

2025

Measuring and modeling aviation-related air pollution in near-airport communities

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BOSTON UNIVERSITY
SCHOOL OF PUBLIC HEALTH

Dissertation

**MEASURING AND MODELING AVIATION-RELATED AIR POLLUTION
IN NEAR-AIRPORT COMMUNITIES**

by

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Submitted in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

2025

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“Being human means throwing your whole life on the scales of destiny when need be, all the while rejoicing in every sunny day and every beautiful cloud.”

~Rosa Luxemburg~

DEDICATION

This dissertation is dedicated to my parents, Peter and Ruth

ACKNOWLEDGMENTS

I stand on the shoulders of giants and acknowledge the vast network who supported me throughout the odyssey of graduate school.

I would like to acknowledge my dissertation committee chair, Kevin Lane, for his unconditional support from field work to Zoom rooms, for giving me the freedom to chart my own course, and for nurturing my growth as an independent researcher. I am also deeply grateful to my other committee members: Prasad Patil, for your advisement and machine learning expertise, which had a profound effect on guiding Chapter 3, Jeff Geddes, for deepening my understand of both the science and philosophy of air quality, and Neelakshi Hudda, for showing me the value of taking ‘just a measurement’ and supporting my data collection efforts in Chapter 4. A special thank you to my outside reader, Elena Austin, for reviewing this work and participating in my defense.

Additionally, I would also like to acknowledge:

My FAA ASCENT Project 018 colleagues — Jon Levy, the unsung hero of my dissertation, for providing invaluable research, writing (and dental) advisement; John Durant, for your thorough reviews of my manuscripts, presentations, and field plans, which helped me grow tremendously as a researcher; and the current and former project staff who supported the foundation of the project, from keeping our instruments alive in the field to trudging through data processing and cleaning: Flannery Black-Ingersoll, Nina Franzen Lee, Emma Gause, Beth Haley, Breanna van Loenen, Tiffany Duhl, Isabelle Berman, Arianna Cozza, and Matt Simon for originally setting up the Chelsea monitoring site many years ago.

The EH Department — you all supported me during an extraordinarily challenging period of my life. From kind words and happy hours to supporting my Boston Marathon effort, this department made me feel welcomed and whole. Thank you to all the EH faculty who served as mentors throughout this program, especially Wendy Heiger-Bernays, for holding me to the highest standard and reminding me it's always 'a good day to do science'; Pat Kinney, for supporting my IoC grant, effectively laying the foundations for Chapter 4; and, Jonathan Buonocore, for always making an effort to stop by my office and include me on all things air quality. Thank you to the EH administrative team for assisting with the endless logistics of being a student collecting their own data. A heartfelt thank you to my fellow doc students, a special group of people who can truly empathize with the trials and tribulations of this pursuit. Stephanie Grady, for your advisement and celebrating my accomplishments big and small. Noelle Henderson, for jumping headfirst into my Marathon endeavors and having a meme for every possible situation. Two special groups of people, the Aromo Haus dawgs (Kathryn Rodgers, Sam Hall, Quinn Adams) and the OOW Team (Chad Milando, Steph Grady, Caitlin Brand, Erin Polka, Madeleine Scammell). Quinn, thank you for running the final sprint of the dissertation gauntlet with me. Finally, to my starting cohort: Dr. Alina McIntyre, Dr. Emily Pennoyer, and (soon to be Dr.) Pilar Botana Martinez — thank you for your support every step of the way.

BU URBAN — thank you to Pamela Templer, Lucy Hutyra, and Jon Levy for allowing me to jointly pursue my academic interests across atmospheric science and public health. Thank you to the Program Managers, Evan Kuras and Emily Walton, and

especially Heather Ho, for your indelible support of my research and Boston Marathon effort.

My longtime mentors — this academic journey began far before I stepped foot in Talbot. Ariel Serkin and Claire Ingelfinger (MHS); Elizabeth Keating and Erik Linnane (BU); Sarah Anderson (UCSB); Taro Pusina and Lee Tarnay (USFS) — thank you for believing in me, inspiring me, and demanding the best of me.

My friends and family — what an extraordinary group of people encompassing all phases of my life: Matt Au, Rick Sobey, the Mansfield hipsters, the PwC and BU bros, and the UCSB Brennies. Uncle Rick, thank you for sharing your engineering expertise and getting just as excited as me about valves and flow rates. Henry, thank you for taking such a genuine interest in my work, from the logistics of field work to the *n*th iteration of ‘Figure 4’. Bre, thank you for your support during the oscillating peaks and valleys of Chapter 3, and I fear more importantly, for keeping my sleep score above a 60. Finally, to my parents Peter and Ruth — Dad, my OG advisor, your humor, guidance, and debate prowess are missed every day, and Mom, thank you for supporting my nonlinear evolution from CPA to PhD and serving as my most trusted sounding board in all my pursuits.

**MEASURING AND MODELING AVIATION-RELATED AIR POLLUTION
IN NEAR-AIRPORT COMMUNITIES**

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ABSTRACT

The aviation industry drives substantial economic growth and is the fastest-growing mode of transportation worldwide, but consequently contributes to adverse environmental and public health concerns. Of interest is the impact of airport and aircraft activities on particulate matter (PM) air pollution exposure to communities living near airports. The type of fuel used in aircraft affects the size and composition of PM. Jet fuel, with its relatively high sulfur content, contributes to substantial ultrafine particle (UFP; particles with aerodynamic diameter <100 nanometers) formation, whereas piston-engine aircraft burning leaded aviation gasoline emit lead along with other combustion by-products into the environment. Isolating the contributions of in-flight aircraft emissions from ground-based airport activities and other location sources (e.g. roadway traffic) presents a significant methodological challenge. Aviation source attribution is complicated by multiple complex interactions between aircraft activity, exhaust plume dynamics, and meteorology. Because aviation emissions carry profound implications for human health and climate, there is a pressing need for research to improve source apportionment techniques and to inform effective mitigation strategies.

The goal of my dissertation was to enhance our understanding of the spatial,

temporal, and compositional heterogeneity of aviation-related air pollution in communities near airports. This work collectively provides insight on the breadth of potential air pollution exposures across two distinct airport types: Commercial Service Airports (CSA), which have high operation volumes but are geographically limited, and General Aviation Airports (GAA), which have lower operation volumes but are widely distributed.

In Chapter Two, we leveraged a natural experiment during the COVID-19 pandemic to disentangle source-specific UFP contributions at a long-term monitoring site impacted by multiple UFP sources in Chelsea, MA. Results show that mean UFP concentrations closely tracked road traffic activity patterns, whereas peak UFP levels occurred when the site was downwind of the airport, implicating aviation emissions as the driver of episodic high-UFP events. This analysis lays foundational evidence that aviation emissions can be distinguished from roadway emissions, underscoring the importance of considering aviation as a distinct source in exposure assessments.

In Chapter Three, we built on Chapter Two findings by applying an interpretable machine learning (ML) model to the long-term Chelsea UFP dataset to quantify aircraft contributions to ambient UFP. In summary, we were able to reliably model UFP concentrations and disentangle nonlinear interactions between meteorology and flight activity to quantify aviation contributions to community exposures. These overarching results are further supported by a detailed apportionment of aviation contributions to ambient UFP at an hourly resolution, distinguishing between arrivals, departures, and runway-specific impacts over the study period (2014–2022, Boston, MA). These results

provide a novel framework for retrospective exposure assessment to aviation emissions, offering opportunities for epidemiological studies to examine health impacts of aviation air pollution.

In Chapter Four, we expanded our focus beyond large commercial airports to investigate air pollution exposures around GAAs. We conducted ambient sampling of fine particulate-bound elements at two contrasting GAAs — one dominated by piston-engine activity and one by jet activity — and compared these measurements to data from U.S. Environmental Protection Agency (EPA) monitors. Results showed PM enriched in bromine, arsenic, lead, sulfur, and zinc — contaminants indicative of aviation fuel combustion — at levels substantially above background. These findings confirm that distance from the airport is a key determinant of pollutant concentration gradients, and importantly, reveal that communities near GAAs may be exposed to hazardous air pollutants beyond lead.

Recent developments magnify the significance of these research gaps. In 2021, the World Health Organization published guidance for recommended maximum hourly and daily exposure to UFP; the recorded measurements from Chapter Two and Three exceeded these guideline values. In 2023, the EPA issued a final endangerment determination of aircraft lead emissions and is required to set regulatory standards protective of public health; our measurements in GAA communities indicated ambient lead and other hazardous air pollutant concentrations above background levels. Air pollution exposure in communities near airports, both from CSAs and GAAs, will be a key area of interest for future research and health assessments.

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LIST OF ABBREVIATIONS

avgas	aviation gasoline
BLL	blood lead level
CAA	Clean Air Act
CPC	Condensation Particle Counter
CSA	Commercial Service Airport
CSN	Chemical Speciation Network
Dp	particle diameter
EPA	U.S. Environmental Protection Agency
FAA	Federal Aviation Administration
FEM	Federal Equivalency Method
GAA	General Aviation Airport
IMPROVE	Interagency Monitoring of Protected Visual Environments
IS	impact sector
LTO	landing and takeoff operations
MADT	monthly average daily traffic
NAAQS	National Ambient Air Quality Standards
NE	natural experiment
NEI	National Emissions Inventory
NIS	non-impact sector
PM _{2.5}	particulate matter less than 2.5 microns in aerodynamic diameter
PNC	particle number concentrations

SOE..... state of emergency
UFP ultrafine particles
Xgboost.....Extreme Gradient Boosting Algorithm
XRF.....Energy dispersive x ray spectroscopy

CHAPTER ONE. INTRODUCTION

Air pollution is a ubiquitous global environmental and public health challenge and exposure to particulate matter (PM) can harm nearly every organ in the body.¹ Effective management of air pollution requires source apportionment — the process of identifying and quantifying the contributions of specific emissions sources to ambient air pollution levels. This step is crucial for designing targeted mitigation strategies and improving public health outcomes.² The aviation industry represents a significant and growing contributor to air pollution, yet its emissions, fate and transport, and resulting human exposures are inherently complex and nonlinear. Communities near airports face differential exposures to PM size and composition due to differences related to airport operations (i.e. airport size, flight activity, and aircraft engine types), meteorology (i.e. wind speed and direction) as well as distance and angle of communities from the airport and runways. Jet aircraft engines emit ultrafine particles (particles < 100 nanometers in aerodynamic diameter; UFPs) at high rates that can remain airborne and travel long distances downwind³, whereas piston-engine aircraft emit combustion by-products of leaded aviation gasoline (avgas), making this sector the single largest source of airborne lead in the United States.⁴ Understanding aviation-related PM exposures and their health impacts is critical. Yet, due to the complex nature of aviation emissions and limited monitoring infrastructure in near-airport communities, our ability to attribute ambient pollution to aviation remains limited.

This dissertation investigates the impacts of aviation activities on UFP concentrations and on the multi-element composition of fine PM in communities living

near airports. By advancing exposure assessment methodologies, this research addresses several critical knowledge gaps necessary for epidemiological studies and evidence-based public health policy: (1) differentiating the impacts of aircraft landing, takeoff, and ground operations, (2) apportioning aviation-related UFP contributions from aviation and other common sources (e.g. road traffic) in near-airport areas, and (3) characterizing air pollution exposures around general aviation airports, including exposures to lead and other hazardous air pollutants.

The Aviation Industry: A Complex and Growing Source of Air Pollution

The aviation industry is a vital part of the global economy and has grown significantly in recent decades. Before the COVID-19 pandemic, air travel was the fastest-growing mode of transportation, with a forecasted 5% annual increase in U.S. aviation activity over the next 20 years.⁵ The U.S. is home to nearly 20,000 airports of varying sizes and functions, commonly categorized as:⁶

- *Commercial Service Airports (CSAs)*: Handling > 2,500 annual enplanements and supporting domestic and international airline services, primarily using jet engines.
- *General Aviation Airports (GAAs)*: With fewer than 2,500 annual enplanements, GAAs serve specialized purposes such as aeromedical flights, corporate travel, and law enforcement. These serve as the primary hub for piston-engine aircraft, which rely on leaded aviation gasoline.

Aircraft engines produce a wide array of air pollutants, including carbon dioxide (CO₂), nitrogen oxides (NO_x), oxides of sulfur (SO_x), volatile and semi-volatile organic compounds (VOCs/SVOCs), PM, and trace metals (Figure 1.1).⁷

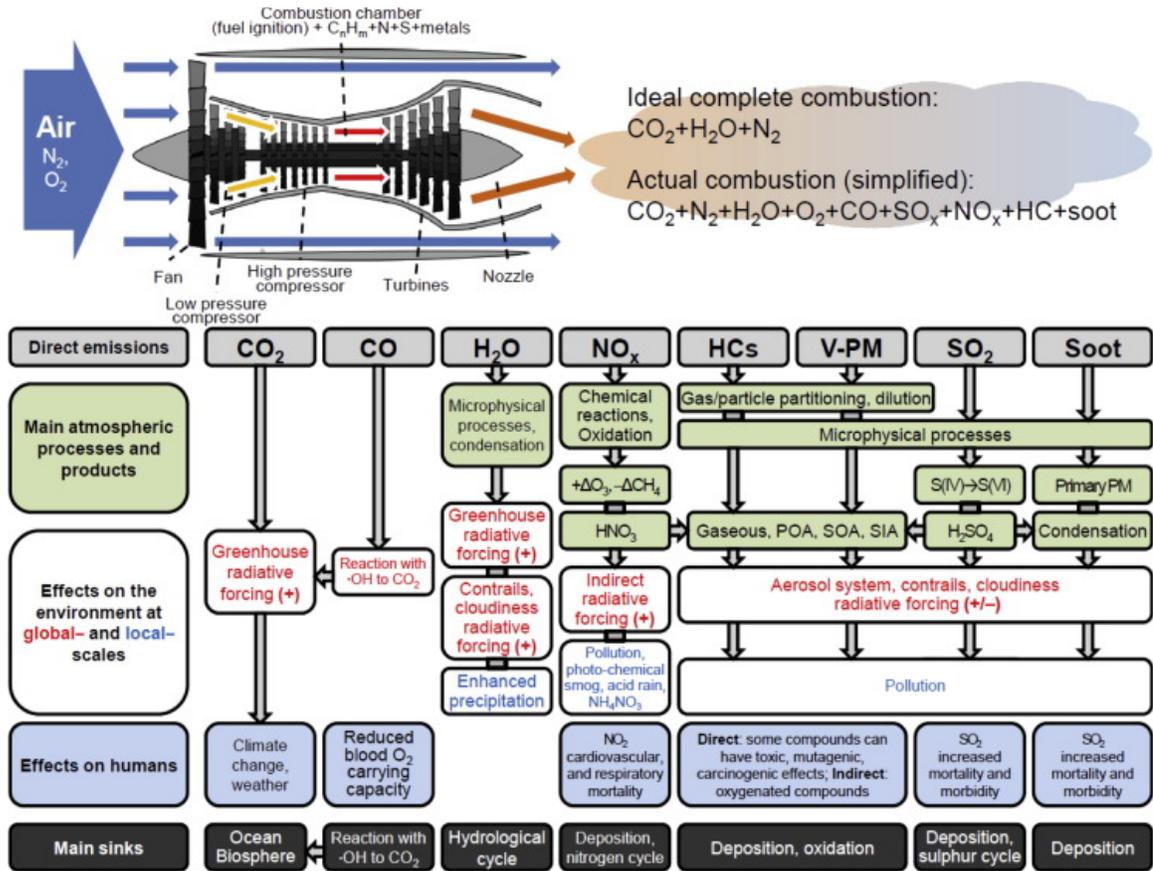


Figure 1.1 - Simplified diagram of a turbofan (upper left); products of ideal and actual combustion in an aircraft engine (upper right); and related atmospheric processes, products, environmental effects, human health effects and sinks of emitted compounds (bottom). Reproduced from Masiol and Harrison (2014).

Of particular concern for near-airport communities are two pollutant classes:

- Ultrafine Particles (UFPs)*: Generated by incomplete combustion in aircraft engines, UFPs can be emitted directly in exhaust or formed secondarily via atmospheric nucleation and coagulation processes. These particles (defined as < 100 nm in diameter) exhibit high mobility in ambient air and can penetrate deeply into human lungs.
- Lead (Pb)*: Emitted from piston-engine aircraft burning leaded aviation gasoline. 100 Low Lead (100LL, maximum Pb concentration of 0.56 g/L) aviation gasoline is the

primary fuel for piston-engine aircraft, containing tetraethyl lead ($C_8H_{20}Pb$) as an anti-knock agent.

While exhaust plumes from aircraft engines are considered to account for most airport-related emissions, aircraft are only one of several sources of emission at an airport.⁸ The airport environment is a wide and complex mixture of sources including aircraft (maneuvering, taxiing, landing, takeoffs, auxiliary power), construction and maintenance work, ground power units, ground service equipment (passenger buses, refilling trucks, de/anti-icing vehicles) and buildings (heating facilities, restaurants for passengers and operators). Few studies to date have considered all aspects of the airport emission ecosystem simultaneously,⁷ which complicates efforts to isolate the impacts of aircraft engines alone on local air quality. This complexity means that communities around airports may be exposed to a mix of pollutants from multiple sources, and to attribute exposure to aviation-specific activities requires concerted study design and analysis.

Health Impacts of Aviation-Related Air Pollutants

Exposure to particulate matter has well-documented links to respiratory and cardiovascular disease exacerbation.^{1,9} Fine PM has been associated with increases in mortality, and there is growing concern that the smallest particles (UFPs) may be disproportionately responsible for certain adverse health outcomes.¹⁰ However, directly attributing health outcomes to UFP exposure remains challenging because UFPs often co-occur with larger particles and gaseous co-pollutants.¹⁰⁻¹² In 2019, a comprehensive review of epidemiological studies on the health effects of UFPs concluded that there was

insufficient evidence to infer causal associations with morbidity and mortality.¹³

However, the study authors noted that halting or reducing UFP pollution should result in improved health status.¹⁴ UFPs enter the body via inhalation, directly causing lung inflammation and, because of their small size, can diffuse from the lungs to reach systemic circulation, where they have been found in many compartments of the body.¹⁵ Furthermore, UFPs have a relatively large surface area per mass, increasing the potential capacity to carry adsorbed toxic compounds into the body.¹⁶ Aviation-related UFP exposure, in particular, has been understudied in human populations.^{17,18} There is some evidence that UFPs from jet aircraft (which are often rich in <20 nm “nuclei-mode” particles) could be especially toxic.^{19–21} Studies of short and long-term exposures to airport-associated UFPs in healthy adults, adults with asthma, and children in the U.S. (Los Angeles International Airport) and Europe (Amsterdam Airport Schiphol) showed potential associations with systemic inflammation and cardiopulmonary risks, but the evidence remains inconclusive as there are substantial challenges with distinguishing airport emissions from background urban pollution.^{22–25}

Lead (Pb) is a well-established toxin with no safe level of exposure, especially affecting children’s neurodevelopment. Leaded gasoline additives were historically used in automobiles until they were phased out in the U.S., which led to major drops in population blood levels.²⁶ However, the continued use of leaded gasoline in hundreds of thousands of aircraft means that lead emissions persist as a local hazard around GAAs. Children living near GAAs can inhale lead particulate or ingest lead that has settled from the air into soil and dust. Lead exposure in early life is associated with cognitive and

behavioral deficits, including lowered IQ, attention difficulties, and academic underachievement.^{27–29} Infants and young children are particularly vulnerable; importantly, research shows that the toxic effects of lead are more pronounced at lower blood lead levels with measurable harm in the 2–3 ug/dL range.³⁰ Consistent with this, the U.S. Centers for Disease Control and Prevention (CDC) states that no level of lead in blood is safe for children.³¹ However, communities near GAAs remain an unresolved hotspot for lead exposure risk, disproportionately affecting communities with less resources.^{32–34} It is estimated that 16 million people (including 3 million children) live or attend school in the U.S. within 1 km of GAA airports,³⁵ highlighting the significant population potentially at risk from leaded aviation gasoline emissions. While lead is the focal pollutant of concern at GAAs, emerging evidence suggests that other hazardous air pollutants associated with aviation activities may also impact local air quality. To date, these co-emitted hazardous air pollutants have been largely understudied in community exposure assessments, which solely focus on Pb. This highlights a need for more comprehensive monitoring of the full suite of aviation-related combustion by-products impacting near-airport communities.

Regulatory Context

Many countries, including the U.S., have adopted ambient air quality standards for PM that differentiate by particles size (e.g. coarse [PM₁₀] vs. fine [PM_{2.5}] U.S. National Ambient Air Quality Standards [NAAQS]). However, these mass-based standards (mass/volume) do not account for particle number (number/volume) or composition, and thus do not fully capture UFPs or PM elemental constituents. Evidence

shows that particle composition can influence health effects independently of mass,³⁶ and UFPs — which contribute negligibly to PM_{2.5} mass — are not captured by the current EPA national air pollution monitoring network.³⁷ Currently, there are no U.S. regulatory standards or routine monitoring requirements for UFPs. Recent EPA Integrated Science Assessments (ISA) have consistently called for improved UFP monitoring and health research to support potential guidelines.¹² In 2021, the World Health Organization (WHO) took a first step by issuing guidance values (‘good practice statements’) for UFP, classifying 24-hour average UFP counts above 10,000 particles / cm³ and 1-hour average above 20,000 particles / cm³ as “high” pollution levels.³⁸ These WHO guidelines reflect growing concern in the scientific community that UFP exposure poses unique health risks, even in the absence of formal standards.

With respect to Pb, the current U.S. NAAQS for Pb in total suspended particles is 150 ng / m³ (3-month rolling average).³⁹ Violations of this standard are relatively rare and geographically limited compared with other air pollutants for which NAAQS are established e.g. PM_{2.5} and Ozone.⁴⁰ However, recognizing the continued emissions from aviation gasoline, the EPA has moved toward regulating this major legacy lead emission source. In 2022, the EPA issued a proposed endangerment finding, and in 2023 it finalized the determination that lead emissions from piston-engine aircraft endanger public health.⁴¹ This finding triggers a mandate for the EPA to develop lead emission standards for aircraft engines, and it places responsibility on the U.S. Federal Aviation Administration (FAA) to certify fuels or engines that meet those standards. Notably, the EPA itself cannot ban or regulate fuel content under the Clean Air Act — this authority

lies with the FAA.⁴² In anticipation of this, the FAA launched the Eliminate Aviation Gasoline Lead Emissions initiative in 2022, aiming to transition the general aviation fleet to unleaded fuels by 2030.⁴³ These regulatory developments heighten the relevance of research on GAA pollution: as rules are formulated, policymakers will need data on lead dispersion, exposure, and co-pollutants to set appropriate standards and mitigation measures.

Challenges in UFP Source Apportionment of Aviation Emissions

Modeling and apportioning aviation emissions presents a unique set of challenges due to the dynamic nature of aircraft movement and the complex dispersion processes that govern exhaust plumes.^{44,45} Unlike stationary or ground-level sources, aircraft are moving sources that emit pollutants across a range of altitudes and speeds. While road traffic emissions are largely confined to near-ground corridors, aviation emissions occur in a three-dimensional flight space, introducing vertical distribution and long-distance transport of pollutants. In-flight aircraft emissions interact with atmospheric dynamics (e.g. jet exhaust can form coherent hot plumes that rise and are carried downwind aloft), making it difficult to predict where those emissions will come to ground-level. Pollutant emission rates also vary with engine power setting: for instance, NO_x emissions increase at high thrust, whereas non-volatile UFP formation (soot and precursor condensation particles) is associated with lower-thrust conditions and incomplete combustion.⁴⁶ Furthermore, aircraft generate complex aerodynamic wakes (trailing vortices and turbulence) that can enhance or alter dispersion patterns. As aircraft climb, their vortices can transport emissions over long distances before the plume mixes to the surface,

whereas during approach, descending plumes and wake turbulence can deposit emissions over a broad area downwind of runways.⁴⁶⁻⁴⁸ Despite these well-understood physical processes, accurately predicting ground-level concentrations of aviation-generated emissions remains a scientific challenge.

Another key challenge is determining the relative contributions of different phases of aircraft operation (landing, takeoff, and ground-idle) to community UFP levels. There is conflicting evidence in the literature regarding which phase of the landing-and-takeoff (LTO) cycle has the greatest impact on downwind UFP exposure. Many studies have documented intense UFP emissions during takeoff, when engines operate at high power, and also during extended taxi/idle periods on the ground.⁴⁹⁻⁵² On the other hand, recent field measurements taken outside the airport complex have shown that landing aircraft can elevate UFP concentrations several kilometers downwind of airports. Hudda and Fruin (2016) observed sharp spikes in UFP up to 3 km from LAX due to landing jets, with smaller nucleation-mode particles persisting at elevated levels out to 18 km downwind. These findings suggest that while takeoffs and ground operations create localized peaks in UFP near the airfield, landing approaches can disperse UFP across a much wider area. To date, isolating the contributions of each LTO segment to ambient UFP has been difficult because these operations often occur simultaneously at a busy airport.

Present knowledge on UFP concentrations near airports has largely come from localized monitoring studies. Prior studies often rely on measurements taken on runways or airport fence lines, and use those data to infer community exposure gradients.⁴⁸ While

useful, such approaches can miss the combined influence of multiple sources in populated areas. In practice, researchers have applied statistical techniques like wind-sector analysis, multivariable regression, and receptor models (factor analysis) to apportion sources of UFP at major airports.¹⁷ These methods have provided evidence that airport-related UFP can be separated from traffic-related UFP by using indicators such as wind direction (e.g., downwind vs. upwind concentrations)⁵³, or by using particle size distribution (e.g., smaller particles linked to jet exhaust vs large from road vehicles).^{19,20} However, these apportionment approaches have limitations: they often assume linear additivity and may not capture the nonlinear, interactive effects of meteorology on dispersion. For example, an analysis technique that attributes all sub-30 nm particles to aircraft and 50–100 nm particles to road traffic could misclassify sources if atmospheric conditions favor secondary particle formation or if there are overlapping size ranges.^{17,54,55} Similarly, principal component/factor analysis might not fully account for the covariance of aviation and traffic emissions, since such methods rely on statistical associations and may be sensitive to collinearity and shared temporal patterns.⁵⁶ These constraints can introduce exposure misclassification, which is problematic for health studies in communities near airports.

Challenges in PM Composition Source Apportionment at General Aviation Airports

Exposure characterization at GAAs begets its own set of unique challenges. Unlike large commercial airports that tend to be in major urban centers, GAAs are geographically widespread and often embedded in suburban or rural communities. The U.S. EPA estimates that 16 million people reside and 3 million children attend school

near GAAs hosting piston-engine aircraft operations.⁵⁷ Existing studies of GAAs focus almost exclusively on lead and often rely on distance to airport as a proxy for exposure. While findings consistently show that individuals living within 500 meters to 1 kilometer of airports face elevated exposure risks,^{32,58-60} these studies often simplify the spatial and temporal complexity of pollutant dispersion. For example, while some studies have considered wind direction and piston-engine traffic in their exposure assessments,⁶⁰ empirical validation of lead emissions directly attributable to piston-engine aircraft remains lacking. Furthermore, the potential contribution of other toxic avgas-byproducts beyond lead to localized pollution has been largely overlooked. Emerging research highlights the need to expand the focus of GAA exposure assessments to include a broader analysis of air pollutants beyond lead. Studies at commercial service airports indicate that several toxic heavy metals are associated with aircraft engine emissions: sulfur (S), arsenic (As), lead (Pb), chromium (Cr), zinc (Zn), cobalt (Co), nickel (Ni), cadmium (Cd), and mercury (Hg).^{49,61,62} Together, these findings indicate the need for comprehensive monitoring of hazardous air pollutants in communities near GAAs to accurately characterize the cumulative environmental health impacts of these sources.

Approach

In this dissertation, we address the aforementioned challenges by using a combination of environmental monitoring and modeling to apportion aviation-related air pollutants in near-airport communities that are influenced by multiple emission sources. Each research aim employs distinct but complimentary methods to characterize aviation contributions to ambient air pollution, collectively providing a robust framework for

understanding community-level exposure. Specifically, we investigate aviation air pollution using three approaches: Chapter 2: a natural experiment to assess the impact of emissions reductions, Chapter 3: interpretable machine learning regression, and Chapter 4: enrichment factor analysis and particle size fractionation of multi-elemental PM components.

We leveraged data from two in situ monitoring studies, one in the vicinity of a major international airport (Logan Airport in Boston, supporting Chapters 2–3) and the other involved targeted measurements at two GAAs in Massachusetts (supporting Chapter 4). Each aim’s methodology is detailed in its respective chapter, and an overview is provided in Table 1.1.

Table 1.1 Overview of dissertation chapters.

Chapter	Pollutant of Interest	Airport (ICAO Name, City)	Source Apportionment Method
Two	Ultrafine Particles	Logan Airport (KBOS, Boston)	Descriptive: Emissions Reduction Impact via Natural Experiment
Three	Ultrafine Particles	Logan Airport (KBOS, Boston)	Statistical: Interpretable Machine Learning Modeling
Four	Mass of PM _{2.5} -bound Elements	Mansfield Municipal Airport (1B9, Mansfield and Norton) Hanscom Field (KBED, Bedford)	Descriptive: Enrichment Factors and Size Distribution

Particle Number Concentrations in Chelsea, MA

In collaboration with the Federal Aviation Administration (FAA) Center of Excellence for Alternative Jet Fuels and Environment (ASCENT) Project 018 (Health Impacts Quantification for Aviation Air Quality Tools) we have monitored ambient PNC in several communities near the General Edward Lawrence Logan International Airport (Logan Airport) in Boston, Massachusetts for approximately the past decade. The primary goal of this project is to conduct new air pollution monitoring in communities impacted by arrival and departure flight paths into Logan Airport using a protocol specifically designed to determine the magnitude and spatial distribution of UFP in the vicinity of flight paths. The monitoring sites were explicitly chosen to distinguish the aviation contribution to ambient PNC from other sources: deploying at least 200-meters away from major roads to avoid large motor vehicle traffic contributions and deploying downwind of airport runways. Each stationary site has a climate-controlled enclosure that allows for year-round sampling and are located in residential and mixed land use areas to capture and characterize exposure to nearby communities where people live, work, and play. In this dissertation, we specifically analyze PNC data collected atop a third story rooftop in a mixed use area of Chelsea, MA, located approximately 2.5 km northwest of Logan Airport. Chelsea, MA is a densely populated environmental justice community that boasts some of the highest rates of asthma and other cardiorespiratory diseases in MA.^{63,64} The monitoring site was outfitted with a TSI Model 3783 water-based condensation particle counter (CPC), which can record 1-second average concentrations of PNC between 7 nm and 1000 nm. This fast time resolution of the CPC is a key

advantage for monitoring UFP exposures in rapidly changing environments, such as street canyons and airports.

PM Elemental Analysis in Mansfield and Bedford, MA

We conducted two separate measurement campaigns across two GAAs in Massachusetts from Summer 2023 – Fall 2024 to characterize particulate matter elemental composition and size distribution. The same experimental design and analytical methods were used across campaigns: single-stage Harvard Personal Exposure Monitor (HPEM, 1-single 37mm 3-um pore size filter, 10L/min) to collect bulk particles <2.5um, and multi-stage Sioutas Personal Cascade Impactors (PCIS, 1 37mm filter, 2 25mm filters, 9L/min) to collect specific size fractions of particles (coarse, accumulation, and quasi-UFP). Teflon filters were analyzed at Alliance Technical Group (Tigard, OR) for gravimetry and elemental concentrations via energy dispersive X-ray fluorescence spectrometry (XRF). We studied Mansfield Municipal Airport (ICAO: 1B9, located in the towns of Mansfield and Norton, MA, approximately 30 miles south-west of Boston) and Hanscom Field (ICAO: KBED, located in Bedford, MA, approximately 15 miles north-west of Boston), both GAAs surrounded by residential communities including homes within a few hundred meters of the airport runways. We opportunistically selected to study these two airports which created a unique opportunity to contrast air pollution concentration among heterogenous GAAs. Monitoring at 1B9 was conducted as part of a pilot study to better understand methods for measuring and apportioning aviation-related air pollution, while monitoring at KBED was conducted as part of a community-driven research project to understand community impacts from a proposed airport expansion project.

**CHAPTER TWO. CHANGES IN ULTRAFINE PARTICLE CONCENTRATIONS
NEAR A MAJOR AIRPORT FOLLOWING REDUCED TRANSPORTATION
ACTIVITY DURING THE COVID-19 PANDEMIC**

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KEYWORDS: COVID-19, air pollution, aviation, ultrafine particles, natural experiment, traffic, emissions reduction impact

SYNOPSIS: Impacts on near-airport particle number concentrations are quantifiable despite the multitude of sources because of differences in source contributions since the onset of the pandemic.

ABSTRACT

Mobility reductions following the COVID-19 pandemic in the United States were higher, and sustained longer, for aviation than ground transportation activity. We evaluate changes in ultrafine particle (UFP, $D_p < 100$ nm, a marker of fuel-combustion emissions) concentrations at a site near Logan Airport (Boston, Massachusetts) in relation to mobility reductions. Several years of particle number concentration (PNC) data pre-pandemic [1/2017 – 9/2018] and during the state-of-emergency (SOE) phase of the pandemic [4/2020 – 6/2021] were analyzed to assess the emissions reduction impact on PNC, controlling for season and wind direction. Mean PNC was 48% lower during the first three months of the SOE than pre-pandemic, consistent with 74% lower flight activity and 39% (local) – 51% (highway) lower traffic volume. Traffic volume and mean PNC for all wind directions returned to pre-pandemic levels by 6/2021; however, when the site was downwind from Logan Airport, PNC remained lower than pre-pandemic levels (by 23%), consistent with lower-than-normal flight activity (44% below pre-pandemic levels). Our study shows the effect of pandemic-related mobility changes on PNC in a near-airport community, and it distinguishes aviation-related and ground transportation source contributions.

INTRODUCTION

Natural experiments have provided insight about air pollution source impacts. For example, policies to reduce vehicular traffic and congestion during the 1996 Olympics (Atlanta, Georgia, USA) reduced peak daily ozone concentrations by 28%⁶⁵; the temporary shutdown of a large steel mill in Utah (USA) in 1986 reduced PM₁₀ concentrations by nearly half⁶⁶; and during the 2008 Olympics (Beijing, China) air pollution emission controls reduced traffic-related emissions between 21–61%.⁶⁷ A recent and significant change to source activities coincided with the onset of the COVID-19 pandemic in 2020. In that year, road transportation and commercial flight activity decreased globally by 50% and 60%, respectively, relative to pre-pandemic levels.⁶⁸ In comparison to the shutdown of commercial aviation operations in response to the September 11, 2001 attacks, the COVID-19 pandemic disrupted aviation service more substantially in the short term (96% during COVID-19 vs 33% following 9/11), and travel restrictions continued for a longer period of time.⁶⁹

Changes in air quality associated with the COVID-19 pandemic have been documented in numerous locations, including Asia^{70,71}, Europe⁷², India⁷³, and the United States.⁷⁴ These studies largely focused on short-term (i.e., two to three months) impacts during periods of pandemic-related economic and social disruptions. However, such short-term studies may not adequately capture air pollution changes from differential activities across sectors, especially for pollutants with strong seasonality. This is important for pollutants like ultrafine particles (UFP; <100 nm in aerodynamic diameter) in urban areas with multiple emission sources. Few studies have documented the UFP air

quality impacts of the COVID-19 pandemic; a systematic review⁷⁵ noted only two articles measuring ultrafine particles, with an additional article published more recently. The studies measuring or modeling UFP were short-term in nature, with the longest monitoring campaign being ~7 weeks, and all were focused on road traffic.⁷⁶⁻⁷⁸ Although UFP exposure in near-airport communities has been shown to be elevated¹⁷ in the U.S.^{3,19,79} as well as other countries^{20,25,80,81} during normal airport operations, to date little work has been done to characterize air quality impacts due to sharp decreases in aviation activity during the pandemic.

The goal of this study was to quantify the changes in UFP (measured as particle number concentration, or PNC) at a near-airport site in response to an unprecedented change in flight activity. We analyze PNC measurements collected over multiple years at a rooftop site near a major airport (Logan International Airport, Boston, Massachusetts, USA). Our objectives were to (1) quantify the overall decrease in PNC during the early state-of-emergency (SOE) period that coincided with the maximum decrease in activity for all modes of transportation, and (2) examine if changes in PNC in the year following the start of the SOE corresponded to the differential rates of recovery of aviation and road traffic.

MATERIALS AND METHODS

Boston Logan International Airport and Monitoring Site

Logan International Airport is located 1.6 km east of downtown Boston. The airport has six runways, with a preferred operational runway configuration for each wind-direction quadrant. Continuous monitoring of PNC was conducted atop a three-story building located in a mixed-use (including residential) community in Chelsea, 4.0 km NW of the airport. This site and the surrounding area have been described elsewhere;^{53,82} briefly, the site is near several other transportation modalities (major roadway 400 m to the west, a commuter rail line 50 m to the north, and an active shipping channel 1 km to the southeast; see Supporting Information (SI) Figure S1)). During SE winds, which occur at 7% frequency and orient the site downwind of the airport, emissions from the airport (i.e., from ground transportation and idling and taxiing aircraft) as well as aircraft landing on runway 15 are advected toward the monitoring site.

Massachusetts State-of-Emergency (SOE)

In response to the COVID-19 pandemic, a state-of-emergency (SOE) was declared in Massachusetts on March 10, 2020, which was lifted on June 15, 2021.⁸³ At the beginning of the SOE period a stay-at-home-advisory was issued, requiring all non-essential businesses, schools, and other organizations to close their physical workplaces, and recommending residents to stay home and avoid travel. The ending of the stay-at-home-advisory on May 18, 2020 initiated the reopening of the Massachusetts economy, with restrictions being relaxed in a gradual process according to four pre-determined

phases. However, after restrictions were eased from May 2020 through November 2020, they were increased again starting in November 2020 given increasing COVID-19 cases and hospitalizations, and gradually rescinded starting in February 2021. Air quality measurements were made from April 2020 through June 2021 and were compared with pre-pandemic measurements from 2017 and 2018.

Instrument and Data Acquisition

Ambient PNC was monitored using a water-based Condensation Particle Counter (CPC, TSI Inc. Model 3783, D_{50} of 7 nm) from January 2017 through June 2021, with several discrete periods where monitoring did not occur, notably October 2018 through March 2020. Field procedures, the quality assurance (QA) protocol, and the calibration procedures are described in the SI (Table S1). Approximately 5% of data were removed prior to analysis mainly due to automatically flagged CPC parameter exceedances (e.g., nozzle pressure and pulse height). Hourly landing and takeoff (LTO) (hourly totals for landings (arrivals) and takeoffs (departures)) from January 2017–June 2021 were obtained from the Federal Aviation Administration Aviation System Performance Metrics Database.⁸⁴ Meteorological data collected at Logan Airport (KBOS) were obtained from the National Centers for Environmental Information Automated Surface Observing Systems (ASOS) program and aggregated to hourly resolution via the U.S. Environmental Protection Agency’s AERMINUTE and AERMET processors.⁸⁵ In short, AERMINUTE converts the ASOS 2-minute wind direction to x and y-component wind directions and follows a unit-vector approach to average within a given hour to calculate the hourly wind direction; further details can be found elsewhere.^{86,87} Monthly average

daily traffic (MADT) from January 2017–June 2021 was obtained from the Massachusetts Department of Transportation Data Management System.⁸⁸ Four traffic counters were used, with three counters representing local roads (Rt 1A Revere (Station ID 8087), Rt 1A Boston (Station ID: AET16), and US 1 Boston Tobin (Station ID: AET15)), and a fourth representing an interstate highway at Medford I-93 (Station ID: 82) (Figure S1).

Data Processing and Analyses

Data collected prior to August 2017 were recorded at 30-second averaging periods, with subsequent data recorded at 1-second averages. Processed data were aggregated to hourly resolution ($n = 41,904$ h) and merged with flight activity (landings, takeoffs, and sum of landings and takeoffs [LTO]), meteorological data, and MADT. Data were classified into impact-sector or non-impact-sector depending on whether the hourly average wind direction positioned the site downwind of the airport. Impact-sector was defined as 135° to 175° based on the azimuth angle of the site to the widest span of runways as done previously (Figure S2).⁵³ Additionally, data were classified as pre-pandemic (before March 10, 2020), the early SOE period (March 11, 2020 – March 2021, when Massachusetts returned to its Phase III Step 2 reopening) and the late SOE period (April – June 2021). Monthly average and 25th, 50th, 75th, 95th, and 99th percentile PNC were calculated for these three periods.

We used an approach analogous to emissions reduction impact methods within air quality modeling to evaluate the changes in PNC and transportation activity throughout the study period. This approach, described elsewhere², estimates the impact of a source

on pollutant concentration when emissions are reduced in a given sector. First, Equation 1 was applied to PNC, road traffic, and aviation to scale the data by pre-pandemic mean to visualize temporal trends:

$$C_i' = \frac{C_i}{\mu} \quad (1)$$

where C is the measurement value at its highest resolution (hourly for PNC and LTO, monthly for road traffic), i is the data type (PNC, road traffic, LTO), and μ is the mean measurement value for the i^{th} data type for data before March 10, 2020.

We examined aviation and road traffic activity over the entire study period to identify changes in transportation patterns. To control for seasonal variation and the non-linear nature of the COVID-19 activity restrictions, we stratified the dataset and performed targeted analysis comparing the months of April, May, and June (AMJ) across the dataset within the three time-periods (pre-pandemic, early SOE, late SOE) because these months correspond with large changes in transportation patterns (Figure 2.1C).

These changes were analyzed following Equation 2:

$$\Delta_m = \frac{\mu_{m,1} - \mu_{m,2}}{\mu_{m,2}} * 100 \quad (2)$$

where $\mu_{m,1}$ is the 3-month (AMJ) mean in 2020 or 2021, $\mu_{m,2}$ is the 3-month (AMJ) mean in 2017–2019, and Δ_m is the % change. We did not record PNC data for 2019, but LTO and MADT were available for all three preceding years. Given the influence of meteorological variability on PNC and to control for it, we limited the comparison to the same season (spring/summer months) and further, the mean and standard deviations of key variables (e.g. temperature, precipitation, relative humidity, etc.) were compared

between years; we observed no substantial differences in our time period of interest (Table S2).

To visualize and explore PNC trends with respect to wind direction and wind speed, we created bivariate polar plots that group PNC by wind speed and direction using the ‘openair’ R package.⁸⁹

RESULTS

Changes in Transportation Activity During the Pandemic

Both flight and ground traffic were reduced following the start of the SOE. While flight activity was reduced by 74%, road traffic was reduced by only 39% based on counts from the three nearest surface road counters and 51% on the nearest interstate highway counter during AMJ 2020 compared to the pre-pandemic (2017–2019) average for the same months. Upon easing of the travel restrictions, road traffic recovered to pre-pandemic volume ($\pm 10\%$) by AMJ 2021; however, flight activity remained 44% lower (Table S3 and Figures S7–S8).

The diurnal pattern of flight activity during early and late SOE was similar to pre-pandemic years, but at lower volumes (Figure 2.1). Flight activity peaked in the morning (0600 – 1000 hours) and the afternoon (1500 – 1900 hours); the morning had a higher percentage of departures and the afternoon had a higher percentage of arrivals (Figure 2.1 (A)–(B)). Throughout the study period flight activity during 0100 – 0400 hours was minimal, in accordance with noise abatement policy.

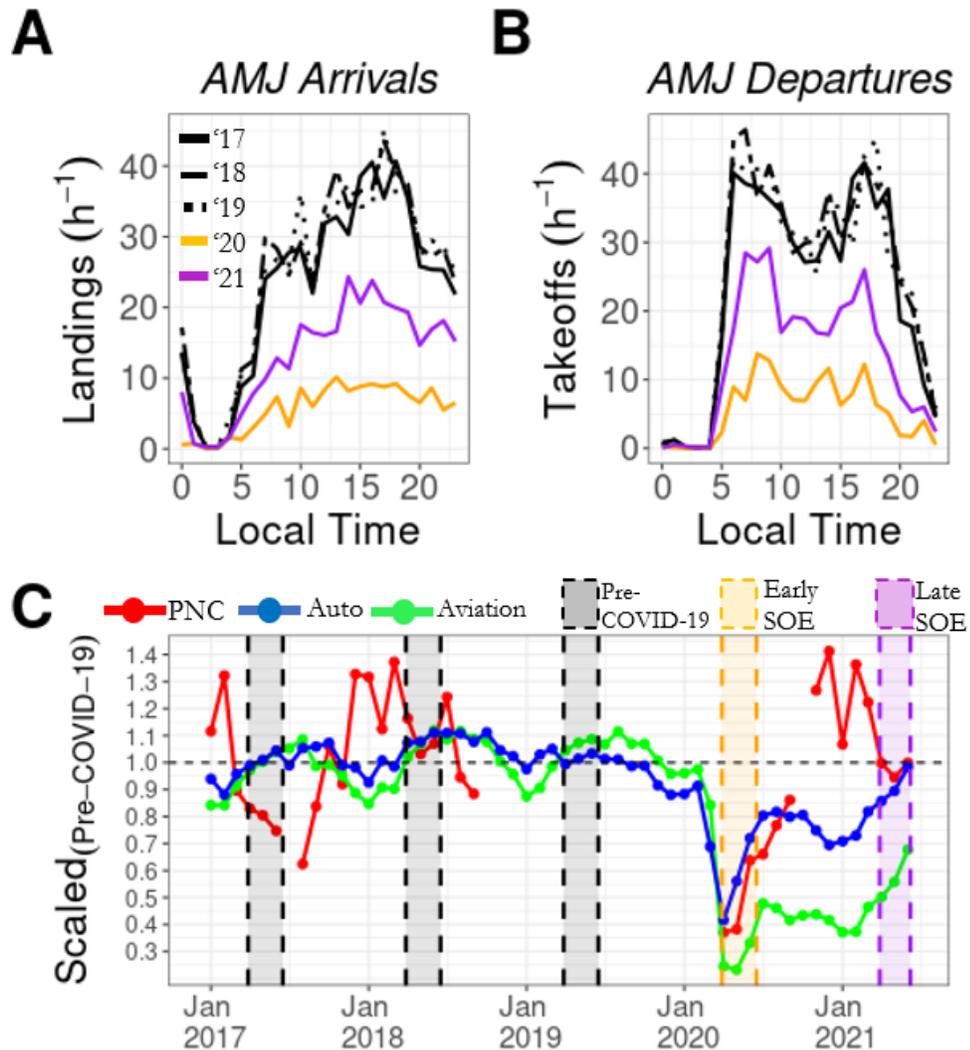


Figure 2.1. (A–B) Landings and takeoffs per hour for (A) Arrivals and (B) Departures at Logan Airport from 2017 to 2021 for the months of April, May, and June (AMJ). (C) Time series for PNC (particles/cm³) for all wind directions, automobile traffic at US1 Boston Tobin (AET15, Monthly Average Daily Traffic), and combined landings and takeoffs (operations h⁻¹) scaled by pre-pandemic mean (before March 10, 2020) following Equation 1. Points represent the monthly average of the pre-pandemic mean scaled value per respective time series. Highlighted boxes within the dotted lines represent the time periods selected for analysis, AMJ 2017–2019 (black), AMJ 2020 (orange), AMJ 2021 (purple).

Changes in PNC During the Pandemic

Overall, mean PNC was 48% lower during early SOE compared to pre-pandemic mean for AMJ (Figure 2.1 (C)), but by late SOE it was comparable to pre-pandemic

mean ($\pm 5\%$). Reductions during early SOE were greater for impact sector winds (-61.4%) than non-impact sector winds (-48.0%). During late SOE (AMJ 2021), mean PNC remained lower than pre-pandemic for impact sector (-23.1%) but not non-impact sector winds (+5.4%).

During the early SOE both the concentrations and the impact sector vs. non-impact sector difference were reduced (Table S3). Mean impact sector PNC (14000 ± 8600 particles/cm³) was 2.1 times higher than mean non-impact sector PNC (6700 ± 4000 particles/cm³) in early SOE compared to mean impact-sector PNC (36300 ± 24900 particles/cm³) being 2.8 times higher than mean non-impact sector PNC (12900 ± 9100 particles/cm³) in the pre-pandemic period. These patterns (i.e. impact-sector PNC greater than non-impact sector PNC, a reduced relative difference between impact sector and non-impact sector PNC during early SOE, and a recovery to pre-pandemic levels for non-impact sector PNC but not impact-sector PNC during late SOE) were consistent across all hourly aggregations of PNC (25th, 50th, 75th, 95th, and 99th percentile PNC — Table S3 and Figure S9).

Furthermore, the greatest decrease in impact-sector PNC in the early SOE period occurred during regular LTO activity (0500 – 0000): a 62% decrease compared to pre-pandemic (Table S4), i.e., 40900 ± 24900 particles/cm³ vs. 15600 ± 9100 particles/cm³. During regular LTO activity, impact-sector PNC in early SOE period (15600 ± 9100 particles/cm³) was essentially comparable to non-impact sector PNC pre-pandemic (13700 ± 9500 particles/cm³). Prior to the pandemic, during impact sector winds PNC was 2.7 times higher during regular LTO (60 flights h⁻¹) as compared to periods of

limited LTO (2 flights h^{-1}); however, in early SOE, impact sector wind PNC was only 1.8 times higher during regular LTO (14 flights h^{-1}) than during limited LTO (1 flight h^{-1}). Analyses by wind speed and direction (Figure 2.2) indicate a pronounced signal under impact sector winds at relatively high wind speeds during regular LTO activity pre-pandemic, which is muted in the SOE periods during regular LTO activity.

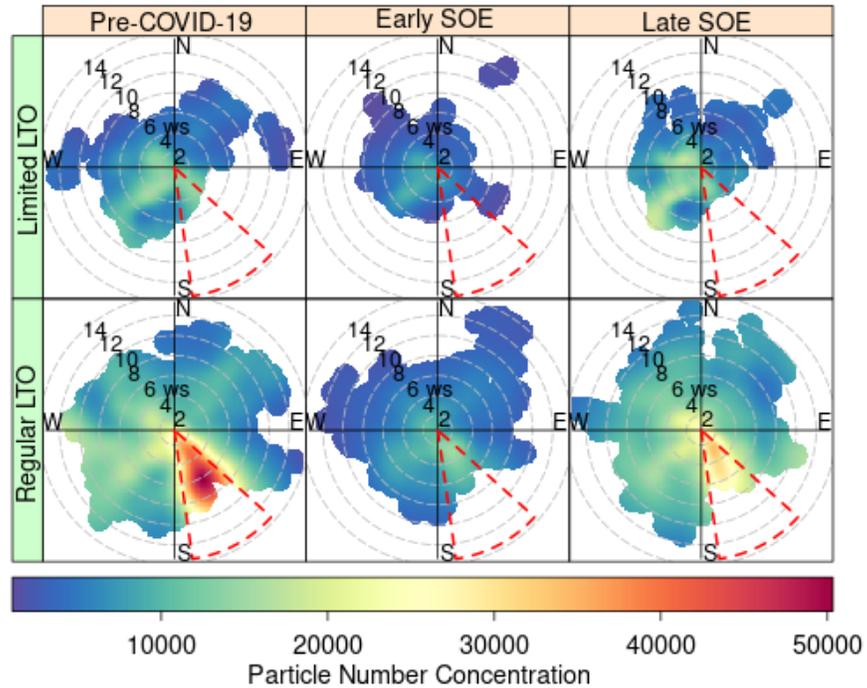


Figure 2.2 Polar plots showing the interaction between the hourly mean PNC (particles/cm³) during April, May, and June (AMJ), wind speed (ms⁻¹), and wind direction. Columns subset data by pre-pandemic (mean AMJ of 2017 and 2018), in the early months of the Massachusetts State of Emergency (SOE) (AMJ 2020), and a year later (AMJ 2021), while rows subset by periods of limited LTO (0100 – 0400) and regular LTO (0500 – 0000). Dotted red lines represent winds from the aviation impact sector. Variations in plot shape are a function of wind speed and wind direction while variations in color are a function of PNC (particles/cm³).

DISCUSSION

Air quality management involves identifying and quantifying the emissions sources that contribute most to air pollution levels in a given area or region. The dramatic decrease in transportation sector activity in response to the COVID-19 pandemic provided a natural experiment with which we could better understand the emissions reduction impact of transportation sources on ambient PNC in a near-airport setting. During the early months of the COVID-19 pandemic, we observed that PNC was dramatically reduced (48% on average, for all wind directions) near an international airport, and that daytime PNC was similar to pre-pandemic PNC during nighttime hours with no flight activity. In addition, we observed that mean PNC mirrored automobile ground traffic volume patterns throughout the pandemic, but that under wind conditions that placed the monitor downwind from the airport, mean PNC more closely followed flight activity volume patterns. The fact that the two predominant source types in a near-airport setting had different activity profiles and different associations with wind speed and direction allowed us to better differentiate their relative impacts on ambient PNC. While the highest PNC was observed when the site was downwind from the airport throughout the study period, the difference between downwind and non-downwind PNC was negligible during the early SOE, providing a sharp contrast to clearly indicate airport contributions under aviation-impact sector winds.

Our findings can be compared with previous studies of PNC during the pandemic, although most previous studies were conducted over a shorter duration and with a primary focus on road traffic-related emissions. For example, Hudda et al. 2020⁷⁶

quantified changes in air quality in Somerville, MA due to traffic reductions using a seven-week-long mobile monitoring campaign at the onset of the pandemic. They found daily traffic on a major highway in the community (I-93) decreased approximately 50% and that median PNC was 44–57% lower in March–May 2020 as compared to pre-pandemic concentrations. We found a similar magnitude reduction though with the ability to better distinguish between specific source contributions over time. Xiang et al. 2020⁷⁷ found a more modest 7% reduction in PNC near a major interstate in Seattle, WA, USA, where median traffic volume decreased by 37% at the onset of pandemic-related activity restrictions. They identified larger relative decreases in smaller diameter ultrafine particles (<20.5 nm), but were only able to compare with approximately 2 weeks of UFP measurements prior to the onset of the pandemic. Dai et al. 2021⁷⁸ used dispersion-normalized positive matrix factorization analysis to investigate source contributions to PNC before and during the COVID-19 outbreak in a suburban site in Tianjin, China. They found that traffic-related PNC decreased 44% after the outbreak, and that residential heating was the largest source of PNC before and during the outbreak. The magnitude of PNC decrease we observed during the pandemic is comparable to the road-based study in Boston, MA, USA⁷⁶ and the suburban site study in Tianjin, China⁷⁸ but were substantially larger than the road-based study in Seattle, Washington, USA.⁹⁰ However, our study is the only one performed to date in a near-airport community with a long-term monitoring campaign specifically sited to distinguish the separate contributions from roadway and airport emissions.

A limitation of natural experiments is that they are observational in nature and potential confounders cannot be manipulated; therefore, it is necessary to try to control for them in analysis.⁹¹ For a pollutant like PNC that exhibits substantial seasonality, it is essential to have the appropriate comparison period, which we addressed by matching month-to-month percent change in PNC across three distinct time periods within a given season. While we had approximately 20 months of PNC data to establish baseline conditions, we had a data gap in 2019. However, our findings regarding impact sector PNC in our baseline period agree with a prior study assessing aviation impacts on UFP in Boston.⁵³ This reinforces the value of long-term monitoring for UFP and other pollutants to capture both acute and gradual shifts in source contributions, ideally with monitoring locations that capture emissions sources beyond road traffic to allow for analyses of source impacts in complex urban environments which contain multiple emission sources. Such data can provide the foundation for more accurate source attribution analyses.

ACKNOWLEDGEMENTS

We are grateful to The Neighborhood Developers in Chelsea for housing our stationary site. This research was funded by the U.S. Federal Aviation Administration Office of Environment and Energy through ASCENT, the FAA Center of Excellence for Alternative Jet Fuels and the Environment, Project 18 through FAA Award Number 13-C-AJFE-BU under the supervision of Jeetendra Upadhyay. Any opinions, findings, conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the FAA. S.M. was supported by a National Science Foundation Research Traineeship (NRT) grant to Boston University (NSF NRT DGE 1735087).

**CHAPTER THREE. QUANTIFYING AVIATION-RELATED CONTRIBUTIONS
TO AMBIENT ULTRAFINE PARTICLE NUMBER CONCENTRATIONS USING
INTERPRETABLE MACHINE LEARNING**

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ABSTRACT

Ultrafine particles (UFP, $D_p < 100$ nm) are emitted in large numbers by aircraft, and impacts on ambient concentrations have been observed far from airports. However, quantifying aircraft contributions to UFP number concentrations (PNC) remains challenging due to limited understanding of plume dynamics and meteorology. We applied a machine learning (ML) model to a multi-year PNC dataset collected at an urban site near Boston Logan International Airport to distinguish aircraft contributions by arrival and departure runway to hourly PNC, accounting for road traffic, on-ground operations, and meteorology. Using interpretable ML to explain model output ($R^2 = 0.66$), we found that aircraft arrivals contributed more to PNC than departures or airport on-ground operations, particularly during use of runways oriented perpendicular to the monitor-airport axis. This suggests that aircraft not flying directly overhead can substantially impact ground-level air quality through lateral dispersion under crosswinds. Aviation impacts were further modulated by boundary layer dynamics, with the strongest contributions from arrivals occurring under mixing heights that were shallow enough to limit dilution but deep enough to entrain overhead plumes. This approach enables hourly-resolved source attribution for retrospective exposure assessment and provides a transferable framework for characterizing aviation-related UFP exposure in near-airport communities.

Key Words: air pollution, aircraft, ultrafine particulate matter, landing and takeoff operations, source apportionment, XGBoost, interpretable machine learning, SHAP

Synopsis: We apply interpretable machine learning methods to distinguish in-flight aircraft activity's contribution to ambient PNC by runway and operation.

INTRODUCTION

Ultrafine particles (UFPs; particulate matter with an aerodynamic diameter <100 nm) are ubiquitous in urban air and pose significant health risks.³⁸ Due to their small size, UFPs can penetrate deep into the lungs contributing to local and systemic inflammation.^{10,11,92,93} UFPs originate from multiple combustion sources, including motor vehicles and aviation activities, and can also form through atmospheric chemical reactions.^{16,94} Aircraft operations, particularly during arrivals and departures, release UFPs smaller than those emitted by road vehicles,^{19,20,50,95} raising concerns about heightened health risks near airports.^{18,22–25} While motor vehicles are typically regarded as the primary UFP source in urban areas,^{94,96,97} the omission of aviation emissions in many air quality studies has created a gap in understanding their impact.^{17,98}

Although aircraft exhaust plumes are considered to be the largest source of airport-related UFP emissions, airports encompass multiple emission sources — including ground support equipment, auxiliary power units, and passenger vehicles — making it difficult to isolate the role of in-flight aircraft.⁹⁵ Disentangling in-flight aircraft-related UFP emissions from other sources is further complicated by the transient and dynamic nature of aircraft movements and plume dispersion near airports.^{48,99} Present knowledge on aviation UFP concentrations is mostly limited to local modeling studies and in situ measurements that treat the airport complex as a single source. High-resolution dispersion modeling studies in near-airport communities remain challenging, given emission uncertainties, sparse and discontinuous ambient monitoring infrastructure, coarse model resolution, and challenges with modeling nonlinear and complex source

characteristics (i.e., high speed mobile sources moving in 3-dimensions).^{48,100–102} In practice, statistical methods such as wind direction impact-sector correlations, multivariable regression, and receptor models have been more commonly applied for source apportionment in major international airports — including Los Angeles (LAX),^{3,103,104} London Heathrow (LHR),^{20,105} Berlin-Tegel (TXL),¹⁰⁶ Amsterdam Schiphol (AMS),⁸⁰ Seattle-Tacoma (SEA),¹⁹ and Boston Logan (BOS)^{53,107,108} — to separate aviation UFPs from other sources. These methods offer simpler ways to isolate sources but often fail to account for nonlinear dynamics and complex emission patterns generated across various airport operations, especially under changing weather conditions. Addressing these limitations is critical for improving health research in near-airport communities; the limited number of epidemiological studies have relied on principal components analysis to assign exposure,²⁴ or particle size as a proxy for source attribution,²³ by linking smaller particles to aviation and larger particles to road traffic. These approaches are not able to fully capture the nonlinear interactions of aircraft UFP dispersion and could introduce exposure misclassification.

Machine learning (ML) models are increasingly employed in air pollution studies to address these limitations.^{109,110} Unlike traditional statistical methods, non-parametric ML models excel at capturing nonlinear relationships and interactions among multiple variables and have consistently outperformed linear approaches in predicting air pollutant concentrations, including UFPs.^{111–115} Prior ML-based UFP studies have primarily focused on road traffic emissions, neglecting aviation-related predictors,^{115–122} despite evidence that aircraft emissions significantly contribute to UFP levels near airports.

However, the complexity of ML models, particularly ensemble approaches combining multiple learners, makes them difficult to interpret, often obscuring how specific factors influence predictions.¹²³ Addressing these challenges requires ML methods that incorporate granular aviation-specific predictors, generate high-temporal-resolution predictions, and provide physically interpretable insights to advance exposure assessment and health research.

In this study, we applied a ML model to a multi-year UFP dataset collected in a community near Boston Logan Airport, incorporating aircraft flight activity, on-ground airport operations, meteorology, and road traffic predictors. To enhance interpretability, we leveraged SHapley Additive Explanations (SHAP) — a game-theory-based approach developed to fairly attribute value in collaborative systems — to quantify both independent and interactive effects of these predictors on UFP concentrations.^{124,125} Our temporal model provides source attribution at hourly resolution, allowing us to isolate in-flight aircraft from other sources and quantify fine-scale UFP variations at a fixed site in a near-airport urban community. This capability advances the understanding of aviation's role in UFP pollution and supports retrospective exposure assessments, improving the ability to link aviation-related UFP pollution to potential health outcomes in epidemiological studies.

MATERIALS AND METHODS

Study Site and UFP Monitoring

We monitored PNC at a site in Chelsea, Massachusetts, USA (Figure 3.1) from January 2014 through December 2022. The dataset builds upon one described previously in Mueller et al. 2022.¹⁰⁷ Compared to our earlier work,¹⁰⁷ the new dataset includes several more years of data, approximately doubling the sample size. The monitoring site is approximately 4.0 km northwest of Boston Logan International Airport (Boston, MA, USA) and oriented downwind of the airport during southeasterly winds, which occurred 7% of the time during the study (Figure 3.1a–b). We define winds that orient the monitoring site downwind of the entire airport complex as impact sector winds, 135° to 175°, as has been done previously.⁵³ To minimize the influence of hyper-local emission sources on measurements, the monitoring site was located on the roof of a 3-story building and greater than 200 m from major roadways. Given the substantial decay in concentration of UFPs as a function of distance from roadway,¹²⁶ this study design ensures that observed UFP concentrations reflect broader pollution trends rather than just localized traffic contributions. Logan Airport has six runways, and the runways are operated to allow aircraft to take off and land into the prevailing wind in ideal weather conditions (Figure S1 of the Supporting Information). During ideal weather conditions, the airport can accommodate >100 operations per hour utilizing a three-runway configuration.

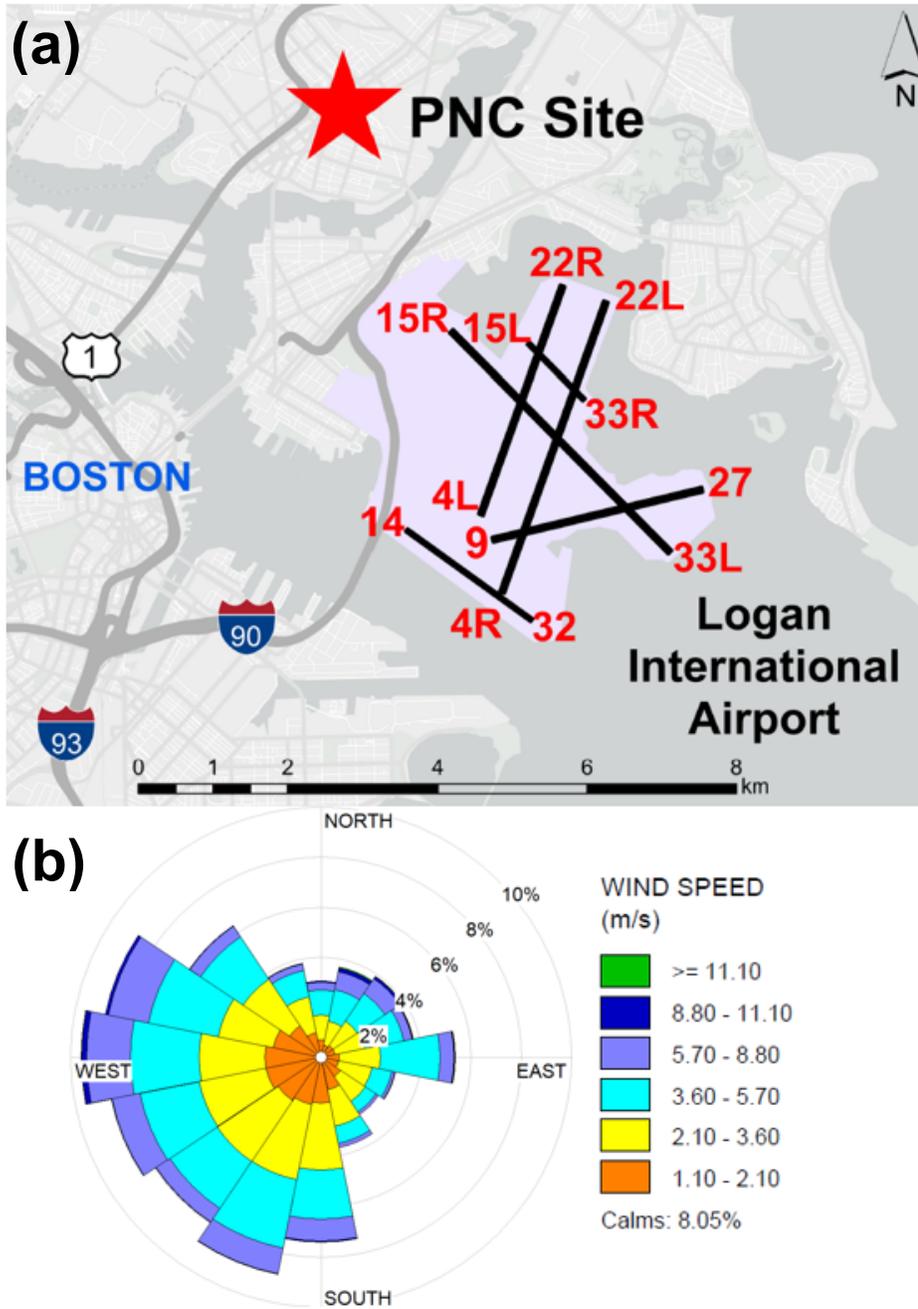


Figure 3.1. (a) Runway configuration at Logan International Airport (Boston, MA, USA) and location of the monitoring site. The numbers on an airport runway indicate the magnetic heading and its position relative to other runways, with “L” indicating “left” and “R” indicating “right”. (b) Wind rose of 2014–2022 hourly data from the High-Resolution Rapid Refresh (HRRR) model.

We used a water-based condensation particle counter (CPC, TSI Inc. Model 3783, D_{50} of 7 nm) to collect particle number concentration (PNC) measurements. The instrument was operational for 62% of the hours between 01/06/2014 and 12/29/2022, with data collected across multiple distinct monitoring campaigns interspersed with periods of no monitoring, notably from October 2018 to March 2020 (Figure S2). Approximately 4.5% of data were removed prior to analysis primarily due to automatically flagged CPC parameter exceedances (e.g., nozzle pressure and pulse height). Additional details on the CPC quality assurance and quality control (QA/QC) protocol, calibration, and data cleaning are described in the Supplementary Information (Table S1).

Model Input Features

Flight activity, traffic data, and meteorology serve as independent variables in our machine learning regression model and are referred to in the text as model ‘features’ (Table S2). Flight activity data were obtained from the Federal Aviation Administration’s Count of Operations (CountOps) database.¹²⁷ In addition to hourly counts of arrivals and takeoffs by runway, we used hourly summations of estimates of taxi time for arriving and departing flights from the FAA’s Aviation System Performance Metrics (ASPM) database to assess ground-based activity at the airport.⁸⁴

Hourly traffic counts were obtained from the MassDOT Transportation Data Management System.⁸⁸ Given the limited number of hourly traffic counters in our study domain, we opted to use one counter to represent the general temporal traffic patterns in the study area, assuming that local traffic patterns had similar diurnal, day of week, and

seasonal patterns as those measured at the selected highway traffic monitor. The road counter represents traffic from a major interstate leading to Boston (Location ID 8011, Interstate 93 South of Ramp I-93 North Bound to Route 60) and is approximately 6.5 km northwest of the PNC monitoring location. The nearest major roadway to the monitoring site is approximately 400 m west.

We used the NOAA Earth System Research Laboratory High-Resolution Rapid Refresh (HRRR) model for hourly 3-km resolved meteorological parameters.¹²⁸ HRRR has been validated against ground-based monitors and its parameters have been used previously as independent variables in air quality regression models.^{129,130} We extracted 13 meteorological parameters from the HRRR analysis dataset (F00) using the Amazon Web Services S3 Open Registry Archive in Zarr format¹³¹ and GRIB2 format via the Herbie¹³² package in Python (V3.10.12) for the grid cell with the closest Euclidean distance to our PNC monitoring site. These parameters were wind speed (m/s) and direction (°) at 10 m above surface and 850 millibars (mb), henceforth referred to as surface and aloft winds, respectively, surface temperature (K), surface pressure (Pa), dewpoint at 2 m above surface (K), surface moisture availability (%), convective available potential energy (J/kg), middle cloud cover (%), atmospheric reflectivity (dB), geopotential height at 850 mb (gpm), and planetary boundary layer height (m). See SI Text 1 for further details about HRRR feature acquisition and selection process.

Data Harmonization and Pre-Processing

1-s PNC measurements that passed QA/QC procedures were aggregated to hourly resolution and merged with flight activity, traffic data, and meteorological data by

timestamp. We chose a study period of September 30, 2014 to December 29, 2022 to reflect the first instance of available HRRR data. We included temporal indicators for Hour (0–23), Month (1–12), Year (2014–2022), and a dummy variable for Weekend (1 = yes, 0 = no). Only records with valid, non-missing PNC measurements were retained for modeling (N=41,742 hours of data). Further details about data pre-processing are in SI Text 2.

Machine Learning Model Development

The primary objective of our ML approach is to investigate the relationship between in-flight aircraft activity and predicted PNC, and to consider how this is affected by meteorological conditions.

We used the extreme gradient boosting algorithm (XGBoost, Python 3.10.12, Scikit-Learn API) to predict hourly PNC. XGBoost sequentially builds decision trees, with each new tree correcting errors from previous trees via gradient descent, capturing complex and infrequent patterns.^{133,134} Given the sporadic but substantial influence of aviation-impact sector winds on PNC at our site,^{53,107} XGBoost's iterative error correction provided advantages over other tree-based methods. Unlike linear regression, XGBoost handles correlated predictors effectively, but the interpretation methods we use for feature importance are sensitive to multicollinearity.¹³⁵ To address this, we computed Spearman's Rho (ρ) among features, confirming correlations were within acceptable limits used in prior air pollution studies (Figure S3).^{111,136}

Model evaluation strategy depends on the intended model application; we selected a random hold-out validation approach to assess interpolation accuracy, aligning with

best practices for retrospective exposure assessment.¹³⁷ We randomly selected 80% of the dataset to train the model using 5-fold cross validation with Bayesian hyperparameter optimization to create an optimized model that was predictive and parsimonious (n=33,394). The final model was applied to the held-out 20% of the dataset to test model generalizability (n=8,348). This process was repeated 10 times with different train-test splits and hyperparameters to verify robustness. We evaluated model performance on the following metrics: 1) coefficient of determination (R^2), 2) root mean square error (RMSE), and 3) mean absolute error (MAE). Cross-validation metrics were averaged across folds and then across models, while generalizability metrics are reported as means and standard deviations from the test-sets. Final hourly PNC predictions were obtained by averaging predictions from all 10 XGBoost models.

Model and Feature Interpretation

We used partial dependence plots (PDPs) to visualize the marginal contribution of a feature to predicted PNC. PDPs quantify the marginal contribution of a feature to predictions by showing how changes in a feature's value affect predictions, while holding all other features constant; for example, how one additional arrival on runway 22L would change PNC. This process increments over the full range of the feature of interest to illustrate its average impact on the model's output.¹³⁸

We used SHAP values to quantify each feature's contribution to predicted PNC (\hat{y} , particles/cm³). SHAP is a post-hoc, model-agnostic, additive approach for explaining machine learning model predictions at the individual record level. It applies cooperative game theory principles to fairly distribute the difference between \hat{y} and the mean model

prediction (ϕ_0) by assigning each feature (i) a contribution (ϕ_i), which represents its marginal effect on the prediction after considering all possible feature interactions.^{124,125} Because SHAP values are in the same unit as the model's dependent variable (PNC, particles/cm³), ϕ_i directly quantifies how much a given feature in a given record increased or decreased the predicted PNC relative to \hat{y} . To capture nonlinear feature interactions, we also computed SHAP interaction values (ϕ_{ij}) which measure the pairwise interaction effects between features i and j .¹³⁹ To systematically summarize global feature contributions, we calculated mean absolute SHAP values (MASV, Equation 1) to assess overall feature importance, and Spearman's ρ between MASV and feature values to quantify the directional relationship between feature magnitude and its effect on PNC.

$$MASV_i = \frac{1}{N} \sum_{r=1}^N |\phi_i^{(r)}|$$

(Equation 1)

Where N is the total number of records and $\phi_i^{(r)}$ is the SHAP value for feature i in record r . We evaluate MASV for individual features and collective feature groups (in-flight aircraft, road traffic, on-ground airport operations, etc.) because many variables in our dataset represent related processes. Because SHAP values are derived from the trained model, and we generated ten distinct models (as detailed in Section 2.4), we computed SHAP values and SHAP interaction values for all records in each iteration to ensure consistency in comparisons. Final values were obtained by averaging the contributions across the ten runs for each record. To assess feature importance stability across models, we calculated the standard deviation of MASV and expressed it as a percentage of the

corresponding mean value. To improve interpretability and reduce overplotting in visualizations of the SHAP dataset (N=41,742) we binned SHAP values by feature magnitude in select plots. SHAP and SHAP interaction values were generated via the TreeExplainer, using the 'shap' Python package (V0.43.0).

RESULTS AND DISCUSSION

Descriptive Statistics and Model Performance

PNC at the monitoring site were lognormally distributed, exhibited seasonality (the highest concentrations were observed in winter [December–February] and lowest in summer [June–August]), generally decreased from the start of the study period [2014] to the end of the study period [2022], were higher on weekdays than on weekends, and exhibited a bimodal diurnal pattern (peaks in morning 06:00–08:00 and evening 18:00–20:00) (Figure S4). These patterns are consistent with prior research on PNC in our study site.^{53,79,107,108}

Overall, mean PNC was $14,700 \pm 12,200$ particles/cm³ and was approximately 50% higher during impact sector winds (135–175°, Figure S5). Previously, Hudda et al. 2016 reported PNC measured from January 2012–August 2015 at the Chelsea site was, on average, 100% higher during impact sector winds.⁵³ Our lower estimate can be explained in part by the prolonged decrease in aviation activity as a result of the COVID-19 pandemic.¹⁰⁷ The fact that our dataset includes a wide range of transportation activity, including previously unseen conditions such as substantially reduced flight and road traffic during typical operating hours, validates its applicability under a wider range of conditions.

Runway-specific operations and their alignment with prevailing wind conditions influence PNC levels at the monitoring site. PNC were most correlated with arrivals on runway 22L (22L-Arrivals, $\rho = 0.27$) and departures on runway 22R (22R-Departures, $\rho = 0.25$). As part of the airport's preferred configuration during southwest winds, these

two runways were frequently used in tandem, with simultaneous operation occurring 78% of the time when either runway was in use, resulting in a high correlation ($\rho = 0.87$, Figure S6). Although runways 22L-22R are preferentially operated during southwest winds—runways aligned perpendicular to the vector connecting the airport and the monitoring site (Figure 2.1a)—they operated during southwest winds only 34% of the time. Southeast winds, which elevate PNC at the monitoring site (i.e. impact sector winds), occur during a comparable proportion of operations for 22L-22R and 15R: southeast winds are present during 11–12% of 22R-22L operations and 14% of 15R operations. However, the total average hourly count of operations on 22R-22L is 8-fold greater than on 15R, amplifying their potential impact during impact sector winds. Although 15R is aligned parallel to the vector connecting the airport and the monitoring site — making its emissions more likely to directly impact the site during impact sector winds — the substantially higher activity levels on 22R-22L during crosswinds likely drive the observed correlations with PNC. This reinforces how advection, in combination with runway-specific activity levels, plays a critical role in determining PNC variability at the monitoring site.

Across all iterations of the XGBoost model — regressing PNC on flight operations by runway, airport ground operations (via taxi time), automobile road traffic, meteorological conditions, and temporal components — the mean (standard deviation) model fit statistics on the test-set were as follows: $R^2 = 0.66$ (0.014), $RMSE = 7200$ (150) particles/cm³, and $MAE = 4300$ (75) particles/cm³ (Figures S7–S8). Performance on the test-set was consistent across all runs and was similar to the respective run’s training-CV

metrics ($R^2 = 0.65 \pm 0.004$), suggesting a robust model outcome. Model residuals were non-normally distributed and exhibited heteroscedasticity (Figure S8). The model performed better for measurements at or below the 75th percentile (17,900 particles/cm³), where the mean (standard deviation) RMSE and MAE were 4600 (100) particles/cm³ and 3000 (50) particles/cm³, respectively. This outcome is consistent with both the data's distribution and the nature of model optimization for global error minimization. This performance difference highlights how the infrequent high 'spikes' in PNC values disproportionately affected model accuracy. Very high but infrequent and short duration events have been noted to affect machine learning model accuracy for air pollution prediction;¹⁰⁹ methods to address this have noted a tradeoff between global performance and peak performance.¹¹³ Addressing this tradeoff remains an important area for future air pollution research.

Key Drivers of Particle Number Concentrations

Our results show that surface meteorology had the largest overall influence on the model — evaluated by mean absolute SHAP value (MASV) \pm standard deviation (expressed as a percentage of MASV) across the 10 XGBOOST model runs, with Spearman's ρ indicating the correlation between feature value and change in PNC prediction — with surface wind direction (MASV: $2,230 \pm 2\%$ particles/cm³, Spearman's $\rho =$ non-significant [NS]), surface temperature ($2,190 \pm 2\%$ particles/cm³, $\rho = -0.91$), and surface wind speed ($1,910 \pm 2\%$ particles/cm³, $\rho = -0.84$) representing the three most important features (Figure 2.2a). The analysis also identified the planetary boundary layer height ($1,420 \pm 3\%$ particles/cm³, $\rho = -0.92$) as a strong contributor to

predicted PNC. The broad, right-skewed distribution of SHAP values for these surface and upper air features suggest nonlinear associations and substantial interactions with other features. Among emissions-related features, transportation activity was positively correlated with increased predicted PNC, with road traffic ($1,600 \pm 4\%$ particles/cm³, $\rho = 0.87$) emerging as the most important emission feature. Because this reflected a traffic counter 6.5 km from the monitoring site and given the siting of our monitor > 200 m from major roads, this term likely reflects temporal trends in traffic contributions integrated across the region. Among aviation features, arrivals on runway 22L (22L-Arrivals, $1,290 \pm 7\%$ particles/cm³, $\rho = 0.80$) and departures on runway 22R (22R-Departures, $840 \pm 8\%$ particles/cm³, $\rho = 0.73$) contributed most to predicted PNC, with their mean absolute impacts doubling under impact sector winds (22L-Arrival = 2,700 particles/cm³, 22R-Departure = 1,800 particles/cm³). In contrast, the runway with the highest mean flight volume (33L, Figure 2.1c) had a de minimis impact (MASV < 100 particles/cm³), indicating minimal influence on PNC at the monitoring site. SHAP values for road traffic clustered tightly around small positive contributions to predicted PNC, while aviation features exhibited right-skewed distributions, indicative of episodic high-impact events and stronger interactions with other variables.

Prior studies in near-airport settings in Boston^{53,108} and other near-airport locations^{103,104,140,141} have shown that aircraft and roadway sources exhibit distinct wind speed-direction dependencies on PNC, with elevated concentrations at higher wind speeds more indicative of aircraft impacts. Our SHAP results capture these differential effects on predicted PNC, reinforcing the physical interpretability of the model and the

utility of SHAP for source attribution (Figure 2.2b). We observed elevated contributions to predicted PNC from 22L-Arrivals and 22R-Departures under high speed impact sector winds. This pattern is consistent with buoyant aircraft plumes transported by wind driven advection.^{142–144} In contrast, SHAP values for road traffic showed minimal dependence on wind speed-direction. Given the short atmospheric lifetime and limited transport range of near-surface UFPs,^{126,145} these results support the interpretation that elevated PNC under specific meteorological conditions is primarily attributable to in-flight aircraft emissions rather than local surface sources (Figures S9–12).¹⁰⁷ Although U.S. and European emissions inventories implicate road traffic as the dominant source of particle number emissions,^{94,146} our results highlight the important role on in-flight aircraft on PNC in a near-airport community. Previous studies in other near-airport communities using statistical or receptor-based methods have, on average, attributed comparable PNC contributions to aviation and roadway sources.^{95,130} Our analysis aligns with these findings, while further demonstrating the value of machine learning interpretation tools like SHAP in capturing local nonlinear interactions between emissions and meteorology — beyond what is feasible with standard linear or second-order interaction terms (Figure S13).

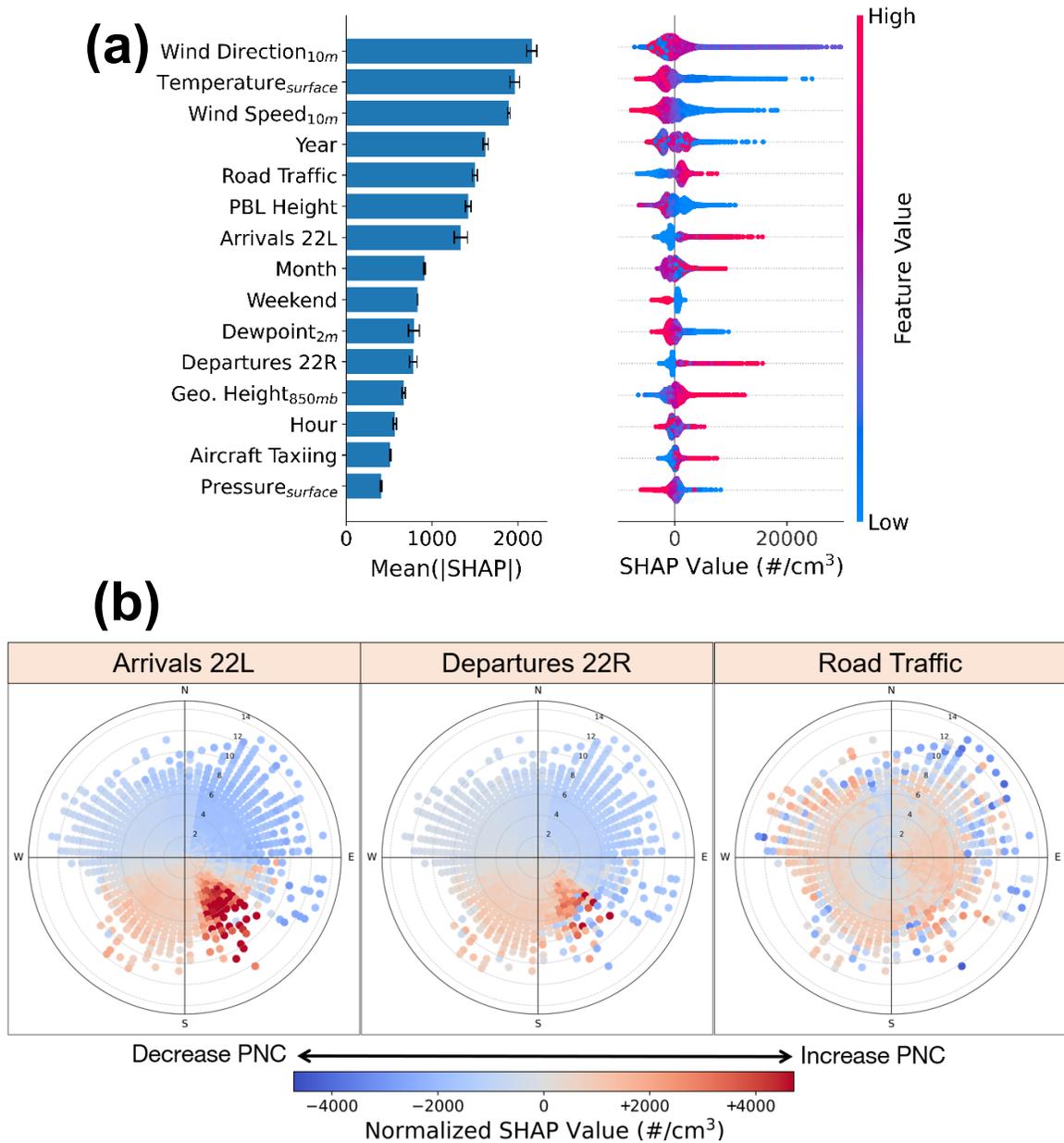


Figure 3.2. (a) Top fifteen features ranked by mean absolute SHAP values (MASV), representing their contributions to predicted PNC (particles/cm³). Left: MASV with error bars (± 1 standard deviation) across model runs ($n = 10$). Right: distribution of SHAP values colored by feature value. (b) Pollution roses showing binned hourly average SHAP values (normalized to 99th percentile) for aircraft arrivals on Runway 22L, aircraft departures on Runway 22R, and automobile road traffic, plotted against wind direction and speed.

Marginal Effects of Arrival vs Departure Aircraft

The joint marginal effect of wind direction and runway operations reveals complex, nonlinear associations with PNC, underscoring the challenges of source attribution when multiple interacting factors influence pollution levels (Figure 3.3). We present results for runway-operation configurations with the highest MASVs, 22L-Arrivals and 22R-Departures, and for runway 15R, which is oriented to operate during impact sector winds (see Figure S14 for road traffic and aircraft taxi). Runways 22L and 22R are typically used simultaneously under southwest winds, while runway 15R operates during southeast winds, directly aligning with the aviation impact sector. Marginal effects on PNC were minimal for 22L-Arrivals and 22R-Departures during their operationally aligned southwest winds (20 and 30 particles/cm³ per operation-hr, respectively). During southeast winds (i.e., crosswinds), however, 22R-Departures exhibited a greater marginal effect on PNC (270 particles/cm³ per departure-hr) compared to 22L-Arrivals (150 particles/cm³ per arrivals-hr), consistent with prior findings that departures produce higher emissions due to greater engine thrust during takeoff.^{51,147} However, our results suggest that arriving aircraft exert a greater cumulative influence on PNC (Figure 3.2a), particularly during low-activity periods, due to their more consistent impact across a range of conditions. These findings are corroborated by prior field observations near a Louisville, KY, USA airport; Loehr and Turner (2023) noted that sustained crosswinds can lead to elevated ground-level PNC, as a longer segment of the flight path contributes emissions to the site through lateral dispersion.¹⁴⁸ 15R-Arrivals contributed to elevated PNC during high flight activity periods (> 20

arrivals/hr), while 15R-Departures had minimal impact on PNC. This pattern likely results from 15R's alignment, positioning arriving flights directly over the monitoring site. Flights departing 15R, by contrast, may reach higher altitudes more rapidly because of the steeper climb-out, or deviate more quickly from the runway path, characteristic of departing aircraft. Thus, despite 15R's proximity and alignment with impact-sector winds, its overall impact on PNC was smaller than runways 22R-22L. While the model's partial dependence analysis shows distinct relationships between runway operations and PNC, these effects are likely interdependent due to the airport's operational constraints, especially its reliance on wind direction and the simultaneous use of multiple runways. This operational coupling highlights the difficulty of attributing sources when multiple factors interact, making it challenging for global marginal contribution methods, like PDP, to capture the full complexity of the airport's impact on PNC.

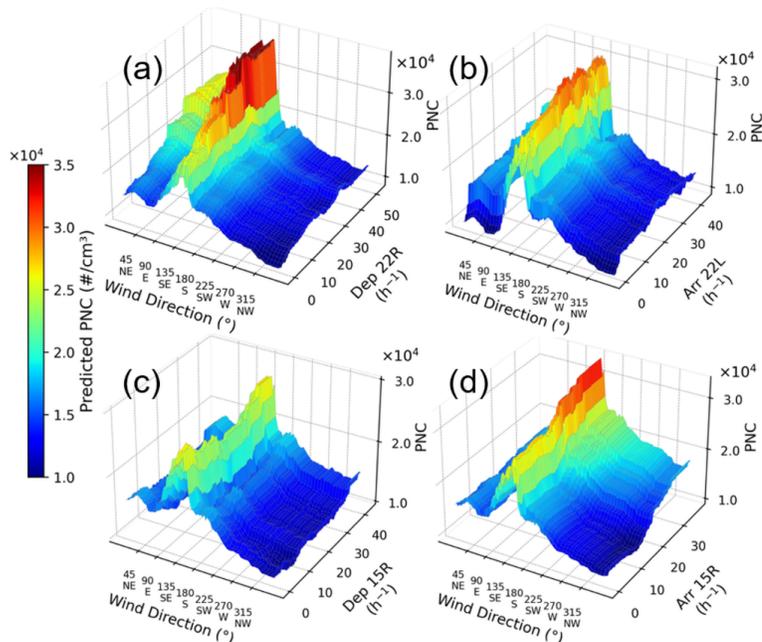


Figure 3.3. Bivariate partial dependence plots for predicted particle number concentration (particles/cm³) showing the joint marginal contribution of surface wind direction and operations on runways (a) 22R (b) 22L (c-d) 15R.

Aircraft Operations and Meteorology Interactions on Modeled PNC

To better understand the conditions under which in-flight aircraft influence PNC in a near-airport community, we examined the main (SHAP) and interaction (SHAP interaction) effects between 22L-Arrivals and key meteorological features (Figure 3.4). Among the most important features, surface wind direction, temperature, and planetary boundary layer height (PBL) exhibited highly nonlinear main effects and interacted strongly with arriving aircraft.

While the dependence of aircraft plume behavior on wind direction and speed has been documented previously,^{104,142,143} SHAP enables direct quantification of these interactions with greater granularity. Winds from the defined aviation-impact sector (135°–175°) consistently increased predicted PNC (i.e., positive SHAP values), contributing to the highest model estimates (> 100,000 particles/cm³). In contrast, winds outside this sector typically reduced predicted PNC (71% negative SHAP values). SHAP values during impact sector winds ranged widely (+1,600 – +29,700 particles/cm³), largely driven by interactions with aircraft activity. SHAP interaction values between impact sector winds and arrivals on 22L were elevated (+2,000 – +6,000 particles/cm³) when arrivals exceeded 10 per hour. Crucially, SHAP analysis revealed substantial interactions between arriving aircraft and winds outside the traditional impact sector, specifically under east-southeast winds (90°–145°). This further supports the hypothesis that aircraft plumes can be laterally advected and impact ground-level air quality beyond the conventionally defined downwind corridor.¹⁴⁸ These findings effectively extend the boundaries of the previously established impact sector and demonstrate that crosswind

conditions can contribute to elevated PNC near the airport.

Surface temperature exhibited an inverse relationship with predicted PNC, with the strongest aviation-related interactions occurring near freezing temperatures (~275 K) during periods of high flight activity. Several studies in urban areas have shown a seasonal influence on PNC, with some identifying positive correlations with temperature^{90,141} while others report negative or mixed associations.^{107,149,150} We postulate that elevated PNC in our study domain reflects reduced vertical mixing and suppressed particle growth rates.¹⁵¹ While seasonal variation in emission activity and engine efficiency (e.g., cold-start effects) may also elevate PNC under cold conditions,^{152,153} minimal interaction was observed between temperature and road traffic (Figure S15). Furthermore, photochemically driven nucleation is unlikely to fully explain these patterns, as such events require intense solar insolation and low preexisting condensations sinks,^{154–156} conditions uncommon in Boston's winter. These results suggest that cold conditions may amplify the contribution of aircraft to local PNC, motivating a closer examination of vertical mixing potential via PBL height.

While PBL main effects similarly showed an inverse relationship with predicted PNC, interactions between PBL height and arrival aircraft were most elevated in the morning (0000 – 0600 ET) and evening (1800 – 0000 ET) hours when the PBL was shallow (100–600 m) but dynamically evolving (Figure S16). These transitional periods coincide with peak flight activity¹⁰⁷ and limited vertical mixing potential, creating conditions conducive to emissions accumulation near the ground. This finding is consistent with results from the Louisville airport study, which conducted nighttime and

early morning measurements specifically to capture the effects of shallow boundary layers on ground-level UFP concentrations.¹⁴⁸ Our findings extend this physical interpretation: when the PBL was extremely shallow (<100 m), SHAP interaction values became negative during periods of high flight activity, suggesting that under very stable conditions, aircraft plumes may remain aloft and not be entrained into the surface layer. This nuance highlights that while shallow PBLs generally enhance near-source pollution levels, there is a threshold below which insufficient mixing prevents ground level entrainment of aloft emissions. Whereas linear and receptor models often identify main effects (e.g. decreasing PNC with increasing temperature), they may either deem variables like PBL statistically insignificant³⁴ or lack the ability to directly incorporate meteorology into factor loadings.^{19,95} In contrast, our SHAP-based approach better elucidates these complex meteorological and aircraft plume interactions.

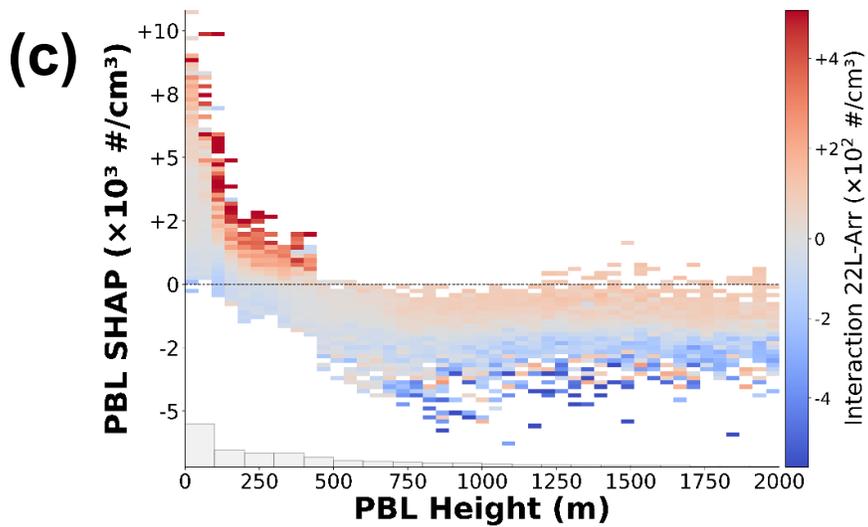
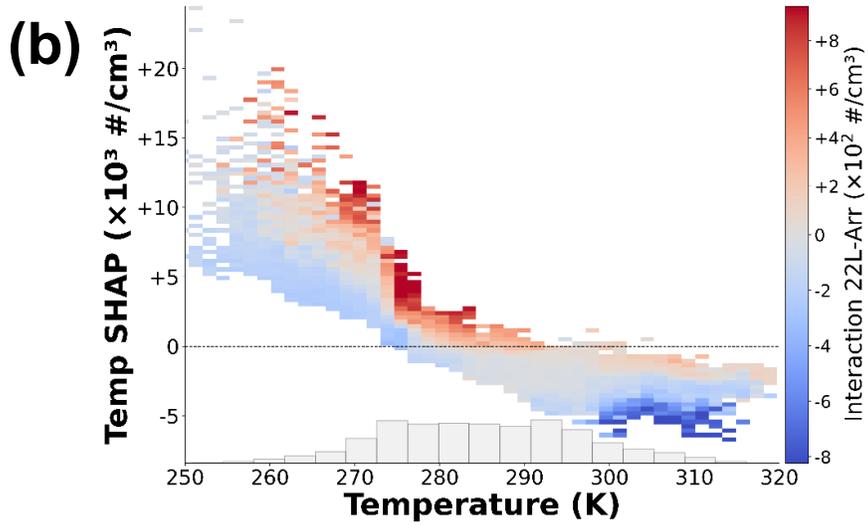
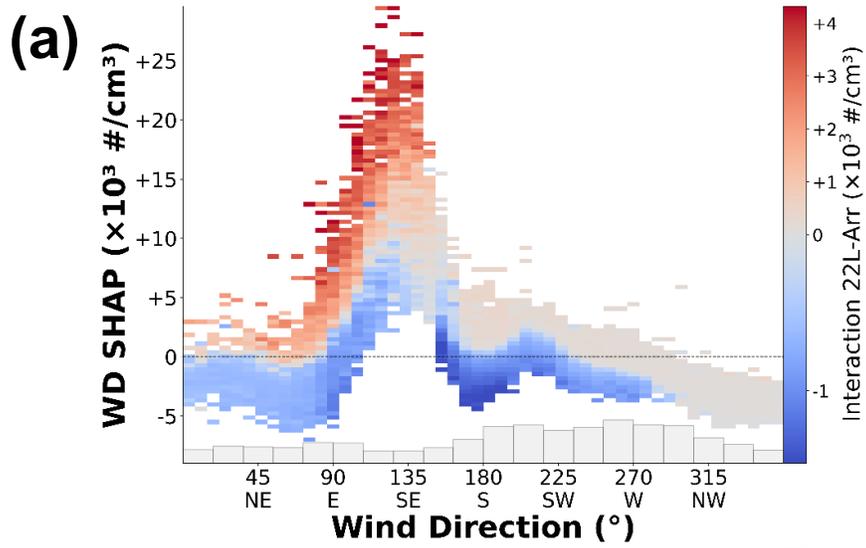


Figure 3.4. Feature main effects conditioned on aviation interaction effects. Binned SHAP values versus feature values for three meteorological variables: (a) surface wind direction, (b) surface temperature (K), and (c) planetary boundary layer (PBL) height (m). Each panel shows the average SHAP value (i.e., estimated impact on predicted particle number concentration, PNC, in $\#/cm^3$) within bins of the feature value (x-axis) and corresponding SHAP value (y-axis), colored by the mean SHAP interaction value between each respective feature and 22L runway arrival activity. Gray bars along the bottom of each panel represent the feature distribution.

IMPLICATIONS

Our machine learning models quantify how in-flight aircraft activity interacts with meteorological conditions to influence PNC in near-airport communities, accounting for automobile traffic and on-ground airport operations. We identify arrivals as the most influential source of aviation-related UFPs, with impacts extending beyond the immediate downwind sector. Specifically, we demonstrate that lateral plume dispersion during crosswind conditions can expose areas not directly aligned with runway axes. We also find that in-flight activity contributes more to predicted PNC than on-ground airport operations — differences that have been challenging to disentangle using standard statistical approaches. Furthermore, SHAP interaction analysis reveals a boundary layer threshold effect: when the boundary layer is too shallow, emissions may remain aloft and fail to reach ground-level, while deep layers may dilute emissions before they impact the surface. These nonlinear effects would likely be missed by traditional linear or receptor modeling approaches. Importantly, this work yields a high-resolution dataset of aviation-attributable PNC that can support retrospective exposure assessments for epidemiologic analyses. Elevated UFP has been measured in communities located several kilometers from airport complexes, and as air traffic continues to increase globally,⁵ understanding how aircraft emissions influence ground-level air pollution is critical for protecting public health. Future research should integrate interpretable machine learning with receptor and chemical transport models, where ML outputs can help parameterize emissions or dispersion inputs, enabling hybrid approaches that improve source apportionment and characterization of aviation-related UFP exposure across diverse locations.

ACKNOWLEDGEMENTS

We are grateful to The Neighborhood Developers in Chelsea for housing our stationary site. This research was funded by the U.S. Federal Aviation Administration Office of Environment and Energy through ASCENT, the FAA Center of Excellence for Alternative Jet Fuels and the Environment, and Project 18 through FAA Award Number 13-C-AJFE-BU under the supervision of Jeetendra Upadhyay. Any opinions, findings, conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the FAA.

**CHAPTER FOUR. EXPOSURE TO HAZARDOUS AIR POLLUTANTS IN
COMMUNITIES NEAR U.S. GENERAL AVIATION AIRPORTS**

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ABBREVIATIONS

100LL Low Lead Aviation Gasoline (100 octane rating)

1B9 Mansfield Municipal Airport

As Arsenic

Avgas Aviation Gasoline

Br Bromine

CDC U.S. Centers for Disease Control

CSA Commercial Service Airports

CSN Chemical Speciation Network

EF Enrichment Factor

EPA U.S. Environmental Protection Agency

FAA U.S. Federal Aviation Administration

GAA General Aviation Airports

ICAO International Civil Aviation Organization

ICP-MS Inductively Coupled Plasma Mass Spectrometry

IMPROVE Interagency Monitoring of Protected Visual Environments

KBED Hanscom Field

MDL Minimum Detection Limit

Pb Lead

PEA Piston-Engine Aircraft

PM_{2.5} Fine Particulate Matter; aerodynamic diameter < 2.5 microns

TFMSC Traffic Flow Management System Counts

WHO World Health Organization

ABSTRACT

Hazardous PM_{2.5} elemental constituents associated with aviation activity—including lead (Pb), bromine (Br), and arsenic (As)—have been identified at large commercial service airports (CSAs), yet their presence at general aviation airports (GAAs) remains largely unexplored. This gap is concerning, as GAAs vastly outnumber CSAs in the United States, with thousands of facilities serving piston-engine aircraft (PEA) that primarily operate on leaded aviation gasoline (avgas). While prior studies have linked GAAs to airborne Pb emissions, the potential contribution of additional air pollutants of concern from GAA activities have received limited scrutiny. To address this, we conducted ambient PM_{2.5} elemental monitoring at two Massachusetts, U.S. GAAs—Mansfield Municipal Airport (1B9) and Hanscom Field (KBED)—quantifying 38 elements, including known aviation-associated hazardous air pollutants. Enrichment factor and particulate size fractionation analysis identified Pb, Br, and As as primarily from anthropogenic sources, with concentrations declining with distance from the airport. Comparisons with regulatory monitoring networks highlight gaps in existing frameworks for capturing localized exposures. These findings highlight the need for expanded monitoring at GAAs to assess a broader range of emissions, informing regulatory efforts following the U.S. Environmental Protection Agency’s 2023 endangerment determination for PEA emissions. Our study provides critical data to support exposure assessments and mitigation strategies in near-airport communities.

INTRODUCTION

General aviation airports (GAAs, defined as having < 2,500 annual enplanements) represent a substantial yet understudied source of air pollution due to their role as primary hubs for the United States' (U.S.) estimated 170,000 piston-engine aircraft (PEA) fleet operating primarily on leaded aviation gasoline (avgas).¹⁵⁷ 100 Low Lead (100LL, maximum Pb concentration of 0.56g/L) avgas is the primary fuel for these PEA,¹⁵⁸ containing tetraethyl lead (C₈H₂₀Pb) as an anti-knock agent, making it the largest single contributor to airborne lead (Pb) emissions in the United States.⁴ PEA that use avgas are widely distributed across approximately 3,000 airports in the U.S. Although these airports are typically located near population centers, they are not always within major metropolitan areas. In contrast, larger Commercial Service Airports (CSAs, defined as having > 2,500 annual enplanements) are located only in a few major metropolitan areas.^{159,160} Collectively, the PEA fleet and the airports that service it form a critical infrastructure for general aviation,¹⁵⁹ yet one that disproportionately impacts nearby communities due to continued reliance on leaded avgas.¹⁶¹ The U.S. Centers for Disease Control and Prevention (CDC) states “no safe blood lead level in children has been identified”,³⁰ with cognitive impairment seen at low blood lead levels. With GAA operations projected to increase,¹⁶² the urgency of addressing these environmental health challenges is growing. In recognition of this issue, the U.S. Environmental Protection Agency (EPA) issued a final determination in 2023 that lead emissions from PEA endanger public health and welfare. Under the Clean Air Act, this finding compels the EPA to propose and promulgate regulatory standards to address lead emissions from

piston-engine aircraft engines.⁴² However, the scientific literature provides limited guidance to inform these efforts, particularly regarding exposures to near airport communities.^{33,161}

Air pollution monitoring, exposure and health studies of near GAA communities have remained understudied compared to commercial service airports.¹⁶³ Existing studies of ambient air pollution in near-field GAA communities have focused predominantly on lead-bounded particulate matter and often rely on distance to airport as a proxy for exposure. Studies have consistently reported that individuals living within 500 meters to 1 kilometer of airports face elevated air pollution and lead exposure risks.^{32,58-60} All studies we found assessing the impact of lead exposure of near-field community health simplified the spatial and temporal complexity of pollutant dispersion with this distance based metric. For example, while Zahran et al. 2023 expanded beyond distance to integrate wind direction and PEA volume to improve exposure assessment,⁶⁰ empirical validation of lead emissions monitoring attributable to PEA to support the distance to airport proxy exposures remains limited in near-GAA communities which is important to support the aviation-assigned health impacts. Furthermore, the potential contribution of other hazardous air pollutants from aviation beyond lead to localized pollution has been largely overlooked. Emerging research highlights the need to expand the focus of GAA exposure assessments to include a broader analysis of air pollutants beyond lead. Studies at commercial service airports indicate that several hazardous air pollutants are associated with aircraft engine emissions: sulfur (S), arsenic (As), lead (Pb), chromium (Cr), zinc (Zn), cobalt (Co), nickel (Ni), cadmium (Cd), and mercury (Hg).^{49,61,62} Together, these

findings indicate the need for comprehensive monitoring of heavy metals near airports, including GAAs.

Our study addresses these gaps by providing empirical data relevant to the EPA's impending requirement for regulatory standards under the Clean Air Act. Specifically, we conducted ambient monitoring of PM_{2.5} elemental constituents near two Massachusetts GAAs—Mansfield Municipal Airport (ICAO: 1B9) and Hanscom Field (ICAO: KBED)—which differ significantly in scale and activity. By measuring toxic elements such as bromine, arsenic, and others in addition to lead, we provide a more comprehensive understanding of the pollution profile associated with PEA activity and the resulting exposures in near-field GAA communities. We also present a comparison of concentrations measured across MA through the EPA's monitoring network to evaluate the adequacy of existing frameworks for capturing localized exposure risks. By integrating direct measurements of multiple hazardous air pollutants with an assessment of spatial and temporal pollutant dynamics, we aim to inform the EPA's regulatory decision-making process and emphasize the need to assess a broader range of emissions to mitigate the health risks posed by GAAs.

MATERIALS AND METHODS

Description of Study Area

Massachusetts is home to 79 airports, with 30 classified as GAA.¹⁶⁴ We studied Mansfield Municipal Airport (ICAO: 1B9, located in the towns of Mansfield and Norton, MA, approximately 30 miles south-west of Boston) and Hanscom Field (ICAO: KBED, located in Bedford, MA, approximately 15 miles north-west of Boston). Both 1B9 and KBED GAAs are surrounded by residential communities including homes within a few hundred meters of the airport runways. Among the state's airports, we opportunistically selected to study these two airports which created a unique opportunity to contrast air pollution concentration among heterogenous GAAs. Monitoring at 1B9 was conducted as part of a pilot study to better understand methods for measuring and apportioning aviation-related air pollution, while monitoring at KBED was conducted as part of a community-driven research project to understand community impacts from a proposed airport expansion project. 1B9 is a smaller GAA classified as "General Aviation" and has an average of 3 operations per day, while KBED is the largest GAA in the New England region and is classified as a "Reliever with Commercial Services" and averages 140 operations per day.¹⁶⁴ 1B9 has a majority of piston-engine aircraft usage (82% PEA), while KBED has a majority of jet-engine aircraft (73% Jet-engine, 11% PEA, Figure 4.1).¹⁶⁵ KBED has two asphalt-grooved runways while 1B9 has two runways, one asphalt and one turf.

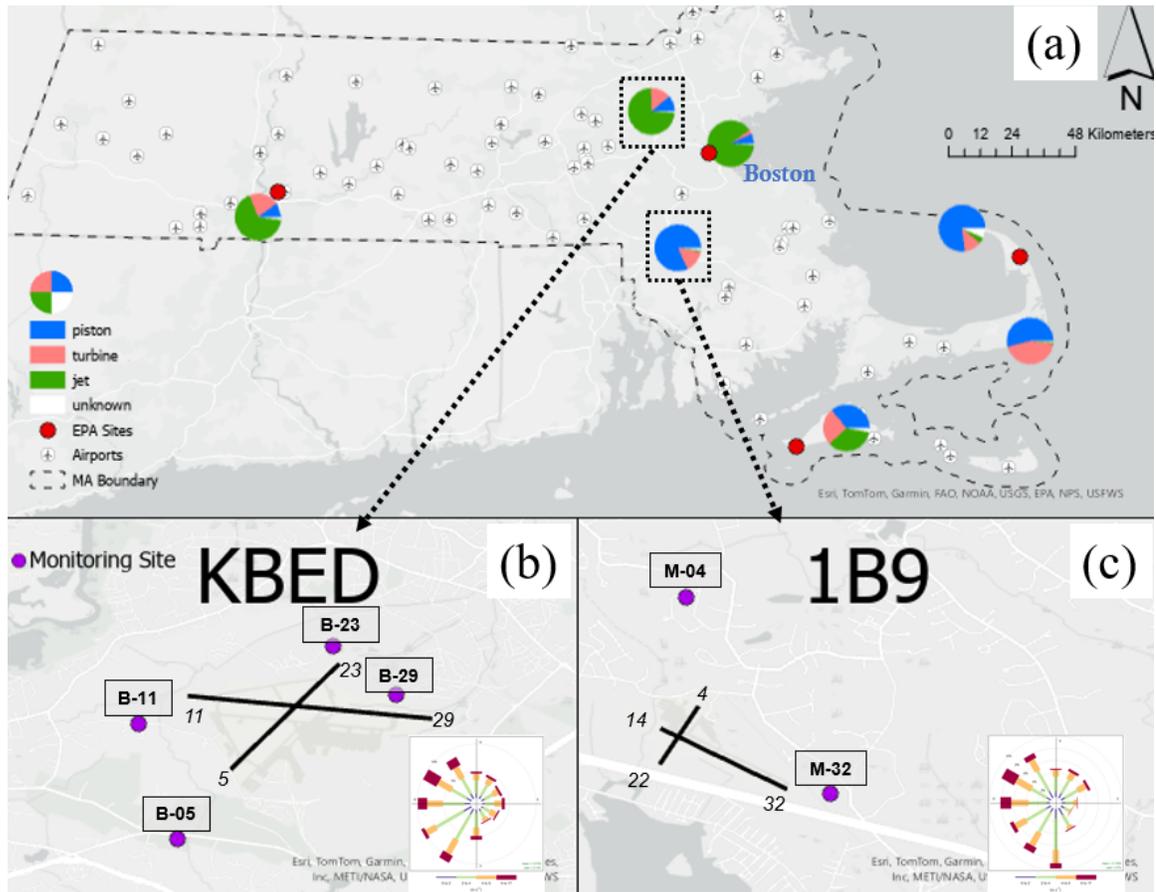


Figure 4.1 (A) Study domain (Massachusetts, U.S.A.) and monitoring sites. Pie charts identify proportion of operations by engine type at co-located general aviation airports. (B) Hanscom Field (KBED) monitoring site with windrose for 2017–2024 (C) Mansfield Municipal Airport (1B9) monitoring site with windrose for 2017–2024.

Monitoring Locations and Pollutant Measurements

Table 4.1 Monitoring Period Summary (Flight Activity, Distance to Airport, Meteorological Conditions)

Monitoring Site	Monitoring Network	Proximal Airport (ICAO)	Monitoring Site distance to nearest Airport Centroid (km)	Airport Average Daily Operations (2021–2024)	Airport Piston-Engine Operations (% , 2021–2024)	Proximal Meteorological Station	Aviation-Impact Sector (% , Jul–Sep, 0700–1800, 2021–2024)
M-32	SPBI (BU)	1B9	0.3 SE	3	82	KOWD ASOS	15
B-29	HFAC (EMP, LLC)	KBED	0.3 NE	140	11	KBED ASOS	39
B-23	HFAC (EMP, LLC)	KBED	0.5 N	140	11	KBED ASOS	29
B-11	HFAC (EMP, LLC)	KBED	0.7 W	140	11	KBED ASOS	16
M-04	SPBI (BU)	1B9	1.0 NW	3	82	KOWD ASOS	18
B-05	HFAC (EMP, LLC)	KBED	1.1 SW	140	11	KBED ASOS	7
Chicopee	IMPROVE (EPA)	KCEF	2.2 W	6	10	KCED ASOS	15
Boston	CSN (EPA)	KBOS	7.3 SW	865	7	KBOS ASOS	8
Aquinnah	IMPROVE (EPA)	KMVY	16 SW	60	36	KMVY ASOS	10
Truro	CSN (EPA)	KPVC	20 SE	10	77	KPVC ASOS	6

***SPBI = Small Particles Big Impact, BU Ignition Funding**

***HFAC = Hanscom Field Advisory Committee**

***IMPROVE = Interagency Monitoring of Protected Visual Environments**

***CSN = Chemical Speciation Network**

Monitoring was conducted at two sites aligned with the runways of 1B9 and four sites aligned with the runways of KBED (Table 4.1), conducted in two phases: 1B9 monitoring occurred intermittently from July 17, 2023 – July 17, 2024, and at KBED from July 17, 2024 – October 1, 2024. During 1B9 monitoring, sampling occurred simultaneously at the two sites; at KBED, sampling occurred simultaneously at up to two of the four sites, with site pairs rotating over the monitoring period. We refer to each monitoring site based on the airport runway they are oriented towards (M-04, M-32, B-29, B-23, B-11, and B-05). Across both phases, weather-resistant enclosures were set up at ground level at each monitoring site to house the air quality instruments. Time-integrated $PM_{2.5}$ samples were collected on PFTE (Teflon) filters for elemental analysis. We used both single-stage Harvard Personal Exposure Monitor (HPEM, 1-single 37mm 3-um pore size filter, 10L/min) to collect bulk particles $<2.5\mu m$, and multi-stage Sioutas Personal Cascade Impactors (PCIS, 1 37mm filter, 2 25mm filters, 9L/min) to collect specific size fractions of particles (coarse, accumulation, and quasi-UFP). Duplicates, lab blanks, and field blanks (clean filtered handled like samples deployed in the field not connected to an active sampling pump) were collected and analyzed alongside experimental samples to account for impurities added inadvertently to the filters during lab and field activities. Samples were analyzed via gravimetry and energy dispersive X-ray fluorescence spectrometry (XRF) at Alliance Technical Group (Tigard, OR) to quantify $PM_{2.5}$ mass concentrations as well as the elemental content (38 elements inclusive of Na and Pb). Sites were serviced every 2–3 days for air flow audits; filter changes occurred every 1–2 weeks and instruments were cleaned between deployments.

Mean sampling time per sample in 1B9 sites was 11.8 days +/- 3.0 days, while mean sampling time per sample in KBED was 7.41 days +/- 1.9 days.

Data Acquisition and Processing

Flight activity statistics for 2017–2024 were downloaded from the FAA Operations & Performance Database to examine longer-term spatial and temporal patterns across several airports with different airport class usages across MA.¹⁶⁶ Traffic flow management system counts (TFMSC) are operational counts created when pilots file flight plans and/or when flights are detected by the national airspace system (NAS), usually via RADAR. While GA operations at airports with FAA and contract traffic control service decreased significantly between 2019 and 2020, operations levels made a near full recovery in 2021.¹⁶² Subsequently, we retained data from 2021 onwards for flight activity and subsequently described covariates, to capture multi-year patterns that were not impacted by the COVID-19 GAA transportation related activity changes.

We leveraged the U.S. EPA long-term speciated PM_{2.5} publicly available datasets to compare our findings with regulatory monitors. The Massachusetts Department of Environmental Protection (MassDEP) operates four particulate matter composition monitoring stations: two through the Chemical Speciation Network (CSN; Boston [Site 0042], Chicopee [Site 0008]) and two through the Interagency Monitoring of Protected Visual Environments program (IMPROVE; Aquinnah [Site 0001] and Truro [Site 0002]). While the CSN and IMPROVE networks were designed with different objectives, they apply similar analytical methods to filter samples and report many of the same species that we collected. While the CSN monitors typically represent more urban populated

locations, IMPROVE monitors are placed in Federally protected areas (i.e., Class 1). Both CSN and IMPROVE collect particulate matter on PTFE filters over 24 hours and are analyzed using XRF at the same laboratory (University of California, Davis). These networks generally show good collocation agreement when measurements are above the minimum detection limit (MDL).¹⁶⁷ The MDLs for CSN are generally higher than those for IMPROVE because the CSN sample deposit is less dense.¹⁶⁷ However, while broadly the EPA's PM speciation methods and ours follow the same protocol (i.e., time-integrated PTFE filters analyzed via gravimetry and XRF), EPA's methods differ from our methods on several facets: time-integration, sampler, flow rate, filter size, and filter storage/transportation temperature requirements. Notably, several MassDEP PM speciation sites are located proximally to commercial and non-commercial airports (Table 4.1). Data on PM_{2.5} bound-metals was acquired from January 2021 – May 2024, representing the latest publicly available data at the time of this writing. CSN sites collect particulate matter on PTFE filters over 24 hours and are analyzed using energy dispersive X-ray fluorescence for a suite of 33 elements, operating on a 1-in-3 day sample collection schedule. We retained only EPA records with either no qualifier or a qualifier that the sample was below MDL. Given the challenges with CSN and IMPROVE agreement among samples below MDL, we ran a sensitivity analysis, including and excluding MDL samples.

Meteorological data collected at KBED via automated surface observing stations (ASOS) were obtained from the Integrated Surface Database (ISD) at hourly resolution. 1B9 does not have an automated weather observing system, instead it relies on an on-site

windsock and information from other near-by airports for operational meteorology. We used ISD from Norwood Memorial Airport (ICAO: KOWD) ASOS, approximately 21 km northeast of 1B9, to represent local wind conditions. Notably, we chose not to represent 1B9 meteorological via nearby coastal airports nor the closest airport (Taunton Municipal Airport, 20km from 1B9 centroid) because of topographical differences in the adjacent terrain. The other matching monitoring sites, proximal airports, and representative meteorological sites are listed in Table 4.1. Hours were classified into impact-sector winds on whether the hourly average wind direction positioned the monitoring site downwind of the proximal airport based on the azimuth angle of the site to the widest span of runways as done previously.^{53,107} We report aviation-impact-sector winds for a subset of data matching conditions when active monitoring was occurring, not impacted by COVID-19, during typical flight operation hours: 0700 – 1800.

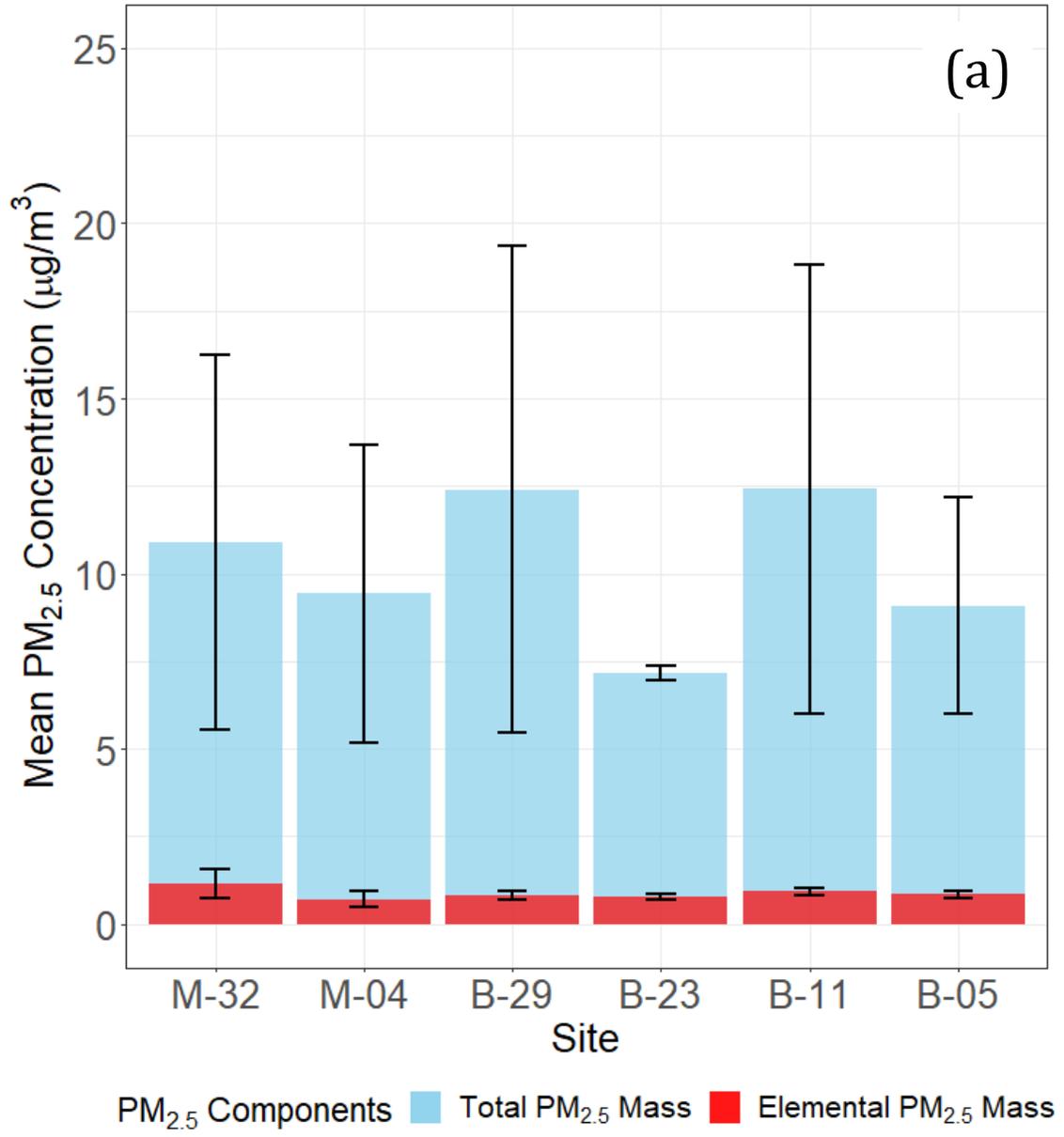
Enrichment Factors

Crustal enrichment factors (EFs) were used to distinguish naturally occurring crustal elements from those released by anthropogenic sources.¹⁶⁸ We compared filter-extracted elemental concentrations X to background continental concentrations from Rudnick and Gao¹⁶⁹, normalized by measured crustal iron (Fe) concentrations, which is predominantly from natural sources (Equation 1). By comparing air concentrations to soil concentrations, we can estimate the extent to which our air samples align with natural sources (e.g. dust resuspension) or anthropogenic activities. This method provides a conservative estimate of anthropogenic contributions, as the Fe fraction in soil is spatially

consistent¹⁷⁰ and any anthropogenic Fe in the air would reduce the calculated enrichment factor.

$$EF_X = \frac{[X/Fe]_{Filter}}{[X/Fe]_{Rudnick\ and\ Gao}} \quad (1)$$

RESULTS and DISCUSSION



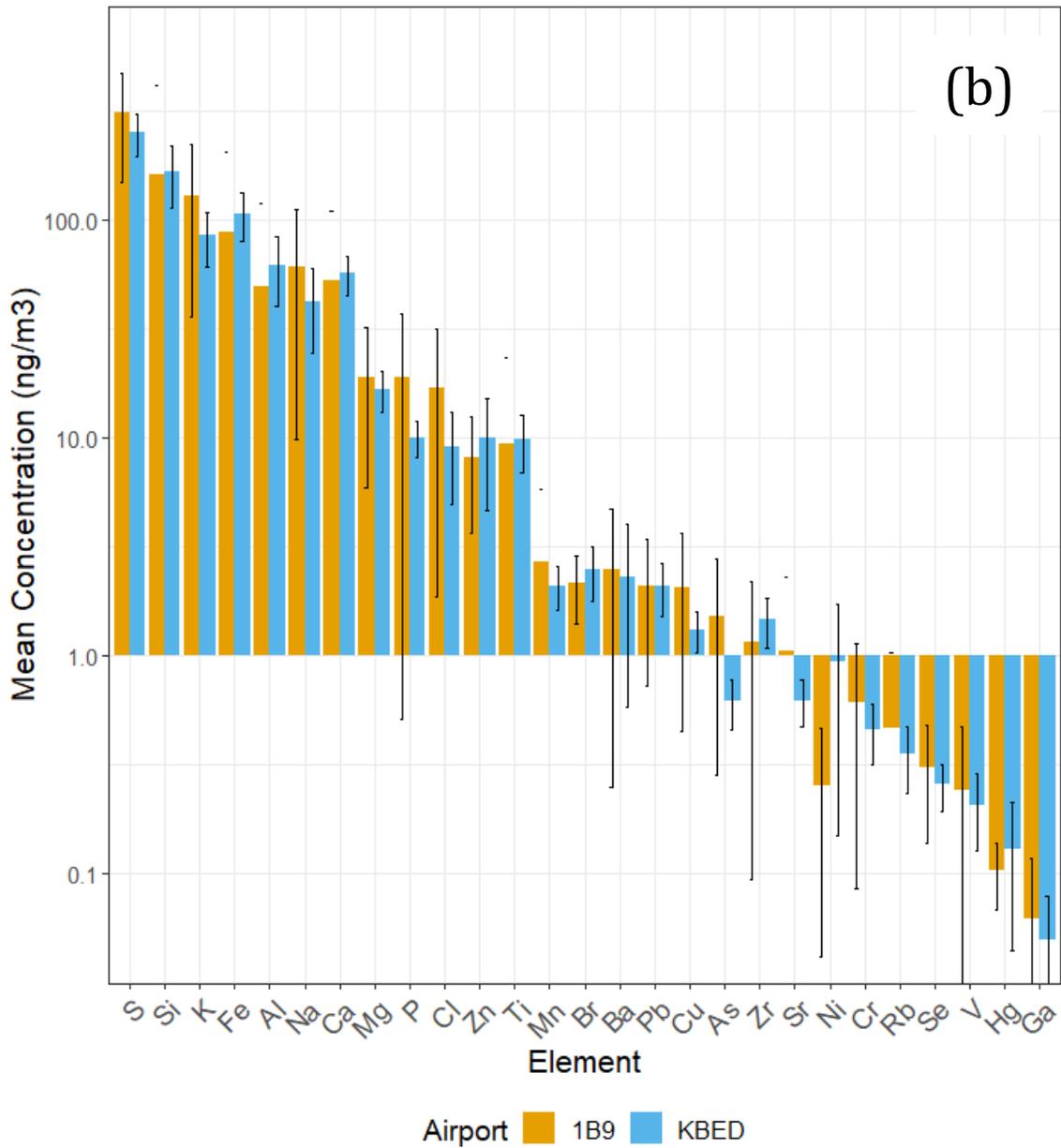


Figure 4.2 (A) Mean PM_{2.5} mass concentrations (ug/m³) at GAA sites Mansfield Municipal Airport (1B9) and Hanscom Field (KBED) with standard deviation bars shown. Overlaid red bars show total measured elemental mean mass concentrations for each site with standard deviation. (B) Mean PM_{2.5} elemental concentrations (ng/m³) by GAA site for elements with >25% detections.

The mean PM_{2.5} mass concentrations at each monitoring site are shown in Figure 1a. Of the six sites, B-29 had the highest mean PM_{2.5} levels at 12.4 +/- 6.9 ug/m³, closely followed by B-11 at 12.3 +/- 6.4 ug/m³ and M-32 at 11.0 +/- 5.4 ug/m³ (SI Table 1).

Important QAQC considerations: (1) simultaneous samples at the same airport site were largely in agreement in PM_{2.5} concentrations, indicating no individual site was disproportionately influenced by an external emission source, (2) duplicate measurements were within +/- 10% of measured concentrations, indicating high precision, (3) field blanks showed no evidence of contamination (95% of field blank measurements were below XRF MDL) and no subsequent blank corrections were made (SI Figure 1).

Elements above XRF detection limits for > 25% of samples were considered; Cd, In, Pd, Sb, Ag, Mo, Y, Ge, La, Co, and Sn did not satisfy this requirement, and are not discussed here. Individual elements were examined to understand their distributions across sites. On average, S, Si, K, Fe, Al, Na, Ca, and Mg were the most abundant elements at both sampling sites Figure 4.1a. S is a pollutant that is emitted by combustion of aviation fuel and has been seen at elevated levels in commercial service and general aviation airports.^{61,171} Si, K, Fe Al, Ca, Mg derive mainly from crustal sources.¹⁷² Among the indicated elements S, K, Na, Mg, P, Cl, Mn, Cu, and As had higher concentrations on average at 1B9 in comparison to KBED.

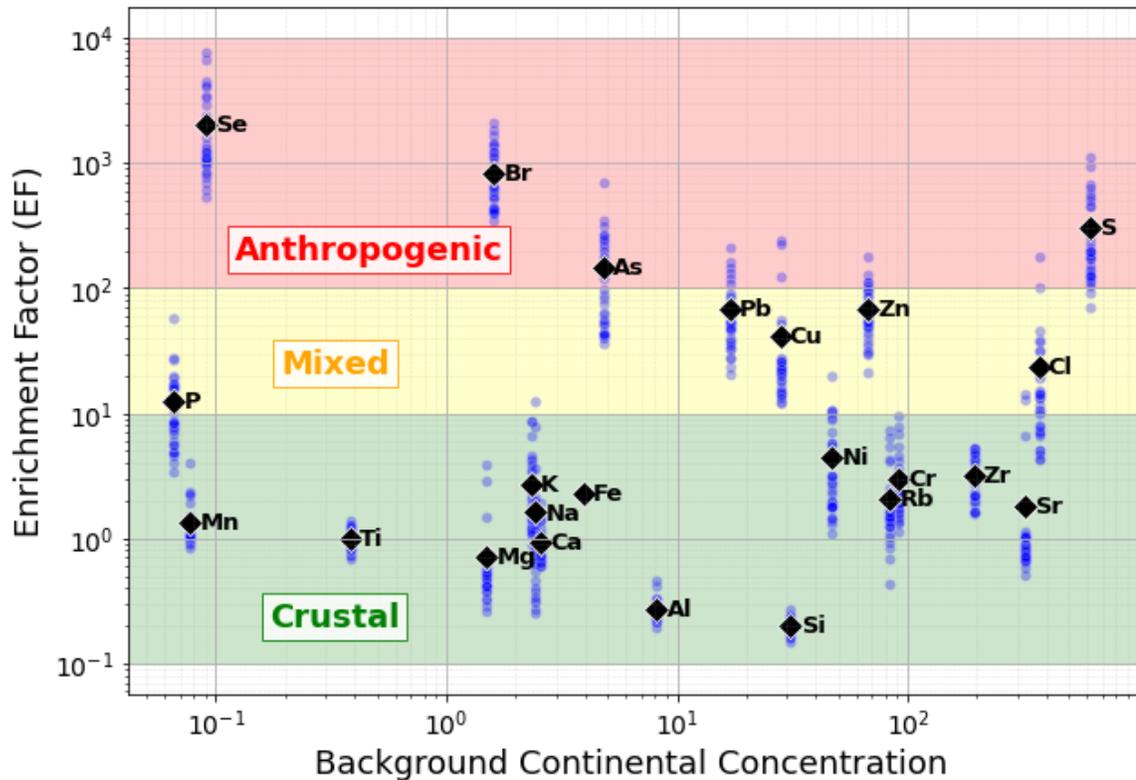


Figure 4.3 Crustal enrichment factors for PM_{2.5} relative to crustal ratios of the given element and iron (Fe) vs their background concentration per Rudnick and Gao (2002),

Enrichment factors vary by orders of magnitude depending on the element.

Enrichment factors > 100 indicate elements with largely anthropogenic sources.^{168,170} The highest levels of enrichment across the study domain (space and time) were Se, Br, S, As, Pb, and Zn (Figure 4.3). From Equation 1 an element can have a high EF for two reasons: the element is significantly enriched due to anthropogenic sources, or the background concentration (from natural sources) is low, biasing the EF. For example, Figure 4.2a indicates Se is highly enriched (EF > 100), but this may be a function of a low natural baseline per Rudnick and Gao.¹⁶⁹ Elements Se, Br, S, As, Pb, Cu, and Zn are enriched at levels that indicate largely anthropogenic sources. The S, Br and Pb enrichment are

indicative of aviation activities: ethylene dibromide ($C_2H_4Br_2$) is added to leaded avgas to prevent Pb accumulation in engines.¹⁷³ Similarly, As has been reported to be emitted from aircraft engine exhaust.⁴⁹ Zn is frequently attributed to tire wear.¹⁷⁴ Particle size distributions can also provide insights into likely sources, where anthropogenic emissions tend to produce smaller size particles compared to those generated from natural dust resuspension.¹⁴⁴ We see evidence that, across all study sites, Pb, Br, As, and S are dominated by particles in the quasi-ultrafine range (SI Figure 3). This contrasts with the Fe particles, which show no evidence of enrichment, and are dominated by the coarse particle fraction, indicating crustal origin. Global Se concentration derive mainly from coal combustion¹⁷⁵, but since there are no coal emitting sources it could reflect the dominant aviation-emissions.

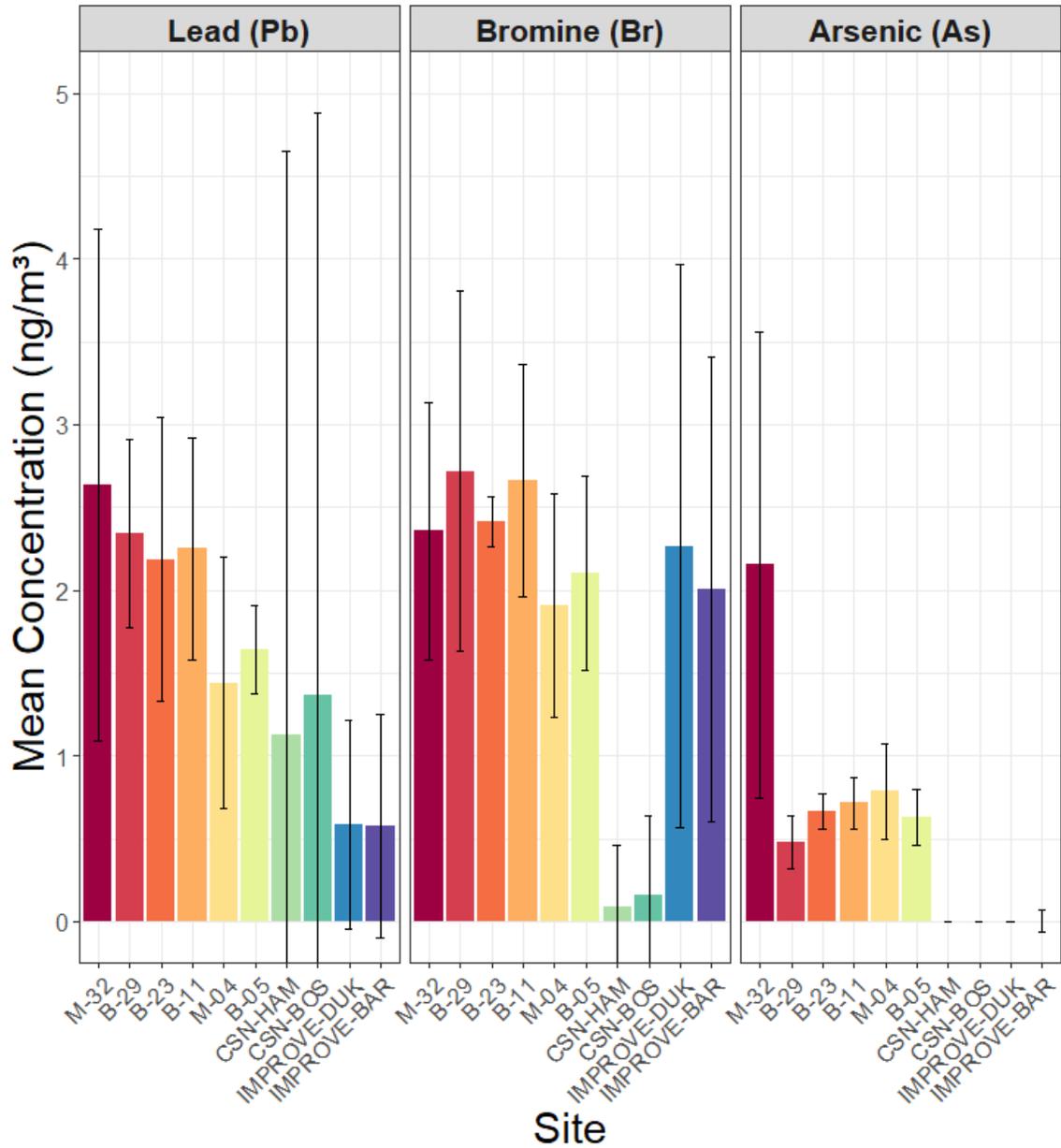


Figure 4.4 Mean $PM_{2.5}$ concentrations (ng/m^3) for enriched elements across study sites and EPA monitoring network sites. Bar charts with standard deviation are ordered from closest to furthest distance from the nearest airport centroid.

Figure 4.4 presents Pb, Br and As mean mass concentrations at the GAA sites compared to EPA sites. Our GAA study sites, Pb and Br concentrations were similar

across sites, with average concentrations decreasing with greater distance from the airport centroid. As concentrations were 2.5-fold higher at the closest 1B9 site (M-32) as compared to all other sites. As concentrations at M-32 were right-skewed, however, removing the largest sampled As concentration from the dataset did not have a material effect on the site average As concentration (mean +/- sd: *with highest reading*: 2.15 +/- 1.40, *without highest reading*: 1.82 +/- 0.85). During the highest measurement sample, net PM_{2.5} mass concentrations were within a factor of 1.5 between 1B9 sites (M-32: 9.0 ug/m³, M-04: 6.5 ug/m³ and 6.8 ug/m³), indicating potential moderate influences from local emissions sources. We explored this further, noting that the predominant wind direction during the summer of 2023 was from the south, however, during the 2-week sampling period, the winds were predominantly from the west-northwest, which positions M-32 downwind from 1B9 (SI Figure 2). Our Pb measurements are smaller in magnitude compared to other studies at GAAs: Hudda et al. 2022 monitored at a residential site located 0.3 km from Santa Monica Airport and reported 14-day integrated PM_{2.5} Pb of 4.7 +/- 2.0 ng/m³ from a sample of two sets of duplicate samples.¹⁷¹ These differences could be due to differences in flight activity (SMO average daily operations in 2017 [220] were nearly double the operations of the MA GAAs), fuel composition, and site specific meteorology in Santa Monica Airport in 2017 compared to the airports we monitored.

The greatest difference between GAA and EPA sites was observed in the As concentrations: As was detected in >90% of samples in the GAA sites, but only had one measurement above detection limit among the EPA sites. This could be explained due to limitations with XRF when samples contain Pb: As and Pb have overlapping XRF

emission lines, meaning their peaks can interfere in the spectrum, creating difficulty in distinguishing their contributions.¹⁷⁶ To explore this hypothesis, we digested a subset of samples via an alternative analytical method, Inductively Coupled Plasma Mass Spectrometry (ICP-MS) and noted As and Pb concentrations +/- 10% of XRF readings for the samples, indicating the As readings from our samples are measuring As in the sample. Although our monitoring protocol mirrors EPA protocols (i.e. time integrated PTFE filter analyzed via XRF), these differences in As detection between our study and EPA samples may be due to nuanced differences in data collection and sample analysis. Global monitoring has shown enriched airborne As, deriving from anthropogenic sources, with the single U.S. urban site (Atlanta, Georgia) showing enriched As.¹⁷⁷ Mean EPA Pb concentrations from the CSN sites mirrors average measurements at the GAA sites, while the IMPROVE sites show smaller mean Pb. Lead emissions are primarily associated with anthropogenic activities, and thus the sites located next to a (1) general aviation airport (e.g. leaded avgas) and (2) urban area¹⁷⁸ (e.g. industrial, soil, buildings) would have higher Pb concentrations compared to IMPROVE sites in protected federal areas. We see the opposite for Br: with Br levels at the EPA IMPROVE sites mirroring average measurements at the GAA sites, while the CSN sites show smaller mean Br. Br is often emitted from sea salt aerosols¹⁷⁹, which is indicative of the coastal IMPROVE monitoring site locations used here. However, the Chicopee CSN site is 2 km upwind from a GAA which we would hypothesize would have Br concentrations on the order of what we measured at the GAA sites. However, this highlights that GAAs are not homogeneous: KCEF has low average daily operations and only 10% of these operations involve piston

engine aircraft (Table 4.1), which would be operating primarily on leaded aviation gasoline with bromide additives. This, coupled with the low relatively aviation-impact sector winds (Table 4.1), can help explain the observed low Br concentrations at the site 2 km from a GAA.

IMPLICATIONS

There are guidelines for the concentrations of Pb and As in ambient air. The US National Ambient Air Quality Standards exposure limit for Pb is a 3-month mean concentration of 150 ng/m³ in total suspended particulate matter.³⁹ While our observed air concentrations are orders of magnitude below the NAAQS (and were not taken for regulatory purposes), it is important to note: (1) CDC states that there is no safe level of lead, and that adverse effects can be observed even at low levels³¹ (2) the guideline for total suspended particulate matter encompasses a wider size range of particulates than what we reported (PM_{2.5}), so measured concentration of PM_{2.5}-Pb may underestimate the ambient concentrations. The World Health Organization reports that there is no safe level for As inhalation, with an excess lifetime risk level of 1:1,000,000 at an air concentration of 0.66 ng/m³, which is comparable to the average concentrations measured at the GAA sites.³⁸ While no ambient air standard has been promulgated for Br, ethylene dibromide (avgas additive) is listed as a Hazardous Air Pollutant under the US EPA Clean Air Act and is “likely to be carcinogenic to humans” based on strong evidence of carcinogenicity in animals and inconclusive evidence in humans.¹⁸⁰

Our results underscore the need for reliable, scalable methods to assess avgas exposure in communities near PEA-servicing airports, given the EPA’s recent

endangerment findings. Our study confirms that distance from the airport is a helpful metric for exposure, particularly for time-integrated samples such as those used in the EPA's 3-month rolling average Pb NAAQS. We further demonstrate that, for such samples, proximity may outweigh downwind/upwind meteorological considerations, reinforcing the importance of where pilots perform their engine run-ups during pre-takeoff checks.³³ Importantly, our findings extend beyond lead, highlighting potential exposure to additional PM_{2.5} elemental constituents such as bromine (Br) and arsenic (As), which may pose carcinogenic risks. These findings emphasize the importance of expanded environmental monitoring to quantify contributions from avgas and other potential sources. By providing an empirical assessment of exposure metrics via time-integrated elemental composition, this study offers tools for communities and regulators working to mitigate risks associated with PEA traffic.

ACKNOWLEDGEMENTS

We thank the residents of the towns of Mansfield, Norton, Bedford, Concord, and Lincoln for providing access to monitoring locations. We thank Arianna Cozza and Isabelle Berman for field support. Funding for this work came from the BU Initiative on Cities, BU Predoctoral Research Ignition Award, and the Hanscom Area Town Select Boards. The views presented in this manuscript are solely those of the authors.

CHAPTER FIVE. CONCLUSIONS

This dissertation employed in situ environmental monitoring coupled with statistical modeling to apportion aviation-related emissions and evaluate their impacts on ambient air quality in communities near airports. This research provides comprehensive new insights into the contributions of aviation activities to UFP and PM_{2.5} pollution, while accounting for complex non-linear interactions with meteorology and other concurrent emission sources. Collectively, these findings enhance our understanding of how aviation emissions intersect with community exposures, offering valuable implications for regulatory policy and targeted air pollution mitigation strategies.

Chapter Summaries

Chapter Two: Changes in ultrafine particle concentrations near a major airport following reduced transportation activity during the COVID-19 pandemic

Chapter Two investigates the contributions of two major sources of urban ultrafine particles (measured as particle number concentration, PNC)—automobile road traffic and airport operations—at a monitoring site in Chelsea, Massachusetts, U.S.A. located near a major interstate-highway and Logan International Airport. By leveraging the unprecedented mobility reductions following the COVID-19 pandemic as a natural experiment, we were able to differentiate the contributions of these sources more clearly. Given that reductions in aviation activity were both larger and more sustained than those for ground transportation, this period offered a unique opportunity to isolate the impact of aviation on PNC. By comparing air quality data collected before the pandemic, during the

Massachusetts state-of-emergency (SOE), and up to a year following the SOE, we found that mean PNC generally mirrored changes in road traffic activity. However, the highest PNC levels were consistently observed when winds carried emissions from the airport, highlighting aviation as a significant and complex contributor. These elevated pollution periods were notably diminished during the period of SOE reduced aviation activity. This chapter lays the groundwork for distinguishing aviation-related contributions to ambient PNC in near-airport communities. More broadly, it quantifies how shifts in transportation patterns can influence local air quality and highlights the need to consider aviation as a distinct and impactful source when assessing exposure and developing mitigation strategies.

Chapter Three: Quantifying aviation-related contributions to ambient ultrafine particle number concentrations using interpretable machine learning

Chapter Three builds on the previous chapter by quantitatively assessing how in-flight aviation activity contributes to PNC at the Chelsea, Massachusetts monitoring site at an hourly basis. We applied a machine learning (ML) model to isolate in-flight aviation-related impacts while accounting for other influences such as road traffic, ground-level airport operations, and meteorological conditions. Our approach captured the complex, nonlinear interactions between PNC and aviation activity, using the Shapley Additive Explanations (SHAP) interpretable machine learning tool to reveal how these variables collectively influence hourly PNC. Results showed that specific flight activities—particularly arrivals on certain runways—significantly impacted local air quality, with effects varying based on wind direction and atmospheric conditions. This

work establishes a framework for retrospective exposure assessment by generating a high-resolution dataset that can delineate in-flight aircraft contributions. This dataset offers valuable opportunities for future epidemiological studies to assess the health impacts of aviation-related air pollution in near-airport communities.

Chapter Four: Exposure to hazardous air pollutants in communities near U.S. General Aviation Airports

In Chapter Four, we expanded our study domain beyond Commercial Service Airports to study the impacts of General Aviation Airports (GAAs) on near airfield community air pollution exposure. GAAs are defined as public airports with scheduled service of <2500 passenger boardings annually and serve as primary hubs for the U.S.’ approximately 200,000 piston-engine aircraft fleet operations primarily on leaded aviation gasoline (avgas). We collected data on particulate-bound elements at two contrasting GAAs (one piston-engine dominated, one jet-engine dominated) and compared measurements with U.S. Environmental Protection Agency (EPA) monitors. Samples indicated aviation signatures and were enriched in Bromine, Arsenic, Lead, Sulfur, and Zinc at levels indicating substantial anthropogenic sources. Our results reinforce distance as an important indicator of pollutant concentrations and highlight other potential pollutant exposures beyond Lead that near-airport communities may be exposed to.

Study Strengths

This dissertation adds to a growing body of literature on aviation-specific emissions contribution to ambient air quality. Currently, only a small number of analyses have attempted to disentangle aviation-specific emissions from other sources. Our work can be distinguished from others in several ways: (1) We leveraged a uniquely long-term dataset of ultrafine particles measurements collected in the community (not just at the airport fence line) where people live, work, and recreate. Long duration monitoring at 1-second resolution (used in Chapters 2 and 3) provided the statistical power to discern influences and rare events. (2) We exploited the unprecedented COVID-19 related mobility reductions of 2020–2021 to observe the atmosphere under dramatically altered source conditions (i.e. sharp declines in flight and road traffic). This scenario allowed us to train and validate models under a wide range of conditions — including scenarios of very low aviation activity — strengthening the generalizability of the model developed in Chapter 3. (3) We implemented rigorous quality assurance and control in data collection and analysis, improving confidence in our apportionment results. (4) We expanded the research domain beyond CSAs to include GAAs, initiating one of the first detailed field investigations of general aviation emissions in community air (Chapter 4). Given there are ~3,000 GAAs in the U.S., our study at two sites provides a template for broader assessments. (5) Our study was designed specifically to capture aviation impacts: we sited UFP monitors at least 200 m from major roadways to minimize direct traffic influence and in alignment with runways to maximize sensitivity to aircraft plumes. This strategic placement improved our ability to detect aviation signals. (6) Lastly, we

incorporated relevant covariates for both surface and upper-level meteorology, as well as an on-ground aircraft activity proxy (taxi/runway time) in the Chapter 3 UFP model, which helped us to distinguish landing versus takeoff contributions by runway. Together, these strengths mean that our findings are robust and our methods can be adapted to other locations to continue advancing air quality research.

Study Limitations

While each chapter discusses its specific limitations in detail, there are several overarching limitations to acknowledge.

A primary challenge is the generalizability of our findings beyond the specific sites and conditions studied. Chapters 2 and 3 relied on data from a single monitoring location near one major airport (Logan Airport). Thus, the UFP source apportionment model we developed is optimized to the mix of emissions and meteorology patterns characteristic of that site. Given that UFPs are highly influenced by local meteorology and tend to remain in the atmosphere on the order of minutes, collecting localized data is essential for accurate model development. However, this reliance on site-specific data can limit the direct transferability of the model developed in Chapter 3 to other geographic locations or timeframes. Despite this limitation, the methodological framework — applying machine learning models combined with SHAP interpretation using analogous data inputs — remains broadly applicable. This approach can be effectively adapted to other communities to assess aviation-related UFP contributions. Similarly, Chapter 4 involved only two GAAs with limited non-concurrent samples. The small number of sites and samples constrains our ability to perform more sophisticated

spatial analyses.

Another limitation involves the trade-offs of our methodological approaches. In Chapters 2 and 4, we used primarily descriptive and inferential analyses (comparing period, calculating enrichment factors), which are useful for hypothesis generation and for quantifying different, but they do not provide a mechanistic explanation. In Chapter 3, we utilized an empirical-based statistical model instead of a first-principles dispersion model. We made this choice because certain microphysical processes governing UFP formation and evolution in aircraft plumes (e.g. interactions between hot exhaust and ambient humidity, nucleation bursts in cooling plumes) are still not fully understood or readily parameterized.⁴⁸ By using ML, we circumvented the need to explicitly model these processes; however, this means our model's predictors and SHAP interpretation, while insightful, do not replace a causal atmospheric process model. A physics-based dispersion model (with chemistry) could directly simulate scenarios (e.g. introducing sustainable aviation fuels or altered flight paths) in ways our statistic model cannot with new training data. Thus, our approach should be seen as complementary to, rather than a replacement for, chemical transport modeling efforts.

We also recognize that airports are complex emission environments and our models include only proxies for some of these various emission sources. In Chapter 3, for instance, we included a covariate for total aircraft taxi time per hour as an indicator of ground emissions from aircraft and support equipment. This helped isolate the in-flight signal, but it is an imperfect measure that cannot fully capture all ground-based activities (ground support vehicles, auxiliary power units, etc.). There likely remains residual

contributions from these sources that we did not explicitly model.

Furthermore, instrumentation and measurement limitations present another caveat. Our UFP data come from concentration particle counters (CPCs) measuring total particle number concentrations (PNC) above a certain minimum detection limit ($D_{50} > 7$ nm). While PNC is a widely used proxy for UFP exposure, it does not provide size-resolved information. Different UFP size fractions have different behaviors and health implications, and particle size distribution measurements are frequently used to distinguish source characteristics. A key challenge lies in the lack of a universally accepted definition for UFPs; the most common threshold ($D_p < 100$ nm) is somewhat arbitrary and does not effectively capture total particle number (dominated by nucleation mode, $D_p < 30$ nm) or particle mass (dominated by accumulation mode, $100 \text{ nm} > D_p > 1000$ nm).¹⁸¹ The lack of standardized metrics for UFP size classification, detection methods, instrument calibration, and quality control complicates cross-study comparisons. In Chapter 4, our filter-based sampling integrated measurements over 7–14 days, so we could not directly tie elemental peaks to specific short-term airport activities or meteorological events. Despite these constraints, our multi-method approach provided complementary perspectives that offer valuable insights into source contributions and exposure assessment in near-airport communities.

Moreover, while the insights from Chapters 2, 3, and 4 offer valuable contributions to understanding aviation-related air pollution in near-airport communities, further work is needed to extend these findings to epidemiological applications. Specifically, for our models to be applied in population-level health studies, there must

be a deeper understanding of the spatial variation in UFP concentrations within communities, as well as across different microenvironments. Total personal exposure to UFPs is influenced not only by ambient concentrations, but also by individual time-activity patterns, including time spent indoors, commuting, and in occupational settings.^{79,182,183} Without accounting for these contextual factors, exposure misclassification could bias health effect estimates.

Public Health Impact

Commercial and general aviation operations in the U.S. are projected to grow significantly in the coming decades, and this growth — coupled with the EPA's recent finding that leaded avgas endangers health — creates an increasing urgency to understand and mitigate the environmental health consequences of aviation. Our research highlights several key public health implications of aviation emissions, particularly their disproportionate impact on populations living near airports.

Chapters 2 and 3 demonstrated that people in airport-adjacent communities are regularly exposed to elevated UFP levels. In our study area, the average 1-hour PNC throughout 2014–2022 was on the order of 15,000 particles / cm³, which approaches the WHO's suggested 1-hour guideline of 20,000 particles / cm³. During hours affected by aviation emissions, 1-hour average UFP counts were often two-fold higher than this guideline, indicating episodes of very poor air quality by the WHO UFP guidelines. It is important to note that UFPs remain unregulated and largely unmonitored in the U.S., even though they have significant potential to harm human health due to their size and reactivity. Our findings add to a growing recognition that airport-related UFP exposure is

a distinct concern: unlike roadway UFP, which dissipates within a few hundred meters, aviation UFP can affect communities many kilometers away, potentially impacting a larger population footprint. This begets policymakers to considering monitoring UFP in near-airport areas and evaluating the need for UFP-specific guidelines, as a complement to existing PM standards.

Although the potential health risks of UFP exposure are well recognized, their direct role in adverse health outcomes remains debated. The EPA Integrated Science Assessment found short-term UFP exposure to be suggestive of cardiovascular and respiratory effects, but not sufficient to infer a causal relationship. Similarly, the Health Effects Institute concluded that existing evidence does not definitively link health effects to UFP exposure alone. Both organizations emphasized the need for further research of UFP spatial and temporal variability and the importance of distinguishing UFP impacts from those of other co-pollutants. By quantitatively apportioning aviation UFP from other sources, our work can help improve exposure classification in future studies — for example, allowing researchers to compare health data between time periods or locations with high modeled aviation UFP versus low aviation UFP. Such improved exposure assessment is a step toward clarifying the role airport UFP exposures contribute to health effects. Our research shows that, even in the absence of formal UFP regulations, there are practical mitigation opportunities that airport authorities could pursue. Chapter 3's granular results on contributions from different operational modes provide actionable data: airport managers could use this dataset to optimize taxiing routes or adjust runway usage patterns during certain wind conditions to reduce community exposures.

Additionally, acknowledging that jet fuel composition influences UFP formation, the aviation industry's ongoing transition toward sustainable aviation fuels (SAFs) offers a potential strategy to reduce UFP emissions at the source. While SAF adoption raises concerns regarding land use changes and competition with food production, our work provides a baseline against which such changes could be measured, and it emphasizes the need to consider trade-offs in the broader context of public health benefits.

In contrast to UFP — an emerging pollutant of concern — Chapter 4 addresses a well-known hazard: lead exposure. Lead's toxicity has been recognized for centuries, and it can damage virtually every organ system, with children being particularly vulnerable and persistent racial and ethnic disparities in lead exposure. Through past policy interventions, the U.S. achieved dramatic reductions in lead exposure from sources like vehicle fuel and paint, resulting in a significant reduction in average childhood blood lead levels over the last few decades. However, this success story has a notable exception in the aviation sector. The Clean Air Act (CAA) enabled the EPA to regulate lead as a criteria pollutant and set vehicle fuel standards, but aviation fuel was not subject to the same regulations because authority over aircraft fuel lies with the FAA. Given the EPA's 2023 endangerment finding on leaded aviation gasoline, regulatory action is now required. However, uncertainty remains regarding exposure pathways, particularly given the widespread use of piston-engine aircraft—nearly 170,000 across 2,500 general aviation airports (GAAs) in the U.S. Our study reinforces why this action is vital: we found that ambient lead levels around GAAs are elevated above background, confirming that communities near GAAs are continually exposed to this health hazard. We also

provided field validation for using distance as a proxy for lead exposure — a simpler metric often used in risk assessments and policy discussions. The fact that lead concentrations in our data dropped off with distance supports the current practice of focusing mitigations (like land-use restrictions or educational outreach for blood lead testing) on the most proximate neighborhoods. However, our findings also raise new concerns. The detection of other hazardous elements (such as arsenic and bromine) around GA airports suggests that phasing out lead alone will not eliminate all pollution risks from piston-engine aircraft. While removing lead from avgas will yield tremendous health benefits, communities near GAAs may continue to experience air quality impacts from the combustion of 100LL's replacement fuel, as well as from the remaining activities at these airports. The cumulative environmental health impact of GA airports — considering noise, lead, UFPs, and other pollutants — warrants further study and attention. In the interim, public health officials in affected areas might consider additional measures, such as installing filtration systems in schools near busy GA runways or implementing buffer zones and operational changes on high-pollution days to protect residents.

In conclusion, this dissertation's findings come at a pivotal moment for the aviation industry. The sector is balancing ambitious growth and modernization plans with environmental responsibilities. Airlines and airports have committed to net-zero greenhouse emissions by 2050, but achieving this will require not only addressing CO₂ through cleaner fuels and efficiency but also tackling co-pollutants like UFPs and lead that directly affect local communities. Our work provides a scientific basis for some

immediate steps: it identifies when and where aviation emissions matter most for local air quality, and it suggests that interventions targeting specific aspects of airport operations can yield tangible exposure reductions. As aviation regulators and stakeholders work to craft policies, we hope that the evidence presented here — quantifying the distinct contributions of landings vs. takeoffs, separating aircraft emissions from road traffic, and revealing the multi-pollutant nature of GAA plumes — will inform risk assessments and mitigation efforts. Continued research should build on these findings, expanding to more airports and incorporating health outcome data, to ultimately ensure that the benefits of aviation do not come at the expense of the health of those living under the flight paths.

Directions for Future Work

While this dissertation has advanced our understanding of aviation emissions and their public health impacts, it also highlights several research gaps for further investigation:

- Engine Exhaust Plume Dynamics: Further research is needed to characterize the size, composition, and transformational behavior of both volatile and non-volatile particles as they are transported downwind from aircraft exhaust plumes.
- Alternative Fuels and UFP: As sustainable aviation fuels are tested, it is important to investigate changes in UFP emissions under varying sulfur contents beyond controlled settings to assess the trade-offs of sustainable aviation fuels.
- LTO cycle and UFP: Our work suggests arriving aircraft can contribute at least as much to community UFP exposures as departures, aligning with some studies while diverging from others. Understanding the conditions under which arrivals versus

departure aircraft dominate UFP impacts will be key for optimizing flight operations to minimize pollution.

- Standardization of UFP Measurement Protocols: A recurring issue in UFP research is the lack of standardized measurement protocols. Studies use different size cut-offs, averaging times, and instrumentation, which hampers direct comparison. There is a need for the scientific community and regulators to converge on standard UFP metrics and methods. This could involve establishing a reference method for UFP number concentration or size distribution, akin to how PM_{2.5} is standardized, and conducting inter-comparison workshops for UFP monitors.
- GAA Monitoring Infrastructure: With thousands of GAAs in the country and a wide diversity among them, our Chapter 4 findings should be validated and extended. Setting up monitoring at a representative sample of GAAs — capturing different climates, operational scales, and surrounding community types — would help determine how generalizable our observations are. Such studies should not only monitor lead but also other pollutants (UFP, black carbon, VOCs, etc.) to provide a better estimate of the cumulative air quality burden borne by nearby communities. GAAs are highly heterogenous in terms of engine types, operations, and emissions.

Addressing these future work areas will further close the research gaps identified in this dissertation. Through continued interdisciplinary efforts, including engineering, atmospheric science, exposure assessment, and epidemiology, we can ensure that the benefits of aviation are balanced with health-protective measures for nearby communities.

BIBLIOGRAPHY

- (1) Schraufnagel, D. E.; Balmes, J. R.; Cowl, C. T.; Matteis, S. D.; Jung, S.-H.; Mortimer, K.; Perez-Padilla, R.; Rice, M. B.; Riojas-Rodriguez, H.; Sood, A.; Thurston, G. D.; To, T.; Vanker, A.; Wuebbles, D. J. Air Pollution and Noncommunicable Diseases: A Review by the Forum of International Respiratory Societies' Environmental Committee, Part 1: The Damaging Effects of Air Pollution. *Chest* **2019**, *155* (2), 409–416. <https://doi.org/10.1016/j.chest.2018.10.042>.
- (2) Thunis, P.; Clappier, A.; Tarrason, L.; Cuvelier, C.; Monteiro, A.; Pisoni, E.; Wesseling, J.; Belis, C. A.; Pirovano, G.; Janssen, S.; Guerreiro, C.; Peduzzi, E. Source Apportionment to Support Air Quality Planning: Strengths and Weaknesses of Existing Approaches. *Environment International* **2019**, *130*, 104825. <https://doi.org/10.1016/j.envint.2019.05.019>.
- (3) Hudda, N.; Gould, T.; Hartin, K.; Larson, T. V.; Fruin, S. A. Emissions from an International Airport Increase Particle Number Concentrations 4-Fold at 10 Km Downwind. *Environmental Science & Technology* **2014**, *48* (12), 6628–6635. <https://doi.org/10.1021/es5001566>.
- (4) US U.S. Environmental Protection Agency. *National Emissions Inventory (NEI)*. <https://www.epa.gov/air-emissions-inventories/national-emissions-inventory-nei> (accessed 2022-05-06).
- (5) Federal Aviation Administration. *FAA Aerospace Forecast Fiscal Years 2024–2044*. https://www.faa.gov/data_research/aviation (accessed 2022-06-22).
- (6) Federal Aviation Administration. *Airport Categories*. https://www.faa.gov/airports/planning_capacity/categories (accessed 2025-01-13).
- (7) Masiol, M.; Harrison, R. M. Aircraft Engine Exhaust Emissions and Other Airport-Related Contributions to Ambient Air Pollution: A Review. *Atmospheric Environment* **2014**, *95*, 409–455. <https://doi.org/10.1016/j.atmosenv.2014.05.070>.
- (8) International Civil Aviation Organization (ICAO). *Airport Air Quality Manual*; Doc 9889; Montreal, Quebec, Canada, 2011. https://www.icao.int/sites/default/files/2025-04/9889_cons_en.pdf
- (9) Dockery, D. W.; Pope, C. A.; Xu, X.; Spengler, J. D.; Ware, J. H.; Fay, M. E.; Ferris, B. G.; Speizer, F. E. An Association between Air Pollution and Mortality in Six U.S. Cities. *New England Journal of Medicine* **1993**, *329* (24), 1753–1759. <https://doi.org/10.1056/NEJM199312093292401>.

- (10) Schraufnagel, D. E. The Health Effects of Ultrafine Particles. *Experimental & Molecular Medicine* **2020**, *52* (3), 311–317. <https://doi.org/10.1038/s12276-020-0403-3>.
- (11) Health Effects Institute. . *Understanding the Health Effects of Ambient Ultrafine Particles*. Health Effects Institute. <https://www.healtheffects.org/publication/understanding-health-effects-ambient-ultrafine-particles>.
- (12) U.S. Environmental Protection Agency. *Integrated Science Assessment (ISA) for Particulate Matter (Final Report, Dec 2019)*; Reports & Assessments EPA/600/R-19-188; U.S. Environmental Protection Agency: Washington, DC, 2019.
- (13) Ohlwein, S.; Kappeler, R.; Kutlar Joss, M.; Künzli, N.; Hoffmann, B. Health Effects of Ultrafine Particles: A Systematic Literature Review Update of Epidemiological Evidence. *International Journal of Public Health* **2019**, *64* (4), 547–559. <https://doi.org/10.1007/s00038-019-01202-7>.
- (14) Schraufnagel, D. E.; Balmes, J. R.; De Matteis, S.; Hoffman, B.; Kim, W. J.; Perez-Padilla, R.; Rice, M.; Sood, A.; Vanker, A.; Wuebbles, D. J. Health Benefits of Air Pollution Reduction. *Annals of the American Thoracic Society* **2019**, *16* (12), 1478–1487. <https://doi.org/10.1513/AnnalsATS.201907-538CME>.
- (15) Geiser, M.; Rothen-Rutishauser, B.; Kapp, N.; Schürch, S.; Kreyling, W.; Schulz, H.; Semmler, M.; Hof, V. I.; Heyder, J.; Gehr, P. Ultrafine Particles Cross Cellular Membranes by Nonphagocytic Mechanisms in Lungs and in Cultured Cells. *Environmental Health Perspectives* **2005**, *113* (11), 1555–1560. <https://doi.org/10.1289/ehp.8006>.
- (16) Kwon, H.-S.; Ryu, M. H.; Carlsten, C. Ultrafine Particles: Unique Physicochemical Properties Relevant to Health and Disease. *Experimental & Molecular Medicine* **2020**, *52* (3), 318–328. <https://doi.org/10.1038/s12276-020-0405-1>.
- (17) Stacey, B. Measurement of Ultrafine Particles at Airports: A Review. *Atmospheric Environment* **2019**, *198*, 463–477. <https://doi.org/10.1016/j.atmosenv.2018.10.041>.
- (18) Bendtsen, K. M.; Bengtson, E.; Saber, A. T.; Vogel, U. A Review of Health Effects Associated with Exposure to Jet Engine Emissions in and around Airports. *Environmental Health* **2021**, *20* (1), 10. <https://doi.org/10.1186/s12940-020-00690-y>.
- (19) Austin, E.; Xiang, J.; Gould, T. R.; Shirai, J. H.; Yun, S.; Yost, M. G.; Larson, T. V.; Seto, E. Distinct Ultrafine Particle Profiles Associated with Aircraft and Roadway Traffic. *Environmental Science & Technology* **2021**, *55* (5), 2847–2858. <https://doi.org/10.1021/acs.est.0c05933>.

- (20) Stacey, B.; Harrison, R. M.; Pope, F. Evaluation of Ultrafine Particle Concentrations and Size Distributions at London Heathrow Airport. *Atmospheric Environment* **2020**, *222*, 117148. <https://doi.org/10.1016/j.atmosenv.2019.117148>.
- (21) Vallabani, N. V. S.; Gruzieva, O.; Elihn, K.; Juárez-Facio, A. T.; Steimer, S. S.; Kuhn, J.; Silvergren, S.; Portugal, J.; Piña, B.; Olofsson, U.; Johansson, C.; Karlsson, H. L. Toxicity and Health Effects of Ultrafine Particles: Towards an Understanding of the Relative Impacts of Different Transport Modes. *Environmental Research* **2023**, *231*, 116186. <https://doi.org/10.1016/j.envres.2023.116186>.
- (22) Lenssen, E. S.; Janssen, N. A. H.; Oldenwening, M.; Meliefste, K.; de Jonge, D.; Kamstra, R. J. M.; van Dinther, D.; van der Zee, S.; Keuken, R. H.; Hoek, G. Beyond the Runway: Respiratory Health Effects of Ultrafine Particles from Aviation in Children. *Environment International* **2024**, *188*, 108759. <https://doi.org/10.1016/j.envint.2024.108759>.
- (23) Lammers, A.; Janssen, N. a. H.; Boere, A. J. F.; Berger, M.; Longo, C.; Vijverberg, S. J. H.; Neerincx, A. H.; Maitland-van der Zee, A. H.; Cassee, F. R. Effects of Short-Term Exposures to Ultrafine Particles near an Airport in Healthy Subjects. *Environment International* **2020**, *141*, 105779. <https://doi.org/10.1016/j.envint.2020.105779>.
- (24) Habre, R.; Zhou, H.; Eckel, S. P.; Enebish, T.; Fruin, S.; Bastain, T.; Rappaport, E.; Gilliland, F. Short-Term Effects of Airport-Associated Ultrafine Particle Exposure on Lung Function and Inflammation in Adults with Asthma. *Environment International* **2018**, *118*, 48–59. <https://doi.org/10.1016/j.envint.2018.05.031>.
- (25) Janssen, N. a. H.; Hoekstra, J.; Houthuijs, D.; Jacobs, J.; Nicolaie, A.; Strak, M. *Effects of Long-Term Exposure to Ultrafine Particles from Aviation around Schiphol Airport*; Report; Rijksinstituut voor Volksgezondheid en Milieu RIVM, 2022. <https://rivm.openrepository.com/handle/10029/625854> (accessed 2022-06-30).
- (26) World Health Organization. *Toolkit for Establishing Laws to Eliminate Lead Paint, Second Edition*; License: CC BY-NC-SA 3.0 IGO; Geneva, 2021.
- (27) Bellinger, D. C.; Bellinger, A. M. Childhood Lead Poisoning: The Torturous Path from Science to Policy. *Journal of Clinical Investigation* **2006**, *116* (4), 853–857. <https://doi.org/10.1172/JCI28232>.
- (28) World Health Organization. *Lead poisoning*. <https://www.who.int/news-room/fact-sheets/detail/lead-poisoning-and-health>.

- (29) Woolley, D. E. A Perspective of Lead Poisoning in Antiquity and the Present. *Neurotoxicology* **1984**, 5 (3), 353–361.
- (30) Ruckart, P. Z.; Jones, R. L.; Courtney, J. G. Update of the Blood Lead Reference Value - United States, 2021. **2022**.
- (31) U.S. Centers for Disease Control. *CDC Updates Blood Lead Reference Value*. Childhood Lead Poisoning Prevention. <https://www.cdc.gov/lead-prevention/php/news-features/updates-blood-lead-reference-value.html> (accessed 2025-01-29).
- (32) Miranda, M. L.; Anthopolos, R.; Hastings, D. A Geospatial Analysis of the Effects of Aviation Gasoline on Childhood Blood Lead Levels. *Environmental Health Perspectives* **2011**, 119 (10), 1513–1516. <https://doi.org/10.1289/ehp.1003231>.
- (33) National Academies of Sciences, Engineering, and Medicine. *Options for Reducing Lead Emissions from Piston-Engine Aircraft*; The National Academies Press: Washington, DC. <https://doi.org/10.17226/26050>.
- (34) Teye, S. O.; Yanosky, J. D.; Cuffee, Y.; Weng, X.; Luquis, R.; Farace, E.; Wang, L. Exploring Persistent Racial/Ethnic Disparities in Lead Exposure among American Children Aged 1–5 Years: Results from NHANES 1999–2016. *International Archives of Occupational and Environmental Health* **2021**, 94 (4), 723–730. <https://doi.org/10.1007/s00420-020-01616-4>.
- (35) US EPA, O. *Protecting Children from Lead Exposures*. <https://www.epa.gov/children/protecting-children-lead-exposures> (accessed 2022-05-06).
- (36) Rohr, A. C.; Wyzga, R. E. Attributing Health Effects to Individual Particulate Matter Constituents. *Atmospheric Environment* **2012**, 62, 130–152. <https://doi.org/10.1016/j.atmosenv.2012.07.036>.
- (37) Hinds, W. C.; Yifang, Z. *Aerosol Technology: Properties, Behavior, and Measurement of Airborne Particles*, Third; John Wiley & Sons, Inc.: Hoboken, NJ, USA, 2022.
- (38) World Health Organization. Global Air Quality Guidelines, 2021. 9789240034228-eng.pdf (who.int).
- (39) U.S. Environmental Protection Agency. *Review of the National Ambient Air Quality Standards for Lead*; 2016; Vol. EPA-HQ-OAR-2010-0108.
- (40) U.S. Environmental Protection Agency. *Nonattainment Areas for Criteria Pollutants (Green Book)*. <https://www.epa.gov/green-book> (accessed 2025-01-29).

- (41) *Finding That Lead Emissions From Aircraft Engines That Operate on Leaded Fuel Cause or Contribute to Air Pollution That May Reasonably Be Anticipated To Endanger Public Health and Welfare*. Federal Register.
<https://www.federalregister.gov/documents/2023/10/20/2023-23247/finding-that-lead-emissions-from-aircraft-engines-that-operate-on-leaded-fuel-cause-or-contribute-to> (accessed 2024-12-23).
- (42) U.S. Environmental Protection Agency. *Clean Air Act*; 1963; Vol. §§ 7401 et seq.
- (43) *Building an Unleaded Future by 2030 | Federal Aviation Administration*.
<https://www.faa.gov/unleaded> (accessed 2025-03-27).
- (44) Blázquez, A. L. G. Mathematical Modelling for Analysis of Nonlinear Aircraft Dynamics. *Computers & Structures* **1990**, 37 (2), 193–197.
[https://doi.org/10.1016/0045-7949\(90\)90401-M](https://doi.org/10.1016/0045-7949(90)90401-M).
- (45) Bossioli, E.; Tombrou, M.; Helmis, C.; Kurtenbach, R.; Wiesen, P.; Schäfer, K.; Dandou, A.; Varotsos, K. V. Issues Related to Aircraft Take-off Plumes in a Mesoscale Photochemical Model. *Science of The Total Environment* **2013**, 456–457, 69–81. <https://doi.org/10.1016/j.scitotenv.2013.02.091>.
- (46) Graham, A.; Raper, D. W. Transport to Ground of Emissions in Aircraft Wakes. Part I: Processes. *Atmospheric Environment* **2006**, 40 (29), 5574–5585.
<https://doi.org/10.1016/j.atmosenv.2006.05.015>.
- (47) Graham, A.; Raper, D. W. Transport to Ground of Emissions in Aircraft Wakes. Part II: Effect on NO_x Concentrations in Airport Approaches. *Atmospheric Environment* **2006**, 40 (30), 5824–5836.
<https://doi.org/10.1016/j.atmosenv.2006.05.014>.
- (48) Barrett, S. R. H.; Britter, R. E.; Waitz, I. A. Impact of Aircraft Plume Dynamics on Airport Local Air Quality. *Atmospheric Environment* **2013**, 74, 247–258.
<https://doi.org/10.1016/j.atmosenv.2013.03.061>.
- (49) Agrawal, H.; Sawant, A. A.; Jansen, K.; Wayne Miller, J.; Cocker, D. R. Characterization of Chemical and Particulate Emissions from Aircraft Engines. *Atmospheric Environment* **2008**, 42 (18), 4380–4392.
<https://doi.org/10.1016/j.atmosenv.2008.01.069>.
- (50) Herndon, S. C.; Jayne, J. T.; Lobo, P.; Onasch, T. B.; Fleming, G.; Hagen, D. E.; Whitefield, P. D.; Miake-Lye, R. C. Commercial Aircraft Engine Emissions Characterization of In-Use Aircraft at Hartsfield-Jackson Atlanta International Airport. *Environmental Science & Technology* **2008**, 42 (6), 1877–1883.
<https://doi.org/10.1021/es072029+>.
- (51) Stacey, B.; Harrison, R. M.; Pope, F. D. Emissions of Ultrafine Particles from Civil Aircraft: Dependence upon Aircraft Type and Passenger Load. *npj Climate*

- and Atmospheric Science* **2023**, 6 (1), 1–9. <https://doi.org/10.1038/s41612-023-00477-1>.
- (52) Mazaheri, M.; Bostrom, T. E.; Johnson, G. R.; Morawska, L. Composition and Morphology of Particle Emissions from In-Use Aircraft during Takeoff and Landing. *Environmental Science & Technology* **2013**, 47 (10), 5235–5242. <https://doi.org/10.1021/es3046058>.
- (53) Hudda, N.; Simon, M. C.; Zamore, W.; Brugge, D.; Durant, J. L. Aviation Emissions Impact Ambient Ultrafine Particle Concentrations in the Greater Boston Area. *Environmental Science & Technology* **2016**, 50 (16), 8514–8521. <https://doi.org/10.1021/acs.est.6b01815>.
- (54) Gordon, T. D.; Presto, A. A.; May, A. A.; Nguyen, N. T.; Lipsky, E. M.; Donahue, N. M.; Gutierrez, A.; Zhang, M.; Maddox, C.; Rieger, P.; Chattopadhyay, S.; Maldonado, H.; Maricq, M. M.; Robinson, A. L. Secondary Organic Aerosol Formation Exceeds Primary Particulate Matter Emissions for Light-Duty Gasoline Vehicles. *Atmospheric Chemistry and Physics* **2014**, 14 (9), 4661–4678. <https://doi.org/10.5194/acp-14-4661-2014>.
- (55) Zimmerman, A.; Petters, M. D.; Meskhidze, N. Observations of New Particle Formation, Modal Growth Rates, and Direct Emissions of Sub-10 Nm Particles in an Urban Environment. *Atmospheric Environment* **2020**, 242, 117835. <https://doi.org/10.1016/j.atmosenv.2020.117835>.
- (56) Watson, J.; Chow, J. Receptor Modeling for Air Quality Management. *Air and Waste Management Association's Magazine for Environmental Managers* **2004**, 10, 27–36. [https://doi.org/10.1016/S0922-3487\(08\)70127-8](https://doi.org/10.1016/S0922-3487(08)70127-8).
- (57) U.S. Environmental Protection Agency. *National Analysis of the Populations Residing Near or Attending School Near U.S. Airports*; EPA-420-R-20-001; Research Triangle Park, NC, 2020. <https://nepis.epa.gov/Exe/ZyNET.exe/P100YG4A.TXT?ZyActionD=ZyDocument&Client=EPA&Index=2016+Thru+2020&Docs=&Query=&Time=&EndTime=&SearchMethod=1&TocRestrict=n&Toc=&TocEntry=&QField=&QFieldYear=&QFieldMonth=&QFieldDay=&IntQFieldOp=0&ExtQFieldOp=0&XmlQuery=&File=D%3A%5Czyfiles%5CIndex%20Data%5C16thru20%5CTxt%5C00000017%5CP100YG4A.txt&User=ANONYMOUS&Password=anonymous&SortMethod=h%7C-&MaximumDocuments=1&FuzzyDegree=0&ImageQuality=r75g8/r75g8/x150y150g16/i425&Display=hpfr&DefSeekPage=x&SearchBack=ZyActionL&Back=ZyActionS&BackDesc=Results%20page&MaximumPages=1&ZyEntry=1&SeekPage=x&ZyPURL> (accessed 2025-01-13).
- (58) Soale, A.-N.; Callender, R.; Guignet, D.; Shadbegian, R.; Miranda, M. L. Association between Residential Distance to Airport and Blood Lead Levels in

- Children under 6 Living in North Carolina, 1992–2015. *Environmental Health Perspectives* **2024**, *132* (8), 087701. <https://doi.org/10.1289/EHP14362>.
- (59) Zahran, S.; Iverson, T.; McElmurry, S. P.; Weiler, S. The Effect of Leaded Aviation Gasoline on Blood Lead in Children. *Journal of the Association of Environmental and Resource Economists* **2017**, *4* (2), 575–610. <https://doi.org/10.1086/691686>.
- (60) Zahran, S.; Keyes, C.; Lanphear, B. Leaded Aviation Gasoline Exposure Risk and Child Blood Lead Levels. *PNAS Nexus* **2023**, *2* (1), pgac285. <https://doi.org/10.1093/pnasnexus/pgac285>.
- (61) Shirmohammadi, F.; Lovett, C.; Sowlat, M. H.; Mousavi, A.; Verma, V.; Shafer, M. M.; Schauer, J. J.; Sioutas, C. Chemical Composition and Redox Activity of PM_{0.25} near Los Angeles International Airport and Comparisons to an Urban Traffic Site. *Science of The Total Environment* **2018**, *610–611*, 1336–1346. <https://doi.org/10.1016/j.scitotenv.2017.08.239>.
- (62) Bendtsen, K. M.; Brostrøm, A.; Koivisto, A. J.; Koponen, I.; Berthing, T.; Bertram, N.; Kling, K. I.; Dal Maso, M.; Kangasniemi, O.; Poikkimäki, M.; Loeschner, K.; Clausen, P. A.; Wolff, H.; Jensen, K. A.; Saber, A. T.; Vogel, U. Airport Emission Particles: Exposure Characterization and Toxicity Following Intratracheal Instillation in Mice. *Particle and Fibre Toxicology* **2019**, *16* (1), 23. <https://doi.org/10.1186/s12989-019-0305-5>.
- (63) Healthy Chelsea. Who We Are: Our History, 2025. <https://healthychelsea.org/who-we-are/>.
- (64) Executive Office of Energy and Environmental Affairs. *Environmental Justice Populations in Massachusetts*. <https://www.mass.gov/info-details/environmental-justice-populations-in-massachusetts> (accessed 2025-02-20).
- (65) Friedman, M. S.; Powell, K. E.; Hutwagner, L.; Graham, L. M.; Teague, W. G. Impact of Changes in Transportation and Commuting Behaviors During the 1996 Summer Olympic Games in Atlanta on Air Quality and Childhood Asthma. *JAMA: The Journal of the American Medical Association* **2001**, *285* (7), 897–905. <https://doi.org/10.1001/jama.285.7.897>.
- (66) Pope, C. A.; Schwartz, J.; Ransom, M. R. Daily Mortality and PM₁₀ Pollution in Utah Valley. *Archives of Environmental Health* **1992**, *47* (3), 211–217. <https://doi.org/10.1080/00039896.1992.9938351>.
- (67) Wang, Y.; Hao, J.; McElroy, M. B.; Munger, J. W.; Ma, H.; Chen, D.; Nielsen, C. P. Ozone Air Quality during the 2008 Beijing Olympics: Effectiveness of Emission Restrictions. *Atmospheric Chemistry and Physics* **2009**, *9* (14), 5237–5251. <https://doi.org/10.5194/acp-9-5237-2009>.

- (68) *Global Energy Review 2020 – Analysis*. IEA. <https://www.iea.org/reports/global-energy-review-2020> (accessed 2022-04-21).
- (69) *Twenty Years Later, How Does Post-9/11 Air Travel Compare to the Disruptions of COVID-19?* | Bureau of Transportation Statistics. <https://www.bts.gov/data-spotlight/twenty-years-later-how-does-post-911-air-travel-compare-disruptions-covid-19> (accessed 2022-04-21).
- (70) He, G.; Pan, Y.; Tanaka, T. The Short-Term Impacts of COVID-19 Lockdown on Urban Air Pollution in China. *Nature Sustainability* **2020**, *3* (12), 1005–1011. <https://doi.org/10.1038/s41893-020-0581-y>.
- (71) Lu, D.; Zhang, J.; Xue, C.; Zuo, P.; Chen, Z.; Zhang, L.; Ling, W.; Liu, Q.; Jiang, G. COVID-19-Induced Lockdowns Indicate the Short-Term Control Effect of Air Pollutant Emission in 174 Cities in China. *Environmental Science & Technology* **2021**, *55* (7), 4094–4102. <https://doi.org/10.1021/acs.est.0c07170>.
- (72) Eleftheriadis, K.; Gini, M. I.; Diapouli, E.; Vratolis, S.; Vasilatou, V.; Fetfatzis, P.; Manousakas, M. I. Aerosol Microphysics and Chemistry Reveal the COVID19 Lockdown Impact on Urban Air Quality. *Scientific Reports* **2021**, *11* (1), 14477. <https://doi.org/10.1038/s41598-021-93650-6>.
- (73) Yadav, S. K.; Kompalli, S. K.; Gurjar, B. R.; Mishra, R. K. Aerosol Number Concentrations and New Particle Formation Events over a Polluted Megacity during the COVID-19 Lockdown. *Atmospheric Environment* **2021**, *259*, 118526. <https://doi.org/10.1016/j.atmosenv.2021.118526>.
- (74) Bekbulat, B.; Apte, J. S.; Millet, D. B.; Robinson, A. L.; Wells, K. C.; Presto, A. A.; Marshall, J. D. Changes in Criteria Air Pollution Levels in the US before, during, and after Covid-19 Stay-at-Home Orders: Evidence from Regulatory Monitors. *Science of The Total Environment* **2021**, *769*, 144693. <https://doi.org/10.1016/j.scitotenv.2020.144693>.
- (75) Silva, A. C. T.; Branco, P. T. B. S.; Sousa, S. I. V. Impact of COVID-19 Pandemic on Air Quality: A Systematic Review. *International Journal of Environmental Research and Public Health* **2022**, *19* (4), 1950. <https://doi.org/10.3390/ijerph19041950>.
- (76) Hudda, N.; Simon, M. C.; Patton, A. P.; Durant, J. L. Reductions in Traffic-Related Black Carbon and Ultrafine Particle Number Concentrations in an Urban Neighborhood during the COVID-19 Pandemic. *The Science of the Total Environment* **2020**, *742*, 140931. <https://doi.org/10.1016/j.scitotenv.2020.140931>.
- (77) Xiang, J.; Austin, E.; Gould, T.; Larson, T.; Shirai, J.; Liu, Y.; Marshall, J.; Seto, E. Impacts of the COVID-19 Responses on Traffic-Related Air Pollution in a

- Northwestern US City. *The Science of the Total Environment* **2020**, 747, 141325. <https://doi.org/10.1016/j.scitotenv.2020.141325>.
- (78) Dai, Q.; Ding, J.; Song, C.; Liu, B.; Bi, X.; Wu, J.; Zhang, Y.; Feng, Y.; Hopke, P. K. Changes in Source Contributions to Particle Number Concentrations after the COVID-19 Outbreak: Insights from a Dispersion Normalized PMF. *Science of The Total Environment* **2021**, 759, 143548. <https://doi.org/10.1016/J.SCITOTENV.2020.143548>
- (79) Hudda, N.; Simon, M. C.; Zamore, W.; Durant, J. L. Aviation-Related Impacts on Ultrafine Particle Number Concentrations Outside and Inside Residences near an Airport. *Environmental Science & Technology* **2018**, 52 (4), 1765–1772. <https://doi.org/10.1021/acs.est.7b05593>.
- (80) Keuken, M. P.; Moerman, M.; Zandveld, P.; Henzing, J. S.; Hoek, G. Total and Size-Resolved Particle Number and Black Carbon Concentrations in Urban Areas near Schiphol Airport (the Netherlands). *Atmospheric Environment* **2015**, 104, 132–142. <https://doi.org/10.1016/j.atmosenv.2015.01.015>.
- (81) Ungeheuer, F.; van Pinxteren, D.; Vogel, A. L. Identification and Source Attribution of Organic Compounds in Ultrafine Particles near Frankfurt International Airport. *Atmospheric Chemistry and Physics* **2021**, 21 (5), 3763–3775. <https://doi.org/10.5194/acp-21-3763-2021>.
- (82) Simon, M. C.; Hudda, N.; Naumova, E. N.; Levy, J. I.; Brugge, D.; Durant, J. L. Comparisons of Traffic-Related Ultrafine Particle Number Concentrations Measured in Two Urban Areas by Central, Residential, and Mobile Monitoring. *Atmospheric Environment* **2017**, 169, 113–127. <https://doi.org/10.1016/j.atmosenv.2017.09.003>.
- (83) *COVID-19 State of Emergency | Mass.gov*. <https://www.mass.gov/info-details/covid-19-state-of-emergency> (accessed 2022-04-21).
- (84) *Federal Aviation Administration*. <https://aspm.faa.gov/> (accessed 2022-04-21).
- (85) *Automated Surface/Weather Observing Systems (ASOS/AWOS)*. National Centers for Environmental Information (NCEI). <http://www.ncei.noaa.gov/products/land-based-station/automated-surface-weather-observing-systems> (accessed 2022-04-21).
- (86) US EPA, O. *Meteorological Processors and Accessory Programs*. <https://www.epa.gov/scram/meteorological-processors-and-accessory-programs> (accessed 2022-05-16).
- (87) *EPA - Meteorological Monitoring Guidance for Regulatory Modeling Applications*. <https://dokumen.tips/documents/epa-meteorological-monitoring-guidance-for-regulatory-modeling-applications.html> (accessed 2022-07-11).

- (88) *Transportation Data Management System*.
<https://mhd.public.ms2soft.com/tcds/tsearch.asp?loc=Mhd&mod=> (accessed 2022-04-21).
- (89) Carslaw, D. C.; Ropkins, K. Openair — An R Package for Air Quality Data Analysis. *Environmental Modelling & Software* **2012**, 27–28, 52–61.
<https://doi.org/10.1016/j.envsoft.2011.09.008>.
- (90) Xiang, J.; Austin, E.; Gould, T.; Larson, T.; Shirai, J.; Liu, Y.; Marshall, J.; Seto, E. Impacts of the COVID-19 Responses on Traffic-Related Air Pollution in a Northwestern US City. *The Science of the Total Environment* **2020**, 747, 141325.
<https://doi.org/10.1016/j.scitotenv.2020.141325>.
- (91) Rich, D. Q. Accountability Studies of Air Pollution and Health Effects: Lessons Learned and Recommendations for Future Natural Experiment Opportunities. *Environment International* **2017**, 100, 62–78.
<https://doi.org/10.1016/j.envint.2016.12.019>.
- (92) Patten, K. T.; Valenzuela, A. E.; Wallis, C.; Berg, E. L.; Silverman, J. L.; Bein, K. J.; Wexler, A. S.; Lein, P. J. The Effects of Chronic Exposure to Ambient Traffic-Related Air Pollution on Alzheimer’s Disease Phenotypes in Wildtype and Genetically Predisposed Male and Female Rats. *Environmental Health Perspectives* **2021**, 129 (5), 57005. <https://doi.org/10.1289/EHP8905>.
- (93) Oberdörster, G.; Oberdörster, E.; Oberdörster, J. Nanotoxicology: An Emerging Discipline Evolving from Studies of Ultrafine Particles. *Environmental Health Perspectives* **2005**, 113 (7), 823–839. <https://doi.org/10.1289/ehp.7339>.
- (94) Kumar, P.; Morawska, L.; Birmili, W.; Paasonen, P.; Hu, M.; Kulmala, M.; Harrison, R. M.; Norford, L.; Britter, R. Ultrafine Particles in Cities. *Environment International* **2014**, 66, 1–10. <https://doi.org/10.1016/j.envint.2014.01.013>.
- (95) Masiol, M.; Harrison, R. M.; Vu, T. V.; Beddows, D. C. S. Sources of Sub-Micrometre Particles near a Major International Airport. *Atmospheric Chemistry and Physics* **2017**, 17 (20), 12379–12403. <https://doi.org/10.5194/acp-17-12379-2017>.
- (96) European Union. Industrial Emissions of Nano- and Ultrafine Particles: Final Report, 2013. <https://op.europa.eu/en/publication-detail/-/publication/f5002bc6-ddaa-48cb-9033-a9d12574a32e>.
- (97) Venecek, M. A.; Yu, X.; Kleeman, M. J. Predicted Ultrafine Particulate Matter Source Contribution across the Continental United States during Summertime Air Pollution Events. *Atmospheric Chemistry and Physics* **2019**, 19 (14), 9399–9412.
<https://doi.org/10.5194/acp-19-9399-2019>.

- (98) Riley, K.; Cook, R.; Carr, E.; Manning, B. A Systematic Review of The Impact of Commercial Aircraft Activity on Air Quality Near Airports. *City and Environment Interactions* **2021**, *11*, 10.1016/j.cacint.2021.100066. <https://doi.org/10.1016/j.cacint.2021.100066>.
- (99) Graham, A.; Raper, D. W. Transport to Ground of Emissions in Aircraft Wakes. Part I: Processes. *Atmospheric Environment* **2006**, *40*, 5574–5585. <https://doi.org/10.1016/j.atmosenv.2006.05.015>
- (100) Arter, C. A.; Arunachalam, S. Assessing the Importance of Nonlinearity for Aircraft Emissions' Impact on O₃ and PM_{2.5}. *Science of The Total Environment* **2021**, *777*, 146121. <https://doi.org/10.1016/j.scitotenv.2021.146121>.
- (101) Arunachalam, S.; Wang, B.; Davis, N.; Baek, B. H.; Levy, J. I. Effect of Chemistry-Transport Model Scale and Resolution on Population Exposure to PM_{2.5} from Aircraft Emissions during Landing and Takeoff. *Atmospheric Environment* **2011**, *45* (19), 3294–3300. <https://doi.org/10.1016/j.atmosenv.2011.03.029>.
- (102) Elleman, R. A.; Covert, D. S. Aerosol Size Distribution Modeling with the Community Multiscale Air Quality Modeling System in the Pacific Northwest: 1. Model Comparison to Observations. *Journal of Geophysical Research: Atmospheres* **2009**, *114* (D11). <https://doi.org/10.1029/2008JD010791>.
- (103) Adamkiewicz, G.; Hsu, H.-H.; Melly, S.; Zarubiak, D.; Spengler, J.; Levy, J. Contributions of Aircraft Activity, Local Sources and Meteorology to Ultrafine Particle Counts Near a Large Airport. *Epidemiology* **2011**, *22* (1), S216. <https://doi.org/10.1097/01.ede.0000392347.07581.a5>.
- (104) Hsu, H.-H.; Adamkiewicz, G.; Houseman, E. A.; Zarubiak, D.; Spengler, J. D.; Levy, J. I. Contributions of Aircraft Arrivals and Departures to Ultrafine Particle Counts near Los Angeles International Airport. *Science of The Total Environment* **2013**, *444*, 347–355. <https://doi.org/10.1016/j.scitotenv.2012.12.010>.
- (105) Stacey, B.; Harrison, R. M.; Pope, F. D. Evaluation of Aircraft Emissions at London Heathrow Airport. *Atmospheric Environment* **2021**, *254*, 118226. <https://doi.org/10.1016/j.atmosenv.2021.118226>.
- (106) Fritz, S.; Grusdat, F.; Sharkey, R.; Schneider, C. Impact of Airport Operations and Road Traffic on the Particle Number Concentration in the Vicinity of a Suburban Airport. *Frontiers in Environmental Science* **2022**, *10*.
- (107) Mueller, S. C.; Hudda, N.; Levy, J. I.; Durant, J. L.; Patil, P.; Lee, N. F.; Weiss, I.; Tatro, T.; Duhl, T.; Lane, K. Changes in Ultrafine Particle Concentrations near a Major Airport Following Reduced Transportation Activity during the COVID-19

- Pandemic. *Environmental Science & Technology Letters* **2022**, 9 (9), 706–711.
<https://doi.org/10.1021/acs.estlett.2c00322>.
- (108) Chung, C. S.; Lane, K. J.; Black-Ingersoll, F.; Kolaczyk, E.; Schollaert, C.; Li, S.; Simon, M. C.; Levy, J. I. Assessing the Impact of Aircraft Arrival on Ambient Ultrafine Particle Number Concentrations in Near-Airport Communities in Boston, Massachusetts. *Environmental Research* **2023**, 225, 115584.
<https://doi.org/10.1016/j.envres.2023.115584>.
- (109) Bellinger, C.; Mohamed Jabbar, M. S.; Zaïane, O.; Osornio-Vargas, A. A Systematic Review of Data Mining and Machine Learning for Air Pollution Epidemiology. *BMC Public Health* **2017**, 17 (1), 907.
<https://doi.org/10.1186/s12889-017-4914-3>.
- (110) Peng, Z.; Zhang, B.; Wang, D.; Niu, X.; Sun, J.; Xu, H.; Cao, J.; Shen, Z. Application of Machine Learning in Atmospheric Pollution Research: A State-of-Art Review. *Science of The Total Environment* **2024**, 910, 168588.
<https://doi.org/10.1016/j.scitotenv.2023.168588>.
- (111) Chen, J.; de Hoogh, K.; Gulliver, J.; Hoffmann, B.; Hertel, O.; Ketzel, M.; Bauwelinck, M.; van Donkelaar, A.; Hvidtfeldt, U. A.; Katsouyanni, K.; Janssen, N. A. H.; Martin, R. V.; Samoli, E.; Schwartz, P. E.; Stafoggia, M.; Bellander, T.; Strak, M.; Wolf, K.; Vienneau, D.; Vermeulen, R.; Brunekreef, B.; Hoek, G. A Comparison of Linear Regression, Regularization, and Machine Learning Algorithms to Develop Europe-Wide Spatial Models of Fine Particles and Nitrogen Dioxide. *Environment International* **2019**, 130, 104934.
<https://doi.org/10.1016/j.envint.2019.104934>.
- (112) Kerckhoffs, J.; Hoek, G.; Portengen, L.; Brunekreef, B.; Vermeulen, R. C. H. Performance of Prediction Algorithms for Modeling Outdoor Air Pollution Spatial Surfaces. *Environmental Science & Technology* **2019**, 53 (3), 1413–1421.
<https://doi.org/10.1021/acs.est.8b06038>.
- (113) Ren, X.; Mi, Z.; Georgopoulos, P. G. Comparison of Machine Learning and Land Use Regression for Fine Scale Spatiotemporal Estimation of Ambient Air Pollution: Modeling Ozone Concentrations across the Contiguous United States. *Environment International* **2020**, 142, 105827.
<https://doi.org/10.1016/j.envint.2020.105827>.
- (114) Vachon, J.; Buteau, S.; Liu, Y.; Van Ryswyk, K.; Hatzopoulou, M.; Smargiassi, A. Spatial and Spatiotemporal Modeling of Intra-Urban Ultrafine Particles: A Comparison of Linear, Nonlinear, Regularized, and Machine Learning Methods. Rochester, NY June 15, 2024. <https://doi.org/10.2139/ssrn.4866426>.
- (115) Xu, J.; Zhang, M.; Ganji, A.; Mallinen, K.; Wang, A.; Lloyd, M.; Venuta, A.; Simon, L.; Kang, J.; Gong, J.; Zamel, Y.; Weichenthal, S.; Hatzopoulou, M.

- Prediction of Short-Term Ultrafine Particle Exposures Using Real-Time Street-Level Images Paired with Air Quality Measurements. *Environmental Science & Technology* **2022**, *56* (18), 12886–12897. <https://doi.org/10.1021/acs.est.2c03193>.
- (116) Abdillah, S. F. I.; You, S.-J.; Wang, Y.-F. Characterizing Sector-Oriented Roadside Exposure to Ultrafine Particles (PM_{0.1}) via Machine Learning Models: Implications of Covariates Influences on Sectors Variability. *Environmental Pollution* **2024**, *359*, 124595. <https://doi.org/10.1016/j.envpol.2024.124595>.
- (117) Amini, H.; Bergmann, M. L.; Taghavi Shahri, S. M.; Tayebi, S.; Cole-Hunter, T.; Kerckhoffs, J.; Khan, J.; Meliefste, K.; Lim, Y.-H.; Mortensen, L. H.; Hertel, O.; Reeh, R.; Gaarde Nielsen, C.; Loft, S.; Vermeulen, R.; Andersen, Z. J.; Schwartz, J. Harnessing AI to Unmask Copenhagen's Invisible Air Pollutants: A Study on Three Ultrafine Particle Metrics. *Environmental Pollution* **2024**, *346*, 123664. <https://doi.org/10.1016/j.envpol.2024.123664>.
- (118) Jung, C.-R.; Chen, W.-T.; Young, L.-H.; Hsiao, T.-C. A Hybrid Model for Estimating the Number Concentration of Ultrafine Particles Based on Machine Learning Algorithms in Central Taiwan. *Environment International* **2023**, *175*, 107937. <https://doi.org/10.1016/j.envint.2023.107937>.
- (119) Pandey, G.; Zhang, B.; Jian, L. Predicting Submicron Air Pollution Indicators: A Machine Learning Approach. *Environmental Science. Processes & Impacts* **2013**, *15* (5), 996–1005. <https://doi.org/10.1039/c3em30890a>.
- (120) Rahman, M. M.; Karunasinghe, J.; Clifford, S.; Knibbs, L. D.; Morawska, L. New Insights into the Spatial Distribution of Particle Number Concentrations by Applying Non-Parametric Land Use Regression Modelling. *Science of The Total Environment* **2020**, *702*, 134708. <https://doi.org/10.1016/j.scitotenv.2019.134708>.
- (121) Weichenthal, S.; Ryswyk, K. V.; Goldstein, A.; Bagg, S.; Shekharizfard, M.; Hatzopoulou, M. A Land Use Regression Model for Ambient Ultrafine Particles in Montreal, Canada: A Comparison of Linear Regression and a Machine Learning Approach. *Environmental Research* **2016**, *146*, 65–72. <https://doi.org/10.1016/j.envres.2015.12.016>.
- (122) Yang, C.; Dong, H.; Chen, Y.; Xu, L.; Chen, G.; Fan, X.; Wang, Y.; Tham, Y. J.; Lin, Z.; Li, M.; Hong, Y.; Chen, J. New Insights on the Formation of Nucleation Mode Particles in a Coastal City Based on a Machine Learning Approach. *Environmental Science & Technology* **2024**, *58* (2), 1187–1198. <https://doi.org/10.1021/acs.est.3c07042>.
- (123) Belle, V.; Papantonis, I. Principles and Practice of Explainable Machine Learning. *Frontiers in Big Data* **2021**, *4*. <https://doi.org/10.3389/fdata.2021.688969>.

- (124) Shapley, L. S. A Value for N-Person Games. In *Contributions to the Theory of Games*; Princeton University Press, 1953; pp 307–318.
<https://doi.org/10.1515/9781400881970-018>.
- (125) Lundberg, S. M.; Lee, S.-I. A Unified Approach to Interpreting Model Predictions. In *Proceedings of the 30th International Conference on Neural Information Processing Systems*; NIPS'17; Curran Associates Inc.: Red Hook, NY, USA, 2017; pp 4768–4777.
https://papers.nips.cc/paper_files/paper/2017/file/8a20a8621978632d76c43dfd28b67767-Paper.pdf
- (126) Karner, A. A.; Eisinger, D. S.; Niemeier, D. A. Near-Roadway Air Quality: Synthesizing the Findings from Real-World Data. *Environmental Science & Technology* **2010**, *44* (14), 5334–5344. <https://doi.org/10.1021/es100008x>.
- (127) *CountOps Reports - ASPMHelp*.
https://aspm.faa.gov/aspmhelp/index/CountOps_Reports.html (accessed 2024-03-08).
- (128) Dowell, D. C.; Alexander, C. R.; James, E. P.; Weygandt, S. S.; Benjamin, S. G.; Manikin, G. S.; Blake, B. T.; Brown, J. M.; Olson, J. B.; Hu, M.; Smirnova, T. G.; Ladwig, T.; Kenyon, J. S.; Ahmadov, R.; Turner, D. D.; Duda, J. D.; Alcott, T. I. The High-Resolution Rapid Refresh (HRRR): An Hourly Updating Convection-Allowing Forecast Model. Part I: Motivation and System Description. **2022**.
<https://doi.org/10.1175/WAF-D-21-0151.1>.
- (129) Lee, T. R.; Buban, M.; Turner, D. D.; Meyers, T. P.; Baker, C. B. Evaluation of the High-Resolution Rapid Refresh (HRRR) Model Using Near-Surface Meteorological and Flux Observations from Northern Alabama. **2019**.
<https://doi.org/10.1175/WAF-D-18-0184.1>.
- (130) Wang, W.; Liu, X.; Bi, J.; Liu, Y. A Machine Learning Model to Estimate Ground-Level Ozone Concentrations in California Using TROPOMI Data and High-Resolution Meteorology. *Environment International* **2022**, *158*, 106917.
<https://doi.org/10.1016/j.envint.2021.106917>.
- (131) Gowan, T. A.; Horel, J. D.; Jacques, A. A.; Kovac, A. Using Cloud Computing to Analyze Model Output Archived in Zarr Format. *Journal of Atmospheric and Oceanic Technology* **2022**, *39* (4), 449–462. <https://doi.org/10.1175/JTECH-D-21-0106.1>.
- (132) Blaylock, B. K. Herbie: Retrieve Numerical Weather Prediction Model Data, 2024.
<https://doi.org/10.5281/zenodo.10884251>.
- (133) Friedman, J. H. Stochastic Gradient Boosting. *Computational Statistics & Data Analysis* **2002**, *38* (4), 367–378. [https://doi.org/10.1016/S0167-9473\(01\)00065-2](https://doi.org/10.1016/S0167-9473(01)00065-2).

- (134) Chen, T.; Guestrin, C. XGBoost: A Scalable Tree Boosting System. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining; KDD '16*; Association for Computing Machinery: New York, NY, USA, 2016; pp 785–794. <https://doi.org/10.1145/2939672.2939785>.
- (135) Molnar, C. *Interpreting Machine Learning Models With SHAP*; Leanpub, 2023.
- (136) Castelli, M.; Clemente, F. M.; Popović, A.; Silva, S.; Vanneschi, L. A Machine Learning Approach to Predict Air Quality in California. *Complexity* **2020**, *2020*, e8049504. <https://doi.org/10.1155/2020/8049504>.
- (137) Tang, D.; Zhan, Y.; Yang, F. A Review of Machine Learning for Modeling Air Quality: Overlooked but Important Issues. *Atmospheric Research* **2024**, *300*, 107261. <https://doi.org/10.1016/j.atmosres.2024.107261>.
- (138) Friedman, J. H. Greedy Function Approximation: A Gradient Boosting Machine. *The Annals of Statistics* **2001**, *29* (5), 1189–1232.
- (139) Lundberg, S. M.; Erion, G.; Chen, H.; DeGrave, A.; Prutkin, J. M.; Nair, B.; Katz, R.; Himmelfarb, J.; Bansal, N.; Lee, S.-I. From Local Explanations to Global Understanding with Explainable AI for Trees. *Nature Machine Intelligence* **2020**, *2* (1), 56–67. <https://doi.org/10.1038/s42256-019-0138-9>.
- (140) Hudda, N.; Fruin, S. A. International Airport Impacts to Air Quality: Size and Related Properties of Large Increases in Ultrafine Particle Number Concentrations. *Environmental Science & Technology* **2016**, *50* (7), 3362–3370. <https://doi.org/10.1021/acs.est.5b05313>.
- (141) Wang, C.; Xiang, J.; Austin, E.; Larson, T.; Seto, E. Quantifying the Contributions of Road and Air Traffic to Ambient Ultrafine Particles in Two Urban Communities. *Environmental Pollution*, **2024**, *348*, 123892. <https://doi.org/10.1016/j.envpol.2024.123892>.
- (142) Carslaw, D. C.; Beevers, S. D.; Ropkins, K.; Bell, M. C. Detecting and Quantifying Aircraft and Other On-Airport Contributions to Ambient Nitrogen Oxides in the Vicinity of a Large International Airport. *Atmospheric Environment* **2006**, *40* (28), 5424–5434. <https://doi.org/10.1016/j.atmosenv.2006.04.062>.
- (143) Yu, K. N.; Cheung, Y. P.; Cheung, T.; Henry, R. C. Identifying the Impact of Large Urban Airports on Local Air Quality by Nonparametric Regression. *Atmospheric Environment* **2004**, *38* (27), 4501–4507. <https://doi.org/10.1016/j.atmosenv.2004.05.034>.
- (144) Seinfeld, J. H.; Pandis, S. N. *Atmospheric Chemistry and Physics: From Air Pollution to Climate Change*, 2nd ed.; Wiley-Interscience, 2006.

- (145) Patton, A. P.; Collins, C.; Naumova, E. N.; Zamore, W.; Brugge, D.; Durant, J. L. An Hourly Regression Model for Ultrafine Particles in a Near-Highway Urban Area. *Environmental Science & Technology* **2014**, *48* (6), 3272–3280. <https://doi.org/10.1021/es404838k>.
- (146) Paasonen, P.; Visshedjik, A.; Kupiainen, K.; Klimont, Z.; Denier van der Gon, H.; Kulmala, M. *Aerosol Particle Number Emissions and Size Distributions: Implementation in the GAINS Model and Initial Results*. <https://pure.iiasa.ac.at/id/eprint/10740/>, <https://iiasa.dev.local/> (accessed 2025-03-31).
- (147) Abegglen, M.; Durdina, L.; Brem, B. T.; Wang, J.; Rindlisbacher, T.; Corbin, J. C.; Lohmann, U.; Sierau, B. Effective Density and Mass–Mobility Exponents of Particulate Matter in Aircraft Turbine Exhaust: Dependence on Engine Thrust and Particle Size. *Journal of Aerosol Science* **2015**, *88*, 135–147. <https://doi.org/10.1016/j.jaerosci.2015.06.003>.
- (148) Loehr, M.; Turner, J. Ultrafine Particle Ground-Level Impacts During Aircraft Approach and Climb-out Operations at a Major Cargo Hub. *Transportation Research Record* **2023**, *2677* (1), 1108–1117. <https://doi.org/10.1177/03611981221103590>.
- (149) Gómez-Moreno, F. J.; Pujadas, M.; Plaza, J.; Rodríguez-Maroto, J. J.; Martínez-Lozano, P.; Artíñano, B. Influence of Seasonal Factors on the Atmospheric Particle Number Concentration and Size Distribution in Madrid. *Atmospheric Environment* **2011**, *45* (18), 3169–3180. <https://doi.org/10.1016/j.atmosenv.2011.02.041>.
- (150) Singh, M.; Phuleria, H. C.; Bowers, K.; Sioutas, C. Seasonal and Spatial Trends in Particle Number Concentrations and Size Distributions at the Children’s Health Study Sites in Southern California. *Journal of Exposure Science & Environmental Epidemiology* **2006**, *16* (1), 3–18. <https://doi.org/10.1038/sj.jea.7500432>.
- (151) Kulmala, M.; Vehkamäki, H.; Petäjä, T.; Dal Maso, M.; Lauri, A.; Kerminen, V.-M.; Birmili, W.; McMurry, P. H. Formation and Growth Rates of Ultrafine Atmospheric Particles: A Review of Observations. *Journal of Aerosol Science* **2004**, *35* (2), 143–176. <https://doi.org/10.1016/j.jaerosci.2003.10.003>.
- (152) Zhu, R.; Wei, Y.; He, L.; Wang, M.; Hu, J.; Li, Z.; Lai, Y.; Su, S. Particulate Matter Emissions from Light-Duty Gasoline Vehicles under Different Ambient Temperatures: Physical Properties and Chemical Compositions. *Science of The Total Environment* **2024**, *926*, 171791. <https://doi.org/10.1016/j.scitotenv.2024.171791>.
- (153) Clairotte, M.; Adam, T. W.; Zardini, A. A.; Manfredi, U.; Martini, G.; Krasenbrink, A.; Vicet, A.; Tournié, E.; Astorga, C. Effects of Low Temperature on the Cold Start Gaseous Emissions from Light Duty Vehicles Fuelled by

- Ethanol-Blended Gasoline. *Applied Energy* **2013**, *102*, 44–54.
<https://doi.org/10.1016/j.apenergy.2012.08.010>.
- (154) Brines, M.; Dall’Osto, M.; Beddows, D. C. S.; Harrison, R. M.; Gómez-Moreno, F.; Núñez, L.; Artíñano, B.; Costabile, F.; Gobbi, G. P.; Salimi, F.; Morawska, L.; Sioutas, C.; Querol, X. Traffic and Nucleation Events as Main Sources of Ultrafine Particles in High-Insolation Developed World Cities. *Atmospheric Chemistry and Physics* **2015**, *15* (10), 5929–5945. <https://doi.org/10.5194/acp-15-5929-2015>.
- (155) Holmes, N. S. A Review of Particle Formation Events and Growth in the Atmosphere in the Various Environments and Discussion of Mechanistic Implications. *Atmospheric Environment* **2007**, *41* (10), 2183–2201.
<https://doi.org/10.1016/j.atmosenv.2006.10.058>.
- (156) Stanier, C. O.; Khlystov, Andrey Y.; and Pandis, S. N. Nucleation Events During the Pittsburgh Air Quality Study: Description and Relation to Key Meteorological, Gas Phase, and Aerosol Parameters Special Issue of Aerosol Science and Technology on Findings from the Fine Particulate Matter Supersites Program. *Aerosol Science and Technology* **2004**, *38* (sup1), 253–264.
<https://doi.org/10.1080/02786820390229570>.
- (157) *General Aviation and Part 135 Activity Surveys* | *Federal Aviation Administration*.
https://www.faa.gov/data_research/aviation_data_statistics/general_aviation (accessed 2022-05-06).
- (158) U.S. Environmental Protection Agency, A. and S. D., Office of Transportation and Air Quality. *Lead Emissions from the Use of Leaded Aviation Gasoline in the United States*; Technical Support Document EPA420-R-08–020; 2008; p 82.
<https://nepis.epa.gov/> (accessed 2025-01-13).
- (159) Federal Aviation Administration. *General Aviation Airports: A National Asset*; 800 Independence Ave. SW. Washington, DC 20591, 2012; p 34.
- (160) *Airport Categories* | *Federal Aviation Administration*.
https://www.faa.gov/airports/planning_capacity/categories (accessed 2022-11-09).
- (161) U.S. Environmental Protection Agency. *Finding That Lead Emissions From Aircraft Engines That Operate on Leaded Fuel Cause or Contribute to Air Pollution That May Reasonably Be Anticipated To Endanger Public Health and Welfare*; 2023; Vol. EPA-HQ-OAR-2022-0389.
- (162) FAA. *Terminal Area Forecast (TAF)* | *Federal Aviation Administration*.
https://www.faa.gov/data_research/aviation/taf (accessed 2024-12-23).
- (163) South Coast Air Quality Management District. *General Aviation Airport Air Monitoring Study*; 2010; p 107.

- (164) Bureau of Geographic Information (MassGIS), Commonwealth of Massachusetts, Executive Office of Technology and Security Services. <https://www.mass.gov/info-details/learn-about-massgis-data> (accessed 2025-01-13).
- (165) FAA. *Traffic Flow Management System Counts*. <https://aspm.faa.gov/tfms/sys/main.asp> (accessed 2025-01-13).
- (166) TFMSC - ASPMHelp. <https://aspm.faa.gov/aspmhelp/index/TFMSC.html> (accessed 2022-05-06).
- (167) Gorham, K. A.; Raffuse, S. M.; Hyslop, N. P.; White, W. H. Comparison of Recent Speciated PM_{2.5} Data from Collocated CSN and IMPROVE Measurements. *Atmospheric Environment* **2021**, *244*, 117977. <https://doi.org/10.1016/j.atmosenv.2020.117977>.
- (168) Barbieri, M. The Importance of Enrichment Factor (EF) and Geoaccumulation Index (Igeo) to Evaluate the Soil Contamination. *Journal of Geology & Geophysics* **2016**, *5* (1), 1–4.
- (169) Rudnick, R. L.; Gao, S. 4.1 - Composition of the Continental Crust. In *Treatise on Geochemistry*; Elsevier, 2014; pp 1–51.
- (170) Cesari, D.; Contini, D.; Genga, A.; Siciliano, M.; Elefante, C.; Baglivi, F.; Daniele, L. Analysis of Raw Soils and Their Re-Suspended PM₁₀ Fractions: Characterisation of Source Profiles and Enrichment Factors. *Applied Geochemistry* **2012**, *27* (6), 1238–1246. <https://doi.org/10.1016/j.apgeochem.2012.02.029>.
- (171) Hudda, N.; Fruin, S.; Durant, J. L. Substantial Near-Field Air Quality Improvements at a General Aviation Airport Following a Runway Shortening. *Environmental Science & Technology* **2022**, *56* (11), 6988–6995. <https://doi.org/10.1021/acs.est.1c06765>.
- (172) Haxel, G. B.; Hedrick, J. B.; Orris, G. J. *Rare Earth Elements-Critical Resources for High Technology*; Fact Sheet 087–02; U.S. Geological Survey, 2002. <https://pubs.usgs.gov/fs/2002/fs087-02/>.
- (173) *Lead Fouling | Preventing Lead Fouling in Aircraft | Shell Global*. <https://www.shell.com/business-customers/aviation/aeroshell/knowledge-centre/technical-talk/lead-fouling.html> (accessed 2025-01-14).
- (174) Councell, T. B.; Duckenfield, K. U.; Landa, E. R.; Callender, E. Tire-Wear Particles as a Source of Zinc to the Environment. *Environmental Science & Technology* **2004**, *38* (15), 4206–4214. <https://doi.org/10.1021/es034631f>.
- (175) Pacyna, J. M.; Pacyna, E. G. An Assessment of Global and Regional Emissions of Trace Metals to the Atmosphere from Anthropogenic Sources Worldwide. *Environmental Reviews* **2001**, *9* (4), 269–298. <https://doi.org/10.1139/a01-012>.

- (176) U.S. Environmental Protection Agency. *SW-846 Test Method 6200: Field Portable X-Ray Fluorescence Spectrometry for the Determination of Elemental Concentrations in Soil and Sediment*; 2007. <https://www.epa.gov/hw-sw846/sw-846-test-method-6200-field-portable-x-ray-fluorescence-spectrometry-determination>.
- (177) McNeill, J.; Snider, G.; Weagle, C. L.; Walsh, B.; Bissonnette, P.; Stone, E.; Abboud, I.; Akoshile, C.; Anh, N. X.; Balasubramanian, R.; Brook, J. R.; Coburn, C.; Cohen, A.; Dong, J.; Gagnon, G.; Garland, R. M.; He, K.; Holben, B. N.; Kahn, R.; Kim, J. S.; Lagrosas, N.; Lestari, P.; Liu, Y.; Jeba, F.; Joy, K. S.; Martins, J. V.; Misra, A.; Norford, L. K.; Quel, E. J.; Salam, A.; Schichtel, B.; Tripathi, S. N.; Wang, C.; Zhang, Q.; Brauer, M.; Gibson, M. D.; Rudich, Y.; Martin, R. V. Large Global Variations in Measured Airborne Metal Concentrations Driven by Anthropogenic Sources. *Scientific Reports* **2020**, *10* (1), 21817. <https://doi.org/10.1038/s41598-020-78789-y>.
- (178) Levin, R.; Zilli Vieira, C. L.; Rosenbaum, M. H.; Bischoff, K.; Mordarski, D. C.; Brown, M. J. The Urban Lead (Pb) Burden in Humans, Animals and the Natural Environment. *Environmental Research* **2021**, *193*, 110377. <https://doi.org/10.1016/j.envres.2020.110377>.
- (179) Zhu, L.; Jacob, D. J.; Eastham, S. D.; Sulprizio, M. P.; Wang, X.; Sherwen, T.; Evans, M. J.; Chen, Q.; Alexander, B.; Koenig, T. K.; Volkamer, R.; Huey, L. G.; Le Breton, M.; Bannan, T. J.; Percival, C. J. Effect of Sea Salt Aerosol on Tropospheric Bromine Chemistry. *Atmospheric Chemistry and Physics* **2019**, *19* (9), 6497–6507. <https://doi.org/10.5194/acp-19-6497-2019>.
- (180) U.S. Department of Health and Human Services, Agency for Toxic Substances and Disease Registry. Toxicological Profile for 1,2-Dibromoethane, 2018. <https://www.atsdr.cdc.gov/toxprofiles/tp37.pdf>
- (181) Baldauf, R. W.; Devlin, R. B.; Gehr, P.; Giannelli, R.; Hassett-Sipple, B.; Jung, H.; Martini, G.; McDonald, J.; Sacks, J. D.; Walker, K. Ultrafine Particle Metrics and Research Considerations: Review of the 2015 UFP Workshop. *International Journal of Environmental Research and Public Health* **2016**, *13* (11), 1054. <https://doi.org/10.3390/ijerph13111054>.
- (182) Lane, K. J.; Levy, J. I.; Scammell, M. K.; Peters, J. L.; Patton, A. P.; Reisner, E.; Lowe, L.; Zamore, W.; Durant, J. L.; Brugge, D. Association of Modeled Long-Term Personal Exposure to Ultrafine Particles with Inflammatory and Coagulation Biomarkers. *Environment International* **2016**, *92–93*, 173–182. <https://doi.org/10.1016/j.envint.2016.03.013>.
- (183) Wallace, L.; Ott, W. Personal Exposure to Ultrafine Particles. *Journal of Exposure Science & Environmental Epidemiology* **2011**, *21* (1), 20–30. <https://doi.org/10.1038/jes.2009.59>.

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