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THE IMPACT OF AVIATION ACTIVITIES ON AMBIENT PARTICLE NUMBER CONCENTRATION AND INCIDENT HYPERTENSION

by

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Dedication

This dissertation is dedicated to my father, Jin Whan Chung, and my mother, Hae Soon Lee, who have always given me the greatest love and support throughout my life's journey.

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ABSTRACT

Aviation industry has played an essential role in modern society by providing social and economic benefits, but with inevitable environmental and public health implications. Communities living near airports are potentially affected by increased exposures to aviation-related emissions as well as noise. Better characterization of the impacts of aircraft emissions and noise is of great public health concern, especially for those living in communities near airports. The goal of my dissertation was to investigate the contribution of arrival aircraft to ambient ultrafine particulate matter (UFP) concentration as well as to examine the impact of aircraft noise on hypertension.

Various aviation-related air pollutants have been studied, including UFP, due to the high emission rates from aircraft and potential adverse health effects. Multiple studies have concluded that aircraft arrivals contribute significantly to ambient UFP concentration over a broad geographic area, but few studies have had the necessary monitoring infrastructure to formally evaluate the magnitude and spatial extent of impact. Because of its small size and negligible mass, UFP has significant spatial and temporal variability, which warrants further

investigation in order to better understand its dispersion patterns and impact in communities near airports. In our study, we collected UFP concentration data, measured as particle number concentration (PNC), at multiple locations near a major arrival flight path into Boston Logan International Airport, gathering concurrent flight activity and meteorological data for the purpose of source attribution. Two study aims were developed in order to better understand the arrival aircraft contribution to ambient PNC: 1) to investigate the spatiotemporal pattern of PNC concentrations across multiple study sites that are at varying distances from arrival aircraft flight paths, and 2) to quantify the PNC contribution from individual aircraft while explicitly accounting for meteorology, considering the implications of utilizing different averaging times and distributional characterizations (e.g., mean, 95th percentile). Results of the first aim of this study indicated that being downwind of the airport as well as the arrival flight path under higher wind speed was associated with elevated PNC. In addition, during hours of high flight activity, the aircraft contribution to ambient PNC was detectable even at a site 17 km away from the airport. The second aim of the study found a significant contribution of arrival aircraft to ambient PNC even when controlling for other important predictors in multivariable regression models. Our models also revealed that using the 95th percentile PNC within an hour led to larger estimates of arrival aircraft contributions than using the mean PNC, corresponding to strong and intermittent signal from aviation.

Similar to UFP, aircraft noise also displays strong spatiotemporal variability and has been shown to be associated with an array of adverse health outcomes including sleep disturbance and increased blood pressure in exposed communities. Though there is accumulating evidence of the association between aircraft noise and hypertension, existing studies are not without limitations. In our study, we developed long-term time-varying aircraft noise estimates for 90 airports in the U.S. using a single noise model and assigned noise estimates based on geocoded addresses of participants in Nurses' Health Studies (NHS and NHS II), two existing large prospective cohorts of women. The aim of this study was to examine the association between aircraft noise and incident hypertension in female nurses utilizing high temporal and spatial resolution aircraft noise exposure estimates in order to reduce potential exposure misclassification while accounting for temporality. Our study results showed an increased risk for incident hypertension associated with increased aircraft noise in both cohorts controlling for potential confounders. Our study also confirmed the impact of aircraft noise on hypertension apart from that of air pollution.

In summary, we found that aircraft activity can contribute significantly to ambient PNC. We developed a spatiotemporal model of aircraft noise and found that it is significantly associated with increased risk for hypertension in a large prospective cohort study, independent of the effects of air pollution on hypertension. Together, our work reinforces the importance of quantifying the environmental and public health impacts of aviation activities and provide future directions for research.

TABLE OF CONTENTS

Dedication iv

Acknowledgements v

ABSTRACT vi

LIST OF TABLES xi

LIST OF FIGURES xii

CHAPTER 1: Introduction 1
- Aviation Activities 1
- Aircraft Emissions and Ambient Ultrafine Particle Concentration 2
- Aircraft Noise and Hypertension 3
- Study Aims 5

CHAPTER 2: Spatial and temporal patterns of ultrafine particle concentrations in near-airport communities along a major arrival flight path in Boston, Massachusetts 7
- Introduction 10
- Methods 13
- Results 17
- Discussion 20
- Conclusions 24
- Tables 25
- Figures 26

CHAPTER 3: Assessing the impact of arrival aircraft on ambient ultrafine particle concentrations near a large international airport in the U.S. 30
- Abstract 31
- Introduction 34
- Methods 36
- Results 41
- Discussion 44
- Conclusions 50
- Tables 53
- Figures 57
- Supplemental material 59

CHAPTER 4: Long-term aircraft noise exposure and risk of hypertension in the Nurses' Health Studies 63
- Abstract 64
- Introduction 66
- Methods 68
- Results 74
- Discussion 77
- Conclusions 82

Tables 84
Figures 88

CHAPTER 5: Conclusion 90
Chapter 2: Spatial and temporal patterns of ultrafine particle concentrations in near-airport communities along a major arrival flight path in Boston, Massachusetts 91
Chapter 3: Assessing the impact of arrival aircraft on ambient ultrafine particle concentrations near a large international airport in the U.S. 93
Chapter 4: Long-term aircraft noise exposure and risk of hypertension in the Nurses' Health Studies 95
Public Health Implications 97

CURRICULUM VITAE 111

LIST OF TABLES

Table 2.1. Characteristics of each monitoring site 25

Table 2.2. Distribution of 1-second PNC across monitoring sites 25

Table 3.1. Multivariable regression model results of hourly and 10-minute mean PNC at multiple monitoring sites, accounting for autocorrelation 53

Table 3.2. Multivariable regression model results of hourly and 10-minute 95th percentile PNC at multiple monitoring sites, accounting for autocorrelation 55

Table S.3.1. Multivariable regression model results of hourly and 10-minute mean PNC at multiple monitoring sites, accounting for autocorrelation 59

Table S.3.2. Multivariable regression model results of hourly and 10-minute 95th percentile PNC at multiple monitoring sites, accounting for autocorrelation 61

Table 4.1. Baseline characteristics of 61,879 participants in the Nurses' Health Study and 94,592 participants in the Nurses' Health Study II free of hypertension at baseline dichotomized at the DNL 55 dB(A) level 84

Table 4.2. Numbers (percentages) of participants exposed to three different noise classifications in NHS and NHS II at baseline 86

Table 4.3. Hazard ratios (95% CIs) for hypertension associated with aircraft noise in NHS, NHS II, and meta-analysis of both cohorts 87

LIST OF FIGURES

Figure 2.1. Map of monitoring sites and flight paths 26

Figure 2.2. Diurnal pattern of PNC under high vs. no arrival aircraft activity conditions 27

Figure 2.3. Pollution roses displaying the interaction between wind speed and wind direction of PNC under high vs. no arrival aircraft activity conditions .. 28

Figure 2.4. Time series of PNC at 1-second resolution on selected sampling days at three monitoring sites during arrival flight activity (red lines) and no flight activity periods under varying wind conditions**Error! Bookmark not defined.**

Figure 3.1. Boxplots displaying 4L/4R arrival aircraft contributions to estimated ambient PNC (95th percentile, 1-hour average) using multivariable regression model predictions with actual arrival activity and assuming no arrival aircraft restricting to time-periods with non-zero 4L/4R arrival aircraft activity 57

Figure 3.2 Plots displaying the association between wind speed and log-transformed PNC for impact vs. non-impact winds using the hourly 95th percentile PNC multivariable regression model output. 58

Figure 4.1. A map of 90 airports included in our study by region........................ 88

Figure 4.2. Hazard ratios (95% CIs) for hypertension associated with aircraft noise in NHS and NHS II (DNL>55 dB(A) vs. <= 55 dB(A)), with sensitivity analyses restricting data based on DNL levels and the availability of air pollution and area-level SES data 89

CHAPTER 1: Introduction

Aviation Activities

Aviation provides a number of social and economic benefits and is essential for human activities.[1] Aviation contributes to improved quality of life by enabling people to travel to visit family and friends and by growing economies worldwide.[2] However, there are also environmental and public health concerns associated with aviation. It is well understood that aviation activities lead to increases in ambient air pollutant and noise levels, which is a particular concern for residents living in the vicinity of airports and underneath flight paths.[1,2] Aircraft exhaust includes similar fuel combustion-related air pollutants as vehicles such as carbon monoxide, sulfur oxides, nitrogen oxides, hydrocarbons and particulate matter,[2–4] and their emissions has been a concern from the beginning of commercial aviation.[3] Aircraft also create noise pollution that can affect quality of life by creating communication difficulties, sleep disturbance, and discomfort.[1] Aircraft noise exposure also has been shown to be associated with a wide range of adverse health effects including hearing loss, cardiovascular disease, and cognitive impairment in children.[5–9] Overall, in the U.S., both air pollution and noise from individual aircraft have declined due to the advancement of emission control and noise reduction technologies;[1,2,10,11] however, the combination of increased air travel demand and more concentrated flight paths for increased fuel efficiency may put some communities living near airports in the U.S. at higher risk of potential adverse health effects.[2]

Aircraft Emissions and Ambient Ultrafine Particle Concentration

Ultrafine particles (UFP) are smaller than 0.1μm in aerodynamic diameter and can come from direct emissions from engine combustion and from secondary formation in ambient air.[2,12] Both ground-level traffic and aircraft activities are known to be important sources of UFP in communities.[13] It is well understood that UFP coming from ground-level vehicles are rapidly removed as a function of distance from the roads, while understanding of UFP dispersion patterns at ground-level from aviation activities is much more limited, especially for aircraft in flight. That said, the high temporal and spatial heterogeneity shown in studies of vehicle-associated UFP due to UFP's small size can also be expected in studies of aviation-associated UFP.[14–16] Even though aircraft emissions are less frequent and farther from communities compared to emissions from ground-level vehicles, they can still affect overall air quality, especially in communities near airports, because the emission rates are higher compared to ground-level vehicle emissions. In addition, distinct characteristics of aircraft plumes, which are of higher temperature at the point of emission, and aircraft activity correlated with wind speed and direction, could lead to more complex dispersion patterns.

Several studies have shown a geographically widespread impact of aviation activities on ambient PNC downwind from airports and runways.[12,17–20] However, most monitoring sites included in these studies were located close to major roads, which makes distinguishing individual contributions from aircraft vs.

motor vehicles more difficult. In addition, some of these studies focused on only downwind locations from the airport either because the selected airports had relatively little variability in prevailing winds or because of their site selection criteria, resulting in lack of ability to gain a more comprehensive understanding of aircraft plume dispersion patterns.

There is a keen interest in UFP from both exposure assessment and epidemiology perspectives due to its potential respiratory and cardiovascular effects.[13] However, assessing population level UFP exposures is challenging given its high spatiotemporal variability and multiple sources, which makes conducting epidemiological studies looking at the association between UFP and health outcomes also difficult.[12] Investigation of the impact of aviation activities on ambient UFP concentration is essential in order to improve our understanding of aviation-related UFP exposure patterns, leading to more accurate exposure assessments in epidemiological studies.

Aircraft Noise and Hypertension

Noise is defined as unwanted sound,[5] which includes both objective and subjective components. The Federal Aviation Administration (FAA) uses Day-Night average sound level (DNL) for their guidelines and defines aircraft noise above 65 dB(A) as significant noise. This threshold is used to make policy assessments to: 1) reduce the number of people exposed to significant noise, 2) establish the appropriate level of aircraft noise for residential areas, and 3) establish the aircraft noise level below which the impacts in the residential areas are deemed to not be significant. It is important to note that the 65 dB(A) threshold is based on annoyance rather than health impacts.[11]

The effects of noise on health has long been overlooked in the U.S., despite its widespread prevalence and potential to affect a large number of people chronically.[5,7] In recent years, there has been an increasing interest in examining the health impact of noise, but more focus has been placed on road traffic noise than aircraft noise, related both to the number of people living near major roads and the challenges in ascertaining aircraft noise exposures. Chronically elevated noise exposure can cause adverse health effects, which puts certain communities living near airports at higher health risks. An array of health outcomes have been suggested to be linked to chronic aircraft noise exposure such as children's learning, disturbed sleep, cardiovascular diseases, and hypertension.[5–9,21] Aircraft noise is of particular interest due to its chronicity and prevalence in certain communities near airports. Aircraft noise is distinct in its pattern as it is more of an intermittent yet elevated source of noise rather than continuous noise coming from road traffic.[21] In addition, people report the highest levels of annoyance and self-reported sleep disturbance at the same equivalent noise level for aircraft noise compared to other noise sources such as roads and railways.[8,22]

The impact of noise on hypertension has been extensively studied, although with more evidence for traffic noise than aircraft noise.[23] The impact of noise on blood pressure has been shown in both experimental and epidemiological studies. For example, real-world experiments in humans provided the biological plausibility of noise-induced hypertension, showing instantaneously increased blood pressure following exposure to varying levels of noise.[24–26] A proposed pathway by which noise exposure can impact blood pressure, is by inducing the sympathetic and endocrine systems, more pronouncedly associated with nocturnal noise, which result in increases in stress hormones such as cortisol and catecholamines; this can then lead to both instantaneous and permanent pathophysiological adaptations including increased blood pressure.[8,23,27] Multiple epidemiological studies reported a positive association between aircraft noise and chronic changes in blood pressure.[10,23,28–33] However, there have been only few prospective cohort studies examining the association between aircraft noise and hypertension, and none exist in the U.S.

Study Aims

Our studies were designed to advance our understanding of the environmental and health impacts of aviation activities by addressing some of the limitations of existing studies.

The first two projects (chapter 2 and 3) evaluated the impact of arrival aircraft activities on ambient PNC through both descriptive and regression analyses using data collected around a primary arrival flight path into a local airport (Boston Logan International Airport) for the purpose of determining the relative contribution of aviation sources across the study sites located at varying distances from the airport and flight path. We designed our study to look at both spatial and temporal impact of aircraft flights under a wide range of meteorological conditions by conducting semi long-term (6 months) data collection. In an effort to quantify arrival aircraft contribution to ground-level PNC across our study sites, we developed regression models using different temporal resolution and distributional characterization for each study site, while explicitly controlling for meteorology.

In chapter 4, we investigated the association between aircraft noise and hypertension in the U.S. using data from two prospective cohorts - the Nurses' Health Studies (NHS and NHS II). To accomplish this, we developed a model to predict time-varying aircraft noise exposure at a high spatial resolution at participants' geocoded addresses. We used a time-varying Cox proportional hazards model in order to correctly account for time-varying noise exposure, which has been decreasing over time, as well as variations in other personal risk factors, such as diet and income.

CHAPTER 2: Spatial and temporal patterns of ultrafine particle concentrations in near-airport communities along a major arrival flight path in Boston, Massachusetts

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Abstract

Background: Aircraft emissions contribute to overall ambient air pollution including ultrafine particles (UFP; particles ≤ 100 nm in aerodynamic diameter), which has been shown to be potentially more potent than larger particles. Individual aircraft UFP emissions have declined with the advancement of emission control technologies, but the continuous growth of total air travel worldwide necessitates an accurate understanding of the extent of aviation contributions to ambient air quality.

Objectives: The objective of this study was to describe the spatiotemporal distribution of particle number concentrations (PNC), a proxy measure for UFP, across multiple study sites that are at varying distances from arrival aircraft flight paths by utilizing real-time aircraft activity and meteorological data and PNC measurements.

Methods: We collected high temporal resolution (1-second) PNC data at six monitoring sites along a primary arrival flight path in the vicinity of Boston Logan International Airport from April to September 2017. We used three condensation particle counters (CPC, TSI Model 3783) to measure at three sites simultaneously for one week at a time, rotating between six sites in order to capture as many different spatial and meteorological combinations as possible. We compared PNC distributions as a function of meteorological conditions and flight activity.

Results: Ambient PNC at all six monitoring sites were similar at the median, but had greater variation at the 95th and 99th percentiles with more than two-fold increases in PNC observed at sites closer to the airport compared to sites farther away from the airport. PNC were elevated during the hours with high aircraft activity especially under aviation impact sector winds compared to no aircraft activity at all sites. Sites closest to the airport had stronger aviation impact sector wind signals that dissipated at sites further from the airport.

Discussion: PNC monitoring data, which had relatively similar median concentrations across monitoring sites, but divergent concentrations at the upper percentiles, suggest strong but intermittent aviation contributions especially at monitoring sites closer to the airport. Stratification by flight activity and meteorology confirmed the non-trivial contribution of arrival aircraft activities to ambient PNC at all our study sites. Our study also demonstrated both the advantage and challenge of using high temporal resolution data in ascertaining aircraft signal on the ground level.

Introduction

Aviation activities can impact human health by increasing concentrations of ambient air pollutants,[34] such as carbon monoxide, methane, nitrogen oxides, sulfur oxides and particulate matter (PM).[2,3] Even though emissions from individual aircraft have declined due to the advancement of emission control technologies,[2] an accurate understanding of the extent of the impacts of aviation activities is becoming more important as air travel is expected to continuously expand as the fastest growing transport mode over the next 20 years nationally and internationally.[35–37] In the U.S., the switch from radar-based to GPS-based systems for air traffic control has led to increased fuel efficiency,[2] but the resulting flight paths are more concentrated and exposure patterns may have shifted, with the potential for an increase in exposure for a subset of the population and a decrease for others. The combination of increased air travel demand and more concentrated flight paths may put some communities living near airports at risk of higher exposure to air pollution, but exposure patterns are understudied. Furthermore, airports are often located in densely populated areas and near major roadways, creating some potential for co-varying UFP exposures and putting a large number of people at risk of being affected by the associated exposures. Disentangling these contributions can be challenging, as aircraft and motor vehicles emit similar air pollutants, but emission patterns, composition of particles, and dispersion characteristics can differ substantially, given the unique plume dynamics of aviation activities.[2,38,39]

Ultrafine particles (UFP; particles $\leq$ 100 nm in aerodynamic diameter), measured as particle number concentration (PNC), the focus of this study, can come from direct emissions from aviation and vehicle traffic as well as from secondary formation in ambient air.[2,12] In recent years, UFP has received more public and scientific attention for its potential effects on human health [40,41], because of its elevated lung deposition efficiency, smaller size and larger surface area to mass ratio relative to larger particles. [42,43] Monitoring studies near airports have shown aviation activities as another important source of ambient UFP in addition to ground-level vehicle activities.[12,18,19] UFP is known to have high temporal and spatial heterogeneity due to its small size and rapid removal processes as shown in monitoring studies near major roadways.[14,15,44] Aircraft impacts on ambient UFP concentrations have been shown to affect a much broader geographic area compared to emissions from motor vehicles.[18] These co-varying contributions of aircraft and motor vehicle emissions to ambient UFP warrant an investigation focusing on aviation sources in order to distinguish local contributions of UFP from aircraft and motor vehicles.

Particulate matter emissions at cruising altitudes (on average ~12 km) are considered to have minimal impact on local ground-level or near-ground air quality,[2,45] while there have been mixed findings of the impact of aircraft at lower altitudes on ambient air quality, though more recent studies have suggested a larger and more geographically distributed impact downwind of airports or aircraft activity.[17–19] For example, one study conducted at Boston Logan International

Airport found 1.33-fold and 2-fold higher average PNC at sites 7.3 km and 4 km, respectively, downwind from the airport.[18] A study performed at Los Angeles International Airport found large mean PNC increases up to 18 km downwind of the airport.[17] A study done in the Netherlands has also shown increased annual mean PNC at 7 km downwind of Schiphol airport[12]. Some of these studies have shown elevated levels of PNC under arrival flight paths[17], with higher concentrations as compared with surrounding urban locations with similar road traffic characteristics.[20] On the other hand, a study done at a mid-sized airport (T.F. Green Airport in Rhode Island with 1/5th of annual flight activity compared to Logan Airport) found a pronounced influence of flight activity on 1-min average PNC only in a neighborhood located at the immediate end of a runway (< 1 km) with small average contributions, but concentrations at the 99th percentile exceeded those from traffic.[46]

Emission rates of UFPs are much higher during take-offs compared to approaching,[47,48] though emissions from arrival aircraft can potentially influence exposures over broader geographic areas due to flying at lower altitudes for longer. However, it is unclear how large or sustained those contributions are, relative to departure aircraft or other emission sources. Most studies to date have ascertained concentration patterns downwind of the airport, but have not formally considered flight paths and the intermittent and variable nature of the corresponding emissions. Here, we evaluate in-flight aircraft contributions to ground-based PNC, leveraging real-time meteorological and flight activity data to better understand important but highly variable community UFP exposure patterns associated with aircraft arrivals.

Methods

Study Design

The field sampling campaign was conducted from April to September 2017 in the vicinity of Boston Logan International Airport (hereafter, Logan). The arrival flight paths to runway 4L and 4R were the main focus of this study, 4R being the primary arrival runway configuration used when the wind is from the northeast,[49] but also during multiple other meteorological conditions. Six monitoring sites were selected that were at varying distances from the airport and flight paths to runway 4L/4R (Figure 2.1 and Table 2.1), and therefore have potentially varying UFP contributions from aircraft arrivals. Based on their distances to the airport as well as based on the average flight altitudes (Table 2.1), two sites closest to the airport were named N1 and N2 (near sites), two sites that were intermediate distances to the airport as I1 and I2 (intermediate sites), and two farthest away sites as F1 and F2 (far sites) as shown on the map. Selection criteria for monitoring locations prioritized sites in terms of potential to distinguish the aviation contribution to ambient PNC from other sources such as traffic. We did so by creating a 200-meter buffer around major roads to avoid large motor vehicle traffic contributions to ambient PNC at the study sites based upon previously published distribution patterns of traffic-related UFP.[14] All potential sites were visited in person and site-by-site determinations were made after considering multiple factors including the surrounding environment (e.g. local traffic volume, restaurants, etc.). One of the six sites (F2) was 160 meters from a designated major roadway, but was still included as a study site because field observations indicated relatively low traffic volume and preliminary measurements confirmed moderate baseline PNC.

Table 2.1 summarizes the characteristics of different set-ups at the six monitoring sites. Two sites (N2 and F1) were within 0.5 km of the 4R arrival flight path, while the other four sites (N1, I1, I2, and F2) were at varying distances to the west of the 4R flight path. Sites also varied by their proximity to the airport, the corresponding altitude of aircraft as they flew by the monitoring sites, and whether the monitor was at ground level or on the first or second floor.

Instrument and Data Processing

The monitoring strategy was to measure at three sites simultaneously for one week at a time, rotating between six sites in order to capture as many different spatial and meteorological combinations as possible. We used three condensation particle counters (CPC, TSI Model 3783, 1-second averaging), enclosed in weatherproof Pelican cases to allow for flexible field deployment and easy transport among the sites. Multiple pilot tests were conducted to ensure the portable configurations met the temperature requirements of the instrument.

The instruments were deployed either indoors or outdoors depending on what space was available at each site (Table 2.1). The same instrument configuration was used for both indoor and outdoor sites. For indoor deployment, the CPC remained inside with Tygon tubing connected to the inlet placed through a window. For outdoor deployment, the CPC was placed under a roof to prevent any weather damage with Tygon tubing connected to the inlet extending to an outdoor area. The same length of tubing was used at all sites for consistency, given potential deposition and line loss of UFP. CPC co-location testing at N2 showed a strong positive correlation among the instruments (Pearson correlation coefficient=0.98).

Observations with automatic error flags by the instrument were reviewed and those observations with errors affecting the data quality were removed (2.7% at N1, 0.27% at N2, 0% at I1, 9.6% at I2, 3.2% at F1, and 9.0% at F2). The majority of these errors related to external vacuum pump malfunctions rather than CPC issues. Performance Data Analysis and Reporting System (PDARS) data were obtained for the entire study period from the U.S. Federal Aviation Administration (FAA). The data provided real-time three-dimensional location information (latitude, longitude and altitude) for all arrival flights landing at Logan Airport excluding military aircraft. Meteorological data was acquired from the U.S. National Weather Service station located at Logan Airport (KBOS).

Statistical Analyses

We summarized PNC distributions at the measured resolution (1-second) to develop hypotheses about the influence of aviation and meteorology on concentrations. Specifically, we characterized percentiles from the 0.1st to the 99.9th by study site across the entire study period.

To characterize the influence of aircraft arrival activity on PNC patterns, we used PDARS data to calculate the number of aircraft landing on either 4L or 4R runways for each hour across the entire study period. We then constructed a new variable to indicate no ($n = 0$), moderate ($0 < n < 30$) and high ($n \geq 30$) arrival aircraft activity, using the median number of arrival aircraft in an hour as the cut-point (median number of arrival aircraft = 29 among hours with non-zero flight activity). Further, we would hypothesize increased PNC associated with aviation activity during meteorological conditions when the monitoring site was downwind from the airport. We therefore defined the hypothesized aviation impact sector as the wind direction range that positioned monitoring sites downwind of the airport ±15°, which would also capture the impact of arrival aircraft at the tail of the 4L/4R flight trajectories with arrival aircraft very close to the ground.[50]

We characterized diurnal PNC patterns using boxplots stratified by the level of arrival aircraft activities (high vs. none), which described the distribution of the data between the 5th and 95th percentiles (5th, 25th, 50th, 75th, 95th) and the mean. Concentration roses were generated to display PNC associations with varying wind speeds and wind directions at the study sites, stratified by arrival aircraft activity (high vs. none) excluding data from 02:00 to 07:00 in order to remove the impact of early morning time periods when there is limited airport activity, based on the flight activity data.

Lastly, we developed time-series plots of 1-second resolution PNC and flight activity over 1-hour long periods under 4 different runway conditions (high vs. none) and wind condition (NE vs. NW wind) combinations to visually assess the association between individual flights (marked with red lines) and PNC. Data from the 23:00-0:00 period from four different days at N1, N2, and F1 were used for these plots in order to capture time periods with flight activity but minimal ground-level vehicle traffic, and to show differing impacts at sites closer and farther away from the airport.

All analyses were conducted using R-3.5.2 and Excel and maps were created using ArcMap 10.6.

Results

In total, we collected PNC measurements across 546 sampling days, distributed approximately evenly across the six sites, for a total of > 41 million individual 1-second resolution measurements (Table 2.2). While median PNC was similar across the six study sites, concentration patterns differed at higher percentiles, with elevated PNC above the 95th percentile at sites closer to the airport (N1 and N2). While N1 and N2 had comparable or lower PNC at the median and below as compared with other monitoring sites, they had the highest concentrations above the 95th percentile. Sites F1 and F2, which were farthest from the airport with overhead aircraft at higher elevation, generally had lowest concentrations across all percentiles. Sites I1 and I2 had the highest concentrations at the median but lower concentrations at the 99th and 99.9th percentile and above in comparison with sites N1 and N2.

The influence of flight activity on concentrations at the six monitoring sites was first examined by characterizing diurnal PNC patterns stratified by level of flight activity (Figure 2.2). PNC during hours without arrival aircraft were generally similar at the six study sites, with most hourly PNC averages < 25,000 particles/cm^3. We observed only a modest increase in concentrations during the morning rush hour when there was zero flight activity on 4L/4R, consistent with our selection of sites with limited local traffic. By comparison, during hours with arrival aircraft, there were notable increases in PNC at most of our study sites. Mean, 75th, and 95th percentile 1-second PNC were elevated throughout the day when there was high arrival aircraft activity on the 4L/4R runways compared to when there was no flight activity. This pattern was more pronounced at sites relatively closer to the airport (N1, N2, I1, and I2). The elevated PNC patterns associated with high flight activities were consistently shown across all hours at N1 and I1. Sites F1 and F2, which were farthest from the airport, had smaller differences in PNC between high and no flight activity and less consistent temporal patterns (Figure 2.2).

We further stratified PNC by wind speed and direction to examine the meteorological factors influencing source contributions at each monitoring site (Figure 2.3). PNC during periods of high arrival flight activity were highest under the hypothesized aviation impact sector winds, at near-airport sites N1 and N2, and to a lesser extent at I1 and with a modest increase at I2. Under these meteorological conditions, these monitoring sites were simultaneously downwind from arrival flight trajectories and the airport, and during high flight activity we observed mean PNC ranging from 50,000 particles/cm^3 to 60,000 particles/cm^3 at N1 and N2. However, the elevation pattern was not perfectly aligned with the aviation impact sector wind at site N2. The highest PNC were typically at higher wind speeds under the high flight activity condition, most pronouncedly shown at site N1.[18] I1 showed a similar pattern but the signal was lower with an average ranging from 40,000 particles/cm^3 to 50,000 particles/cm^3. In general, PNC seemed to vary widely depending on wind speed and direction under the high arrival flight activity condition, while it did not vary as much under the no flight activity condition. Even though there was no clear meteorological pattern of increased PNC associated with arrival aircraft at sites F1 and F2, overall PNC was slightly elevated compared to when there was no arrival aircraft activity.

In addition to observing the combined impact of arrival aircraft on PNC, we wanted to use our high temporal resolution data to illustrate the impact of individual aircraft. Figure 2.4 displays four time-series of PNC between 23:00 and 00:00 at three of the study sites (N1, N2, and F1) with arrival aircraft activities marked with red lines. Figure 2.4(a) shows the concentration patterns under northeasterly wind, where the monitoring sites would have been located downwind of the arrival flight path and the airport. N1 observed elevated concentrations throughout the hour, albeit not highly correlated with individual flights, while, N2 only observed intermittent concentration increases above background. Under northwesterly wind (Figure 2.4(b)), the concentrations were similarly elevated as with northeasterly winds, but with higher concentrations at N2 and without substantive minute-by-minute variability compared to what was shown in Figure 2.4(a). PNC measured with northeasterly and northwesterly winds, when no aircraft landed on 4L/4R, were much lower (Figure 2.4(c) & 2.4(d)) than when there was activity on 4L/4R. PNC levels at F1 were low under all conditions corresponding with the results from Figures 2.2 and 2.3.

Discussion

Our 1-second resolution PNC monitoring data, which had relatively similar median concentrations across monitoring sites, but divergent concentrations at the upper percentiles, suggest strong but intermittent aviation contributions especially at monitoring sites closer to the airport. Stratification by flight activity and meteorology indicated that PNC was higher during hours of high arrival flight activity (Figure 2.2) and under wind conditions when the monitoring sites were downwind from the flight path and the airport (Figure 2.3). The pattern of aviation contribution to ambient PNC was more difficult to detect at sites farther away. The signal was small but still discernable at F1 and F2. Pollution roses in Figure

2.3 reinforced the likelihood that PNC increases were related to arrival aircraft in-flight at lower altitudes rather than ground level activities at the airport. For example, under conditions without flight arrivals on 4L/4R but winds from the northeast (airport direction), PNC increased far less.

While studies have shown that ground-level vehicle traffic tends to dominate ambient UFP over aviation activities,[20,48] our stratified analyses suggest that the additional exposure to UFP from aviation is still notable, especially in communities that are close to aviation sources (horizontal distance to airports and vertical distance to aircraft in-flight). Our study also clearly indicated the impact of aircraft arrivals on ambient PNC, while a number of other studies only displayed a noticeable impact from take-offs but not arrivals, in part because of their site selection.[51,52] In addition, our study reinforces that using mean or median PNC over a longer averaging time, as is common in the literature,[12,18] may not capture the large but intermittent contributions from aircraft. Similar results have been shown in a study for a departure runway where much larger contributions were shown to be associated with upper percentile PNC observations.[52] Whether large but intermittent contributions to ambient PNC with a more modest contribution to long-term average concentrations is a potential public health concern is beyond the scope of this study, but our work does reinforce that aviation source attribution studies are strengthened by considering higher-resolution monitoring data and upper percentile contributions.

One limitation of this study was the varying surrounding environments at the monitoring sites. Even though we selected sites at appreciable distances from major roads and other identifiable combustion sources, the level of non-aviation UFP contributions was non-zero and varied across sites. However, based on our descriptive analyses, the non-aviation UFP contributions did not preclude us from observing intermittent concentration increases consistent with aviation contributions. In addition, there were several construction projects at N2 throughout monitoring period, which would have contributed to our measured PNC at times.

Although our findings provided compelling evidence of an association between aircraft arrivals and ground-level PNC over a relatively large geographic area, there were some clear challenges in associating individual PNC peaks with real-time flight activity data, which may be due to the coarser temporal resolution of the meteorological data. For example, the difference shown in Figures 1.4(a) and 1.4(b), both with frequent flight activities, is difficult to explain with available data and is suggestive of different dispersion patterns. In theory, high temporal resolution PNC could be analyzed in conjunction with real-time flight activity and meteorological data. However, there are many challenges with such an analysis, including the uncertain dynamics of the high-temperature plumes and wing-tip vortices from aircraft, and the associated variability in lag between emissions aloft and surface concentrations.

In spite of these challenges, our study offers novel and valuable insight regarding arrival aircraft contributions. One of the strengths of this study was the selection of monitoring sites specifically intended for aviation arrival source attribution, as opposed to some prior studies in which post hoc analyses were conducted at sites intended for other purposes. Sites were placed at varying distances from the airport and from the arrival pathway and not proximate to major roadways, as opposed to multiple prior studies with sites very close to airports or directly at the end of runways. In addition, while variable meteorology often observed in Boston creates some challenges in analyzing and interpreting PNC data, it also allows for the assessment of the impacts of varying meteorological conditions on aircraft arrival PNC patterns. Lastly, the portable instrument configuration allowed for easy semi long-term data collection at different sites under various site combinations, which provided insight over a wider geographic area than would have been available with a more limited number of sites.

In conclusion, our findings suggest a strong and intermittent contribution from arrival aircraft to ambient PNC, amplified under certain wind conditions and at sites in closer proximity to the source. Our findings indicate that some populations closer to airports, who are in the vicinity of aircraft arrivals at lower altitude, may see increased exposures to PNC, even if they are not directly under the flight paths. Future studies utilizing available high-temporal resolution flight activity, meteorology, and PNC data may be able to improve our understanding of the complex UFP dispersion patterns associated with arrival aircraft as shown in our time-series plots.

Conclusions

In conclusion, our study captured clear arrival aircraft signal on ambient PNC in all six monitoring sites with varying magnitudes, with most elevated PNC observed under the aviation impact sector wind during hours with high flight activity. More generally, our study finding indicated the upper percentile PNC to be associated with aircraft activities corresponding strong and intermittent aircraft source contribution. Though, making the direct connection between the observed peaks and real-time flight activity data were shown to be challenging, our findings indicated the value of using high temporal resolution data in capturing the nature of aircraft emissions that can be considered in future studies.

Acknowledgements

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Tables

Table 2.1. Characteristics of each monitoring site

Site	Distance to flight path 4R (km)	Distance to airport (km)	Average altitudes of arrival aircraft (m)	Monitoring configuration
N1	1	3	210	Indoor*: second floor office space facing the ocean
N2	< 0.5	4	300	Outdoor: open shed on a boat dock
I1	2	7	400	Indoor*: first floor restroom facing a small parking area
I2	2	9	460	Outdoor: open shed in the backyard in residential area
F1	< 0.5	12	610	Indoor*: second floor classroom
F2	4	17	850	Outdoor: greenhouse at a farm

* For any indoor deployment, the monitor was placed indoors with tubing running outside to measure ambient concentrations.

Table 2.2. Distribution of 1-second PNC (particles/cm^3) across monitoring sites

	N1	N2	I1	I2	F1	F2
Sample Size (days)	98	94	86	92	84	92
Sample Size (seconds)	7,468,604	7,537,890	6,685,191	6,928,122	6,473,741	7,038,958
0.1st percentile	390	530	1,200	850	800	880
1st percentile	930	1,300	2,100	1,300	1,200	1,200
5th percentile	2,000	2,400	3,500	2,500	2,000	2,000
25th percentile	4,600	4,800	6,300	5,100	3,900	3,900
50th percentile	7,400	7,500	9,200	7,900	5,700	5,800
75th percentile	12,000	11,000	14,000	12,000	7,800	8,200
95th percentile	29,000	28,000	29,000	22,000	13,000	15,000
99th percentile	59,000	58,000	48,000	34,000	22,000	24,000
99.9th percentile	94,000	110,000	74,000	49,000	39,000	46,000

Figures

Figure 2.1. Map of monitoring sites and flight paths

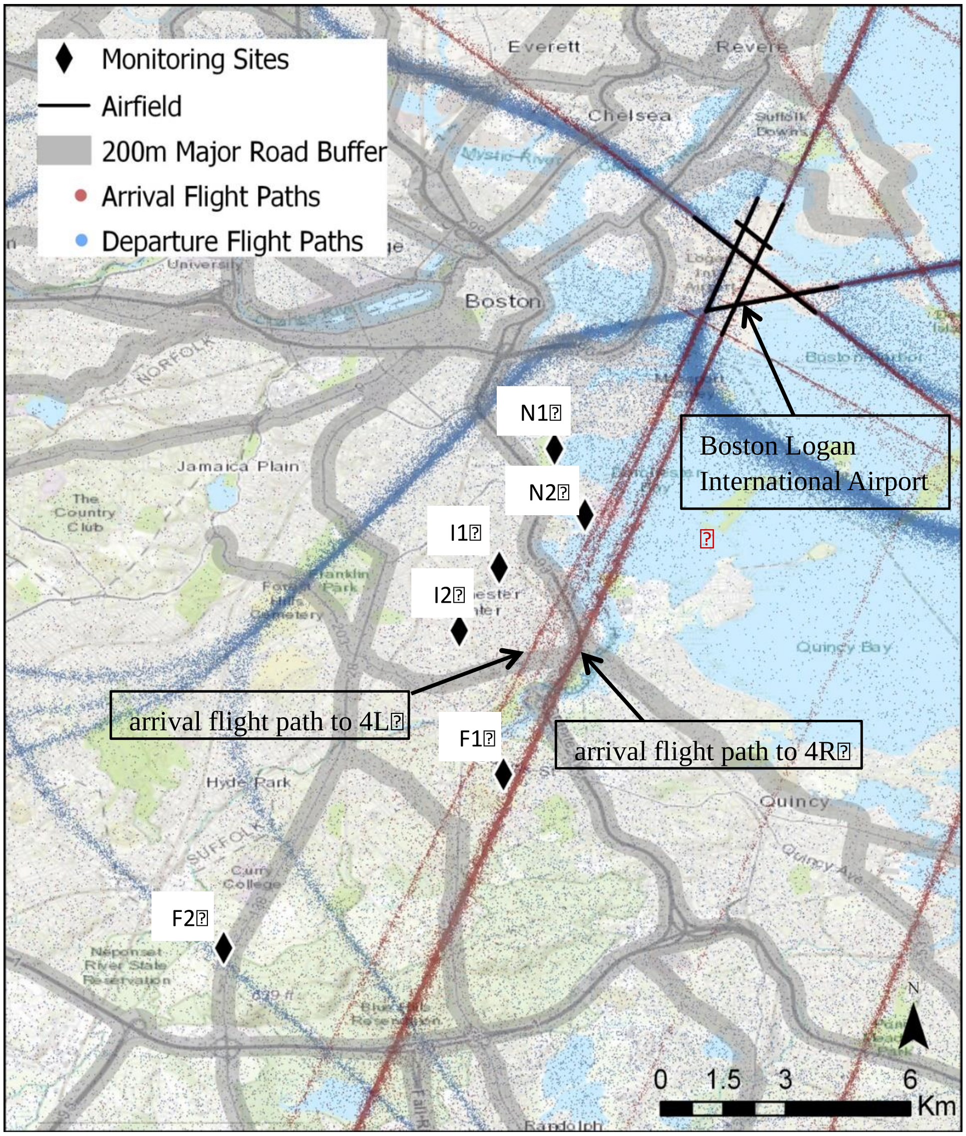
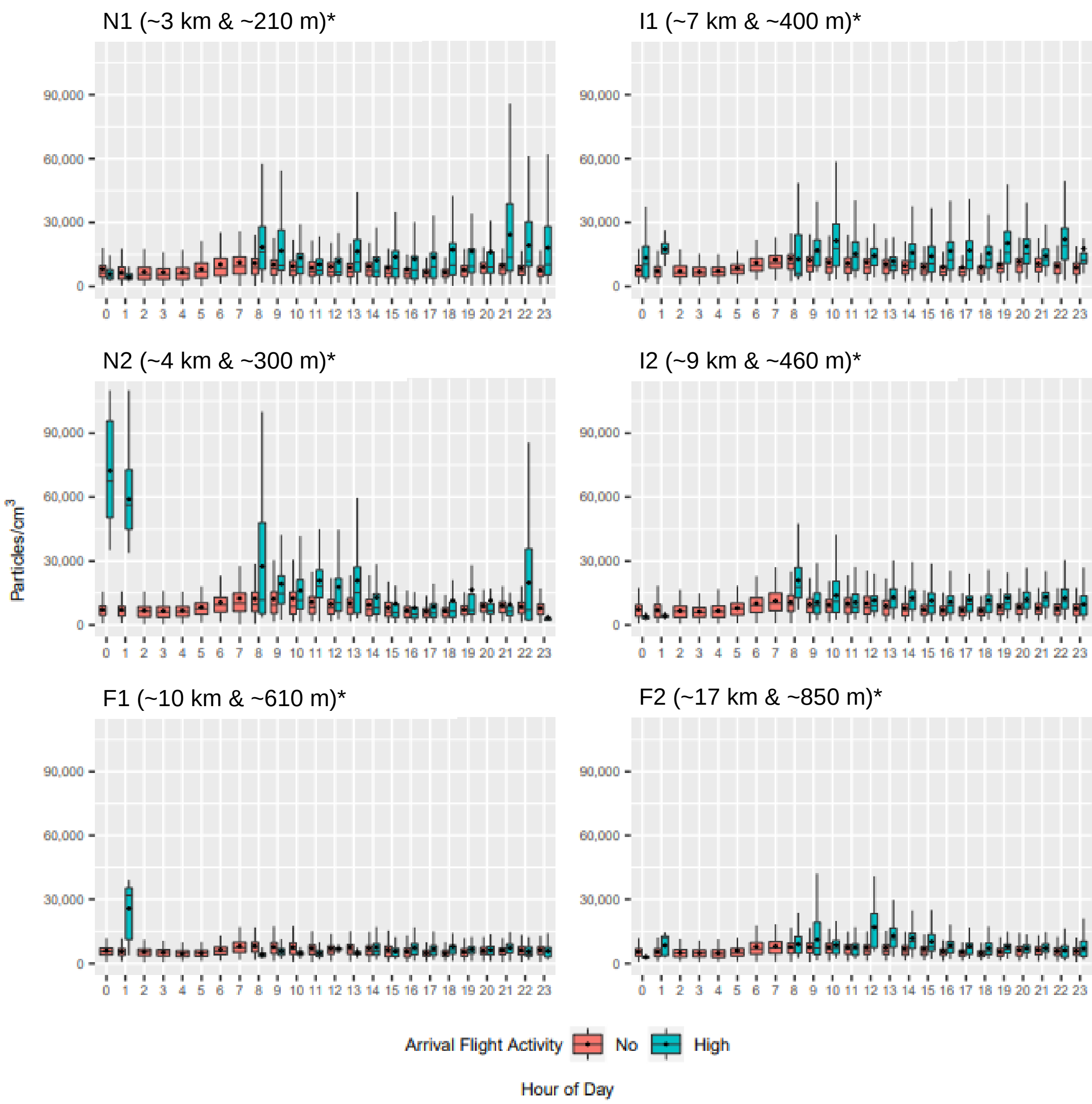
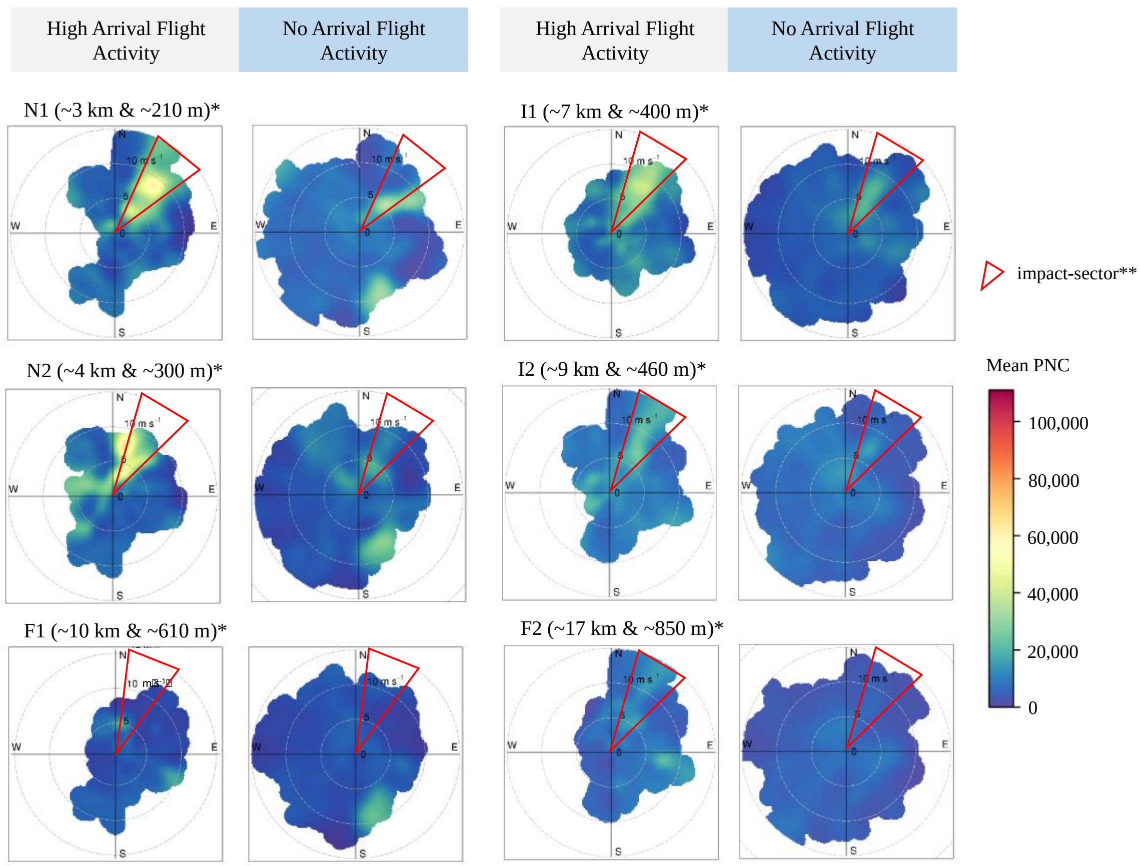


Figure 2.2. Diurnal pattern of PNC under high vs. no arrival aircraft activity conditions



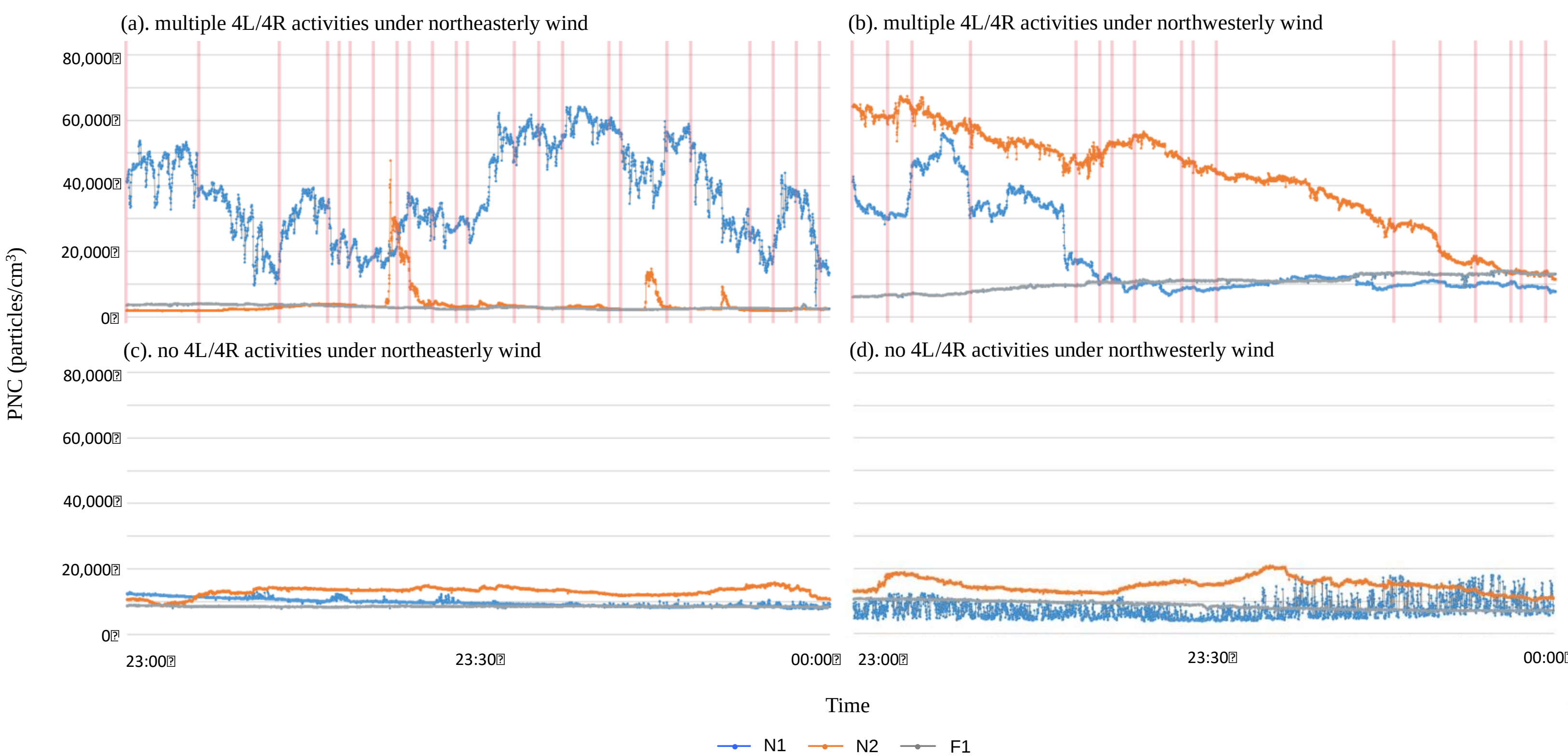
* distance to the airport and average altitudes of arrival aircraft over the site

Figure 2.3. Pollution roses displaying the interactions between wind speed and wind direction on PNC under high vs. no arrival aircraft activity conditions



* distance to the airport and average altitudes of arrival aircraft over the site
** wind sector that positions monitoring sites downwind of the airport and the arrival flight paths to 4L/4R runways

Figure 2.4. Time series of PNC at 1-second resolution on selected sampling days at three monitoring sites during arrival flight activity (red lines) and no flight activity periods under varying wind conditions



CHAPTER 3: Assessing the impact of arrival aircraft on ambient ultrafine particle concentrations near a large international airport in the U.S.

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Abstract

Background: Ultrafine particles (UFP; particles ≤ 100 nm in aerodynamic diameter), one of the air pollutants produced by aircraft engines, has been shown to be associated with an array of adverse health effects given its ability to reach the alveolar region of the lungs once inhaled, cross the epithelial barrier and circulate in blood throughout the human body. Literature has shown non-trivial contribution of aircraft activity to ambient UFP concentrations. However, accurately ascertaining aviation contribution to ambient UFP is challenging due to the high spatio-temporal variation of UFP along with intermittent aircraft emissions. In addition, even though, most existing studies used mean or median PNC when assessing aircraft contribution, the influence of utilizing different temporal and UFP distributional data has not been well examined.

Objectives: The objective of this study was to understand the impact of individual arrival aircraft on ambient UFP concentration, measured as particle number concentration (PNC), while explicitly evaluating the influence of meteorology. We also examined if the aircraft contribution was differently ascertained when using high vs. low temporal resolution and mean vs. upper percentile PNC data.

Methods: PNC data were collected using condensation particle counters (CPC, TSI Model 3783) at six monitoring sites along a major arrival flight path in the

vicinity of Boston Logan International Airport from April to September 2017. Regression models were developed for each site using two different temporal resolutions (1-hour and 10-minute) and distributional characterizations (mean and 95th percentile PNC), while accounting for temporal autocorrelation.

Results: Overall, our study found significant contribution of individual arrival aircraft to ambient PNC controlling for the impact of other aircraft activity as well as meteorology. In general, the hourly regression models showed a larger increase in PNC associated with 4L/4R arrival activity than the 10-minute average regression models, and the 95th percentile models had a larger increase in PNC than the mean models. We also found that during the hours with aircraft activities, the aircraft contribution to ambient PNC was non-trivial, accounting for maximum 50% of total estimated PNC, while the contribution was much smaller (maximum of 26%) when looking at all hours with and without aircraft activities. Lastly, our study confirmed the inverse association between wind speed and ambient PNC associated with aircraft activity, which was only shown at sites that were close to the airport.

Discussion: Overall, our study found a significant impact of individual aircraft on measured ambient PNC at all monitoring sites that were at varying distances from the airport. More importantly, our study demonstrated the influence of using different time resolution and PNC distributional data in understanding aircraft impact. The selection of which temporal and distributional characterizations to be used for regression model for aviation source attribution should be carefully determined based on site locations as well as specific research questions to be answered. Overall, our study laid the groundwork for future studies to consider in order to more accurately examine aviation contributions to ambient air pollution.

Introduction

Ultrafine particles (UFP) are defined as airborne particles with an aerodynamic diameter less than 0.1μm, which can come directly from combustion sources as well as from secondary formation in the air.[2,12] Smaller particles are potentially more harmful to human health given their ability to enter the bloodstream, penetrate into lung tissues, and circulate throughout the body.[42,43] Given its small size and mass, and rapid formation and removal processes, UFP is known to have high temporal and spatial variability.[14,15,44]

In addition to UFP contributions from ground-level traffic, there is growing evidence of a contribution from aviation activities to ambient UFP in settings near airports. It has been shown that the aviation contribution to UFP can affect a much greater geographic area compared to the contribution from ground-level vehicle traffic, with corresponding exposure and health implications.[17–19] While emission rates from arrival aircraft are much lower compared to departure aircraft given its distinctive engine thrust setting,[53] studies have documented elevated UFP concentrations under arrival flight paths with evidence for a larger spatial domain of impact than for departures.[17,20] However, the magnitude and spatiotemporal patterns of UFP contributions from arrival aircraft have not been sufficiently characterized to date.

There are multiple factors that make it challenging to ascertain aviation source contributions to ambient UFP concentrations. Studies examining the contributions of aircraft activities to ambient UFP concentrations often focused on mean or median UFP across longer averaging times (i.e., an hour).[12,18,19] However, our previous study (Chapter 2) indicated that the UFP contribution from aircraft is likely to be better captured in the upper percentiles given the strong and intermittent nature of aircraft emission patterns. The question of the ideal temporal resolution to capture these intermittent peaks is also challenging and unresolved. With shorter averaging times, the intermittency of aircraft activities coupled with lags between overhead flights and changes in ground-level concentrations may make it difficult to capture aviation contributions. On the other hand, using lower temporal resolution data may lead to aggregating the observations over longer time periods than necessary and reduce the ability to identify aircraft-associated peaks. It is therefore important to formally examine the impact of using different temporal resolution data in order to preserve and identify the peak observations associated with aircraft activities.

The role of meteorology, which has an effect on plume dynamics and dispersion as well as aircraft activity, can also be further investigated. A few studies have identified a positive association between wind speed and UFP from buoyant plumes. A study done in Boston showed increases in UFP with higher wind speed with wind blowing from the airport (consistent with aircraft contributions), and increases in UFP with lower wind speed with wind coming from other directions (consistent with traffic contributions).[18] Another study performed near Los Angeles International Airport showed increases in PNC with increases in wind speed when the monitoring site was along the flight trajectory, again indicating aircraft contributions.[52] However, the monitoring sites included in these studies were relatively close to the airport (maximum distance of 8 km to the airport) and had limited ability to identify atmospheric dispersion from higher altitudes. Lastly, the frequency of landing and take-off operations (LTO) is what is commonly used in order to assess the impact of aircraft activity on ambient UFP.[48,54] However, this omits the differential emission rates as a function of landing vs. take-off vs. idling, engine type, aircraft weight, and other factors.[53]

Our study was designed to investigate the impact of individual arrival aircraft on ambient UFP concentration (measured as particle number concentration (PNC)), explicitly evaluating the influence of meteorology. We collected high-resolution data at multiple monitoring sites at varying distances to the main arrival flight path at Boston Logan International Airport (hereafter Logan), and evaluated the influence of arrival aircraft and whether it was differentially ascertained using high vs. low temporal resolution data as well as mean vs. upper percentile PNC.

Methods

Study Design

PNC was measured from April to September 2017 in the vicinity of Logan Airport. Multiple potential monitoring sites were considered that were at varying distances from the airport and the flight paths to 4L and 4R runways (Figure 2.1), 4R being the most utilized arrival runway at Logan, in order to capture potentially varying UFP contributions from aircraft arrivals. The six monitoring sites were selected to ensure variability in distance from the flight path and the airport, sufficient distance from major roads (at least 200-meters away from major roads in order to avoid large motor vehicle traffic contributions to PNC), and observations from in-person visits to each site. One of the sites fell within the 200-meter major road buffer, but was still included in our study based on preliminary data showing limited impact from ground-level traffic. Based on their distances to the airport as well as based on the average flight altitudes (Table 2.1), two sites closest to the airport were named N1 and N2 (near sites), two sites that were intermediate distances to the airport as I1 and I2 (intermediate sites), and two farthest away sites as F1 and F2 (far sites) as shown on the map. Our semi long-term monitoring regime allowed us to capture multiple different meteorological conditions at each study site.

Instrument, Data Collection, and Data Processing

PNC were measured at 1-second resolution at three sites simultaneously for one week at a time using three research-grade condensation particle counters (TSI CPC 3783). The instruments were rotated across the six sites in order to capture as many different spatial and meteorological combinations as possible. Over the course of our data collection, there was less than 5% erroneous data (mainly due to pump malfunctions), which were removed from the data for final analyses. In addition to the PNC data that we collected, we obtained meteorological data collected at the airport as well as real-time flight activity data (PDARS – Performance Data Analysis and Reporting System) provided by the Federal Aviation Administration (FAA). PDARS provided real-time aircraft location information (latitude, longitude, and altitude) along with aircraft classification information (weight class and performance category). More details about our study design, data collection, and data processing are available elsewhere (Chapter 2).

Statistical Analysis

All data (PNC, meteorology, and PDARS) were aggregated into hourly and 10-minute averages and were merged by date and time. Aggregation was done through the mean, 95^{th}, and 99^{th} percentile for PNC. Aggregated means were calculated for wind speed, wind direction, temperature, relative humidity, mixing height, atmospheric pressure, and precipitation. Several new variables were created. The number of arrival aircraft landing on the 4L/4R runways and the number of all other aircraft activities (all departures + all arrivals - 4L/4R arrivals) were calculated at both 10-minute and hourly resolution. The number of aircraft for each of the 20 unique weight class (heavy, F-757, large, small, and unknown) and performance category (jet, turbo prop, prop, and unknown) combinations were calculated in order to investigate potentially varying PNC emission rates from different aircraft types. Additional derived variables included weekday/weekend (yes/no) and traffic (yes/no rush hour – rush hours defined as

7- 9AM and 4-6PM). An aviation impact sector variable (yes/no) was also created using the wind direction range that positioned monitoring sites downwind of the airport ±15°, which would also capture the impact of arrival aircraft in-flight at the tail of the 4L/4R flight trajectories with arrival aircraft close to the ground.[55]

Regression models were developed using two temporal resolutions (1-hour and 10-minutes) using three different measures of PNC within those time periods (mean, 95th percentile, and 99th percentile) in order to understand the contribution of arrival aircraft as well as the impact of meteorological conditions to measured PNC. These regression models were developed for each site in order to capture potentially varying impact of arrival aircraft as well as meteorology across our study sites. Log-transformed PNC were used as the outcome variable. We examined all variables in our data that were known to be important predictors for PNC based on previously published studies[8-10] and results in Chapter 2: wind direction, wind speed, temperature, relative humidity, mixing height, atmospheric pressure, precipitation, traffic, and weekday/weekend. In addition, all the derived flight activity terms were assessed in our models in order to characterize aircraft contribution. Traffic and all other airport activity terms created multicollinearity issues in the models, and traffic was removed from the final model given our focus on understanding the impact of aircraft activity on ambient PNC. Aircraft type information we obtained from PDARS were shown to be unable to accurately ascertain varying contributions of different aircraft types to ambient PNC, and therefore were not included in our final models.

We used generalized least squares models and accounted for autocorrelation in the residuals since we had time-series data. Forward step-wise regression method with an AIC criterion was used to select the variables for the final model using the stepAIC function in MASS R package. In order to make the results comparable across different models and sites, the most exhaustive list of variables were used in all models. Bonferroni correction was used in determining statistical significance of the predictors in order to adjust for multiple testing. Exponentiated regression coefficients from regression models were presented, which represent the relative magnitude of PNC per one unit increase in 4L/4R arrival aircraft, controlling for all other aircraft, temperature, relative humidity, and wind speed, and being under impact sector, on weekday, as well as the interaction between wind speed and impact sector wind.

Autocorrelation function (ACF) and partial autocorrelation function (pACF) plots were examined in order to identify appropriate autocorrelation structures. Our data suggested AR(1) and AR(6) to be most appropriate for the hourly and 10-minute data, respectively. We also performed a series of sensitivity analyses by deploying various autocorrelation structures in our regression models in order to assess their impact on the model fit and effect estimates.

In order to quantify arrival aircraft flight contributions, we used the regression models to predict hourly 95th percentile PNC, and then calculated both the predicted concentration with actual 4L/4R arrival activity and the predicted concentration if there were no 4L/4R flights in the given hour. The data were restricted to time periods with non-zero arrival aircraft activity with 27%, 23%, 27%, 30%, 21%, and 25% of total data used at N1, N2, I1, I2, F1, and F2, respectively. This was an effort to compare the different magnitudes of arrival aircraft impact across the sites while controlling for all other aircraft activity as well as meteorological conditions. Several plots were generated using the coefficients from the regression models, including comparisons of the predicted PNC with and without 4L/4R arrival activity. We also created plots displaying different patterns of association between wind speed and PNC under impact and non-impact wind sectors.

Results

In total, we collected more than 41 million individual 1-second PNC measurements throughout the study period at the six monitoring sites. After removing PNC observations flagged as erroneous by the monitoring instrument, we had on average 2,000 hourly and 12,000 10-minute data points at each site. Regression model results for N1, I1, and F1 sites are presented in Table 3.1 (mean PNC) and Table 3.2 (95^{th} percentile PNC). The results from modeling 99^{th} percentile data are not presented, as they were similar to the results of 95^{th} percentile PNC. Results for the other three sites (N2, I2, and F2) can be found in supplemental material (Table S3.1 and S3.2).

Overall, our regression models indicated a positive and significant association between 4L/4R arrival aircraft frequency and measured PNC. In general, the hourly regression models showed a larger increase in PNC associated with 4L/4R arrival activity than the 10-minute average regression models (with the exception of the 95th percentile models for site N1), and the 95th percentile models had a larger increase in PNC than the mean models. The exponentiated coefficients from different models are not directly comparable as the models have different intercepts, but we can still compare the absolute contributions of 4L/4R activity across the sites by considering both the intercept and the relative 4L/4R arrival aircraft contribution, while holding all other variables constant. For example, at I1, the estimated percent change in measured 95th percentile 10-minute PNC with one additional 4L/4R arrival aircraft was 1.1% compared to 0.3% for the mean model, with a larger intercept for the 95th percentile PNC model. In other words, the estimated absolute contribution of 4L/4R arrival aircraft on PNC at I1 is larger in the 95th percentile model than in the mean model. On the other hand, the impact of all other aircraft activity at all sites was fairly similar between the mean and the 95th percentile models. The coefficients for aircraft activity, including both the 4L/4R arrival aircraft and all the other aircraft activity, were lowest at the far site (F1) compared to the near and intermediate sites (N1 and I1) (Table 3.1 and 3.2).

In order to directly compare the varying contributions of arrival aircraft to ambient PNC across different models while accounting for other predictors, we calculated PNC estimates using hourly 95th percentile model coefficients under two different arrival aircraft scenarios (zero vs. actual arrival aircraft in an hour).

While accounting for other predictors in the model, there was a clear contribution of arrival aircraft at all six study sites. The aircraft contribution at N1 was the largest compared to all other sites (Figure 3.1). For the 27% of hours with arrival aircraft on 4L/4R, the estimated arrival aircraft contribution at site N1 had a mean of 11,100 particles/cm^3 (50% of total PNC). The second and third largest aircraft contributions were shown at I1 and N2 with the estimated arrival aircraft contribution of 9,200 and 6,500 particles/cm^3, respectively, during the hours with arrival aircraft activity. Both the background level PNC and aircraft contribution at I2, F1, and F2 were lowest compared to other sites, with aircraft contributions ranging from 2,300 to 5,000 particles/cm^3. Across all hours (not restricting the data to hours with 4L/4R arrival aircraft activity), the mean predicted arrival aircraft contributions ranged from 7% to 26% with the highest observed at N1 and lowest at F1.

Beyond the focus on the individual arrival aircraft impact, our models also identified varying influence of impact sector winds across the study sites. The effect of impact sector wind varied substantially across the four models and across the study sites. A statistically significant positive association between impact sector winds and PNC was observed only at N1 using the hourly 95th percentile PNC and at I1 using the hourly mean PNC, with 36% and 21% increases in PNC under impact sector wind, respectively (Table 3.1 and Table 3.2). The coefficients for impact sector winds were generally greater in the hourly models than the 10-minute models and there were positive associations in many models, but overall, there was no consistent pattern shown for impact sector wind across the sites across the models (Table 3.1, 3.2, S3.1, and S3.2).

We also observed different patterns of association between wind speed and PNC under impact and non-impact sector winds. Wind speed displayed an inverse association with concentrations under non-impact sector winds, but at N1 and N2, near airport sites, there was a positive association under impact sector winds (Figure 3.2). Overall, the interaction between wind direction, wind speed, and PNC was shown to be complex and not uniform across our study sites.

It is also important to mention the impact of temporal autocorrelation and the influence of accounting for it in our analyses. There was significant temporal autocorrelation in both the hourly and 10-minute data as anticipated. Not accounting for autocorrelation at all resulted in a much higher AIC compared to models that accounted for autocorrelation, suggesting a relatively poorer fit of the model. Accounting for autocorrelation had two primary effects on model coefficients. First, the intercepts were decreased compared to the models without an autocorrelation structure. Second, the effect size for the arrival aircraft term was also decreased after properly accounting for autocorrelation (results not shown).

Discussion

The dispersion pattern of UFP (both vertical and horizontal) from aircraft in-flight is highly complex and difficult to capture given the high volatility of UFP, high velocity and temperature of the plume, intermittent in-flight aircraft contribution, distance between the aircraft and the ground, and variable flight direction and speed over time and space that correlate with meteorological conditions. Despite this complexity, our study found significant contributions of arrival aircraft to ambient PNC at all of our monitoring sites in a regression model controlling for other predictors, at least for some combinations of averaging time and distributional characterization used. Our findings showed that the contribution of arrival aircraft was generally greater using the 95th percentile PNC with greatest absolute contribution of 11,100 particles/cm^3 (50% of total estimated PNC during the hours with 4L/4R activity) at N1. The aircraft contribution to overall ambient PNC was not trivial during the hours of aircraft activity indicating the importance of further investigating the impact of aircraft activity on ambient PNC. However, over all hours during our study period, the contribution of aircraft to total ambient PNC was relatively small (ranging from 7% to 26%). Our finding also reinforced the fact that a mean or median concentration may not be suitable for capturing the strong and intermittent aviation signal. This finding can be useful especially when examining the combined UFP exposures from multiple sources. UFP composition varies by source, which may be associated with specific health outcomes.[56] The effort to ascertain more accurate contribution of aircraft to overall ambient PNC will result in more appropriate source apportionment that can be utilized in epidemiological studies investigating the association between UFP from multiple sources and different health outcomes.

To our knowledge, our study is the first to focus explicitly on the sensitivity of aircraft source attribution results to choices about temporal resolution (hourly vs. 10-minute average) and distributional characterization (mean vs. 95th percentile) of PNC data. Many studies in the literature rely on hourly mean or median concentrations. There are a limited number of studies that included peaks or upper percentile measurements in their analyses; however, for those that did, it was either using a more descriptive approach or not the main focus of the study.[48,51] Our results suggest that modeling upper percentile PNC using higher temporal resolution data will capture a stronger PNC signal associated with aircraft activity at locations that are close to the sources (i.e. N1), both based on horizontal distance to the airport and vertical distance to aircraft in-flight. However, lower temporal resolution (hourly) data showed larger contributions of arrival aircraft at locations that are more distant from the sources (i.e. I1), potentially related to the dampened and variable signal. Looking at the literature, studies comparing the aviation impact across multiple sites often use the same temporal resolution data,[18,20] but this may not be the most meaningful way to assess aviation contribution, especially if a study involves multiple sites with a large geographic spread. While our quantitative estimates may not generalize to other airports, our findings provided the rationale and evidence for the importance of exploring the effects of using different temporal resolution and distributional characterization of PNC data in order to correctly answer particular research questions of interest.

Another finding was the varying influence of impact sector wind on PNC at hourly and 10-minute resolution across the sites. Previous literature showed a positive association between impact sector wind and PNC at hourly resolution, similar to what was shown in our data.[18] However, we found no such association with our 10-minute data. One potential explanation for this difference is the time needed for the plumes to reach a given ground-level monitoring location. Some experimental studies reported the time for the vortices to collapse into aircraft turbulence is between 1.5 and 3 minutes, which allows for the particles from the vortices to disperse into the ambient air, and the descending rate of the wake vortices to be between 1.2 and 2.4 m/s.[57,58] The combination of these two suggests that it is possible that the particles emitted from arrival aircraft might not reach the ground level within the 10-minute window at some of our monitoring sites based on the average altitudes of aircraft at a given site (Table 2.1). While in theory models incorporating lag structures could be utilized, given variable dispersion patterns and frequent flight arrival activity, they would be unlikely to fully capture this phenomenon. We should note that these numbers were generated under an experimental setting, so there are likely to be even more variability in our study setting.

Corresponding to the findings of other recent studies, our study confirmed the large geographic extent of the impact of arrival aircraft on ambient PNC, as illustrated by the increase in PNC associated with individual arrival aircraft shown at site F1 and F2.[18,19] In addition, our study also confirmed the differential patterns of association between wind speed and PNC associated with aviation activities versus ground-level traffic, similar to what was shown in previous airport and PNC studies.[18,52] The monitoring sites included in previous studies displaying a positive association between wind speed and PNC were located either directly at the end of the runways or very close to the airport, which is similar to where sites N1 and N2 were located in our study (3 km and 4 km from the airport, respectively). Sites further from the airport did not exhibit comparable patterns, indicating either dominant contributions from ground-level UFP sources or that the plumes no longer had the same buoyancy characteristics at an appreciable distance from the source.

Our study also found that crude categorization of aircraft was not enough to identify specific emission levels associated with individual aircraft at our study sites. Though PDARS data provided aircraft identifying information such as weight class and performance category, the results of including those data in the regression models were largely uninterpretable. This may indicate that the crude data on aircraft type do not provide sufficient information to ascertain individual aircraft emissions since factors such as engine type, engine age, and number of passengers, which are not available in PDARS data, would greatly impact the emission levels of individual aircraft. On the other hand, this may indicate the difficulty of assessing the impact of different emission rates based on individual aircraft type when we are trying to examine the ground-level impact of aircraft at high altitudes. There is a study that detected a positive association between a similarly crude aircraft identifying information (aircraft weight) and measured PNC.[51] However, in that study, PNC were measured directly at the takeoff blast fence, which minimized other meteorological and surrounding environment impacts on measured PNC.

Beyond our findings on quantified aircraft impact on PNC, we also found the importance of correctly accounting for temporal autocorrelation, as not properly accounting for autocorrelation resulted in differences in effect estimates with substantially larger AIC. There are only a few studies conducting aviation source attribution that account for temporal autocorrelation, while most other studies ignore it.[12,46,52,59] Not correctly accounting for autocorrelation can result in a biased intercept as well as coefficients of interest. Future studies building regression models must consider temporal autocorrelation in order to obtain unbiased study results and to improve model fit.

Our study had a few limitations. First, even though the PNC measurements were made at six different locations, the meteorological data were from one location, the airport. The local conditions such as surrounding buildings, which can alter meteorological conditions on a smaller scale, could have affected the particle dispersion. However, the regional meteorology would have likely played a more important role in particle dispersion from arrival aircraft emissions. Another limitation is our inability to directly associate the PNC peaks with aircraft activity, which is largely a function of our study sites being farther away from the runways with aircraft at much higher altitudes than many other studies, resulting in variable time lags from emission to the measured PNC on the ground.

In spite of these limitations, our study offers some valuable insights for future studies of contributions of aircraft or other intermittent sources to PNC. First, our study provides a novel approach in assessing aircraft contribution to ambient PNC. To our knowledge, our study is the first study to extensively investigate the effect of modeling for mean and upper percentile PNC using high and low temporal resolution data in regression models. This approach is reasonable given a strong and intermittent source characteristic of aircraft. Second, our study formally accounted for autocorrelation, which was often unaccounted for in other studies. The differences in model outputs with and without accounting for autocorrelation demonstrate the importance of correctly accounting for autocorrelation in future studies. Third, all of our study sites were strategically selected to capture arrival aircraft impact, minimizing the influence of ground-level traffic on our measurements and with limited correlation between aircraft arrival activity and traffic. Lastly, the highly varying meteorological conditions at Logan allowed us to examine the widely varying impact of different wind directions and speeds on ambient PNC, which was not always available in previous studies.[17,19,52]

Conclusions

Our study aimed to advance our understanding of arrival aircraft contributions to ambient PNC near a large airport by employing a novel approach of using varying temporal resolution and distributional characterization of PNC data. Our study found a significant impact of individual arrival aircraft on measured ambient PNC at all of our monitoring sites that were at varying distances from the airport. In addition, we found that modeling higher percentiles of PNC allowed us to capture the strong and intermittent individual aircraft contribution, which has a direct implication for future aviation and air pollution studies. We also showed the importance of appropriate time resolution selection for aviation source attribution, with the selection potentially varying as a function of proximity to the airport as well as the specific research question of interest. Overall, our study laid the groundwork for future studies to more accurately determine aviation contributions to ambient air pollution.

Acknowledgements

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contributions by the community partners that allowed our research team to take measurements at their homes, offices, and facilities.

Tables

Table 3.1. Multivariable regression model results of hourly and 10-minute mean PNC at multiple monitoring sites, accounting for autocorrelation

	Mean PNC (particles/cm^3)			
	Hourly		10-Minute	
	Exponentiated Regression Coefficients	95% CI	Exponentiated Regression Coefficients	95% CI
	N1			
Intercept	15,100	(9,800, 23,100)	9,500	(6,500, 13,900)
4L4R runway arrival aircraft frequency	1.016	(1.013, 1.020)	1.008	(1.001, 1.015)
All other aircraft activity frequency	1.007	(1.006, 1.009)	1.002	(0.999, 1.005)
Temperature (Celsius)	0.982	(0.969, 0.994)	0.989	(0.976, 1.001)
Relative humidity (%)	0.993	(0.990, 0.997)	1.000	(0.997, 1.002)
Wind speed (m/s)	0.934	(0.910, 0.959)	0.983	(0.971, 0.995)
Mixing height (m)	1.000	(1.000, 1.000)	1.000	(1.000, 1.000)
Atmospheric pressure (millibar)	0.986	(0.976, 0.997)	1.011	(0.998, 1.025)
Precipitation (mm/hour)	0.966	(0.934, 1.000)	0.989	(0.970, 1.008)
Weekday vs. weekend	1.062	(0.889, 1.267)	1.050	(0.844, 1.306)
Impact sector (yes)	1.119	(0.855, 1.466)	0.941	(0.868, 1.020)
Wind speed (m/s)*Impact sector (yes)	1.114	(1.056, 1.176)	1.031	(1.014, 1.047)
	I1			
Intercept	24,900	(17,600, 35,300)	12,300	(8,900, 17,000)
4L4R runway arrival aircraft frequency	1.015	(1.012, 1.018)	1.003	(0.997, 1.008)
All other aircraft activity frequency	1.010	(1.009, 1.012)	1.003	(1.000, 1.005)
Temperature (Celsius)	0.964	(0.954, 0.974)	0.989	(0.978, 1.000)
Relative humidity (%)	0.995	(0.993, 0.998)	0.999	(0.997, 1.001)
Wind speed (m/s)	0.913	(0.893, 0.933)	0.986	(0.977, 0.995)
Mixing height (m)	1.000	(1.000, 1.000)	1.000	(1.000, 1.000)
Atmospheric pressure (millibar)	1.003	(0.994, 1.012)	1.012	(1.000, 1.024)
Precipitation (mm/hour)	0.991	(0.963, 1.02)	0.997	(0.983, 1.012)

Weekday vs. weekend	0.904	(0.796, 1.025)	0.996	(0.813, 1.221)
Impact sector (yes)	1.244	(1.021, 1.516)	0.963	(0.908, 1.022)
Wind speed (m/s)*Impact sector (yes)	1.038	(0.997, 1.079)	1.021	(1.007, 1.036)
		F1		
Intercept	20,100	(13,100, 30,8003)	6,100	(4,500, 8,100)
4L4R runway arrival aircraft frequency	1.010	(1.007, 1.013)	0.999	(0.994, 1.003)
All other aircraft activity frequency	1.004	(1.003, 1.005)	1.001	(0.999, 1.002)
Temperature (Celsius)	0.982	(0.970, 0.994)	1.000	(0.990, 1.010)
Relative humidity (%)	0.990	(0.987, 0.993)	0.999	(0.997, 1.000)
Wind speed (m/s)	0.904	(0.884, 0.925)	0.992	(0.985, 1.000)
Mixing height (m)	1.000	(1.000, 1.000)	1.000	(1.000, 1.000)
Atmospheric pressure (millibar)	0.997	(0.986, 1.007)	1.012	(1.000, 1.023)
Precipitation (mm/hour)	1.024	(0.979, 1.071)	1.004	(0.986, 1.022)
Weekday vs. weekend	1.094	(0.946, 1.266)	1.094	(0.900, 1.330)
Impact sector (yes)	1.079	(0.861, 1.354)	1.016	(0.963, 1.072)
Wind speed (m/s)*Impact sector (yes)	1.023	(0.964, 1.086)	0.995	(0.908, 1.009)

Table 3.2. Multivariable regression model results of hourly and 10-minute 95th percentile PNC at multiple monitoring sites, accounting for autocorrelation

	95th Percentile PNC (particles/cm^3)			
	Hourly		10-Minute	
	Exponentiated Regression Coefficients	95% CI	Exponentiated Regression Coefficients	95% CI
	N1			
Intercept	18,300	(12,200, 27,600)	15,400	(10,100, 23,600)
4L4R runway arrival aircraft frequency	1.025	(1.021, 1.029)	1.034	(1.024, 1.044)
All other aircraft activity frequency	1.008	(1.006, 1.01)	1.004	(0.999, 1.008)
Temperature (Celsius)	0.969	(0.958, 0.981)	0.976	(0.963, 0.989)
Relative humidity (%)	0.997	(0.994, 1.000)	0.999	(0.996, 1.002)
Wind speed (m/s)	0.955	(0.929, 0.983)	0.988	(0.972, 1.004)
Mixing height (m)	1.000	(1.000, 1.000)	1.000	(1.000, 1.000)
Atmospheric pressure (millibar)	1.006	(0.995, 1.016)	1.014	(1.000, 1.029)
Precipitation (mm/hour)	0.971	(0.934, 1.009)	0.998	(0.974, 1.023)
Weekday vs. weekend	1.054	(0.903, 1.230)	1.074	(0.871, 1.323)
Impact sector (yes)	1.356	(1.003, 1.835)	0.982	(0.874, 1.102)
Wind speed (m/s)*Impact sector (yes)	1.081	(1.018, 1.148)	1.033	(1.009, 1.057)
	I1			
Intercept	30,900	(21,600, 44,100)	16,500	(11,100, 24,500)
4L4R runway arrival aircraft frequency	1.020	(1.016, 1.023)	1.011	(1.002, 1.019)
All other aircraft activity frequency	1.012	(1.011, 1.014)	1.006	(1.002, 1.009)
Temperature (Celsius)	0.954	(0.945, 0.964)	0.982	(0.969, 0.995)
Relative humidity (%)	0.997	(0.995, 1.000)	0.999	(0.996, 1.002)
Wind speed (m/s)	0.919	(0.897, 0.941)	0.983	(0.970, 0.997)
Mixing height (m)	1.000	(1.000, 1.000)	1.000	(1.000, 1.000)
Atmospheric pressure (millibar)	1.006	(0.997, 1.015)	1.017	(1.003, 1.030)
Precipitation (mm/hour)	0.995	(0.963, 1.029)	1.001	(0.981, 1.021)
Weekday vs. weekend	0.906	(0.804, 1.020)	1.005	(0.818, 1.234)

Impact sector (yes)	1.213	(0.970, 1.519)	0.955	(0.869, 1.049)
Wind speed (m/s)*Impact sector (yes)	1.064	(1.018, 1.112)	1.035	(1.013, 1.058)
			F1	
Intercept	24,500	(15,200, 39,400)	6,800	(4,600, 10,000)
4L4R runway arrival aircraft frequency	1.012	(1.008, 1.016)	1.000	(0.993, 1.008)
All other aircraft activity frequency	1.006	(1.004, 1.007)	1.002	(0.999, 1.004)
Temperature (Celsius)	0.976	(0.963, 0.989)	1.002	(0.99, 1.014)
Relative humidity (%)	0.990	(0.987, 0.993)	0.997	(0.995, 1.000)
Wind speed (m/s)	0.913	(0.888, 0.939)	0.990	(0.978, 1.003)
Mixing height (m)	1.000	(1.000, 1.000)	1.000	(1.000, 1.000)
Atmospheric pressure (millibar)	0.999	(0.988, 1.011)	1.015	(1.002, 1.028)
Precipitation (mm/hour)	1.022	(0.965, 1.081)	1.002	(0.974, 1.031)
Weekday vs. weekend	1.177	(1.019, 1.36)	1.163	(0.963, 1.403)
Impact sector (yes)	0.986	(0.741, 1.312)	1.042	(0.950, 1.143)
Wind speed (m/s)*Impact sector (yes)	1.072	(0.996, 1.155)	0.990	(0.966, 1.015)

Figures

Figure 3.1. Boxplots displaying 4L/4R arrival aircraft contributions to estimated ambient PNC (95th percentile, 1-hour average) using multivariable regression model predictions with actual arrival activity and assuming no arrival aircraft restricting to time-periods with non-zero 4L/4R arrival aircraft activity.

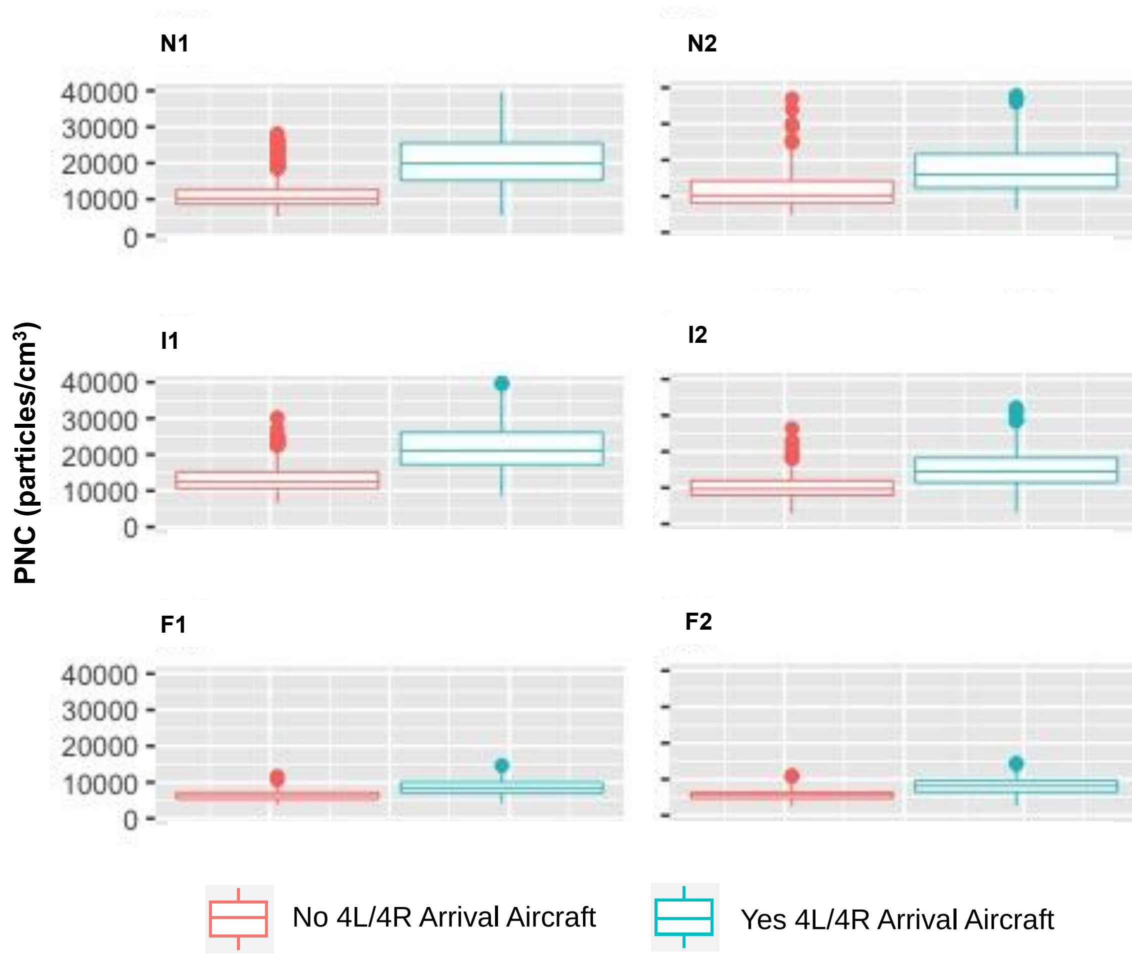
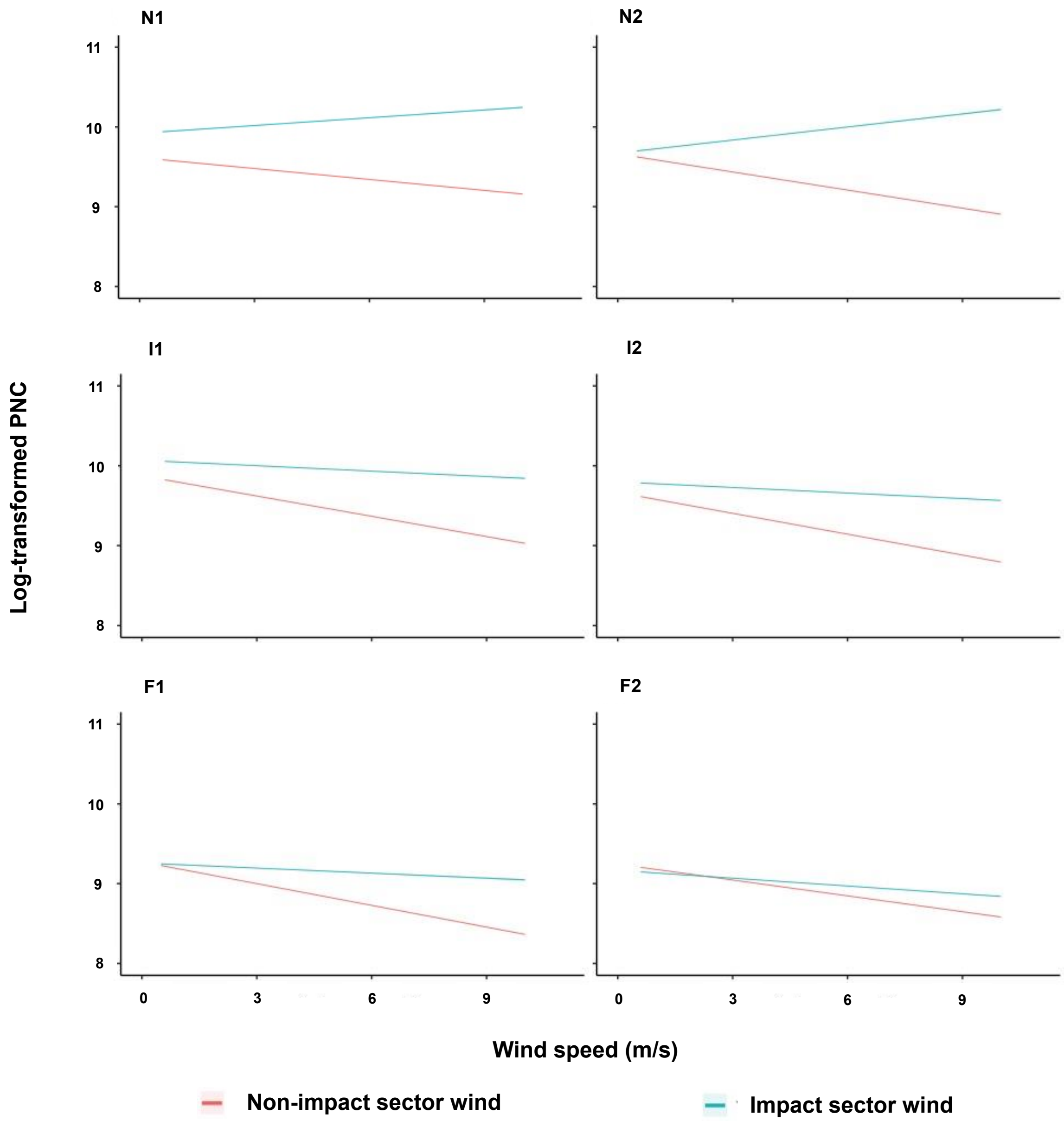


Figure 3.2._Plots displaying the association between wind speed and log-transformed PNC for impact vs. non-impact winds using the hourly 95th percentile PNC multivariable regression model output.



Supplemental material

Table S3.1. Multivariable regression model results of hourly and 10-minute mean PNC at multiple monitoring sites, accounting for autocorrelation

	Mean PNC (particles/cm^3)			
	Hourly		10-Minute	
	Exponentiated Regression Coefficients	95% CI	Exponentiated Regression Coefficients	95% CI
	N2			
Intercept	29,000	(18,500, 45,400)	8,900	(6,100, 13,000)
4L4R runway arrival aircraft frequency	1.010	(1.006, 1.013)	1.000	(0.994, 1.007)
All other aircraft activity frequency	1.008	(1.006, 1.010)	1.000	(0.998, 1.003)
Temperature (Celsius)	0.961	(0.948, 0.974)	0.992	(0.980, 1.005)
Relative humidity (%)	0.991	(0.988, 0.994)	0.999	(0.996, 1.001)
Wind speed (m/s)	0.921	(0.896, 0.946)	0.982	(0.972, 0.993)
Mixing height (m)	1.000	(1.000, 1.000)	1.000	(1.000, 1.000)
Atmospheric pressure (millibar)	0.993	(0.981, 1.006)	1.007	(0.992, 1.023)
Precipitation (mm/hour)	0.991	(0.952, 1.032)	0.996	(0.976, 1.016)
Weekday vs. weekend	1.239	(1.046, 1.467)	1.267	(1.006, 1.596)
Impact sector (yes)	0.948	(0.726, 1.238)	0.924	(0.849, 1.006)
Wind speed (m/s)*Impact sector (yes)	1.099	(1.034, 1.169)	1.021	(0.999, 1.043)
	I2			
Intercept	30,100	(20,900, 43,200)	9,100	(6,300, 13,100)
4L4R runway arrival aircraft frequency	1.012	(1.009, 1.015)	1.000	(0.995, 1.005)
All other aircraft activity frequency	1.008	(1.007, 1.010)	1.002	(1.000, 1.004)
Temperature (Celsius)	0.966	(0.956, 0.976)	0.999	(0.987, 1.011)
Relative humidity (%)	0.990	(0.988, 0.993)	0.998	(0.995, 1.000)
Wind speed (m/s)	0.919	(0.898, 0.94)	0.990	(0.980, 0.999)
Mixing height (m)	1.000	(1.000, 1.000)	1.000	(1.000, 1.000)
Atmospheric pressure (millibar)	0.998	(0.990, 1.007)	1.003	(0.991, 1.016)
Precipitation (mm/hour)	0.990	(0.963, 1.017)	0.998	(0.984, 1.011)

Weekday vs. weekend	0.984	(0.848, 1.143)	1.075	(0.846, 1.365)
Impact sector (yes)	1.094	(0.908, 1.318)	0.962	(0.912, 1.014)
Wind speed (m/s)*Impact sector (yes)	1.047	(1.015, 1.080)	1.010	(1.001, 1.020)
	F2			
Intercept	12,000	(8,200, 17,600)	6,100	(4,400, 8,300)
4L4R runway arrival aircraft frequency	1.010	(1.007, 1.013)	0.998	(0.994, 1.003)
All other aircraft activity frequency	1.005	(1.004, 1.007)	1.000	(0.999, 1.002)
Temperature (Celsius)	0.987	(0.976, 0.998)	1.001	(0.990, 1.012)
Relative humidity (%)	0.993	(0.991, 0.996)	0.999	(0.997, 1.001)
Wind speed (m/s)	0.934	(0.915, 0.955)	0.988	(0.980, 0.996)
Mixing height (m)	1.000	(1.000, 1.000)	1.000	(1.000, 1.000)
Atmospheric pressure (millibar)	1.007	(0.998, 1.017)	1.010	(0.999, 1.022)
Precipitation (mm/hour)	0.999	(0.974, 1.024)	1.009	(0.997, 1.020)
Weekday vs. weekend	1.069	(0.905, 1.262)	1.062	(0.857, 1.315)
Impact sector (yes)	0.886	(0.751, 1.045)	0.997	(0.955, 1.041)
Wind speed (m/s)*Impact sector (yes)	1.032	(1.003, 1.062)	0.999	(0.991, 1.007)

Table S3.2. Multivariable regression model results of hourly and 10-minute 95th percentile PNC at multiple monitoring sites, accounting for autocorrelation

	95th Percentile PNC (particles/cm^3)			
	Hourly		10-Minute	
	Exponentiated Regression Coefficients	95% CI	Exponentiated Regression Coefficients	95% CI
	N2			
Intercept	36,500	(22,500, 59,000)	13,700	(8,600 21,600)
4L4R runway arrival aircraft frequency	1.017	(1.013, 1.021)	1.012	(1.002, 1.022)
All other aircraft activity frequency	1.010	(1.008, 1.012)	1.000	(0.996, 1.004)
Temperature (Celsius)	0.954	(0.941, 0.967)	0.986	(0.971, 1.001)
Relative humidity (%)	0.992	(0.989, 0.996)	0.997	(0.994, 1.000)
Wind speed (m/s)	0.927	(0.898, 0.957)	0.978	(0.963, 0.994)
Mixing height (m)	1.000	(1.000, 1.000)	1.000	(1.000, 1.000)
Atmospheric pressure (millibar)	0.996	(0.983, 1.009)	1.010	(0.993, 1.027)
Precipitation (mm/hour)	1.002	(0.954, 1.053)	0.993	(0.965, 1.021)
Weekday vs. weekend	1.300	(1.102, 1.533)	1.316	(1.052, 1.647)
Impact sector (yes)	1.009	(0.732, 1.392)	0.861	(0.753, 0.985)
Wind speed (m/s)*Impact sector (yes)	1.139	(1.059, 1.225)	1.049	(1.014, 1.085)
	I2			
Intercept	41,000	(28,600, 58,600)	15,600	(10,300, 23,600)
4L4R runway arrival aircraft frequency	1.015	(1.012, 1.018)	1.006	(0.998, 1.014)
All other aircraft activity frequency	1.010	(1.008, 1.012)	1.005	(1.001, 1.009)
Temperature (Celsius)	0.955	(0.945, 0.964)	0.983	(0.970, 0.997)
Relative humidity (%)	0.992	(0.989, 0.994)	0.997	(0.994, 1.000)
Wind speed (m/s)	0.917	(0.894, 0.94)	0.980	(0.966, 0.994)
Mixing height (m)	1.000	(1.000, 1.000)	1.000	(1.000, 1.000)
Atmospheric pressure (millibar)	1.000	(0.992, 1.009)	1.008	(0.995, 1.022)
Precipitation (mm/hour)	0.996	(0.965, 1.028)	1.001	(0.982, 1.02)

Weekday vs. weekend	0.989	(0.868, 1.127)	1.081	(0.870, 1.342)
Impact sector (yes)	1.141	(0.917, 1.421)	0.976	(0.894, 1.066)
Wind speed (m/s)*Impact sector (yes)	1.066	(1.028, 1.105)	1.013	(0.997, 1.029)
		F2		
Intercept	16,500	(11,000, 24,800)	8,000	(5,400, 11,900)
4L4R runway arrival aircraft frequency	1.014	(1.010, 1.017)	1.002	(0.993, 1.01)
All other aircraft activity frequency	1.007	(1.005, 1.009)	1.003	(1.000, 1.007)
Temperature (Celsius)	0.975	(0.964, 0.986)	0.995	(0.982, 1.007)
Relative humidity (%)	0.994	(0.991, 0.997)	0.998	(0.995, 1.001)
Wind speed (m/s)	0.936	(0.912, 0.961)	0.981	(0.968, 0.994)
Mixing height (m)	1.000	(1.000, 1.000)	1.000	(1.000, 1.000)
Atmospheric pressure (millibar)	1.010	(1.000, 1.02)	1.015	(1.003, 1.028)
Precipitation (mm/hour)	0.994	(0.961, 1.027)	1.015	(0.997, 1.034)
Weekday vs. weekend	1.138	(0.976, 1.328)	1.122	(0.921, 1.368)
Impact sector (yes)	0.925	(0.745, 1.148)	0.971	(0.895, 1.054)

CHAPTER 4: Long-term aircraft noise exposure and risk of hypertension in the Nurses' Health Studies

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Abstract

Background: Aircraft noise can affect populations living near airports, with pronounced spatial and temporal variability. Chronic exposure to aircraft noise has been associated with cardiovascular health effects including hypertension. However, previous studies have been limited in their ability to characterize avaiation-related noise exposures over time and to adequately control for confounders.

Objectives: The aim of this study was to examine the association between aircraft noise and incident hypertension in a cohort of female nurses, utilizing aircraft noise exposure estimates with high spatial resolution over a 20-year period.

Methods: We modeled long-term time-varying aircraft noise levels from 1995 to 2015 for 90 airports in the U.S. and assigned noise estimates to participants in the Nurses' Health Study (NHS) and NHS II based on their geocoded addresses. We used time-varying Cox proportional hazards models to estimate hypertension risk associated with time-varying aircraft noise exposure adjusting for both fixed and time-varying covariates.

Results: Our study results showed an indication of an increased risk for incident hypertension associated with increased exposure to aircraft noise in both

cohorts. The meta-analysis across both cohorts showed a hazard ratio (HR) of 1.02 (95% CI: 0.98, 1.07) and HR of 1.08 (95% CI: 0.98, 1.18) for the multivariable model using 45 and 55 dB(A) as cut-points, respectively. The results from sensitivity analyses demonstrated the robustness of our findings. Our study also found an independent association between aircraft noise and hypertension independent of that of air pollution.

Discussion: Our study suggests potential health effects of annual aircraft noise exposure below the regulatory threshold (65 dB(A)). More generally, we demonstrated the ability to develop robust longitudinal aircraft noise estimates across the entire U.S., which could be applied to many nation-wide cohorts to understand effects on the general population or subpopulations of interest.

Introduction

Individuals are exposed to multiple sources of noise every day from occupational to residential settings. Even though individuals can habituate to noise exposures at a certain level,[8] chronic noise exposures can still lead to changes in the autonomic nervous system and the endocrine system, resulting in adverse health effects such as increases in blood pressure, blood lipids and glucose levels.[5,7–9,23,60] Hypertension, in particular, has been examined extensively given both the biological plausibility of the association and the importance of hypertension as a public health issue given that it is prevalent in the population and is a major risk factor for cardiovascular disease.[22,33,61,62] The biological plausibility of noise leading to hypertension and cardiovascular effects has often been tested under occupational or experimental settings, but it is being linked to environmental noise exposures as well.[63]

Aircraft noise, the unwanted sound created by flight activities, has been shown to have a greater impact than many other noise sources in exposed communities. For example, people report the highest levels of annoyance and self-reported sleep disturbance at the same equivalent noise level for aircraft noise compared to other transportation noise sources such as roads and railways.[8,22] In addition, adverse health effects such as increased blood pressure were shown to be more strongly associated with aircraft noise compared to white noise of the same level.[64] In other words, the distinct characteristics associated with aircraft noise exposure are likely to be important in its associations with adverse health effects.[64,65] Aircraft noise is also of particular interest due to its chronicity and prevalence in certain communities near airports or beneath flight paths.

Though there is accumulating literature investigating the relationship between chronic exposure to aircraft noise and hypertension, the magnitudes and strengths of the association vary substantially across different studies.[23,28,65] Some studies found increased hypertension risk associated with increased aircraft noise,[28–30] while others found no association.[28,66,67] Several studies reported a stronger exposure-response relationship for nighttime aircraft noise,[31–33] consistent with effects associated with sleep disturbance,[68] while one study reported a stronger association for day-night average noise level.[23] A range of diverse sensitive populations to aircraft noise was identified in different studies including older people, non-smokers, men, and people with normal glucose tolerance and higher level of annoyance.[10,30,32]

A number of factors could contribute to the inconsistency in the literature, including differences in study populations, exposure characterization methods, and ability to control for potential confounders.[28,69] In particular, more studies are cross-sectional or case-control, with limited numbers of prospective cohort studies conducted in Europe and none in the U.S.[10,31–33,70] There are also few studies with extensive longitudinal noise data at high spatial resolution. High spatial and temporal resolution data would reduce the level of exposure misclassification and allow for changing noise exposures over time in addition to other time-varying covariate information. The ability to appropriately control for potential confounders would allow us to more accurately examine the magnitude of the association between aircraft noise exposure and hypertension.

In this study, we modeled noise exposure around multiple airports using a single noise model at high geographic resolution across a 20-year period, and we connected these longitudinal data with large national-scale prospective Nurses' Health cohort studies. To our knowledge, this study is the first multi-airport prospective cohort study examining aircraft noise impacts on hypertension in the U.S.

Methods

Study Populations

The two prospective cohorts included in this study were Nurses' Health Study (NHS) and Nurses' Health Study II (NHS II). The NHS cohorts are among the largest and most well-recognized longitudinal studies to investigate the risk factors for chronic diseases in women. NHS started in 1976 and was composed of 121,700 female nurses, who were born between 1921 and 1946, living in one of 11 populous states (CA, CT, FL, MD, MA, MI, NJ, NY, OH, PA, and TX) in the U.S. NHS II enrolled 116,000 female nurses, who were born between 1946 and 1964, living in 14 states (CA, CT, IN, IA, KY, MA, MI, MO, NY, NC, OH, PA, SC, and TX). Questionnaires were sent every two years with relatively high response rates (80~90%),[71,72] which included extensive questions on demographic and physical characteristics, health status and lifestyle, and family disease history.

Aircraft Noise Exposure

We worked collaboratively with the Federal Aviation Administration (FAA) and the John A. Volpe National Transportation Systems Center to design modeled annual noise contours for epidemiological applications for 1995, 2000, 2005, 2010, and 2015 for 90 U.S. airports (Figure 4.1). The source of aircraft operations data came from Official Airline Guide (OAG - air travel intelligence) for 1995, and from ETMS (Enhanced Traffic Management System) for all other years. Operations were annualized into a single average annual day, using the following data: Aircraft Noise and Performance (ANP) aircraft type, day (7am to 10pm local time) or night (10pm to 7am location) time, and operation airport. In addition, detailed departure and arrival runway, flight path utilization, and stage length data were acquired for the 90 airports included in the study to approximate tracks taken in an annualized year. The Aviation Environmental Design Tool (AEDT) was then used to compute the noise exposure data using the annualized flight track information.[73] AEDT models both noise and emissions based on flight activity patterns and aircraft attributes, and is the tool used by U.S. regulatory bodies for domestic planning, environmental compliance, and research analyses.[74] AEDT replaced the Integrated Noise Model (INM), one of the widely used legacy noise modeling tools, with improved algorithms to better capture aircraft performance and positioning.[74]

Our aircraft noise contours were estimated at 1 decibel (dB) resolution down to a minimum of 45 dB(A), considered a quiet background level, characterized for both day (7am to 10pm local time) and night (10pm to 7am local time) at ~600-feet spatial resolution. We focused on the noise metric of the Day-Night Average Sound Level (DNL), a 24-hour weighted average that applies a 10 dB(A) penalty for nighttime noise, which is the metric used in U.S. aviation decision-making.

The modeled exposure surfaces were intersected with the participants' geocoded addresses during follow-up and were assumed to have remained the same in each of the 5-year time intervals. There was a very small percentage (less than 1%) of people that lived close to more than one airport. The sum of the noise contours was calculated for those participants (noting that noise is measured on a log-scale and therefore was summed subsequent to statistical transformation). Participants that did not live within the modeled noise contours of the 90 airports were assumed to be exposed to less than DNL 45 dB(A) aircraft noise.

Hypertension Incidence

Participants of each cohort self-reported hypertension diagnosis biennially. Medical records were not used to confirm the disease diagnosis; however, a validation study showed a very high correlation between the self-report and the medical records.[75]

Covariates

Both fixed and time-varying covariate data were available from questionnaires. We selected a large set of *a priori* variables to be examined as confounders and/or effect modifiers including age, alcohol use (grams/day), body mass index (BMI; kilograms per meter squared), calendar year, comorbidities (diabetes, hearing loss, hypercholesterolemia), current smoking status (yes/no), diet (the dietary approaches to stop hypertension (DASH) score),[76] hearing problem, family history of hypertension, individual-level socioeconomic status (SES) (educational attainment, marital status, and partner's educational attainment), medication use (current statin and nonnarcotic analgesic intake drug use), menopausal status, physical activity (metabolic equivalent hours per week - MET), and race, as well as area-level (census-tract median income and house value) SES, air pollution ($PM_{2.5}$ and $PM_{2.5\text{-}10}$), and covariates for region and latitude. Most covariate data came from the questionnaires, except for air pollution and area-level SES data, and were updated biennially. We had limited data on air pollution and area-level SES (from 1994 to 2007) that were matched with participants' geocoded addresses. Air pollution estimates were developed using a GIS-based spatial smoothing model using central monitor data. Detailed methods for air pollution estimates are available elsewhere.[77,78]

Each individual variable was added to the basic model that included age and calendar year and its confounding effect was assessed. Those known to be important risk factors for hypertension or had a significant association with the outcome of interest were kept in the final multivariable model.

Population for Analysis

Women who reported a diagnosis of hypertension at baseline (1994 for NHS and 1995 for NHS II) were excluded from the analysis, corresponding to the earliest date of their respective survey cycle with available noise estimates. After this exclusion, there were a total of 61,879 and 94,592 participants from NHS and NHS II, respectively, available for analysis. No imputation was performed on our missing data due to computational limitations given the large sample size and large number of covariates. Instead, a missing category was created for each categorical covariate, and was included in the analysis. Percent missing ranged from 1% to 18% with largest missing shown in physical activity, diet, and alcohol consumption data, which were collected every four years (Table 4.1).

Statistical Analysis

Our analyses were limited to years 1994-2013 for NHS and 1995-2012 for NHS II based on the availability of noise data along with questionnaire data. Participants started contributing person-time from the return date of the baseline questionnaire until they developed hypertension, or were censored at the time of death or end of follow-up. On average, there were approximately 7% and 2% lost to follow-up or death for NHS and NHS II, respectively. We assessed socio-demographic characteristics of participants of each cohort categorized into two groups using a 55 dB(A) cut-point using t-test and chi-square test to determine any exposure status-specific underlying differences.

We used time-varying Cox proportional hazards models to estimate hypertension risk associated with time-varying aircraft noise exposure adjusting for both fixed and time-varying covariates stratifying by age in months and 2-year calendar period in order to adjust for trends over time. For analyses of the association of interest, we used dichotomous classification for aircraft noise using two different cut-points (45 and 55 dB(A) DNL), and subjects below these cut-points were considered as the reference group. We used a 45 dB(A) cut-point, which is the lowest noise level developed in our noise models, in order to assess the impact of modeled aircraft noise exposure that is often considered as background. A 55 dB(A) cut-point reflects guidelines from the WHO related to nighttime noise, with levels above 55 dB(A) likely to trigger adverse health effects, such as hypertension.[79]

The analyses were first conducted separately by cohort, then as a meta-analysis in order to combine the results from the two cohorts. In the meta-analysis, we applied inverse-variance weighting and heterogeneity of the two cohorts was examined to determine if random-effects meta-analysis was warranted.

We also conducted a few sensitivity analyses in order to examine the robustness of our results using the 55 dB(A) cut-point. First, we restricted our analyses to those participants that lived close to one of the 90 airports included in noise exposure modeling (those with assigned DNL >= 45 dB(A)) in an effort to address potential exposure error and to minimize the impact of potential differences in populations among those living proximate to airports versus farther away. Second, we excluded participants that had exposure above DNL 65 dB(A), because this is the eligibility threshold to receive noise abatement measures through the FAA and some individual airports, and therefore there is potential for increased exposure error. Lastly, we restricted our data to time periods with air pollution and area-level SES data (available up to 2008), which resulted in shorter time periods included in the analysis, to verify the independent impact of noise on hypertension apart from air pollution and area-level SES.

We evaluated effect modification by including a multiplicative term of exposure and current smoking status, diabetes status, family history of hypertension, hearing problem, menopause status, and statin use, in order to identify potentially sensitive populations in our cohorts.

Statistical Analysis System (SAS) 9.4 was used for all analyses.

Results

As expected, given the earlier recruitment date for NHS, age distributions and some age-related outcomes (e.g., diabetes, hypercholesterolemia and statin use, hearing loss and menopause) differed between NHS and NHSII. For other variables, the baseline characteristics were relatively similar between the two cohorts, except for a fairly large difference in family history of hypertension, and small differences in alcohol consumption and current smoking status. A number of baseline characteristics of exposed and unexposed participants were relatively similar in both cohorts, such as age and BMI. However, there was some dissimilarity such as higher percentage of non-Caucasian and higher air pollution levels in the exposed group compared to the non-exposed group (Table 4.1).

The percentages of participants exposed to different levels of aircraft noise in each cohort at baseline are displayed in Table 4.2. Less than 10% of the overall NHS and NHS II participants at baseline were exposed to aircraft noise as a result of living near one of the 90 airports included in our noise exposure assessment. Less than 1% of the participants were exposed to aircraft-associated DNL above 55 dB(A), with even fewer participants exposed to DNL above 65 dB(A).

The basic model includes adjustment for age and calendar year, while the multivariable model includes adjustment for a number of additional covariates (alcohol use, BMI, comorbidities (diabetes, hypercholesterolemia), current smoking status, DASH, family history of hypertension, medication use (current statin and NSAID use), menopause status, and MET). There were 31,421 and 29,086 hypertension cases over 716,442 and 1,300,400 follow-up years in NHS and NHS II, respectively.

Table 4.3 presents results from time-varying Cox proportional hazards models using two different dichotomous variables for aircraft noise (DNL>=45 and >55 dB(A)). All four models for NHS, using 45 and 55 dB(A) cut-points and the basic and multivariable models, showed an increased risk of hypertension associated with aircraft noise. Being exposed to DNL above 55 dB(A) was associated with a 5% increased risk of hypertension in the multivariable model (95% CI: -14%, 20%). No increased risk was shown in NHS II cohort associated with being exposed to DNL >=45 dB(A). However, when considering DNL above 55 dB(A) as the cut-point, a larger impact was shown in the multivariable model in NHS II compared to NHS, with a 11% increase in hypertension risk (95% CI: -2%, 26%). In the meta-analysis of the two cohorts, there was an indication of elevated hypertension risk associated with aircraft noise. We observed a 2% (95% CI: -2%, 7%) and 8% (-2%, 18%) increase in hypertension risk for the multivariable model using 45 and 55 dB(A) as cut-points, respectively. Within the meta-analysis, no heterogeneity was observed between the two cohorts.

Overall, there was no significant confounding observed in our study for individual covariates. However, the effect estimates were slightly shifted from the basic to the multivariable model in both cohorts (NHS: 8% to 5% and NHS II: 15% to 11%) only when using the 55 dB(A) cut-point.

There were no sensitive sub-groups identified in our study populations, with no significant effect modification observed by the covariates (current smoking status, diabetes status, family history of hypertension, hearing problem, menopause status, and statin use) we examined.

The results from our sensitivity analyses using the 55 dB(A) cut-point demonstrated the robustness of our findings as shown in Figure 4.2. Restricting the analyses to participants that lived near one of the 90 airports for the noise model resulted a significant reduction in sample size in both cohorts. The risk of hypertension was increased marginally in NHS II, while aircraft noise was shown to be negatively associated with hypertension risk in NHS, both with slightly wider confidence intervals. Excluding participants with DNL above 65 dB(A) had little influence given the small number of participants excluded from the model. Including air pollution and SES data similarly also had only a minimal effect. The analyses including air pollution and SES showed that both coarse and fine PM were positively associated with hypertension risk, which still did not confound the association of our interest (result not shown).

Discussion

Our study, which is the first to look at the relationship between aircraft noise and hypertension in nation-wide cohorts in the U.S., found an indication of increased risk of hypertension associated with aircraft noise in female nurses, while controlling for other risk factors. Exposure to DNL >55 dB(A) was associated with 5% and 11% increase in hypertension risk in NHS and NHS II, respectively, with the meta-analysis of the two cohorts showing 8% increased risk in hypertension associated with exposure to DNL >55 dB(A).

Although previous studies have used different exposure measures and reflected multiple epidemiological study designs, complicating direct comparison of our quantitative estimates, our findings are broadly consistent with the literature investigating the association between aircraft noise and hypertension.[28] Beyond study design and exposure assessment, an additional factor potentially contributing to differences is our focus on an all-female population. While meta-analyses have shown generally similar odds ratios for men vs. women,[28] a few studies have shown null associations in women in contrast to positive associations shown in men.[10,32] Our estimated hazard ratios could be low compared to other studies if women are less sensitive to aircraft noise compared to men, as well as if our study population is less sensitive to noise given their socio-demographic characteristics. It is important to acknowledge that our cohorts were comprised of women with a unique occupation, which may be associated with better baseline health status and access to healthcare. Therefore, the potential underlying differences should be considered when applying our study results to women with different characteristics.

Our results were robust, as the hazard ratios were relatively stable across multiple sensitivity analyses, and the associations (while attenuated) generally persisted after controlling for a number of confounders. Excluding participants that did not live close to one of the 90 airports included in our noise modeling had a relatively large impact on the HR in NHS, but not in NHS II. Given that the effect observed in NHS was smaller compared to NHS II, the significant reduction in sample size associated with this exclusion criterion may have led to less stable estimates and reduced power to detect the associations of interest. Excluding participants with DNL larger than 65 dB(A) resulted in a very small increase in risk for hypertension associated with aircraft noise in NHS, which may be related to the effect of the noise abatement programs, although given the small number of participants excluded it is difficult to make definitive conclusions. It is also worth noting that the effect of aircraft noise was not confounded by air pollution in our study, similar to the findings from other studies.[80,81]

There were a few limitations of our study. First of all, hypertension status was self-reported, though a validation study showed very good correlation between the self-report and diagnosis.[75] Having direct blood pressure measurements and considering blood pressure as a continuous measure, which was not available in our cohorts, may have strengthened our ability to detect the effects of aircraft noise. Understanding the effect of DNL on hypertension is important, as that is the metric used for policy purposes. However, DNL may not be the most sensitive measure of the impact of aircraft noise on hypertension, especially if sleep disturbance is considered a key pathway. In previous studies, nighttime noise has been shown to be more relevant.[26,31–33,82] That said, by applying a penalty to nighttime noise, DNL potentially captures some concerns about sleep disturbance. Additional analyses using nighttime noise or other noise metrics would be valuable in better establishing the mechanism by which noise influences hypertension.

Our study populations were not highly exposed to aircraft noise, which is to be expected for a nation-wide cohort not recruited specifically for aircraft noise epidemiology. This makes identifying the association or determining the shape of the exposure-response function more challenging, especially if the association happens at a higher exposure level and/or the magnitude of the effect is very small. However, because of our relatively large population sizes, we were still able to see an indication of the association between aircraft noise as measured in DNL and hypertension, even if the confidence intervals were at times wide. In addition to the small number of participants exposed to a high level of aircraft noise, the noise estimates developed based on the residential addresses may not represent the true exposure levels of the participants, both because of time spent at home versus at work and because of home-specific factors, such as window opening behavior or the level of soundproofing.[83] Time spent at home versus at work is less of a concern for NHS, in which many participants had retired during the course of follow-up and were more likely to spend time at home. Home-specific factors can affect the individual noise exposure levels since people spend more time indoors than outdoors. However, it is unclear whether the exposure misclassification related to indoor and outdoor activity patterns and home-specific factors could be differential. In theory, those with higher ambient noise could take actions such as window closing to reduce their personal exposures. This would have resulted in biasing the results towards the null. But overall, the probability of substantial differential exposure misclassification is likely small, as most individuals spend a significant amount of time indoors at home, these populations have comparable workplace characteristics, and there is only a very small percentage of participants exposed to high levels of aircraft noise.

Another potential source of exposure misclassification arises due to the fact that the noise estimates were only developed for 90 airports in the U.S.; therefore, participants that lived close to an airport that was not one of the 90 airports for our noise models would have been incorrectly assigned a lower DNL and included in the reference group. In an effort to address this limitation as well as the concern that populations not living near airports may differ in multiple ways from those who live near airports, we conducted a sensitivity analysis only including individuals that lived near one of the 90 airports included in our noise modeling. While our findings were broadly consistent, this exclusion criterion led to losing a large portion of data resulting in reduced power to detect the effect of aviation noise on hypertension in NHS (Figure 4.2).

Our study also had several strengths. One of the strengths is the prospective cohort study design providing a wide range of time-varying exposure, outcome, and covariate information to ensure temporality. The combination of having extensive cohort data and motivated medical professionals as participants led to very good internal validity with potentially small residual confounding. We were also able to assess the impact of an array of potential confounders and the robustness of our findings using high quality self-reported data, and given that these cohorts are extremely well-characterized, the set of candidate confounders was very well determined. Another strength is the consistency of how aircraft noise estimates were developed, where the same protocol was used for developing noise contours for all 90 airports. This addresses one of the limitations often mentioned for meta-analysis investigating this association that used noise and outcome data that were developed under different protocols and models.

Conclusions

In conclusion, we found evidence of a positive relationship between aircraft noise exposure at DNL above 55 dB(A) and incident hypertension in both NHS and NHS II cohorts. Given that the FAA uses a 65 dB(A) DNL threshold for sound mitigation, based on older evidence related to annoyance rather than health outcomes, our study results suggest further investigation regarding the health effects of aircraft noise exposure below the regulatory threshold. More generally, the changing spatial patterns of noise exposure given more concentrated flight paths may result in health benefits for some populations but increased negative consequences for others, meriting further investigation. Our study also demonstrated the ability to develop robust longitudinal aircraft noise estimates across the entire U.S., which could be applied to other nation-wide cohorts to understand effects on the general population or subpopulations of interest.

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Tables

Table 4.1. Baseline characteristics of 61,879 participants in the Nurses' Health Study and 94,592 participants in the Nurses' Health Study II free of hypertension at baseline dichotomized at the DNL 55 dB(A) level

	DNL <= 55 dB(A) Mean (SD) or %	DNL > 55 dB(A) Mean (SD) or %
Characteristic	**NHS (1994)**	
n	61,457	422
Age (years)	59.1 (7.08)	59.6 (6.89)
BMI (kg/m^2)	25.5 (4.58)	25.6 (4.72)
DASH score	23.9 (4.95)	24.2 (4.90)
Physical activity (MET hr/week)	18.9 (22.8)	17.1 (19.9)
Alcohol consumption (g/day)*	5.06 (8.78)	4.26 (6.98)
Census-tract median income (USD)*	65,500 (26,000)	60,900 (18,300)
Census-tract median home value (USD)*	177,000 (135,000)	195,000 (102,000)
$PM_{2.5}$ (μg/m^3)*	13.0 (2.88)	14.3 (2.47)
$PM_{2.5-10}$ (μg/m^3)	8.74 (3.88)	10.2 (3.93)
White*	94.68	88.15
Diabetes (yes)	3.21	2.37
Hypercholesterolemia (yes)	29.16	32.23
Statin use (yes)	18.2	21.33
Post-menopause (yes)	87.82	88.63
Current smoking status (yes)	15.15	15.88
Family history of hypertension (yes)	36.89	38.39
	NHS II (1995)	
n	93,810	782
Age, (years)	40.1 (4.63)	39.9 (4.57)
BMI (kg/m^2)	25.3 (5.43)	25.5 (5.69)
DASH score*	23.9 (5.09)	23.4 (5.03)
Physical activity (MET hr/week)	18.7 (23.0)	19.3 (26.03)
Alcohol consumption (g/day)	3.50 (6.59)	3.61 (6.42)
Census-tract median income (USD)*	64,300 (23,700)	62,000 (19,500)
Census-tract median home value (USD)*	164,000 (123,000)	198,000 (97,100)
$PM_{2.5}$ (μg/m^3)*	9.79 (4.07)	10.8 (3.48)
$PM_{2.5-10}$ (μg/m^3)*	14.0 (2.97)	15.0 (2.58)
White*	93.8	81.3

Diabetes (yes)	1	1.66
Hypercholesterolemia (yes)	9.43	8.06
Statin use (yes)	3.76	3.96
Post-menopause (yes)	12.34	10.49
Current smoking status (yes)	11.2	13.7
Family history of hypertension (yes)	49.3	50.8

***** p-value < 0.05 for testing the difference between two exposure groups
Abbreviations: BMI, Body Mass Index; DNL, Day-Night average sound Level; DASH, Dietary Approaches to Stop Hypertension; HR, Hazard Ratio; NHS, Nurses' Health Study; NHS II, Nurses' Health Study II; MET, metabolic equivalent; PM, particulate matter;

Table 4.2. Numbers (percentages) of participants exposed to three different noise classifications in NHS and NHS II at baseline

Cohort	**44<DNL<=55 dB(A)** **N (%)**	**55< DNL<=65 dB(A)** **N (%)**	**DNL>65 dB(A)** **N (%)**
NHS (1994)	4,085 (6.60)	407 (0.66)	15 (0.02)
NHS II (1995)	6,821 (7.21)	752 (0.79)	30 (0.03)

Abbreviations: DNL, Day-Night average sound Level; NHS, Nurses' Health Study; NHS II, Nurses' Health Study II;

Table 4.3. Hazard ratios (95% CIs) for hypertension associated with aircraft noise in NHS, NHS II, and meta-analysis of both cohorts

Exposure category	Cases	Person Years	Basic Model[a] HR (95% CI)	Multivariable Model[b] HR (95% CI)
NHS				
DNL>=45 dB(A)	31,421	716,442	1.04 (1.00, 1.09)	1.04 (0.99, 1.08)
DNL>55 dB(A)			1.08 (0.95, 1.23)	1.05 (0.86, 1.20)
NHS II				
DNL>=45 dB(A)	29,086	1,300,400	1.00 (0.96, 1.04)	1.00 (0.95, 1.04)
DNL>55 dB(A)			1.15 (1.02, 1.31)	1.11 (0.98, 1.26)
Meta-analysis				
DNL >=45 dB(A)	60,507	2,016,842	1.07 (0.98, 1.18)	1.02 (0.98, 1.07)
DNL >55 dB(A)			1.12 (1.02, 1.22)	1.08 (0.98, 1.18)

[a]Adjusted for age and calendar year
[b]Adjusted for age, calendar year, alcohol use, BMI, comorbidities (diabetes, hypercholesterolemia), current smoking status, DASH, family history of hypertension, medication use (current statin and NSAID use), menopause status, and MET
Abbreviations: BMI, Body Mass Index; DNL, Day-Night average sound Level; DASH, Dietary Approaches to Stop Hypertension; HR, Hazard Ratio; NSAID, nonnarcotic analgesic intake drug; NHS, Nurses' Health Study; NHS II, Nurses' Health Study II; MET, metabolic equivalent;

Figures

Figure 4.1. A map of 90 airports included in our study by region

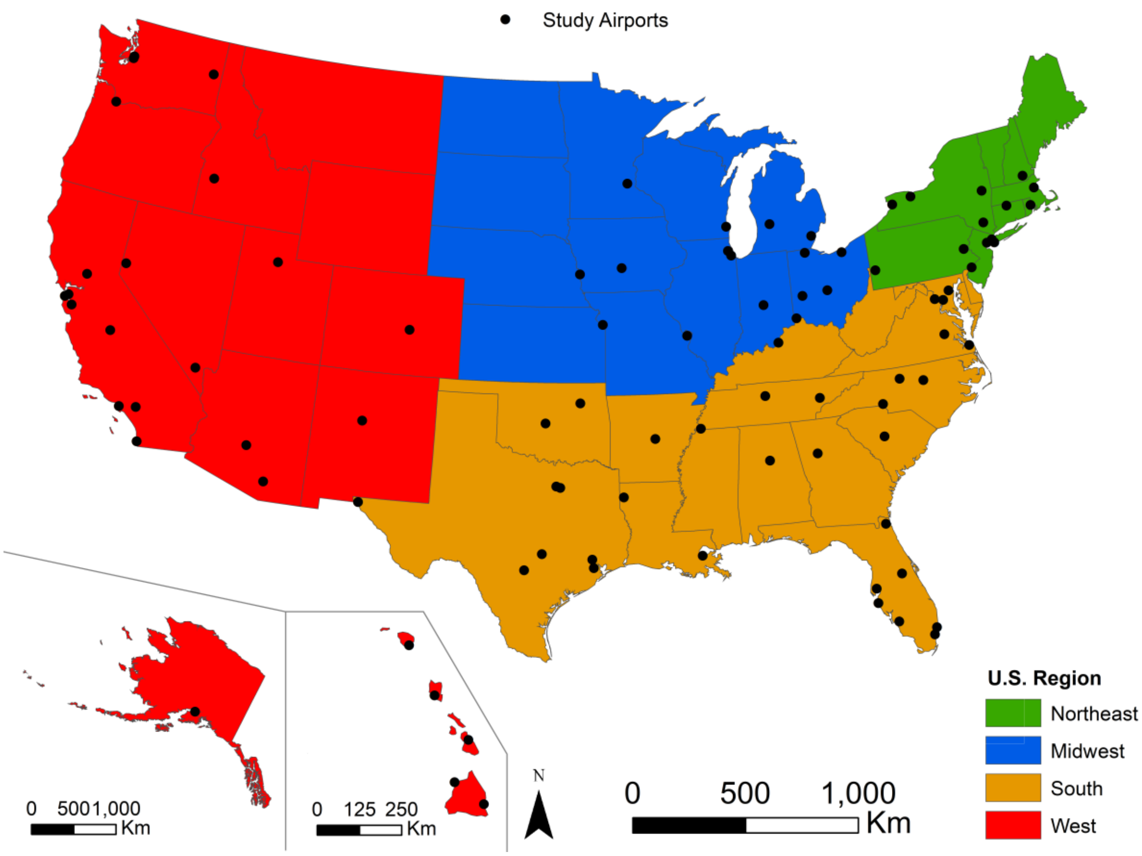
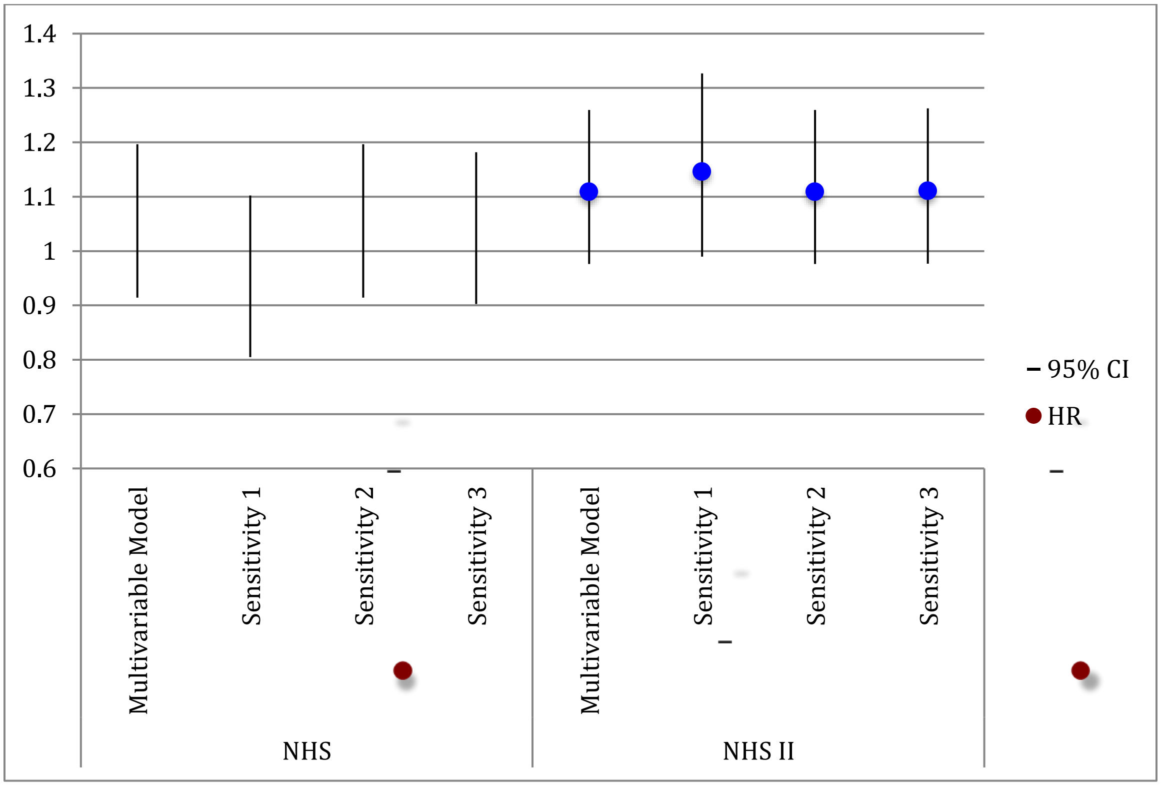


Figure 4.2. Hazard ratios (95% CIs) for hypertension associated with aircraft noise in NHS and NHS II (DNL>55 dB(A) vs. <= 55 dB(A)), with sensitivity analyses restricting data based on DNL levels and the availability of air pollution and area-level SES data



Multivariable Model: adjusted for age, calendar year, alcohol use, BMI, comorbidities (diabetes, hypercholesterolemia), current smoking status, DASH, family history of hypertension, medication use (current statin and NSAID use), menopause status, and MET
Sensitivity 1: restricting participants to those living close to one of the 90 airports (>=45 dB(A)) included in the noise modeling
Sensitivity 2: removing participants with DNL larger than 65 dB(A)
Sensitivity 3: additionally adjusting for air pollution and area-level SES, which restricts to time periods with air pollution ($PM_{2.5}$ and $PM_{2.5-10}$) and area-level SES (census-tract median income and median home value) data (NHS: 1994-2008, NHS II: 1995-2007)
Abbreviations: BMI, Body Mass Index; DNL, Day-Night average sound Level; DASH, Dietary Approaches to Stop Hypertension; HR, Hazard Ratio; NSAID, nonnarcotic analgesic intake drug; NHS, Nurses' Health Study; NHS II, Nurses' Health Study II; MET, metabolic equivalent; SES, socio-economic status

CHAPTER 5: Conclusion

The overall objective of my dissertation was to investigate the environmental and health impacts of aviation activities. In Chapter 2, we examined the impact of arrival aircraft activities on ambient PNC mainly by using descriptive analyses and visualizations. Our results confirmed strong and intermittent contributions of PNC from arrival aircraft, especially at sites close to the airport. We saw notable increases in PNC throughout the day with high arrival flight activities and under specific wind conditions. In Chapter 3, we developed site-by-site regression models using two different temporal resolution (10-minute and hourly) and two different PNC distributional characterizations (mean and 95^{th} percentile). Individual arrival aircraft were shown to significantly contribute to ambient PNC across all study sites, while controlling for all other aircraft activities as well as meteorology. Overall, the 95^{th} percentile PNC models indicated larger contributions of individual arrival aircraft to ambient PNC, consistent with the strong and intermittent PNC emissions from aircraft. Our results also emphasized the importance of carefully considering both site locations and research questions of interest when determining the temporal resolution and distributional characterization of PNC data within regression models. The last project (Chapter 4) showed an increased risk of incident hypertension in two Nurses' Health Studies cohorts while appropriately accounting for time-varying noise and other risk factors. Though the effect size was relatively small, we saw a positive association in women, who were not shown as a sensitive subgroup for noise effect in some studies,[10,32]. We also saw an association using DNL, while most other studies found a positive association only with nighttime aircraft noise[32,33], which might be expected if sleep disturbance were related to the increased hypertension risk.

Chapter 2: Spatial and temporal patterns of ultrafine particle concentrations in near-airport communities along a major arrival flight path in Boston, Massachusetts

In Chapter 2, we examined PNC at six monitoring sites that were at varying distances from the airport as well as the primary arrival flight path into Boston Logan International Airport. Instead of aggregating up the PNC observations as done in many other studies, we used 1-second time resolution data in order to better investigate the peaks associated with aircraft activities given the nature of aircraft emissions.[12,18] Collecting PNC data at 1-second resolution allowed us to preserve the peaks that are likely to be associated with aircraft activities. Such peaks could have been missed or reduced if we collected data at lower temporal resolution such as 10-minutes or even lower. However, since it is difficult to directly link the observed peaks to aircraft activities due to varying temporal lags from emissions at high altitudes down to the ground-level under different meteorological conditions, we may be fine with slight lower temporal resolution than 1-second, such as 10-seconds. More generally, the decision of which time resolution data to use will depend on the research question. If a researcher were interested in identifying the strong aircraft signal, then higher temporal resolution data would be ideal as the magnitude of PNC will likely become lower when aggregating the data up. If the research question is more on the overall impact of aircraft activities on ambient air quality, such as daily or annual averages, higher resolution data may not be necessary.

Our site selection criteria as well as the use of stratification based on the level of flight activities allowed us to confirm our ability to capture aviation signals apart from other ground-level PNC contribution even at a site that is 17 km away from the airport. Our pollution roses indicated a very clear wind direction and wind speed pattern associated with aircraft UFP at each site. This result confirmed that being downwind of the source and higher wind speed are associated with increased PNC, especially at sites closer to the airport, as shown in other studies.[55,59] Our pollution roses confirmed that the elevated PNC observed at our studies were associated with arrival aircraft to 4L/4R runways rather than other aircraft or ground-level activities at the airport. However, there is still the question of whether these elevated concentrations were from arrival aircraft on the ground after they landed or from when aircraft were still in the air, which our study were not able to answer. Emission rates during approach was shown to be slight higher than during taxiing and idling.[84] On the other hand, emissions during aircraft approach occur at higher altitudes compared to that during taxiing and idling leading to more opportunity and time for dispersion until the particles reach the ground level. A unique study design and meteorological conditions will be required if we want to distinguish the contribution from aircraft in-flight and aircraft from the ground. For example, if a monitoring site is located downwind of the flight path, but not of the airport, ideally very close to the airport, we can potentially observe the varying magnitudes of aircraft impact when the wind is from the airport direction compared to from the flight path direction. However, it may not be easy to capture such a dynamic since runway configuration is often determined based on wind conditions, and it may not be possible to find such a perfect meteorological scenario to answer the question of our interest. Our monitoring strategy did have the potential to answer this question since we observed varying wind conditions with 4L/4R arrival runway configuration, but our study results did not show elevated PNC associated with aircraft in-flight, while not being directly downwind of the airport. A different monitoring site that is much closer to the airport may have allowed us to answer this question.

Chapter 3: Assessing the impact of arrival aircraft on ambient ultrafine particle concentrations near a large international airport in the U.S.

In Chapter 3, we used the same data used in Chapter 2, but aggregated them up to 10-minutes and 1-hour. We developed regression models in order to quantify the individual arrival aircraft contribution to ambient PNC, while assessing the role of meteorology. Four regression models were developed for each site by modeling for the mean and 95th percentile PNC using the 10-minute and 1-hour aggregated data in an effort to understand the influence of the choice of temporal resolution and distributional characterization would have on study findings.

Most existing aviation studies have used either the mean or median to develop regression models for aviation source attribution. However, in our study, modeling for upper percentile PNC resulted in larger contribution of aircraft, corresponding to expected strong emission levels associated with aircraft activity. This novel approach in examining aircraft contribution may allow us to more accurately ascertain how much total UFP are attributable to aircraft compared to other sources. This is important when conducting epidemiological studies, since UFP compositions vary by source, which may be associated with specific health outcomes.[56] There is still a lot more to be done for this novel approach to be useful in real epidemiological studies, such as making the model into a more universal and predictive model that can be used in multiple different environmental settings. The models we developed were more explanatory than predictive, which make it difficult to be used in epidemiological studies with different available predictors, surrounding environments, and other UFP sources. However, this is still a useful finding and can inform other researchers in designing the exposure models for their epidemiological studies.

The complex wind and PNC dynamic was differently captured at two different time resolutions emphasizing the importance of carefully considering the model choice based on research questions of interest. Another important finding of this study was the geographic extent of impact of buoyant plumes. Buoyant plumes are known to reach the ground faster under higher wind speed.[55] In our study, this positive association between PNC and wind speed was only shown at two sites that were closest to the airport under aviation impact sector wind. In other words, we are possibly capturing the aircraft plumes at an earlier stage when it is still hot at the near sites, in other words, plumes with buoyant characteristics, while we are probably capturing the plumes at a later phase at farther away sites. These are novel findings and should be further investigated in future studies.

Chapter 4: Long-term aircraft noise exposure and risk of hypertension in the Nurses' Health Studies

The objective of Chapter 4 was to investigate the association between aircraft noise and incident hypertension using time-varying exposure and risk factor data in two nation-wide prospective cohorts, NHS and NHS II. Even though there is accumulating evidence of this suggested association, there are methodological limitations in the existing studies including the lack of the ability to confirm temporality, inconsistency in how noise estimates were developed, and lack of sufficient confounder information. We were able to address these limitations in our study. Our study found an increased risk of hypertension with aircraft-associated DNL in both cohorts while accounting for time-varying exposure and covariate data. The meta-analysis of multivariable analysis showed

HR of 1.02 (95% CI: 0.98, 1.05) and 1.05 (95% CI: 0.96, 1.15) using the 45 and 55 dB(A) cut-points, respectively. This finding is meaningful as an association was suggested even using relatively low cut-point of 45 dB(A) in women, while men were often shown as the sensitive group.[10,32]

Efforts were made in order to obtain temporally resolved noise estimates at 1-dB(A) resolution for our analysis. We did not observe non-linear association between aircraft noise and hypertension, and dichotomization of the exposure was used in our analysis. Based on our study findings, the necessity of developing and using 1-dB(A) resolution data is not well supported. In other words, the decision to use already existing relatively lower resolution noise estimates for epidemiological analysis can be supported, especially given the resources required to develop high resolution aircraft noise data. However, the efforts to develop and use high resolution aircraft noise estimates should still be encouraged as we are still learning about the potential mechanisms of how aircraft noise may be associated with various health outcomes. There is a value in using temporally resolved noise estimates in epidemiological studies since there is a clear decreasing trend of aircraft noise, especially when investigating repeated acute effect of aircraft noise, which then can lead to a chronic change in the body. Overall, researchers need to be open to using existing noise estimates that are easily accessible and do not require much additional resources, while continue to advance our ability to conduct more accurate exposure assessments and epidemiological studies.

Public Health Implications

Our studies presented important public health implications of aviation activities, especially given how it could disproportionately affect more vulnerable populations that live close to airports. We investigated two different exposures associated with aviation activities.

Our first two projects (Chapter 2 and 3) showed significantly elevated ambient PNC over a broad geographic area associated with arrival aircraft, which can adversely affect human health by increasing individual exposures to UFP in addition to its direct negative impact on the overall air quality. In recent years, UFP has been being extensively investigated for its potential impact on respiratory and cardiovascular system, and the health effects associated with UFP were shown to be similar to that of fine particles.[13] Currently, UFP is not regulated by the United States Environmental Protection Agency (US EPA), in part due to the lack of long-term UFP exposure data and lack of evidence for the independent effects of UFP on health.[13] The ability to quantify aircraft contribution to ambient PNC is a critical part of exposure assessment for epidemiological studies in order to accurately assess how much of the total PNC and how much of different adverse health effects can be attributable to aviation activities.

Public health implications of our last project (Chapter 4) are multi-dimensional. First, our study showed an association between aircraft noise and incident hypertension using a cut-point that is lower than what is considered “unsafe” by the FAA (65-dB(A)). Even though the FAA guideline is based on annoyance, not health effect,[11] our study finding suggests the importance of considering the health effects associated noise below the FAA guideline to be protective of public health. Second, the impact of aviation noise on incident hypertension was shown in our study population of nurses that are with relatively good health and higher SES. This may indicate potentially even larger impact of aviation noise on hypertension in more vulnerable populations that live close to airports. Lastly, hypertension is a major risk factor for other more severe cardiovascular outcomes, such as stroke, which implies the small added risk from the environment may have a major impact on public health.[32,33] Overall, our study findings of the impact of aircraft noise on hypertension among relatively healthy population with relatively lower exposure levels suggest a value in conducting large-scale epidemiological studies to explore health effects of lower aircraft noise exposures focusing on potentially more vulnerable populations and identify more susceptible/sensitive populations.

In summary, aviation activities showed both environmental and public health consequences, which we investigated in separate studies. However, there are subsets of populations that could be affected by the combination of these two exposures, likely leading to a higher risk for developing hypertension as well as other adverse health effects that are associated with both exposures. Future research studies should investigate the joint effect of the two, which may have a different pattern and magnitude of effect compared to traffic-related exposures.

Bibliography

1. Whitelegg, J. Aviation: the social, economic and environmental impact of flying. *Ashden Trust* (2000). https://www.semanticscholar.org/paper/AVIATION%3A-the-social%2C-economic-and-environmental-of-Whitelegg-Ltd/bbf138045f3a03a1eb97398a545eb7d8be207f99
2. FAA. *Aviation Emissions, Impacts & Mitigation – A Primer*. https://www.faa.gov/regulations_policies/policy_guidance/envir_policy/media/Primer_Jan2015.pdf (2015).
3. Kurniawan, J. S. & Khardi, S. Comparison of methodologies estimating emissions of aircraft pollutants, environmental impact assessment around airports. *Environmental Impact Assessment Review.* **31**, 240–252 (2011).
4. Colvile, R. N., Hutchinson, E. J., Mindell, J. S. & Warren, R. F. The transport sector as a source of air pollution. *Atmospheric Environment.* **35**, 1537–1565 (2001).
5. Basner, M. *et al.* Auditory and non-auditory effects of noise on health. *The Lancet* **383**, 1325–1332 (2014).
6. Eriksson, C. *et al.* Long-Term Aircraft Noise Exposure and body mass index, waist circumference, and type 2 diabetes: a prospective study. *Environmental Health Perspectives* **122**, 687 (2014).

7. Hammer, M. S., Swinburn, T. K. & Neitzel, R. L. Environmental noise pollution in the United States: developing an effective public health response. *Environmental Health Perspectives.* **122**, 115 (2014).
8. Münzel, T., Gori, T., Babisch, W. & Basner, M. Cardiovascular effects of environmental noise exposure. *European Heart Journal.* **35**, 829–836 (2014).
9. Sørensen, M. *et al.* Long-term exposure to road traffic noise and incident diabetes: a cohort study. *Environmental Health Perspectives.* **121**, 217 (2013).
10. Eriksson, C., Bluhm, G., Hilding, A., Östenson, C.-G. & Pershagen, G. Aircraft noise and incidence of hypertension—gender specific effects. *Environmental Research.* **110**, 764–772 (2010).
11. FAA history of noise. https://www.faa.gov/regulations_policies/policy_guidance/noise/history/#threshold.
12. 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.* **104**, 132–142 (2015).
13. Understanding the health effects of ambient ultrafine particles. *Health Effects Institute* https://www.healtheffects.org/publication/understanding-health-effects-ambient-ultrafine-particles (2013).

14. Karner, A. A., Eisinger, D. S. & Niemeier, D. A. Near-roadway air quality: synthesizing the findings from real-world data. *Environmental Science & Technology.* **44**, 5334–5344 (2010).
15. Padró-Martínez, L. T. *et al.* Mobile monitoring of particle number concentration and other traffic-related air pollutants in a near-highway neighborhood over the course of a year. *Atmospheric Environment. 1994* **61**, 253–264 (2012).
16. Patton, A. P. *et al.* An hourly regression model for ultrafine particles in a near-highway urban area. *Environmental Science & Technology.* **48**, 3272–3280 (2014).
17. 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.* **50**, 3362–3370 (2016).
18. 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.* **50**, 8514–8521 (2016).
19. 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.* **48**, 6628–6635 (2014).
20. Riley, E. A. *et al.* Ultrafine particle size as a tracer for aircraft turbine emissions. *Atmospheric Environment.* **139**, 20–29 (2016).

21. Basner, M. *et al.* Aviation noise impacts: state of the science. *Noise & Health* **19**, 41–50 (2017).
22. Ising, H. & Kruppa, B. Health effects caused by noise : evidence in the literature from the past 25 years. *Noise & Health* **6**, 5 (2004).
23. Babisch, W. & Kamp, I. van. Exposure-response relationship of the association between aircraft noise and the risk of hypertension. *Noise & Health* **11**, 161 (2009).
24. Peterson, E. A., Augenstein, J. S., Tanis, D. C. & Augenstein, D. G. Noise raises blood pressure without impairing auditory sensitivity. *Science* **211**, 1450–1452 (1981).
25. Schmidt, F. P. *et al.* Effect of nighttime aircraft noise exposure on endothelial function and stress hormone release in healthy adults. *European Heart Journal.* **34**, 3508–3514a (2013).
26. Schmidt, F. *et al.* Nighttime aircraft noise impairs endothelial function and increases blood pressure in patients with or at high risk for coronary artery disease. *Clinical Research in Cardiology.* **104**, 23–30 (2015).
27. Münzel, T. & Sørensen, M. Noise pollution and arterial hypertension. *European Cardiology.* **12**(1), 26–29 (2017).
28. Huang, D. *et al.* Is there an association between aircraft noise exposure and the incidence of hypertension? A meta-analysis of 16784 participants. *Noise & Health* **17**, 93–97 (2015).

29. Pyko, A. *et al.* Transportation noise and incidence of hypertension. *International Journal of Hygiene and Environmental Health* **221**, 1133–1141 (2018).
30. Eriksson, C. *et al.* Aircraft noise and incidence of hypertension. *Epidemiology* **18**, 716 (2007).
31. Dimakopoulou, K. *et al.* Is aircraft noise exposure associated with cardiovascular disease and hypertension? Results from a cohort study in Athens, Greece. *Occupational and Environmental Medicine.* **74**, 830–837 (2017).
32. Evrard, A.-S., Lefèvre, M., Champelovier, P., Lambert, J. & Laumon, B. Does aircraft noise exposure increase the risk of hypertension in the population living near airports in France? *Occupational and Environmental Medicine.* **74**, 123–129 (2017).
33. Jarup Lars *et al.* Hypertension and Exposure to Noise Near Airports: the HYENA Study. *Environmental Health Perspectives.* **116**, 329–333 (2008).
34. Penn, S. L. *et al.* Modeling variability in air pollution-related health damages from individual airport emissions. *Environmental Research.* **156**, 791–800 (2017).
35. FAA. FAA Aerospace Forecast - Fiscal Years 2016-2036. https://www.faa.gov/data_research/aviation/.
36. IATA - IATA Forecasts Passenger Demand to Double Over 20 Years. http://www.iata.org/pressroom/pr/Pages/2016-10-18-02.aspx.

37. Lee, Joosung J., Stephen P. Lukachko, Ian A. Waitz & A. Schafer. Historical and Future Trends in Aircraft Performance, Cost, and Emissions. *Annual Review of Energy and the Environment.* **26**, 167–200 (2001).

38. Shirmohammadi, F. *et al.* Chemical composition and redox activity of PM0.25 near Los Angeles International Airport and comparisons to an urban traffic site. *Science of the Total Environment.* **610–611**, 1336–1346 (2018).

39. Morawska, L., Ristovski, Z., Jayaratne, E. R., Keogh, D. U. & Ling, X. Ambient nano and ultrafine particles from motor vehicle emissions: Characteristics, ambient processing and implications on human exposure. *Atmospheric Environment.* **42**, 8113–8138 (2008).

40. Ostro, B. *et al.* Associations of mortality with long-term exposures to fine and ultrafine particles, species and sources: results from the California Teachers Study Cohort. *Environmental Health Perspectives.* **123**, 549–556 (2015).

41. Lane, K. J. *et al.* Association of modeled long-term personal exposure to ultrafine particles with inflammatory and coagulation biomarkers. *Environment International.* **92–93**, 173–182 (2016).

42. Kumar, P. *et al.* Ultrafine particles in cities. *Environment International.* **66**, 1–10 (2014).

43. Sioutas, C., Delfino, R. J. & Singh, M. Exposure Assessment for Atmospheric Ultrafine Particles (UFPs) and Implications in Epidemiologic Research. *Environmental Health Perspectives.* **113**, 947–955 (2005).

44. Patton, A. P. *et al.* Spatial and temporal differences in traffic-related air pollution in three urban neighborhoods near an interstate highway. *Atmospheric Environment.* **99**, 309–321 (2014).

45. Filippone, A. Cruise altitude flexibility of jet transport aircraft. *Aerospace Science and Technology.* **14**, 283–294 (2010).

46. Hsu, H.-H., Adamkiewicz, G., Houseman, E. A., Spengler, J. D. & Levy, J. I. Using mobile monitoring to characterize roadway and aircraft contributions to ultrafine particle concentrations near a mid-sized airport. *Atmospheric Environment.* **89**, 688–695 (2014).

47. Tesseraux, I. Risk factors of jet fuel combustion products. *Toxicology Letters.* **149**, 295–300 (2004).

48. Hsu, H.-H. *et al.* The relationship between aviation activities and ultrafine particulate matter concentrations near a mid-sized airport. *Atmospheric Environment.* **50**, 328–337 (2012).

49. Massport - How Logan Operates. http://www.massport.com/environment/environmental-reporting/noise-abatement/how-logan-operates/.

50. 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 and Technology.* **52**, 1765–1772 (2018).

51. Zhu, Y., Fanning, E., Yu, R. C., Zhang, Q. & Froines, J. R. Aircraft emissions and local air quality impacts from takeoff activities at a large International Airport. *Atmospheric Environment.* **45**, 6526–6533 (2011).

52. Hsu, H.-H. *et al.* Contributions of aircraft arrivals and departures to ultrafine particle counts near Los Angeles International Airport. *Science of the Total Environment.* **444**, 347–355 (2013).

53. Masiol, M. & Harrison, R. M. Aircraft engine exhaust emissions and other airport-related contributions to ambient air pollution: A review. *Atmospheric Environment.* **95**, 409–455 (2014).

54. Mazaheri, M., Johnson, G. R. & Morawska, L. An inventory of particle and gaseous emissions from large aircraft thrust engine operations at an airport. *Atmospheric Environment.* **45**, 3500–3507 (2011).

55. 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 and Technology.* **52**, 1765–1772 (2018).

56. Hime, N. J., Marks, G. B. & Cowie, C. T. A Comparison of the health effects of ambient particulate matter air pollution from five emission sources. *International Journal of Environmental Research and Public Health* **15**, (2018).

57. Schilling, V., Siano, S. & Etling, D. Dispersion of aircraft emissions due to wake vortices in stratified shear flows: A two-dimensional numerical study. *Journal of Geophysical Research. Atmospheres.* **101**, 20965–20974 (1996).
58. Gerz, T., Dürbeck, T. & Konopka, P. Transport and effective diffusion of aircraft emissions. *Journal of Geophysical Research. Atmospheres.* **103**, 25905–25913 (1998).
59. Lopes, M., Russo, A., Monjardino, J., Gouveia, C. & Ferreira, F. Monitoring of ultrafine particles in the surrounding urban area of a civilian airport. *Atmospheric Pollution Research.* **10**, 1454–1463 (2019).
60. Babisch, W. The noise/stress concept, risk assessment and research needs. *Noise & Health* **4**, 1–11 (2002).
61. Zhang, Z., Laden, F., Forman, J. P. & Hart, J. E. Long-term exposure to particulate matter and self-reported hypertension: a prospective analysis in the Nurses' Health Study. *Environmental Health Perspectives.* **124**, 1414–1420 (2016).
62. Fu, W. *et al.* Association between exposure to noise and risk of hypertension: a meta-analysis of observational epidemiological studies. *Journal of Hypertension.* **35**, 2358–2366 (2017).
63. Hansell, A. L. *et al.* Aircraft noise and cardiovascular disease near Heathrow airport in London: small area study. *BMJ: British Medical Journal.* **347**, f5432 (2013).

64. Münzel, T. *et al.* Environmental noise and the cardiovascular system. *Journal of the American College of Cardiology.* **71**, 688–697 (2018).

65. van Kempen, E. E. M. M. *et al.* The association between noise exposure and blood pressure and ischemic heart disease: a meta-analysis. *Environmental Health Perspectives.* **110**, 307–317 (2002).

66. Carugno, M. *et al.* Effects of aircraft noise on annoyance, sleep disorders, and blood pressure among adult residents near the Orio al Serio International Airport (BGY), Italy. *La Medicina del Lavoro.* **109**, 253–263 (2018).

67. Zeeb, H. *et al.* Traffic noise and hypertension - results from a large case-control study. *Environmental Research.* **157**, 110–117 (2017).

68. Perron, S., Tétreault, L.-F., King, N., Plante, C. & Smargiassi, A. Review of the effect of aircraft noise on sleep disturbance in adults. *Noise & Health* **14**, 58 (2012).

69. Chang, T.-Y. *et al.* Occupational noise exposure and incident hypertension in men: a prospective cohort study. *American Journal of Epidemiology.* **177**, 818–825 (2013).

70. Fuks, K. B. *et al.* Long-term exposure to ambient air pollution and traffic noise and incident hypertension in seven cohorts of the European study of cohorts for air pollution effects (ESCAPE). *European Heart Journal.* **38**, 983–990 (2017).

71. Hart, J. E. *et al.* Exposure to hazardous air pollutants and risk of incident breast cancer in the Nurses' Health Study II. *Environmental Health* **17**, 28 (2018).
72. Bao, Y. *et al.* Origin, methods, and evolution of the three Nurses' Health Studies. *American Journal of Public Health* **106**, 1573–1581 (2016).
73. Aviation Environmental Design Tool (AEDT). https://www.faa.gov/about/office_org/headquarters_offices/apl/research/models/aedt/.
74. AEDT: Product information. https://aedt.faa.gov/productreleases.aspx.
75. Colditz, G. A. *et al.* Validation of questionnaire information on risk factors and disease outcomes in a prospective cohort study of women. *American Journal of Epidemiology.* **123**, 894–900 (1986).
76. Harrington, J. M. *et al.* DASH diet score and distribution of blood pressure in middle-aged men and women. *American Journal of Hypertension.* **26**, 1311–1320 (2013).
77. Puett, R. C. *et al.* Chronic fine and coarse particulate exposure, mortality, and coronary heart disease in the Nurses' Health Study. *Environmental Health Perspectives.* **117**, 1697–1701 (2009).
78. Paciorek, C. J. & Liu, Y. Limitations of remotely sensed aerosol as a spatial proxy for fine particulate matter. *Environmental Health Perspectives.* **117**, 904–909 (2009).

79. WHO night noise guidelines for Europe. http://www.euro.who.int/en/health-topics/environment-and-health/noise/policy/who-night-noise-guidelines-for-europe (2019).
80. Stansfeld, S. A. Noise effects on health in the context of air pollution exposure. *International Journal of Environmental Research and Public Health* **12**, 12735–12760 (2015).
81. Héritier, H. *et al.* A systematic analysis of mutual effects of transportation noise and air pollution exposure on myocardial infarction mortality: a nationwide cohort study in Switzerland. *European Heart Journal.* **40**, 598–603 (2019).
82. Torjesen, I. Long term aircraft noise is linked to incidence of high blood pressure. *BMJ: British Medical Journal* **357**, j2872 (2017).
83. Lercher, P., Widmann, U. & Kofler, W. Transportation noise and blood pressure: the importance of modifying factors. In *InterNoise 2000, Proceedings of the 29th International Congress on Noise Control Engineering* (2000). http://www.conforg.fr/internoise2000/cdrom/data/articles/000569.pdf
84. Chati, Y. S. & Balakrishnan, H. Analysis of aircraft fuel burn and emissions in the landing and take off cycle using operational data. In *ICRAT2014, 6th International Conference on Research in Air Transportation* (2014). http://www.icrat.org/icrat/seminarContent/Author/Yashovardhan%20SushilChati842/PRESENTATION-642-cfp-Chati.pdf

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M.P.H., Epidemiology
September 2012 – January 2014
Boston University School of Public Health (BUSPH), Boston, MA
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B.S., Molecular Biology
January 2008 – January 2012
Liberty University, Lynchburg, VA
Honors Scholarship recipient (2009-2012)

PROFESSIONAL RESEARCH EXPERIENCE

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September 2014 – Present
Department of Environment, BUSPH

- Collected, cleaned, merged, and managed multiple large datasets containing more than 60 million data points on air pollution, meteorology, and aviation activities.
- Utilized three large national cohort data sets (Nurses' Health Study 1 & 2, and Health Professionals Follow-up Study) containing more than 1 million participants to identify potential effect modifiers and confounders to investigate the association between aircraft noise and hypertension using time-varying Cox Proportional models.
- Conducted analyses using high performance shared computing cluster.
- Prepared and presented multiple oral and poster presentations for various conferences.
- Conducted guest lectures in a graduate-level course.

East Asia and Pacific Summer Institutes Research Fellow
June 2017 – August 2017
School of Environment, Tsinghua University, Beijing, China

- Calculated and compared the numbers of preventable premature deaths from air pollution under three different $PM_{2.5}$ reduction policy scenarios using demographic data, concentration-response function, and air pollution estimates.
- Provided insights on the interpretation of the results and made recommendations to colleagues in the field to further reduce personal exposure to air pollution in China.

Research Assistant
May 2013 – August 2014
Center for Future Technologies in Cancer Care, Boston University

- Conducted literature reviews to identify existing barriers to providing cancer care in urban primary care settings.
- Designed an online questionnaire for primary care physicians to better understand physicians' preferences in using point-of-care cancer screening technologies.
- Processed and analyzed the collected data from the survey and generated a final report.

PUBLICATIONS

Levy JI, Woo MK, Penn SL, Omary M, Tambouret Y, **Kim CS**, Arunachalam S (2016). *Carbon Reductions and Health Co-Benefits from US Residential Energy Efficiency Measures*. Environmental Research Letters 11(3):34017

Kim CS, Vanture S, Cho M, Klapperich CM, Wang C, Huang FW (2016). *Awareness, Interest, and Preferences of Primary Care Providers in Using Point-of-Care Cancer Screening Technology.* PLoS ONE 11(1): e0145215

PRESENTATIONS

Oral Presentation: "Time-Varying Aircraft Noise Exposure and Incident Hypertension in the Nurses' Health Study". Poster Presentation: "Spatial and Temporal Patterns of Ambient Ultrafine Particles (UFP) in Communities Along an Aircraft Arrival Trajectory". Joint Annual Meeting of International Society of Exposure Science and International Society of Environmental Epidemiology. Ottawa, Canada, August 2018.

Oral Presentation: "The Impact of Aviation Emissions on Ultrafine Particulate Matter (UFP) Concentrations in Communities at Varying Distances from Flight

Paths”. International Society of Exposure Science. Raleigh, North Carolina, October 2017.

Oral Presentation: “Estimating $PM_{2.5}$-Related Health Benefits from the Air Pollution Control and Prevention Action Plan”. East Asia And Pacific Summer Institutes Fellowship Closing Ceremony. Beijing, China, August 2017.

Poster Presentation: “Magnitude and Spatial Patterns of Ultrafine Particulate Matter Associated with Aircraft Arrivals near Boston Logan Airport”. International Society of Exposure Science. Utrecht, Netherlands, October 2016.

Oral Presentation: “Benefits of Increased Residential Energy Efficiency Measures in Single-Family Homes in the U.S.”. Gijs van Seventer Environmental Health Seminar. Boston, Massachusetts, January 2016.

TEACHING EXPERIENCE

Teaching Assistant, Exposure Assessment (M.S., M.P.H., and Ph.D. course). BUSPH. Boston, 2016 – 2017
Teaching Assistant, Intro to Epidemiology (M.S., M.P.H., and Ph.D. course). BUSPH. Boston, 2014

AWARDS

Joseph A. Hartman Student Paper Competition Award. Aviation Sustainability Center. Seattle, Washington, 2018
East Asia and Pacific Summer Institutes Fellowship. National Science Foundation. Washington, D.C., 2017

OTHER SKILLS

Languages: Native in Korean, fluent in English and Mandarin Chinese
Software expertise: R, SAS, ArcGIS, and Microsoft Suite
Interpersonal skills: Dependable, collaborative, respectful, professional and encouraging
Problem solving skills: Curious, creative, precise, to the point, thorough, and organized