An Ecological Study of Airport-Related Exposures and Population Health Outcomes in King County, Washington

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Abstract

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Background: Public Health – Seattle and King County (PHSKC) is currently assessing community health outcomes at varying radii from the Sea-Tac airport to help give context to airport-related exposures. This study aims to supplement those analyses by exploring exposure distributions and associations with community health outcomes through an alternative set of methods using a cross-sectional, ecological approach and only publicly available data.

Methods & Analysis: Aircraft activity and air and noise pollution exposure profiles were estimated for local communities. Exposure distributions were compared between race and ethnicity-defined groups on Lorenz-type curves and through difference-in-means tests. Additionally, ordinary least squares regression was used to evaluate area-level associations between aircraft activity, air and noise pollution exposures, and cause-specific mortality rates such as heart disease-related deaths.

Results: The exposure analyses provided strong evidence for different levels of exposures between race/ethnicity-defined subgroups in King County. Non-Hispanic White populations had higher distributions in lower exposure tracts and higher socioeconomic status (SES) tracts. Hispanic/Latinx and American Indian and Alaska Native (AIAN) populations had higher mean exposures and lower mean neighborhood

SES score than the county as a whole. Black and Native Hawaiian Pacific Islander (NHPI) populations were consitently more distributed in higher exposure tracts. The regression analysis did not provide strong evidence for an association between the six health outcomes of interest and the three primary exposures. This part of the analysis was limited by sample size, data limitations, and severe multicollinearity.

Conclusion: This study of King County adds to local documentations of environmental exposures, especially among NHPI and AIAN communities with smaller local populations. While this study could not draw definitive conclusions about associations between local airport exposures and health outcomes, the results may still be helpful alongside the results from the PHSKC analyses to piece together what is happening locally. Future work on this same local issue would benefit from more recent and more granular data and multi-level methods that can incorporate data at different geographic scales.

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Acknowledgments

This project was an excellent learning experience for me, and it would not have been possible without the help and guidance of many generous people. I am tremendously grateful to each of you.

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This thesis grew out of my involvement in a larger project related to the health impacts of airports with Public Health-Seattle and King County (PHSKC) and University of Washington Center for Health Innovation and Policy Science (CHIPS). Kris Johnson (PHSKC) spent countless hours reflecting on the relevant literature with me which helped me form my analysis questions. Molly Firth and Aaron Katz (CHIPS) coordinated and supported my involvement in the larger project and connected me with Dr. Seto. My advisor - Sarah Knerr (Health Services) – provided crucial support early-on in my thesis process when I was putting together project ideas and concerned about finding committee members. Elena Austin (DEOHS) graciously provided access to flight data and code for aggregating the flight data. The flight data proved to be an essential variable in this analysis.

It is as important to understand what your results do not say, as what they do say. Feedback from Maria Batayola (El Centro de la Raza and Beacon Hill Council) and Roseanne Lorenzana (DEOHS and Beacon Hill Seattle Community Noise Team) helped me understand the limitations of my analyses, and I regret not consulting them early on the process to improve my methods. Everything I have learned through this project makes me more appreciative of the community members who are engaged in this work locally. I admire the work they do to mobilize and promote the wellbeing of their communities.

I also want to acknowledge that this project, like so much other work that looks at local communities or is produced/used by local communities, relied heavily on freely available data from the Census. I

acknowledge this out of concern that the Census Bureau's current move to differential privacy may threaten the reliability of such data for future work.

Introduction

Worldwide, airport operations have expanded rapidly with the growth of air travel and air freight. Concern regarding health effects of increased airport operations has been rising nationally and locally. In King County, Washington (WA), community groups have mobilized their legislators and local government to investigate potential airport-related exposures, associated health effects, and appropriate mitigation steps.

Exposures

Air pollution and noise pollution are the two main health-related exposures of concern for communities surrounding commercial airports.

Noise pollution – also called environmental noise – refers to elevated levels of unwanted sound in the environment that are disruptive or harmful for health. Road traffic noise and aircraft activity are the main sources of noise pollution related to airports. Regulations for noise pollution usually apply to average noise levels over 24-hour periods measured in units called decibels (dB). A ten unit increase in decibels is the same as roughly doubling the perceived sound level. Nighttime noise is understood to be more disruptive, so 10dB is added to each hour of nighttime noise in the calculation of the day-night average noise level (also called Ldn). Sometimes an additional 5dB is added for each hour of evening noise in the calculation of a day-evening-night average sound level (Lden).

The Federal Aviation Administration (FAA) maintains that Ldn below 65dB is compatible for schools and residential land use (ECFR, n.d.). In 2018, the World Health Organization (WHO) revised guidelines for Europe to set aircraft noise thresholds at 45dB daily average (Lden) and 40dB at night to reduce health effects (WHO, 2018).

Air pollution related to airport activities includes many different pollutants with known health effects. $PM_{2.5}$ is the primary pollutant of concern because it dominates the health effects associated with airport exposures (NASEM, 2015). $PM_{2.5}$ is a group of non-gaseous air pollutants distinguished by their aerodynamic diameter of less than 2.5 micrometers. The primary sources of $PM_{2.5}$ related to airports are aircraft emissions and road vehicle emissions. Black carbon PM makes up 95% of the mass of PM aircraft emissions during takeoff, and at least 80% during other thrust settings (NASEM, 2008). Additionally, secondary PM can form from aircraft emissions several miles downwind from airports (NASEM, 2015).

Health Effects

Noise pollution is considered one of the top environmental risks to health by the WHO (WHO, 2018). Noise pollution primarily impacts health by disrupting important activities like sleep, work, or school, and by triggering stress and annoyance. Noise pollution can contribute to chronic stress by activating the stress response (Recio et al., 2016). Noise pollution can also disrupt sleep which limits the body's recovery from stress (2016). The body's stress response to noise does not have to be triggered by conscious annoyance with noise levels. Annoyance can impact the stress response, but stress response is also triggered automatically, even if noise levels are not consciously registered as annoying (Recio et al., 2016; Basner et al., 2014). Annoyance can amplify the effects of noise pollution on health by adding to the body's stress response and increasing the disruption that noise causes in daily activities like sleeping. Aircraft noise is typically more annoying than other transportation-related environmental noise (Guski, Schreckenberg, & Schuemer; 2017), so aircraft noise may lead to slightly stronger effects than other transportation-related noise whenever annoyance is a relevant modifier.

Long-term environmental noise exposure can lead to chronic stress, inflammation, and oxidative stress which can lead to increased risk of hypertension (Munzel et al., 2017; Van Kempen & Babisch, 2012) and heart disease (Van Kempen et al., 2018; Vienneau et al., 2015; Babisch, 2014; Munzel et al., 2014). These exposures also increase risk of stroke (Weihofen et al., 2015), heart attack (Stansfield, 2015), heart-related hospitalizations, and cardiovascular-related death (Basner et al., 2015).

Evidence also suggests long-term noise pollution exposures may have metabolic effects. Studies have observed higher rates of diabetes and other metabolic outcomes in communities exposed to higher noise pollution, controlling for other factors (Zare Sahkvidi et al., 2015; Dzhambov, 2015; Munzel et al., 2017; Van Kempen et al., 2018). The evidence is still limited to a small number of studies. Researchers expect the effects of noise pollution on stress response and sleep disturbance can impact metabolic functions and insulin sensitivity (Munzel et al., 2014).

Air pollution – especially $PM_{2.5}$ – contributes to wide ranging, serious health effects. $PM_{2.5}$ is an especially concerning air pollutant because the small size of the particles allows them to move past the lungs into the bloodstream and circulate to other parts of the body.

Short- and long-term $PM_{2.5}$ exposures cause cardiovascular problems according to the Environmental Protection Agency's (EPA's) 2019 Integrated Science Assessment (ISA) on Particulate Matter (US EPA, 2019). People with heart disease or hypertension are at higher risk of heart attack, stroke, and cardiac-related death following days of higher $PM_{2.5}$ levels. People without underlying heart disease can experience increases in blood pressure and heart rate variability following days of higher $PM_{2.5}$ levels. Populations exposed to even moderate levels of $PM_{2.5}$ over many years develop higher rates of heart disease and hypertension. These populations experience more heart attacks, strokes, and cardiac-related death (US EPA, 2019).

Short- and long-term $PM_{2.5}$ exposures likely cause respiratory problems (US EPA, 2019). Though many experts have concluded the evidence is strong enough to say that both short and long-term exposures "cause" (rather than "likely cause") respiratory effects (Frey et al., 2018; Frey et al., 2019). During days of higher $PM_{2.5}$ levels, people with asthma are at higher risk of asthma attack. People with COPD and people with allergies are likely to experience worsened symptoms. People with underlying respiratory illness are more likely to experience respiratory death. Populations without underlying respiratory conditions are at increased risk of contracting respiratory infections on days following higher $PM_{2.5}$ levels. Young children exposed to moderate $PM_{2.5}$ over several years are more likely to develop asthma. Their lungs may also not develop fully. Populations exposed to moderate $PM_{2.5}$ over several years experience more respiratory infections and have higher rates of respiratory related death (US EPA, 2019).

Long-term $PM_{2.5}$ exposure likely causes lung cancer-related death (US EPA, 2019). Populations exposed to moderate $PM_{2.5}$ over several years have higher rates of lung cancer and lung cancer related deaths.

Evidence suggests short- and long-term $PM_{2.5}$ exposure may lead to metabolic problems (US EPA, 2019). Following days of higher $PM_{2.5}$ levels, populations with diabetes and metabolic disease are likely to experience worsened symptoms and require hospitalizations. On these days, populations without underlying diabetes or metabolic disease are likely to have increases in blood sugar and insulin levels. Populations exposed to moderate levels of $PM_{2.5}$ over several years are likely to develop higher rates of metabolic syndrome and type 2 diabetes. These populations will also see higher rates of metabolic- and diabetes-related death (US EPA, 2019).

Recent studies have attributed over 100,000 early deaths annually to $PM_{2.5}$ exposure in the U.S. (Goodkind et al., 2019; Tessum et al., 2019). Cardiovascular-related deaths make up over half of all $PM_{2.5}$-associated mortality in the U.S (Bowe et al., 2019). The Institute for Health Metrics and Evaluation (IHME) also estimated that, for 2017, $PM_{2.5}$ in the U.S. caused (IHME, 2017):

- 43,000 cardiovascular-related deaths (nearly 5% of all cardiovascular-related deaths)
- 23,000 respiratory-related deaths
- 8,800 cancer-related deaths
- 8,800 diabetes-related deaths

Aircraft emissions appear to be relatively small contributors to the overall mortality from $PM_{2.5}$. One FAA-sponsored study estimated 160 deaths annually from aircraft $PM_{2.5}$ emissions during takeoff and landing between the 325 airports studied from 2005 to 2006 (Ratliff et al., 2009). A second FAA-sponsored study in 2008 estimated $PM_{2.5}$ deaths attributable to three major airports (Levy, Hsu, & Melly, 2008). Chicago O'Hare, an airport with typical emissions for a large airport and high numbers of people living near the airport, had 15 deaths per year attributed to airport emissions of $PM_{2.5}$ compared with 7 deaths annually from Hartsfield International Airport in Atlanta and less than one death annually at T.F. Green Airport in Rhode Island (Levy et al., 2008). These estimates vary between the airports based on differences in emissions, population density around airports, and other factors that impact how $PM_{2.5}$ disperses. It is worth noting that these estimates of airport $PM_{2.5}$ impacts look only at mortality and do not consider the wider health effects of $PM_{2.5}$. Additionally, $PM_{2.5}$ emissions from road vehicles going to and from the airport are often on par or higher than aircraft $PM_{2.5}$ emissions (NASEM, 2015) and are not included in these mortality estimates.

Differential Exposures

Air pollutant exposures and noise levels vary across areas near airport activity (including flight paths and road traffic) over time, distance, local geography, and weather conditions. Additionally, noise sensitivity can vary by factors such as age, underlying medical/sleep conditions, work schedule, and noise insulation at home or work.

Risk of exposure to noise and air pollution is strongly patterned by socioeconomic status (SES) and race. SES is a measure related to income, wealth, occupation, and education, and is often used to describe patterns in economic resources for individuals, households, neighborhoods, or across different population groups. Both individual SES and average SES of neighborhood independently impact health (Diez Roux & Mair, 2010). People of higher SES living in lower SES neighborhoods have resources that may allow them to avoid or overcome health hazards from their neighborhood. For example, they may be able to better insulate their home to reduce their individual exposure to noise pollution. However, because this study is not multilevel, the analyses only looks at neighborhood-level SES.

People of color (POC) and people of lower SES are more likely to be exposed to higher levels of air pollution and noise pollution due to economic and racial segregation and disparities in institutional power and influence on local land uses. Additionally, lower SES people are more likely to hold jobs where they are exposed to air pollutants and/or high noise levels, increasing baseline risk for health effects from neighborhood pollutant exposures. Many of the noise sensitivity factors such as overnight shift work, poor sound insulation in buildings, and underlying medical or sleep conditions are also likely to be more concentrated in lower SES neighborhoods.

Nationally, the distribution of exposures to $PM_{2.5}$ is disproportionately concentrated among Black and Hispanic/Latinx communities (Tessum et al., 2019). Additionally, a 2019 study of noise pollution in Georgia found noise pollution exposures disproportionately concentrated among Black and Hispanic/Latinx communities compared to non-Hispanic White populations, and these general trends held across the state as a whole and across metro areas (Cohen et al., 2019).

While the EPA regulates ambient concentrations of air pollutants like $PM_{2.5}$, local concentrations can vary well above regulation levels. Apart from lead emissions, EPA monitors are generally not intended to monitor local areas of highest concentrations; the monitors tend to be located where they can measure background concentrations (NRC, 2004). Even when those monitored concentrations are within EPA standards, communities closer to sources of these air pollutants will be exposed to higher concentrations than what the monitors reflect. Studies in various regions of the U.S. have found that these communities tend to have higher populations of POC and higher rates of poverty (Rowangould, 2013; Stuart, Mudhasakul, & Sriwatanapongse, 2009). A 2010 study measuring street-level pollutants in Seattle's International District found much poorer air quality than that measured by the nearest air quality monitoring station (Bassok et al., 2010). The EPA standards and monitoring process is not a system designed to protect neighborhoods closest to emission sources.

Differential Effects

The EPA recently concluded that POC are both more likely to be exposed to $PM_{2.5}$ and more likely to die early from health effects related to $PM_{2.5}$ (EPA, 2019). In a 2019 study that followed 4.5 million veterans from 2006 to 2016 and found nearly 200,000 deaths related to $PM_{2.5}$ exposure, the study concluded that Black veterans and veterans living in poorer communities experienced disproportionately higher numbers of deaths related to $PM_{2.5}$ than other veterans (Bowe et al., 2019). Additionally, 99% of deaths were due to $PM_{2.5}$ exposure levels below the current EPA standard for $PM_{2.5}$ concentration (2019). The current primary $PM_{2.5}$ standard is set to 12.0 $\mu g/m^3$ three-year average (US EPA, 2012). Experts have called for the $PM_{2.5}$

standard to be lowered considerably to save tens of thousands of lives annually (Di et al., 2017; Bennett et al., 2019).

Phelan & Link identify both racism and SES as fundamental causes of health inequities (Phelan & Link 2015). Racism largely impacts health through creating and maintaining racial differences in SES, but it also acts independent of SES through several additional flexible and replaceable pathways such as racism-related stress, discrimination, and mass incarceration, among others (2015). POC and people of lower SES bear larger burdens of underlying health conditions and increased activation of biological pathways- such as chronic stress - that increase risk of health effects from air pollution and noise pollution. These factors structure risk for conditions like diabetes, heart disease, and respiratory conditions. They also structure risk for higher severity of health conditions and poorer access to quality medical care. The biological pathways that connect air pollution and noise pollution to heath (inflammation, oxidative stress, chronic stress, DNA damage, and epigenetic changes) are also activated by other types of exposures that POC and people of lower SES are more likely to face, such as discrimination-related stress. Epigenetic changes from exposures to previous generations may increase susceptibility to health effects from air pollution today (Thayer & Kuzawa, 2011). Ultimately, POC and people of lower SES face higher health risks from air pollution and noise pollution compared to non-Hispanic White populations and people of higher SES (O'Neill et al., 2003).

Studies in King County

There are two large airports in King County: Sea-Tac International Airport and King County International Airport- Boeing Field. Several smaller municipal and private airports also operate in the county, though they primarily serve small aircraft. The larger airports have been the subjects of several studies on aircraft-related exposures and mortality.

Across Seattle's Beacon Hill neighborhood, noise samples collected by students and citizen scientists spanned a range of Ldn's between 52 dB and 85.5 dB between April and September of 2018 (BHNMP, 2018). The median Ldn across the 52 measurement sites was 68.1 dB, and five sites had Ldn's over 80 dB.

The Beacon Hill Neighborhood is a quarter mile from the Boeing Field runways and 3.5 miles from the Sea-Tac Runways.

One FAA-sponsored study estimated that Sea-Tac aircraft $PM_{2.5}$ emissions during landing and takeoff made up approximately 0.25% of all $PM_{2.5}$ emissions in the Seattle-Tacoma region and 0.87% of all $PM_{2.5}$ from mobile sources in the region between 2005 and 2006 (Ratliff et al., 2009). Another study estimated that between 1.63% and 2.46% of deaths in King and Pierce Counties were caused by mobile sources of $PM_{2.5}$ over the same time period (Fann, Fulcher, & Baker, 2013). These Sea-Tac airport studies took place prior to the opening of the third runway in 2008.

While this study does not deal directly with ultrafine particulate matter (UFP) exposures, aircraft emissions are largely carbon-based UFP (NASEM, 2008). Experts anticipate UFP may be of particular importance for health (WHO, 2013). The first study measuring UFP emissions from aircraft traffic near Sea-Tac Airport was completed last year (UW DEOHS, 2019). While UFP from aircraft sources were observed at lower concentrations than roadway sources, they were spread over larger areas near the airport, potentially exposing more people. The proximity of major roadways and flight paths may compound risks in some communities near these airports as well. A 2007 study of Seattle found that lower income households and POC disproportionately live near highways and major arterials compared to non-Hispanic Whites and middle-income households, leading to higher exposures to traffic-related air pollutants and noise (Bae et al., 2007).

Finally, a 2017 study of 66 major airports estimated around 0.7 deaths annually to Sea-Tac emissions and around 0.1 deaths annually from Boeing Field emissions, primarily from $PM_{2.5}$ and secondary $PM_{2.5}$ formation (Penn et al., 2017). Additional work is needed to investigate the community health impacts of local airport operations.

Aims

Public Health- Seattle and King County (PHSKC) is currently assessing community health outcomes at varying radii from the Sea-Tac airport to provide additional context around airport-related exposures. The overall objective of this study is to supplement those analyses by exploring exposure distributions and associations with community health outcomes through an alternative set of methods. The analyses follow three primary aims:

(1) *Estimate average community-level exposures to aircraft activity and air and noise pollution.*

(2) *Examine the distributions of these exposures by race and ethnicity.*

(3) *Evaluate community-level associations between these exposures and relevant population health outcomes.*

This study uses a cross-sectional, ecological approach to explore this local health equity issue. Only publicly available data was used so that if community groups find any of these analyses potentially helpful, they may add them to their own toolkits and explore these datasets further with their own methods.

In this analysis, the author hypothesized that communities of color in King County – especially Black and Hispanic/Latinx populations- will face significantly higher exposures on average than Non-Hispanic White populations, based on the results of a wealth of similar studies in other regions. It was also hypothesized that neighborhood proximity to flight paths and, separately, neighborhood $PM_{2.5}$ and noise levels will hold small but positive associations with at least heart disease mortality rates, as the effect sizes in the research literature are largest for this outcome. However, data quality and resolution were expected to affect model performance. Testing these hypotheses provides additional evidence to support local efforts to understand and mitigate airport impacts on community health.

Data

All data are for the extent of King County, WA. Data range from 2009 to 2018, and all data are publicly available. Data came in various forms but were all aggregated to census tracts and Health Reporting Areas

(HRAs) for analysis. These two geographic units were chosen based on availability of data. Census tracts are a commonly used geography for ecological studies of neighborhood-level exposures and convenient for working with American Community Survey (ACS) data. In this analysis, $PM_{2.5}$ data could only be found at the census tract-level. Additionally, health outcome and health behavior data for the whole county could only be found at the HRA-level. HRAs tend to approximate ZIP code and large neighborhood boundaries; there are 48 HRAs in King County. An HRA shapefile was obtained from PHSKC's Assessment, Policy Development and Evaluation Unit's data request service (King County, 2019b). There are 398 census tracts in King County; one tract was excluded from analysis because it represented boat docks and no population. Census tract and block group shapefiles clipped for bodies of water were obtained from King County GIS Open Data (King County, 2011).

Exposure data

Flight data were used to approximate neighborhood exposure to aircraft activity. Proximity to flight paths is considered here as a proxy measurement of air and noise pollution exposures from aircraft activity. Flight data was simplified to annual counts of flights below 750m altitude. This cutoff is used because emissions above 3,000ft altitude tend to mix with higher air and have negligible effects on local air quality (NASEM, 2015). The 3,000ft cut-point is less significant for noise pollution – aircrafts are louder the lower they fly, but the noise level can vary broadly based on the type of plane, trajectory and direction, and local geography. Medium and large aircraft flying over 3,000ft of altitude can still produce noise reaching the 70-80 dB range at the ground below (NATS, n.d.).

Flight count data from all of 2018 was obtained from faculty from the UW Department of Environmental and Occupational Health Sciences (FAA, 2019). The data was originally obtained through Freedom of Information Act request from the Federal Aviation Administration (FAA). The flight data for all of 2018 was aggregated to grid points spaced 0.008 degrees longitude and 0.005 degrees latitude (or approximately 1,800ft North-South and 2,000ft East-West) across all of King County. Flight counts at each grid point represent a count of all flights below 750m in the airspace closer to that grid point than any other (aggregation was completed by rounding lat-long coordinates to 0.005 and 0.008, respectively). The gridded data is mapped in ***Figure 1***.

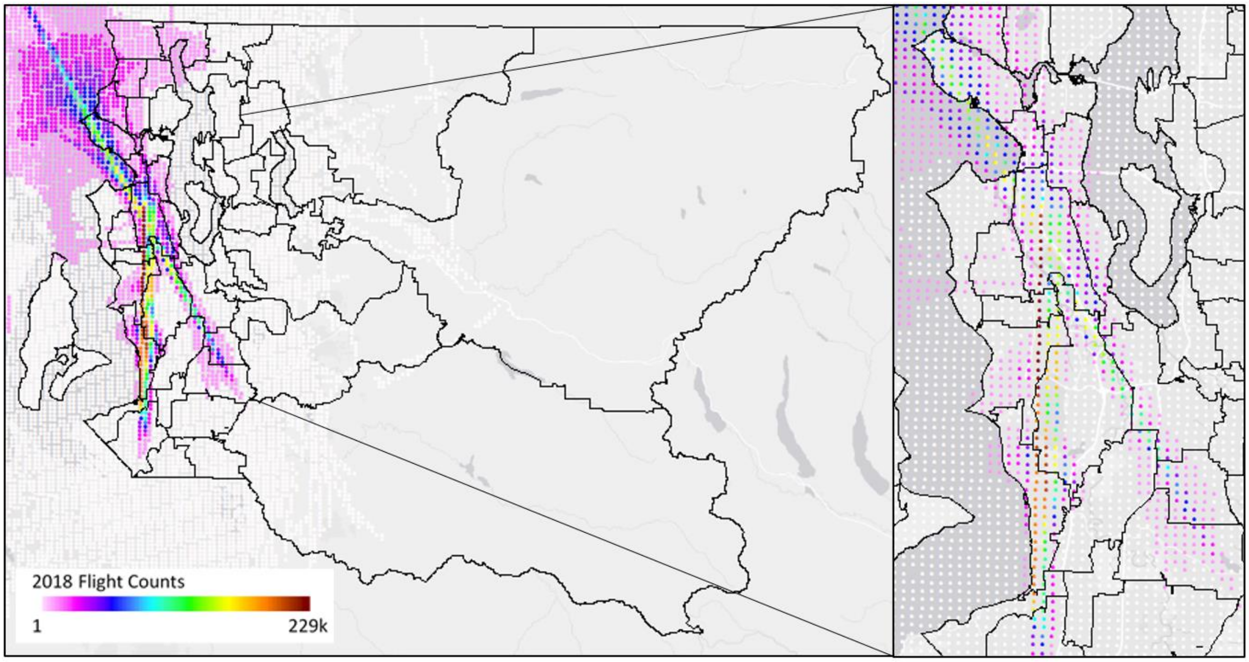

Figure 1. Gridded 2018 flight counts for King County, WA, with zoomed inset (right).

The gridded flight data was converted to census-tract- and HRA-level measures for analysis. The area-level estimates were sensitive to the locations and spacing of the grid points, especially the smallest census tracts which did not contain any grid points. The grid was converted to a continuous surface before aggregation to census tracts and HRAs to reduce bias from the grid locations. The continuous surface was created by constructing Thiessen polygons around the grid points. Other interpolation methods were considered, such as kriging and inverse distance weighting, but these methods performed poorly with diagonal flight patterns in the grid. Thiessen polygons attribute the value of a grid point to the area around the grid point that is closer to that point than any other, so they should generally approximate the areas generated by rounding the lat-long coordinates. This method is computationally straightforward and allows for re-aggregation to census tracts and HRAs. Census tract-level and HRA-level annual flight frequencies were calculated by area-weighted averaging of the Thiessen polygons within the boundaries of the census tracts and HRAs.

Air pollution data is modelled annual average of 24hr concentration of $PM_{2.5}$. The data are based on three-year averages from 2009 to 2011 (the only data years available) and were originally provided as averages over census tracts. The data were accessed from the Washington Tracking Network's (WTN) Information by Location tool (WTN, 2019). WTN aggregated the data to census tracts and three-year averages from predictive grids from AIRPACT, an air quality modeling project of Washington State University. For analysis with the health data, $PM_{2.5}$ concentrations were aggregated to HRAs using area-weighted average of the census-tract level concentrations within each HRA.

Noise pollution data was obtained from the U.S. Department of Transportation's National Transportation Noise Map (USDOT, 2018). These data represent A-weighted 24-hour equivalent sound levels (LAEQ) related to traffic and aircraft noise for 2017-2018. The data is a 60m by 60m cell raster file that represents modeled transportation noise from both air traffic and road traffic. A-weighting is an adjustment to the sound level measure that accounts for how frequency impacts perceived level of sound; this is a standard adjustment in environmental noise measurement. The metadata indicates that the noise data is simplified and should not be used to evaluate noise levels at specific locations. This should not present an issue for these analyses since the focus is on relative exposures between areas rather than absolute values. The continuous noise data is mapped in ***Figure 2***.

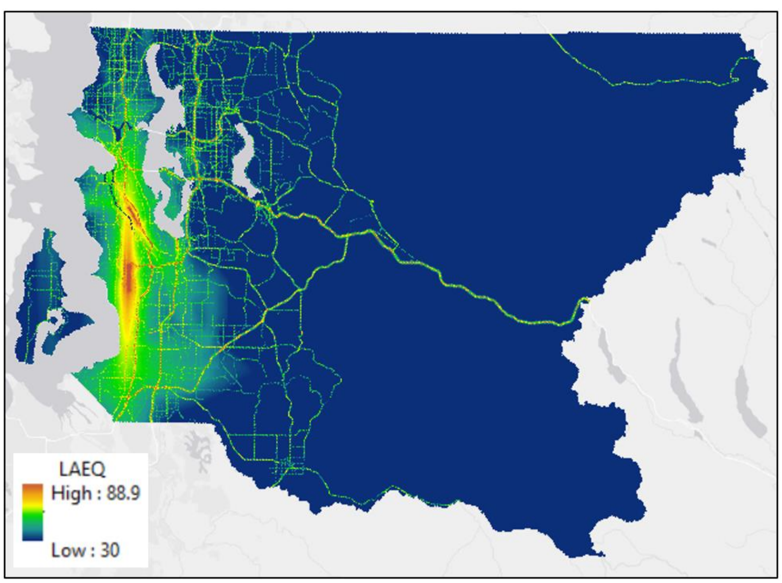

Figure 2. USDOT modelled transportation noise data, 2017-2018, with 30dB default values.

The USDOT noise data did not include modeled noise level values below 35dBA. The intent of the data was to model air and road traffic noise, so it did not include noise levels for areas projected to be much less impacted by these sources. In a 2019 study of noise pollution exposure in Georgia, the authors used a 0dBA value for all null cells in the raster (Cohen et al., 2019). This approach was considered, but a default value of was chosen 30dBA instead. 30dBA is typical of a quiet rural area (IAC Acoustics, 2019), and this is not too far from the minimum value of 35dBA in the original data. Where 0dBA obviously biases aggregate estimations considerably downward, it is not clear which direction a default value of 30dBA biases estimates. However, 30dBA is a more reasonable estimate than 0dBA (the softest level of audible sound), leading to less bias overall. All null values in the original noise raster were replaced with 30dBA. Then the noise data were aggregated to census tracts and HRAs by averaging the cell values within each geographic unit.

Health outcome data

This analysis examines associations of the above exposures with population-level health outcomes aggregated in HRAs from PHSKC City Health Profile Data (King County, 2019a). HRAs tend to approximate ZIP code and large neighborhood boundaries. Health outcomes were chosen for their established biological associations with $PM_{2.5}$ and/or noise pollution exposures, but choices were limited by what was reported at the HRA level by PHSKC. The outcomes selected for this analysis are listed in ***Table 1***. Summary statistics are also provided. These outcomes are all five-year age-adjusted rates (per 100,000 person-yrs) based on state death records data from 2011 to 2015 and aggregated to HRAs by PHSKC.

Table 1. Summary of health outcome measures.

Cause-Specific Mortality Rates	Outcome Definition from PHSKC	King County	HRA-level Rates Std. dev.	Min.	Max.	Relevant Exposures
Heart Disease Deaths	Deaths due to congestive heart failure, cardiac dysrhythmias, acute myocardial infarction (ie. heart attack), or coronary artery disease	125.7	25.0	80.0	210.6	PM2.5 & Noise
Stroke Deaths	Deaths due to cerebrovascular disease (ie. stroke) as primary cause	30.6	6.6	19.0	48.6	PM2.5 & Noise
Chronic Lower Respiratory Disease Deaths	Deaths from bronchitis, emphysema, chronic obstructive pulmonary disease (COPD), or asthma	29.8	10.5	13.0	62.6	PM2.5
Lung Cancer Deaths	Deaths due to lung cancer as primary cause	33.9	8.8	11.9	55.2	PM2.5
Diabetes Deaths	Deaths with diabetes mellitus as primary cause	18.5	7.4	4.2	38.4	PM2.5 & Noise
Diabetes-Related Deaths	Deaths with diabetes mellitus as primary or contributing cause	60.4	23.2	22.0	124.9	PM2.5 & Noise

Note: All rates are five-year, age adjusted rates (per 100,000)

There are significant ranges between the HRAs with the highest and lowest rates of each outcome. For heart disease deaths, the most prevalent cause of death examined, the HRA with the highest rates has 130 more deaths per 100,000 person-yrs than the lowest HRA. For every outcome, rates more than double between the highest and lowest HRAs. Diabetes deaths increase by a factor of nine between the highest and lowest HRAs. The likelihood that these differences are due to instability in the rates is low. PHSKC does not report standard error with these data, but the populations of each HRA are large, the outcomes are not rare, and the rates are averaged over a five-year period.

Other covariate data

Additional covariates of interest include area socioeconomic SES indicators, race/ethnicity composition, and health behavior indicators.

Neighborhood SES was estimated using an index of variables related to income, education, employment, and housing. Six ACS variables were chosen to model SES after reviewing methods in a range of similar studies. 2018 ACS data was used to calculate these variables (ACS, 2018b-f). The six SES variables – percent with at least a bachelor's degree, percent with at least a high school diploma, percent at or above the federal poverty line (FPL), log of median household income, employment rate, percent of housing units owner occupied – were used to construct an area-level SES index variable. Indexing was done for both census tracts and HRAs, separately. HRA variables were aggregated from census block groups since they are smaller than tracts and generally followed the boundaries of the HRAs. Block groups were mapped to HRAs based on the location of their centroids when centroids were constrained to be within the boundaries of each block group. This process was used to sum block group counts of the SES-related variables within HRAs. HRA-level estimates were constructed from these counts.

For each of the six variables, standard scores were calculated for each census tract and HRA by subtracting the county-wide average (as reported by ACS) from the local average and dividing by the standard deviation. The standard scores for all six variables were averaged together and rescaled between 0 and 1. The resulting SES indices (one for census tracts and one for HRAs) estimate area-level SES such that a score closer to 0 represents lower area-level SES and a score closer to 1 represents higher SES.

Race and ethnicity composition was modelled using 2018 ACS five-year estimates for census tracts and block groups (ACS, 2018a). Block group-level data was used to estimate HRA-level race and ethnicity composition in the same aggregation process described for SES index construction. For comparisons across race and ethnicity in the second portion of the analysis, seven demographic subgroups based were constructed based on census-defined race and ethnicity categories: All Hispanic/Latinx, Non-Hispanic American Indian or Alaska Native (NH-AIAN), Non-Hispanic Asian (NH-Asian), Non-Hispanic Black (NH-Black), Non-Hispanic Native Hawaiian or other Pacific Islander (NH-NHPI), Non-Hispanic other race or two or more races (NH-other), and Non-Hispanic White (NH-White). The NH-Other subgroup is a combination of those enumerated as "other" for race and those who are enumerated as two or more races but are not enumerated as Hispanic. These specific groupings were chosen in effort to balance strata stability, relevance and comparability to other reporting of health inequities, and preservation of data granularity. However, these selection decisions do have implications for results. Additionally, the census counts for these subgroups are non-overlapping and sum to the total population.

For the regression analyses, area-level race composition was operationalized as percent of the population racialized as Black, based on the ACS data from the descriptive analyses. This decision was based on other studies of cardiovascular-related mortality rates (Ford, 2011; Thomas, 2005) and the highly disparate rates of the outcomes of interest among Black populations compared to most other groups (Cunningham et al., 2017). Adjusting for area-level Black population is intended as an adjustment for area-level unmeasured anti-Black racism-related exposures that result in significantly increased risk for the outcomes of interest, typically above all other race/ethnicity-defined subgroups. Many of these anti-Black racism exposures operate through and interact with the measured exposures – SES stratification and segregation and increased exposure to air pollution and noise pollution- but many also operate outside of these variables.

Health behavior covariates were limited to HRA-level smoking prevalence. This data is reported by PHSKC (King County, 2019a). PHSKC notes the original data is from the Behavioral Risk Factor Surveillance System (BRFSS) and aggregated from 2013 to 2017. Health behaviors such as physical activity and fruit and vegetable consumption are also relevant at the individual level for some heart disease-related variables and were considered for inclusion. However, it was expected that these variables, especially aggregated over such large areas, do not capture dimensions significantly different from the combined SES and smoking variables. Smoking prevalence, however, was included for its strong associations with cardiovascular and respiratory outcomes and large effect sizes compared with other health behavior variables.

Analysis & Results

Analyses were completed in ArcMap *v. 10.7.1*, Microsoft Excel, and R *v. 3.6.2*.

Aim 1: Characterizing Exposures

Primary exposures are average $PM_{2.5}$ concentrations, average noise level, and average annual flight counts. Additional covariates include neighborhood SES, percent Black, and prevalence of smoking. Summary descriptive statistics were calculated for each of the primary exposures and covariates by census tract and HRA. These are presented in ***Table 2***.

Table 2. Descriptive statistics for primary exposures and additional covariates.

	King County	Census Tracts (n=397)			Health Reporting Areas (n=48)		
		Std. dev.	Min.	Max.	Std. dev.	Min.	Max.
Flights	2195	11009	1	88349	7644	1	29138
$PM_{2.5}$	6.2	0.8	3.8	7.9	0.9	3.9	7.5
Noise	42.9	8.0	30.1	65.6	7.5	30.4	58.2
Smoking Prevalence	11	-	-	-	4.6	3	22
% Black	6.1	7.3	0	35.5	6.1	0.0	23.8
SES Index							
- *% with atleast Highschool Diploma*	93.0	6.8	60.0	100.0	5.4	79.3	98.6
- *% with atleast Bachelor Degree*	51.4	20.7	6.0	87.0	18.9	19.5	78.8
- *Median Household Income*	$95,009	$35,676	$20,950	$222,500	$28,517	$55,929	$187,331
- *% above Federal Poverty Line*	90.7	8.4	31.2	99.9	4.6	81.2	97.7
- *Employment Rate*	96.1	2.4	82.4	99.3	1.3	92.8	98.0
- *% Owner Occupied Housing Units*	56.0	22.0	0.0	96.3	14.9	18.4	88.6

Average flights, noise, and $PM_{2.5}$ exposure levels for the county were calculated by census tract-level population-weighted averages. County-level percent Black and SES variables are directly reported from ACS 2018 county-level data. County-wide smoking prevalence is directly reported from PHSKC based on BRFSS data. Smoking prevalence data was only available at the HRA-level.

As illustrated in ***Table 2***, the data aggregated at HRAs have much smaller ranges than the data aggregated at census tracts. This helps illustrate data resolution lost in the aggregation to the large HRAs. The large geographies smooth over more heterogeneity than census tracts, reducing the signal in the data.

Figures 3 through ***5*** map the primary exposures to illustrate their distribution over the county and the change in distribution between census tracts and HRAs. All three exposures are highest in the southwest portion of the county, lower in the northwest portion of the county, and lowest in the eastern part of the county. In the shift from census tracts to HRAs, this general pattern holds, but smaller trends are obviously lost. This appears especially true for the flight count data and noise data because the values can be very different in neighboring census tracts that are then combined into the same HRA. The $PM_{2.5}$ values have a smoother pattern that seemed to translate better to HRAs, except for the south-central part of the county. Beacon Hill/ Georgetown/ South Park, North Highline, Burien, SeaTac/ Tukwila, and Des Moines/ Normandy Park HRAs are all consistently highly exposed across all three exposures.

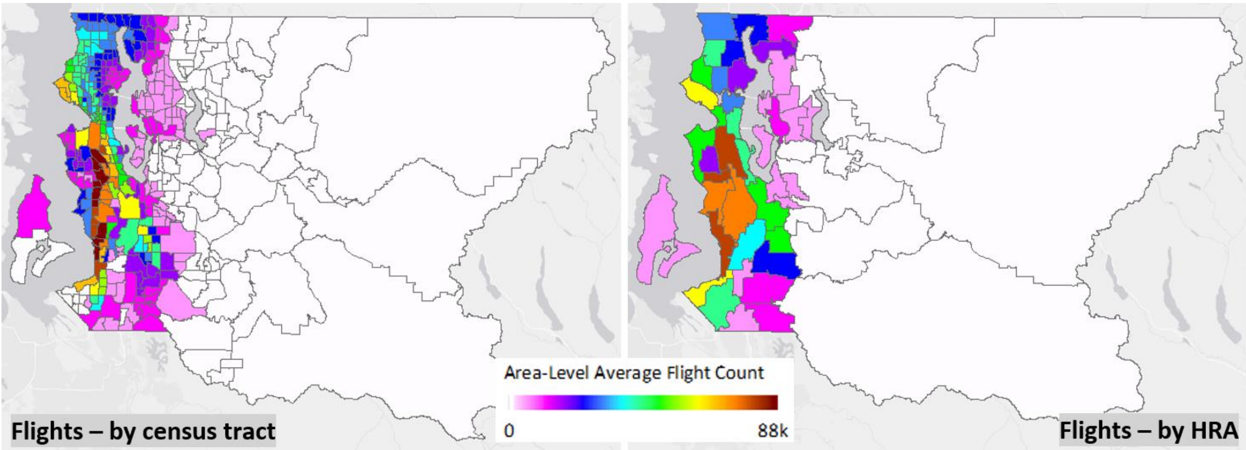

Figure 3. 2018 flight counts by census tract (left) and HRA (right).

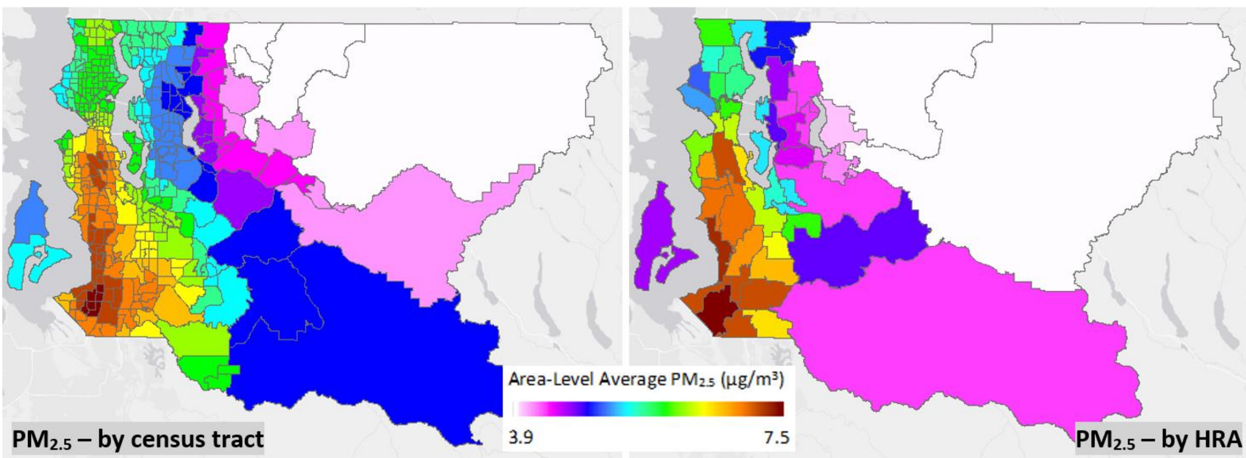

Figure 4. $PM_{2.5}$ *data by census tract (left) and HRA (right).*

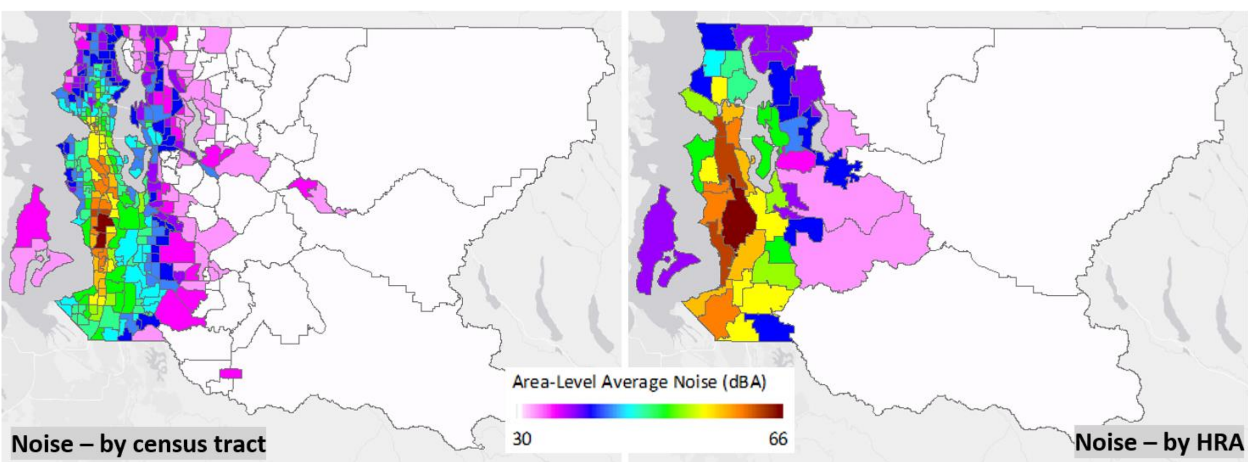

Figure 5. Noise data by census tract (left) and HRA (right).

The other covariates were also mapped for comparison with the exposures. These are shown in ***Figure 6*** and ***Figure 7***. The HRA-level exposure and SES estimates are also reported in ***Table 5*** in the Appendix.

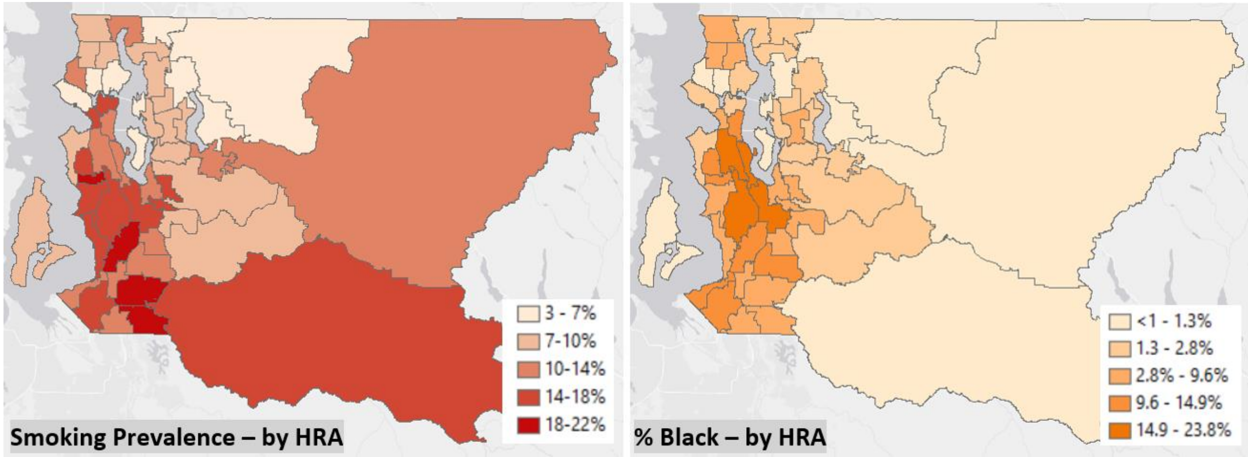

Figure 6. HRA-level smoking prevalence (left) and percent Black (right).

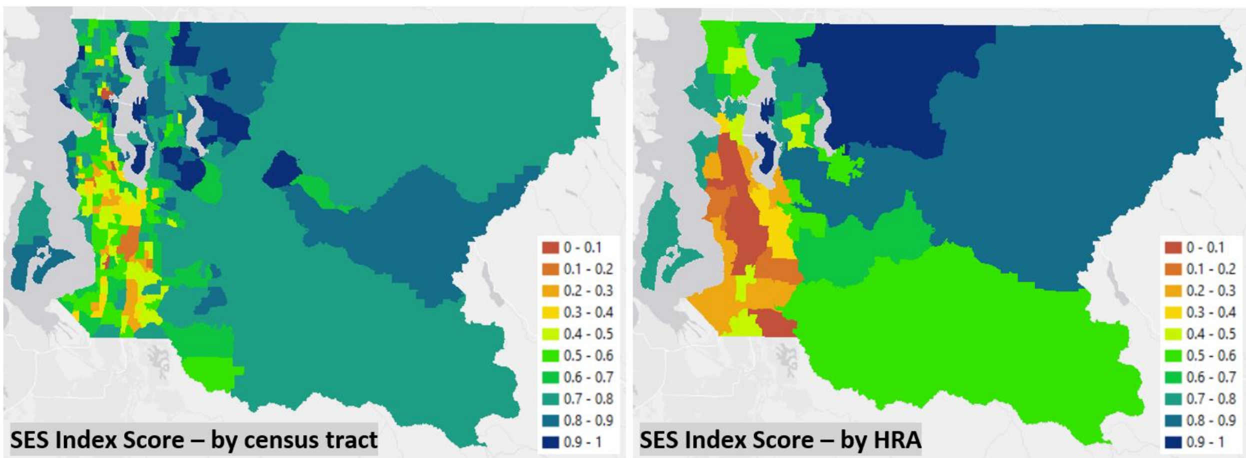

Figure 7. SES index scores calculated for census tracts (left) and HRAs (right).

Smoking prevalence is highest in the southwest and southeast parts of the county as well as central Seattle. Smoking prevalence is lowest in North Seattle and the larger Bellevue area/central county. Black residents live predominantly in the region between central Seattle and the southwest portion of the county, with some smaller populations in the northwest corner of the county and the Bellevue region. For SES, a lot of small-scale variation is lost in the change from census tracts to HRAs. The HRA map shows lowest neighborhood SES between central Seattle and the southwest county.

In addition to the maps, exposures and covariates were plotted against each other to provide additional comparison. HRA-level flight counts were log transformed to adjust for skew. ***Figure 8*** shows all covariates (at the HRA level) plotted against each other to judge general trends and collinearity.

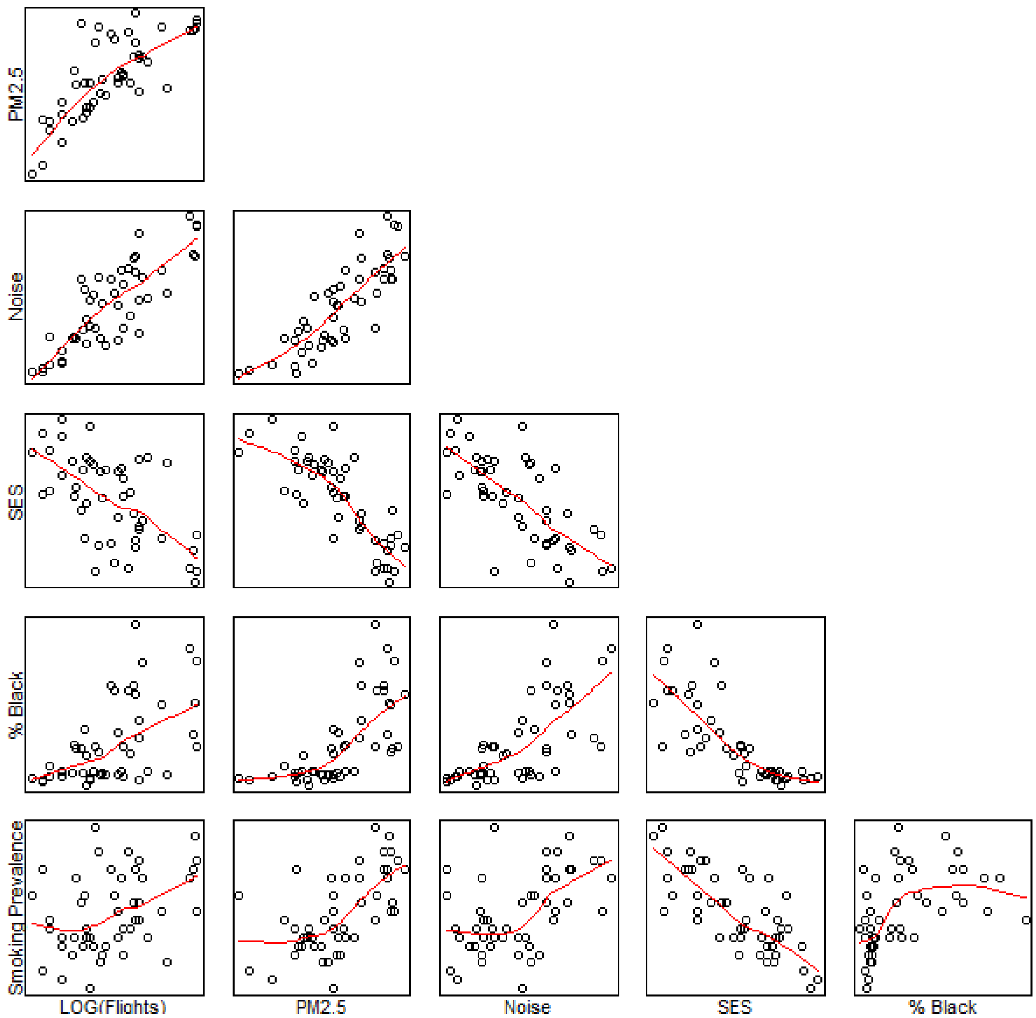

Figure 8. Collinearity plots with LOWESS curves for trend approximation.

Aim 2: Exposures by Race and Ethnicity

Lorenz-type Curves

Lorenz-type curves were constructed to examine the relative distributions of each exposure across population subgroups. The incorporation of these curves is based on a study of noise pollution exposure disparities in Georgia (Cohen et al., 2019). The study used these curves as an effective and concise comparison of noise pollution exposures between race and ethnicity-defined subgroups. They are employed here for the same purpose.

The Lorenz-type curves plot the cumulative percent of the population against the census tract-level exposure for each of the seven race/ethnicity subgroups and the total population. To construct the curves for each environmental exposure (including neighborhood SES), census tracts were ordered from lowest exposure level to highest. Then each subgroup's cumulative percent of population were calculated based on the population in each census tract. These curves were then plotted in R. The curves are presented in ***Figures 9*** through ***12***.

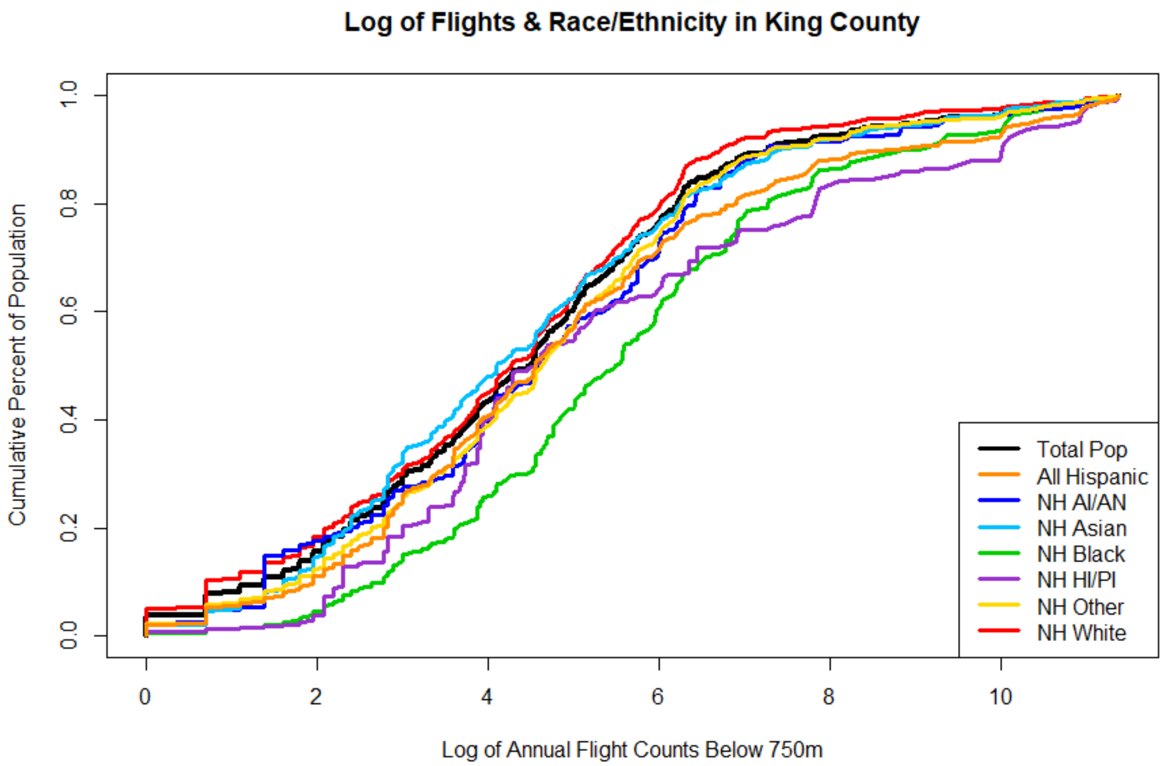

Figure 9. Lorenz-type curve for flights exposure by race and ethnicity in King County

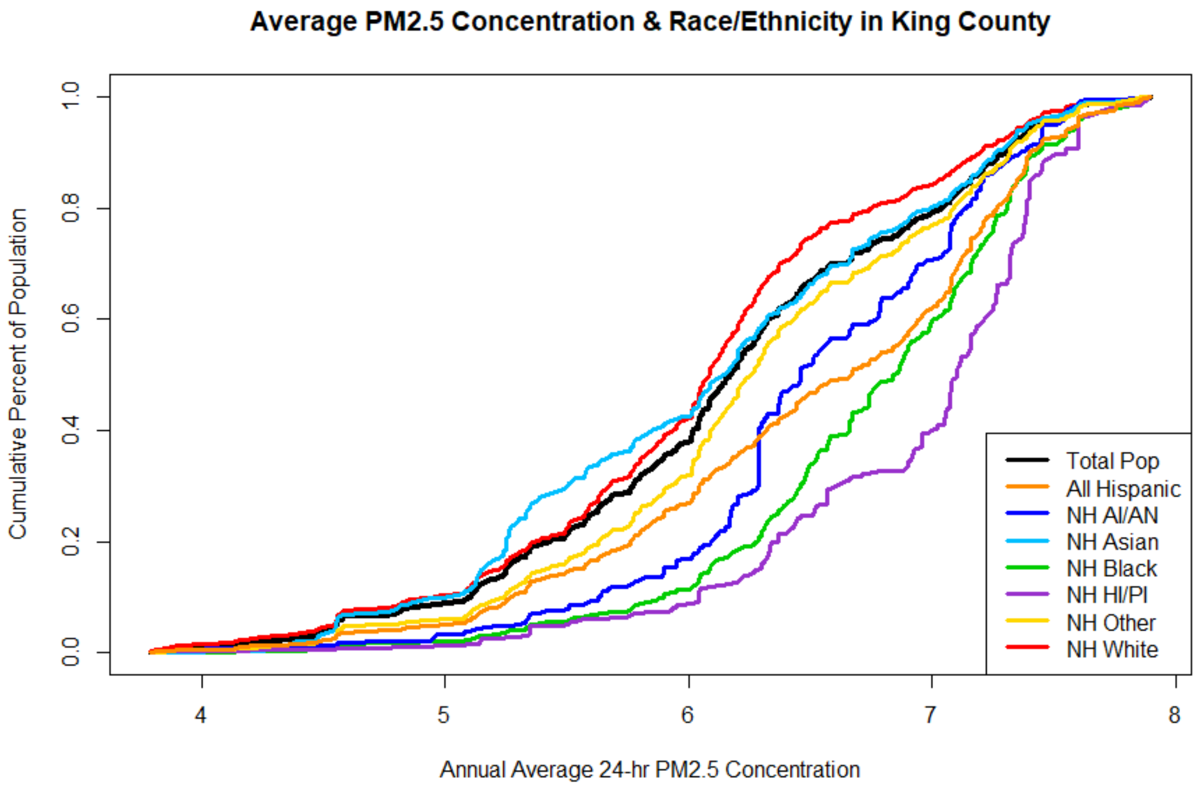

Figure 10. Lorenz-type curve for average $PM_{2.5}$ exposure by race and ethnicity in King County

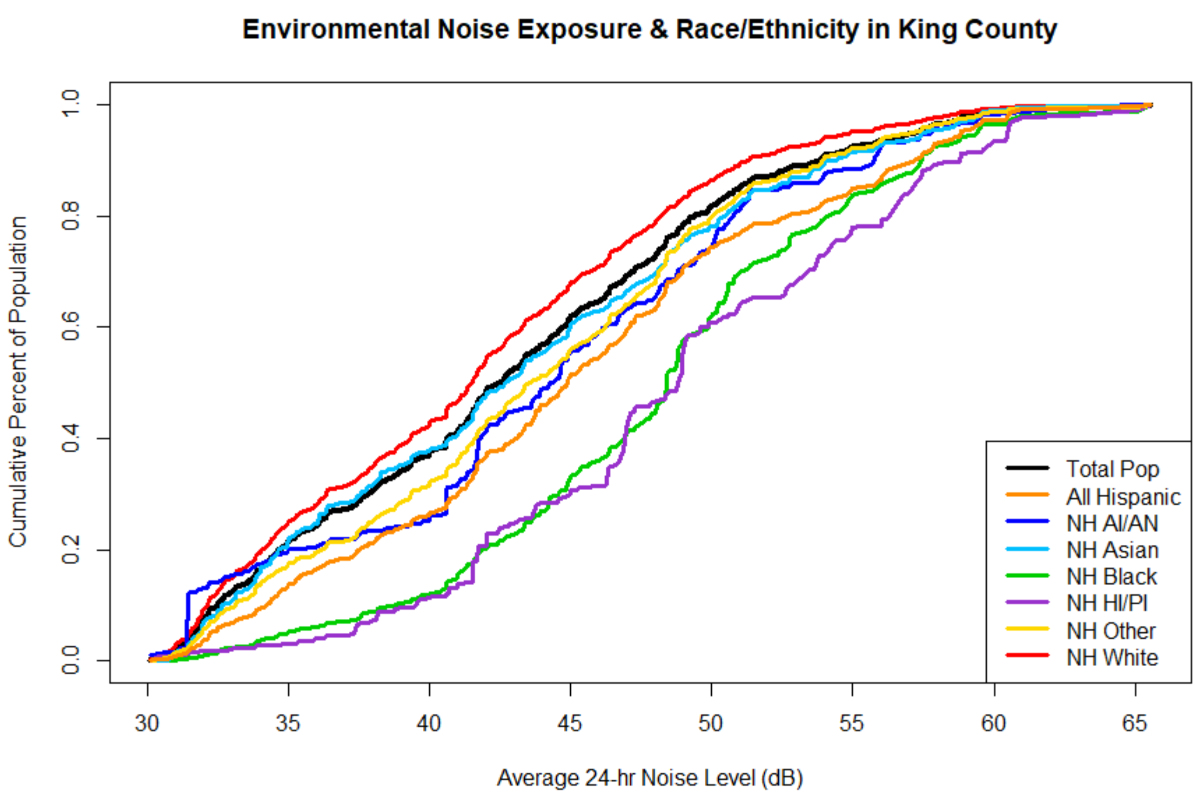

Figure 11. Lorenz-type curve for environmental noise exposure by race and ethnicity in King County

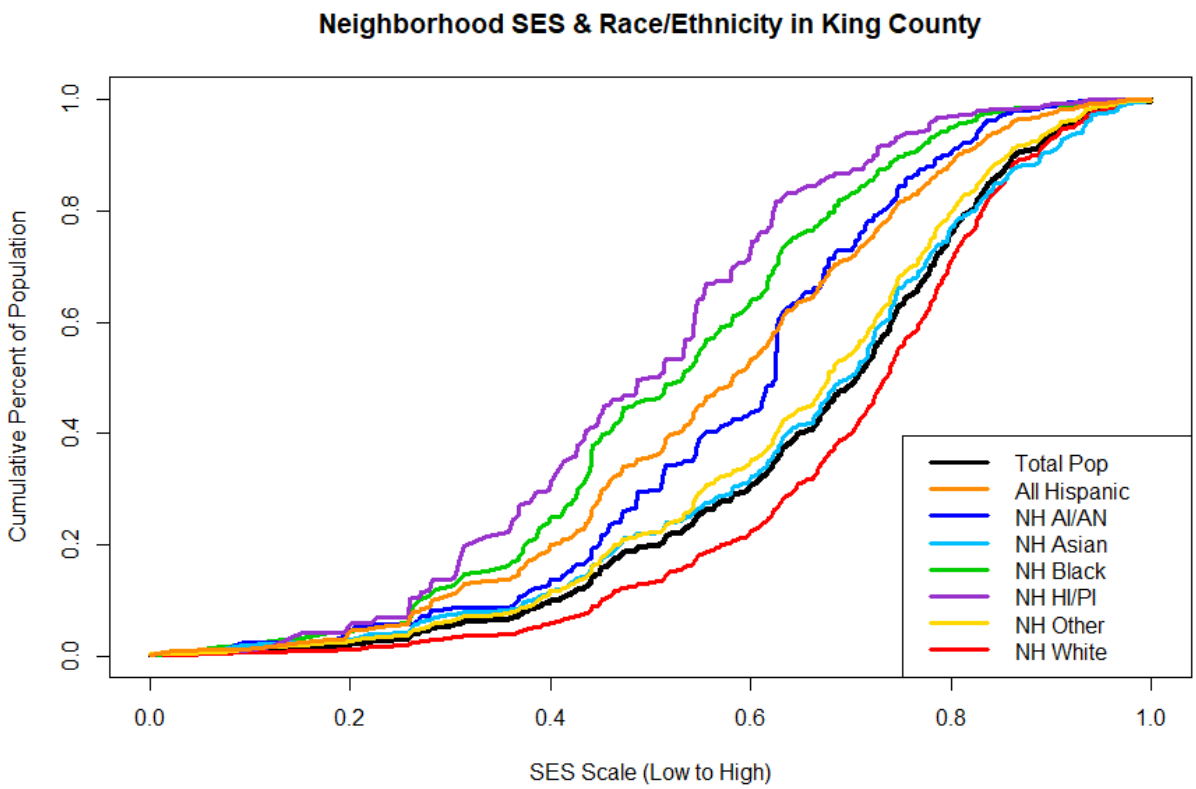

Figure 12. Lorenz-type curve for neighborhood SES by race and ethnicity in King County

If the distribution of county-wide exposures did not vary significantly by race and ethnicity, the curves for each subgroup would approximate the curve for the total population. For ***Figures 9 - 11***, deviation above the curve indicates less of the subgroup population in higher exposure tracts and more subgroup population in lower exposure tracts. For all three curves, this pattern is only consistently seen for the NH-White populations. For ***Figure 12***, SES is coded such that higher SES exposure is exposure to higher level of SES which acts as a protective factor for health. For the SES curve, deviation below the curve indicates more population in higher SES tracts. Again, the NH-White populations are the only subgroup on the more advantaged side of the overall curve. NH-Asian populations generally follow the overall curves closely in all four figures.

Deviation below the total population curve in ***Figures 9 – 11*** indicates more of the subgroup population is in higher-exposure census tracts than the county population as a whole. For the flights exposure in ***Figure 9***, most of the subgroups have similar distributions of exposure, but the NH-Black populations have consistently higher exposures across the curve. The population median exposure is approximately 200 flights/year higher than the county as a whole and most other subgroups. Additionally, while approximately 20% of NH-Black, NH-NHPI, and Hispanic/Latinx populations are exposed to more than 3,000 flights/yr, only about 10% of other subgroup populations are in these high exposure tracts.

For the $PM_{2.5}$ exposure curve (***Figure 10***), there is a 1μg/m^3 difference in median exposure between NH-White and NH-NHPI subgroups. NH-Black, Hispanic/Latinx, and NH-AIAN populations are also all more distributed in higher exposure tracts. There is no safe threshold for $PM_{2.5}$ exposure, so even small differences in average exposure carry significance for health and health inequities.

For the environmental noise exposure curve (***Figure 11***), NH-Black and NH-NHPI populations are again more highly exposed than other subgroups. The median exposure-level for these two subgroups is close to 10 dBA higher than for NH-White populations. This is approximately double the perceived sound.

Deviation above the total population curve in ***Figure 12*** indicates more of the subgroup population is in lower SES census tracts than the population as a whole. NH-NHPI and NH-Black populations are more distributed in lower SES tracts than other groups, followed by NH-AIAN and Hispanic/Latinx populations as well. While the units of the SES scale are difficult to interpret, it is illustrative that the spread at the population median is over one-fifth of the entire SES range, and that spread holds at the 20% and 80% population marks, too.

The NH-White populations are the only subgroup consistently advantaged compared to the total population curve. This indicates that this subgroup population is more distributed among lower exposure and higher SES tracts compared with the population as a whole and each other subgroup. Conversely the NH-Black populations and the NH-NHPI populations were consistently more likely than other subgroups to live in higher exposure and lower SES tracts.

Difference in Means Tests

Continuing the approach of Cohen et al., two-sample t-tests were employed in addition to the curves to examine whether there was a statistically significant difference in mean exposures between each of the seven race/ethnicity-defined subgroups and the mean exposure levels for the county. If distribution of these county-wide mean exposures is not patterned by race and ethnicity in King County, we would expect to see little if any difference between the seven subgroups and the overall county exposure means. The statistical test will help assess whether any difference seen in these means is larger than what we might expect by chance if the true subgroup and overall county-wide means are equal. The results of these test are summarized in ***Table 3***.

Table 3. Difference in mean exposures between race/ethnicity subgroups and county means

		King County	Hispanic/ Latinx	NH-Asian	NH-AIAN	NH-Black	NH-NHPI	NH-other	NH-White
Flights	Mean	2195	4412	2204	2671	3715	6109	2353	1620
	Difference		2217 **	9 .	476 .	1520	3914 **	158 .	-575 .
PM2.5	Mean	6.2	6.5	6.1	6.5	6.7	6.9	6.3	6
	Difference		0.3 ***	-0.1 .	0.3 ***	0.5 ***	0.7 ***	0.1	-0.2 ***
Noise	Mean	42.9	45.3	43.2	44.2	48.1	48.8	43.8	41.7
	Difference		2.4 ***	0.3 .	1.3 *	5.2 ***	5.9 ***	0.9 .	-1.2 *
SES	Mean	0.66	0.57	0.65	0.58	0.52	0.49	0.64	0.7
	Difference		-0.09 ***	-0.01 .	-0.08 ***	-0.14 ***	-0.17 ***	-0.02 .	0.04 **

Significance level: . $p > 0.1$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Reflecting the patterns observed in the Lorenz-type curves, the NH-White populations nearly always differed from the overall county mean in an opposite direction of all other subgroups for each exposure. While the flight counts were presented log-transformed in the Lorenz-type curve for visualization reasons, they are presented as counts in the table for ease of interpretation. The NH-White populations are the only subgroup with a smaller mean flight exposure than that of the county overall, though the difference did not reach statistical significance. While the flights curve suggested the most significant disparity in flight exposures was among NH-Black populations, the mean difference here just failed to reach statistical significance (p = 0.056). Meanwhile the mean exposures for Hispanic/Latinx and NH-NHPI populations were higher and did reach statistical significance. This has to do with the tail in the data and the extremely high flight counts in a small portion of the census tracts in which approximately 10% of these two subgroups live.

Mean $PM_{2.5}$ exposures were significantly higher for Hispanic/Latinx, NH-AIAN, and especially, NH-Black and NH-NHPI. All of these differences in mean exposures reached high statistical significance. NH-White populations had a lower mean exposure than all other groups, and this also reached high statistical significance. NH-Asian and NH-Other subgroups' mean exposures were not significantly different from the overall county mean. The difference in mean exposures was nearly 1μg/m^3, similar to the median difference in exposures from the Lorenz-type curves.

Noise and SES exposures followed the same pattern for each subgroup as $PM_{2.5}$ in terms of mean exposures and significant differences from the overall county mean. The difference between the highest and lowest mean noise exposure levels was 7.1 dBA, slightly less than what was estimated from the Lorenz-type curves. The range in average SES index score was 0.21 which also corresponds to the median observed from the curves.

Ultimately the difference in means tests reinforce the patterns observed in the Lorenz-type curves and provide additional context in the robustness of the observed differences.

Aim 3: Exploring Associations with Health Outcomes

The third part of the analysis aims to examine connections between the exposures and community health outcomes. Six health outcomes were included in these analyses based on known biological associations with $PM_{2.5}$ and/or environmental noise exposures (summarized in ***Table 1***). The rates are shown mapped by HRA in ***Figure 13***. The southwest portion of the county has higher rates of each outcome, while the north Seattle and Bellevue regions have lower rates for each outcome. There does not appear to be a consistent trend in more rural eastern parts of the county.

Multivariable ordinary least squares regression was employed to regress the five-year age-adjusted cause-specific mortality rates on the exposures of interest in two separate models – one with log-flights as the primary exposure, and the other with air and noise pollution as the primary exposures. Both models adjust for neighborhood SES, percent Black, and smoking prevalence. Variables were selected for inclusion in the full models based on and approaches in similar studies rather than empirical testing. The models were not reduced based on empirical testing because the aim of the regression was not prediction but rather to compare explanatory value of the models between outcomes and between the models themselves. Additionally, in model checking, insignificant variable eliminations did not generally improve adjusted R^2 values.

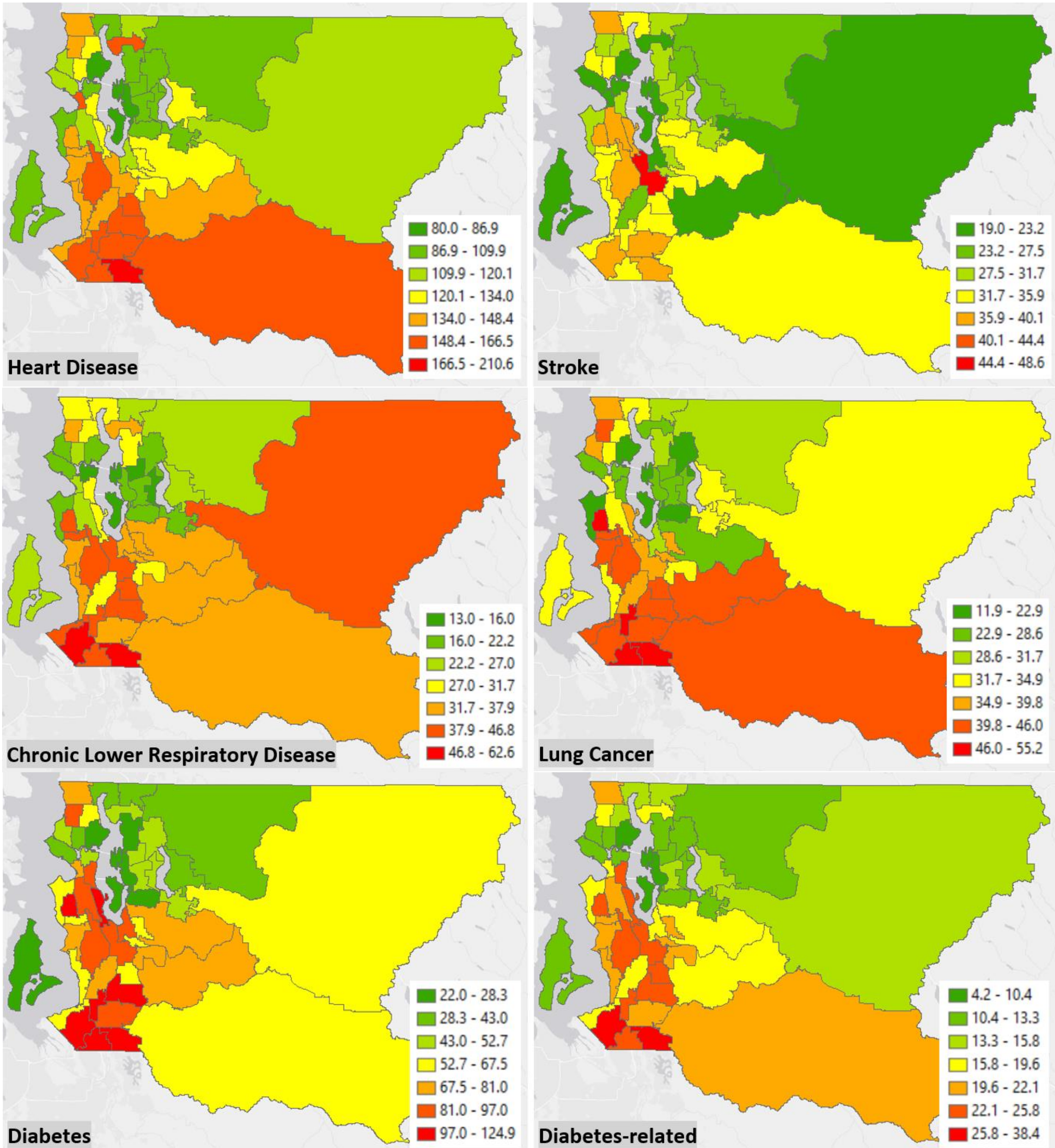

Figure 13. Five-year cause-specific mortality rates (per 100,000py) by HRA.

For two outcomes – deaths from chronic lower respiratory disease and lung cancer disease – noise exposure was excluded from the model because there is insufficient evidence in the literature that environmental noise exposure is associated with these outcomes. The final models are shown in equations (i), (ii), and (iii) below, where CSDR represents the cause-specific death rate.

(i) $CSDR = \beta_0 + \beta_1 * LOGFLIGHTS + \beta_2 * SMOKING + \beta_3 * \%BLACK + \beta_4 * SES$

(ii) $CSDR = \beta_0 + \beta_1 * PM25 + \beta_2 * NOISE + \beta_3 * SMOKING + \beta_4 * \%BLACK + \beta_5 * SES$

(iii) $CSDR = \beta_0 + \beta_1 * PM25 + \beta_2 * SMOKING + \beta_3 * \%BLACK + \beta_4 * SES$

While models (ii) and (iii) look more directly at environmental exposures and model (i) uses flights as a proxy variable, the flights model is the only model that uses a variable directly attributable to airport activity. Models (ii) and (iii) examine associations between the area-level proximal exposures of interest, but these exposures are related to other activities (such as road traffic) in addition to aircraft activity. These relationships are important to note for model interpretation. Model (i) doesn't include variables for other exposure sources such as road traffic, so we expect large residuals in the model, and the patterning of the residuals would reflect both road traffic and other major sources plus any other unmeasured covariates and random noise. Models (ii) and (iii) account for various sources but the exposures and resulting relationships cannot be attributed specifically to airport activity- even the effects seen in the vicinity of the airport- due to confounding effects of major roadways nearby.

Model (i) and either (ii) or (iii) were run for each of the six health outcomes. Performance of these models were assessed through coefficient t-tests and interpretation with regard to expected direction of effect. Regression coefficients and significance-tests are summarized in ***Table 4***.

Table 4. Summary of OLS results

Cause of Death	Model	Intercept	Log Flights	PM25	Noise	Smoking	% Black	SES	adj R^2
Heart Disease	(i)	133.4 ***	-1.71 .			2.27 *	-25.48 .	-42.69	0.474
	(ii)	118.3 **	-	16.10 **	-2.42 ***	2.28 **	24.28 .	-28.10 .	0.589
Stroke	(i)	22.2 **	0.01 .			0.31 .	57.39 *	1.46 .	0.314
	(ii)	15.2 .		4.57 *	-0.54 **	0.28 .	70.28 **	4.77 .	0.424
Chronic Lower Respiratory Disease	(i)	33.8 **	-1.10 *			0.85 *	17.86 .	-16.70	0.470
	(iii)	26.9 .		-0.32 .		0.96 *	8.30 .	-11.19 .	0.417
Lung Cancer	(i)	43.1 ***	-0.55 .			0.43 .	-10.87 .	-20.27 *	0.407
	(iii)	39.1 *		-0.08 .		0.49 .	-15.75 .	-17.36	0.389
Diabetes	(i)	19.0 **	-0.93 **			0.42	61.31 **	-8.42 .	0.613
	(ii)	9.9 .		3.85 *	-0.55 **	0.48 *	67.52 ***	-1.68 .	0.625
Diabetes-Related	(i)	46.3 *	-1.66			1.98 **	169.94 **	-20.10 .	0.685
	(ii)	19.5 .		15.12 ***	-2.01 ***	2.02 ***	206.00 ***	-2.64 .	0.787

Significance level: . $p > 0.1$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Across each outcome, based on adjusted R2, model (ii) ($PM_{2.5}$ +Noise) performed better than model (i) (Log-Flights), while model (i) performed better than model (iii) ($PM_{2.5}$).

With regards to expected direction of effects, SES is expected to have a negative coefficient and all other variables are expected to have positive coefficients given the known direction of associations at the individual level. The Diabetes (ii) model is the only model in which the sign of the coefficients align with expected direction of effects. Notably, flight exposure was nearly always negatively associated with the outcomes, though usually not statistically significant. The noise coefficients were also all negative, and they did reach significance. $PM_{2.5}$ coefficients achieved significance and followed expected direction of effect in the models for all outcomes except chronic lower respiratory disease mortality and lung cancer. For these two models, the negative $PM_{2.5}$ coefficients did not reach statistical significance.

Interesting patterns emerged in the covariates that were included for adjustment. Neighborhood SES coefficients almost never reached significance. While SES ought to have had some of the strongest effects, it is possible that the neighborhood effects did not differ greatly from what was captured in other variables. Smoking dominated the effects in the lung cancer model, though the coefficients did not reach significance. The diabetes and diabetes-related mortality models performed the best with regards to adjusted R^2. Looking at the coefficients for percent Black in these models, it appears that this variable dominates the performance of the model. Even though the coefficients cannot be directly interpreted, the strength of these coefficients and explanatory performance of the model for these two outcomes underscores the dramatic disparity in diabetes deaths and diabetes-related deaths for Black populations in King County.

Investigation of Residuals

Examining the spatial distributions of the residuals could help with investigating model performance issues. The heart disease death rate was hypothesized a priori to have the strongest model performance based on the known causal effects for both $PM_{2.5}$ and noise exposure and the strength of those effects relative to the other outcomes. Because the heart disease mortality models did not perform as well as the diabetes and diabetes-related mortality models, that data was further investigated for spatial patterns in the residuals. Fitted values and residuals for heart disease deaths from both models (i) and (ii) were mapped for comparison with each other and with the observed values to assess model performance. These maps are shown in ***Figure 14***.

In the residual plots, positive residuals (in red tones) are model underestimations, and negative residuals (in blue tones) are model overestimations.

There do not appear to be obvious patterns in the spatial residuals for either model. Both models generally underestimated the rates of heart disease mortality across the southern and south-central parts of the county. Both models also overestimated rates in the Bellevue and northeast Seattle areas. For the flights model, we would have expected rates to be underestimated along regions of other significant $PM_{2.5}$ exposures (such as the I-5 corridor or just the most densely populated areas), since these other sources of air and noise pollution are not accounted for in the flights model. That pattern is visible to some degree and disappears in the vicinity of the airport. One interesting result is that the flights model (i) did a better job of predicting the outcome in the HRA where Sea-Tac Airport is located than the $PM_{2.5}$ and noise model (ii) did. However, the flights model also had a negative coefficient for the exposure, and this presents a challenge for interpreting patterns in the residuals.

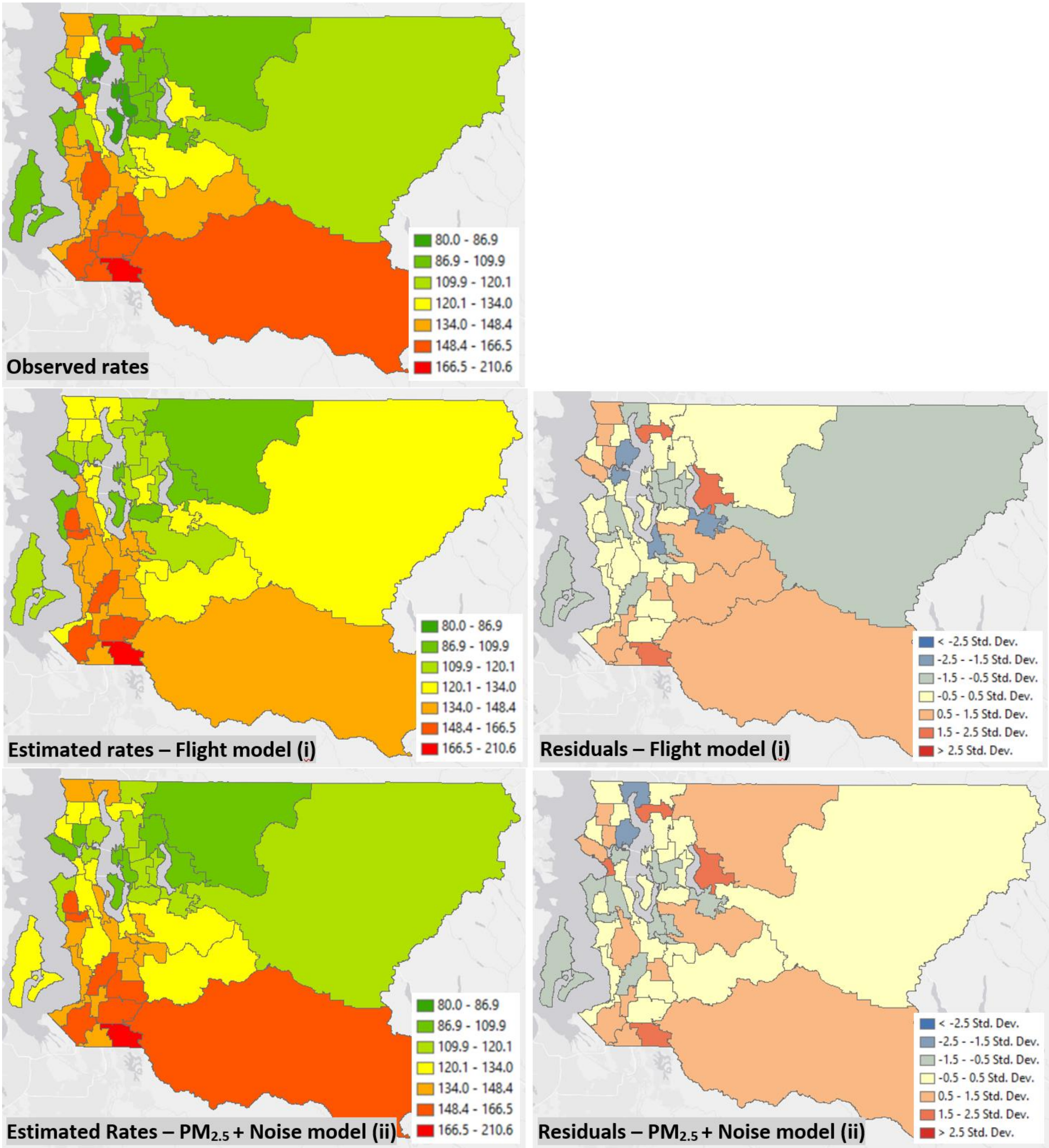

Figure 14. Model performance assessment for heart disease death rates. Observed rates (top), model (i) fitted values and residuals (center), and model (ii) fitted values and residuals (bottom).

Discussion

Aim 1: Characterizing Exposures

For ease of incorporation into future work and community use, the HRA-level exposure and SES estimates are reported in ***Table 5*** in the Appendix. ***Figure 8*** illustrates trends between the HRA-level covariates.

There appear to be relatively strong negative trends between SES and all other covariates in the model. Trends between all other combinations of variables appear generally positive. These associations are all as would be predicted by associations in the literature.

Especially of interest for this study is how the flights data correlate with $PM_{2.5}$ and noise exposure in order to assess appropriateness of flight counts as a proxy variable and, to a degree, the contribution of aircraft activity to the air and noise pollution measures. The flight data is the only data in this study directly associated with airport activities. While $PM_{2.5}$ and noise are highly associated with airport activity, they are also associated with road traffic. Road traffic makes up a much higher proportion of $PM_{2.5}$ emissions in the county. Additionally, the proximity of the flight paths to major highways and areas of high population density limit attribution of $PM_{2.5}$ and noise levels in the flight paths to flights alone. Even so, the highest log-flights counts are also areas with the highest noise values and $PM_{2.5}$ concentrations, and the same pattern follows for low values. $PM_{2.5}$ and noise exposures are also highly correlated.

The plots demonstrate a relatively high level of collinearity among nearly all the variables. Because of these high levels of correlation, each of the covariates likely did not contribute much unique signal to accounting for ranges in the health outcomes. Combined with a small sample size, this presented issues for regression in the third part of the analysis.

Aim 2: Exposures by Race and Ethnicity

The Lorenz-type curves and difference-in-means tests provided strong evidence for different distributions of exposure between race/ethnicity-defined subgroups in King County. County-wide NH-Asian population trends did not differ significantly from overall county trends for any of the three exposures or neighborhood SES. NH-White populations were more distributed in lower exposure tracts and higher SES tracts. Hispanic/Latinx and AIAN populations had higher mean exposures and lower mean neighborhood SES score than the county as a whole. Black and NHPI populations were consistently more distributed in higher exposure tracts.

This two-part methodology was modelled on the work of Cohen et al. in their study of environmental noise inequities in Georgia (2019). The combined methods provide a compelling view of the county-wide distribution of exposures across population subgroups and estimates of uncertainty to support the interpretation of the curves. Their use in this study provided stark illustration of the compounded environmental exposures faced by Black and NHPI populations especially, as well as by Hispanic/Latinx and AIAN populations in King County.

The exposure distributions in this study generally reflect the literature on environmental inequities, though the methods borrowed from Cohen et al. also allowed for investigation of trends for subgroups with smaller populations that are often left out of similar analyses. NH-Whites are frequently underrepresented in areas with more environmental harms, while Black and Hispanic/Latinx populations are frequently overrepresented in these areas. AIAN and NHPI populations are rarely explicitly considered in similar studies of environmental exposures due to small numbers. One study of environmental exposures in Los Angeles County found that NHPI populations experience similar rates of disparate exposures to air pollution from toxic release sites, freeways, and industrial sources, as Black and Hispanic/Latinx populations in the county (Morey, 2014).

The only exposure of the three primary exposures that directly represents airport activity are the flight counts below 750m altitude. Clear difference in exposure by race/ethnicity is observed for the flight exposures. However, while the $PM_{2.5}$ and environmental noise are both highly correlated with the flights data, the differences in exposures cannot be directly tied to airport activities from the analyses completed here. The $PM_{2.5}$ and noise exposure distributions are still generally informative for mitigation efforts both broadly and specific to airport activities.

After these analyses were completed, community members expertly pointed out that this Lorenz-type curve analysis captures how *county-wide* distributions differ – when other dimensions of the distributions of these exposures may be more relevant. Beacon Hill, a neighborhood home to large Asian and Pacific Islander populations, is close to two King County airports (and below the flight paths for both), and the community has mobilized because they experience high exposures related to aircraft activity. While this analysis concluded that Asian populations are not disproportionately exposed *county-wide*, it does not mean that Asian populations in neighborhoods like Beacon Hill are not still highly impacted by these exposures. A 2013 Cumulative Impact Analysis looking at socioeconomic factors, sensitive populations, environmental exposures, environmental effects, and public health effects, found that Beacon Hill/Georgetown/South Park had the highest cumulative impact score among Seattle ZIP codes (Gould & Cummings, 2013). That the current analysis missed these high exposure trends points to the limitation of the county-wide methods used here. Additional analysis could identify the most highly exposed tracts and examine distributions of race and ethnicity-defined subgroups that are most represented to examine another dimension of inequitable exposures.

Aim 3: Exploring Associations with Health Outcomes

The regression analysis did not provide strong evidence for an association between the six health outcomes of interest and the three primary exposures. Some models appeared to perform better than others, but the results overall were difficult to assess and interpret. However, some of the issues that arose were instructive regarding the associations of interest. The high multicollinearity of the variables illustrate the degree to which lower SES areas also experience the compounded exposures of higher noise and air pollution, and that the county's Black populations are more likely to live in these areas and be subject to these compounded exposures. Meanwhile, the higher SES areas are less exposed to air and noise pollution. These patterns follow what we would expect based on how SES stratification and environmental racism operate, but it is informative to see that the collinearity is so strong that the models perform poorly. There are several other limitations affecting model performance as well.

Limitations

There are many limitations associated with ecological study design. Ecological studies only allow for inference on group-level associations. While only group-level variables are used in these analyses and earnest attempt was made to draw only group-level conclusions, ecological bias is still of concern as unrecognized individual-level assumptions are likely still at play.

Multicollinearity is a common problem in ecological analyses with a small number of large regions (Morgenstern, 1995). It is also a common problem with variables like SES and environmental exposures since they can be more strongly correlated with each other at the group level than at the individual level (1995). The regression analyses in this study met both of these criteria. Multicollinearity can result in severely distorted effect estimates with large variances (1995), and that seemed to be the case here. Additionally, coefficients in ecological studies are difficult to interpret because associations at the group level do not always follow associations at the individual level due to cross-level confounding. Combined with the severe multicollinearity in this study, inference from the model results was extremely limited.

There are several other data limitations to consider. The flight exposure data does not take elevation into account, so it underestimates exposures for those living at higher elevations. The temporal relationships between data in these analyses are not ideal but limited by data availability and access. More recent $PM_{2.5}$ and health outcome data were sought out unsuccessfully. PHSKC reports HRA-level health outcome data for 2011-2015 and health behavior data for varying ranges between 2013 to 2017. The $PM_{2.5}$ data is from 2009 to 2011. Flight data was for 2018, and all ACS data are five-year estimates for 2018. Noise data was also from 2018. This “cross-sectional” analysis assumes the variables are relatively unchanging over a decade. This is a strong and probably unreasonable assumption in a rapidly changing region, but the analyses can be repeated with more temporally appropriate data when available.

Though based on methods used in several other studies, the SES index used in this study is not a validated measure of neighborhood SES. The standardized index used has uniform weights and treats the components of SES like they are all independent. Principal components analysis (PCA) may have been a more appropriate variable selection and indexing method for SES. PCA helps account for both the correlation in the SES indicators and the different dimensions they represent.

The race and ethnicity subgroups were chosen to limit the number of strata and generally correspond to some groupings in other studies, however the selection of these groups directly influences the results and limits the conclusions reached. The groupings likely do not reflect the most relevant local populations to consider and certainly grade over vast heterogeneity within these groupings. Future work could use a similar method but identify populations of local interest to parse out from the county (or smaller area) trends rather than relying on these large groupings.

It is difficult to work with aggregated $PM_{2.5}$ concentrations over such large areas. $PM_{2.5}$ concentrations can vary strongly over city blocks. The data has also been manipulated and re-aggregated several times, from grids to census tracts to HRAs, and because the effects tend to be small, that loss of specificity is costly. The data was aggregated from census tracts to HRAs using an area-weighted average process that essentially assumes that the concentration is the same across the census tract but then across the street in the neighboring census tract it might be quite different. Once those are averaged together in an HRA, that may not matter as much. Another strategy for re-aggregation is to interpolate $PM_{2.5}$ concentrations between census tract centroids and then re-aggregate across HRA's. This process assumes variation in concentrations within census tracts but is subject to interpolation method assumptions. It also does not perform well when large barriers like bodies of water (very relevant for King County) prevent two places that are near each other from influencing each other in the way these methods assume. It is not clear what difference this process might have made, though the analyses could be re-run to investigate this further.

Additionally, p-values (or more specifically the significance level reached by the p-values) are reported in the second and third parts of the analyses. However, they should be interpreted cautiously. P-values are only most informative when both the model assumptions for the underlying data are correct and after repeat sampling.

HRA-level analyses presented many difficulties. Statistical power was low due to small sample size (n=48) in regression analyses. Because HRAs are large, they smooth over a lot of heterogeneity, but they also provide more stable rates for health outcomes due to larger population sizes. A method that can incorporate geographies of different scales – such as working with census tract level data for covariates at which census tract data is available and HRA-level data for health outcomes- may be a better approach.

Ecological studies tend to over-rely on regression when better techniques are available (Dufault & Klar, 2011). This study would likely have benefitted from a different technique such as weighted regression approach or Bayesian methods, but the author's knowledge was limited on how to employ these methods.

Strengths

This project responds to a local community health issue by analyzing publicly available data with methods that are relatively computationally simple. The use of the Cohen et al. methodology to illustrate exposure distributions in King County adds to local documentations of environmental exposures, especially among NHPI and AIAN communities with smaller local populations.

Finally, this study was detailed in documenting methods and rationale for the purpose of review and reproducibility. Ecological epidemiology studies face several challenges for dealing with ecological bias appropriately and drawing conclusions that do not overstep the data. With those challenges in mind, the author aimed to incorporate best practices for reporting on ecological studies that were outlined in a review of ecological study approaches (Dufault & Klar, 2011).

Future work on this same local issue would benefit from more recent and granular data and multi-level analysis that can incorporate data at different geographic scales. Additionally, more advanced spatial methods might be a strong alternative to the regression techniques used here.

Conclusion

This study uses a cross-sectional, ecological approach to explore this local community health issue. Only publicly available data was used so that if community groups find any of these analyses potentially helpful, they may add them to their own toolkits and explore these datasets further with their own methods. While some analyses provided more useful results than others, overall this study was informative in several ways.

This study estimated aircraft activity and air and noise pollution exposure profiles for local communities and characterized differences in exposures by race and ethnicity at the King-county level. Non-Hispanic White populations were more distributed in lower exposure tracts and higher SES tracts. Hispanic/Latinx and American Indian and AIAN populations had higher mean exposures and lower mean neighborhood SES score than the county as a whole. Black and NHPI populations were consistently distributed in higher exposure tracts. This study adds to local documentations of environmental exposures, especially among NHPI and AIAN communities with smaller local populations. Nationally, Black and Hispanic populations are exposed to much higher levels of $PM_{2.5}$ pollution than they produce, while non-Hispanic White populations produce much more $PM_{2.5}$ pollution than to what they are exposed (Tessum et al., 2019). On average, Black populations were exposed to 56% more $PM_{2.5}$ than they produced, and Latinx/Hispanic populations were exposed to 63% more $PM_{2.5}$ than they produced (2019). While this project did not look at demographics of who benefits the most from local airport activities such as passenger travel, freight movement, and economic gains, it did add some information about who bears the costs of these activities locally. However, because county-wide analysis misses informative smaller-scale trends (such as the known high-exposures among Beacon Hill residents), additional work with more disaggregated data is needed. While this study begins to look at differences in county-wide environmental exposures across race and ethnicity, it in no way constitutes an environmental justice assessment as outlined under federal regulations or makes use of an adverse impact analysis (Exec. Order 12898, 1994; US DOT, 2012). These tools would strongly benefit local understanding of exposure inequities and support more-effective, targeted mitigation strategies.

The regression analysis did not provide strong evidence for an association between the six health outcomes of interest and the three primary exposures. This part of the analysis was limited by sample size, data limitations, and severe multicollinearity. The high multicollinearity of the variables illustrate the degree to which lower SES areas also experience the compounded exposures of higher noise and air pollution, and that the county's Black populations are more likely to live in these areas and be subject to these compounded exposures. This adds to the evidence of what many local communities already know- that environmental exposures in King County are spatially compounded and structured by racism and SES inequities.

Finally, while this study could not draw definitive conclusions about associations between local airport exposures and health outcomes, the results may still be helpful alongside the new community health profiles from PHSKC to piece together what is happening locally and inform mitigation efforts. Future work on this same local issue would benefit from more recent data and multi-level analysis that can incorporate data at different geographic scales and more accurately assess likely connections to health outcomes.

Appendix

Table 5. Exposure Estimates and SES Index Values by Health Reporting Area

Health Reporting Area	Flights	Noise (LAeq)	PM2.5	SES Index
Auburn-North	62	47.3	7.3	0.22
Auburn-South	48	38.4	6.9	0.06
Ballard	769	37.4	5.8	0.75
Beacon Hill/Georgetown/South Park	27496	56.8	7.3	0.06
Bear Creek/Carnation/Duvall	2	31.1	4.1	0.91
Bellevue-Central	30	39.9	5.3	0.49
Bellevue-Northeast	24	37.9	5.2	0.69
Bellevue-South	6	34.3	5.3	0.90
Bellevue-West	46	44.2	5.6	0.72
Black Diamond/Enumclaw/Southeast County	2	30.6	5.2	0.54
Bothell/Woodinville	67	36.4	5.8	0.68
Burien	22002	51.5	7.2	0.19
Capitol Hill/East Lake	249	48.7	6.2	0.70
Central Seattle	545	50.8	6.6	0.42
Covington/Maple Valley	6	32.5	5.5	0.65
Delridge	132	47.2	7.1	0.23
Des Moines/Normandy Park	29138	56.3	7.4	0.29
Downtown	737	55.3	6.6	0.32
East Federal Way	22	47.2	7.3	0.44
Fairwood	14	36.7	6.3	0.53
Federal Way-Central/Military Road	585	51.1	7.6	0.21
Federal Way-Dash Point	3107	48.7	7.3	0.26
Fremont/Greenlake	293	46	6.1	0.64
Issaquah	3	36.7	4.9	0.56
Kenmore/Lake Forest Park	200	36.2	6.0	0.68
Kent-East	763	43.2	6.6	0.35
Kent-Southeast	175	44.6	7.0	0.11
Kent-West	385	49	7.1	0.09
Kirkland	36	38.5	5.4	0.74
Kirkland North	95	35.3	5.7	0.69
Mercer Island/Point Cities	37	43.2	6.0	0.96
Northeast Seattle	80	42.6	6.1	0.51
Newcastle/Four Creeks	3	31.9	5.1	0.81
North Highline	26344	51	7.2	0.00
North Seattle	213	42.5	6.1	0.40
Northwest Seattle	460	40.5	6.0	0.55
Queen Anne/Magnolia	4280	44.6	5.9	0.74
Redmond	12	36.5	5.1	0.74

Health Reporting Area (cont.)	**Flights**	**Noise (LAeq)**	**PM2.5**	**SES Index**
Renton-East	15	36.4	6.0	0.58
Renton-North	27	45.2	6.0	0.26
Renton-South	935	47.3	6.6	0.37
Sammamish	6	32.2	4.7	1.00
Southeast Seattle	633	48.4	6.9	0.26
SeaTac/Tukwila	18394	58.2	7.2	0.08
Shoreline	302	38.2	6.2	0.53
Snoqualmie/North Bend/Skykomish	1	30.4	3.9	0.80
Vashon Island	28	35.6	5.4	0.77
West Seattle	1298	43.7	6.5	0.76

Please see study text for data units, years, and interpretation.

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