constructs of Perceived Usefulness (PU) and Perceived Ease of Use (PEU) were predictive of having the Behavioral Intention (BI) to use PACs in schools.

**Conclusions**: There is a critical need for meaningful solutions to circumvent challenges to implementing PACs in schools. This characterization provides critical insight for future efforts to promote use of PACs in schools impacted by poor IAQ.

**Keywords**: School health; Indoor Air Quality; Portable Air Cleaners; Ventilation; Filtration

## 2B.2 INTRODUCTION

Emerging studies suggest there is significant infiltration of wildfire smoke into elementary and secondary school indoor air.[115] There are an estimated 7.4 million children in the United States affected by wildfire smoke annually, with many of them in the Southeast, Pacific Northwest, and California.[116] A recent study using a fire prediction model identifying communities estimated the regions that will suffer the steepest increase in wildfire smoke risk are central Colorado, southeastern Idaho, southern Montana, and eastern Washington.[115] Given the adverse effects of wildfire smoke to children, it is vital to develop and implement interventions to reduce exposures, particularly for children in disadvantaged communities in Washington State.[73,117] Notably, the Washington State Department of Health (WA DOH) has recommended the use of portable air cleaners (PACs) with High Efficiency Particulate Air (HEPA) filters to keep indoor air clean during wildfire events.[118]

PACs that have already been purchased and distributed as part of concerted COVID-19 response strategies can be leveraged to reduce exposures to wildfire smoke in schools. This effort was promoted by the White House-led “Clean Air Buildings Challenge”.[119] The program is a call to action and set of guiding principles and best practices to assist building owners and operators to reduce risks from airborne viruses and other indoor contaminants.[119,120] The Biden-Harris Administration and US Congress have provided hundreds of billions of dollars in federal funds eligible for use in schools, public buildings, and other settings to improve indoor air quality (IAQ), including $122 billion for schools[121], through the “American Rescue Plan Elementary and Secondary School Emergency Relief (ARP ESSER)” fund.[119] An important gap in leveraging this effort to improve IAQ, is to go beyond funding PACs for classrooms by supporting schools to successfully use and maintain the PACs that were obtained during the height of the COVID-19 pandemic.

PACs have been widely used in recent years due to their effective removal of indoor air pollutants.[122] In developed countries 10%–30% of homes are equipped with PACs for improving IAQ.[123] PACs with HEPA filters are safer and more effective in removing indoor air particles than electrostatic filter systems, ionizers, and ozone generators with large source chambers.[124] HEPA filters can directly remove at least 99.97% of dust, pollen, mold, bacteria, and any airborne particles with a size of 0.3 µm in size.[125] Particle removal efficiency in a given room depends on the flow through the filter, exchange rate between the room and outdoors, and size distribution of the particles. Home-based studies demonstrated PACs with HEPA filters reducing fungal spores and pollen concentration by 80%[126], cigarette smoke particulate matter by 30–70%[127], and wildfire smoke particulate matter by 48–78%.[128] A university classroom-based study found PACs with HEPA filters captured more than 95% of ultrafine fine particles (UFPs) and coarse particles, and ranged between 82–88% particles in the accumulation range (0.3–2 µm).[129] Similarly, a school-based study found PACs with HEPA filters were an effective short-term intervention to improve the air quality in classroom environments, with sufficient removal efficiencies for total UFPs (83%), aircraft particles (67%), and traffic particles (73%).[130] PACs with HEPA filters have also been found to reduce exposure to simulated exhaled aerosol particles, simulating COVID-19, by up to 65%.[131]

Furthermore, the University of Washington (UW) Department of Environmental & Occupational Health Sciences (DEOHS) led the *Healthy Air, Healthy School* community-engaged study to measure and identify sources of UFPs in classrooms in urban and rural settings in Washington State.[132] The study examined the removal efficiency of PACs with HEPA filters in classrooms and found that, after HEPA units were deployed, UFPs in classrooms dropped to about one-tenth of outdoor levels.[130] Report back materials were developed with feedback of the UW Ultrafine Particle Advisory Group, UW Interdisciplinary Center for Exposure, Diseases, Genomics, and Environment (EDGE) Community Engagement Core (CEC), and two school districts. Report back meetings found study partners were concerned with PAC deployments, but poor participation in those meetings prompted our research group to explore ways to better understand sentiments raised about PAC use in schools.

To advance the promotion of PAC use in schools, we conducted interviews based on the widely-used technology acceptance model (TAM).[133] The present study was based on semi-structured interviews with school district administration, facilities, maintenance, and operations personnel in Washington State. The purpose of this analysis was to characterize factors which influence schools' intention to purchase and use PACs with HEPA filters. This characterization can provide critical insights to guide future efforts to promote the use of PACs in schools impacted by poor IAQ.

## 2B.3 METHODS

### Participants

Recruitment of key information interviewees took place between March – June 2022. First, we contacted all Washington State public school district Superintendents (N=306) via email to invite them to participate in our interviews. If initial contact with a school district was not successful, we reached out to Directors of Operations, Directors of Facilities, Directors of Maintenance, Maintenance Supervisors, and Directors of Environmental Health and Safety, District Nurses, Health Directors, and Occupational and Physical Therapists. Our final recruitment wave focused on contacting Parent Teacher Association (PTA) members.

### Instrumentation

The interview instrument was developed with feedback from colleagues at Public Health – Seattle & King County (PHSKC). Interviews had four main parts: (a) school role and evaluation of the *Healthy Air, Healthy Schools* report, (b) general IAQ concerns and strategies, (c) perceptions and considerations of PACs, and (d) strategies to address air pollution sources (aircrafts, wildfires, and infectious diseases).

Each interview question addressed TAM constructs. **Table 1** shows our interview questions in relation to their respective TAM construct. First, we asked questions about external factors impacting use of PACs, such as being concerned about IAQ in schools and previous strategies used to improve IAQ. Second, we asked questions about perceived usefulness (PU) of PACs in schools. Third, we asked questions about the perceived ease of use (PEU) of PACs and concerns about the feasibility and sustainability of using PACs. Fourth, we asked questions about the attitude (A) towards using PACs and what considerations informed those feelings. Fifth, we asked their behavioral intention (BI) to use PACs and if they have recommended their use. Lastly, we documented the schools' estimated use of PACs.

### Procedure

Interview participants were identified by searching publicly available contact information from the Washington State Office of Superintendent of Public Instruction (OSPI) website and through snowball recruitment from interviewee recommendations. Subjects were recruited via email using a standardized contact email. Educational resources and the *Healthy Air, Healthy Schools* Technical Information webpage[134] were provided to participants. A pre-interview questionnaire was distributed to learn more about the school's PAC use. Interviews were conducted over Zoom and were transcribed using the software's transcription feature. Transcriptions were reviewed against interview recordings to ensure the accuracy of transcripts.

### Data Analysis

Qualitative analysis of transcripts was conducted using Atlas.ti (Version 8) software.[135] The study team developed a codebook with *a priori* codes and definitions based on potential responses to questions using a TAM framework. Deductive coding captured concepts that emerged from the data. Codes were grouped based on overarching categories, with individual codes labeled as barriers or facilitators to using PACs. Each code was distinct to capture different concepts within a group code category.[136] Hierarchical coding helped identify relational patterns in our data. We also examined the relationships between barriers and facilitators in urban and rural regions. We used rural-urban commuting area (RUCA) codes to classify school districts as either an urban or rural census tract.[137]

#### Group Sentiment Analysis

We conducted a sentiment analysis to examine the emotional tone associated with interview question responses and TAM constructs. A sentiment analysis classifies sentences into different classes of positive or negative emotions.[138] We examined sentiment by a variety of factors including the location of school district (urban or rural), levels of PAC use (no use, limited use, wide use), and job title (administration, facilities, maintenance and operations, health professional, PTA, and other). “No use” was defined as never using PACs, “limited use” was defined as only using PACs in specific use, and “wide use” was defined as being used in many classrooms throughout the school district. We used the R package “sentimentr” to calculate scores for positive, negative, or neutral sentiment.[139,140]

### Predictive Capability of TAM

The predictive capability of the TAM was tested using a logistic regression with independent variables of PEU and PU, and dependent variables of BI and Actual System Use. Sentiment scores were calculated for each individual participant response to the constructs PEU and PU. A score of 0 or 1 was assigned to BI and Actual System Use based on interview responses on their intention to use PACs and their reported use. Actual System Use may differ from BI if school districts had positive feelings towards using PACs but did not have funding to purchase and distribute PACs. We fit a logistic regression between PEU and BI, PU and BI, PU and Actual Use, and PEU and Actual Use. We used the R packages “stats”[141] to conduct the logistic regression and “emmeans” to estimate population marginal means[84].

### School Ventilation Survey

The PHSKC COVID-19 Recovery Operations Team also administered a School Ventilation Survey to gauge the public schools’ actions and needs to improve ventilation during the pandemic in King County, Washington. The overarching goal was to better inform the county’s technical assistance support to schools, including distribution of PACs acquired with ARP funds. The instrument was constructed to better understand the types of ventilation systems operating in schools, their maintenance, school needs due to various limitations, and actions schools were taking to improve IAQ to reduce the transmission risk of COVID-19.

The survey took place in July – November of 2021, with follow-up calls in early 2022. The survey instrument was an electronic self-administered questionnaire comprised of both open- and closed-ended questions. Convenience sampling was used to select participants. An email explaining the purpose of the survey, along with a copy of the survey instrument, was sent to each school in King County via the following contacts: principal, facilities/operations managers, and district-level superintendents. Follow-up phone calls were made to schools to encourage participation, answer questions, and verbally administer the survey if requested. Survey data were analyzed using descriptive statistics in Microsoft® Excel®. Frequencies and proportions were calculated for the closed-ended questions, while the open-ended questions were analyzed using content analysis to identify recurring themes.

## 2B.4 RESULTS

### Interview Participants

We established contact with 24 potential interviewees. A potential interviewee was defined as an individual who responded to an initial contact email as being interested in participating. However, 11 were lost to follow-up due to participants not responding to subsequent emails or failing to attend scheduled interviews. In the end, interviews were conducted with 13 individuals. Twelve interviews were conducted, each lasting 30-60 minutes. One interview was conducted with two concurrent participants. Each interview lasted 30-60 minutes. **Table 2** describes the participant characteristics. Most participants were male (62%) and held roles in school administration, facilities, and maintenance and operations. The 11 school districts were distributed throughout Washington State with seven districts in rural counties. All 11 school districts interviewed received federal Elementary and Secondary Emergency Relief (ESSER) funds.[142] Most participants (54%) held district-level positions, making decisions for a total of 45,502 students in Washington State.

In addition, we were interested in whether there were differences in facilitators and barriers to using PACs between urban and rural schools. We categorized each participating school district as either rural or urban based on their county. Out of 11 school districts in eight counties, five were urban and three were rural. **Figure 1** shows the geographic distribution of participating school districts.

### Thematic Analysis

**Table 3** shows a summary of facilitators and barriers to the uptake and continued use of PACs in schools. Facilitators included having a positive attitude about PACs, knowledge on PACs or similar instruments, believing PACs are easy to use, and believing PACs improve air quality. In contrast, barriers included having the perception that PACs have negative features, lack of training or education on how to use PACs, lack of education on PAC effectiveness, and concerns about maintenance and sustainability required to continue using PACs.

Barriers and facilitators to using PACs in schools differed by urban or rural category. While staff from rural schools found PACs were desirable and worthwhile to improve IAQ, the largest barrier was acquiring funding for PACs. In contrast, their urban school counterparts had less funding barriers, but were less willing to use PACs because many prioritized upgrading heating, ventilation, and air conditioning (HVAC) systems.

> You know it's one more thing to manage. If it can be managed [through] the HVAC system and [then] I don't feel the need to use them. If you don't have the funds, I get that. Or if it's just not structurally feasible at the time, then portable makes sense, but if you have another option I wouldn't.
> *Superintendent / Principal*

School districts, particularly those in urban counties, took advantage of state and federal funding to purchase PACs. We found staff from urban schools applied for federal funding while their rural counterparts noted they did not have the capacity to apply.

> We came to this purchase because of the pandemic. [We had] to spend money that became available, but we prioritized air cleaners as one of our initiatives to take advantage of those funds.
> *Director of Operations*

Similarly, rural school staff reported they lacked knowledge and experience necessary to use PACs, while urban schools reported they had the knowledge and experience necessary to use PACs. However, urban school interviewees noted concerns about PACs not being used as intended due to a lack of guidance or knowledge of how to use them.

> I think they can be a really effective tool when used properly. But I think that a lot of these centers are really busy when implementing the tool and may not have necessarily the correct knowledge or the correct

> infrastructure built into schools actually check up on the units and understand how they're impacting the space.
>
> *Health and Environmental Investigator*

In addition, some school districts reported not having enough education on PAC efficiency, and the ability of PACs to filter classroom-sized rooms.

> Most of the research that I have done on portable air cleaners is that they do not provide that much efficacy in [a room] the actual size of a classroom.
>
> *Director of Facilities and Sustainability*

Additional findings from inductive coding illuminated IAQ disparities at children's homes. An emerging theme was the concern about worse air quality at children's homes, compared to school buildings with higher air filtration capacity.

> We are in a lower socioeconomic area, 93% of our kids qualify for free or reduced lunch and, honestly, for many families, school is the best place for them. That goes for air quality, for food nutrition services, you name it. School is the best place for a lot of these kids and if it's unhealthy for them to be outside then it's going to be unhealthy for them to probably be at their house… They're probably not going to have air purifiers, are probably not going to even have AC, sometimes they have the door open

> because it's just too hot it's just a reality, so school is best. Closing school would be a detriment, in most cases, to their health.
>
> *Director of Operations*

## Sentiment Analysis

Positive and negative sentiment of the PU and PEU constructs were analyzed. Positive sentiment for PU was higher than PEU. Participants in rural school districts had a slightly higher mean positive PU sentiment score than participants in urban school districts (**Figure 2a**). Small differences in sentiment between school districts with different levels of PAC use were found, but there was no clear relationship (**Figure 2b**). The highest mean positive sentiment score was present in participants whose school districts used PACs in a limited manner. Selective use included rooms requiring more filtration due to the absence of an HVAC system or rooms with higher potential for COVID exposures such as band rooms.

Participants in rural school districts had a slightly higher mean positive PEU sentiment score than participants in urban school districts (**Figure 3a**). Minor differences in PEU sentiment between school districts with distinct levels of PAC use were found, but there was no clear relationship (**Figure 3b**). The highest mean positive sentiment score was present in participants whose school districts used PACs in a limited manner. Although these results are not statistically significant, they do reveal patterns in participating school districts.

## School Ventilation Survey

A total of 17 participants at the district or school level completed a survey administered by PHSKC. Schools throughout rural, suburban, and urban King County responded, representing about half of all school districts in the county. Participants represented 11 public school districts, two of which also participated semi-structured interviews. Most school districts (73%) reported having plans set in place to continue improvements to their ventilation systems and applied or were planning to apply to ESSER (or other) funding to conduct IAQ improvements for their schools. School districts reported using strategies to increase ventilation including opening doors and windows when conditions allow (73%), routine maintenance of HVAC systems (82%), routine replacement of filters (82%) and using PACs (64%). However, cost or lack of funding (64%) and inadequate infrastructure for a better HVAC system (27%) remain a barrier to some school district respondents. While most school districts surveyed (91%) have an HVAC professional on staff or within the district or a contract with an HVAC management company, smaller school districts lack these resources and may experience challenges obtaining contracts with HVAC management companies.

## Predictive Capability of TAM

We fit logistic regression models to determine the odds of having positive BI to use PACs based on PU or PEU sentiment. We selected the 25th (-0.02) and 75th percentiles of PU and PEU sentiment scores to estimate odds in our models. We found having positive PU or PEU sentiment was predictive of having the intention to use PACs in schools. PEU was found to have a stronger relationship with BI than PU. The odds ratio (OR) of having positive BI to use PACs in schools is 1.77 (SE: 1.68) when comparing individuals with high PU sentiment vs. low PU sentiment. The OR of having positive BI to use PACs in schools is 28.6 (SE: 84.7) when comparing individuals with high PEU sentiment vs. low PEU sentiment.

In addition, we found the model was predictive of having positive BI to use PACs among rural school districts where the OR of having positive BI to use PACs in schools is 1.56 (SE: 1.41) when comparing individuals with high PU sentiment vs. low PU sentiment. Among urban school districts, the OR of having positive BI to use PACs in schools is 1.0 (SE: 8458 when comparing individuals with high PU sentiment vs. low PU sentiment. Among rural school districts, the OR of having positive BI to use PACs in schools is 5368 (SE: 48651) when comparing individuals high PEU sentiment vs. low PEU sentiment. In contrast, among urban school districts, the OR of having positive BI to use PACs in schools is 1.0 (SE: 14657) when comparing individuals with high PEU sentiment vs. low PEU sentiment. SE values were very large due to the small sample size when grouping data by school location designation.

Furthermore, we conducted an exploratory analysis using a mixed effects model. We predicted PU or PEU sentiment based on school district location (urban or rural), PAC level use (wide, limited, or none), and a random intercept for each subject. We found negative associations between PU or PEU sentiment and predictors including urban school locations, using PACs widely in a school district, and not using PACs in a school district.

We also used a mixed effects logistic regression model to model the binary outcome of BI to determine if we can predict BI based on subject characteristics. Subject characteristics included PU and PEU sentiment, school district location (urban or rural) and PAC level use (wide, limited, or none), and a random intercept for each subject. The model found a stronger relationship with BI was associated with PEU (OR = 6.6) sentiment than PU (OR = 2.11) sentiment. However, the results show very wide confidence intervals and limit the interpretability of these exploratory results.

## 2B.5 DISCUSSSION

The present study was conducted to understand factors influencing schools' uptake and continued use of PACs with HEPA filters. Concerns that emerged during the *Healthy Air, Healthy Schools* report back activities framed the development of the present study. A survey deployed as part of the *Healthy Air, Healthy Schools* report back process found parents were concerned about the cost and maintenance of PACs with HEPA filters but were overwhelmingly supportive in their belief that PACs with HEPA filters were an effective strategy for improving IAQ. In addition, parents were more concerned about maintenance and cost as barriers to using PACs. Parents also rated outdoor air pollution as a bigger concern than indoor air pollution. However, the *Healthy Air, Healthy Schools* study found about one-half of outdoor UFP pollution was measured inside classrooms before PACs were installed.[130]

The *Healthy Air, Healthy Schools* phase I study encountered challenges recruiting research participants but had more success recruiting for phase II during wildfire events. This points to the possibility of schools recognizing IAQ is something they cannot control and have an increased interest in interventions. Wildfires have impacted the readiness to improve IAQ in schools, with school districts citing the occurrence of wildfire smoke events as a motivating factor to implement improvements to HVAC systems prior to the COVID-19 pandemic.

Public schools also provide an opportunity to improve the equity of interventions because these environments are available to every child. This makes it crucially important that schools in disadvantaged communities be prioritized for school-based interventions. However, there are several obstacles to making schools safe and healthy locations during wildfire smoke events.[73] PACs are a solution recommended by WA DOH, the White House, and US EPA, but more resources ~~on~~ for maintenance, education and training need to be provided for this intervention to be successful. Additional funding should address the ongoing costs of filter replacement and staff time needed for cleaning and changing filters regularly.

Recently the Centers for Disease Control (CDC) conducted a telephone survey of ventilation improvement strategies among 8,410 US K-12 public school districts (representing 61.7% of enrolled public school students in the US) between August – December 2022.[143] Among ventilation improvements examined, 51% of school districts reported maintaining continuous airflow in classrooms; 34% reported having HVAC system improvements in progress or completed, and 28% reported planned or completed use of HEPA-filtered in-room air cleaners.[143] High-poverty school districts (as designated by the U.S. Census Bureau Small Area Income Poverty Estimates [SAIPE]) more frequently reported ventilation improvements in most schools than did low- and mid-poverty school districts.[143] Rural school districts less frequently reported replacing or upgrading HVAC systems and using HEPA-filtered in-room air cleaners than did school districts in other locales.[143] This difference might be due to limitations in resource availability, and difficulty finding contractors available and willing to complete capital improvements.[144]

Although federal funding was dispersed to improve ventilation in schools, it is difficult to know how much funding was invested to purchase and deploy PACs. ESSER funding records are not granular enough to determine whether funding was spent to purchase and deploy PACs. We do not know how these units are being used now that schools are longer concerned about transmission of COVID-19. Additional knowledge is necessary to provide guidance on funding and resource allocation for unit maintenance. A campaign is needed to characterize ongoing PAC usage, given the barriers of staff time and maintenance costs. Future trainings and PAC selection should consider noise impacts, since decreasing fan speed may result in not meeting the optimal

ACH. PACs are a potential intervention for a wide range of uses including removing pollution from wildfires[128], traffic-related air pollution[130], and COVID transmissibility[131]. We currently do not know how PACs are utilized in public schools and if they could potentially benefit from supplemental filtration.

## School Ventilation Survey

The results of the PHSKC survey are in line with findings from the semi-structured interviews. Through follow-up conversations throughout the COVID-19 pandemic, PHSKC staff learned that school facilities managers had similar concerns about staff capacity and funding needed to maintain the units. One recurring theme is that the maintenance of PACs is a barrier to PAC use in schools. PHSKC found that many school personnel felt that interventions would have been more effective if they had received guidance on how to select, use, and maintain the units before purchasing the instruments ~~education~~ . School staff also expressed concerns with classroom noise and time needed to check units were kept on, plugged in and on the correct settings. Another concern often expressed was how to determine the number of units to place in a space to achieve effective air filtration. PHSKC recommendations are also in line with the interview findings. Using IAQ testing instruments to 1) screen classrooms and prioritize interventions where they are needed and 2) evaluate if IAQ improvement interventions worked. IAQ testing can include pollutants such as PM and carbon dioxide ($CO_2$).

## Limitations

Due to our sampling approach, our results may not be generalizable to all of Washington State. There may be systematic differences between participating and non-participating schools, thus impacting the representativeness of the study data. Preexisting concerns about IAQ in schools could cause selection bias among participants. Further research is needed to reach more school health professionals and parents. Additionally, further involvement of specific vulnerable groups, such as parents from low SES homes, would help provide a better understanding of unequal exposure to wildfire smoke and barriers to protective action. More data are also needed to have greater statistical power in our TAM logistic regression analysis, although we present a quantitative method that could examine the predictive ability of the TAM for new technology uptake.

PHSKC also encountered several limitations in their survey and distribution of PACs to schools. First, the survey relied on a convenience sample, which may not represent all schools in King County as those that participated in the study may have a higher level of interest or concern about ventilation systems compared to those that did not participate. Second, the survey relied on self-reported data, thus respondents may have overestimated or underestimated the status of their ventilation systems. Third, the survey was limited to schools in King County, Washington, and the results may not be generalizable to other areas. Finally, the survey did not directly assess IAQ, as information about ventilation systems was used as a proxy.

## 2B.6 CONCLUSIONS

Our findings suggest a gap remains between funding and the means to improve school IAQ. PACs are underutilized and school districts lack access to funding, education, and training for effective implementation and maintenance. PACs with HEPA filters have been shown to be an effective short-term intervention to improve the air quality in school buildings. Facilitators to using PACs, reported by school districts, included having positive attitudes about the instruments, having knowledge on PACs or similar instruments, believing they are easy to use, and believing PACs improve air quality. Barriers to implementing these instruments included noise, lack of education on PAC operation and effectiveness in classroom-sized spaces, and concerns about resources and sustainability of maintaining PACs. With new funding available to improve school IAQ, we encourage PACs as a good intermediate control in the absence of an adequate HVAC system and when mitigating wildfire smoke infiltration. Risk assessments should also be utilized in deployment of this supplemental intervention to determine the appropriate size, and placement, filter types.

## Implications for School Health Policy, Practice, and Equity

The results of this study provide a detailed qualitative lens exploring factors influencing the use of PACs and improving school IAQ. Despite the study's limitations, our findings can provide guidance to groups approaching PAC use in schools nationwide. Large urban school districts mentioned using a "ticket system" for IAQ issues and using QR codes to manage HVAC systems. A similar system could be implemented to manage PACs, integrating PACs into existing centralized management, creating more capacity for facilities staff, and removing the need for assistance from non-facilities staff.

Suggested areas for future interventions include:

1) Improve HVAC systems by upgrading filters within the system's capacity and implementing centralized control systems.
2) Implement effective information management such as a ticket system for tracking IAQ concerns for both PACs and HVAC.

3) Routinely test IAQ and provide financial support for air quality monitoring instruments, personnel, and research. Funding for this work should be accompanied with technical assistance to facilitate schools in identifying and acquiring the best options for their needs.
4) Increase availability of reliable IAQ information and education for facilities staff.
5) Implement management systems for PACs including tracking, maintenance, and supply of filters.

### Human Subjects Approval Statement

The University of Washington's Institutional Review Board determined the study to have exempt status. This PHSKC survey did not meet the definition of human subjects.

### Conflict of Interest

The authors declare no conflicts of interest.

## 2B.7 TABLES & FIGURES

Table 1. Interview Questions based on Technology Acceptance Model Constructs

| TAM Construct | Interview Question |
|---|---|
| External Variables | Are you concerned with the indoor air quality in schools (or childcare centers)?<br>Have you implemented strategies to reduce your exposure to air pollution when indoors? |
| Perceived Usefulness (PU) | What do you think about the use of portable air cleaners in schools (or childcare centers)? |
| Perceived Ease of Use (PEU) | What concerns do you have about the feasibility and sustainability of using portable air cleaners in classrooms? |
| Attitude Towards Using (A) | What considerations have informed your decisions about whether or not to use portable air cleaners in classrooms (or childcare centers)? |
| Behavioral Intention to Use (BI) | When have you used or recommended portable air cleaners in the classroom (or childcare centers)? |

Table 2. Description of Interviewees

| Variable | (Total N=13) N (%) |
|---|---|
| Gender | |
| Male | 8 (62%) |
| Role | |
| Administration | 3 (23%) |
| Facilities | 3 (23%) |
| Maintenance & Operations | 3 (23%) |
| Health Professional | 1 (8%) |
| PTA | 1 (8%) |
| Other | 2 (15%) |
| Location (County Level) | |
| Rural | 7 (54%) |
| ESSER Funds I/II | |
| Received funding | 11 (100%) |

Table 3. Descriptions of Themes of Interviews with School Participants

| **Impact on PAC Use at Schools** | **Theme** | **Definition** | **Codes** | **Prototypical Example** |
|---|---|---|---|---|
| Facilitators | Positive attitude about PACs | Participants feel that PACs are good and have positive feelings towards them. | Good attitude and positive feelings towards PACs | I think they serve a great purpose. It's something that has not been taken very seriously until the pandemic has come along and they're great, I think that they just serve a great purpose.<br>*Director of Operations* |
| | Knowledge on PACs or similar instruments | Participants feel their ability to determine the ease of use of PACs is determined by their past experiences with similar systems and have knowledge and experience necessary to use PACs. | Past experience with similar items; knowledge and experience | Speaking for our school that didn't have an HVAC system and we bought a lot of air filters that were properly ready for the classrooms and didn't have any harmful by products. Those staff members were all very satisfied with that and I'm happy with that solution for that school.<br>*Environmental Safety Coordinator* |
| | Belief that using PACs is easy | Participants believe that using PACs is clear and understandable. | Using PAC is clear and understandable; using PAC is easy to use | They have been pretty easy to use, and they actually have air filtration gauges on them to tell you whether the filters need to be changed or not. Which is something that's pretty handy.<br>*Maintenance Supervisor* |
| | Belief that PACs improve air quality | Participants believe that PACs improve indoor air quality and are very desirable and worthwhile to use for improving indoor air quality. | Using PAC is desirable and worthwhile; improve air quality | One of the things I was impressed about was again taking my handy dandy meter around to all the sites and I would actually walk into a room and they happen to have one, and I would read you know the different levels and |

| | | | | |
|---|---|---|---|---|
| | | | | kind of just do a couple samples of the room… I was pleasantly surprised to find out how much those things really knock things out of the air.<br>*Director of Maintenance and Operations* |
| Barriers | PACs have negative features | Participants perceive PACs have negative features such as producing noise which negatively impacts students. | Noise; special needs | For certain kids I'll turn it off because of the noise. I'm not too bothered by that normally, but with some kids I'll turn the fan level down.<br>*Occupational and Physical Therapist* |
| | Lack of training or education on how to use PACs | Participants reported a lack of training on how to use PACs resulting in misuse of instruments. | Room capacity; instrument being misused; uncomfortable using PACs; no training; stresses out; education on use | My concern is that when people buy them as they obviously they're like "oh I'm going to buy this off Amazon and it's only $50" and I'm like yeah it only covers 100 square feet your classrooms 850 square feet. Yeah and so it's not so, I think, once again it comes down to an education piece, and because of that it also gives a false sense of security to folks.<br>*Facilities Planning Manager* |
| | Lack of education on PAC effectiveness | Participants reported a lack on education on PAC effectiveness. | Education on effectiveness; not sure effective | My thoughts are just questions right now. How effective are they? How are we measuring the effectiveness?<br>*Principal* |
| | PAC maintenance and sustainability | Participants reported being concerned with maintenance and sustainability of using PACs in schools. | Maintenance and sustainability | It's a little worrisome to think about, are teachers gonna notice when it's time to change?<br>*PTA* |

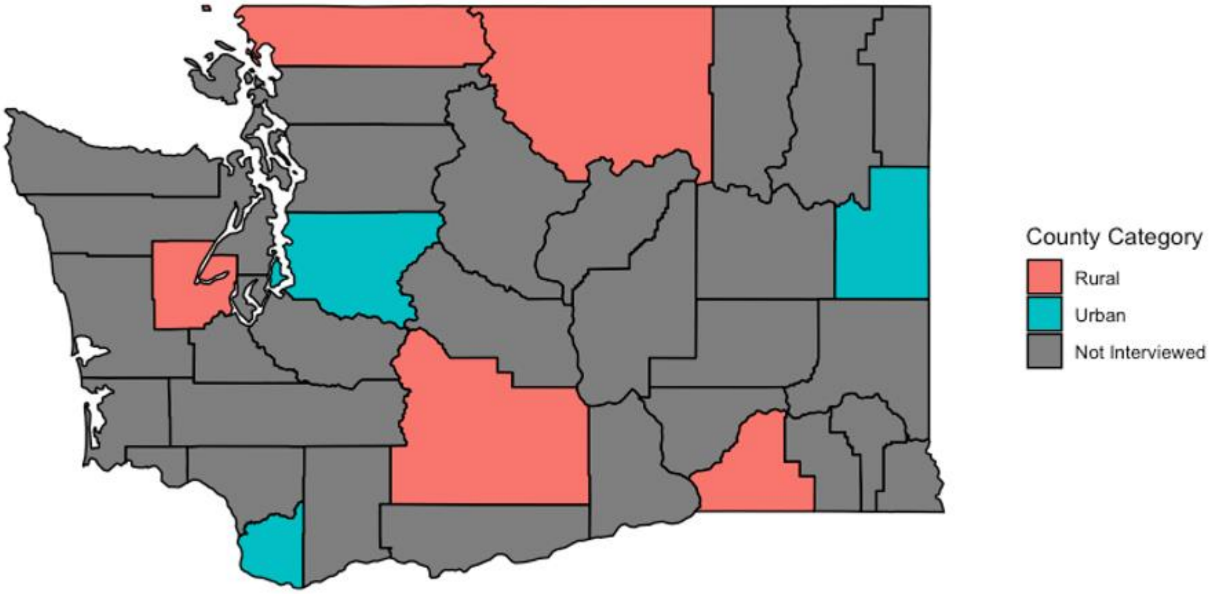
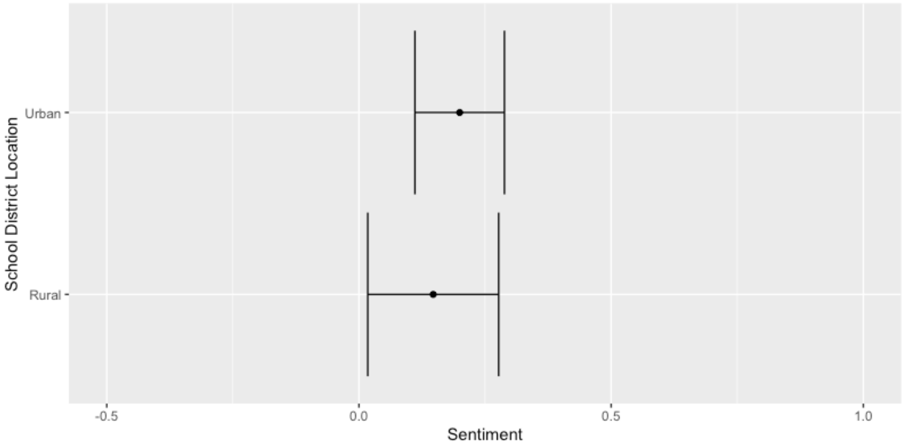


Figure 1. Geographic distribution of participating school districts in Washington State. Counties are shaded by their corresponding RUCA code.

A.



B.

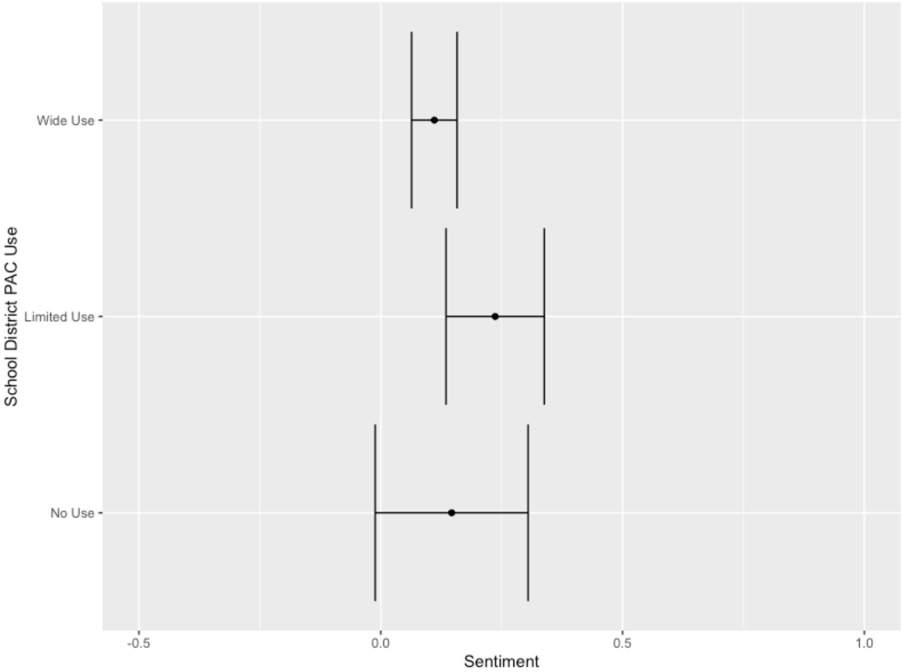


Figure 2. Perceived Usefulness (PU) Sentiment by school district location (a) and PAC use level (b).

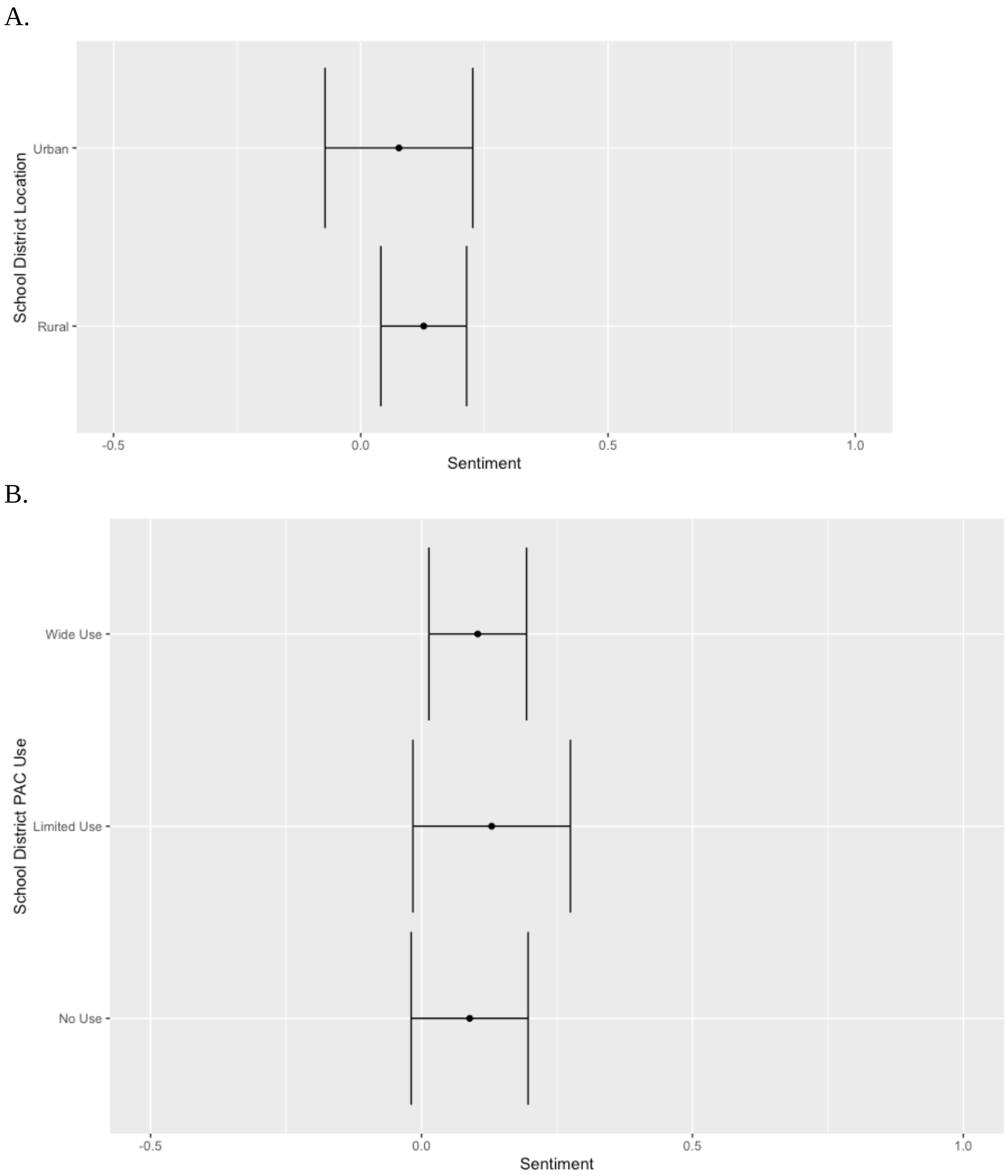


Figure 3. Perceived Ease of Use (PEU) Sentiment by school district location (a) and PAC use level (b).

# Chapter 3. Environmental Health Disparities Map: Assessing the sensitivity of alternate $PM_{2.5}$ model predictions on highly impacted communities

## 3.1 ABSTRACT

Cumulative environmental impact assessment tools are increasingly being used to inform policy decisions. These tools often include multiple data indicators of environmental exposure and population vulnerability factors. However, little work has been conducted to evaluate the sensitivity of indicator choices on cumulative risk rankings. We evaluated the impact of different choices of fine particulate matter data sources on cumulative risk ranking in the Washington Environmental Health Disparities Mapping Tool (WA EHD). In a secondary analysis, we developed a $PM_{2.5}$ indicator layer based on the National Ambient Air Quality Standards (NAAQS). The data sources for $PM_{2.5}$ included the WA Department of Ecology (WA ECY); Center for Air, Climate and Energy Solutions (CACES); University of Colorado's (UC) Reid Lab; and the University of Washington's Adult Changes in Thought – Air Pollution (UW ACT-AP) study. We found the tool was sensitive to fine particulate matter data layers, with 2-6% of census tracts designated as "overburdened communities" (N = 298) dropping out of their designation when the existing WA EHD $PM_{2.5}$ data source was switched to an alternative data source. Similarly, we found that 3-6% of census tracts dropped into the designation of overburdened communities when using an alternate data source. We found the NAAQS based $PM_{2.5}$ indicator ranking identified distinct census tracts as overburdened compared to those identified using WA EHD ranking methods. Results of this sensitivity analysis demonstrate the layer of data used for fine particulate matter data has a small but potentially important impact on

which census tracts are being prioritized for environmental justice policy decisions in Washington State.

## 3.2 INTRODUCTION

The United States Environmental Protection Agency (US EPA) defines cumulative impacts as the total burden from chemical and non-chemical stressors and their interactions that affect the health, well-being, and quality of life of an individual, community, or population at a given point in time or over a period of time.[145] Defining the total burden of direct and indirect effects provide context for characterizing the potential state of vulnerability or resilience of the community.[145] Cumulative impact assessment is the process of accounting for cumulative impacts in the context of problem identification and decision-making.[145] Cumulative environmental impact assessment tools are powerful instruments for informing state and local environmental policy, funding priorities, environmental justice advocacy, and regulation enforcement to identify and reduce health disparities.[11,12] In addition, the National Environmental Justice Advisory Council (NEJAC)[146] and the White House Environmental Justice Advisory Council (WHEJAC)[147] stress the importance of using participatory approaches when developing cumulative impact assessment tools.

Environmental impact assessment tools have been developed on the federal and state level, including Washington and California.[11,12] Federal level tools in include the US EPA Environmental Justice Screening and Mapping Tool (EJSCREEN)[148], the US Centers for Disease Control (CDC) Environmental Justice Index (EJI)[149], and the White House Council on Environmental Quality's Climate and Economic Justice Screening Tool (CEJST).[150] The EJSCREEN and the California Office of Environmental Health Hazards Assessment's Screening

Tool (CalEnviroScreen) integrate vulnerability variables, with the EJSCREEN comparing environmental impacts for populations in census blocks to other census blocks across the US, while CalEnviroScreen compares cumulative environmental impacts for populations in census tracts across California.[11,12] The Washington Environmental Health Disparities (WA EHD) map is based the CalEnviroScreen model that integrates environmental exposures, adverse environmental effects, population sensitivities, and sociodemographic vulnerabilities into a composite score.[12] The WA EHD map development stands out as it was community-driven and explicitly integrated community voices and experiences.[12]

Furthermore, federal and state cumulative impacts tools allow policymakers to identify which communities are highly impacted in comparison to other census blocks or census tracts. In the WA EHD mapping tool, census tracts are ranked from 1 to 10, with 10 having the highest cumulative impact.[12] These rankings have important impacts on the implementation of environmental justice policy. California's Senate Bill 535 uses rankings to designate the top 25% scoring areas as "disadvantaged communities".[151] Funding from the California Global Warming Solutions Act of 2006 (AB 32), a cap-and-trade program, is used to improve the public health and quality of life in the most burdened communities.[151] A similar carbon cap and market-based program, called the WA Climate Commitment Act (CCA), aimed at reducing pollution while generating funds for projects located in disadvantaged communities has also been implemented in Washington.[152] Washington's Senate Bill 5141, also known as the Healthy Environment for All (HEAL) Act, uses rankings to determine "overburdened communities" which are a geographic areas where vulnerable populations face combined, multiple environmental harms and health impacts, and highly impacted communities.[153] The CCA aligns with the requirements of the HEAL Act and generates revenue through a cap-and-invest program.[152] The program will implement a cap on carbon emissions and develop mechanisms for the sale and tracking of tradable emissions allowances. The cap-and-invest program will require a minimum of 35% of funds toward overburdened communities and a minimum of 10% towards tribal projects.[152] Similarly, the federal government is using the CEJST tool to identify disadvantaged communities that are marginalized, underserved, and overburden by pollution.[147] The Justice40 Initiative's goals is to allocate 40% of the overall benefits of federal investments in climate change, clean energy, energy efficiency, clean transit, affordable and sustainable housing, training and workforce development, remediation and reduction of legacy pollution and the development clean water and wastewater infrastructure to these overburdened communities.[147,154]

Given the importance of these rankings, it is vital that overburdened communities are correctly identified, and the implications of uncertainty and variability associated with indicators that form the underlying basis for these cumulative impact tools are explored. To address this, we assessed the sensitivity of WA EHD cumulative impact rankings to alternative $PM_{2.5}$ map layers under the current WA EHD ranking methodology. The alternative $PM_{2.5}$ layers were based on available spatially-explicit $PM_{2.5}$ estimates from the WA Department of Ecology (WA ECY); Center for Air, Climate and Energy Solutions (CACES); University of Colorado's (UC) Reid Lab; and the University of Washington's Adult Changes in Thought – Air Pollution (UW ACT-AP) study. We first assessed the differences in rankings by tract between the different $PM_{2.5}$ layers. We also assessed how the overall cumulative impacts ranking changed when using the different $PM_{2.5}$ layers. Furthermore, we explored an alternate health-based ranking methodology. We conclude the analysis by discussing the potential implications of the cumulative impacts ranking changes for ongoing environmental justice (EJ) policy.

## 3.3 METHODS

### 3.3.1 Fine Particulate Matter Data

We used four data sources including the WA ECY, CACES, UC Reid Lab, and the UW ACT-AP study (Table 1). The selected datasets were developed for different purposes and are not aligned with each other in time but were selected to approximate a three-year long-term average, similar to the reference WA ECY dataset that is currently used in the WA EHD Map. The WA ECY $PM_{2.5}$ layer was developed by the Washington Department of Ecology and consists of census tract level and gridded estimates of average $PM_{2.5}$ concentrations over the period of July 2014 – June 2017. The $PM_{2.5}$ estimates incorporate data from the Air Information Report for Public Awareness and Community Tracking (AIRPACT) forecast model and regulatory agency monitoring data[155] in conjunction with $PM_{2.5}$ measured at regulatory monitoring sites. The AIRPACT model uses pollutant emissions, natural air chemistry and predicted meteorology to predict air quality for the Pacific Northwest. The key models used in the AIRPACT forecast include a weather research and forecasting model (WRF) which predicts future wind speed, temperature, and precipitation, meteorology-chemistry interface processor (MCIP) which reformats WRF results, sparse matrix operator kernel emissions (SMOKE) which imports emissions inventory data, and the community multi-scale model for air quality (CMAQ) which calculates air quality by accounting for chemistry and physics of air pollutants, emissions, transport, vertical mixing, dilution, rain-out and deposition.[155] The mean and 98th percentile $PM_{2.5}$ concentrations were interpolated, at 4 km x 4km grid cell resolution, using the relationship between the ratio of mean $PM_{2.5}$ / 98th percentile $PM_{2.5}$ measured regulatory monitoring sites and median daily forecast $PM_{2.5}$ from the AIRPACT forecast model. The ratios from each monitoring site were calculated and then interpolated across WA using Empirical Bayesian Kriging. The interpolated ratios were multiplied by the median daily forecast $PM_{2.5}$ from AIRPACT at each 4 km x 4 km grid cell to produce an interpolated mean and 98th percentile $PM_{2.5}$. Each census tract was assigned the maximum interpolated mean. Census block centroid predictions were extracted from grid level $PM_{2.5}$ predictions to calculate block population-weighted $PM_{2.5}$ concentrations at the census tract level using population data from the 2010 US Census Bureau.[156]

Second, we used CACES $PM_{2.5}$ estimates from January 2013 – December 2015. The estimates were produced from empirical models described in Kim et al. (2020).[14] CACES is a multi-institutional research center formed to address critical questions on air, climate, and energy. The model uses universal kriging (UK) and land use regression (LUR) to estimate and annual average. The model used Air Quality System (AQS) monitoring data (1979 – 2015) from US EPA Federal Reference Method (FRM) and Integrated Monitoring of Protected Visual Environments (IMProVE) networks.[14] Over 900 geographic variables were considered, but ultimately reduced using partial least squares (PLS) to about 350 including traffic, land use, land cover, and satellite-based estimates of air pollution.[14] The model has been demonstrated to have good predictive accuracy with cross-validated $R^2$ values ranging from 0.84-0.86.[14] Census tract level three-year annual average $PM_{2.5}$ was population weighted at the block level.

Third, we used UC Reid Lab's $PM_{2.5}$ census-tract level estimates from January 2014 – December 2016. The estimates are predictions from ensemble machine learning models trained on 24-hour $PM_{2.5}$ measurements from monitoring station data across 11 states in the western US.[15] $PM_{2.5}$ monitoring data used in the models included EPA Air Now data, EPA IMPROVE Network, California Air Resources Board (stationary and mobile monitoring networks), Federal Land Manager Environmental Database, Fire Cache Smoke Monitor Archive, Utah State University, Utah Department of Environmental Quality and the University of Utah.[15] In addition, the ensemble model incorporated meteorological data from the North American Mesoscale (NAM) model, chemical transport data from the Community Multi-scale Air Quality (CMAQ) from the US EPA from 2008-2016, elevation data from the US Geological Society, land cover class information from the Landsat-derived National Land Cover Dataset (NLCD), population data from the 2010 US Census, vegetation abundance from the Normalized Difference Vegetation Index (NDVI), and road data from the National Highways Planning Network. Notably, the ensemble models also include wildfire data from the Moderate Resolution Imaging Spectroradiometer (MODIS) Thermal Anomalies/Fire Daily L3 Global product.[157] Ten-fold spatial and random cross-validation $R^2$ were 0.66 and 0.73, respectively, for the 2008–2016 model and 0.58 and 0.72, respectively for the 2008–2018 model.[15] Comparing areal predictions to nearby monitored observations demonstrated an overall $R^2$ of 0.70 for the 2008–2016 model and 0.58 for the 2008–2018 model, with higher $R^2$ (>0.80) in many urban areas.[15]

Fourth, we used UW ACT-AP study $PM_{2.5}$ estimates from June 2017 – August 2019. A modeling approach was developed for predicting $PM_{2.5}$ average in the Puget Sound region from 1978 through 2020 as a part of the ACT-AP study. The hierarchical spatiotemporal model includes a long-term spatial mean, time trends with spatially varying coefficients, and a spatiotemporal residual.[158–160] A large set of geographic covariates were reduced using partial least-squares regression. Time trends are estimated from observed time series and spatial smoothing methods to borrow strength between observations. The model used regulatory monitoring data from the Puget Sound Clean Air Agency and The WA Department of Ecology, study-specific data from two previous studies in Seattle[161,162], and low-cost sensor data from the ACT-AP study. The model has demonstrated to have good predictive accuracy with an $R^2$ >

0.80.[163] Block centroid predictions were population-weighted using population data from the 2010 US Census Bureau.[156]

### 3.3.2 Indicator Data

Additional census tract level indicator data from the WA EHD tool were used to calculate cumulative risk ranks. A total of 19 indicators in the categories of environmental exposure, environmental effects, sensitive populations, and socioeconomic factors are used to calculate the final cumulative ranks. Vulnerability data included indices for population living in poverty, toxic releases from facilities, low birth weight, cardiovascular disease mortality, no high school diploma, proximity to wastewater discharge, proximity to risk management plan facilities, proximity to national priorities list facilities, proximity to hazardous waste, lead risk from housing and limited English. Indicators were chosen based on the results of a preliminary PCA analyses on indicators that influence the final ranking.[12] Population living in poverty represents data on poverty from the American Community Survey (ACS) 5-year roll-up, measuring people living under 185% of the federal poverty level. The toxic releases from facilities data displays the toxicity-weighted concentrations of chemical releases to air from facility emissions and off-site incineration averaged over the three-year period July 2014 – June 2017. Low birth weight data represent the number of live born singleton infants born at term (at or above 37 completed weeks of gestation) with a birth weight of less than 2,500 g (about 5.5 lb). Cardiovascular disease mortality data represents the proportion of deaths in a population due to cardiovascular disease, age adjusted per 100,000 population. The no high school diploma data represents the percentage of people who have not received a high school or GED by the age of 25. Proximity to wastewater discharge data presents toxicity-weighted concentration in stream reach segments within 500 m of a block centroid, divided by distance in meters, presented as the population-weighted average of blocks in each block group. Proximity to risk management plan facilities data represents the proximity of facilities with a risk management plan by displaying the count of facilities within 5 km of a tract divided by the distance of the facility. The proximity to national priorities list facilities data represents the count of sites proposed and listed on the national priorities list downloaded from EJSCREEN in 2017. Proximity to hazardous waste data represents the count of all commercial hazardous waste treatment, storage and disposal facilities within 5 km divided by the distance, presented as population-weighted averages of blocks in each census tract. Lead risk from housing data represents the number and percent of housing units built before 1980, including single homes and multiple residence units such as apartments. Limited English data represents the percentage of the population five years and older with limited English proficiency, defined as those who speak English less than “very well” or “not at all”.

### 3.3.3 Washington Environmental Health Disparities Cumulative Ranking

To replicate WA EHD rankings, we applied the disparities rank methodology developed by Min et al. (2019). The model was based on CalEnviroScreen which integrates environmental exposure, adverse environmental effects, sensitivities, and sociodemographic vulnerabilities.[12] The equation used in this model was based on the CalEPA established risk scoring. The CalEnviroScreen model can be conceptualized as:

$$Risk = Threat \times Vulnerability \tag{1}$$

Min et al. (2019) modified the CalEPA equation to use for the WA EHD rankings.[12] The modified model can be written as:

$$\begin{gathered}\textit{Disparities Rank} = \textit{Environmental Exposures and Effects x} \\ \textit{Sensitive Populations and Socioeconomic Factors}\end{gathered} \tag{2}$$

The disparities rank is a decile ranking of 1-10 used in the resulting map. The Pollution Burden Score is a product of Environmental Exposures and Effects. The Population Characteristics score is a product of Sensitive Populations and Socioeconomic Factors.

$$\textit{Final Score} = \textit{Pollution Burden Score x Population Characteristics Score} \tag{3}$$

The Pollution Burden score is an average percentile that summarizes the environmental risk factors and hazards, calculated by the modeled pollution burden. Threat accounts for the damage to environmental quality which can increase environmental risk factors. The Population Characteristic score represents biological and non-biological characteristics that are proxy metrics for vulnerability to environmental risk and may affect the susceptibility to pollution burden. Examples of Population Characteristics are educational attainment and poverty, which modify the environmental risk. A Pollution Burden Score is calculated for each map indicator, which range from environmental exposure, environmental effects, sensitive population, and socioeconomic factors. The indicators are ranked across census tracts throughout WA and based on this ranking are assigned a decile score from 1 to 10. The raw Pollution Burden score is an average percentile; it uses the equation:

$$Pollution\ Burden\ score = \frac{Average\ percentile\ score\ of\ Environmental\ Exposures\ indicators + 0.5\ x\ \ Average\ percentile\ score\ of\ Environmental\ Effects\ indicators}{2} \tag{4}$$

Similar to CalEnviroScreen methodology, the Environmental Effects Indicators are half weighted to account for uncertainty of exposures due to proximity to hazard sites or pollutant sources.[12] The Sensitive Populations and Socioeconomic Factors categories were combined into the Population Characteristics score. The Population Characteristics score assigns a score of 1-10 based on the distribution of Population Characteristics across the WA census tracts as estimated from the following equation:

$$Population\ Characteristics\ score = \frac{Average\ percentile\ score\ of\ Sensitive\ Populations\ indicators\ + Average\ percentile\ score\ of\ Population\ Characteristics\ indicators}{2} \tag{5}$$

The WA EHD Map presents the final score ranking from 1-10, with 10 indicating the highest cumulative impact due to environmental risks and vulnerabilities. Rankings reflect risk on the census tract level relative to other census tracts in WA.

### 3.3.4 Primary Analysis

First, we compared each alternate $PM_{2.5}$ dataset to the WA ECY dataset using bivariate plots. We performed a Pearson correlation test matched on census tract to evaluate the association between $PM_{2.5}$ estimates, with an overlay of the identity line. We also performed a linear regression to evaluate the association between $PM_{2.5}$ estimates, with an overlay of the linear regression line. Correlations were calculated and added to figures using the R package "stat_cor".[164]

$PM_{2.5}$ concentration percent differences were calculated by subtracting the original WA ECY concentration from the alternate concentration and dividing the difference by the original WA ECY concentration. The following equation was used:

$$Percent\ difference\ = \frac{(Alternate\ concentration - \ Original\ ECY\ concentration)}{Original\ ECY\ concentration}\ x\ 100 \tag{6}$$

In addition, we calculated the cumulative impact ranks using each alternate $PM_{2.5}$ dataset. All indicator layers remained constant except for the $PM_{2.5}$ when calculating cumulative impact ranks. We compared how the overall cumulative impacts ranking changes when using the different $PM_{2.5}$ layers. Cumulative rank differences were calculated by subtracting the original cumulative rank from the alternate cumulative rank using the equation:

$$Cumulative\ rank\ change\ =\ Alternate\ cumulative\ rank - \ Original\ cumulative\ rank \tag{7}$$

### 3.3.5 Sensitivity Analysis

Additional analysis was conducted to examine the impact on cumulative ranks on census tracts ranked at 10 or 9 for % people of color (POC) and % poverty. To determine if changes in rank may be related to distance to air quality monitoring sites, we also compared the location of the census tracts dropping out and dropping into cumulative ranks 10 or 9 and air quality monitoring stations. We mapped census tracts dropping out or dropping in with an overlay of the currently active $PM_{2.5}$ air monitoring stations (N = 60) across Washington State.

### 3.3.6 Secondary Analysis

The current EHD map decile ranking approach for air quality indicators such as $PM_{2.5}$ may lead to confusion, as census tracts could be ranked a 10 (i.e., concentrations within the highest decile of tracts within the state), but do not indicate concentrations that exceed $PM_{2.5}$ air quality standards. We propose a new ranking methodology based on the primary $PM_{2.5}$ National Ambient Air Quality Standards (NAAQS). Census tracts are ranked individually of each other and are assigned a rank based on their three-year average $PM_{2.5}$ concentrations. The concentrations are averaged in a similar method to the NAAQS, using an annual average over three years.[165] **Table 2** presents the proposed $PM_{2.5}$ concentrations assigned to each rank. Concentration ranges are scaled linearly, with a rank 10 assigned to any census tracts at or exceeding the primary $PM_{2.5}$ standard of 12.0 $\mu g/m^3$.

## 3.4 RESULTS

### 3.4.1 $PM_{2.5}$ Datasets

Each statewide dataset contains $PM_{2.5}$ estimates for 1459 census tracts within Washington State. We compared alternate $PM_{2.5}$ datasets to the WA ECY census tract level $PM_{2.5}$ concentrations across Washington State shown in bivariate plots (**Figure 1**). The 1:1 plot of ECY $PM_{2.5}$ and ECY (population-weighted) $PM_{2.5}$ shows very strong correlation with a Pearson correlation coefficient of $r = 0.89$ (Figure 1A). Compared to the original ECY dataset, concentrations are lower in the population-weighted ECY census tracts, with only 17 census tracts having higher concentrations than the original ECY $PM_{2.5}$ estimates. Previous applications of population-weighting air pollution concentrations in air pollution studies have also resulted in lower concentrations.[166] The 1:1 plot of ECY $PM_{2.5}$ and CACES $PM_{2.5}$ shows fair correlation with a Pearson correlation coefficient of r = 0.50 (Figure 1B). The 1:1 plot of ECY $PM_{2.5}$ and Reid Lab $PM_{2.5}$ shows fair correlation with a Pearson correlation coefficient of r = 0.52 (Figure 1C). The 1:1 plot of ECY $PM_{2.5}$ and Reid Lab (without CMAQ) $PM_{2.5}$ shows a fair Pearson correlation coefficient of r = 0.33 (Figure 1D). The bivariate plot illustrates that the Reid Lab predictions have a greater range than the ECY or CACES data. Indicating that the Reid Lab methods predict greater variability than other alternate datasets.

We also compared alternate $PM_{2.5}$ datasets to the WA ECY census tract level $PM_{2.5}$ concentrations within the Puget Sound region (**Figure 2**). The region contains $PM_{2.5}$ estimates for 509 census tracts. We found similar correlations within the Puget Sound region as in Washington State for ECY $PM_{2.5}$ and ECY (population-weighted) $PM_{2.5}$ (**Figure 2A**) and ECY $PM_{2.5}$ and Reid Lab (with CMAQ) (**Figure 2C**). We found the correlation between ECY $PM_{2.5}$ and CACES $PM_{2.5}$ dropped from 0.50 to 0.33 when examining the Puget Sound region (**Figure 2B**). We also found the correlation between ECY $PM_{2.5}$ and Reid Lab (without CMAQ) $PM_{2.5}$ dropped from 0.33 to 0.19 (**Figure 2D**). The 1:1 plot of ECY $PM_{2.5}$ and ACT-AP with low-cost sensors $PM_{2.5}$ shows poor correlation with a Pearson correlation coefficient of r = 0.19 (**Figure 2E**). The 1:1 plot of ECY $PM_{2.5}$ and ACT-AP without low-cost sensors $PM_{2.5}$ shows very poor correlation with a Pearson correlation coefficient of r = -0.098 (**Figure 2F**). Notably, we found the ACT-AP without low-cost sensor $PM_{2.5}$ concentrations were lower than the ECY $PM_{2.5}$concentrations throughout the Puget Sound region.

Next, we compared the percent difference in $PM_{2.5}$ estimates across Washington State, calculated by subtracting the original ECY estimates from alternate $PM_{2.5}$ estimates (**Figure 3)**. Percent difference was calculated using equation 6. Population-weighted ECY $PM_{2.5}$ concentrations were lower than original ECY throughout most of Washington State (**Figure 3A**).

We also see large negative differences in eastern Washington State. For example, in **Figure 3B** we see the original ECY data was lower in $PM_{2.5}$ than the CACES dataset in southeastern Washington. The original ECY dataset also had concentrations in northwest Washington State that were 146% lower than Reid Lab without CMAQ dataset estimates (**Figure 3C**). Notably, we found that the Reid Lab without CMAQ dataset resulted in the greatest variability with large positive and negative differences, with concentrations differences ranging from 253% higher to 72% lower than original ECY estimates (**Figure 3D**).

We also compared the percent difference in $PM_{2.5}$ estimates between the original ECY estimates and alternate $PM_{2.5}$ estimates within the ACT-AP modeling region (**Figure 4**). We found that one of the census tracts in the Puget Sound region was not modeled in the ACT-AP dataset due to modeling region constraints. Since the purpose of the selected area was to focus on ACT-AP modeled areas we excluded the census tract in all alternate dataset maps. We found small differences in $PM_{2.5}$ concentrations throughout the Puget Sound region. $PM_{2.5}$ concentrations appear to be similar, consistent across all datasets. However, we found that the Reid Lab without CMAQ dataset resulted in the greatest variability with large positive and negative differences (**Figure 4D**).

### 3.4.2 Cumulative Impact Ranking

We also compared the difference in cumulative ranks when using alternate $PM_{2.5}$ datasets across Washington State. The cumulative ranks presented were calculated using data from 19 indicators, with $PM_{2.5}$ being just one of these data layers. We found small differences in cumulative rank changes across Washington State (**Figure 5**) and within the Puget Sound region (**Figure 6**).

All datasets had similar concentrations across Washington State, with the mean census tract concentrations ranging from 6.07 to 6.83 μg/m$^3$. The Reid Lab datasets contain higher maximum concentrations and the largest variability, with the Reid Lab without CMAQ dataset showing substantially higher concentrations. Concentrations are similar within the Puget Sound region with the mean census tract concentration ranging from 5.38 to 6.87 μg/m$^3$. **Table 3** displays summary statistics for Washington Statewide datasets, while **Table 4** presents the same statistics for Puget Sound region datasets.

**Table 5** summarizes the number of census tracts dropping out of 9/10 cumulative impact ranks. Census tracts with a cumulative rank of 10 remained in their categories, while those with a cumulative rank of 9 dropped out. We found the tool was sensitive to $PM_{2.5}$ data layers, with 2-6% of census tracts designated as "overburdened communities" (N = 298) dropping out of their designation when the existing WA EHD $PM_{2.5}$ data source was switched to an alternative data source. The CACES dataset most exacerbated the ranking system with 17 dropping out or dropping into the overburdened designation. While the ECY population-weighted dataset exacerbated the ranking system the least with 7 dropping out and 8 dropping into the overburdened designation.

Similarly, we found that 3-6% of census tracts dropped into the designation of overburdened communities when using an alternate data source. **Table 6** summarizes the number of census tracts dropping into the 9/10 cumulative impact ranks. We also include the number of census tracts dropping in within the 20% highest POC and poverty indicators. Reid Lab datasets had the second and third highest number of census tracts susceptible to dropping into the 9/10 cumulative impact ranks. The Reid with CMAQ and Reid without CMAQ detests resulted in 13 and 10 census tracts dropping into the overburdened designation, respectively. Considering the

Reid with CMAQ datasets, of the 13 census tracts susceptible to dropping in, 5 were in the highest 20% of POC and 4 were in the highest 20% poverty. While when using the Reid without CMAQ datasets, of the 10 census tracts susceptible to dropping into 9/10 cumulative impact ranks, 6 were in the 20% highest POC and 7 were in the highest 20% of poverty.

**Table 7** summarizes the number of census tracts that dropped out of 9/10 cumulative impact ranks within census tracts with 20% highest POC indicator ranks (N = 294). Considering census tracts susceptible of dropping out or dropping into the overburdened designation using CACES (N=17), 7 of those dropping out and 8 of those dropping in were in the 20% highest POC indicator ranks. While using the ECY population-weighted dataset, 2 of the 7 census tracts susceptible to dropping out and 5 of the 8 census tracts susceptible to dropping into the overburdened designation were in the 20% highest POC indicator ranks.

**Table 8** summarizes the number of census tracts that dropped out of 9/10 cumulative impact ranks within census tracts with 20% highest poverty indicator ranks (N = 299). Using the CACES dataset, 3 of the 17 census tracts susceptible to dropping out of the overburdened designation were in the 20% highest poverty indicator ranks the 17 census tracts susceptible to dropping into the overburdened designation had 10 census tracts in the 20% highest poverty indicator ranks. While considering the ECY population-weighted dataset, 4 of the 7 census tracts susceptible to dropping out but no census tracts susceptible to dropping into the overburdened designation were in the 20% highest poverty indicator ranks. **Table 6** summarizes the number of census tracts susceptible to dropping into the 9/10 cumulative impact ranks within the 20% highest poverty indicator ranks.

**Figure 7** shows the census tracts that would drop out or drop into the overburdened community designation when using an alternate $PM_{2.5}$ dataset to calculate cumulative rank in relation to the locations of currently active $PM_{2.5}$ AQS monitors. We found that the census tracts that are dropped do not appear to be related to lack of regulatory monitoring. In southeast Washington State we found census tracts that would drop out are near monitoring stations. The differences between $PM_{2.5}$ estimates from alternative data sources may reflect greater variability in air pollution and/or how different models incorporate spatial and temporal factors related to $PM_{2.5}$ in this region of the state. It may be useful to examine performance differences between models where there are such discrepancies. Within the Puget Sound region, we found using ECY population-weighted dataset resulted in densely populated census tracts dropping into the overburdened designation (**Figure 8A**). However, we found more census tracts dropped out using CACES (**Figure 8B**) and Reid without CMAQ (**Figure 8D**).

### 3.4.3 NAAQS Based Ranking

In a secondary analysis, we developed new map layers incorporating the NAAQS based ranking. The novel methods ranked census tracts on their absolute $PM_{2.5}$ concentrations, not in relation to other census tracts within Washington State as used by the current EHD Mapping tool. **Figure 9** shows the new map layers using NAAQS based ranking for datasets spanning all of Washington State. **Table 9** shows the number of census tracts in each rank when using alternate datasets and new NAAQS based ranking. We found that most $PM_{2.5}$ datasets (**Figure 9A-9C**) did not reach concentrations assigned to ranks 9 or 10. In fact, we do not see much variation in ranks throughout Washington State. However, the Reid Lab datasets (**Figure 9D-9E**) did reach concentrations with ranks of 9 or 10. We see higher ranks, indicated in red shades, throughout eastern Washington. **Figure 10** shows the new map layers using NAAQS based ranking for datasets within the Puget Sound region. We found that the population-weighted ECY resulted in lower ranks than the original ECY in lower populated census tracts (**Figure 10A-10B**). We found the Reid Lab datasets (**Figure 10D-10E**) reaching indicator ranks of 9 or 10.

## 3.5 DISCUSSION

The EHD Mapping Tool integrates 19 indicators in the categories of environmental exposure, environmental effects, sensitive populations, and socioeconomic factors to calculate cumulative ranks that are used to inform the allocation of funds to overburdened communities. $PM_{2.5}$ is only one indicator within this calculation, but one that has been the focus of recent conversations within the state between the EHD Map development team and air quality experts, due to potential confusion over the meaning of ranks 9 and 10 in terms of the NAAQS. These conversations have further motivated sensitivity analyses to evaluate the impact of alternative $PM_{2.5}$ data sources that might create uncertainty not only in $PM_{2.5}$ indicator ranks, but the uncertainty in the overall cumulative impact ranks for communities in the state. Such uncertainty is important to investigate and quantify, especially given increasing use of the EHD Map in state air pollution emissions reduction policies.[152]

Although sensitivity analyses of environmental justice data tools may have been conducted internally within regulatory agencies, few publications are readily available. Huynh et al. (2023) recently examined the sensitivity of CalEnviroScreen and found that the model was sensitive to subjective model decisions, with 16% of tracts potentially changing designation.[167] The changes in ranks were due to varying health metrics, pre-processing, and aggregating methods. These findings point to the sensitivity of cumulative impact tools to variables which may also occur in the WA EHD tool as it was conceptually based on the CalEnviroScreen tool. However, the CalEnviroScreen does not include an external committee including community groups that can help refine the identification of overburdened communities. The use of expert committees can help identify data issues and address methodological concerns to promote equitable representation and involvement from the public, aligning with the tool's goal of advancing environmental justice.[167]

To address the need for more sensitivity analyses of the WA EHD tool, in this study, we recalculated cumulative impact ranks using alternative $PM_{2.5}$ datasets and examined if using these alternate datasets resulted in differences among the identified overburdened communities. Overall, we found most census tracts with a cumulative rank of 9 or 10 did not change. However, we did find that 2-6% of census tracts designated as "overburdened communities" (N = 298) dropped out of their designation. Similarly, we found that 3-6% of census tracts dropped into the overburdened designation when using an alternate data source. Using the ECY population-weighted dataset, 7 census tracts dropped out of the overburdened community designation. Using the CACES dataset, 17 census tracts dropped out of the overburdened community designation. Using Reid without CMAQ, 12 census tracts dropped out of the overburdened community designation. Using Reid without CMAQ, 9 census tracts dropped out of the overburdened community designation. Although these collective findings suggest that only a relatively small number of tracts could lose their overburdened community status, this occurs with the change of only one of the 19 indicators in the EHD Map, and only one of the five indicators in the Environmental Exposure category of the map. If the prioritization of EJ funding decisions and emission reduction programs are made based on cumulative ranks 9 and 10 designations, the potential disqualification of even a small number of tracts is important to understand, as it could have detrimental effects on these communities' ability to obtain funding for environmental pollution reduction activities.

The dropping of tracts from being designated as overburdened communities when alternative $PM_{2.5}$ data are used, can even affect tracts with higher non-White populations and greater populations living in poverty. We examined census tracts within the 20% highest rank for people of color or the 20% highest rank for poverty (**Table 7** and **Table 8**). Of the 7 census tracts that would be dropped when using the ECY population-weighted dataset, 2 of those census tracts were in the 20% highest rank for POC and 4 of those census tracts were in the 20% highest rank for poverty. Of the 17 census tracts that would be dropped when using the CACES dataset, 7 of those census tracts were in the 20% highest rank for POC and 3 of those census tracts were in the 20% highest rank for poverty. Of the 12 census tracts that would be dropped when using the Reid with CMAQ dataset, 3 of those census tracts were in the 20% highest rank for POC and 2 of those census tracts were in the 20% highest rank for poverty. Of the 9 census tracts that would be dropped when using the Reid without CMAQ dataset, 3 of those census tracts were in the 20% highest rank for POC and 3 of those census tracts were in the 20% highest rank for poverty.

Our analysis observed sensitivity in map ranks that may be related to the subtle differences in the time periods over which $PM_{2.5}$ concentrations are averaged. The current EHD Mapping Tool uses a 3-year average $PM_{2.5}$ dataset to approximate a long-term $PM_{2.5}$ exposure. Comparing the original ECY dataset to alternatives, we found the dataset may not capture variation in $PM_{2.5}$ concentrations that are present in other datasets, which may be due to differences in modeling methodology, but also due to slight differences in the time periods represented by each dataset. Moreover, the long-term average may not be the best indicator of exposure because it attenuates the impact of outliers (e.g., short periods of high concentrations). Short term spikes such as wildfire smoke events are not well-captured in the annual averages. For example, examining time series data (Supplemental Material **Figure S3** and **Figure S4**), we found that the Reid Lab daily data reaches concentrations of 12 μg/m$^3$ and 35 μg/m$^3$ (the NAAQS annual average and 24-hour average concentrations) over some 24-hour periods.[168] Examining the Reid Lab daily data, we also find a lot more variation with valleys and peaks in $PM_{2.5}$ concentrations that could be driving short-term health effects that are not well captured by long-term annual average concentrations. The Reid Lab Data without CMAQ included more data on wildfires in their modeling. Including information on proximity to active fires in the machine learning models is important for capturing short-term $PM_{2.5}$ variation and is needed given the increasing frequency and magnitude of wildfires in the Western US.

Perhaps more troubling than the issue of considering different temporal averages, is that even after computing annual averages across multiple years, there are concentration differences between the $PM_{2.5}$ datasets, and correlations between the datasets are not strong. **Figure 2** shows correlations between all the different combinations of data. The high variation in datasets may suggest that using one prediction modeling approach is not enough, and regulatory agencies implementing cumulative impact tools might benefit from ensemble approaches (e.g., averaging over multiple datasets) for $PM_{2.5}$ layers with environmental justice applications. To varying extents, each of the data sources do integrate various data (e.g., air quality monitoring data, satellite, meteorology, and dispersion, etc.), but there is still ultimately only moderate correlation between the different modeled $PM_{2.5}$ concentrations. In our analysis we found that census tracts that drop out of the overburdened community designation when using an alternate $PM_{2.5}$ dataset were concentrated in southeast Washington State, indicative of variations in the different $PM_{2.5}$ datasets in this region of the state. These differences not only have implications for EJ tools, but potentially are important to consider for other applications of modeled $PM_{2.5}$ exposures, such as air pollution health effects studies.

Another potentially important factor in considering alternative $PM_{2.5}$ datasets is their previous use in EJ analyses. Among the data used in our study, the CACES dataset stands out as having been most used in nationwide EJ studies. For example, Liu et al. (2021) used the population-weighted CACES dataset to quantify exposure disparities among racial/ethnic groups and by income for multiple pollutants and years. The authors found that in 2010, racial/ethnic exposure disparities remained across income levels, in urban and rural areas, and in all states, for multiple pollutants.[169] For $PM_{2.5}$ exposures were at least 5% higher than average in 63% of states for non-Hispanic Black populations; in 33% and 26% of states for Hispanic and for non-Hispanic Asian populations, respectively.[169] The change from 1990 to 2010 in absolute racial-ethnic exposure disparity for Washington State was -0.27 $\mu g/m^3$.[169] If we believe the CACES dataset to be more appropriate to EJ analyses and use in tools, then it is important to note that in our analysis we found the most (17) census tracts were dropped from the overburdened community category when using the CACES dataset. Thus, even though CACES has been used in several previous EJ-related studies, it tends to bias more tracts to lower cumulative ranks than other datasets.

### 3.5.1 NAAQS Based Ranking Methodologies

In a secondary analysis, we used a novel NAAQS based methodology to develop new census tract $PM_{2.5}$ ranks. The novel methods incorporate the primary annual $PM_{2.5}$ NAAQS (12.0 $\mu g/m^3$) on a linear scale. Although the health effects associated with varying $PM_{2.5}$ exposure are not truly linear and there may not be a threshold for these health effects[170], the map layer is useful tool to illustrate $PM_{2.5}$ concentrations as they relate to the health-based NAAQS. The NAAQS based method rank census tracts on their individual $PM_{2.5}$ concentrations, not in relation to other census tracts within WA State unlike current EHD Mapping tool methods. This is a point of potential controversy, as there are trade-offs in utilizing a ranking scale that is based on a regulatory standard versus a ranking scale that identifies relative differences irrespective of a regulatory threshold. The use of a regulatory threshold potentially provides an excuse for regulatory agencies to ignore pollution concerns in a community that do not exceed the NAAQS threshold – despite evidence that suggests that adverse health effects may be observed at low concentrations well below current US standards.[170]

Conversely, regulatory agencies may have other priorities than addressing air pollution in a community that is ranked as a 10 because it has the highest $PM_{2.5}$ concentration in the state from a relative perspective but is well below their regulatory mandate for meeting NAAQS attainment. While the current study does not address these trade-offs directly, it does provide useful findings on a hypothetical change to the EHD Map ranking scheme for an indicator for which NAAQS exist. Notably for WA, we found that most datasets do not reach ranks of 9 or 10 with the NAAQS-based linear ranking. We found the WA ECY dataset did not contain census tracts that exceeded a 3-year average of 12 $\mu g/m^3$. When using NAAQS based ranking for WA ECY data, most census tracts were ranked at a 5 or 6 (83% of all census tracts).

Our NAAQS-based findings may change in the near future. The EPA recently announced its proposed decision to revise the primary (health-based) annual $PM_{2.5}$ standard from its current level of 12.0 $\mu g/m^3$ to within the range of 9.0 to 10.0 $\mu g/m^3$.[165] This decision was made after carefully reviewing the most recent available scientific evidence and technical information, and consulting with the Agency's independent scientific advisors.[171] Creating NAAQS based ranks with the proposed $PM_{2.5}$ standard of 9.0 to 10.0 $\mu g/m^3$ would result in rescaling of concentrations for each rank. Rescaling the concentrations associated with each rank would result in more census tracts reaching ranks of 9 or 10. Additional census tracts would also reach exceedance values. New NAAQS based ranking methodologies should be investigated further with meaningful community engagement to determine if it offers a more useful and actionable perspective for environmental justice tools.

### 3.5.2 Funding Implications for Overburdened Communities

The CCA directs the Environmental Justice Council to make recommendations to the WA Legislature on how to auction revenue.[152] Proceeds from the CCA must be invested in critical climate projects focused on improving clean transportation options, increasing climate resilience in ecosystems and communities and addressing issues of environmental justice and health inequity in Washington.[152]

Currently, the WA ECY has identified 16 regions across Washington State as overburdened. In addition to using the WA EHD tool and EPA's EJScreen mapping tool, the WA ECY used data from social and economic differences, historic redlining, health care access, known health disparities (such as increased asthma and lower life expectancy) to determine the overburdened designation.[172] The identified areas are a mix of urban, suburban, and rural, and vary in population, from about 1,500 to more than 200,000 people.[172] They also range in area, from less than three square miles to 173 square miles.[172] All together, they represent more than 1.2 million people or about 15.5% of Washington's population.[172]

Next steps in the implementation of the CCA include 1) working with tribal governments to identify which of their communities are highly impacted by criteria air pollution, 2) involve identified communities as this work progresses, 3) expand the air monitoring network in identified communities, and 4) collect and analyze data about criteria air pollutants affecting these communities. In addition, new indicator layers such as wildfire smoke impact are being developed.[172,173] As cumulative impacts mapping tools continue to evolve and are increasingly used for state decision-making, our findings that indicate sensitivity in overall rankings with changes to only one exposure indicator, suggest the need to incorporate sensitivity analyses as a formal process in the development of new versions of these tools.

## 3.6 CONCLUSIONS

Cumulative impact tools are an essential component to identifying overburdened communities that are disproportionately affected by environmental pollution. The WA EHD cumulative ranking methodology is sensitive to changes in its $PM_{2.5}$ indicator data, with census tracts dropping out or dropping into “overburdened” designation when using alternate $PM_{2.5}$ datasets. Cumulative impact assessment tools should consider using alternate datasets to more accurately capture overburdened communities who experience acute air pollution events. New ranking methodology should also be further developed and considered as a potential alternative to current relative ranking methods.

## 3.7 TABLES & FIGURES

**Table 1.** Key Features of Exposure Estimate Models

| Data Source | Exposure assessment | Spatial Aggregation | Analysis Time period | Analysis Spatial coverage |
|---|---|---|---|---|
| **WA Dept. of Ecology: Version 2.0** | **Interpolated ratio of monitored and forecast data (**AIRPACT: CMAQ) | Census tract & population-weighted based on block level centroid | July 2014 – June 2017 | WA State |
| | | Population-weighted based on block level centroid | | |
| **Center for Air, Climate, and Energy Solutions (CACES)** | **Prediction:** monitored data, LUR, and UK | Population-weighted based on block level centroid | January 2013 – December 2015 | |
| **University of Colorado, Reid Lab** | **Ensemble machine learning model** (NAM, CMAQ, MAIAC, MODIS) | Census tract | January 2014 – December 2016 | |
| | **Ensemble machine learning model** (NAM, MAIAC, MODIS) | | | |
| **Adult-Changes in Thought-Air Pollution (ACT-AP)** | **Prediction:** local monitoring data, LUR and UK | Population-weighted based on block level centroid | June 2017 – August 2019 | Puget Sound |

**Table 2.** NAAQS based $PM_{2.5}$ Ranking Scale for $PM_{2.5}$ Indicator

| **Proposed $PM_{2.5}$ Concentration Range ($\mu g/m^3$)** | **Rank** |
|---|---|
| $<1$ | 1 |
| $1.1 - 2.4$ | 2 |
| $2.5 - 3.8$ | 3 |
| $3.9 - 5.2$ | 4 |
| $5.3 - 6.5$ | 5 |
| $6.6 - 7.9$ | 6 |
| $8.0 - 9.3$ | 7 |
| $9.4 - 10.6$ | 8 |
| $10.7 - 12$ | 9 |
| $12+$ | 10 |

**Table 3**. Washington State $PM_{2.5}$ Summary Statistics

| **$PM_{2.5}$ Data source** | **$PM_{2.5}$ concentration ($\mu g/m^3$)** Mean (SD) [min, max] |
|---|---|
| ECY Original | 6.39 (0.97) [2.89, 10.52] |
| ECY Population-Weighted | 6.09 (0.97) [2.67, 9.15] |
| CACES | 6.07 (1.16) [3.46, 9.95] |
| Reid with CMAQ | 6.83 (1.08) [2.97, 13.19] |
| Reid without CMAQ | 6.73 (1.47) [1.31, 21.34] |

**Table 4**. Puget Sound $PM_{2.5}$ Summary Statistics

| **$PM_{2.5}$ Data source** | **$PM_{2.5}$ concentration ($\mu g/m^3$)** Mean (SD) [min, max] |
|---|---|
| ECY Original | 6.61 (0.71) [4.47, 8.56] |
| ECY Population-Weighted | 6.43 (0.68) [4.42, 8.56] |
| CACES | 5.81 (0.52) [3.89, 7.01] |
| Reid with CMAQ | 6.87 (0.70) [4.67, 9.28] |
| Reid without CMAQ | 6.27 (0.76) [1.53, 11.11] |
| ACT-AP with LCS | 5.49 (0.46) [3.82, 6.43] |
| ACT-AP without LCS | 5.38 (0.52) [3.81, 6.58] |

**Table 5**. Cumulative Impact Rank Changes in Highly Impacted Census Tracts (N= 298)*

| **Dataset** | **# tracts with cumulative rank 9 that went <9** N (%) | **# tracts with cumulative rank 9 that stayed as 9** N (%) | **# tracts with cumulative rank 9 that went to 10** N (%) |
|---|---|---|---|
| ECY Population-Weighted | 7 (2.34%) | 132 (44.30 %) | 5 (1.68%) |
| CACES | 17 (5.70%) | 111 (37.25%) | 16 (5.37%) |
| Reid with CMAQ | 12 (4.03%) | 122 (40.94%) | 10 (3.36%) |
| Reid without CMAQ | 9 (3.02%) | 125 (41.95%) | 10 (3.36%) |
| **Dataset** | **# tracts with cumulative rank 10 that went <9** N (%) | **# tracts with cumulative rank 10 that went 9** N (%) | **# tracts with cumulative rank 10 that stayed as 10** N (%) |
| ECY Population-Weighted | 0 (0%) | 5 (1.68%) | 149 (50.0%) |
| CACES | 0 (0%) | 16 (5.37%) | 138 (46.31%) |
| Reid with CMAQ | 0 (0%) | 10 (3.36%) | 144 (48.32%) |
| Reid without CMAQ | 0 (0%) | 10 (3.36%) | 144 (48.32%) |

*Percentages are calculated out of the state's 298 census tracts within 9/10 cumulative impact ranks.

Table 6. Cumulative Impact Rank Changes in Non-highly Impacted Census Tracts (N = 1161)*

| | **# tracts with cumulative rank <9 that increased >9** **N (%)** | **# tracts dropping in within highest 20% Poverty** **N** | **# tracts dropping in within highest 20% POC** **N** |
|---|---|---|---|
| ECY Population-Weighted | 8 (<1%) | 0 | 5 |
| CACES | 17 (1.5%) | 10 | 8 |
| Reid with CMAQ | 13 (1.5%) | 4 | 5 |
| Reid without CMAQ | 10 (<1%) | 7 | 6 |

*Percentages are calculated out of the state's 1161 census tracts with cumulative impact ranks below 9.

**Table 7**. Cumulative Impact Rank Changes in 20% Highest POC Census Tracts (N = 294). Percentages in parentheses are the percent of the census tracts in the 20% highest POC indicator rating.

| **Dataset** | **# tracts with cumulative rank 9 that went <9** N (%) | **# tracts with cumulative rank 9 that stayed as 9** N (%) | **# tracts with cumulative rank 9 that went to 10** N (%) |
|---|---|---|---|
| ECY Population-Weighted | 2 (0.68%) | 57 (19.39%) | 4 (1.36%) |
| CACES | 7 (2.38%) | 50 (17.01%) | 6 (2.04%) |
| Reid with CMAQ | 3 (1.02%) | 54 (18.37%) | 6 (2.04%) |
| Reid without CMAQ | 3 (1.02%) | 56 (19.05%) | 4 (1.36%) |
| **Dataset** | **# tracts with cumulative rank 10 that went <9** N (%) | **# tracts with cumulative rank 10 that went 9** N (%) | **# tracts with cumulative rank 10 that stayed as 10** N (%) |
| ECY Population-Weighted | 0 (0%) | 1 (0.34%) | 103 (35%) |
| CACES | 0 (0%) | 11 (3.74%) | 93 (31.63%) |
| Reid with CMAQ | 0 (0%) | 6 (2.04%) | 98 (33.33%) |
| Reid without CMAQ | 0 (0%) | 8 (2.72%) | 96 (32.65%) |

[*] Percentages are calculated out of the state's 294 census tracts within the 20% highest POC indicator.

**Table 8.** Cumulative Impact Rank Changes in 20% Highest Poverty Census Tracts (N = 299). Percentages in parentheses are the percent of the census tracts in the 20% highest poverty indicator rating.

| **Dataset** | **# tracts with cumulative rank 9 that went <9** N (%) | **# tracts with cumulative rank 9 that stayed as 9** N (%) | **# tracts with cumulative rank 9 that went to 10** N (%) |
|---|---|---|---|
| ECY Population-Weighted | 4 (1.34%) | 53 (17.73%) | 2 (0.67%) |
| CACES | 3 (1.00%) | 45 (15.05%) | 11 (3.68%) |
| Reid with CMAQ | 5 (1.67%) | 45 (15.05%) | 9 (3.01%) |
| Reid without CMAQ | 2 (0.67%) | 50 (16.72%) | 7 (2.34%) |
| **Dataset** | **# tracts with cumulative rank 10 that went <9** N (%) | **# tracts with cumulative rank 10 that went 9** N (%) | **# tracts with cumulative rank 10 that stayed as 10** N (%) |
| ECY Population-Weighted | 0 (0%) | 4 (1.34%) | 84 (28.09%) |
| CACES | 0 (0%) | 7 (2.34%) | 81 (27.09%) |
| Reid with CMAQ | 0 (0%) | 6 (2.01%) | 82 (27.42%) |
| Reid without CMAQ | 0 (0%) | 4 (1.34%) | 84 (28.09%) |

[*] Percentages are calculated out of the state's 299 census tracts within the 20% highest poverty indicator.

**Table 9.** PM$_{2.5}$ Indicator Ranks using all Statewide WA Datasets Using NAAQS Based Methods. Census Tracts (N = 1459)

| Rank | Proposed PM$_{2.5}$ Concentration Range (µg/m$^3$) | ECY | ECY Population-Weighted | CACES | Reid with CMAQ | Reid without CMAQ |
|---|---|---|---|---|---|---|
| 1 | <1 | 0 | 0 | 0 | 2 | 0 |
| 2 | 1.1 – 2.4 | 0 | 0 | 0 | 0 | 4 |
| 3 | 2.5 – 3.8 | 3 | 26 | 7 | 7 | 10 |
| 4 | 3.9 – 5.2 | 138 | 218 | 299 | 48 | 37 |
| 5 | 5.3 – 6.5 | 723 | 739 | 742 | 533 | 734 |
| 6 | 6.6 – 7.9 | 487 | 415 | 272 | 636 | 431 |
| 7 | 8.0 – 9.3 | 97 | 47 | 98 | 202 | 175 |
| 8 | 9.4 – 10.6 | 6 | 0 | 27 | 19 | 27 |
| 9 | 10.7 – 12 | 0 | 0 | 0 | 4 | 16 |
| 10 | 12 + | 0 | 0 | 0 | 1 | 18 |

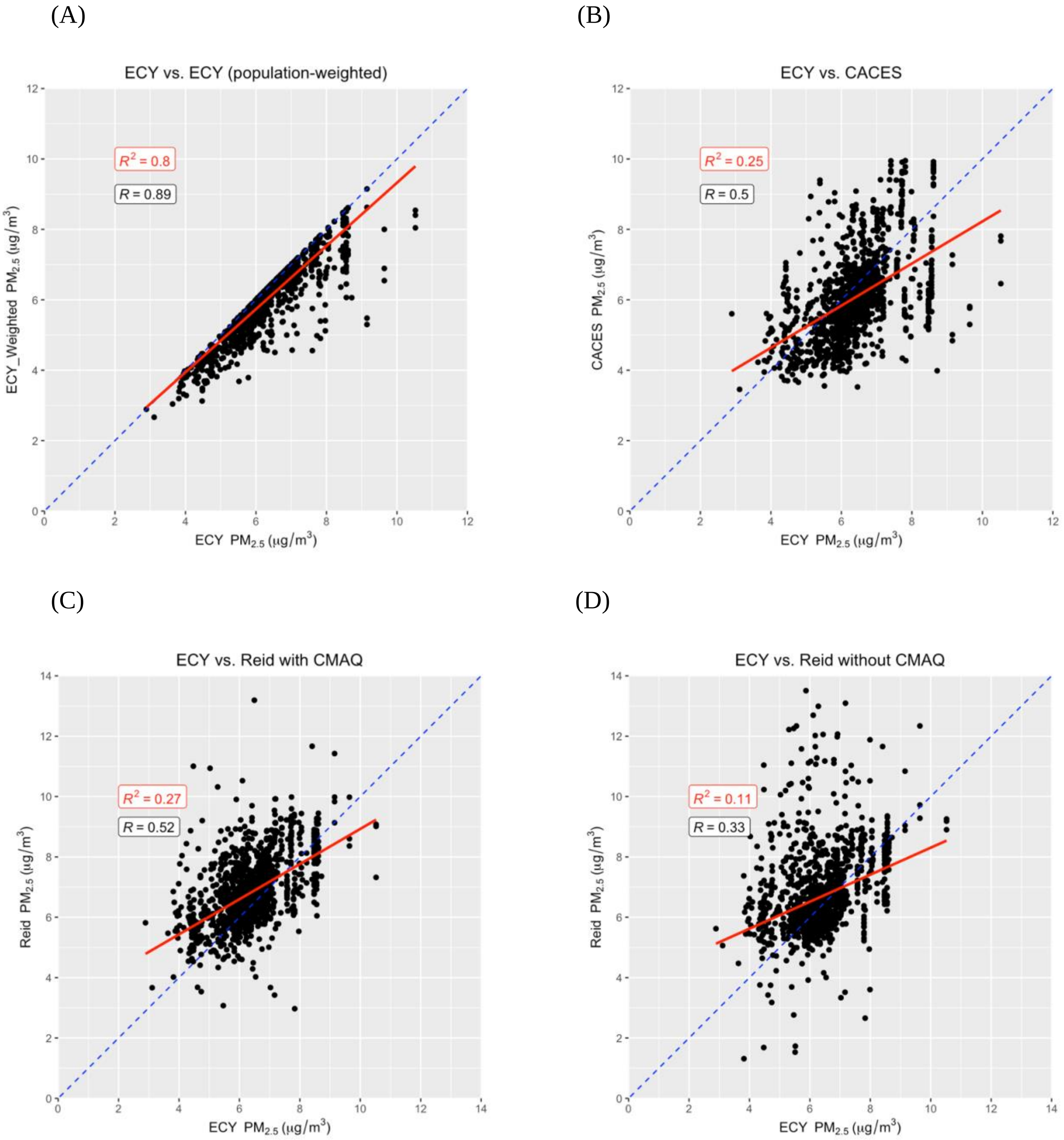


Figure 1. Comparison of ECY $PM_{2.5}$ Concentrations (μg/m$^3$) to Alternate across Washington State. The dashed blue line shows the 1:1 line and solid red line show a linear regression (y ~ x) between $PM_{2.5}$ concentrations. Alternate datasets compared to Original ECY: (A) Population-weighted ECY estimates. (B) CACES. (C) UC Reid Lab with CMAQ. (D) UC Reid Lab without CMAQ.

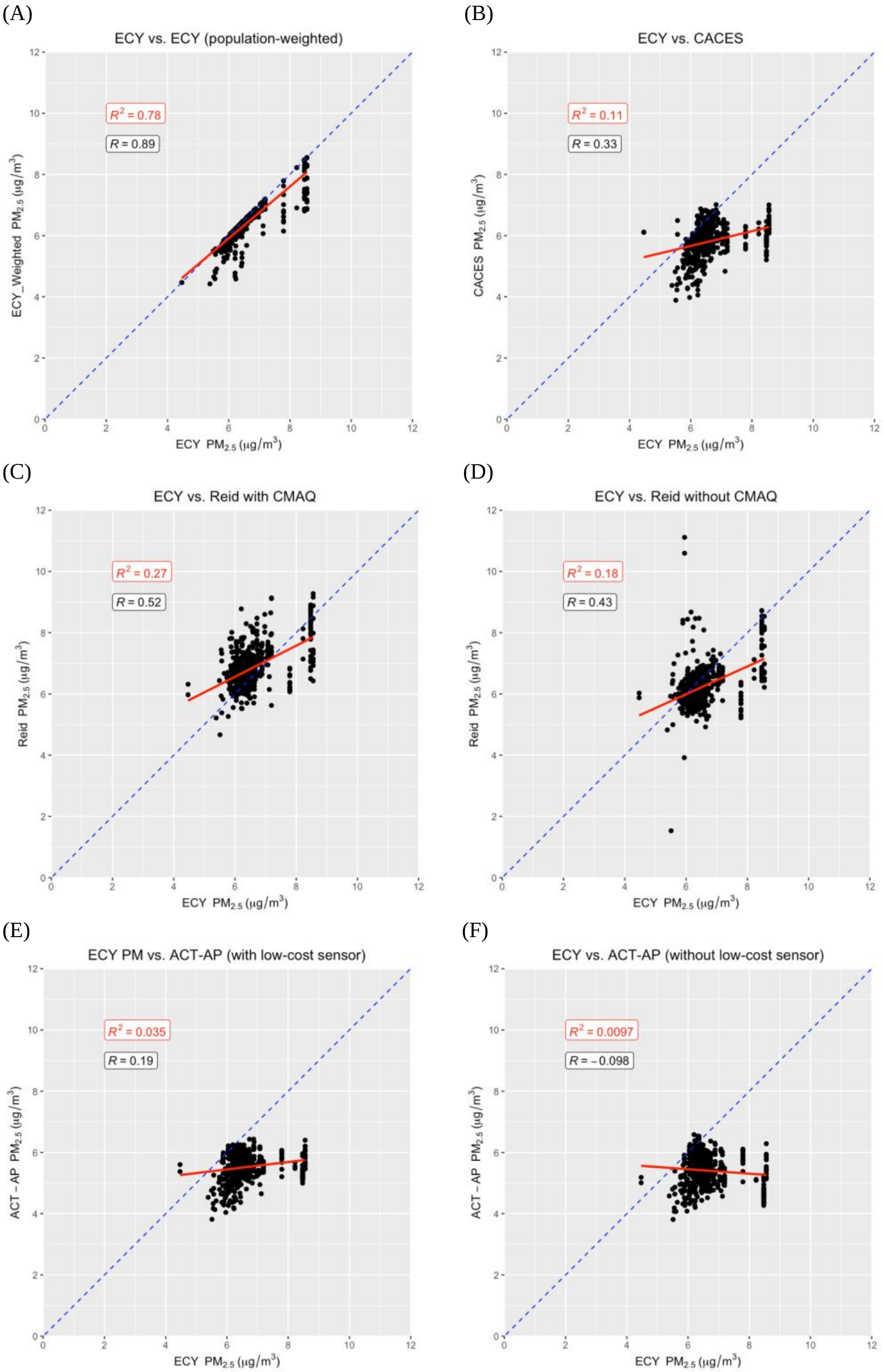


Figure 2. Comparison of $PM_{2.5}$ Concentrations ($\mu g/m^3$) within Puget Sound region. The dashed blue line shows the 1:1 line and solid red line show a linear regression (y ~ x) between $PM_{2.5}$ concentrations. Alternate datasets compared to Original ECY: (A) Population-weighted gridded ECY estimates. (B) CACES. (C) UC Reid Lab with

CMAQ. (D) UC Reid Lab without CMAQ. (E) ACT-AP with low-cost sensor data. (F) ACT-AP without low-cost sensor data.

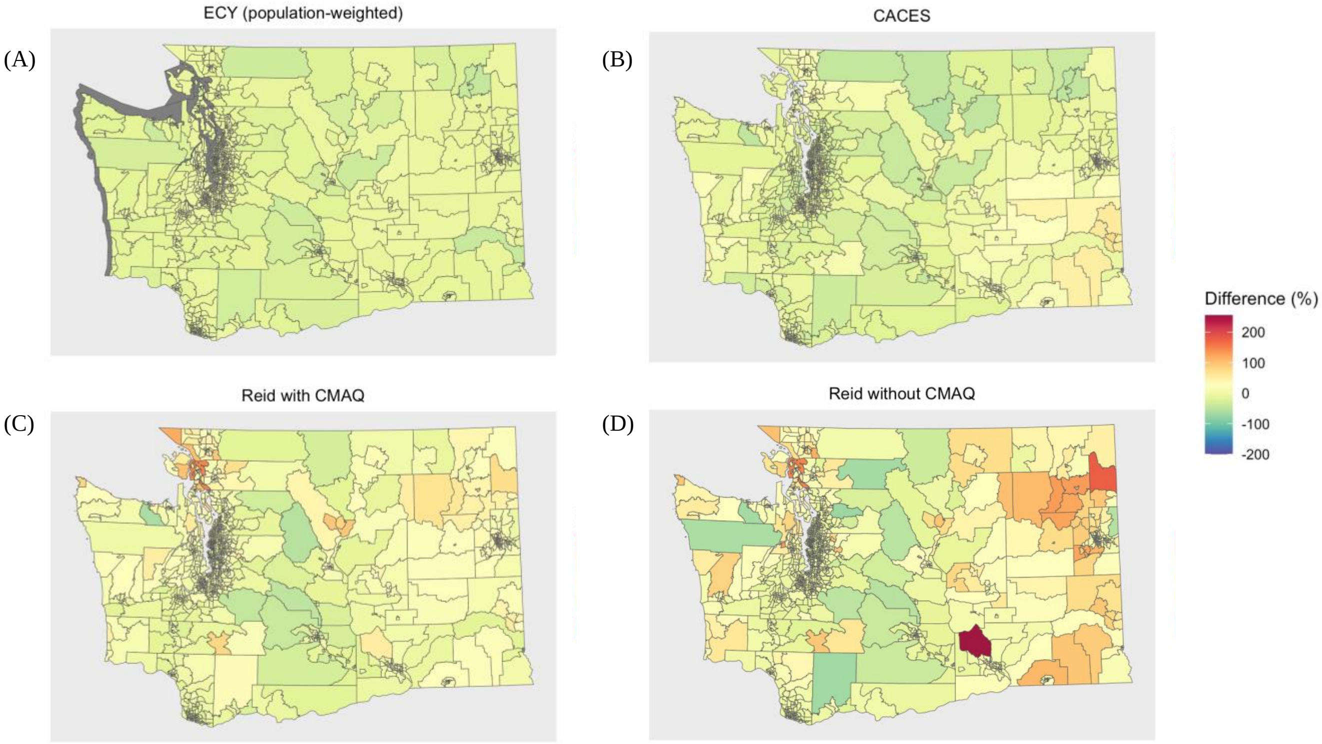


Figure 3. Percent Difference in PM$_{2.5}$ Concentrations comparing ECY and alternate datasets across Washington State. Percent differences were calculated by using equation 6, subtracting alternate estimates from original ECY estimates. Alternate datasets: (A) Population-weighted ECY. (B) CACES. (C) UC Reid Lab with CMAQ. (D) UC Reid Lab without CMAQ.

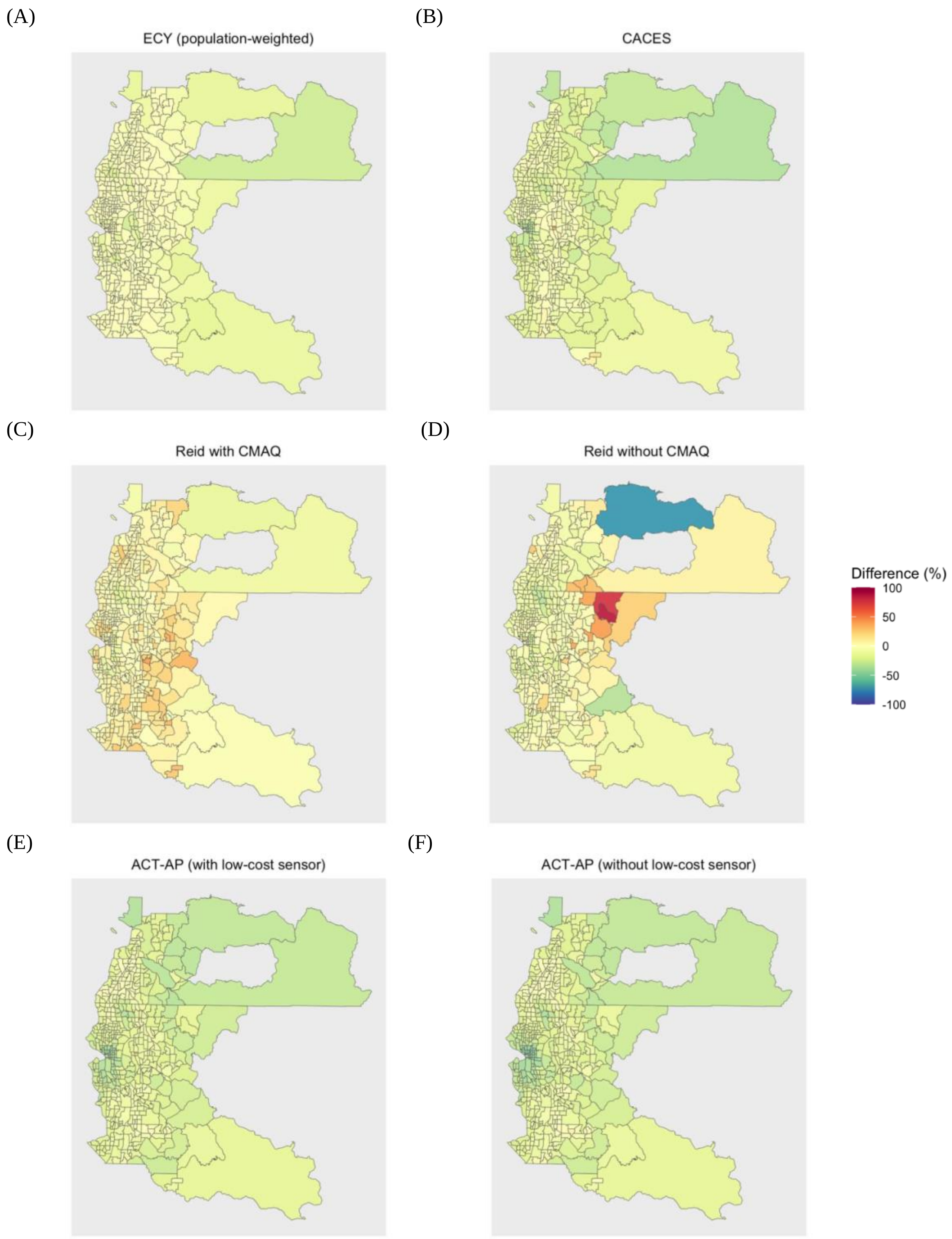
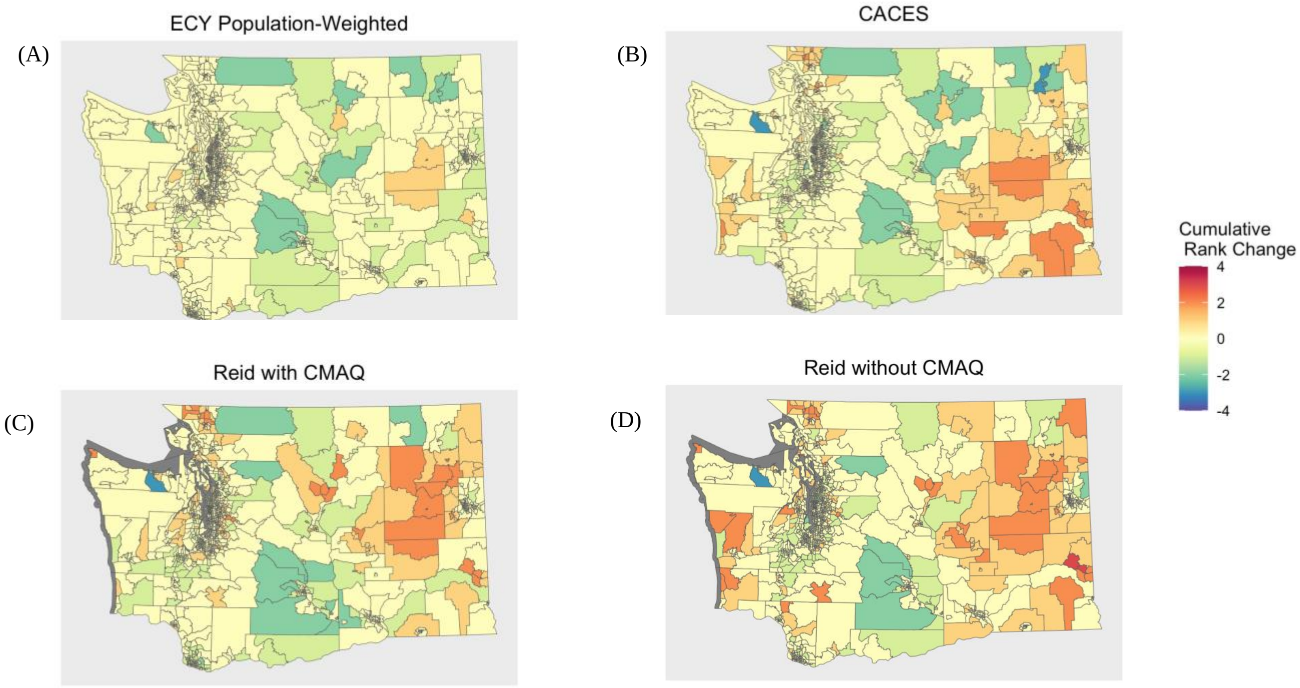


Figure 4. Percent Difference in $PM_{2.5}$ Concentrations comparing ECY and alternate datasets across Washington State. Percent difference was calculated by using equation 6. Alternate datasets: (A) Population-weighted ECY. (B) CACES. (C) UC Reid Lab with CMAQ. (D) UC Reid Lab without CMAQ. (E) ACT-AP with low-cost sensor data. (F) ACT-AP without low-cost sensor data.


(A) ECY Population-Weighted

(B) CACES

(C) Reid with CMAQ

(D) Reid without CMAQ

Figure 5. EHD Cumulative Rank Changes comparing ECY and alternate datasets across Washington State. Cumulative rank difference was calculated using equation 7. Alternate datasets: (A) Population-weighted ECY. (B) CACES. (C) UC Reid Lab with CMAQ. (D) UC Reid Lab without CMAQ.

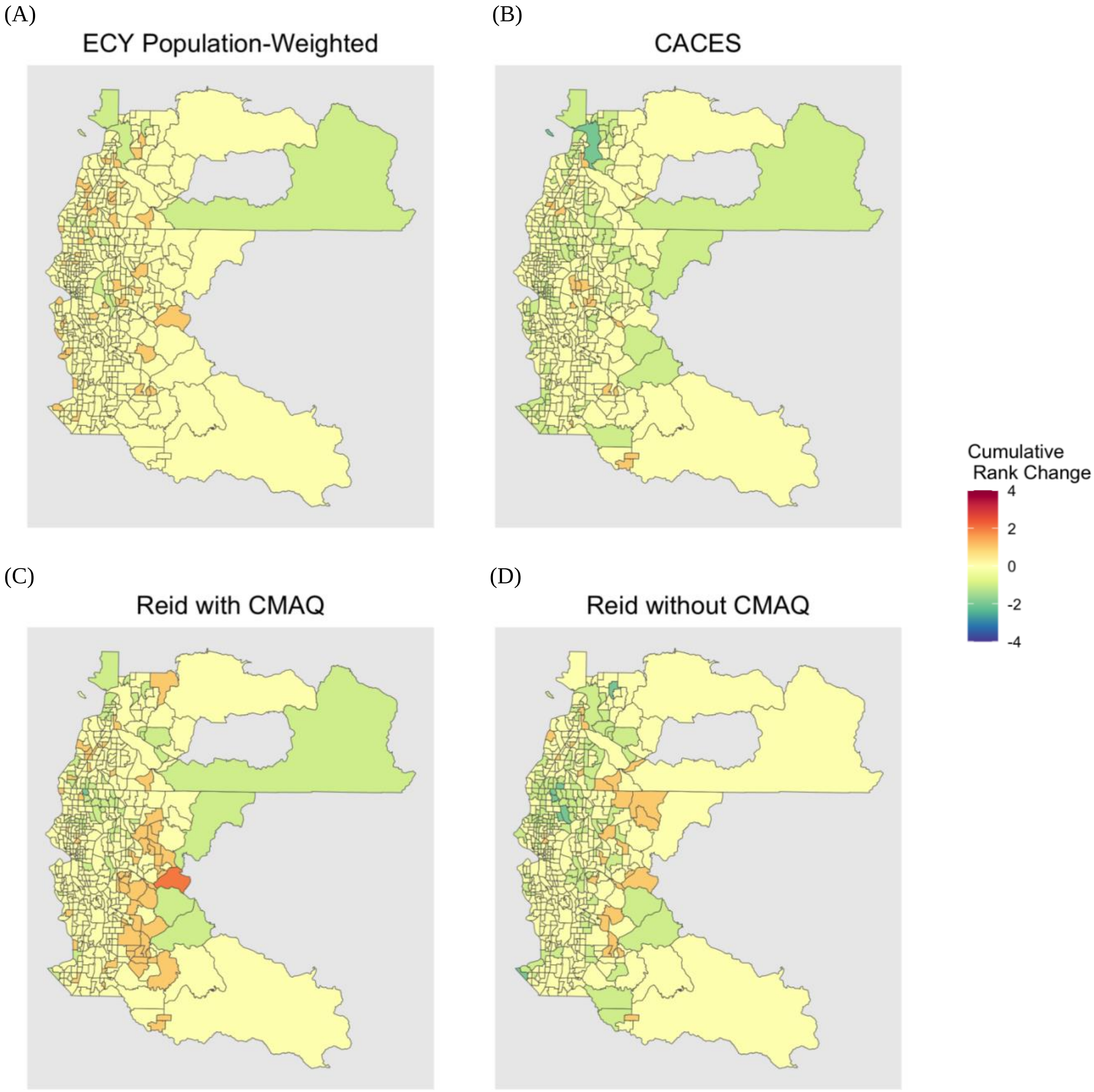


Figure 6. EHD Cumulative Rank Changes comparing ECY and alternate datasets within the Puget Sound region. Alternate datasets: (A) Population-weighted ECY. (B) CACES. (C) UC Reid Lab with CMAQ. (D) UC Reid Lab without CMAQ. (E) ACT-AP with low-cost sensor data. (F) ACT-AP without low-cost sensor data.

Figure 7. Census Tracts dropping out and dropping into Highly Impacted Cumulative Ranks. Census tracts dropping out are shown in red and dropping in are shown in green. Active PM$_{2.5}$ air quality monitoring locations are shown in light blue diamonds (N = 60). Alternate datasets: (A) Population-weighted ECY. (B) CACES. (C) UC Reid Lab with CMAQ. (D) UC Reid Lab without CMAQ.

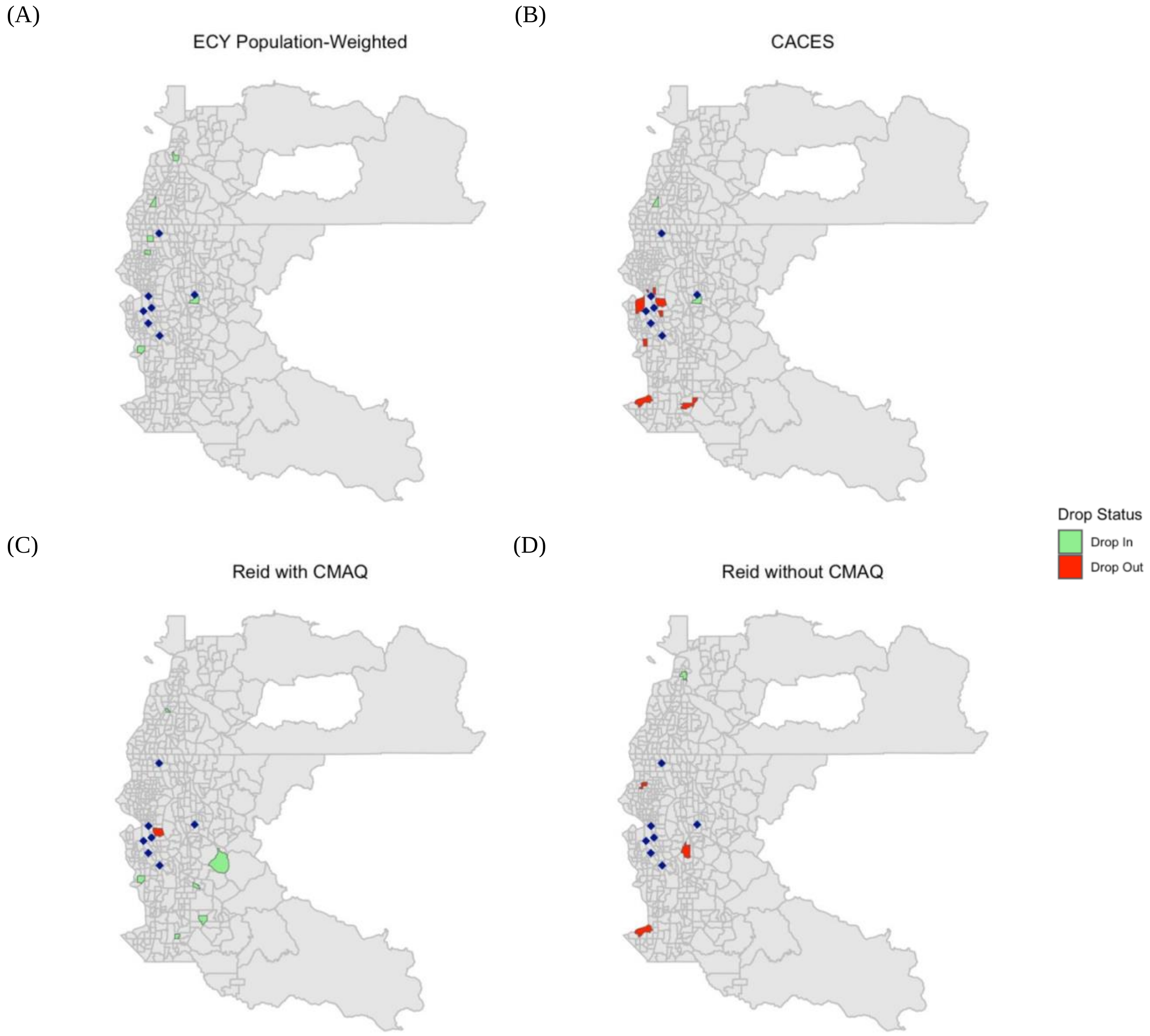


Figure 8. Census Tracts dropping out and dropping into Highly Impacted Cumulative Ranks within the Puget Sound region. Census tracts dropping out are shown in red and dropping in are shown in green. Active $PM_{2.5}$ air quality monitoring locations are shown in dark blue diamonds (N = 7). Alternate datasets: (A) Population-weighted ECY. (B) CACES. (C) UC Reid Lab with CMAQ. (D) UC Reid Lab without CMAQ.

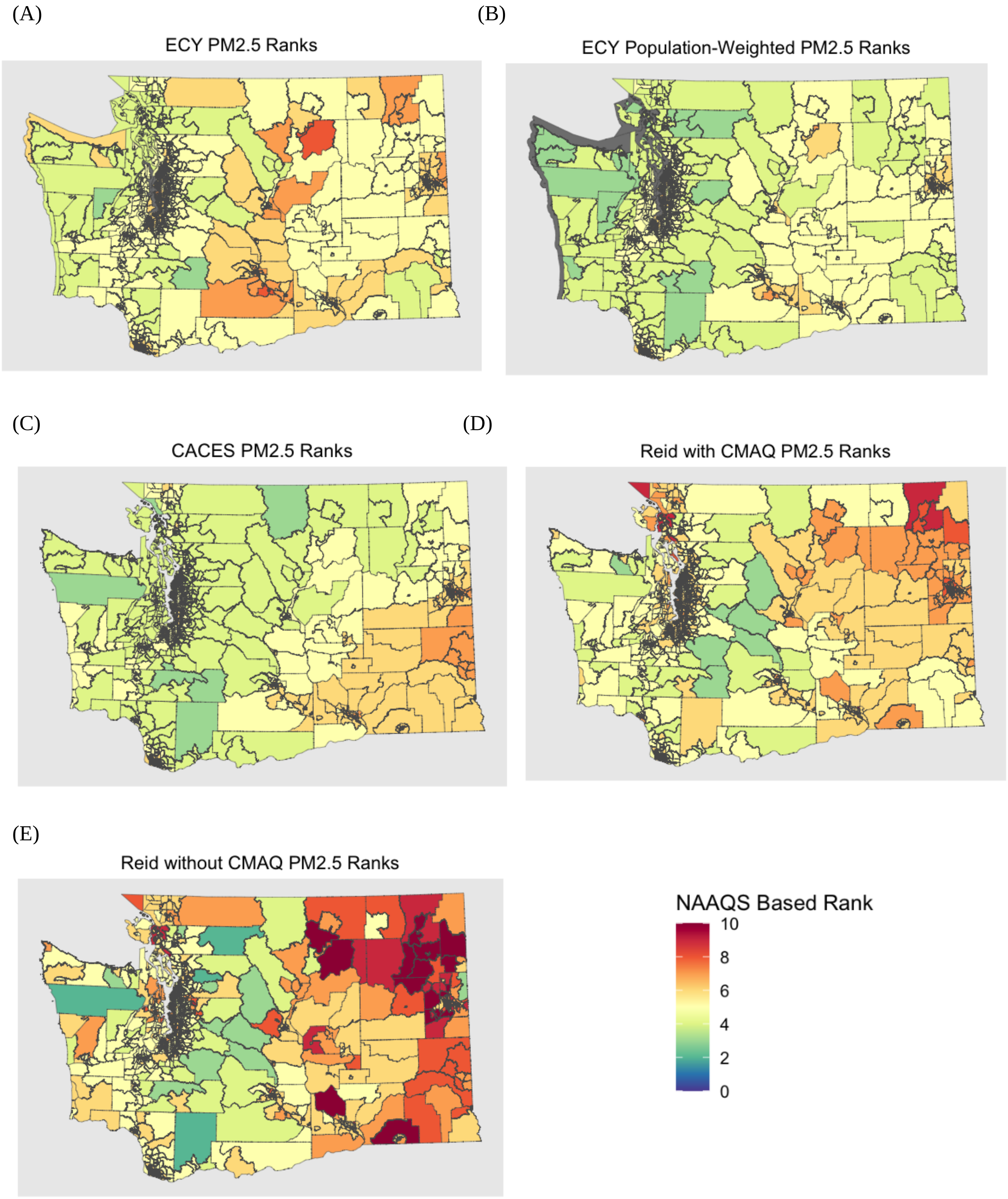


Figure 9. $PM_{2.5}$ Indicator Ranks using new NAAQS Based Ranking across Washington State. Datasets: (A) Original ECY. (B) Population-weighted gridded ECY. (C) CACES. (D) UC Reid Lab with CMAQ. (E) UC Reid Lab without CMAQ.

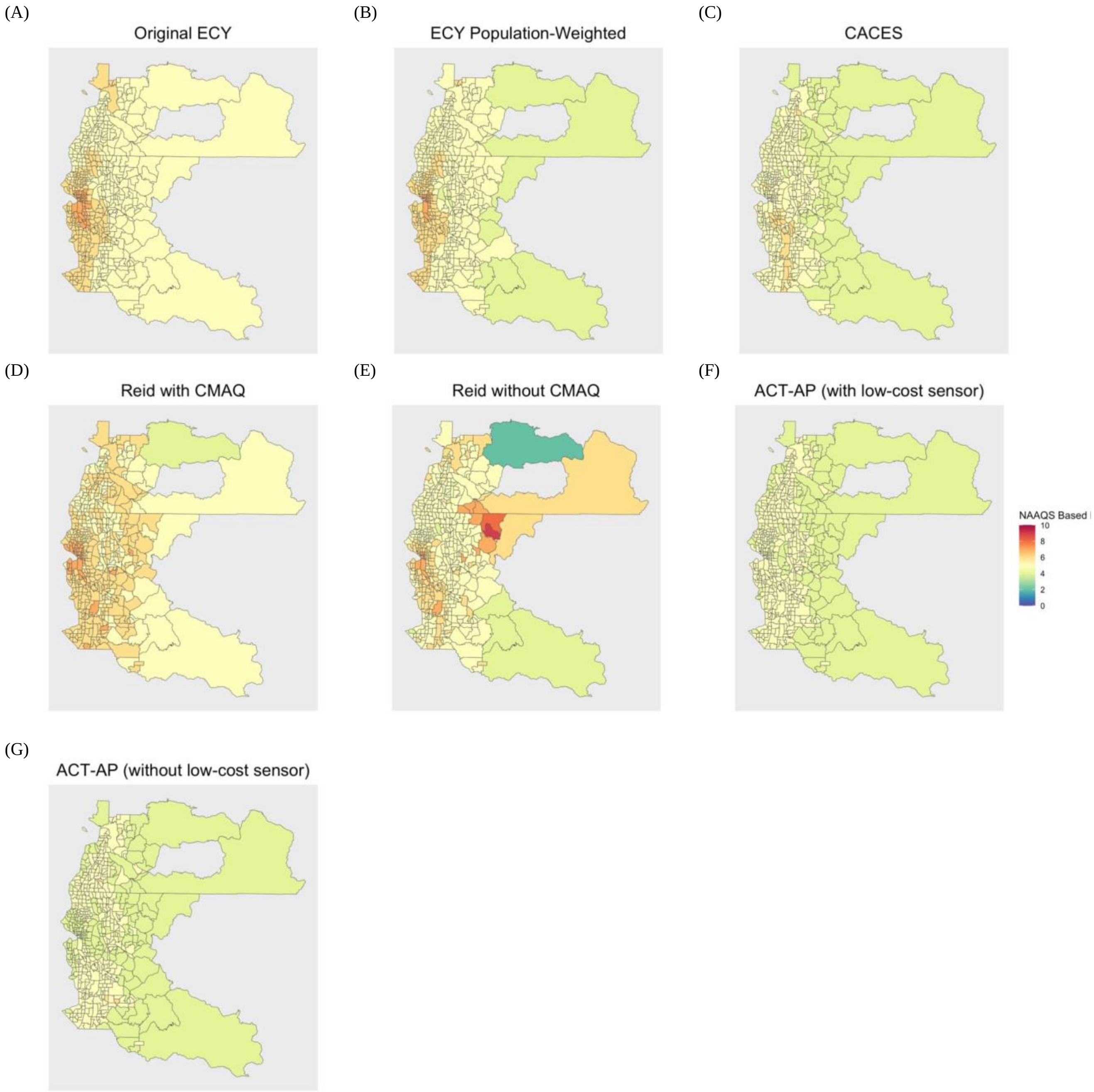


Figure 10. $PM_{2.5}$ Indicator Ranks using new NAAQS Based Ranking within the Puget Sound region. Datasets: (A) Original ECY. (B) Population-weighted gridded ECY. (C) CACES. (D) UC Reid Lab with CMAQ. (E) UC Reid Lab without CMAQ. (F) ACT-AP with low-cost sensor data. (G) ACT-AP without low-cost sensor data.

## 3.8 SUPPLEMENTAL INFORMATION

Figure S1. Time Series Plot of ACT-AP with low-cost sensor data raw data. $PM_{2.5}$ concentrations shown from June 2017 through August 2019 represent block centroid predictions within the Puget Sound region. Data were modeled to a 2-week average.

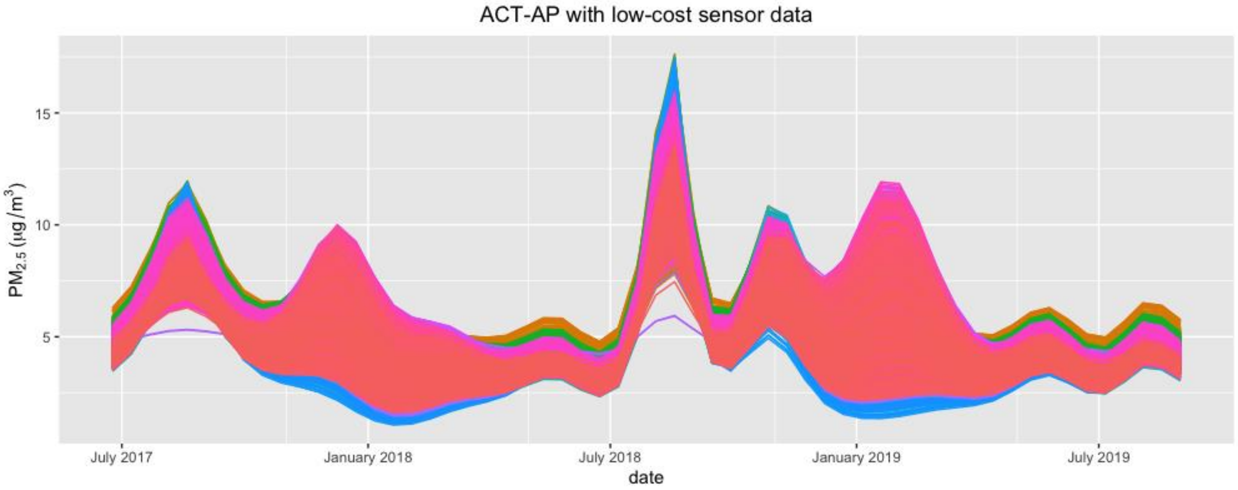


Figure S2. Time Series Plot of ACT-AP without low-cost sensor data raw data. $PM_{2.5}$ concentrations shown from June 2017 through August 2019 represent block centroid predictions within the Puget Sound region. Data were modeled to a 2-week average.

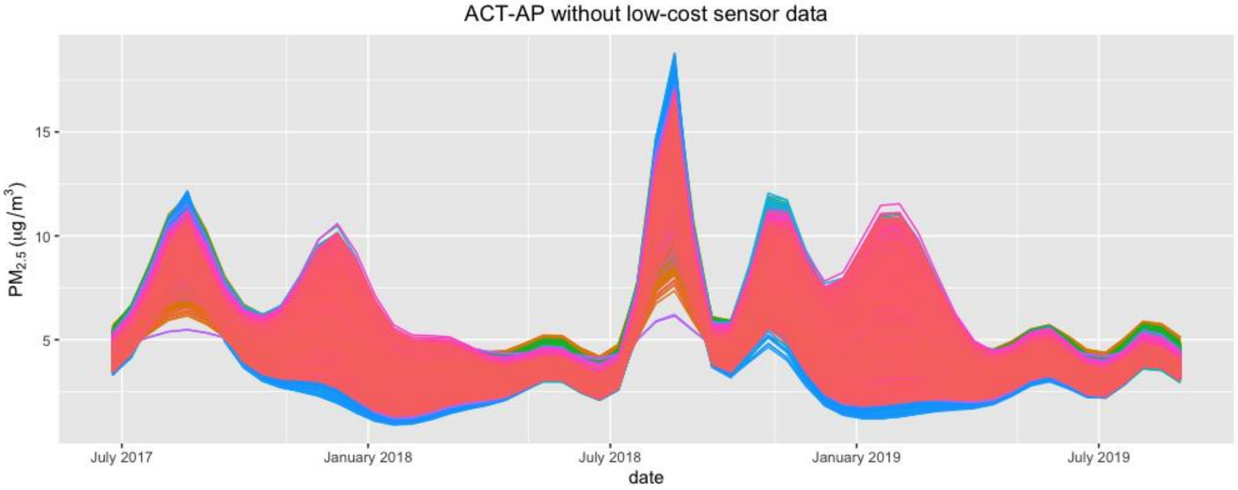


Figure S3. Time Series Plot of Reid with CMAQ raw data. $PM_{2.5}$ concentrations shown from January 2014 through December 2016 represent census tract level predictions across Washington State. Data were modeled to a daily average. Negative exposure estimates were removed from aggregated data.

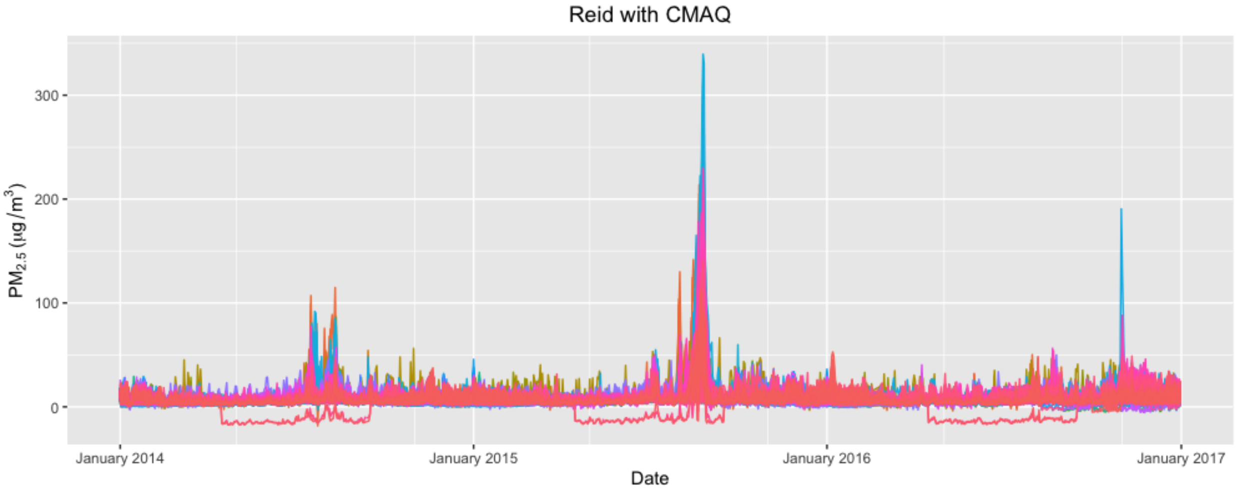
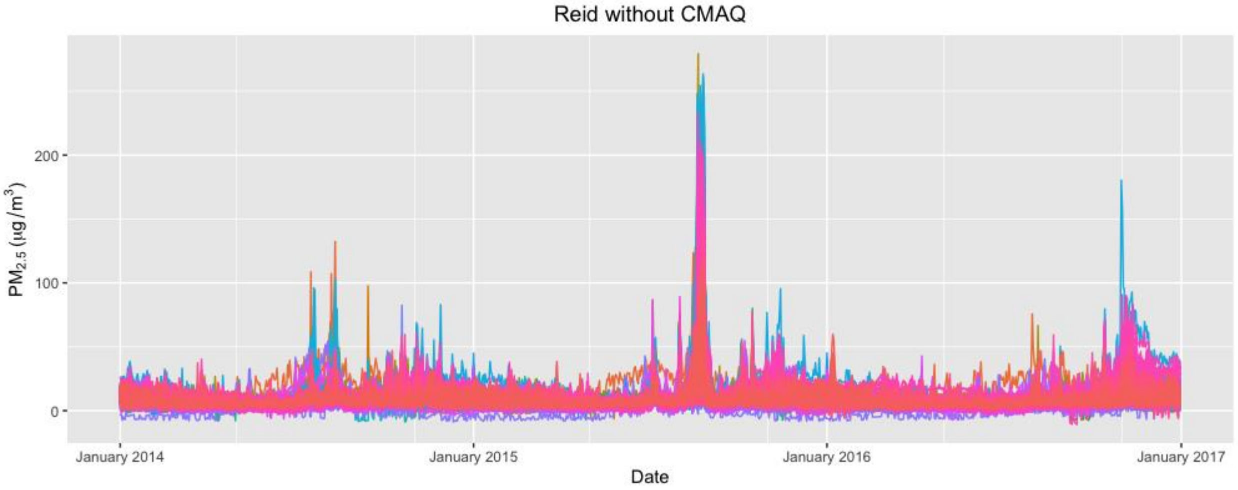


Figure S4. Time Series Plot of Reid with CMAQ raw data. $PM_{2.5}$ concentrations shown from January 2014 through December 2016 represent census tract level predictions across Washington State. Data were modeled to a daily average.



# Chapter 4. Long-term exposure to ambient air pollution in a cohort of older adults: A cross-sectional analysis of the Adult Changes in Thought (ACT) Cohort

## 4.1 ABSTRACT

*Background***:** Recent epidemiological studies have shown that exposure to ambient air pollution is associated with lower cognitive function in older adults.

*Objectives***:** We assessed the association between cognition in older adults and fine particulate matter ($PM_{2.5}$), ultrafine particles (UFP), black carbon (BC) and nitrogen dioxide ($NO_2$).

*Methods***:** Data for this study were taken from the population-based Adult Changes in Thought study cohort carried out in the greater Seattle region. A total of 4,566 older adults completed cognitive assessment using the Cognitive Abilities Screening Instrument between 1994 and 2020. Exposure estimates were determined using two modeling approaches, one based on regulatory monitoring data supplemented with study-specific sampling and the other from a mobile monitoring campaign. We estimated the association between exposure to each pollutant ($PM_{2.5}$, UFP, BC, and $NO_2$) and cognitive function using linear regression models.

*Results***:** We found that cognitive function for each additional 1 $\mu g/m^3$ of time-varying 5-year average $PM_{2.5}$ at baseline was comparable with participants who were 0.62 (95% Confidence Interval (CI): -0.15, 1.28) years older. Using alternate $PM_{2.5}$ exposure estimates from a spatial

(SP) only version of the spatiotemporal (ST) model, we found that cognitive function for each additional 1 μg/m$^3$ of $PM_{2.5}$ was comparable with participants 1.97 (95% CI: 0.44, 3.26) years older. We also used alternate exposure estimates from mobile monitoring (MM) model capturing spatial variability. For MM UFP, we found that for every additional 1900 pt/cm$^3$ of UFP at baseline cognitive function was comparable with participants 0.73 (95% CI: 0.26, 1.13) years older. For MM BC, we found that for each additional 125 ng/m$^3$ of BC at baseline, cognitive function was comparable with participants 0.34 (95% CI: -0.29, 0.87) years older. For ST $NO_2$, we found that for each additional 3 ppb of ST $NO_2$ at baseline, cognitive function was comparable with participants 0.39 (95% CI: -0.05, 0.77) years older, 0.43 (95%CI: -0.38, 1.12) years using SP $NO_2$ and 0.57 (95% CI: -0.17, 1.19) years using MM $NO_2$.

*Conclusion*: This study supports an association between long-term exposure to ambient air pollutants such as $PM_{25}$ and UFP and lower cognitive function in adults.

## 4.2 INTRODUCTION

In the United States, Alzheimer's disease (AD) is the sixth-leading cause of death, hospital admissions, and home health care.[174] The geriatric brain is of increasing concern given the growing aging population with over 54 million residents being 65 years or older.[175] In 2022, the total national cost of caring for people living with AD and other dementias is projected to reach $321 billion, not including the $271.6 billion in unpaid caregiving by family and friends.[174] The identification of risk factors for AD is of importance for prevention and potential treatments. Modifiable risk factors include physical activity, smoking, education, staying socially and mentally active, blood pressure, diet, and air pollution.[3] The 2020 Lancet Commission on dementia prevention, intervention and care suggests that addressing modifiable risk factors might prevent or delay up to 40% of dementia cases.[176]

A growing body of research has reported that ambient air pollution is a new potential modifiable risk factor associated with diminished cognitive function.[176,16,17,177] First, several epidemiological studies suggest that exposure to particulate matter is associated with lower cognitive function in older adults.[177–184] Studies in animal models and in humans have supported the hypothesis that exposure to fine particulate matter ($\leq 2.5\mu$m in diameter or $PM_{2.5}$) is associated with the AD processes, neuroinflammation, and oxidative stress.[4–6,185,186] Two possible pathways of how fine and ultrafine particulate ($\leq 100$ in diameter or UFP) matter can affect neurocognitive function have been hypothesized, the first being through an inflammatory response and subsequent oxidative stress, and the second being through direct entry of particulate matter into the nervous system through the olfactory bulb.[4,187,188,189] A component of $PM_{2.5}$, black carbon (BC), which is formed from the incomplete combustion of diesel fuel, is thought to be associated with decreased cognitive function through inflammation pathways.[190,191]

In the Puget Sound, the Mobile ObserVations of Ultrafine Particles (MOV-UP) study found that particulates such as UFP and BC have different spatial patterns depending on their particle size distribution.[57] Indeed, BC concentrations had different spatial roadway and aircraft features.[57] Some epidemiological studies estimated that UFP exposure was associated with slower cognitive development in children.[192,193] In addition, a study in Mexico City found exposures to high concentrations of $PM_{2.5}$ and UFP during childhood resulted in protein pathologies associated with AD.[194] However, to our knowledge there have been no studies examining the effect of UFP on cognition in older adults.

In a cohort of elderly Puerto Ricans in Greater Boston, Wurth et al. found that BC was associated with lower cognition function across all cognitive domains.[191] Previous studies have found an association between BC and lower global cognition among men in the Normative Aging Study.[195] Given that BC is a component of traffic-related $PM_{2.5}$, proximity to major roadway has also been used as a proxy for BC exposure.[196] Wellenius et al. found that living less than 100 meters from a major roadway was associated with worse cognitive function in older adults.[196] However, Sakhvidi et al. (2022) estimated lower cognition in adults over the age of 45 was associated with pollutant exposures, including $PM_{2.5}$, $NO_2$, and BC, and lower cognition in adults over the age of 45, but the magnitude of the effect size depended on the pollutant and cognitive domain.[197]

Furthermore, $NO_2$ studies have resulted in inconsistent results when using different cognitive scales to measure global cognition and executive function.[182,184,198] Shin et al. (2019) found that an IQR increase in exposure to ambient $NO_2$ was associated with lower executive function scores but improved global cognition.[184] Kulick et al. (2020) found that a IQR increase exposure to $NO_2$ was associated with lower global cognitive score.[198] In a study among middle aged and older cognitively intact adults, Gatto et al. (2014) found that ambient exposure to $NO_2$ greater than 20 ppb, compared to exposure less than or equal to 10 ppb, was associated with lower logical memory but had a smaller effect size with global cognition.[182]

The aim of this study was to investigate the cross-sectional associations of long-term exposure to traffic-related air pollutants ($PM_{2.5}$, UFP, BC, and $NO_2$) and cognition using baseline visit data from the population-based Adult Changes in Thought study. Our primary analysis will use exposure averaged over the 5 years prior to baseline as the primary exposure window.

## 4.3 MATERIALS AND METHODS

### 4.3.1 Study sample

We obtained the study data from the Adult Changes in Thought (ACT) cohort, a population-based cohort drawn from the Group Health Cooperative and then Kaiser Permanente Health Maintenance Organization (HMO) and administered by the Kaiser Permanente Washington Health Research Institute (KPWHRI). The cohort consisted of 5,763 individuals from the Puget Sound region in Washington state enrolled prior to March 2020. Participants were at least 65 years of age at the time of recruitment and on average had been part of the HMO for two decades prior to enrollment. To date there have been three recruitment waves into the ACT cohort. The initial cohort randomly selected members of the HMO in 1994-1996.[199] The cohort was expanded in 2000-2002 and included oversampling clinics with higher proportions of minorities.[199] Continuous enrollment has been in effect since 2005 with a goal of maintaining over 2,000 active participants.[199] Members of the cohort have been assessed biennially for a variety of health outcomes, including cognitive ability, until death, dropout, or dementia diagnosis. The University of Washington and our collaborators at the Kaiser Permanente Washington Research Center have received IRB approval for this study.

### 4.3.2 Cognitive function testing

Cognitive function was assessed using the Cognitive Abilities Screening Instrument (CASI), a global cognitive test. The CASI has a score range of 0 to 100 and assesses attention, concentration, orientation, short-term memory, long-term memory, language abilities, visual construction, list-generating fluency, abstraction and judgement.[200] The screening test typically takes 15 to 20 minutes to complete.[200] The CASI has 40 questions and has been successfully used in large epidemiological cohort studies as a screening tool for detecting dementia.[199,201] The CASI is a longer version of the Mini-Mental State Examination (MMSE) which has been developed to clinically identify patients with mild cognitive impairment.[201] MMSE scores can be determined from a subset of CASI items.

Inherently the CASI has relatively few difficult items and many easy items, resulting in curvilinear scoring, particularly when participants start with different baseline cognitive abilities.[201] However, item difficulties are not considered in standard scoring.[202] Item response theory (IRT) scoring has been found to diminish the impact of differential item functioning (DIF). DIF occurs when different groups of individuals have different probabilities of correctly answering an item, even after controlling for overall ability level. IRT scores also allow for greater sensitivity at higher levels of cognitive function, which is especially important for the detection of early cognitive deficits.[199,201] We will use baseline CASI-IRT scores for this cross-sectional analysis.

### 4.3.3 Exposure assessment

#### Overview

Two distinct datasets and modeling approaches were used to predict various pollutants exposures at participants' residence addresses. The $PM_{2.5}$, and primary $NO_2$ models were based on space-time data and relied on a combination of regulatory monitoring and special data collected as part of the ACT-Air Pollution (ACT-AP) study. Exposures to these pollutants were predicted using spatiotemporal models (ST), as described below. In contrast, the secondary $NO_2$ models as well as models for BC and UFP were based on spatial data obtained from a mobile monitoring (MM) data collection campaign conducted in 2019 to early 2020 under the auspices of the ACT-AP study. We used exposure estimates released in April 2023 for the present analysis.

#### Address history and geocoding

KPWHRI provided residential address history information since enrollment. Address history from billing records was available starting in 1989 and prior to that from the HMO administrative records and a Lexis-Nexis address search.[203] Exposure predictions at geocoded residential addresses were developed for fixed time periods prior to participants' time of enrollment into the ACT cohort based on their residential history. Residential addresses were geocoded using ArcMap (version 10.5).[203]

#### Exposure data

Our spatiotemporal approaches used regulatory monitoring data from the Puget Sound Clean Air Agency (PSCAA) and The Washington State Department of Ecology, study-specific data from two previous studies in Seattle[161,162], and low-cost sensor data from our own ACT-AP study. Agency $PM_{2.5}$ measurements from 1978 through 2020 consisted of three types of regulatory monitoring data including 35 federal regulatory monitors (FRMs), 48 nephelometer (NEPH) monitors and 6 tapered element oscillating microbalance (TEOM) monitors. FRM and TEOM monitors both use gravimetric methods to measure $PM_{2.5}$, while NEPH use light-scattering but are well-correlated with more direct $PM_{2.5}$ measurement approaches.[204] We included NEPH data beginning in 1978 in our model and FRM or TEOM data starting in 1998.[203] Agency $NO_2$ measurements from 1996 through 2020 were measured by chemiluminescent FRM/FEM instruments (Teledyne API, San Diego, CA; model 200 EU).

Supplemental data from the 2012 Diesel Exhaust Exposure in the Duwamish Study (DEEDS) were also included in the $PM_{2.5}$ model. The DEEDS study used Harvard Personal Exposure Monitors (HPEMS) in 25 locations to collect particles on a 37mm Teflon filter with a 50% cut point of 2.5 μm.[162,161] The HPEMS is a single-stage inertial impactor connected to a personal pump.[161] A gravimetric analysis was used to determine the $PM_{2.5}$ mass concentration of the Teflon filter samples.[162]

ACT-AP also conducted its own supplementary measurement campaign at 112 residential locations and ACT cohort participant homes from April 2017 to July 2021 to provide additional spatial coverage. We used community air monitoring instruments, containing two Plantower (PMS A003) $PM_{2.5}$ sensors and an Alphasense $NO_2$ sensor. In addition, Ogawa Passive Samplers (Ogawa & Co., USA, Inc., Pompano Beach, FL) sensors were deployed in 2018 in a “snapshot campaign” to collect passive monitoring of ambient $NO_2$ at 110 locations in 17 clusters and 9 single locations.

Mobile monitoring data were collected over a year at 309 roadside stop sites in the Puget Sound region.[58] Fixed routes were used to sample from March 2019 through March 2020 during all seasons, all days of the week and most hours of the day.[58] The mobile monitoring region was somewhat smaller than the spatiotemporal modeling region.[58] High quality instruments were used to collect measurements including BC (AethLabs MA 200), $NO_2$ (Aerodyne Research Inc. CAPS) and particle number concentration (PNC) as a measure of UFP (TSI Nanoscan 3910).[58] Quality assurance and quality control activities were conducted including collecting duplicate measurements for assessing collocation agreement.[58]

Spatiotemporal modeling approach

A spatiotemporal model was used to quantify space-time-varying exposures. The hierarchical spatiotemporal model includes a long-term spatial mean, time trends with spatially varying coefficients, and a spatiotemporal residual.[158–160] The model accounts for spatial variability and temporal trends, while accommodating agency and supplementary modeling data. As a broad overview of the approach, singular value decomposition (SVD) was used to derive temporal basis functions to describe the variation in temporal trends characterized from the sites with data over long time periods while reducing the residual temporal correlation.[159] The number of temporal basis functions was determined through cross-validation performance measures. Partial least-squares regression (PLS ) was used to reduce a large number of correlated geographic covariates and create composite "scores".[159,163] The model was utilized to develop $PM_{2.5}$ and $NO_2$ predictions.  The spatiotemporal model was fitted using a customized version of the "SpatioTemporal" package (version 1.1.7) in R (version 4.2.0).

We separately aggregated the spatiotemporal model predictions from 2019 using the address history prior to baseline and within the smaller mobile monitoring region to create "spatial only" predictions. We will refer to this 2019 model as the spatial only (SP) model. It was created to be temporally consistent with predictions from the mobile campaign and cover the same geographic area. Due to monitoring campaign features the mobile monitoring model geographical area is smaller than the spatiotemporal modeling region covering 87% of the census tracts of ACT cohort residences.[58] Figure S7 shows the modeling geographical areas.

A modified approach to fitting the spatiotemporal model was used to predict $PM_{2.5}$ from 1978-2020. After removing a long-term trend using a loess smoother, a single temporal trend was determined from SVD based on long-term monitor data. A large set of 874 geographic covariates were reduced using PLS.[163,205] We used the first two principal components from PLS for the land use regression (LUR) process. Using spatiotemporal validation, the $PM_{2.5}$ model demonstrated to have good predictive accuracy with an $R^2 = 0.83$ (RMSE = 0.92 $\mu g/m^3$).[206] Pollutant exposures were aggregated from two-week time averages up to 1-, 5-, 10- and 20-year averages.

The spatiotemporal model was used to predict $NO_2$ from 1996-2020. However, the derivation of the PLS components differed from $PM_{2.5}$. Due to an insufficient number of regulatory agency sites, ACT-AP $NO_2$ snapshot campaign data were used to conduct PLS regression at each the snapshot locations. PLS scores were then predicted at all monitoring locations using their geographic covariates. $NO_2$ ST model performance RMSE = 2.6; $R^2$ = 0.86; $R^2_{reg}$= 0.85.[207] $NO_2$ predictions are available from the spatiotemporal, spatial only, and mobile monitoring models (discussed below). A summary of exposure metrics can be found in Supplementary Table S2.

### Mobile data spatial models and performance

We developed spatial predictions at ACT cohort locations within the mobile monitoring regions using data from the one-year mobile monitoring campaign described above.[58] Predictions of annual average exposures were calculated using pollutant-specific universal kriging (UK) models and partial least squares (PLS) regression components from 191 geographic covariate predictors.[58] Model performance indicated good agreement between estimates and cross-validated predictions, cross-validated MSE-based $R^2$ values were 0.77 for $NO_2$, 0.65 for UFP, and 0.60 for BC. We assume mobile monitoring model (MM) predictions and spatial only predictions are valid for the entire study time period, including the 5-year time period prior to study enrollment (1989 -2020).[208–210]

### 4.3.4 Statistical analyses

We estimated the association between exposure to air pollutants and cognitive function using multiple linear regression models. The model can be written as:

$$Y_i = \beta_0 + X_i\beta_1 + Z_i\beta_2 + e_i$$

The index $i$ represents each participant. $Y_i$ is the measured CASI-IRT score at baseline; $\beta_0$ is the intercept; $X_i$ is the mean pollutant concentration at baseline; $Z_i$ refers to the vector of cross-sectional covariates measured at baseline; and $e_{it}$ residual error. The model quantifies the relationship between exposure and cognitive function; $\beta_1$ is our primary parameter of interest and cross-sectional association between air pollutant exposures before the baseline exam. Our primary exposures of interest were $PM_{2.5}$ (time-varying from the spatiotemporal model) and UFP (mobile monitoring model).

A set of separate multiple linear regression models were constructed for each pollutant exposure. The main *a priori* model (Model 2) included the baseline pollutant exposure and age, gender, calendar year and APOE $\varepsilon 4$ status. Due to the relationship between air pollution and time, we adjusted our models for calendar time categories divided into two-year increments as in our previous ACT publication.[203]

To aide in the interpretability of our results, baseline age was centered at 75 years. To provide more context on the impact of pollutants on cognitive ability, we calculated the cognitive "aging" equivalent defined as $IQR * \hat{\beta}_{pollutant} / \hat{\beta}_{age}$ within each model, where $\hat{\beta}_{pollutant}$ is the estimated pollutant coefficient $\hat{\beta}_{age}$ is the estimated coefficient for one additional year of age, and the pollutant coefficient is multiplied by an IQR-guided increment for the purposes of comparing results between pollutants. Both coefficient estimates come from the same model. We similarly calculated the 95% confidence interval for the "aging" equivalent.

We performed statistical analyses using R version 4.2.2, packages included dplyr, tidyr, stats, gtsummary, data.table, forcats, ggplot2, glmnet, jtools, and splines.

### 4.3.5 Covariates

Covariates for the health effects model included sociodemographic variables, health conditions, and selected lifestyle behaviors that are considered to be risk factors for lower cognitive function. Sociodemographic variables included gender, race, education, and a measure of neighborhood socioeconomic status. We used the year 2000 standardized neighborhood disadvantage index (NDI) value developed from census variables included in the Multi-Ethnic Study of Atherosclerosis (MESA) neighborhood disadvantage index[211,212], where the NDI z-score represents the census tract-level disadvantage relative to other tracts that year. Health measures included depression, body mass index (BMI), diabetes, hypertension, stroke, cerebrovascular diseases, and cardiovascular diseases. The apolipoprotein E (APOE) gene $\varepsilon4$ allele is the most prominent genetic risk factor for the development of AD with a lifetime risk of developing AD more than 10 times higher for individuals with two $\varepsilon4$ alleles than those without the $\varepsilon4$ allele.[8] Lifestyle behaviors included smoking and physical activity. However, physical activity may be a protective factor against cognitive decline.[213]

### 4.3.6 Sensitivity analyses

We performed sensitivity analysis for all models comparing the estimates of $\hat{\beta}_1$ using different exposure model estimates. For $PM_{2.5}$ we considered the spatial only model estimates as sensitivity analyses. In addition, we performed sensitivity analyses for the main models comparing the estimates of $\hat{\beta}_1$ using different amounts of adjustment for precision variables and potential confounders as described above in the covariates section. The reduced model (Model 1) included the 5-year average pollutant level at baseline and baseline age (see Table S1 for all model covariate details). In an extended analysis (Model 3), additional terms were added to the main model (Model 2), including an indicator of White vs. non-White, education, and NDI. The model that considered possibly mediating variables (Model 4) included additional adjustments to the main model (Model 2) with possible mediators and potential risk factors including hypertension, strokes, diabetes, heart diseases, cerebrovascular diseases, respiratory diseases, BMI, exercise level and cigarette smoking.

### 4.3.7 Secondary analyses

In secondary analyses, we examined alternate exposures including $PM_{2.5}$ (SP) and $NO_2$ (SP and MM) and BC (MM). We also evaluated the interaction of APOE $\varepsilon4$ status with individual pollution variables. In addition, we evaluated co-pollutant models that adjusted the main model with a secondary pollutant of $PM_{2.5}$, UFP, BC or $NO_2$. We examined alternate exposure averaging periods of 1-, 10- and 20-years prior to enrollment.

## 4.4 RESULTS

A total of 4,566 eligible participants were included in the present study. Participants were removed from the analysis if they had missingness in variables used in the main model, including having an exposure estimate and APOE $\varepsilon4$ status at baseline. Exposure estimates developed using the mobile monitoring region had a smaller geographical region than the spatiotemporal region resulting in the exclusion of 56 participants. **Table 1** summarizes the baseline characteristics of the cohort for the analysis cohort and full cohort. The full cohort includes participants that were not included in the analytic cohort due to missingness in key variables such as APOE $\varepsilon4$. However, comparing  the proportions for demographics and health characteristics in the two columns indicates that the analytic dataset is representative of the full cohort.

**Figure 1** illustrates the spatial variability of $PM_{2.5}$, UFP, BC, and $NO_2$, throughout the Puget Sound Region. $PM_{2.5}$ concentrations are the least variable of all four pollutants throughout the Puget Sound region, with higher concentrations near major roadways and dense downtown Seattle. Lower $PM_{2.5}$ concentrations are seen in less populated regions. Supplemental material (Figure S2) illustrates 5-year average $PM_{2.5}$ concentrations spanning from 1991 – 2020. We see that the spatial distribution of $PM_{2.5}$ is relatively unchanged, with higher concentrations along major roadways, even as the magnitude of concentrations is reduced in more recent years. In our spatial only model, we make the strong assumption that the spatial distribution of $PM_{2.5}$ has remained constant throughout the study period. UFPs show more spatial variation than $PM_{2.5}$, with higher concentrations again along major roadways but illustrate an aircraft pollution feature near SeaTac International Airport identified in earlier studies[57]. BC concentrations show higher concentrations along major highways, but this is more pronounced in the southern regions of the Puget Sound region. In addition, the concentrations are also highest around the Port of Seattle and near SeaTac International Airport. $NO_2$ also shows spatial variation with higher concentrations along major roadways and downtown Seattle. Supplemental material (Figure S2) also illustrates 5-year average $NO_2$ concentrations spanning from 1991-2020. Similar to $PM_{2.5}$, we find that the spatial distribution of $NO_2$ remained constant while the range of concentrations was lower in the later time periods.

**Table 2** shows the interquartile range of each pollutant at baseline. We will be reporting the results per 1 additional $\mu g/m^3$ of $PM_{2.5}$, 3 ppb of $NO_2$, 1900 $pt/cm^3$ of UFP, 125 $ng/m^3$ BC. This an "IQR guided" increment because there is a different IQR within each pollutant model due to the different data sources and time periods of measurement. To make comparisons between the association of each pollutant and cognitive ability, we present the associations for each pollutant by these IQR-guided increments.

**Table 3** shows the results of our main model for $PM_{2.5}$ , UFP, BC and $NO_2$ by exposure estimate model. The results of the main model showed a lower average baseline CASI-IRT per increment of pollutant, with wide confidence intervals indicating results are consistent with a range of effects. In our primary analysis, using spatiotemporal model predictions, we found that on average for every 1 μg/m$^3$ of $PM_{2.5}$, participants aged 0.62 (95% CI: -0.15, 1.28) years in cognitive ability. Using exposure predictions from the "spatial only" model we found that on average for every 1 μg/m$^3$ of $PM_{2.5}$, participants aged 1.97 (95% CI: 0.44, 3.26) years in cognitive ability. Similarly, using mobile monitoring model predictions, we found that on average for every 1900 pt/m$^3$ of UFP, participants aged 0.73 (0.26, 1.13) years in cognitive ability.

### 4.4.1 Sensitivity Analysis

**Table 4** shows the results of our reduced and extended models.-Participants were removed from these analyses if they had missingness in variables used in any of the models, including race, education, and NDI index. For Model 1, we found that on average for every additional 1 μg/m$^3$ of $PM_{2.5}$ (ST), participants aged 1.07 (95% CI: 0.95, 1.18) years in cognitive ability. For Model 2, we found that on average for every additional 1 μg/m$^3$ of $PM_{2.5}$ (ST), participants aged 0.84 (95% CI: 0.07, 1.5) years in cognitive ability. While for Model 3, we found that on average for every additional 1 μg/m$^3$ of $PM_{2.5}$ (ST), participants aged 0.04 (95% CI: -0.92, 0.84) years in cognitive ability.

### 4.4.2 Secondary Analyses

#### Co-pollutant Models

We also examined a main model with adjustments for traffic-related co-pollutants. **Table 5** shows the results of our co-pollutant models using our primary analysis dataset. We adjusted the main model for the additional co-pollutants of $PM_{2.5}$, UFP, BC, or $NO_2$. In the top row of the table, we show the pollutant coefficient from a main model with one pollutant of interest. For

$PM_{2.5}$ (ST and SP) pollutant models, their effect estimates were robust when $NO_2$ (ST and SP) or BC were included in the model. However, adjusting the model with $PM_{2.5}$ (SP) by UFP attenuated negative effect estimates, from -0.072 (-0.129, -0.015) to -0.044 (-0.107, 0.019). Adjusting the $NO_2$ (SP) model by UFP also attenuated negative effect estimates, from -0.016 (-0.044, 0.013) to 0.068 (0.015, 0.120). Similarly, adjusting the UFP model with $NO_2$ (MM) attenuated negative effect estimates, from -0.021 (-0.047, 0.006) to 0.030 (-0.014, 0.075). For BC, the effect on cognitive ability decreased when adjusting for $PM_{2.5}$ (SP), UFP, or $NO_2$ (MM). However, confidence intervals for these models remain large indicating uncertainty in these results.

Additional secondary analysis results are presented in the supplementary material. Results of an interaction analysis between pollutant and APOE $\varepsilon 4$ status are presented in supplementary material (Table S3). We found no evidence of interactions between pollutant exposure and APOE $\varepsilon 4$ positive status. Results of an analysis of the main model using alternate exposure periods of at 1-, 10- and 20-years prior to enrollment are presented in the supplementary material (Table S4). We found the results were sensitive to using alternate exposure periods, with longer exposure periods of 10 and 20-year averages having smaller effect estimates.

## 4.5 DISCUSSION

The results of the present study suggest an adverse effect of ambient pollution on cognitive function in older adults. This study adds to existing research on air pollution and cognition in non-demented older adults by demonstrating links between long-term average exposure to various traffic-related pollutants, including $PM_{2.5}$, UFP, BC and $NO_2$, and lower cognitive function. To our knowledge this is the first study investigating the association of exposure to UFP and cognitive function in older adults. Comparing the results of our study to previous epidemiological studies is difficult given the use of different cognitive assessments. To make a fairer comparison on the same scale we reported the results in terms of comparable cognitive "aging" per pollutant IQR guided increment.

In our primary analysis we found that a 5-year average 1 μg/m$^3$ increase of $PM_{2.5}$ resulted in an aging effect of 0.62 years. Our results are congruent with Tallon et al. (2017) who examined the association between $PM_{2.5}$ and global cognition among older adults in the National Social Life, Health and Aging Project (NSHAP) cohort study and found that a one-year average IQR increase in $PM_{2.5}$ resulted in an aging effect of 1.6 years.[179] In a secondary analysis, we found that a one-year average IQR guided increment increase in $PM_{2.5}$ resulted in an aging effect of 0.63 years using the spatiotemporal estimates and 2.05 years using spatial only estimates (Table S4 presents 1-year average results). Gatto et al. (2014) examined cross-sectional associations between $PM_{2.5}$ and measures of cognitive function and global function in non-demented older adults and found increased exposure to $PM_{2.5}$ was associated with lower verbal learning, but not with global cogntion.[182]

In addition, we found that for every additional 1900 pt/cm$^3$ of UFP, participants had cognitive ability comparable to participants 0.73 (0.26, 1.13) years older. UFP estimates are best characterized over space and mobile monitoring campaigns have emerged as a valuable method to capture spatial variation of long-term average UFP exposure.

Furthermore, in a secondary analysis we found that a 5-year average 3 ppb increase in $NO_2$ was comparable to an aging effect of $NO_2$ resulted in an aging effect of 0.39 years. Tallon et al. (2017) also examined the association between $NO_2$ and global cognition and found a stronger negative association, with a two-year IQR increase in $NO_2$ being comparable to an aging effect of 1.9 years.[179] Moreover, Cullen et al. (2018) found a positive association between improved cognitive function and higher $NO_2$.[214] However, given there is no previous evidence suggesting a protective relationship of $NO_2$, these results may be spurious false positives or may reflect selection bias in the UK Biobank general population cohort.[214]

### 4.5.1 Rationale for excluding NDI in primary model

We did not adjust our primary model for NDI given our *a priori* analysis plan. Given the complex relationship between air pollution and SES[212], we considered whether NDI is a confounder, effect modifier, or mediator. Bivariate plots show weak to moderate linear associations between pollutant concentrations at baseline and NDI, and CASI-IRT at baseline and NDI. However, given the spatial association between NDI and concentration, we did not want to over correct for the structure of the pollutant data in our primary analysis. Our extended SES model (Model 3) examined the association between air pollution and cognition at baseline when adjusting for NDI, gender, and race. We found smaller effect estimates with narrower confidence intervals when adjusting for these SES variables, indicating that our results are sensitive to the NDI index variable. Based on the empirical evidence from our dataset we are still uncertain of the role of SES as a possible mediator or confounder.

In the present study, for all pollutants considered we found that our main model was sensitive to neighborhood deprivation index with adjustment resulting in a reduction in the negative association between pollutant exposure and cognitive function at baseline. Our findings point to environmental justice concerns because of spatial effect indicating that improved SES attenuated the observed decrease in cognitive ability in association with $PM_{2.5}$. Gatto et al. (2014) study in Los Angeles, California found that participants with lower educational levels or household incomes had greater exposure to $NO_2$ and $PM_{2.5}$.[182] Earlier cross-sectional studies have shown that lower mean global cognitive scores in may reflect inequalities such as educational experience, occupational opportunities, and racism that may lead to late-life differences in cognition.[215,216] Furthermore, there are currently no national air quality standards for UFP, and some toxicology studies indicate that these types of particles may be of greater concern than $PM_{2.5}$ as they can more easily cross the blood-brain barrier and accelerate aging in the adult brain.

### 4.5.2 Exposure Models

Exposure estimation can have substantial impacts on health inference.[217] For our secondary analyses we considered various exposure metrics for the same pollutants ($PM_{2.5}$ and $NO_2$) in our analysis. We investigated how changing the exposure metric of the pollutant measures affects the association between air pollution exposure and cognition. We found that a 5-year average 1 $\mu g/m^3$ increase of $PM_{2.5}$ resulted in an aging effect of 1.97 (0.44, 3.26) years when considering spatial only $PM_{2.5}$ estimates, versus 0.62 (-0.15, 1.28) years when using the spatiotemporal estimates. However, we found that a 5-year 3 ppb of $NO_2$ increase of $NO_2$ resulted in an aging effect of 0.43 (-0.38, 1.12) when using the alternate spatial only estimates, fairly similar to the aging effect of 0.39 (-0.05, 0.77) years when using spatiotemporal estimates and 0.57 (-0.17, 1.19) years when using the mobile monitoring estimates. Markedly, the confidence intervals for the spatial only model are much larger than the spatiotemporal model.

The results from this analysis suggest that the change in air pollution over time could be a source of inconsistency in our findings. However, our linear regression models adjust for calendar time and should be accounting for major pollutant time trends, but not for how pollutants might vary over space in those times. Supplemental Figure S2 illustrates the spatial change in 5-year average $PM_{2.5}$ and $NO_2$ exposure estimates over time (1991 – 2020). The spatial distribution of $PM_{2.5}$ and $NO_2$ is relatively unchanged, with higher concentrations along major roadways, even as the magnitude of concentrations is reduced in more recent years.

The spatial distribution of pollutants can vary because of their different pollutant sources and physical properties. Fine particulate matter is generally uniformly distributed over a region, but atmospheric inversions can lead to heterogeneity in the spatial distribution of fine particulates.[218,219] However, historically (1987 – 1994) the spatial distribution of particle pollutant has been impacted by wood smoke production during wood-burning season.[218–220] Although wood burning has since decreased, a new challenge in the region is wildfire smoke, with the regions highest fine particulate days now taking place during the wildfire smoke days.[221] The spatial distribution of $PM_{2.5}$ has generally remained the same during our study period, but the magnitude has drastically decreased[221] (Supplemental Figure S2). Scatterplots of $PM_{2.5}$ (ST) and $PM_{2.5}$ (SP) 5-year averages at baseline matched by participant illustrate strong Pearson correlations (R = 0.80, 0.98) (Supplemental Figure S3). Using the spatial only model $PM_{2.5}$ estimates removed the possible impact of temporal confounding in the spatiotemporal estimates, but also used a measure that had an average level and variability that were not representative of the earlier time period.

In contrast to $PM_{2.5}$, $NO_2$ has small-scale spatial variations within urban areas.[222] On road vehicles such as trucks and automobiles, off-road vehicles such as construction equipment, marine vessels, and port cargo-handling equipment are the major sources of NOx (NO + $NO_2$) in the Puget Sound region.[223] The spatial distribution of $NO_2$ has largely remained the same throughout the study period (Supplemental Figure S2). The $NO_2$ spatial only model assumes the spatial structure of the pollutant in 2019 has remained constant throughout the study period. Similarly, the mobile monitoring $NO_2$ data obtained in 2019 and assume the spatial structure of the pollutant has remained constant since 1989. Scatterplots of $NO_2$ (ST) and $NO_2$ (SP) 5-year averages at baseline matched by participant illustrate strong linear relationships (R = 0.90 - 0.98) (Supplemental Figure S4). Similarly, scatterplots of $NO_2$ (MM) and $NO_2$ (ST), and $NO_2$ (MM) and $NO_2$ (SP) 5-year averages at baseline matched by participant show moderate to strong linear relationships with R ranging from 0.75 to 0.97 (Supplemental Figure S5) and 0.66 to 0.94 (Supplemental Figure S6), respectively.

The change in exposure model impact on exposure estimates is much larger for $PM_{2.5}$ than $NO_2$, perhaps from the differences in spatial variability of the pollutant. In addition, the confidence intervals for the spatial only model are almost twice as large as the spatiotemporal model. This may be driven by differences in the variation of $NO_2$ between ST and SP predictions as $NO_2$ data were projected back in time 1989 from data from 1996.

The effects of measurement error can vary and result in real effects being hidden, spurious relationships that are not present in error-free data, or even the direction of the effect estimates can be reversed relative to a case with no measurement error.[224] Effect estimates could also be impacted by additional factors such as the monitoring region, modeling region, monitoring instruments, monitoring time period, and prediction time period. Spatial changes in pollutant sources, and exposure monitoring and modeling features should be further investigated to evaluate potential misclassification for participants enrolled in 1994.

Previous studies examining the relationship between $PM_{2.5}$ exposures and cognition in older adults in the United Sates have used exposure estimates after 2000 and do not capture time periods prior to 2000 that experienced higher concentrations of ambient air pollutants.[17] The present study is novel in utilizing $PM_{2.5}$ exposure estimates that leverage historical air monitoring data dating back to 1978. The spatiotemporal estimates also allow us to predict exposure estimates over time, as far back as 1978.

### 4.5.3 Exposure time-period

An additional secondary analysis considered alternate exposure periods of 1-, 10- and 20-years. Given that the AD process can begin 15-16 years prior to any cognitive symptoms [31], new research should examine longer exposure windows of air pollution exposure on brain health.[17,199] Early life and midlife exposures may also contribute to cognitive decline later in life because they represent a cumulative risk.[225] Using spatiotemporal $PM_{2.5}$ predictions, we found that the effect estimates were similar for 1-year and 5-year averages but decreased when using 10-year and 20-year averages (Supplemental Table S4). Spatial only $PM_{2.5}$ predictions showed consistent effect estimates for all time averaging periods, as these estimates only account for changes in pollutant exposure when participants move and not over time. We found similar effect estimates for all time averaging periods are found using UFP mobile monitoring model estimates.

### 4.5.4 Strengths and Limitations

The spatiotemporal model utilizing $PM_{2.5}$ measurements dating back to 1978 enabled us to examine pollution exposures as far back as 20 years prior to study enrollment. In addition, the present study was unique in leveraging mobile monitoring data for UFP. Inherently, UFPs behave differently than $PM_{2.5}$ due to their size and physical characteristics. UFPs also have different spatial patterns due to different sources, such as aircraft pollution from Sea-Tac

International Airport overhead flights. Future control and management strategies should target a decrease of these particles in urban environments.[226]

However, inherent to environmental epidemiological studies, air pollution models estimate long-term exposure based on each participant's residential address, without accessing participants' daily mobility or indoor exposures. We did not account for occupational exposures, although in a cohort of older adults we expect participants to be retired but they could have had occupational exposures earlier in life. Another limitation is the possibility of residual confounding from noise. There is evidence that AP and road traffic noise might act synergistically on cognitive function in adults.[180] Animal studies have found that long-term noise exposure is associated with tau pathology, accelerated overproduction for beta amyloid and increased neuronal oxidative stress.[225]

## 4.6 CONCLUSIONS

Our findings suggest that traffic-related air pollution such as $PM_{2.5}$, UFP, BC, and $NO_2$ have an adverse effect on cognition in older adults. We are enhancing existing literature on $PM_{2.5}$, BC, $NO_2$, and have a novel exposure of UFP which has not been studied before.

## 4.7 TABLES & FIGURES

**Table 1.** Characteristics of study participants in the Adult Changes in Thought (ACT) Cohort at Baseline

| **Variable** | **Analytic Cohort (N=4,566)** | **Full Cohort (N=5,763)** |
|---|---|---|
| | Mean (SD) or N (%) | Mean (SD) or N (%) |
| Age (years) | 74.1 (6) | 74.1 (6) |
| Sex | | |
| Female | 2624 (58%) | 3343 (58%) |
| Male | 1942 (43%) | 2420 (42%) |
| Race | | |
| White | 4119 (90%) | 5147 (89%) |
| Non-White | 442 (10%) | 608 (11%) |
| APOE $\varepsilon 4$ Status | | |
| -APOE $\varepsilon 4$ | 3356 (74%) | 3453 (60%) |
| + APOE $\varepsilon 4$ | 1210 (27%) | 1233 (21%) |
| Education | | |
| Less than HS | 367 (8%) | 463 (8%) |
| GED/HS | 1773 (39%) | 2117 (37%) |
| Bachelors | 1055 (23%) | 1361 (24%) |
| Masters | 686 (15%) | 924 (16%) |
| Doctorate | 262 (6%) | 347 (6%) |
| Other | 422 (9%) | 549 (10%) |
| NDI Index | -0.70 (0.72) | -0.70 (0.72) |
| Hypertension | | |
| No | 2664 (58%) | 3336 (58%) |
| Yes | 1869 (41%) | 2382 (41%) |
| Stroke | | |
| No | 4430 (97%) | 5583 (97%) |
| Yes | 126 (3%) | 164 (3%) |
| Diabetes | | |
| No | 3922 (86%) | 4655 (81%) |
| Yes | 479 (11%) | 582 (10%) |
| Respiratory Disease | | |
| No | 3648 (80%) | 4265 (74%) |
| Yes | 757 (17%) | 906 (16%) |
| Heart Disease | | |
| No | 3766 (83%) | 4767 (83%) |
| Yes | 769 (17%) | 952 (17%) |
| Cardiovascular Disease | | |
| No | 4129 (90%) | 5208 (90%) |
| Yes | 401 (9%) | 504 (9%) |
| Smoking | | |
| Never | 2183 (48%) | 2817 (49%) |
| Former | 2145 (47%) | 2658 (46%) |
| Current | 228 (5%) | 274 (5%) |
| BMI (kg/m$^2$) | 27.4 (5.0) | 27.4 (5.0) |
| Exercise 3x per week | | |
| No | 1256 (28%) | 1597 (28%) |
| Yes | 3303 (72%) | 4153 (72%) |
| CASI-IRT | 0.34 (0.70) | 0.33 (0.71) |

Percentages do not add to 100% due to missing data and rounding.

**Table 2.** Interquartile range for 5-year average exposure at baseline

| Pollutant | IQR |
|---|---|
| $PM_{2.5}$ (ST) | 0.78 |
| $PM_{2.5}$ (SP) | 0.42 |
| UFP (MM) | 1897 |
| BC (MM) | 126.75 |
| $NO_2$ (ST) | 2.77 |
| $NO_2$ (SP) | 1.68 |
| $NO_2$ (MM) | 2.10 |

We calculated a time adjusted IQR for each pollutant from the ST model. Exposure estimates are adjusted for time by subtracting the mean concentration for each year prior to calculating the IQR. The unadjusted IQR of $PM_{2.5}$ (ST) is 4.55 µg/m$^3$ and $NO_2$ (ST) is 3.26 ppb.

**Table 3.** Estimated average difference in cognitive function per IQR increase of pollutant at baseline (N=4,566)

| **Predictor** | **Pollutant** $\hat{\boldsymbol{\beta}}$ $(\mathbf{95\%}\ \boldsymbol{CI})$ | **Aging Equivalent** (years) |
|---|---|---|
| $PM_{2.5}$ (ST) (per 1 µg/m$^3$ ) | -0.023 (-0.051, 0.005) | 0.62 (-0.15, 1.28) |
| $PM_{2.5}$ (SP) (per 1 µg/m$^3$ ) | -0.072 (-0.129, -0.015) | 1.97 (0.44, 3.26) |
| UFP (MM) (per 1900 pt/cm$^3$) | -0.027 (-0.045, -0.009) | 0.73 (0.26, 1.13) |
| BC (MM) (per 125 ng/m$^3$) | -0.012 (-0.034, 0.010) | 0.34 (-0.29, 0.87) |
| $NO_2$ (ST) (per 3 ppb) | -0.014 (-0.030, 0.002) | 0.39 (-0.05, 0.77) |
| $NO_2$ (SP) (per 3 ppb) | -0.016 (-0.044, 0.013) | 0.43 (-0.38, 1.12) |
| $NO_2$ (MM) (per 3 ppb) | -0.021 (-0.047, 0.006) | 0.57 (-0.17, 1.19) |

Coefficients are reported per 1 µg/m$^3$ of $PM_{2.5}$, 1900 pt/cm$^3$ of UFP, 3 ppb of $NO_2$, and 125 ng/m$^3$ of BC. ST refers to spatiotemporal model predictions, SP refers to spatial only model predictions and MM refers to mobile monitoring model predictions.

**Table 4.** Sensitivity analysis of association between exposure to pollutant and cognitive function among 4,432 participants with no missing data for any model covariates

| | **Model 1: Reduced**[a] | **Model 2: Main**[b] | **Model 3: Extended (SES)**[c] |
|---|---|---|---|
| **Predictor** | $\boldsymbol{\beta}$ (**95%** $\boldsymbol{CI}$) | $\boldsymbol{\beta}$ (**95%** $\boldsymbol{CI}$) | $\boldsymbol{\beta}$ (**95%** $\boldsymbol{CI}$) |
| $PM_{2.5}$ (ST) (per 1 μg/$m^3$ ) | -0.038 (-0.045, -0.031) | -0.031 (-0.059, -0.002) | -0.001 (-0.030, 0.027) |
| $PM_{2.5}$ (SP) (per 1 μg/$m^3$ ) | -0.080 (-0.139, -0.020) | -0.080 (-0.138, -0.022) | -0.040(-0.097, 0.017) |
| UFP (MM) (per 1900 pt/$cm^3$) | -0.029 (-0.048, -0.010) | -0.032 (-0.050, -0.013) | -0.005 (-0.025, 0.014) |
| $NO_2$ (ST) (per 3 ppb) | -0.038 (-0.053, -0.022) | -0.018 (-0.034, -0.001) | -0.008 (-0.024, 0.009) |
| $NO_2$ (SP) (per 3 ppb) | -0.016 (-0.046, 0.013) | -0.024 (-0.053, 0.005) | -0.002 (-0.032, 0.028) |
| $NO_2$ (MM) (per 3 ppb) | -0.015 (-0.042, 0.012) | -0.028 (-0.055, -0.001) | -0.018 (-0.045, 0.009) |
| BC (MM) (per 125 ng/$m^3$) | -0.012 (-0.034, 0.011) | -0.019 (-0.041, 0.003) | -0.011 (-0.033, 0.012) |

[a]Adjusted for baseline pollutant and baseline age. [b]Adjusted for baseline pollutant, baseline age, gender, year, APOE $\varepsilon 4$ status. [c]Adjusted for baseline pollutant, baseline age, gender, year, race, education, NDI index.

**Table 5.** Association between co-pollutant exposure and cognitive function at baseline compared to a single pollutant main model

| | Pollutant Coefficient $\beta$ (95% $CI$) | | | | | | |
|---|---|---|---|---|---|---|---|
| Model | $PM_{2.5}$ (ST) | $PM_{2.5}$ (SP) | UFP (MM) | $NO_2$ (ST) | $NO_2$ (SP) | $NO_2$ (MM) | BC (MM) |
| Main Model | -0.023<br>(-0.051, 0.005) | -0.072<br>(-0.129, -0.015) | -0.027<br>(-0.045, -0.009) | -0.014<br>(-0.030, 0.002) | -0.016<br>(-0.044, 0.013) | -0.021<br>(-0.047, 0.006) | -0.188<br>(-0.521, 0.145) |
| $PM_{2.5}$ (ST) + $NO_2$ (ST) | -0.017<br>(-0.046, 0.011) | – | – | -0.012<br>(-0.028, 0.005) | – | – | – |
| $PM_{2.5}$ (ST) + $NO_2$ (SP) | -0.020<br>(-0.049, 0.009) | – | – | – | -0.010<br>(-0.039, 0.020) | – | – |
| $PM_{2.5}$ (SP) + $NO_2$ (SP) | – | -0.068<br>(-0.128, -0.009) | – | – | -0.006<br>(-0.036, 0.024) | – | – |
| $PM_{2.5}$ (SP) + $NO_2$ (ST) | – | -0.063<br>(-0.122, -0.004) | – | -0.010<br>(-0.026, 0.007) | – | – | – |
| $PM_{2.5}$ (SP) + UFP (MM) | – | -0.044<br>(-0.107, 0.019) | -0.021<br>(-0.041, -0.001) | – | – | – | – |
| $PM_{2.5}$ (SP) + BC (MM) | – | -0.076<br>(-0.143, -0.009) | – | – | – | – | 0.003<br>(-0.023, 0.029) |
| UFP (MM) + $NO_2$ (SP) | – | – | -0.063<br>(-0.096, -0.029) | – | 0.068<br>(0.015, 0.120) | – | – |
| UFP (MM) + $NO_2$ (MM) | – | – | -0.043<br>(-0.074, -0.013) | – | – | 0.030<br>(-0.014, 0.075) | – |
| UFP (MM) + BC (MM) | – | – | -0.049<br>(-0.078, -0.020) | – | – | – | 0.035<br>(-0.001, 0.070) |
| $NO_2$ (SP) + BC (MM) | – | – | – | – | -0.009<br>(-0.048, 0.030) | – | -0.008<br>(-0.038, 0.023) |
| $NO_2$ (MM) + BC (MM) | – | – | – | – | – | -0.032<br>(-0.086, 0.021) | 0.011<br>(-0.034, 0.056) |

The model results presented above used all cohort data after applying exclusion criteria (N = 4,566). We report the coefficient for each pollutant in the model. Coefficients are reported per 1 μg/m$^3$ of $PM_{2.5}$, 1900 pt/cm$^3$ of UFP, 3 ppb of $NO_2$, and 125 ng/m$^3$ of BC. We compare the results of the co-pollutant to a main model using a single pollutant indicated by the column label. The estimates are the difference in mean CASI-IRT for an IQR increase in pollutant, given adjustment for co-pollutants which occur in conjunction.

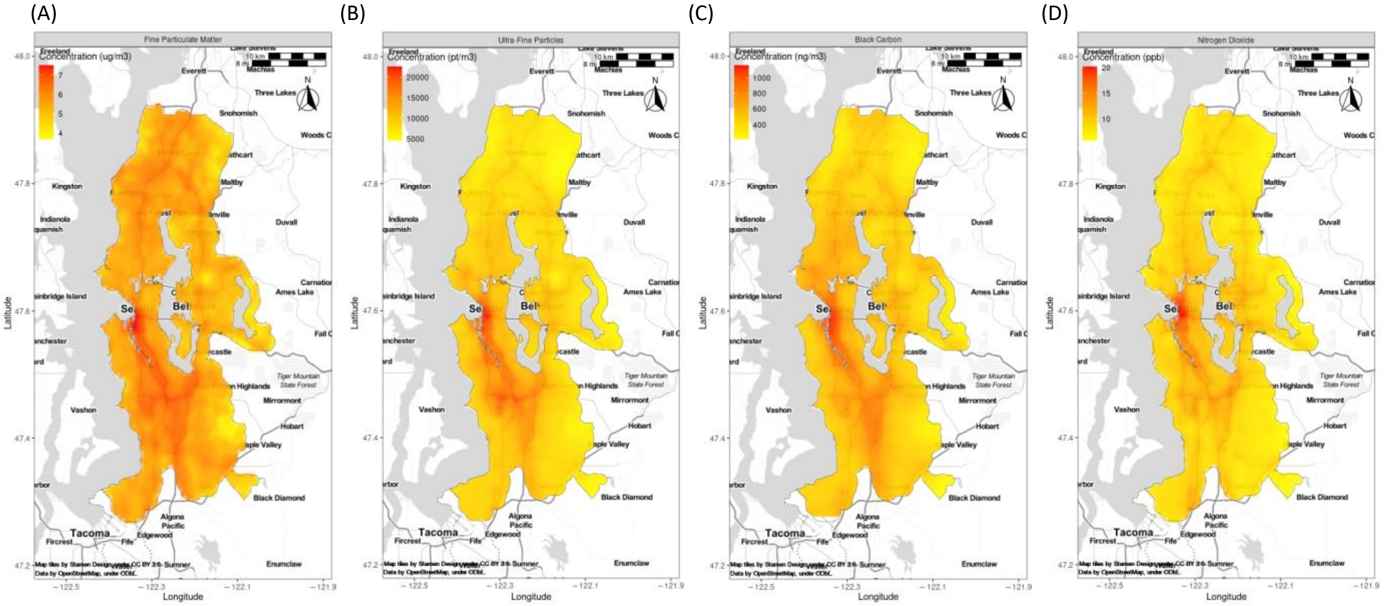


Figure 1. The four panels present exposure predictions (2019) for $PM_{2.5}$, UFP, BC, and $NO_2$. (A) The map shows $PM_{2.5}$ ($\mu g/m^3$) predictions from the spatial only model. (B) The map shows UFP ($pt/cm^3$) predictions from the mobile monitoring model. (C) The map shows predictions for BC ($ng/m^3$) from the mobile monitoring model. (D) The map shows predictions for $NO_2$ (ppb) from the spatial only model.

## 4.8 SUPPLEMENTAL MATERIAL

### Methods

We fit multiple linear regression models with varying amounts of adjustment. We present the models fitted in **Table S1**.

Table S1. Analysis Models

| **Model 1: Reduced Model** |
|---|
| Baseline $PM_{2.5}$ + Baseline Age(linear) |
| **Model 2: A Priori Model** |
| M1 + gender + birth cohort + APOE $\varepsilon 4$ **status** |
| **Model 3: SES Models** |
| M2 + white race/ethnicity + education + NDI |
| **Model 4: Mediation Models** |
| M2 + hypertension + diabetes + heart disease + cerebrovascular diseases + respiratory disease + BMI + exercise level + cigarette smoking |
| **Model 5: Interaction Model** |
| M2 + Baseline $PM_{2.5}$ * APOE $\varepsilon 4$ **status** |
| **Model 6: Co-pollutant Model** |
| M2 + Baseline co-pollutant |

Table S2. Summary of Exposure Metrics

| **Exposure Metric** | **Region** | **Data Input Time Period** |
|---|---|---|
| $PM_{2.5}$ (ST) | ST | 1978-2020 |
| $PM_{2.5}$ (SP) | MM | 1978-2020 |
| UFP (MM) | MM | 2019-2020 |
| BC (MM) | MM | 2019-2020 |
| $NO_2$ (ST) | ST | 1996-2020 |
| $NO_2$ (SP) | MM | 1996-2020 |
| $NO_2$ (MM) | MM | 2019-2020 |

*Secondary Analysis*

We evaluated effect modification by APOE status in an interaction analysis with air pollution variables. The results of the secondary analysis are presented in supplementary material (Table S3). **Table S3** shows the results of the main model with the addition of the interaction term $\hat{\beta}_{pollutant} x \hat{\beta}_{+APOE}$, where $\hat{\beta}_{pollutant}$ is the pollutant coefficient and $\hat{\beta}_{+APOE}$ is the positive APOE status coefficient.

Table S3. Interaction analysis between pollutant and APOE (N = 4566)

| | **Pollutant Model** | | | | | | |
|---|---|---|---|---|---|---|---|
| **Predictor** | **PM$_{2.5}$ (ST)** $\hat{\boldsymbol{\beta}}$ $(\mathbf{95\%}\boldsymbol{CI})$ | **PM$_{2.5}$ (SP)** $\hat{\boldsymbol{\beta}}$ $(\mathbf{95\%}\boldsymbol{CI})$ | **UFP** $\hat{\boldsymbol{\beta}}$ $(\mathbf{95\%}\boldsymbol{CI})$ | **BC** $\hat{\boldsymbol{\beta}}$ $(\mathbf{95\%}\boldsymbol{CI})$ | **NO$_2$ (ST)** $\hat{\boldsymbol{\beta}}$ $(\mathbf{95\%}\boldsymbol{CI})$ | **NO$_2$ (SP)** $\hat{\boldsymbol{\beta}}$ $(\mathbf{95\%}\boldsymbol{CI})$ | **NO$_2$ (MM)** $\hat{\boldsymbol{\beta}}$ $(\mathbf{95\%}\boldsymbol{CI})$ |
| Pollutant | -0.021<br>(-0.049, 0.007) | -0.065<br>(-0.131, 0.002) | -0.036<br>(-0.057, -0.015) | -0.020<br>(-0.045, 0.006) | -0.021<br>(-0.040, -0.003) | -0.038<br>(-0.071, -0.006) | -0.033<br>(-0.063, -0.003) |
| APOE $\varepsilon 4$ | -0.002<br>(-0.168, 0.164) | 0.083<br>(-0.648, 0.815) | -0.275<br>(-0.507, -0.044) | -0.207<br>(-0.442, 0.027) | -0.211<br>(-0.380, -0.042) | -0.369<br>(-0.588, -0.150) | -0.243<br>(-0.446, -0.040) |
| Pollutant * APOE $\varepsilon 4$ | -0.007<br>(-0.023, 0.009) | -0.029<br>(-0.159, 0.102) | 0.000<br>(-0.005, 0.077) | 0.000<br>(-0.022, 0.079) | 0.009<br>(-0.006, 0.063) | 0.030<br>(0.024, 0.154) | 0.017<br>(-0.009, 0.111) |

Coefficients are reported per 1 μg/m$^3$ of PM$_{2.5}$, 1900 pnc/cm$^3$ of UFP, 3 ppb of NO$_2$, and 125 ng/m$^3$ of BC.

We conducted additional secondary analyses examining the main model's results using 1-, 5-, 10- and 20-year average before enrollment. The results of the secondary analysis are presented in **Table S4**.

Table S4. Sensitivity Analysis: Alternate exposure windows (N = 4521)

| **Exposure Period** | **Pollutant Estimates** | | | | | | |
|---|---|---|---|---|---|---|---|
| | **$PM_{2.5}$ (ST)**<br>$\widehat{\boldsymbol{\beta}}$ ($\mathbf{95}\%\boldsymbol{CI}$) | **$PM_{2.5}$ (SP)**<br>$\widehat{\boldsymbol{\beta}}$ ($\mathbf{95}\%\boldsymbol{CI}$) | **UFP**<br>$\widehat{\boldsymbol{\beta}}$ ($\mathbf{95}\%\boldsymbol{CI}$) | **BC**<br>$\widehat{\boldsymbol{\beta}}$ ($\mathbf{95}\%\boldsymbol{CI}$) | **$NO_2$ (ST)**<br>$\widehat{\boldsymbol{\beta}}$ ($\mathbf{95}\%\boldsymbol{CI}$) | **$NO_2$ (SP)**<br>$\widehat{\boldsymbol{\beta}}$ ($\mathbf{95}\%\boldsymbol{CI}$) | **$NO_2$ (MM)**<br>$\widehat{\boldsymbol{\beta}}$ ($\mathbf{95}\%\boldsymbol{CI}$) |
| **1-year exposure** | -0.22<br>(-0.050, 0.006) | -0.075<br>(-0.132, -0.019) | -0.022<br>(-0.039, -0.004) | -0.007<br>(-0.028, 0.015) | -0.010<br>(-0.025, 0.006) | -0.007<br>(-0.034, 0.021) | -0.012<br>(-0.037, 0.014) |
| **5-year exposure** | -0.023<br>(-0.051, 0.006) | -0.069<br>(-0.126, -0.011) | -0.026<br>(-0.044, -0.008) | -0.011<br>(-0.033, 0.011) | -0.015<br>(-0.031, 0.001) | -0.017<br>(-0.045, 0.012) | -0.020<br>(-0.046, 0.006) |
| **10-year exposure** | -0.011<br>(-0.033, 0.012) | -0.063<br>(-0.121, -0.005) | -0.026<br>(-0.044, -0.008) | -0.010<br>(-0.032, 0.013) | -0.016<br>(-0.032, 0.000) | -0.019<br>(-0.048, 0.010) | -0.021<br>(-0.048, 0.006) |
| **20-year exposure** | -0.012<br>(-0.032, 0.007) | -0.060<br>(-0.118, -0.001) | -0.024<br>(-0.043, -0.006) | -0.008<br>(-0.031, 0.015) | -0.015<br>(-0.030, 0.001) | -0.018<br>(-0.047, 0.012) | -0.020<br>(-0.047, 0.008) |

Sample size decreased in this analysis due to missingness in 1-year exposure predictions. Participants with missing exposure data were excluded from this analysis. Coefficients are reported per 1 μg/$m^3$ of $PM_{2.5}$, 1900 pnc/$cm^3$ of UFP, 3 ppb of $NO_2$, and 125 ng/$m^3$ of BC.

**Figure S1** shows a flow-chart depicting the number of participants included in each analysis.

Figure S1. Analytic Cohort Flow-Chart

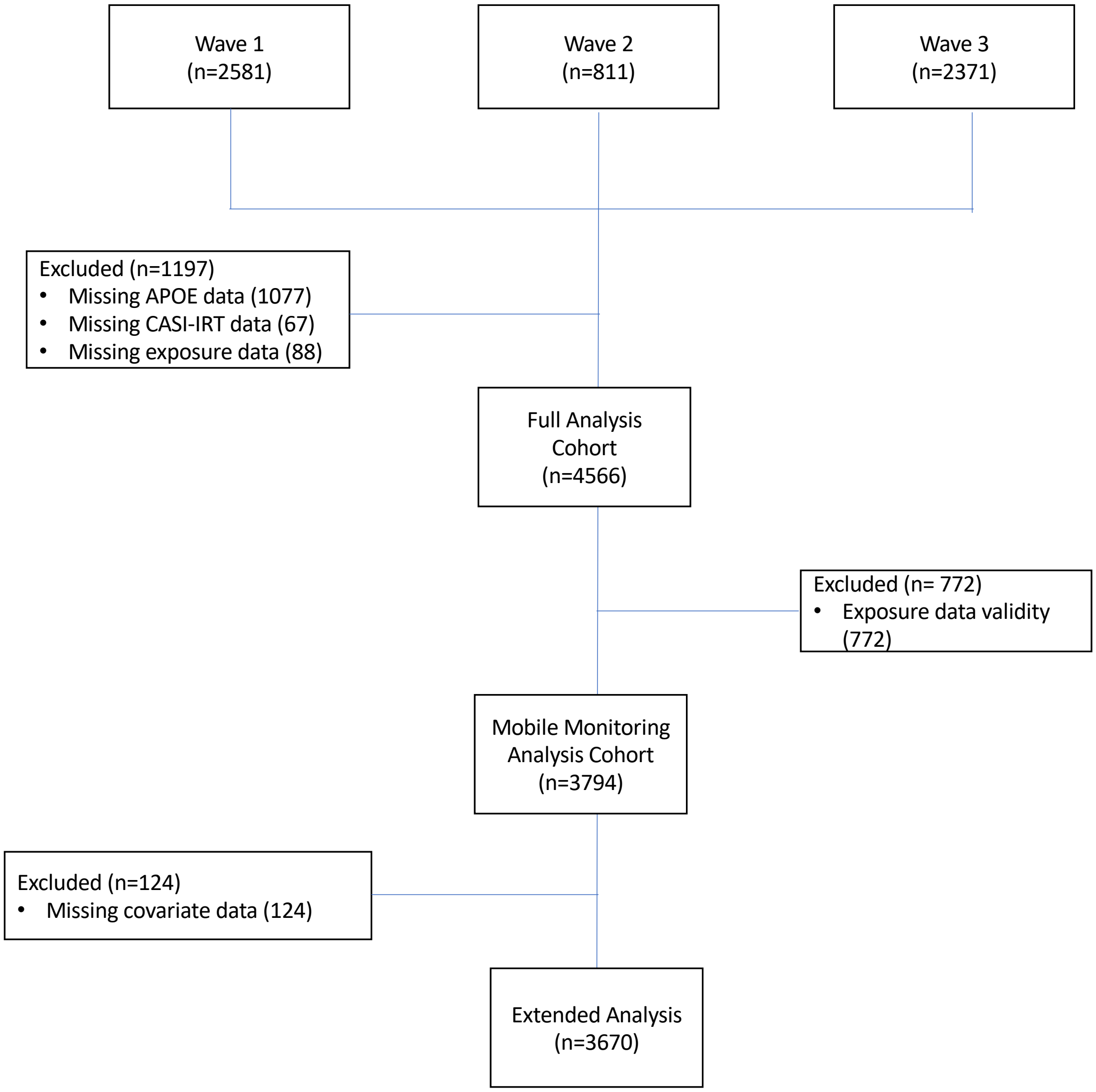
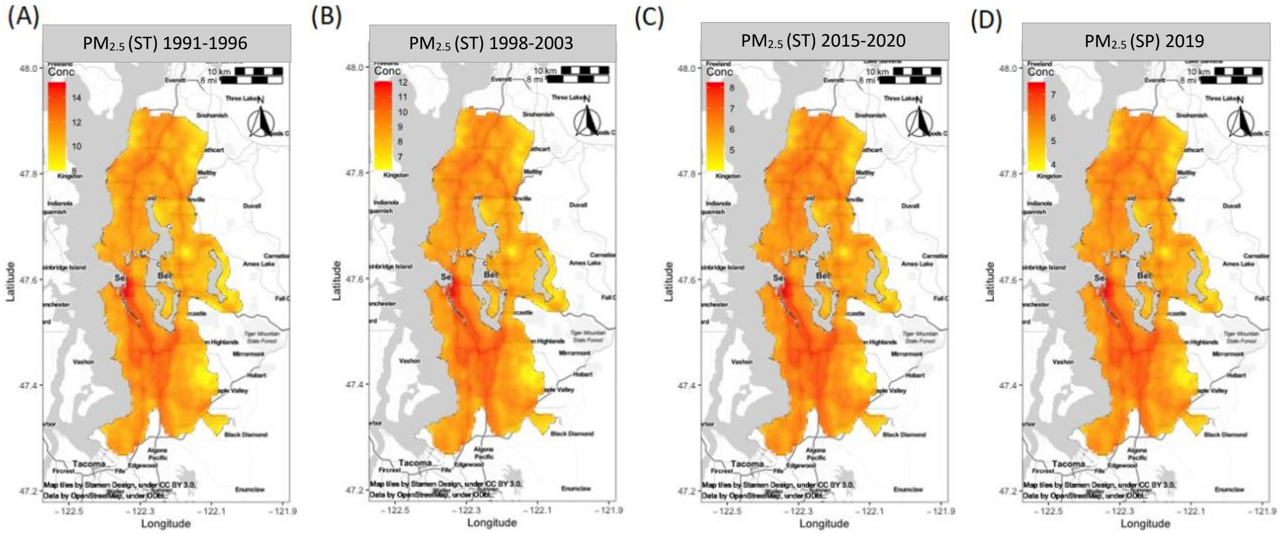
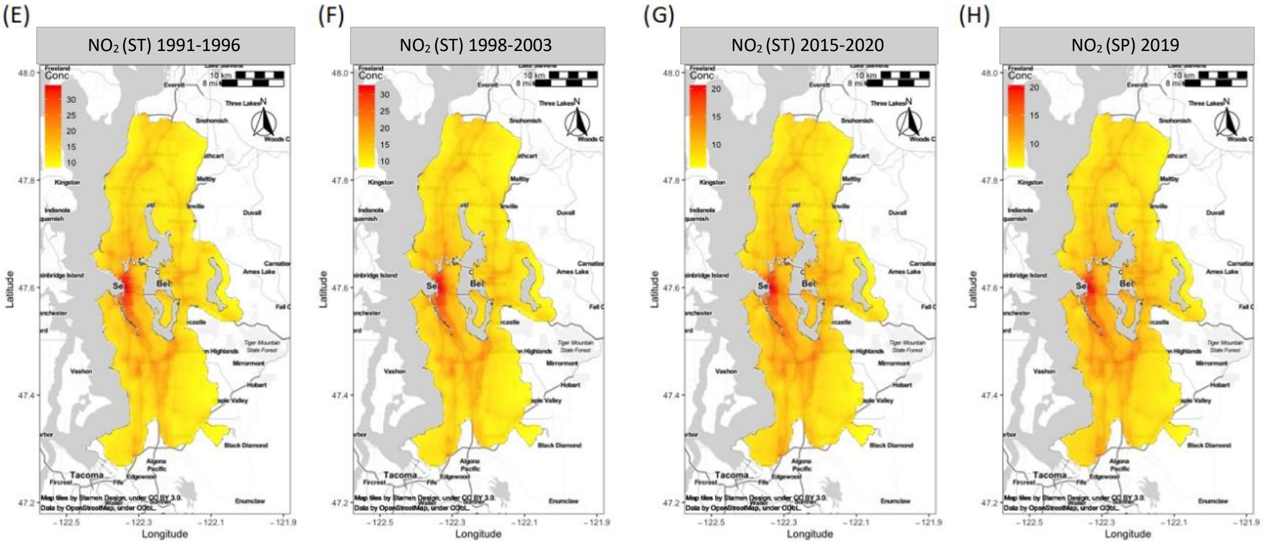


**Figure S2** shows exposure estimates in different time periods for pollutants PM$_{2.5}$ (A)-(D) and NO$_2$ (E)-(H). We selected 5-year averages throughout the lengths of the study to illustrate the spatial change in concentration of pollution over time. The selected time periods are: (A) & (E) 1991-1996, (B) & (F) 1998-2003,(C) & (G) 2015-2020 and (D) & (H) 2019. Each map has an individual scale given there have been large decreases in air pollution in the Puget Sound throughout the length of the study.

Figure S2. Maps of Exposure Estimates for PM$_{2.5}$ and NO$_2$.



Map tiles by Stamen Design, under CC BY 3.0. Data by OpenStreetMap, under ODbL.



**Figures S3 – S6** present correlations between alternate exposure metrics. Exposures are matched by participant ID and faceted by each baseline 5-year average. The solid red line shows a linear regression between the alternate exposure metrics. The correlation coefficient (R) is shown in red text annotation. The dashed blue line shows 1:1 line (x intercept of 0, and slope of 1). Figure S3 shows $PM_{2.5}$ (SP ~ ST), Figure S4 shows $NO_2$ (SP ~ ST), Figure S5 shows $NO_2$ (MM ~ ST) and Figure S6 shows $NO_2$ (MM ~ SP).

Figure S3. Correlation of PM2.5 (ST) and PM2.5 (SP) predictions grouped by participant ID

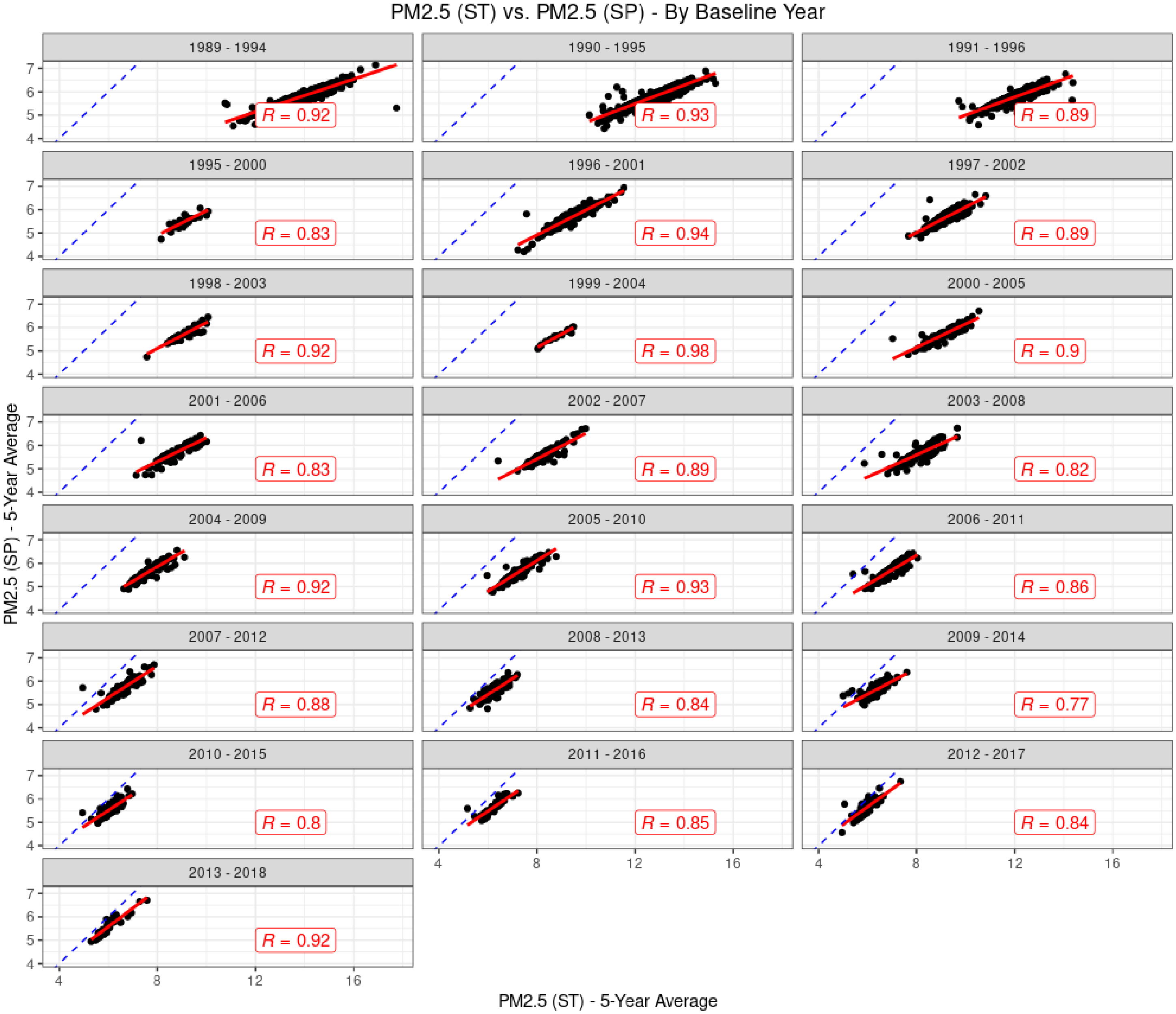


Figure S4. Correlation of $NO_2$ (ST) and $NO_2$(SP) predictions grouped by participant ID

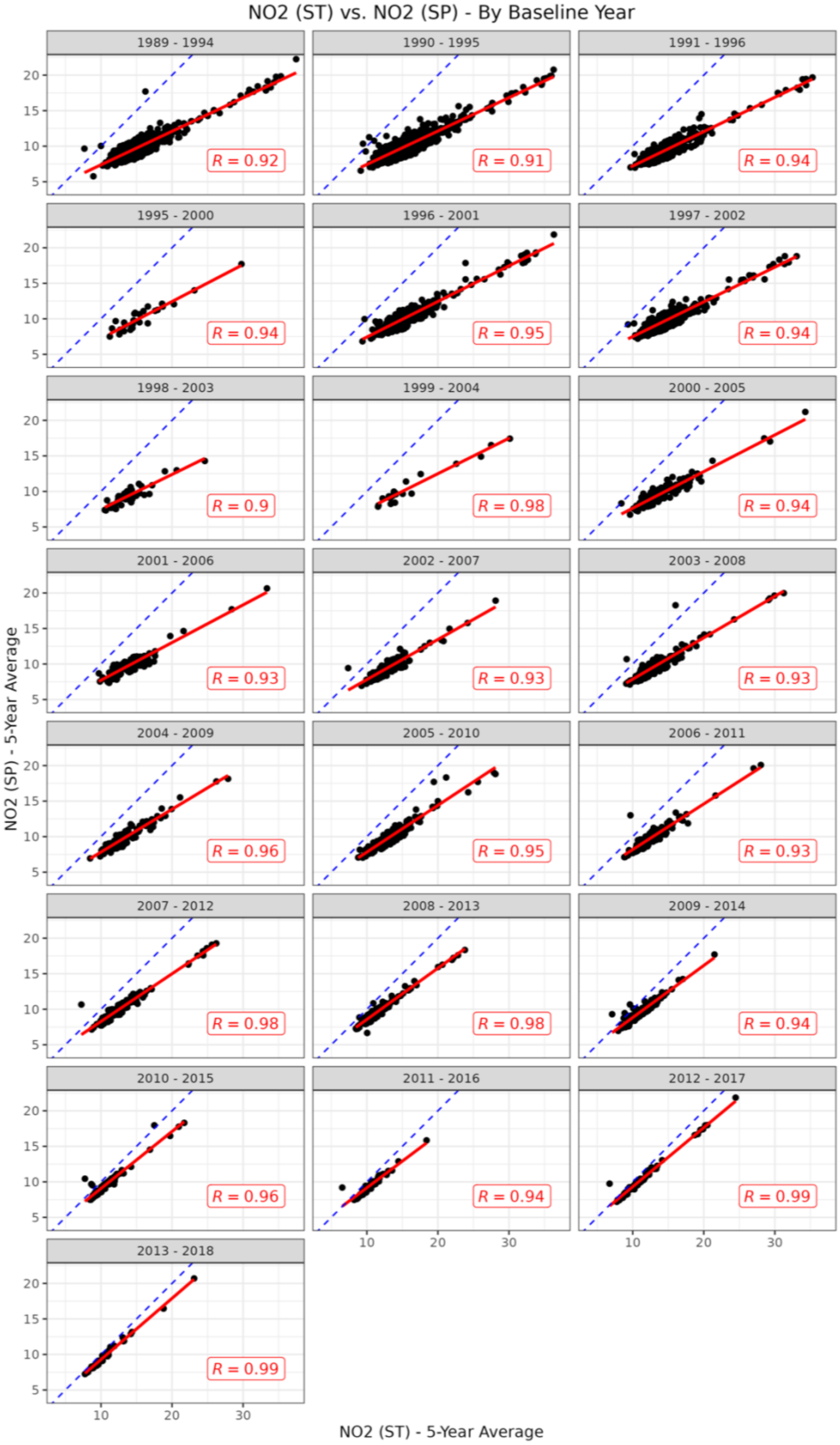


Figure S5. Correlation of $NO_2$ (ST) and $NO_2$(MM) predictions grouped by participant ID

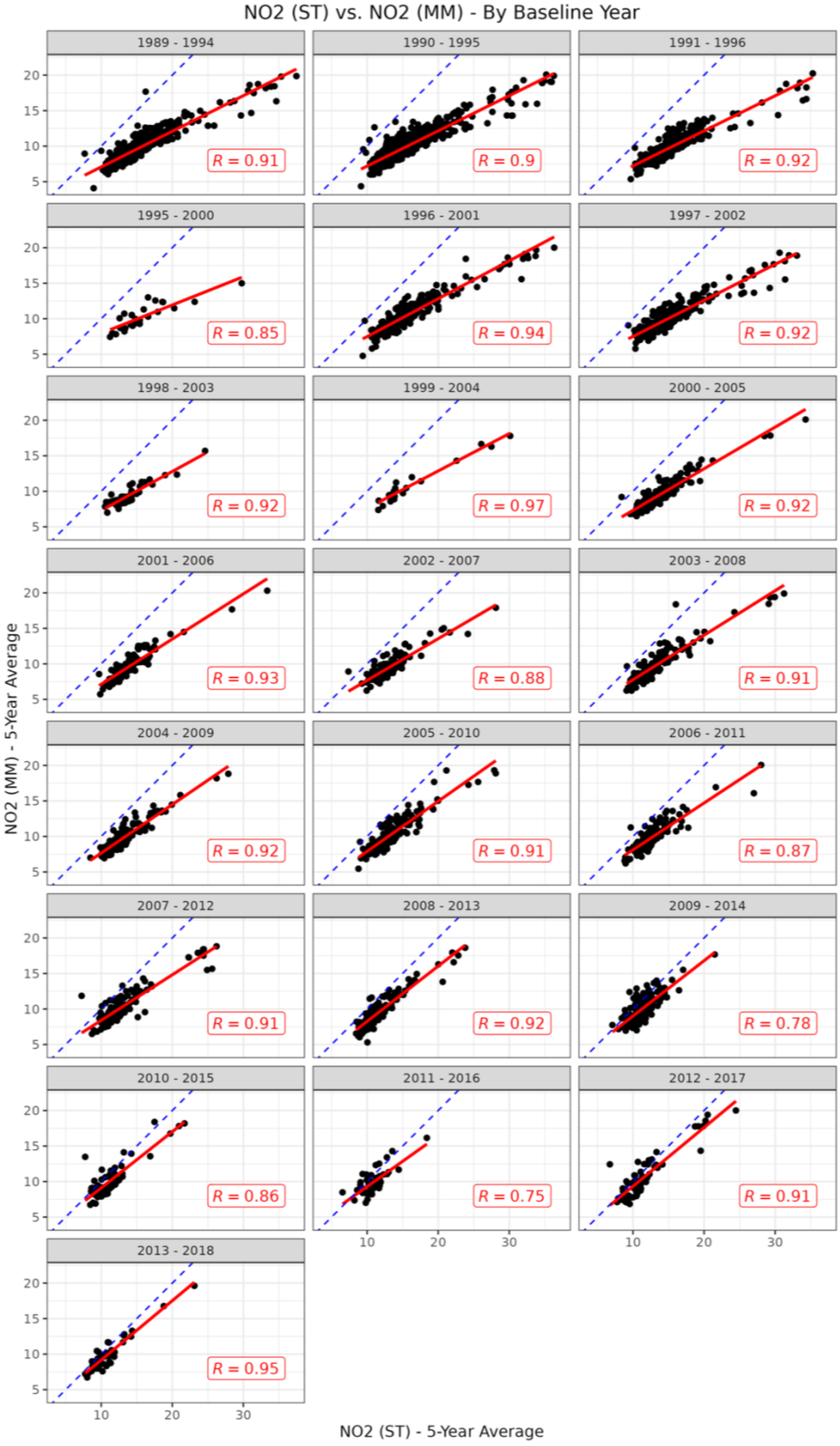


Figure S6. Correlation of $NO_2$ (SP) and $NO_2$(MM) predictions grouped by participant ID

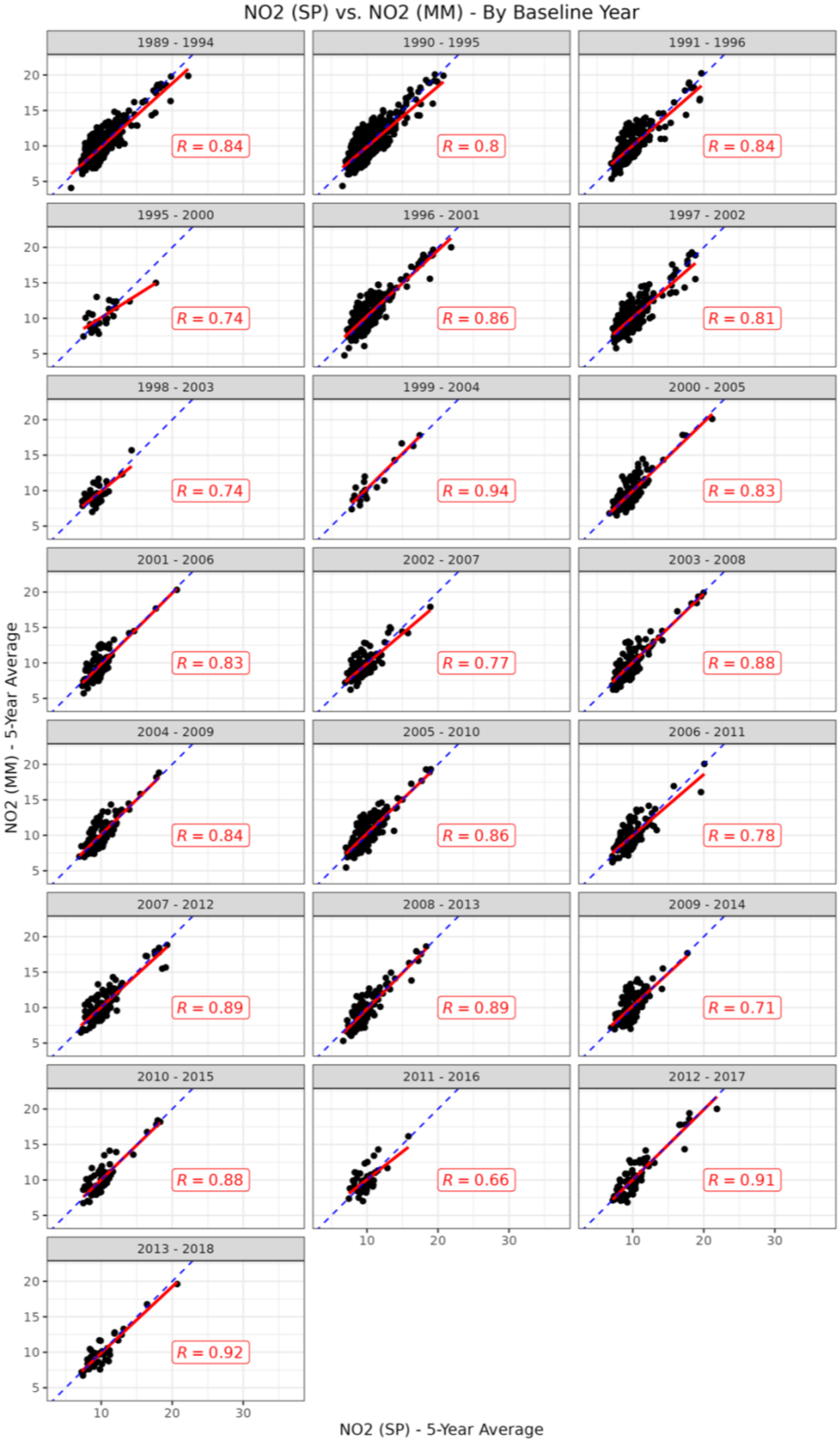
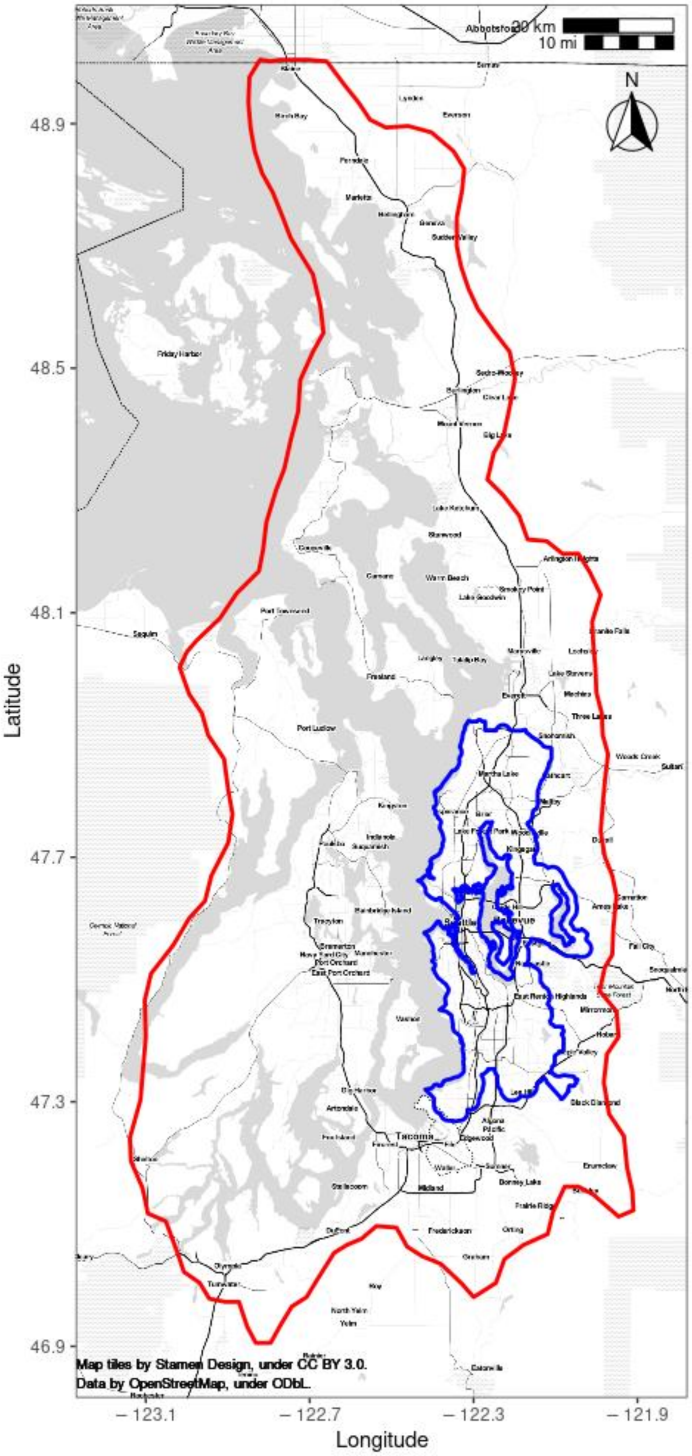


Figure S7. Exposure prediction spatial coverage



Exposure prediction models have varying spatial coverage. The spatiotemporal region (ST) boundaries are shown in red and the mobile monitoring (MM) region boundaries are shown in blue.

# CHAPTER 5. Conclusions

The diverse projects in this dissertation provide a unique view of community engagement in environmental health studies. My work explored community-engaged studies with different funding mechanisms, different study planning and development. The role of the researcher in community-engaged work can vary immensely. This dissertation provides new guidance for reporting air monitoring results and provide greater insight into engaging the public in science activities (Aim 1). In addition, this dissertation illustrates the influence that different air pollution data sources have on community driven cumulative impact tools which ultimately impact funding allocation for overburdened communities (Aim 2). Furthermore, this dissertation also contributes to advancing the state of science of the relationship between $PM_{2.5}$ and UFP and brain health through a novel analysis (Aim 3).

Results from Aim 1 present an overarching framework for engaging with a public audience. Through evaluating community-engaged research methods in the Puget Sound region we learned about the importance of environmental health literacy in report back. We also learned about the potential for overwhelming community members with too much information or using overly complicated language. Chapter 2A demonstrated that portable HEPA cleaners were an effective short-term intervention to improve the air quality in classroom environments, reducing the UFP count concentration from one-half to approximately one-tenth of that measured outside. We also shared the results of the portable HEPA cleaner intervention to provide actionable recommendations from the results of our pilot study to schools across Washington State. Chapter 2B found that Washington State school districts were less inclined to use PACs if they lacked training or education on how to use PACs, lacked education on effectiveness in classroom size spaces, and if they were concerned about maintenance and sustainability of the materials needed to upkeep PACs. Overall, we found that community-engaged research activities require a substantial amount time which may not be reasonable to require from community members with busy lives and schools overwhelmed with their responsibilities.

Results from Aim 2 suggest that the choice in $PM_{2.5}$ layer in a cumulative impact tool has the potential to change a small fraction of communities that are designated as overburdened. Results of this sensitivity analysis demonstrate that $PM_{2.5}$ datasets used in the Washington Department of Health's Environmental Health Disparities Map tool can impact what census tracts are prioritized for funding under Washington State's Healthy Environmental for All Act (HEAL). Regulatory agencies should consider using alternate $PM_{2.5}$ layers to capture peak exposures during wildfire events which are not captured in the current dataset that excludes extraordinary events. Although the primary goal of the WA EHD Map is to identify overburden communities, members of the public may misinterpret current $PM_{2.5}$ ranking as health-based. The new health-based ranking methodologies implemented in this dissertation provide an example of how to provide community members with an informative $PM_{2.5}$ layer.

Results from Aim 3 suggest a negative association between $PM_{2.5}$ and UFP and cognitive function at baseline in older adults. To our knowledge this is the first study investigating the association of exposure to UFP and cognitive function in older adults. However, the wide confidence intervals from these analyses reduce our ability to make strong conclusions. The findings of this study emphasize the need to reduce ambient air pollution exposures to reduce Alzheimer's disease risk.

Overall, this dissertation sought to present novel findings in the areas of report-back and risk communication, environmental health disparities mapping and the association between fine particulate air pollution exposures and cognition. The first aim provides a framework for community engagement and illustrates a variety of methods for engaging with public audiences. While the second aim, developed new $PM_{2.5}$ layers that can be used in cumulative impact mapping tools. In the third aim, we contribute to our understanding of air pollutions potential detrimental effects on brain health in older adults.

Lessons from this dissertation provide evidence and guidance for engaging with the public in a variety of methods. Aim 1 described the Healthy Air, Healthy Schools study which used direct funding from the Washington State Legislature to measure and interpret UFP measurements due to the concern of communities near SeaTac International Airport. While, *CAMPS* was funding and sensor guided study, with a different framework than *Healthy Air, Healthy Schools*. In Aim 1, we also learned about community members environmental health concerns which motivated us to develop a layer that gives them information that is informative for Aim 2. Future studies should further develop new exposure layers to incorporate air quality standards in cumulative impact tools to clearly communicate health risks to community members. Aim 3 leveraged a diversity supplement to include a community guided activity that was used for the Aim 1 *CAMPS* project.

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# APPENDIX A. CAMPS Needs Assessment Survey

## Survey of Community Air Quality

Air Quality Assessment for Seattle Communities

The goal of this study is to collect neighborhood level air data using low-cost air monitors and have residents engaged as decision makers. The following survey was created to learn more about the communities knowledge, attitudes, and practices around the issue of air pollution. Air pollution will be defined here as the presence of chemicals or compounds in the air which can cause negative health effects. The data collected in this study will be used to inform educational materials that will be presented in community workshops in the near future.

The survey is being conducted by a team of researchers at the University of Washington. Please answer the questions to the best of your knowledge. Your participation is voluntary and you may stop participating at any time. We assure you that your responses are anonymous and the individual study results will be confidential. Surveys will be destroyed at the completion of the study.

Thank you for your time and desire to help in this research study. If you have any questions, or if you would like a copy of the study's final report, please contact the lead researcher Nancy Carmona at nancyc9@uw.edu

**<u>Section 1:</u> This section asks for basic information about who you are.**

1. What is your zip code?

   ______________

2. How many years have you lived in the South Seattle community?

(Please enter 0 if you do not live in the South Seattle community)

__________________ [years]

3. How old are you? (Please answer in years)

    _________________ [years]

4. What gender do you identify with?
    a) Male
    b) Female
    c) Other: _____________

5. What race/ethnicity do you identify with?
    a) African American or Black
    b) Alaska Native or Native American
    c) Asian or Pacific Islander
    d) White
    e) Other: _____________

6. Do you consider yourself to be Hispanic or Latino?
    a) Yes
    b) No

7. Do you have children under the age of 18 living in your home?
    a) Yes
    b) No

8. The annual median income for Seattle residents is 80k. What was your most recent yearly household income?
    a) Less than 80k
    b) More than 80k
    c) Don’t know

9. What is the highest level of school you have completed?
    a) Less than high school diploma
    b) High school diploma / GED
    c) Some college
    d) Associates / Technical degree
    e) Bachelor's degree
    f) Graduate degree or higher

**Section 2:** **This section asks information about your overall community. Community will be defined as the neighborhood you live in and spend the majority of your time.**

10. Please rank the following health-related issues that are impacting your community. Use numbers from 1 to 10 where 1 is the lowest impact and 10 the highest impact.

Please use each number only once.

| | **Ranking (1 through 10)** |
|---|---|
| Accidental Injuries (falls, burns, road traffic accidents, etc.) | |
| Alcohol, tobacco, and drug use | |
| Chronic diseases (asthma, heart disease, diabetes, etc.) | |
| Dental health | |
| Disabilities (physical, intellectual, sensory, and developmental) | |
| Environmental pollution (air, water, and soil) | |
| Healthy babies and mothers | |
| Infectious diseases and immunizations (influenza, measles, whooping cough, etc.) | |
| Mental health (depression, anxiety, stress, etc.) | |
| Nutrition and obesity | |

11 How strongly would you rate the importance of funding the following components in your community?

| | Not at all important | Slightly important | Moderately important | Very important | Extremely important |
|---|---|---|---|---|---|
| Access to social services<br>e.g., programs and activies for youth, seniors, and times of crisis | | | | | |
| Clean and healthy environment<br>e.g., walk-able, bikeable communities | | | | | |
| Emergency services<br>e.g., police, fire, rescue services | | | | | |
| Health care<br>e.g., access to health care, medical screenings, education | | | | | |
| Living affordability<br>e.g., affordable, housing, affordable healthy food | | | | | |

**<u>Section 3:</u> This section asks questions about your general knowledge of air pollution.**

12. Do you know how to find information about daily air quality?
    a) Yes
    b) No
    c) Don’t know

13. If yes, how do you find information about daily air quality?

__________

14. When the air is polluted in your community, you can always see and smell it. a) True
    b) False
    c) Don't know

15. Please rank your knowledge about air pollution in your community by indicating how much you agree or disagree with the statements below.

| | Strongly disagree | Disagree | Neither agree nor disagree | Agree | Strongly agree |
|---|---|---|---|---|---|
| I know what to do when the air quality is poor | | | | | |
| I know when air quality is poor | | | | | |
| I know where air quality is poor | | | | | |

16. What health problems do you think are related to air pollution? (Check all that apply)

| | |
|---|---|
| | Asthma |
| | Common cold |
| | Heart problems |
| | Lung cancer |
| | Pneumonia |
| | Other: ________________________ |

17 What are signs and symptoms of respiratory problems? (Check all that apply)

| | |
|---|---|
| | Bloody nose |
| | Coughing |
| | Difficulty breathing |
| | Sneezing and runny nose |
| | Wheezing |
| | Other: ________________________ |

**<u>Section 4:</u> This section asks questions about your beliefs about air pollution.**

18. Were you satisfied with the outdoor air quality in your community in this last year?

| Not at all | Slightly | Moderately | Very Much | Extremely |
|---|---|---|---|---|
| | | | | |

19. How would you describe outdoor air quality in your community compared to downtown Seattle?

| Much Worse | Somewhat Worse | About the Same | Somewhat Better | Much Better |
|---|---|---|---|---|
| | | | | |

20. How would you rate the outdoor air quality at the following places within your community?

If you frequent multiple churches, parks, etc. in your community please rate the one you visit most often.

| | Poor | Fair | Good | Very good | Excellent |
|---|---|---|---|---|---|
| Child care centers | | | | | |
| Churches | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| Densely populated areas | | | | | |
| Elementary schools | | | | | |
| Job locations | | | | | |
| Middle schools | | | | | |
| High schools | | | | | |
| Nursing homes | | | | | |
| Parks | | | | | |

21 Do you think the following are important sources of air pollution in your community?

| | Not at all important | Slightly Important | Moderately Important | Very Important | Extremely Important |
|---|---|---|---|---|---|
| Airport | | | | | |
| Cigarette smoke | | | | | |
| Construction projects | | | | | |
| Diesel vehicles (semi-trucks, transport vehicles) | | | | | |
| Factories or industrial facilities | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| Gas stations | | | | | |
| 1-90 | | | | | |
| I-5 | | | | | |
| Restaurant emissions | | | | | |
| Roadways (nonhighways) | | | | | |
| Restaurant emissions | | | | | |

22. Below are statements that describe how you may feel about air pollution. Please indicate your level of agreement or disagreement with each statement.

| With regards to air pollution: | Strongly disagree | Disagree | Neither agree nor disagree | Agree | Strongly agree |
|---|---|---|---|---|---|
| Corporations are responsible for improving air quality | | | | | |
| Local government is responsible for improving air quality | | | | | |
| We are all responsible for improving air quality | | | | | |

## **Section 5:** This section asks questions about the impacts of air pollution.

23. How often in the past year have you, or a family member in your household experienced the following?

| | Never | Once a day | Once a week | Once a month | Once a year |
|---|---|---|---|---|---|
| Dry cough | | | | | |
| Eye irritation | | | | | |
| Headaches | | | | | |
| Poor visibility | | | | | |
| Trouble breathing | | | | | |
| Unpleasant odor | | | | | |
| Wheezing | | | | | |

24 Do you or anyone in your family household experience any of the following health conditions?

| | Don't Know | No | Yes |
|---|---|---|---|
| Asthma<br>(long-term inflammatory disease of the airways in the lungs. Symptoms include episodes of wheezing, coughing, chest tightness and shortness of breath) | | | |
| Heart Disease (high blood pressure, heart failure, stroke, etc.) | | | |

25. Rate your perception of the impact of air pollution exposure in the following groups.

| | No impact | Slight impact | Somewhat of an impact | Moderate impact | High impact |
|---|---|---|---|---|---|
| Children | | | | | |
| Low income populations | | | | | |
| Non-English speaking populations | | | | | |
| People of color | | | | | |
| People with asthma | | | | | |
| People with poor access to medical care | | | | | |
| People with poor access to transportation | | | | | |
| Retired and/or elderly persons | | | | | |

**<u>Section 6:</u> This section asks questions about your behavior regarding air pollution.**

26. How often have you ever engaged in the following behaviors in order to protect yourself from outdoor air pollution?

| | Never | Once a day | Once a week | Once a month | Once a year |
|---|---|---|---|---|---|
| Checked the current air quality index before going outdoors | | | | | |
| Decreased driving | | | | | |
| Decreased opening windows | | | | | |
| Decreased outdoor physical activity | | | | | |
| Decreased use of fireplace | | | | | |
| Modified daily activities | | | | | |
| Used air purifiers | | | | | |
| Wore a mask to filter air | | | | | |

27 In which of the following ways do you currently access air quality information about your community?

| | Never | Rarely | Sometimes | Often | Always |
|---|---|---|---|---|---|
| Community groups | | | | | |
| Community meetings | | | | | |
| Family and friends | | | | | |
| Government websites | | | | | |
| Newspapers | | | | | |
| Politicians | | | | | |
| Researchers | | | | | |
| Teachers | | | | | |
| Television | | | | | |

**Thank you for supporting our study and completing this survey. Please include any additional comments if you would like the researchers to learn something about your community that was not covered in the survey.**

_____________________________________________________________________

# APPENDIX B. *Healthy Air, Healthy Schools* School Specific Report

## Healthy Air, Health Schools: Phase I

University of Washington

## Introduction

This report provides the results from the University of Washington Healthy Air, Healthy Schools Study: Phase I for Hilltop Elementary. The study was funded by the Washington State Legislature and five cities near Seattle-Tacoma International (Sea-Tac) Airport. The study was led by the UW Department of Environmental & Occupational Health Sciences and the Department of Civil and Environmental Engineering. The study was motivated by an earlier study called Mobile ObserVations of Ultrafine Particles (MOV-UP) study, which found that communities near and underneath the Sea-Tac Airport flightpaths were exposed to ultrafine particles (UFPs) associated with aircraft emissions. UFPs are very small particles that can be breathed in and enter the body's lungs and/or blood vessels, potentially causing disease. Other studies in Los Angeles and Boston have also found that concentrations of UFPs are higher near major airports. The aims of Healthy Air, Healthy Schools: Phase I were to:

- Inform schools, districts, and state legislators about the current ability of building ventilation systems at a small set of schools to effectively remove particles from outdoor sources.
- Quantify the current ability of ventilation systems to remove indoor-generated particles.
- Identify any additional benefits and costs of in-room filtration and air handling systems.
- Based on experiments in an unoccupied classroom, measure the infiltration rates of UFPs from 1) aircraft, 2) road traffic, and 3) wildfire smoke.
- Communicate study results to partners.

UFPs are everywhere in the environment. They are not regulated at the state or federal level, and there are no guidelines for acceptable levels of UFPs outdoors or indoors. Whenever we are outside, we breathe in UFPs, but there are ways to minimize exposure to them in indoor environments. The goal of using HEPA air purifiers is to remove excess particles in the indoor environment. Learn more about UFPs on our website. Some schools may be more exposed to UFPs than others if they are close to roadway traffic or overlap with the plumes from aircraft emissions. The schools participating in Phase I study were chosen to be representative of airport communities near Sea-Tac Airport. Highline Public Schools has proactively purchased HEPA air purifiers for classrooms. HEPA air purifiers are available to individual schools and classrooms upon request to the district. Highline Public Schools will participate in Phase II of the study which will examine the impact of UFPs on student health and academic performance.

## Summary of Results

Outdoor UFPs from road and aircraft traffic can enter indoor environments by infiltration through the walls, windows, and doorways of a building. The Healthy Air, Healthy Schools study found that UFP measurements inside the classroom were about 20% of outdoor levels prior to the installation of HEPA air purifiers. UFP measurements after HEPA air purifiers were used dropped to about 3% of outdoor levels. The primary sources of ultrafine particles at the schools came from general roadway traffic, aircraft traffic, and heavy-duty trucks, in that order. The study also found a significant increase in outdoor particles attributable to aircraft traffic when aircraft were landing overhead.

Overall, using portable HEPA filter units reduced classroom concentrations of ultrafine particles in the schools studied. If HEPA filers are used more widely, the study's model predicts that the amount of UFP reduction will vary depending on the age of the school building and other characteristics.

## Figure 1: Particle Removal using Portable HEPA Filter

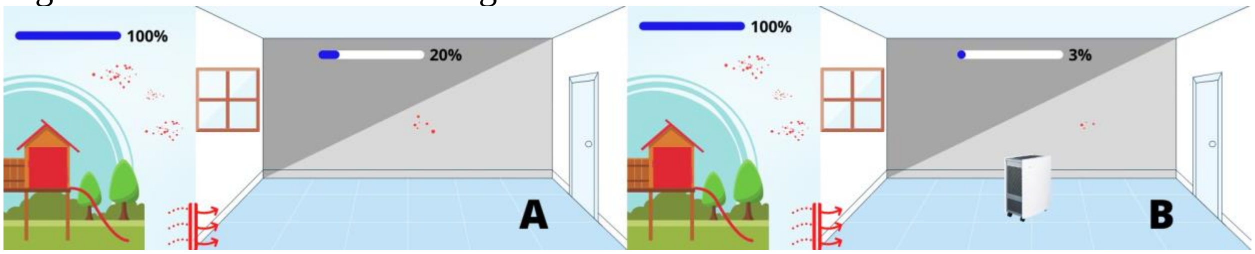


**Figure 1** visualizes the impact of outdoor air pollution on A) classrooms under standard ventilation conditions and B) classrooms with a HEPA filter intervention. The total particle number (general traffic), particles of aircraft origin and truck-traffic particles (BC) all decreased significantly after the HEPA filter deployment. Before the HEPA filter deployment, levels of UFPs in the classroom were approximately 20% of the outdoor levels. After the HEPA filter deployment, approximately 3% of all outdoor UFP were measured indoors. The age of the building and current HVAC system will affect how much of a benefit will result from using a HEPA filter in the classroom. This measure of UFPs is not a complete picture of indoor air quality as there are more air pollutants that were not measured in this report, including carbon monoxide, ozone, radon, and others. Air pollutants that were measured in this study include UFPs, Black Carbon (BC), and Carbon Dioxide ($CO_2$).

## Air Quality

Air quality is impacted by both outdoor and indoor sources. Outdoor pollution can enter the indoor environment. Sources of outdoor air pollution can include particulates and gases from wood smoke, unpaved roads, construction sites, cars, trucks, railways, and aircraft. In contrast, sources of indoor air pollution can include art, biology and chemistry supplies, shop areas, gyms, cleaning solvents, and pesticides. Learn more about air pollution on our website.

Some air pollutants measured in this study were:

- Ultrafine particles (UFPs) are very small particles often from combustion sources, such as aircraft and vehicle traffic exhaust, and wildfire smoke that can be breathed deeply into the body and are a concern for health. Some neighborhoods may be more exposed to UFPs than others if they are close to roadway traffic or overlap with the plumes from aircraft emissions.
- Black carbon (BC) is a component of particulate matter and is formed by the incomplete combustion of fossil fuels and biomass, including wildfires. BC is associated with asthma, and other respiratory problems, heart attacks, and lung cancer.
- Carbon Dioxide ($CO_2$) is exhaled by humans and can build up indoors without proper ventilation. $CO_2$ is also emitted from combustion sources that burn carbon-based fuel, such as tailpipe emissions from gasoline or diesel-fueled engines. It is also often used in air quality studies to understand how indoor air exchanges with outdoor air. Learn more about indoor air quality on our website.

There are many pollutants associated with health effects that can be measured but were not measured in this study. These pollutants include carbon monoxide, ozone, radon, asbestos, volatile organic compounds (VOCs), molds, allergens, bacteria, and tobacco smoke.

## Sampling Description

This report describes the results of a pair of 2-day sampling campaigns that took place between April and July 2021. The measurements collected over this period included indoor and outdoor measures of $CO_2$ gas, and indoor and outdoor UFPs of varied sizes. The data were collected under conditions where building occupancy was low and the classroom where the sampling equipment was set up was unoccupied for the duration of sampling.

## Total Air Exchange Rate

An air exchange rate is a useful measure for indoor air studies for calculating how quickly the indoor air in a room is replaced. The total air exchange rate can include exchange of air with the outdoors, as well as with cleaner air through a filtered HVAC system. The estimated outdoor air changed per hour (outdoor ACH) was defined for our study as a measure of how many times the volume of air within an entire room will be exchanged with outdoor air per hour. The outdoor ACH does not include recirculated filtered air treated through the HVAC system. Learn more about how we estimated the outdoor ACH on our website. For Hilltop Elementary School we estimate there is a 0.6 to 0.9 outdoor ACH which means that we estimate that the room air is replaced approximately one to four times in one hour with outdoor air. However, this does not include recirculated filtered air treated through the HVAC system. The American Society of Heating, Refrigerating, and Air Conditioning Engineers (ASHRAE) recommends that classrooms have a total air exchange rate of at least 5 ACH. The total ACH which includes outdoor ACH and recirculated ACH is available through Highline Public Schools building management.

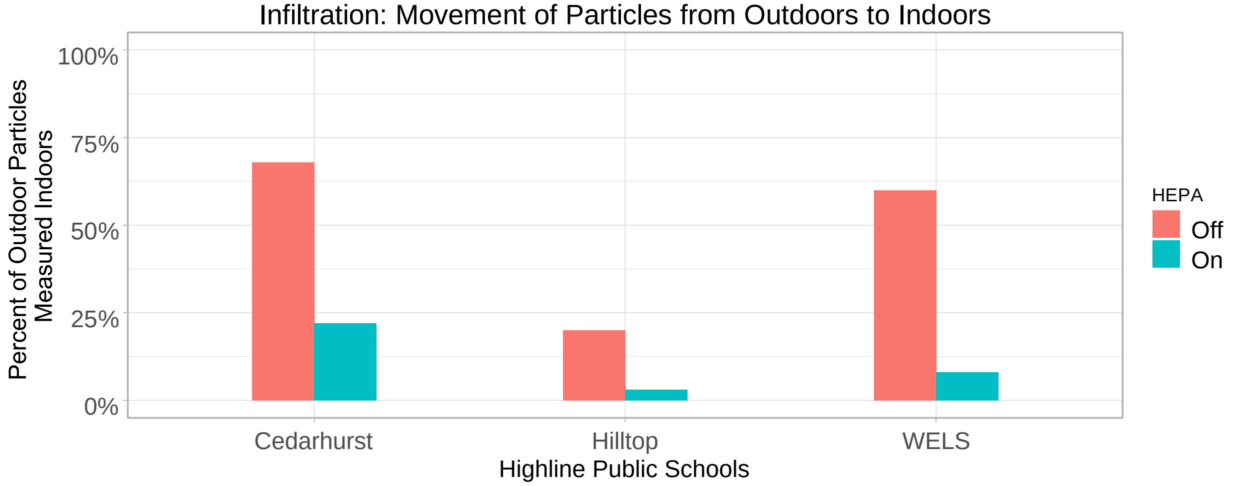
## Particle Movement and Removal of Particles using Portable Air Cleaner with HEPA filter

Infiltration is the unintentional movement of outdoor air pollution into the indoor environment. We measured the ratio of indoor to outdoor particles inside the classroom. A ratio of 1 means that there are equal amounts of particles from the indoors and outdoors inside the classroom. Schools that are near high-traffic roadways, aircraft flight paths and truck routes are at higher risk of indoor air pollution. Jets landing at Sea-Tac Airport contribute significantly to indoor and outdoor ultrafine pollution concentrations in nearby schools.

## Ultrafine Particles: Hilltop Elementary

The amount of outdoor UFPs that entered the classroom varied by school location. **Figure 2** below shows the results at each school location. All schools showed lower levels after the HEPA filters were used, but the amount of change varied by school.

## Figure 2. Movement of Particles from Outdoors to Indoors at Highline Public Schools



A comprehensive report is available summarizing the results from all participating schools. A copy of this report can be found on the University of Washington's study website for Healthy Air, Healthy Schools. The results from this pilot study only covered two days and may not reflect PAC use efficiency over a longer time period. To learn about the feasibility of this PAC with HEPA intervention, a larger study will need to monitor indoor air environments over a longer time period.

### Why does this matter?

Indoor air quality in schools is a factor that can impact the health and academic performance of children. Poor indoor air quality can decrease long- and short-term health of students and staff. Health effects of poor indoor air quality include coughing, eye irritation, headaches, allergic reactions, aggravating asthma, and/or other respiratory illnesses. These health problems can increase absenteeism and reduce academic performance. In addition, air pollution may also negatively impact the developing brain and affect cognition. Learn more about health effects on our website.

Ventilation solutions, such as opening windows or using a fan, can increase the outdoor air exchange. However, increasing outdoor air exchange is not recommended when air pollution is greater outdoors. A filtration intervention is recommended when outdoor air is more polluted than indoor air. Learn more about solutions to improve indoor air quality on our website. The results of this Phase I study will be used to inform a Phase II of the study that will include more schools within Highline Public Schools over the next two years. Phase II of the study will examine the health effects related to UFPs.

# APPENDIX C. *Healthy Air, Healthy Schools* Executive Summary

# Healthy Air, Healthy Schools Study

## Phase 1

## Executive summary

Ultrafine air pollution particles from road and aircraft traffic infiltrate schools around Seattle-Tacoma International Airport, with potential negative effects on health and student academic performance, but using HEPA air purifiers significantly improved classroom air quality, according to a 2021 University of Washington study.

The findings come from the Healthy Air, Healthy Schools Study funded by the Washington State Legislature and five cities near Sea-Tac Airport. The study was led by the UW Department of Environmental & Occupational Health Sciences and the Department of Civil and Environmental Engineering.

The study found that about one-half of all outdoor ultrafine pollution was measured inside classrooms in five schools near the airport before HEPA air purifiers were installed. Measurements after the HEPA units were deployed found that ultrafine pollution in classrooms dropped to about one-tenth of outdoor levels.

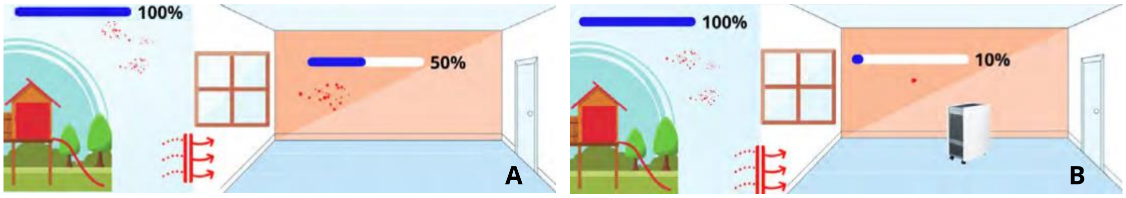
The primary sources of ultrafine particles at the schools came from general roadway traffic, aircraft traffic and heavy-duty trucks, in that order.

The study also found a significant increase in outdoor particles attributable to aircraft traffic when aircraft were landing overhead.

The portable HEPA filter units removed an estimated:

- 83% of total ultrafine particles.
- 67% of aircraft particles.
- 73% of heavy-duty truck particles.

Overall, using portable HEPA filter units could reduce classroom concentrations of ultrafine particles by approximately 70%, depending on the age of the school building and other characteristics, according to the study's models.



*Visualizing the impact of outdoor air pollution on A) classrooms under standard ventilation conditions and B) classrooms with a HEPA filter intervention.*

## Conclusions

This study is unique in focusing on ultrafine particle pollution in school settings and demonstrating that the ultrafine pollution measured in classrooms is primarily of outdoor origin.

- Schools that are near high-traffic roadways, aircraft flight paths and truck routes are at higher risk of indoor air pollution.
- Jets landing at Sea-Tac Airport contribute significantly to indoor and outdoor ultrafine pollution concentrations in nearby schools.
- Portable HEPA filter units can be effectively used in the short term to decrease air pollution in classrooms by removing particles.
- Additional investigation is needed to evaluate long-term portable HEPA filter usage in classrooms to address concerns related to energy efficiency and noise levels.
- Ventilation changes and building-level remediations such as sealing gaps and managing doorways should also be investigated as another approach to reduce infiltration of outdoor particles indoors.

## Next steps

With new funding from the Washington State Legislature and the US Environmental Protection Agency (EPA), the UW research team has launched phase 2 of the Healthy Air, Healthy Schools Study to further investigate the longer-term impacts of improving air quality in classrooms.

Phase 2 is a two-year study in 30 schools in both urban and rural settings in Washington. UW researchers will deploy HEPA air cleaners in classrooms in 20 schools near Sea-Tac Airport to measure the difference in air quality in classrooms with and without the filters over the course of a year with funding from the State of Washington. Researchers will also compare student academic performance during the year in classrooms with and without the filters. Research suggests that air pollution exposure is associated with lower student test scores.

With EPA funding, the team will expand its work beyond airport communities to measure the impact of HEPA air cleaners on air quality in 10 elementary schools around King County, Yakima County and the Yakama Nation, particularly during wildfire smoke events.

The phase 2 study will allow researchers to investigate the effectiveness and optimal usage of HEPA filter units and explore alternate interventions, including building upgrades. They will also examine the health, well-being and academic benefits of reducing concentrations of ultrafine particle pollution in classrooms. These findings will inform future recommendations to improve air quality in schools and other public buildings in Washington.

## Acknowledgments

The UW Department of Environmental & Occupational Health Sciences gratefully acknowledges the contributions of our community and state partners to this study: the Washington State Legislature; the cities of SeaTac, Burien, Federal Way, Normandy Park and Des Moines; Federal Way Public Schools; Highline Public Schools; and the University of Washington Ultrafine Advisory Group.

Special thanks to state Sen. Karen Keiser (D-Kent) and Reps. Steve Bergquist (D-Renton), Tom Dent (R-Moses Lake), David Hackney (D-Tukwila), Jesse Johnson (D-Federal Way) and Tina Orwall (D-Des Moines) for their support.

## More information

- Contact Dr. Elena Austin, UW Department of Environmental & Occupational Health Sciences: elaustin@uw.edu
- Read the full report: https://deohs.washington.edu/healthy_schools

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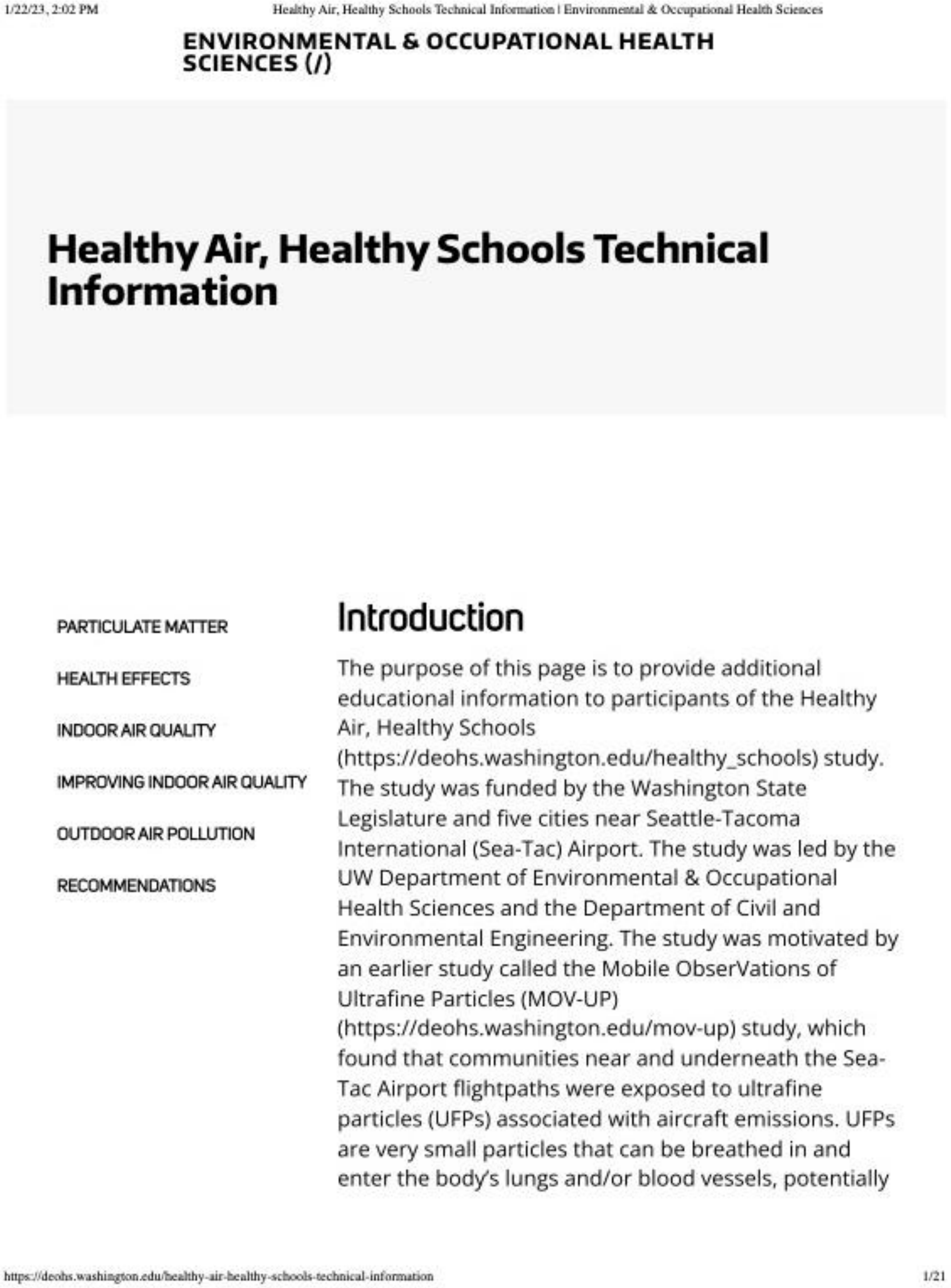
# APPENDIX D. *Healthy Air, Healthy Schools* Technical Information Webpage



1/22/23, 2:02 PM Healthy Air, Healthy Schools Technical Information | Environmental & Occupational Health Sciences

**ENVIRONMENTAL & OCCUPATIONAL HEALTH SCIENCES (/)**

## Healthy Air, Healthy Schools Technical Information

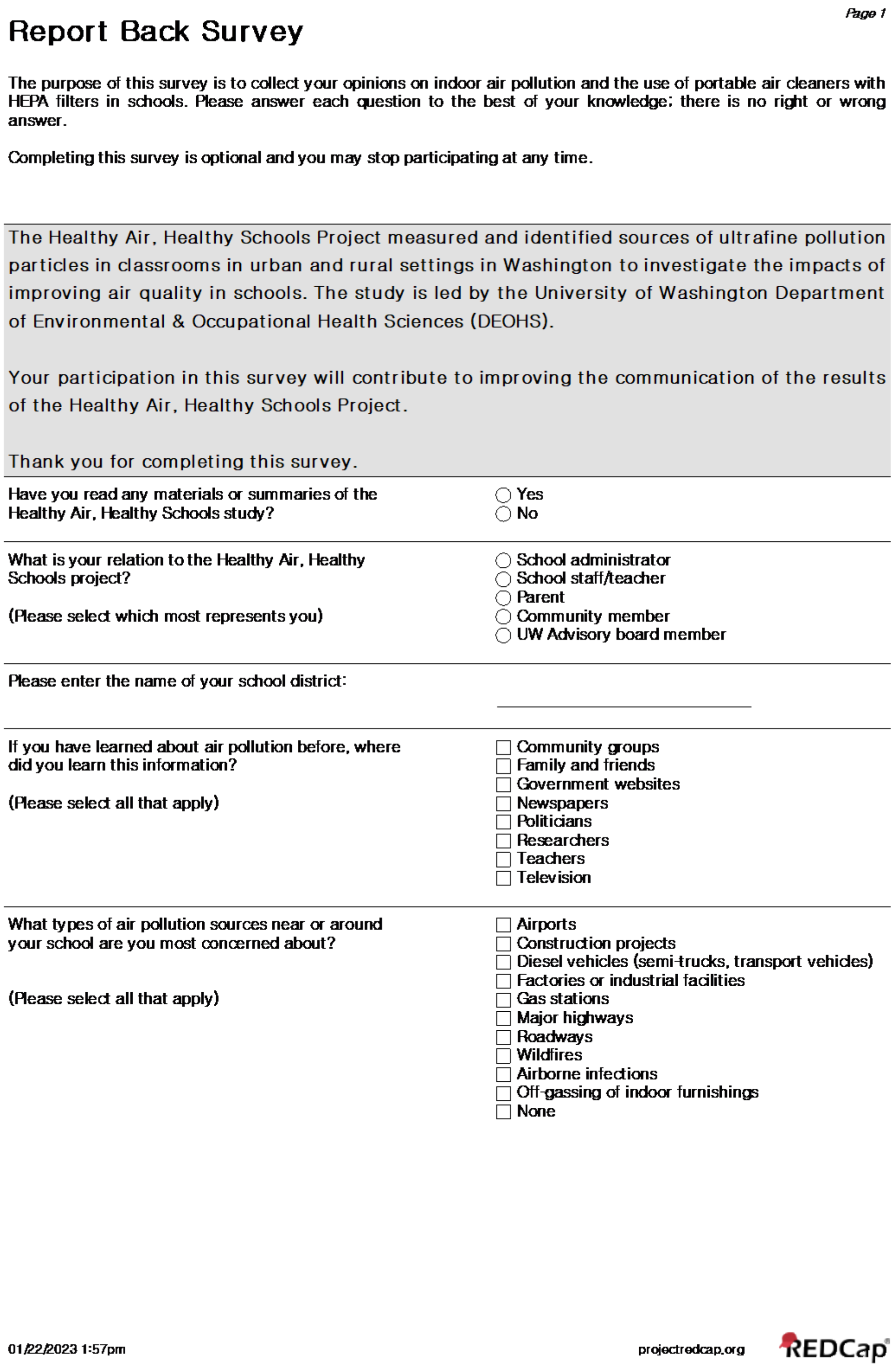
- PARTICULATE MATTER
- HEALTH EFFECTS
- INDOOR AIR QUALITY
- IMPROVING INDOOR AIR QUALITY
- OUTDOOR AIR POLLUTION
- RECOMMENDATIONS

### Introduction

The purpose of this page is to provide additional educational information to participants of the Healthy Air, Healthy Schools (https://deohs.washington.edu/healthy_schools) study. The study was funded by the Washington State Legislature and five cities near Seattle-Tacoma International (Sea-Tac) Airport. The study was led by the UW Department of Environmental & Occupational Health Sciences and the Department of Civil and Environmental Engineering. The study was motivated by an earlier study called the Mobile ObserVations of Ultrafine Particles (MOV-UP) (https://deohs.washington.edu/mov-up) study, which found that communities near and underneath the Sea-Tac Airport flightpaths were exposed to ultrafine particles (UFPs) associated with aircraft emissions. UFPs are very small particles that can be breathed in and enter the body's lungs and/or blood vessels, potentially

https://deohs.washington.edu/healthy-air-healthy-schools-technical-information 1/21

# APPENDIX E. *Healthy Air, Healthy Schools* Evaluation Survey



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## Report Back Survey

The purpose of this survey is to collect your opinions on indoor air pollution and the use of portable air cleaners with HEPA filters in schools. Please answer each question to the best of your knowledge; there is no right or wrong answer.

Completing this survey is optional and you may stop participating at any time.

The Healthy Air, Healthy Schools Project measured and identified sources of ultrafine pollution particles in classrooms in urban and rural settings in Washington to investigate the impacts of improving air quality in schools. The study is led by the University of Washington Department of Environmental & Occupational Health Sciences (DEOHS).

Your participation in this survey will contribute to improving the communication of the results of the Healthy Air, Healthy Schools Project.

Thank you for completing this survey.

| | |
|---|---|
| Have you read any materials or summaries of the Healthy Air, Healthy Schools study? | ○ Yes<br>○ No |
| What is your relation to the Healthy Air, Healthy Schools project?<br>(Please select which most represents you) | ○ School administrator<br>○ School staff/teacher<br>○ Parent<br>○ Community member<br>○ UW Advisory board member |
| Please enter the name of your school district: | __________________________ |
| If you have learned about air pollution before, where did you learn this information?<br>(Please select all that apply) | ☐ Community groups<br>☐ Family and friends<br>☐ Government websites<br>☐ Newspapers<br>☐ Politicians<br>☐ Researchers<br>☐ Teachers<br>☐ Television |
| What types of air pollution sources near or around your school are you most concerned about?<br>(Please select all that apply) | ☐ Airports<br>☐ Construction projects<br>☐ Diesel vehicles (semi-trucks, transport vehicles)<br>☐ Factories or industrial facilities<br>☐ Gas stations<br>☐ Major highways<br>☐ Roadways<br>☐ Wildfires<br>☐ Airborne infections<br>☐ Off-gassing of indoor furnishings<br>☐ None |

01/22/2023 1:57pm projectredcap.org REDCap

Which of the following strategies do you use to protect yourself from air pollution?

(Please select all that apply)

☐ Checking the air quality forecast
☐ Opening windows
☐ Closing windows during wildfires
☐ Decreasing use of fireplace
☐ Using air purifiers
☐ Wearing a mask
☐ None

| | Not important | Slightly important | Moderately important | Important | Very important |
|---|---|---|---|---|---|
| How important do you think it is to prevent outdoor air pollution from entering your school? | ○ | ○ | ○ | ○ | ○ |
| How important do you think it is to prevent outdoor air pollution from entering your home? | ○ | ○ | ○ | ○ | ○ |
| How important do you think it is to improve current indoor air quality at your school? | ○ | ○ | ○ | ○ | ○ |

| | Strongly disagree | Disagree | Neutral | Agree | Strongly agree |
|---|---|---|---|---|---|
| Do you feel you need more information about indoor air pollution? | ○ | ○ | ○ | ○ | ○ |
| Do you think portable air cleaners with a HEPA filter are effective in improving indoor air quality? | ○ | ○ | ○ | ○ | ○ |
| Would you like to learn more about how particles in the air impact children's health? | ○ | ○ | ○ | ○ | ○ |

What concerns do you have using portable air cleaners in your school?

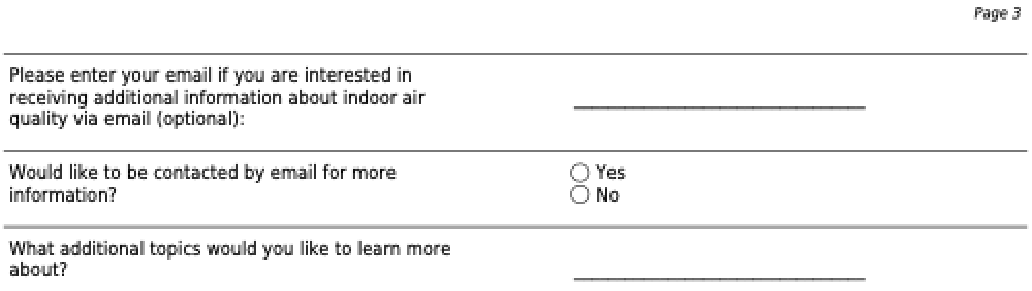
○ Cost of portable air cleaners
○ Produce too much noise
○ Distracting in a classroom
○ Do not think they are effective
○ Unlikely to be maintained
○ Consume too much energy (not energy efficient)
○ Other

Please specify "Other": ________________________________

How do you prefer to receive information about this study?

○ Community meetings
○ Website
○ Email
○ Flyers
○ Other

Please specify "Other": ________________________________



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| | |
|---|---|
| Please enter your email if you are interested in receiving additional information about indoor air quality via email (optional): | ______________________________ |
| Would like to be contacted by email for more information? | ○ Yes<br>○ No |
| What additional topics would you like to learn more about? | ______________________________ |

# APPENDIX F. *Healthy Air, Healthy Schools* Interview Instrument

**Organization:**
**Name of Interviewee:**
**Title:**
**Time:**
**Date:**

## Introduction

Hello, my name is Nancy Carmona and this is Aline Maybank, we are (graduate) students at the University of Washington. We are here today to interview you as part of the Healthy Air, Healthy Schools air monitoring study, which is examining indoor air pollution in schools. Your unique leadership position provides an important perspective on the topics we are looking to address. These questions are designed to collect your opinions and reflections on your experiences.

Thank you for your participation. This interview is expected to take 30 minutes to complete. Your identity will be kept confidential. The only people who will see our notes that we write, or the transcript of this interview will be our study team members and faculty advisor.

In the final report, your name and other identifying information will be removed. We will share this report with the Washington State Office of Superintendent of Public Instruction (OSPI) and researchers. You may decline to answer any questions or stop the interview at any time. Thank you again.

The report will be finalized over the next few months. When we are done, I can send you a copy of the findings via email if you would like.

Do you have any questions about the information I have shared with you? In order to ensure that we accurately capture everything you say, we would like to record this interview on Zoom. The recording of this interview will not be shared outside of our research team and will be saved for 6 months. You may also ask me to stop recording at any point if you so choose. Do we have your permission to record?

Today I will be facilitating the interview and Aline Maybank will be taking notes.

Thank you again for taking the time to interview, your responses are greatly appreciated.

Keep in mind that throughout the interview today we will be talking about infiltration, which we define as the unintentional movement of outdoor air particles to the indoor environment.

Let’s begin!

## Ice Breakers

1. How do your responsibilities intersect with schools or childcare centers?
    - Did you participate in the *Healthy Air, Healthy Schools: Phase 1* study?

**2.** Have you read the *Healthy Air, Healthy Schools: Phase 1 study* report? **(*Skip if no*)**
- What were the take home messages you got from the air monitoring report?
- What did you like or dislike about the air monitoring report?
- What additional information would you want to receive in this report?
- Will the report impact actions of the school moving forward?
- How did the air monitoring report impact your planned use of portable air cleaners in the classroom?
- How has your perception of indoor air quality changed after reading the air monitoring report?
- Have you shared this report with any colleagues?

*Thank you for your responses, now I will be delving into more specific questions about indoor air quality.*

## General Indoor Air Quality

3. Are you concerned with the indoor air quality in schools (or childcare centers)?
    - Can you give a specific example of an air quality concern?
    - What factors in the immediate environment do you think affect indoor air quality in schools?

4. Have you implemented strategies to reduce your exposure to air pollution when indoors?
    - Can you give specific examples of strategies you have used for reducing your exposure to indoor air pollution? If yes, how satisfied were you with this strategy?
    - Are you aware of any strategies being used to address air quality concerns in your school or school district? If yes, how satisfied were you with this strategy?
    - Have your heating, ventilation, and air conditioning (HVAC) systems been retrofitted? If retrofitting was used, did it meet your expectations?
    - What was the motivation for retrofitting your HVAC system?
    - If retrofitting was used, do you know if it improved indoor air quality?
    - Are HVAC systems maintained and inspected? If so, with what frequency and what types of maintenance is performed?

*Thank you for your responses, now I will be delving into questions about portable air cleaners.*

## Portable air cleaner

**5.** What do you think about the use of portable air cleaners in schools (or childcare centers)?
- What do you like or dislike about them?
- Is the use of portable air cleaners dependent on specific classroom activities?

- What are your concerns about using portable air cleaners in schools (or childcare centers)?
- When have you used or recommended portable air cleaners in the classroom (or childcare centers)?
- Does your school (or childcare center) have any guidance (or recommended procedures) on the use portable air cleaners in classrooms? If yes, what prompted the use of portable air cleaners in the classroom?
- Have you personally purchased a portable air cleaner for use in the classroom? If yes, what features were important in your selection?

6. What considerations have informed your decisions about whether or not to use portable air cleaners in classrooms (or childcare centers)?
    - What criteria were used to determine which portable air cleaner to purchase?
    - Where did you get information about the different options for portable air cleaners?
    - How heavily did noise production from portable air cleaner weigh in the decision?
    - What about features such as effectiveness?
    - What about features such as energy efficiency?
    - Do you have a plan or maintenance schedule and if so what is it?
    - What kind of training do you have for the use of the HEPA cleaners?

7. What concerns do you have about the feasibility and sustainability of using portable air cleaners in classrooms?
    - What barriers do you see limiting the use of portable air cleaners in classrooms?
    - What strategies would make it easier to use portable air cleaners in classrooms?
    - What barriers exist to funding the purchase of portable air cleaners in classrooms?
    - How would you describe the overall impact of portable air cleaners in classrooms?

*Thank you for your responses, now I'm going to ask for your thoughts on strategies that could be used for schools (or childcare centers) for different types of air pollution.*

## Air Pollution Sources

8. In our research we found that communities are affected by air pollution created by airplanes. Are there strategies that you think should be used by schools to protect children from exposure to air pollution from airplanes?

9. In recent years, there have been major wildfire smoke episodes. Are there strategies that you think should be used by schools to protect children from exposure to wildfire smoke pollution?
    - What would you need to know about air quality to close schools during wildfire smoke episodes?
    - Have you ever issued a school closure day because of air quality issues?
    - How did you make the decision to close school because of air quality?
    - Would you consider staying home during wildfire events?

10. The Covid pandemic has also created a need to control airborne exposures at schools. Are there strategies that you think should be used by schools to protect children from airborne transmission of infectious diseases?

*Thank you so much for your thoughts on air pollution sources. We just have just two questions left.*

11. How can the *Healthy Air, Healthy Schools* study support improving air quality in schools (or childcare centers)?
    - What improvements do you think will result from this study?
    - What do you anticipate learning from this study?
    - What support does your school need to improve the ventilation systems? (knowledge, resources, connection to experts, or all of the above)?

12. Is there anyone else that you would recommend we speak to?

## ***Closing***

Thank you for meeting with me today. Your insights are very important to our work and will greatly aid us in our assessment. Over the next few months, the interview responses will be compiled into a detailed report and the findings will be disseminated to the community via a presentation.

Are you interested in receiving a final copy of the report?

Can I verify that _________________@________.____ is your correct email address? If you have any questions, please feel free to contact me at nancyc9@uw.edu or the Principal Investigator of Healthy Air, Healthy Schools study Dr. Elena Austin at elaustin@uw.edu. If you have questions or concerns about your rights as a research participant, you can contact the UW Human Subjects Division at email hsdinfo@uw.edu. This concludes our interview, again thank you for participating; your contribution is greatly appreciated.