Analyzing Environmental and Social Impacts of Urban Forestry Practices in Tacoma, WA with PlanIT Geo™

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A Group Project submitted in partial satisfaction of the requirements for the degree of Master of Environmental Science and Management for the Bren School of Environmental Science & Management, University of California, Santa Barbara

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Signature Page

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The Group Project is required of all students in the Master of Environmental Science and Management (MESM) Program. The project is a year-long activity in which small groups of students conduct focused, interdisciplinary research on the scientific, management, and policy dimensions of a specific environmental issue. This Group Project Final Report is authored by MESM students and has been reviewed and approved by:

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Acronyms and Abbreviations

ACS - American Community Survey

ATC - Acres of tree canopy

AQI - air quality index

BenMAP - Environmental Benefits Mapping and Analysis Program

CBG - census block group

EPA - Environmental Protection Agency

GIS - Geographic Information System

i-Tree - software suite which quantifies tree effects in urban and rural settings

LAI - leaf area index

LiDAR - Light Detection and Ranging (remote sensing method)

LU - land use

NAIP - National Agriculture Imaging Program

NCDC - National Climatic Data Center

NDVI - Normalized Difference Vegetation Index

NOAA - National Oceanic and Atmospheric Association

PM - particulate matter

PPA - possible planting areas

PPM - parts per million

UFMP - urban forest management plan

UFORE - urban forest effects model

UHI - urban heat island

UTC - urban tree canopy

Abstract

Urban forestry encompasses street trees, residential trees, park trees and greenbelt vegetation. Despite local groups' efforts and trends in better forest management practices, there is an unequal distribution of urban forests and their associated ecosystem services across most of the United States. Evaluating canopy distribution is the first step to enable cities to better devote limited resources to marginalized communities, which often have additional equity concerns. Our project will help the urban forestry nonprofit, PlanIT Geo™, and their future clients in their urban forestry management plan recommendations and could increase the equitable dispersal of environmental benefits.

In addressing the equity of Tacoma's urban forests, we assessed trees' impacts on air quality and human health. We designed an equity index model to compare census block groups based on five indicators: canopy coverage, demographic, climate, air quality, and health. The air quality and health indicators were derived by analyzing $PM_{2.5}$ reduction through the amount of canopy coverage and the associated health benefits from improved air quality in Tacoma, WA. We then calculated individual indicator scores and a composite environmental equity score for each census block group in Tacoma. Conclusions reveal that there is an overall unequal tree canopy distribution in Tacoma and considering additional indicators broadens PlanIT Geo's awareness of the most vulnerable communities in Tacoma. Through this analysis, we identified priority areas in need of intervention and environmental considerations to maximize socio-economic and environmental benefits while minimizing harm post-intervention.

Significance

While making up just 2% of the earth's land surface, cities account for 60-80% of global energy consumption, 75% of carbon emissions, and over 75% of natural resource consumption (International Resource Panel 2013). As overall land-use trends in the United States are shifting away from forested areas in favor of urbanized spaces, innovation towards how cities are structured are required to reduce their ecological footprint to better reflect their physical size. A 2018 U.S. Forest Service study projects that urban land in the lower 48 states will more than double between 2010 and 2060 (Nowack et al., 2018). This urbanization has resulted in major landscape changes, altering ecological systems and destroying habitats. The increasing rate of land conversion from forests to urban centers will result in a commensurate rise in the importance of urban forests in relation to environmental quality and human well-being

Urban forestry is a discipline that aims to attenuate some of the negative impacts that occur with increased urbanization by establishing more green spaces within cities, therefore providing myriad benefits to urban community members. The practice of urban forestry aims to rearrange urban infrastructure to increase the efficiency of and reduce the total amount of resources required to function, thereby supporting ideals of sustainable development in light of recent urban expansion. Urban forestry can reduce energy, stormwater runoff, waste, and pollutant transport (International Resource Panel, 2013). However, urban forestry does not always garner equitable results, and therefore urban foresters and planners must prioritize understanding how these urban trees impact local communities in differing ways.

The City of Tacoma developed an Urban Forest Management Plan to address inequality and to respond to the challenges of climate change; two variables which are not independent of each other. With thoughtful city planning, urban forests can improve elements of energy usage, stormwater runoff, public health, and other factors. To ensure the benefits from urban forestry are equitably distributed, PlanIT Geo and the city of Tacoma have prioritized evaluating green spaces for all demographics. By reviewing Tacoma's One Canopy multiphase urban forestry management action plan, a methodology can be constructed to provide other cities guidance for improving their urban sustainability across varying landscapes and city structures. Analysis of Tacoma's past and current policies, practices, and management plans for improving the livelihoods of marginalized groups, an equitable system can be formulated to aid other Pacific Northwest cities in improving issues relating to environmental justice using GIS software and an equity index.

Project Objectives

The project developed a methodology for urban planners and community organizations to evaluate the environmental, human health, and socio-economic impacts of urban tree concentrations at neighborhood scales and consider the distributional effects across varying socio-economic regions.

1. Conducted extensive literature review relating to urban forest canopy coverage and equity imbalances across cities. Reviewed statistical methodology approaches and economic analyses related to tree equity and distributional effects including: air quality, stormwater and runoff management, and human health impacts. Reviewed correlating factors which may contribute to uneven tree canopy distribution such as income levels, racial demographics, housing prices, rates of home ownership and proximity to urban density.

2. Used data provided by PlanIT Geo from its canopy assessment of Tacoma, WA to study and incorporate the reviewed methodology approaches to quantify environmental benefit distribution and/or externality impacts across communities. Prioritized air quality, particularly $PM_{2.5}$ pollution and the associated inequitable reduction in health impacts from improved air quality.

3. Researched and catalogued public datasets including: tree canopy assessment, land use classification, air quality records, land surface temperature, watershed hydrology, available health data, housing distribution and economic records. Using this catalogue, developed an equity index to assess tree canopy cover and equity imbalances to be used as a tool for city planning efforts and community organizations in the Pacific Northwest.

4. Developed a geo-spatial model to map these factors and identify Tacoma neighborhoods which display imbalances in equity and negative environmental and health benefits. Using the model, the group identified regions in Tacoma that would most benefit from tree planting campaigns and a recommendation for urban foresters and city planners.

Background

1. Study Area

Bordering Washington's Puget Sound and just 32 miles from Seattle, Tacoma is the third-largest city in the state. It has a population of just over 200,000 and is the largest port in Washington. Though the city enjoyed significant population and industrial growth from the late 19th century to the mid-20th century, suburbanization resulted in an economic decline that lasted until the 1990's. The local government has concentrated on revitalizing downtown, developing more public transportation services, constructing the University of Washington-Tacoma, building more museums, and restoring the waterfront. Tacoma is now known as one of the most walkable cities in America, and it endeavors to continue this legacy by improving its urban forestry.

Tacoma's climate is considered to be Mediterannean and experiences more annual rainfall and days of precipitation than the rest of the United States (Bestplaces.net). Due to high levels of rainfall, Tacoma is susceptible to flooding and subsequent mudslides (Washington State Department of Ecology, 2019). Humidity levels range from 60-80% annually, with the highest humidity from October to January (World Weather & Climate Information). The warmest month of the year is July with an average maximum temperature of 23°C (73°F) and the coldest month is December with an average maximum temperature of 7°C (35°F) (World Weather & Climate Information). Average levels of precipitation, daily high temperatures, and daily low temperatures can be seen in the graph below:

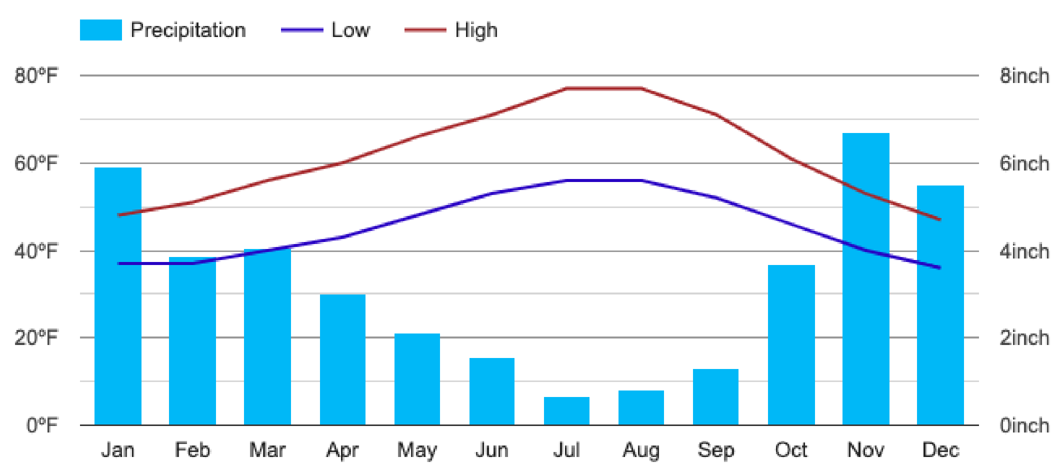

Figure 1. Monthly averages of precipitation and daily and low temperatures for Tacoma, WA.
Analysis reveals that the highest levels of precipitation occur in October- January, the warmest and driest months are May- September, and the coldest months are experienced in November- March (usclimatedata.com).

Before PlanIT Geo started developing its urban forest management plan with Tacoma in 2018, the city already had a significant history of urban forestry efforts. In 1927, Tacoma, through a Washington State ordinance, adopted its first tree protection policy called "9.18 Trees and Shrubs – Trimming and Removal." It was intended to protect streetside trees growing in the right of way. Since then, Tacoma has accepted a number of other urban forestry studies, assessments, and plans, such as the Urban Forest Management Plan, Urban Forest Policy Elements, Urban Forest Manual, Tacoma 2025 Plan, Right-Of-Way Design Manual, Tree Canopy Assessment, Sample Tree Inventory, Tacoma Mall Tree & Planting Inventory (public & private), Urban Heat Island Study, and Urban Forest Management Plan & Tacoma Municipal Code Expert Review. All of these efforts were considered when developing the new management plan. Unlike previous efforts, PlanIT Geo emphasized more community involvement, watershed analysis, and equitable distribution of greenspace.

2. Client and Partners

PlanIT Geo™ is a geospatial technology firm in Arvada, CO, specializing in urban forestry, planning, and natural resources. PlanIT Geo is an industry leader in urban tree canopy assessments, green infrastructure mapping, and web-mapping applications. PlanIT Geo provides a range of urban forestry software and consulting services to clients around the world, including municipalities, federal agencies, nonprofits, universities, and private firms. Outcomes of PlanIT Geo's intervention include:

- empowering urban forest managers and planners with expanded understanding of their urban forest through detailed, modern data on landscape conditions;
- promoting a formal conversation about scientist's research on urban forestry and how to apply that research to help solve environmental and socioeconomic problems within specific communities;
- guiding tree planting, policy, management forecasting, and outreach through map-based tools;
  and
- supporting data driven decision making for land development to optimize the benefits of tree protection, tree plantings, open spaces, and ecological restoration projects.

PlanITGeo has developed their own Geographic Information System (GIS) mapping tool called **TreePlotter™ Software Suite**, which allows users to map, manage, and plan their urban forest according to their goals. The software suite includes:

- TreePlotter Inventory
- TreePlotter Parks
- TreePlotter Jobs
- TreePlotter Canopy

These four apps collect, view, analyze, engage, and manage trees, park amenities, and community assets. At the site-specific scale, these tools are designed for collecting and managing tree and asset inventory data related to condition, safety, health, and aesthetics, and for tracking service requests and work orders. This software suite accommodates high-resolution aerial and satellite imagery, Light Detection and Ranging (LiDAR) elevation data, and other geospatial measurerers, allowing PlanIT Geo's internal GIS and remote sensing specialists to create diverse, contemporary land cover datasets for assessment.

PlanIT Geo aims to bring awareness to the problem of urban forest inequity and guide future forest management practices via working with local groups to discover how urban forestry can be applied to serve their communities. In analyzing current trends and assessing potential locations of additions to an urban forest, PlanIT Geo provides various future scenarios associated with the varying levels of resilience and risks of their client's community to promote welfare. PlanIT Geo uses available environmental and socioeconomic demographic indicators to locate and prioritize ideal areas for future tree plantings.

3. Benefits of Urban Forestry

To explore the benefit of urban forests, research has been conducted to study trees' impact on urban sustainability and cities' abilities to maximize socio-economic and environmental benefits while minimizing harm. All trees within an urban area are considered a part of an urban forest. Urban forestry has several marked benefits throughout various sectors, including environmental, social, and economic benefits.

The environmental benefits of urban forestry go beyond the obvious; increase in trees and green space results in increased carbon sequestration and improved air quality due to overall increases in rates of photosynthesis and capture of airborne particles. A single tree is capable of absorbing 120-240 pounds of particulate pollution such as dirt and soot annually (Wolf, 1998). Additionally, urban forestry results in increased wildlife habitats throughout urban spaces. Trees reduce air pollutants from the atmosphere in myriad ways, including:

- Removal of gaseous pollutants by uptake through leaf stomata or the plant surface itself,
- Interception of airborne particles,

- And contributing to the direct removal of the air pollutants through a dry deposition process via the rough aerodynamic surfaces of leaves, twigs, and branches.

However, the intercepted particle often is resuspended to the atmosphere, washed off by rain, or dropped to the ground with leaf and twig fall (Nowack et al., 2012). Therefore, tree vegetation is only a temporary retention site for many atmospheric particles. Despite this, urban trees have been shown to reduce various types of airborne pollutants. In a multi-city study by Nowack et al., it was found that increased tree cover reduced various types of air pollutants, as can be seen below (Nowack, et al., 2006):

City	%tree cover	% air quality improvement				
		CO	NO_2	O_3	PM_{10}	SO_2
Atlanta, GA	32.9	0.002 (0.001–0.009)	0.5 (0.1–2.5)	0.7 (0.1–4.4)	0.7 (0.3–2.8)	0.7 (0.1–4.3)
Boston, MA	21.2	0.002 (0.000–0.006)	0.4 (0.0–1.8)	0.6 (0.1–3.4)	0.6 (0.1–1.8)	0.5 (0.1–3.4)
Dallas, TX	28.0	0.002 (0.001–0.008)	0.4 (0.1–2.2)	0.6 (0.1–3.9)	0.6 (0.2–2.4)	0.6 (0.1–3.8)
Denver, CO	26.0	0.001 (0.000–0.007)	0.2 (0.0–1.5)	0.3 (0.0–2.1)	0.4 (0.1–2.2)	0.3 (0.0–2.0)
Milwaukee, WI	19.1	0.001 (0.000–0.005)	0.3 (0.0–1.5)	0.4 (0.1–2.7)	0.4 (0.1–1.6)	0.4 (0.0–2.7)
New York, NY	16.6	0.001 (0.000–0.005)	0.3 (0.0–1.4)	0.4 (0.1–2.6)	0.5 (0.1–1.4)	0.4 (0.1–2.6)
Portland, OR	42.0	0.003 (0.001–0.012)	0.6 (0.1–2.7)	0.8 (0.1–3.7)	1.0 (0.3–3.5)	0.7 (0.1–4.0)
San Diego, CA	8.6	0.001 (0.000–0.002)	0.2 (0.0–0.7)	0.3 (0.0–1.4)	0.3 (0.1–0.7)	0.3 (0.0–1.4)
Tampa, FL	9.6	0.001 (0.000–0.003)	0.2 (0.0–0.8)	0.2 (0.0–1.4)	0.2 (0.1–0.8)	0.2 (0.0–1.4)
Tucson, AZ	13.7	0.001 (0.000–0.004)	0.1 (0.0–1.0)	0.1 (0.0–1.7)	0.2 (0.1–1.2)	0.1 (0.0–1.7)
Washington, DC	31.1	0.002 (0.001–0.009)	0.4 (0.2–2.3)	0.6 (0.1–3.9)	0.7 (0.2–2.6)	0.6 (0.1–3.9)

Estimates are given for actual tree cover conditions in city for ozone (O_3), particulate matter less than 10 µm (PM_{10}), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and carbon monoxide (CO) based on local boundary layer height and pollution removal estimates. Bounds of total tree removal of O_3, NO_2, SO_2, and PM_{10} were estimated using the typical range of published in-leaf dry deposition velocities (Lovett, 1994)

Table 1. Estimated percent air quality improvement in selected US cities due to air pollution removal by urban trees. Analysis reveals how varying urban canopy coverage results in different amounts of air quality improvement in 11 different US cities. In assessing the ability of urban trees to absorb 5 different criteria pollutants, researchers found that overall, increased tree cover results in increased air pollution remediation (Nowack et al., 2006).

The leaves of trees improve cities' air quality by absorbing gaseous pollutants like ground-level ozone, nitrogen dioxide, and carbon monoxide. Particulate matter is also stored on the tree's surface instead of the air, also improving air quality (Freer-Smith, 1997). These improvements to air quality reduce smog, increasing visibility, and reducing risks of respiratory diseases such as asthma. Furthermore, forests are extremely efficient in storing atmospheric Carbon Dioxide (CO_2), one of the most harmful and prevalent greenhouse gases, mainly in the form of biomass (Cannell, M. G. R., 1996). As increased age and growth rate of a forested area increase biomass, and increased amounts of biomass represent an increased reduction of atmospheric CO_2, increasing the amount of established forests and therefore biomass worldwide should help mitigate the impacts of climate change (Zheng et al., 2017). Urban forestry also serves as a natural solution for several infrastructural aspects in urban areas including storm-water mitigation (Elmqvist et al., 2015). Full-grown trees can absorb hundreds of gallons of water daily, and in urban areas where water catchment or storm-water drainage is inefficient, urban forests can aid in absorbing excess water runoff during storms.

Additionally, urban forestry has several economic benefits, thereby providing an incentive for local governments to support urban forestry projects within their cities. For example, planting more trees within a city results in increased natural shading, which in turn reduces the need for cooling of buildings in warmer months. Trees also provide economic benefits by increasing property values. In Portland, Oregon, it was “found that a large tree on a residential property can add some $9,000 to the sale price of a house” (Kuo, 2001). A potential downside of increased property values is an increased risk of gentrification of a neighborhood, potentially harming equity. Energy costs can also be reduced by the presence of trees by reducing cooling and heating demands of buildings, with the trees surrounding buildings acting as both heat insulators and heat absorbers.

Water vapor is transpired in the air by trees, cooling the surrounding temperature (Heisler, 1986). Trees thereby lower the urban heat-island effect by altering wind speeds, blocking solar radiation, and shading surfaces (Solecki, 2005). Shade can block harmful UV rays for those outside, such as children, mitigating risks of skin diseases. Since parking lots have low albedo and impervious surfaces, trees placed near parking lots can absorb their toxic stormwater runoff. While the majority of hydrocarbon emissions come from a vehicle’s tailpipe, 16% comes from evaporative emissions when a vehicle’s fuel delivery system is heated. Vehicles parked in areas with 50% canopy cover emit about 8% less evaporative emissions than vehicles parked with only 8% canopy cover. Shaded parking lots also reduces the rate of shrinking and cracking of asphalt, reducing the need for maintenance which includes heavy equipment. Shaded asphalt also releases the volatile components within the asphalt at a slower rate (Klaus, 1998).

Finally, in terms of social benefits of urban forestry, an increase in trees and green spaces can result in an overall bolstered sense of community from an increase in communal spaces (Westphal, 2003). Trees also provide traditionally calming colors, smells, and sounds to cities, with these aesthetic aspects helping to improve the mental health of some citizens (Heisler, 2000). With this, increasing the number of urban trees in a city can help reduce pollution, slow climate change, solve infrastructural problems, bolster local economies and raise property values, reduce energy costs, mitigate urban heat island effects, increase access to green spaces, and reduce rates of negative physical and mental health incidents.

4. Equity

Urban forestry encompasses street trees, residential trees, park trees and greenbelt vegetation. In some cities, trees are purposely planted and carefully managed by residents or the city, while in other cities, the trees are the unfortunate result of land-use changes, economics, and neglect (Miller et al., 2015). Despite efforts of local groups and a national trend in better local forest management practices, overall there is an unequal distribution of urban forests across the United States. Evaluating the equal distribution of urban forests will enable cities to better devote limited resources to communities that need the social and environmental benefits and combat environmental injustice.

Urban tree canopy cover has been shown to improve the wellbeing of urban populations in many ways, but it is clear that urban canopy cover is not equitably distributed. Low-income, underserved, communities of color often have fewer greenspaces, parks, and trees in general (Wolf, 2017). Chronic health conditions occur at higher rates within these impoverished neighborhoods and citizens frequently do not have sufficient access to proper health care. Due to the lack of shade and evaporative cooling from less canopy cover, these neighborhoods suffer from hotter temperatures which can exacerbate chronic conditions and increase demand for emergency medical services (Anderson, 2019). Studies have shown that planting trees in high-density population centers that have increased levels of air pollution would have the greatest overall positive impact on public health (Daniels et al., 2000).

Municipal tree planting efforts in areas with low tree cover can help offset some of these equity discrepancies. However some economic research has revealed that an increase in environmental quality in neighborhoods can indirectly affect the demographics of a neighborhood through real estate prices. As communities increase their tree cover, housing demand and property values increase which leads to an increase in income levels in the area as a result (Banzhaf and Walsh, 2008). The efforts to raise environmental quality through tree planting may lead to gentrification and resident displacement in communities, further straining environmental justice efforts. (Banzhaf and Walsh, 2013). Some studies have found that there may be a margin of urban greening efforts which can retain the original neighborhood demographics and limit gentrification. (Curran and Hamilton, 2012; Eckerd, 2011)

Our analysis helps our client to better understand how this unequal distribution of trees throughout cities results in tangible differences in air pollution remediation and health impacts from these trees. Some of the demographics that were included in this study are average household income, unemployment rate, racial distribution, and the dependency ratio. This was measured by the nine zip codes representing Tacoma, unless other data is obtained to better distinguish the neighborhoods. A regression analysis was completed to determine any relationship between green spaces and the variables. Our analysis of urban forestry practices includes how cities are addressing the disproportionate canopy cover in their urban areas and provide recommendations on how to improve equity in urban tree distribution while considering the potential economic factors which negatively impact these communities.

5. Climate Change Impacts

For all of the benefits that the urban forest provides residents, none are guaranteed in an altered climate future. Urban areas years from now will have to contend with a growing urban heat island effect, increased likelihood of severe drought, increased likelihood of dangerous storm events, and likely other as of yet unknown threats related to climate change (USGCRP, 2017). Because the threats associated with climate change are best predicted at the regional scale, it's important that urban forest management plans incorporate resilience into their objectives (Hibbard et al., 2017).

Municipalities will need to consider existent tree species in planning for climate impacts. Some tree species require high water consumption, redirecting water from streams and watersheds, thereby limiting soil moisture in surrounding vegetation and can intensify drought conditions (Anderaag et al., 2019). Young trees will also be susceptible to higher rates of mortality due to rising temperatures which will reduce their carbon sequestration capability and release carbon into the atmosphere. (Büntgen et al., 2019) There is ample data on how climate change will affect areas of the country locally and cities must take it upon themselves to use that data to make the best decisions about not only what's best for the urban forest today, but what will be sustainable in the longer term (Cutter et al., 2014).

5.1 Pollution Removal by Trees

As mentioned in Figure 2, trees are extremely effective at removing air pollutants. This ability of trees is especially important in urban environments where air pollution levels are typically much higher, resulting in increased harm from these pollutants. composition). Trees impact local air quality through the direct removal of air pollutants, altering local microclimates and through the emission of volatile organic compounds (VOCs), which can contribute to O_3 and $PM_{2.5}$ formation (Nowak et al., 2013). In our analysis of how the inequitable distribution of urban trees throughout Tacoma impacts differing air pollution reduction throughout the city, we address how these trees remove $PM_{2.5}$ on an hourly basis.

$PM_{2.5}$ is removed by the leaves of trees, and therefore to determine how much $PM_{2.5}$ is removed by trees, the Leaf Area Index (LAI) is needed. Deciduous trees lose their leaves seasonally and evergreen trees keep their leaves year round, so we calculate the percent deciduous vs. percent evergreen distribution of trees throughout Tacoma to determine LAI. As previously stated, particles often are resuspended from leaves by rain and wind; therefore hourly particle fluxes and dry/wet deposition rates are also needed (Nowack et al., 2016). LAI is typically assessed from satellite data, often at resolutions too coarse to be applicable on a city-wide or neighborhood scale. Field observations are needed to get a more accurate depiction of the urban environment, especially given that most LAI studies looked at heavily forested areas as opposed to a more heterogeneous urban environment.

Research reveals several limitations regarding how urban trees remove $PM_{2.5}$ based on a lack of available data needed to calculate the LAI, hourly fluxes, and wet and dry deposition rates globally. Much of the data sources input into the varying i-Tree softwares are quite outdated, with the most recent data being from 2013, and therefore inherently cannot provide accurate results (Hirabayashi, 2016). Some of the input data and their associated collection dates are as follows:

- Tree canopy coverage - National Land Cover Database, 2011
- LAI - MODIS/Terra global Leaf Area Index, 2007
- $PM_{2.5}$ Concentration - EPA air quality sensors, 2010
- Weather data (windspeed, precipitation) - National Climate Data Center (NCDC), 2010
- Health Impact Reductions - EPA BenMAP (from Census and EPA AQ sensors), 2010

This information regarding the various limitations of the input data was taken into consideration for our modeling purposes, which will be detailed further in the Methods section.

5.2 Urban Canopy Impacts on Human Health

Benefits of urban forests span a remarkable breadth of health outcomes, with correlational evidence for reduced all-cause mortality, improved healing times, reduced stress, reduced respiratory illness and allergies, improved self-reported well-being and a reduced risk of poor mental health, improved social cohesion, and improved cognitive ability (Shanahan et al., 2015). More neighborhood tree cover, independent from green space access, has been related to better overall health, primarily indicated by lower obesity and better social cohesion, and to a lesser extent by less type 2 diabetes, high blood pressure, and asthma.

Not giving adequate weight to the social benefits of trees may not only underestimate the total value of trees, it may also lead to poorly designed urban-forestry programs. The relationship between green spaces and a range of health outcomes include the following: long-term physical health indicators such as mortality and life expectancy; short-term indicators such as heart rate, blood pressure, and muscle tension; self-reported health and well-being; indicators of attentional and cognitive function; physical exercise; community cohesion and interaction and; even very small areas of trees (as few as half a dozen trees) and grass around residential areas, as opposed to concrete areas, can provide health-related benefits (Williams et al., 2013).

To understand inequities in health benefits from trees, we first must better understand how these health benefits are derived from trees. Understanding the cause-and-effect relationship between nature and health is a complex task as the links can be both direct and indirect, displaced in space and time, and influenced by a range of moderating forces (Shanahan et al., 2015). Direct pathways by which trees impact human health include factors that influence whether nature has an effect on people or the extent to which that effect translates into a measurable health outcome. Indirect pathways by which trees impact human health occur where nature influences the likelihood a person will display positive health behaviors, or where nature reduces the impacts of other risk factors in a person's life (Shanahan et al., 2015). However, positive health outcomes are not detectable for many years after exposure and are subsequently difficult to quantify. It is therefore important to consider urban forest inequity in decision-making as bolstering a city's urban canopy has marked impacts on human health, especially for communities of color who experience disproportionate exposure to less green spaces.

Methods

Our project designed an equity index model for our client used to identify urban areas which display imbalances in equity and negative environmental and health benefits. The model specifically quantifies how urban trees reduce $PM_{2.5}$ levels and the associated health benefits from improved air quality in Tacoma, WA. Our client, PlanIT Geo, was particularly interested in research which explored the effects of urban trees in reducing air pollutants. Prior studies have explored the effects of trees' removal of criteria pollutants in the U.S. such as ozone, nitrogen dioxide, sulfur dioxide, PM_{10} and $PM_{2.5}$. We decided to focus our research explicitly on $PM_{2.5}$ as it has been widely linked to human health concerns including cardiovascular disease, asthma, diabetes, respiratory issues and mortality in urban environments. We also found more sufficient $PM_{2.5}$ data within Tacoma boundaries than any other criteria pollutant data.

To create this model, 3 types of analyses are performed:

1. Quantify hourly, daily and annual rates at which trees reduce $PM_{2.5}$ on a neighborhood scale and associated improvements in air quality.
2. Estimate correlated reductions in health impact exposure; specifically cardiovascular hospital admissions, acute respiratory symptoms, asthma, and mortality rates as a result of improved air quality.
3. Develop a geo-spatial model and index that displays the relationship between canopy coverage, environmental benefits, and sociodemographic indicators determine neighborhoods of greatest inequity.

Our project incorporates three different models, with the first model quantifying the level of $PM_{2.5}$ air pollution reduced by trees in the City of Tacoma on an hourly and daily basis. The second model integrated these results into the BenMap program developed by the EPA which generated the projected health impact reductions correlated to the changes in air pollution utilizing metrics detailed in prior studies. The third model plotted socio-economic differences across the City of Tacoma and was built in ArcGIS. The GIS model integrated indices from socio-demographic variables retrieved from the American Community Survey such as race, poverty, and the dependency ratio, canopy coverage across census block groups, reduction in air pollution and the associated health impact reductions which were scored.

Model 1: Urban Forest Air Pollution Removal Analysis

To quantify the effects of trees in reducing $PM_{2.5}$ concentrations across cities, we developed a model based on the work of David J. Nowak, Satoshi Hirabayshi and fellow researchers from the USDA Forest Service who have done extensive work modelling how trees reduce air pollutants and specifically $PM_{2.5}$, and developed the Urban Forest Effects Model (UFORE). The UFORE model is used explicitly in the i-Tree software product.

i-Tree is a peer-reviewed software suite which quantifies tree effects in urban and rural settings to assist urban forest management programs worldwide. i-Tree software is used by municipalities, nonprofit organizations, and companies (including our client) to factor ecosystem benefits such as stormwater runoff, carbon sequestration and building energy reduction. However the UFORE/iTree model has limitations: the census, meteorological and air quality data which it uses as a baseline was last updated in 2010, and it assumes air pollution concentration is homogenous citywide. However, it is known that urban air pollution distribution is heterogeneous and concentrations vary widely in cities due to a variety of factors including: building heights and density, industrial and commercial areas, pollution emitting sources, topographical elements, and micro-climates.

Therefore, we adapted the UFORE model in order to incorporate heterogeneous distribution of $PM_{2.5}$ concentrations within neighborhoods. We used census block groups (CBGs) as our determinant for neighborhoods. We have opted to use this model because it provides a clear formula on how to calculate air pollutant removal by trees and incorporates publicly available data and tools that would be easy for our client and others to replicate.

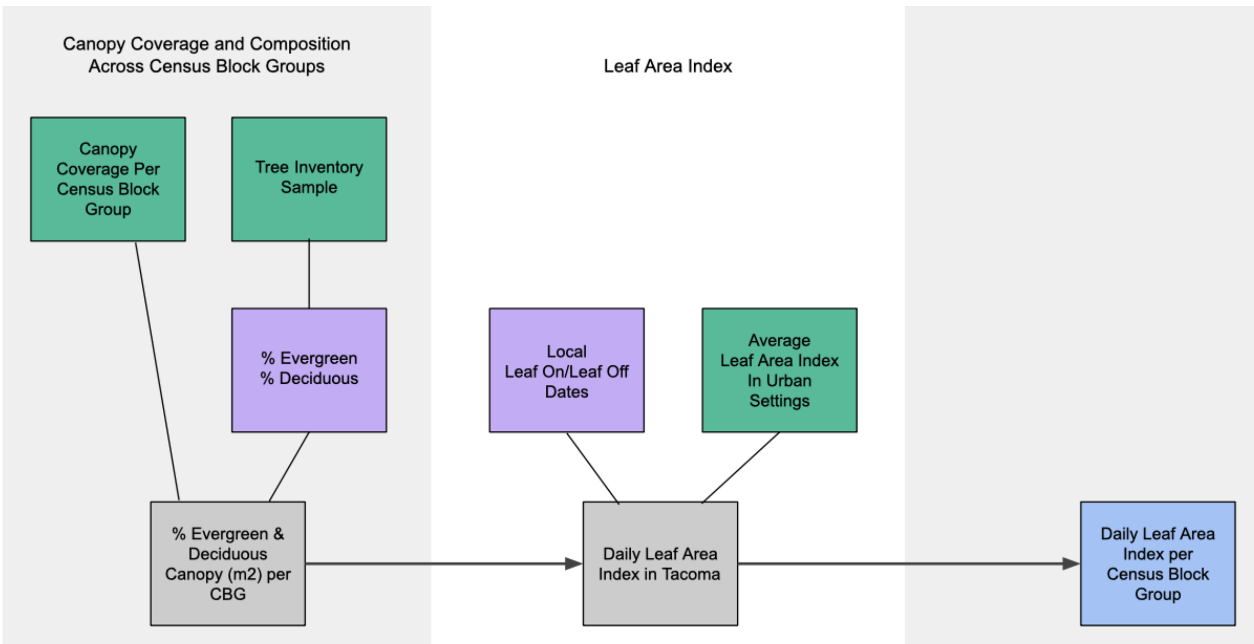

Figure 2. Composition of tree canopy coverage across census block groups model.

The air pollution reduction analysis has 3 major processes:

I. Assess the composition of tree canopy coverage across census block groups

II. Extract air pollution data from sensors placed across the city and project concentrations for each census block group

III. Quantify air quality improvement across these census block groups after determining hourly pollutant removal rates

1.1 Assess the Composition of Tree Canopy Coverage

Trees remove pollution by intercepting airborne particles which retain on the plant surface. Elements such as leaves, twigs, and branches create a rough aerodynamic surface which intercept air pollutant particles and can influence the rates of pollutant removal from the air through a dry deposition process (Beckett et al. 1998). Analysis of tree interception of air pollution particles is dependent on 2 variables: the ratio of tree canopy coverage within the study area and the daily leaf surface area. Generally, a higher ratio of canopy coverage and a higher rate of daily leaf surface area is more effective at intercepting particulate matter than a lower tree count with a reduced leaf surface area. This effectiveness can also be influenced by tree species classification; evergreen and deciduous trees have varying leaf surface areas based on seasonality effects throughout the year.

We used data provided by PlanIT Geo which found the ratio of urban tree canopy within each census block group, which was collected from prior analysis for the City of Tacoma in developing the city's Urban Forest Management Plan. PlanIT Geo used satellite spatial data and land use classification methods in their analysis. This analysis also recorded the total land area of each census block group which we converted to square meters.

We then classified the citywide composition of trees into evergreen and deciduous tree species using a tree inventory sample provided by PlanIT Geo from their TreePlotter software. This sample of over 17,000 tree observations was collected by PlanIT Geo and the City of Tacoma who recorded field observations of publicly-accessible street trees and documented tree diameter at breast height (DBH), the location of each observation, and known species. We referred to the Urban Forest Ecosystem Institute (UFEI) at Cal Poly's SelecTree database and were able to classify each of these observations into their known evergreen and deciduous tree type. With this sample, we determined that the citywide composition of street trees is 76% deciduous and 24% evergreen. This reflects a similar pattern as Seattle; which is approximately 72% deciduous and 28% evergreen. (Seattle Tree Canopy Assessment, 2016) We then applied this estimate of tree type composition to the ratio of canopy coverage present in census block groups to determine the ratio of deciduous and evergreen canopy coverage present in each study area during the 2019 interval. However, it is important to note that the sample we based our assumptions on is not comprehensive; it only includes public trees collected from a small representation of city blocks and does not include the large percentage of trees on private property or city park areas. After discussion with the city's urban forest manager, we believe this assumption underestimates the ratio of evergreen trees which are abundant in park and open space and were left out of this estimation.

1.2 Determine Daily Leaf Area Structure

We then determined the daily leaf area structure per tree type based on seasonality effects. We used the leaf area index, LAI, which is the square meter leaf area per square meter of projected ground area of tree canopy for the estimate of daily leaf area structure. We applied a maximum (mid-summer) LAI value of 4.9. This value was derived by the UFORE/i-Tree model which conducted spatial analysis on the level-4 MODIS/Terra global Leaf Area Index product for the 2011 growing season, and is based on the maximum pixel values within urban environments.

To account for the seasonal effects on deciduous trees, we applied a minimum LAI value of 0 during leaf-loss periods. Leaf loss durations were determined by the first frost date (temperatures reached 32 degrees Fahrenheit) in autumn months and the last frost date in spring months from weather data retrieved from the National Climatic Data Center from the Tacoma Narrows Airport. We also accounted for the transitional period of leaf loss and leaf growth by assuming these transitional periods lasted 4 weeks until deciduous trees lost or regained their full leaf canopy. We applied the following equation to determine the daily leaf area for deciduous trees:

$$LAI_{daily} = \frac{LAI_{max} - LAI_{min}}{1 + e^{-0.37(day_a - day_b)}} + LAI_{min}$$

Where LAI max is 4.9, LAI min is 0, day a is the day of the year and day b is the leaf-on date (spring season) and day is leaf-off and day b is the day of the year (autumn).

Monthly Leaf Area Index For Deciduous, Evergreen, and Citywide Combined Tree Species in Tacoma

Month	Deciduous LAI	Evergreen LAI	Combined LAI
Jan	0.00	4.90	1.18
Feb	0.00	4.90	1.18
Mar	1.14	4.90	2.04
Apr	4.70	4.90	4.74
May	4.90	4.90	4.90
Jun	4.90	4.90	4.90
Jul	4.90	4.90	4.90
Aug	4.90	4.90	4.90
Sep	4.90	4.90	4.90
Oct	4.90	4.90	4.90
Nov	4.64	4.90	4.70
Dec	0.97	4.90	1.91

Table 2. Monthly Leaf Area Index (leaf surface area) (LAI) means for deciduous, evergreen, and citywide combined.
Citywide combined LAI incorporated our assumption that Tacoma's urban forest is 76% deciduous and 24% evergreen, reflecting this estimate.

1.3 Retrieve $PM_{2.5}$ Data

The next step of our analysis is to extract $PM_{2.5}$ air pollution concentration data across Tacoma and interpolate these values to each census block group. In the EPA's AirData Air Quality Monitors app (refer to Appendix), there are currently only two active criteria pollutant monitors for $PM_{2.5}$ within the regional boundary of the city. As our project aims to quantify $PM_{2.5}$ reduction on small spatial scales within city-levels, we sought alternative sources of pollutant data to capture finer resolutions and analyze the distributional effects on the census block group level.

We opted to use hourly air pollution data retrieved from Purple Air, a company which produces low-cost air sensors which residents place outside their home to retrieve local air pollution data. These sensors use dual laser particle counters which have been calibrated to align with EPA air quality monitor standards. These lasers record measurements of average particle density for outdoor particulate matter utilizing an algorithm developed by PMS5003 laser counter manufacturer, PlanTower. Several studies have evaluated the accuracy of Purple Air sensors and determined that they provide a valid measurement of air pollutant data. (South Coast AQMD, 2016) We extracted hourly pollution data for 2019 from 8 Purple Air sensors located throughout the city. These sensors were selected because their collective locations reflected a general neighborhood distribution and had sufficient data throughout the study period.

1.3.1 Preparing Sensor Data

Purple Air sensors record particulate matter levels upon two different channels. These dual readings help to minimize data loss should one laser fail due to mechanical errors or elemental exposure. We plotted each sensors' observations by month using histograms and scatter plots to observe distribution and outliers. These plots revealed a few occurrences in which channels went offline or recorded error values, as can be seen in the figure below which shows that the Lexington sensor's channel B recorded errors during the month of August. We also incorporated an effect size statistical test to observe the range of difference in means between both channels. With these observations, we then selected the channel which most closely recorded normal distribution to use for our analysis. In some instances when both channels recorded a similar range of values and it was difficult to determine which channel to use, we selected the channel which most closely matched the adjacent sensors' monthly mean of $PM_{2.5}$. These channel recordings can be seen in Figure 4 in the Appendix.

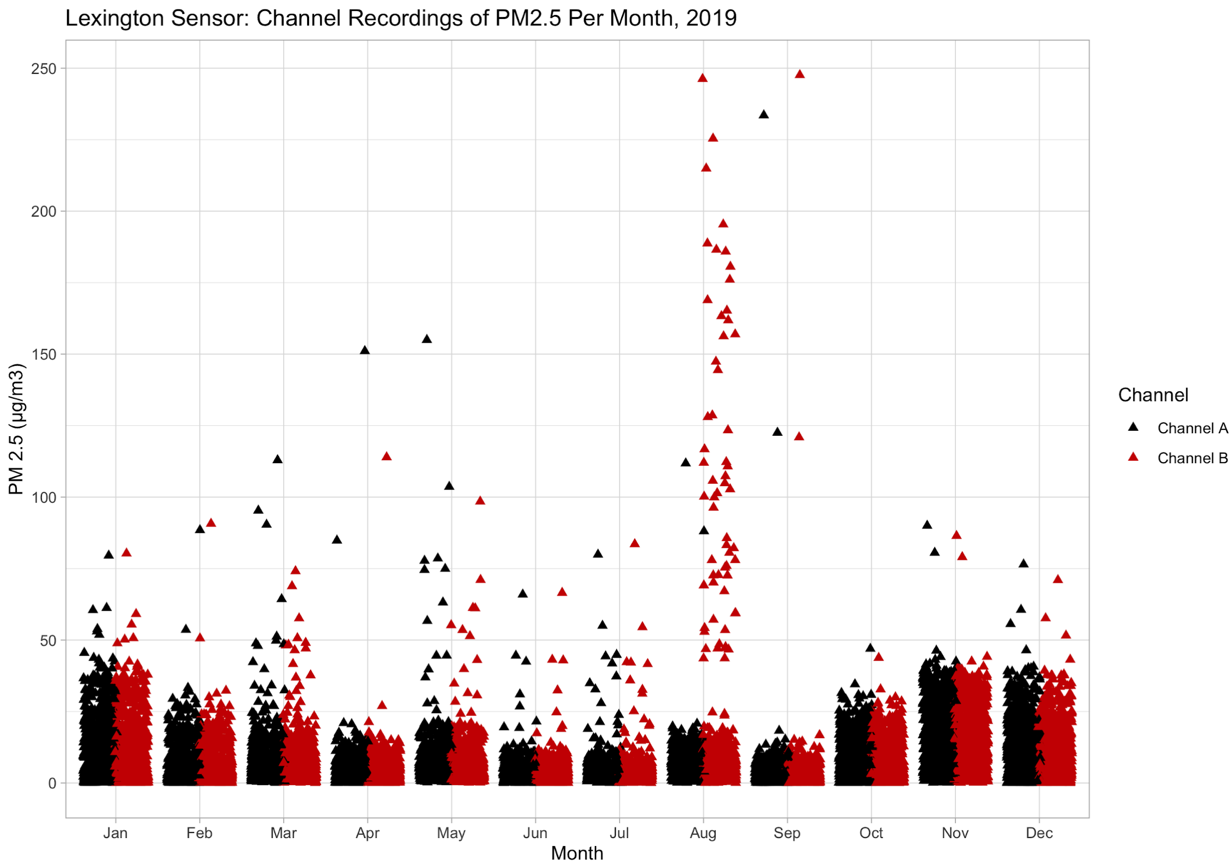

Figure 3. Monthly Lexington sensor channel PM2.5 recordings, 2019.

4 sensors were missing data which ranged from 1 week to 2 months. To address this, we substituted values from the adjacent sensor by isolating each sensor's data to the channel which most closely reflected the citywide hourly mean. We found the median, maximum, standard deviation and standard error of all sensor recordings which can be seen in the boxplot graph below as well as a summary table in the Appendix.

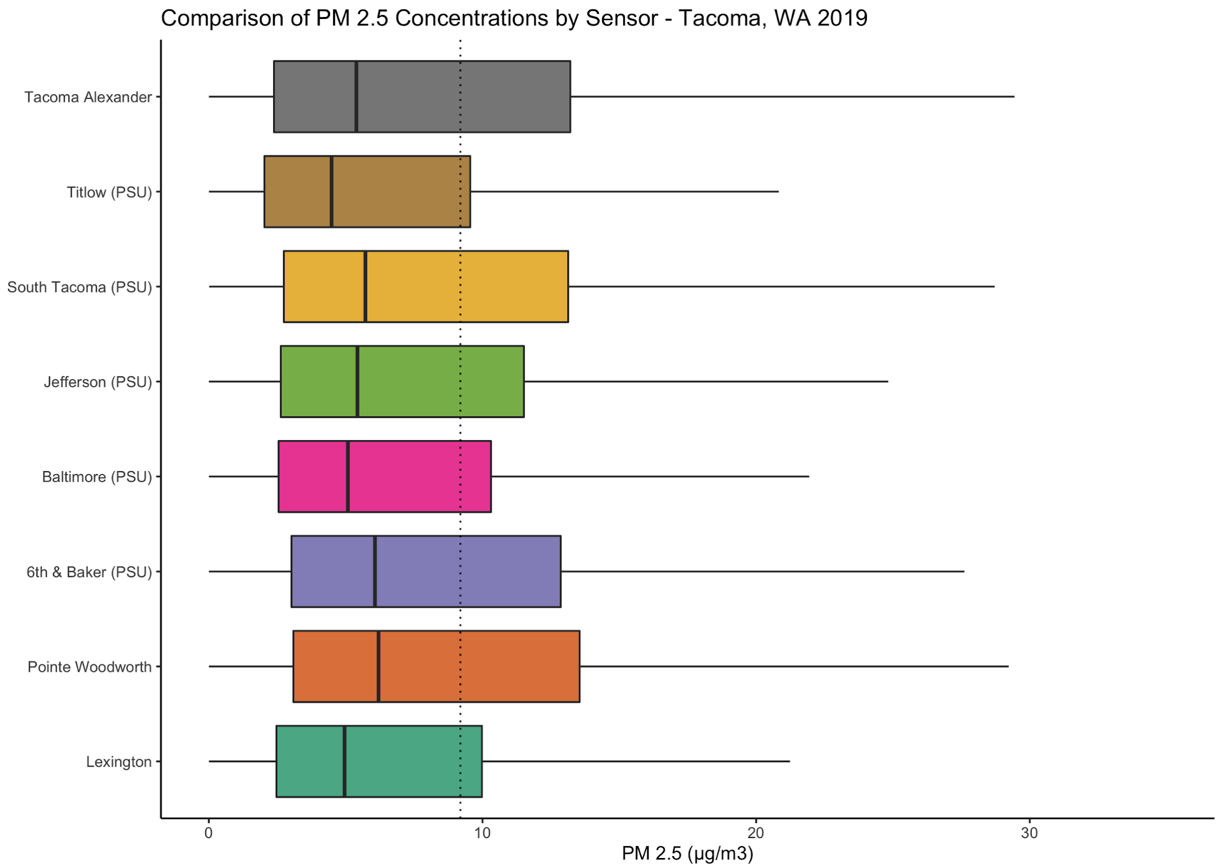

Figure 4. Hourly $PM_{2.5}$ concentrations recorded by Purple Air sensors, 2019

1.3.2 Interpolating Sensor Data to Census Block Groups

We then used ArcGis to map each of the 8 sensor's coordinates and assigned each census block group within the city to the closest Purple Air sensor to represent the best aggregate of $PM_{2.5}$ concentrations in that area. Shown below are maps created to assign census blocks groups to sensors. After creating thiessen groups based on the 8 Purple Air sensors being used for data analysis in ArcGIS, census block group data was overlaid to determine which air sensor each individual census block group should be assigned to. This process follows similar interpolation methods used in the UFORE model, and we assumed that these assignments reflect the present spatial patterns of air quality.

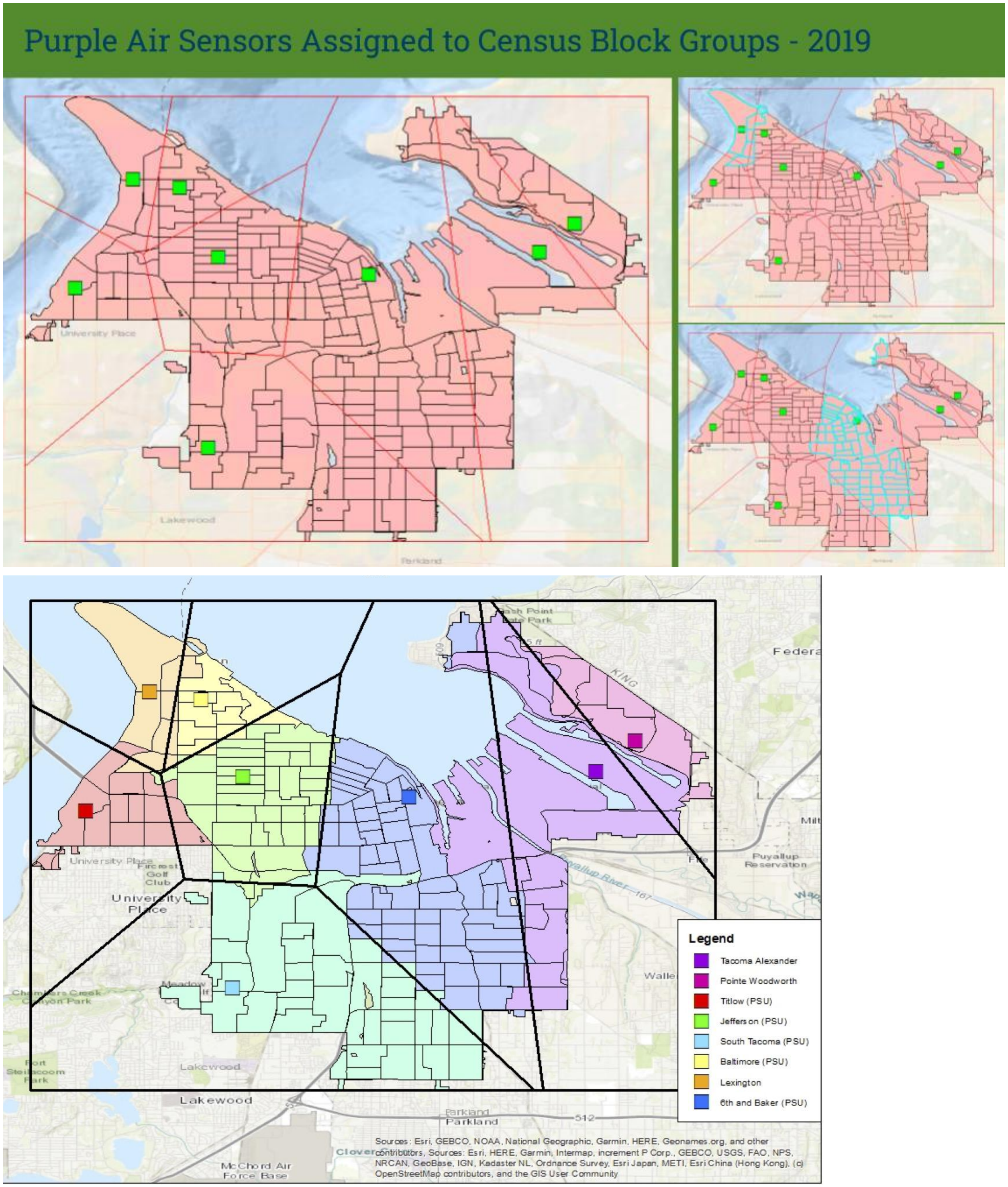

Figure 5. Tacoma, WA census block groups organized by Purple Air sensors.

In the large image on the top left, the green squares represent each individual sensor, black lines indicate census block group boundaries, and red lines indicate thiessen values that are used as the main tool to separate census block groups by the closest sensor. The top right image shows census block groups in Tacoma (highlighted in cyan) that are assigned to the "north_lexington_outside" sensor. The bottom right image similarly shows which census blocks are assigned to the "psu_star_lab_6th_and_baker_outside" sensor, also highlighted in cyan. Each census block group has been assigned to a sensor based on their location within thiessen groups in ArcGIS. The final image on the bottom shows locations and names of specific sensors and further visualizations regarding which census block groups were assigned to each sensor.

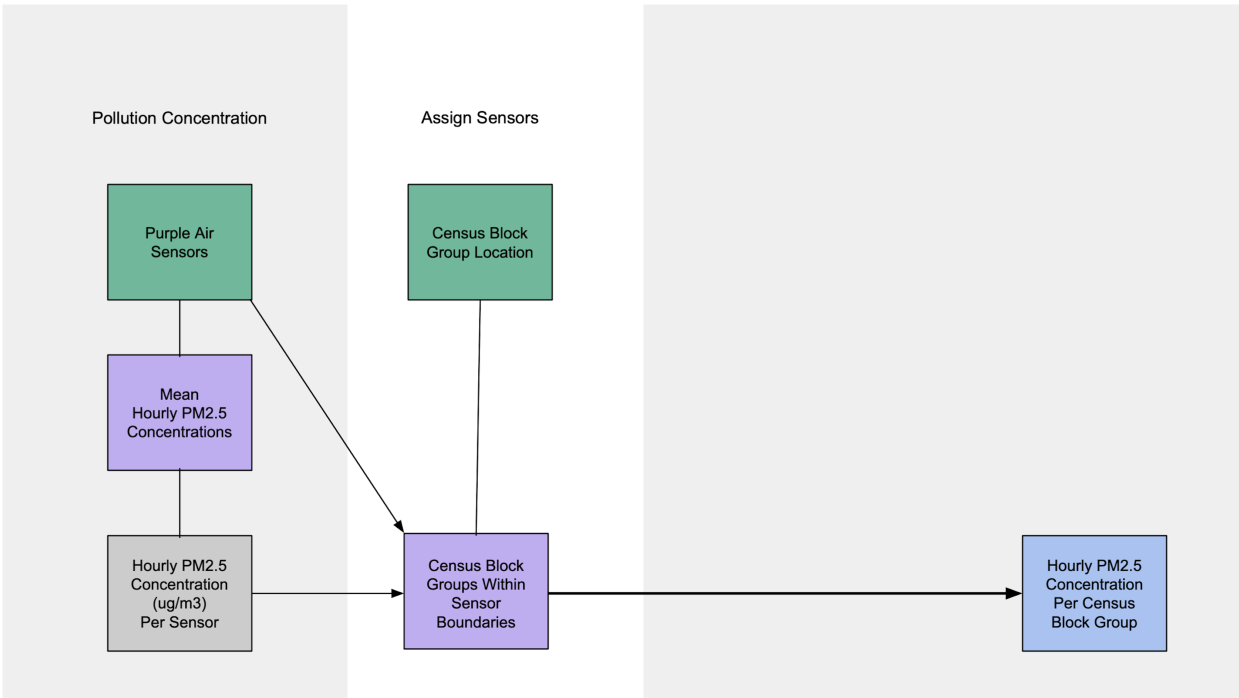

Figure 6. Air Pollution Interpolation Model.

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1.4 Calculating Hourly Pollutant Removal and Resuspension of $PM_{2.5}$ by Trees

To determine the level at which trees can reduce $PM_{2.5}$ concentrations in the atmosphere our analysis applied three formulas to find: the hourly pollutant removal rates by trees, the ratio of air quality improvement and hourly $PM_{2.5}$ concentration changes.

1.4.1 Hourly Pollutant Removal

We found the hourly pollutant removal rate (ug/m2), also known as the pollutant removal flux per unit of tree cover, using the following equation:

$$F = Vd * C$$

Where the flux is equal to the deposition velocity of pollutants to leaf surface areas (m/h) times $PM_{2.5}$ concentration (ug/m3). We applied deposition velocities values generated by prior research (Nowak et al, 2013) which found a range of deposition velocities of 17 tree species with wind speeds ranging from 1 - 10 m/s, shown in Table 3.

PM2.5 Deposition Velocities and Percent Resuspension by Wind Speed per Unit Leaf Area				
Wind Speed	Deposition Velocity			Resuspension
(average meters per second per hour)	Average (meters per hour)	Maximum (meters per hour)	Minimum (meters per hour)	%
0	0	0	0	0
1	1.08	1.512	0.216	1.5
2	3.24	5.868	0.432	3
3	5.4	10.26	0.648	4.5
4	6.12	12.564	0.792	6
5	6.84	14.904	0.9	7.5
6	7.2	17.208	1.044	9
7	20.16	54.216	2.016	10
8	33.12	91.224	2.952	11
9	33.12	91.224	2.952	12
10	75.96	265.212	20.52	13
11	75.96	265.212	20.52	16
12	75.96	265.212	20.52	20
13	75.96	265.212	20.52	23
14	75.96	265.212	20.52	23

Table 3. Deposition velocities and percent resuspension rates as factored by Nowak et al, 2013.

We then found average hourly wind speeds for Tacoma in 2019 using meteorological data from the Tacoma Narrows Airport weather station retrieved from the NOAA NCEI database. For each corresponding hourly wind speed we applied the average, maximum and minimum deposition velocity rates. These deposition velocity values were then multiplied by evergreen and deciduous LAI values. Then we multiplied the hourly concentration from each census block group (as detailed in section 1.3). Finally, we then accounted for the percent of which pollutant particles are resuspended into the atmosphere due to wind by applying the resuspension ratio detailed in Table 3. This gave us the hourly pollutant removal flux which incorporated the leaf surface area, deposition velocities, pollutant concentration and particle resuspension.

1.4.2 Air Quality Improvement Ratio

For each census block group we calculated the hourly air quality improvement as the ratio between the mass of air pollutant removed based on tree canopy coverage in the areas and the mass of air pollutant that existed prior to particle deposition on trees. We used the following formula:

$$I = \frac{F^*TC}{F^*TC + C^*H}$$

Where F is the hourly pollutant removal flux (ug/m2/h), TC is the percent canopy cover, C is the hourly PM2.5 concentration (ug/m3) and H is the hourly mixing height. Mixing height is the level in which air parcels cannot lift higher into the atmosphere. Low mixing heights create stagnant air where pollution can be trapped closer to the ground surface, while high mixing heights allow for more pollution dispersal. Mixing heights are measured in radiosonde observations which record the heights at which air parcel temperatures equal the ambient air temperature.

Mixing Height data was extracted using the Copernicus Climate Change Service ERA5 climate reanalysis model. This atmospheric reanalysis model is a 3D, time-varying dataset which is generated by using a weather forecasting and climate model to match meteorological observations as closely as possible and are used for weather and climate research. We were able to extract the estimates of boundary layer height for hourly and daily observations for 2019 for the extent of Tacoma's geographical boundaries. Boundary layer heights can be affected by factors within urban environments, such as surface temperatures and urban heat island effect, humidity, wind speeds and pollution concentrations. As a result, boundary layers extend to taller heights in cities than in rural settings due to this "urban effect". (Dupont et al, 1997). To account for this, we set the minimum boundary layer heights to 150 meters during night hours (from 18:00 - 5:00) and 250 meters during daytime hours (6:00 - 17:00). The variation in boundary layer heights is shown in Figure 7.

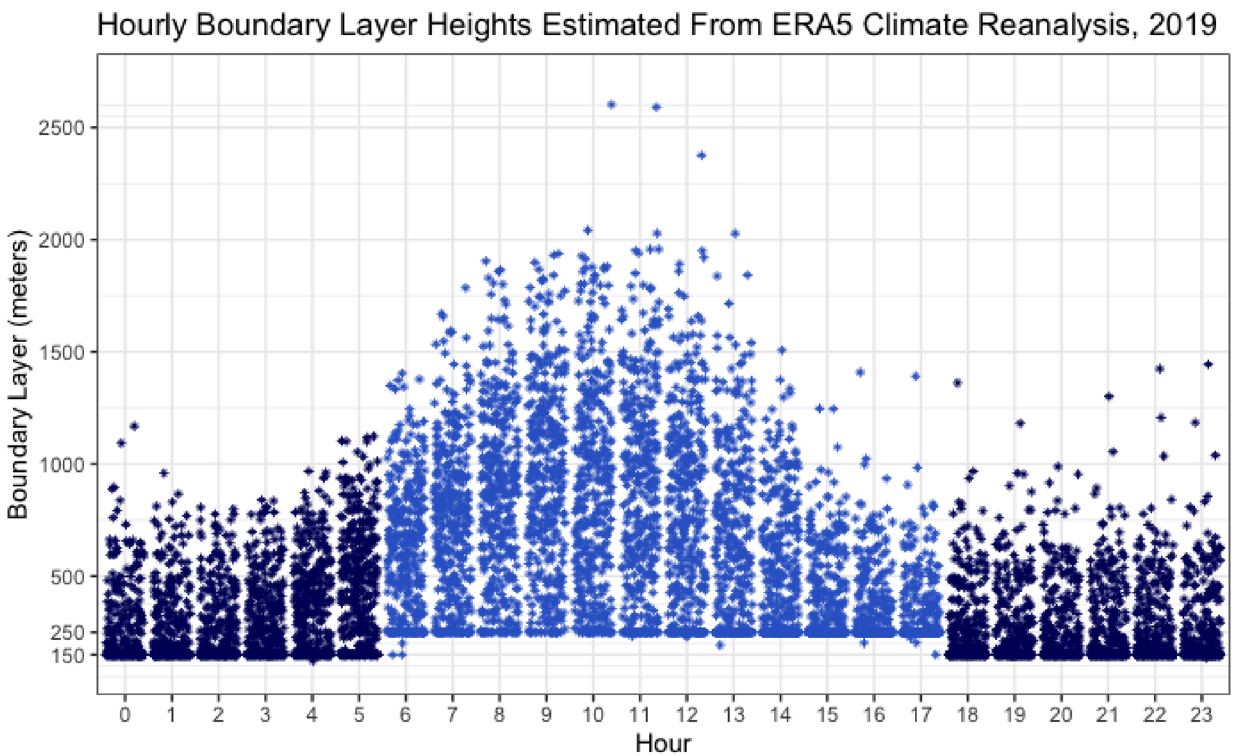

Figure 7. Hourly boundary layer heights, 2019.

1.4.3 Hourly Concentration Change

We found the hourly change in $PM_{2.5}$ concentration (ug/m3) within census block groups using the following formula:

$$\Delta C = \frac{C}{1 - I} - C$$

Where C is the hourly concentration (ug/m3) and I is the hourly improvement ratio.

1.4.4 Accounting for Precipitation

It was important to also factor precipitation into our model, as rainfall washes off pollution particles from the leaf surface areas and lowers trees' pollutant removal. Referring to the Nowak et al 2013 study, we assumed that trees can retain up to 0.2 mm of precipitation on their leaf surface areas before these particles are washed off. We determined the leaf surface area precipitation threshold by multiplying 0.2 x LAI for deciduous and evergreen trees. We averaged hourly precipitation data from the Tacoma Narrows Airport weather station retrieved from the

NOAA NCEI database. We then assigned a value of zero to hourly pollutant fluxes when the hourly precipitation (mm) exceeded the hourly leaf surface area precipitation threshold. Figure 8 below shows the hourly observations when precipitation levels exceeded the daily leaf surface area threshold (n = 244).

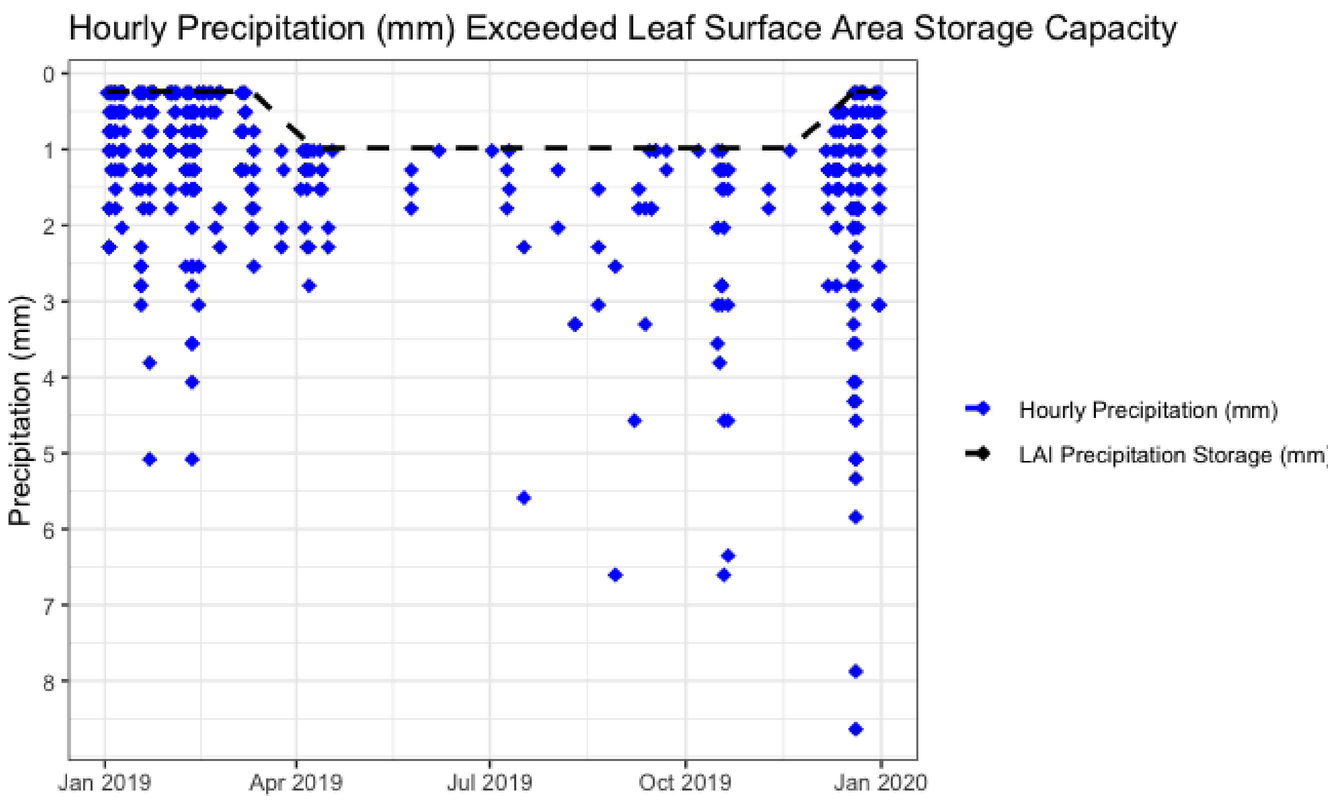

Figure 8. Occurrences when precipitation levels (mm) exceeded daily leaf surface area storage capacity
During these precipitation events, hourly pollution removal reduced to 0 as it was assumed all particulate matter was washed off the leaves.

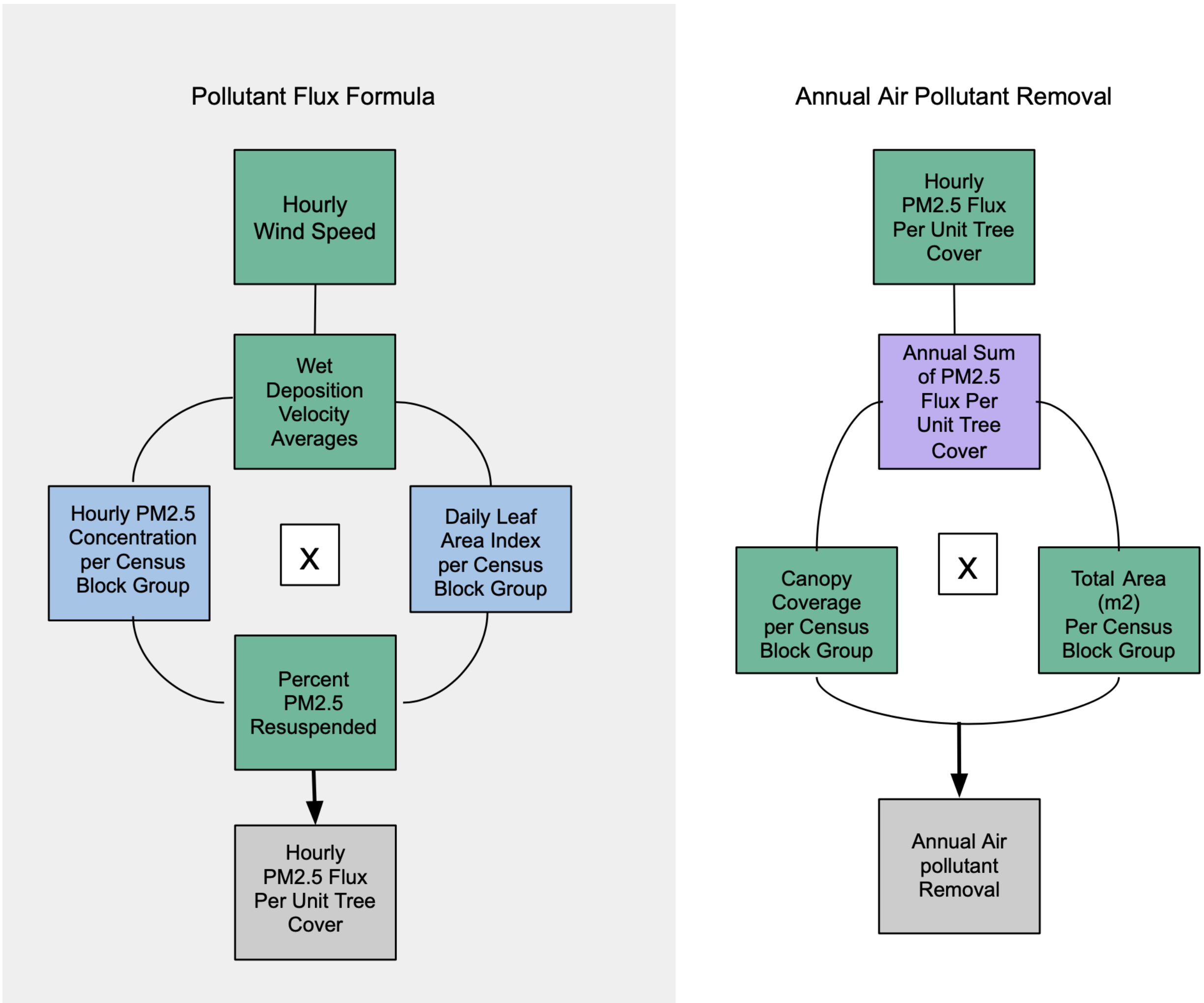

Figure 9. Pollutant flux formula and annual air pollutant removal model.

Model 2: Correlating Urban Canopy Impacts on Health

After finding the hourly concentration change within census block groups, the next step in the model is to assess how the change in air quality might lower the rates of health incidents including acute respiratory symptoms, asthma attacks, ER visits for respiratory symptoms, hospital admissions for cardiovascular symptoms, and hospital admissions for respiratory symptoms. These lowered health incidents that have been linked to PM2.5 also generate an estimate in the associated change in monetary values including the number of projected work loss days and the total cost of associated illness. We used the EPA's BenMAP program for this analysis.

Benmap is a program which incorporates air quality grids, concentration-response functions and valuation functions to estimate the incidence of health impacts when populations experience a change in air quality. It requires the following inputs: modeled air quality changes, population, baseline incidence rates and effect estimates.

The program first requires users to define air quality surfaces which contain air pollution exposure estimates for a particular grid definition. A grid definition can be a rectangle covering the region for analysis, or polygons which correspond to significant boundaries of interest. For our analysis we used a shapefile of Tacoma's census block group boundaries as the grid definition.

Benmap next requires users to select the designated pollutant studied and the air quality metric which incorporates the period of the day over which the pollutant observations are averaged. These metrics can include the daily mean of pollutant levels "D24HourMean", daily maximum level of pollutant levels "D24HourMax", or the average of the 8-hour period during the day when pollutant levels are the highest, "D8HourMax". Baseline and control values must use the exact same metrics. Benmap then averages these metric values to an annual mean value for each grid definition cell. We applied the "D24HourMean" metric as a majority of our health impact functions required it.

The next step was to upload our generated air quality improvement data into the program; Benmap requires a baseline and control using a baseline value of existent $PM_{2.5}$ concentrations, and a control value which subtracted hourly concentration change from existent $PM_{2.5}$ levels. We found the daily mean of $PM_{2.5}$ levels within each census block group which were averaged to the mean value over the course of the year. The inputs the Benmap model requires are a baseline and modeled air quality change. In this analysis, we wanted to compare how health impact reductions might be related to ranges in ambient pollution levels, as well as different tree canopy coverage.

We then applied each of these conditions to a baseline value of the daily ambient mean of $PM_{2.5}$ concentrations with no tree pollutant removal to find the annual health impact reduction for acute respiratory symptoms, asthma symptoms, ER visits for respiratory symptoms, hospital admissions for cardiovascular symptoms, hospital admissions for respiratory symptoms, and associated work loss days in relation to respiratory and cardiovascular incidences. We also used the BenMAP model to filter these results by population age groups of:

- 0 - 14 years old
- 15 - 64 years old
- 65 - 99 years old

Benmap also gave us control to select which epidemiology study to integrate into the program's effect estimate. We used the following studies which were incorporated into the program's function to generate the estimated health incident reductions by affected population:

- Acute respiratory: Ostro, B.D & Rothschild, S. (1989)
- Asthma: Mar et al. (2004)
- ER visits for respiratory symptoms: Glad et al. (2002)
- Hospital admissions for cardiovascular symptoms: Bell, M.L (2012)
- Hospital admissions for respiratory symptoms: Kloog et al. (2012)
- Work loss days: Ostro, B.D. (1987)

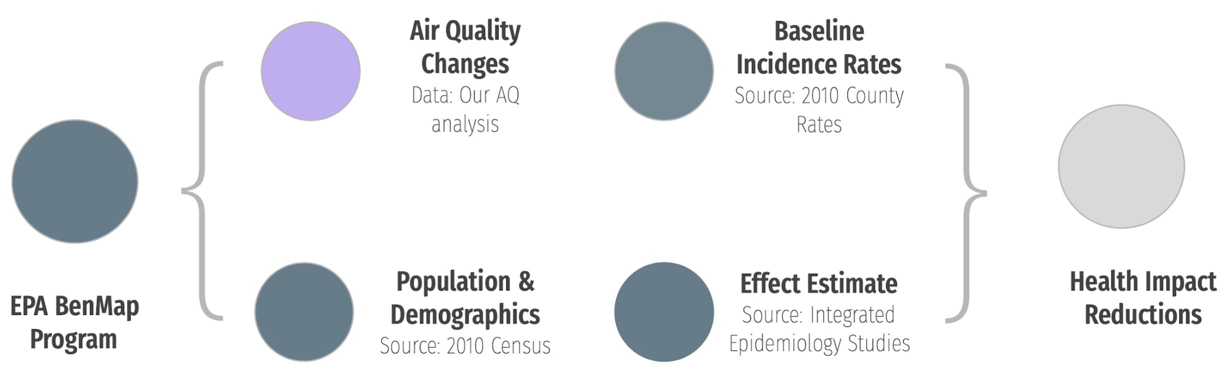

Figure 10. Health Impact Reduction model.

Model 3: Plotting Socioeconomic Disparities

After analyzing air quality and health in Tacoma, we needed to create an index to examine the relationship between canopy coverage, environmental indicators, and the sociodemographic indicators for each census block. We could then compare different census block groups based on a weighted average of these indicators to determine which group had the highest and lowest environmental equity score.

To score the environmental equity of different census block groups in Tacoma, we examined popular environmental equity indexes, such as EJSCREEN (US EPA, 2014a), CalEnviroScreen (OEHHA Admin, 2014), the Washington Environmental Health and Disparities Map (WA index) (Washington State Department of Health), and Tree Equity Score (Tree Equity Score Analyzer, 2021). Individually, each index did not have the resolution or localized data that our model hoped to incorporate. We acknowledge that Tacoma has its own equity index, but it does not incorporate many environmental indicators (Tacoma Equity Index). We used pieces of each of the mentioned indexes to build our index, but some influenced our model more than others. Since PlanIT Geo considered adopting the Tree Equity Score and the score would be applied nationwide, we applied the basis of their canopy gap score and their chosen demographic indicators for our index. The equations used in all other parts of the model were modified from the WA index.

Our model was built in ArcMap Modelbuilder and requires a number of different inputs. We derived the air quality and health inputs from the methodology described in the above sections. PlanIT Geo gave us Tacoma's urban canopy coverage data from their latest Urban Tree Canopy Assessment Report from 2019. The demographic data was extracted from the American Community Survey 5-yr (2015-2019) dataset (Bureau, U.C.). The Tacoma nonprofit, Earth Economics, provided their temperature data from their urban heat island study from 2020 (Wildish, 2020). We also used the Tacoma boundary shapefile from the City of Tacoma's GeoHub to limit our analysis to just inside the city's borders (City Boundary (Tacoma)).

The following section describes the indexes we came across and how we adapted them to refine the scores for the city of Tacoma.

3.1 EJSCREEN

EJSCREEN was developed by the Environmental Protection Agency (EPA), and the most recent version was publicly released in 2015 (August, 2016).

While the tool has been widely recognized, we had to consider that EJSCREEN produces individual scores for different environmental risk factors instead of a composite one, like with CalEnviroScreen or the Washington Environmental Health and Disparity Map (US EPA, 2014b). In the end, we decided to incorporate both a composite and individual indicator score because information can be lost if either one is delivered by itself. Our client would not be able to pick apart different equity indicators or determine which indicator most affected the final score if there was only a composite score. Likewise, individual indicator scores would not provide an immediate and encompassing analysis of each census block group.

3.2 CalEnviroScreen

CalEnviroScreen stands for the California Communities Environmental Health Screening Tool (August, 2016). First released in 2017, the most recent version is now CalEnviroScreen 3.0. It involves 20 different indicators divided into 4 groups: exposure, environmental effects, sensitive population, and socioeconomic factors (August, 2016). Unlike EJSCREEN, this tool created composite scores by census tract. Now, it has become the inspiration for many other environmental equity screening tools, including the Washington Environmental Health and

Disparity Map. We did not use the exact methodology CalEnviroScreen scores because we wanted to find a Washington environmental equity tool that Tacoma policy makers, nonprofits, or residents might find more familiar.

3.3 Washington Environmental Health and Disparity Map

As stated above, the Washington Environmental Health and Disparity Map was adapted from CalEnviroScreen and was released to the public in 2018 (Washington State Department of Health). Unlike CalEnviroScreen, it involved 19 different indicators divided into 4 themes: environmental exposures, environmental effects, sensitive populations, and socioeconomic factors (Washington State Department of Health). Though the tool already evaluated Tacoma, we felt that we could build upon the scores to better fit the city's interests. After all, the Washington index did not look at urban forestry as a factor related to the environmental effects, and the score resolution was at the census tract and not census block group level. In the end, we decided to adopt the scoring equations into our own scoring methodology, if not the actual indicators. All the indicators we incorporated were more localized to Tacoma. These indicators are further described in section 3.4.

3.4 Tree Equity Score

The Tree Equity Score was developed by American Forests and just released in November of 2020 (Tree Equity Score Analyzer, 2021). The Tree Equity Score was based on a simplified methodology from CalEnviroScreen or the Washington Environmental Health and Disparity Map. However, the canopy coverage indicator was brought to the forefront. It examined the canopy gap or the difference between the city's canopy target and the actual canopy coverage. The tool also chose five priority indicators: income, employment, race, age and climate.

While American Forests' tool would one day cover the entire US, the pilot locations only included Rhode Island, Maricopa County, the Phoenix area of Arizona and the San Francisco Bay area of California. There were no scores yet for Tacoma, and the tool did not look at environmental or health effects from tree canopy cover distribution. Therefore, we decided to incorporate the canopy gap score methodology and the five indicators into our model, though we moved climate into its own score. The climate indicator refers to the day temperature readings recorded during Earth Economics' urban heat island study (Voelkel & Shandas, 2017).

3.5 Components of the Environmental Equity Model

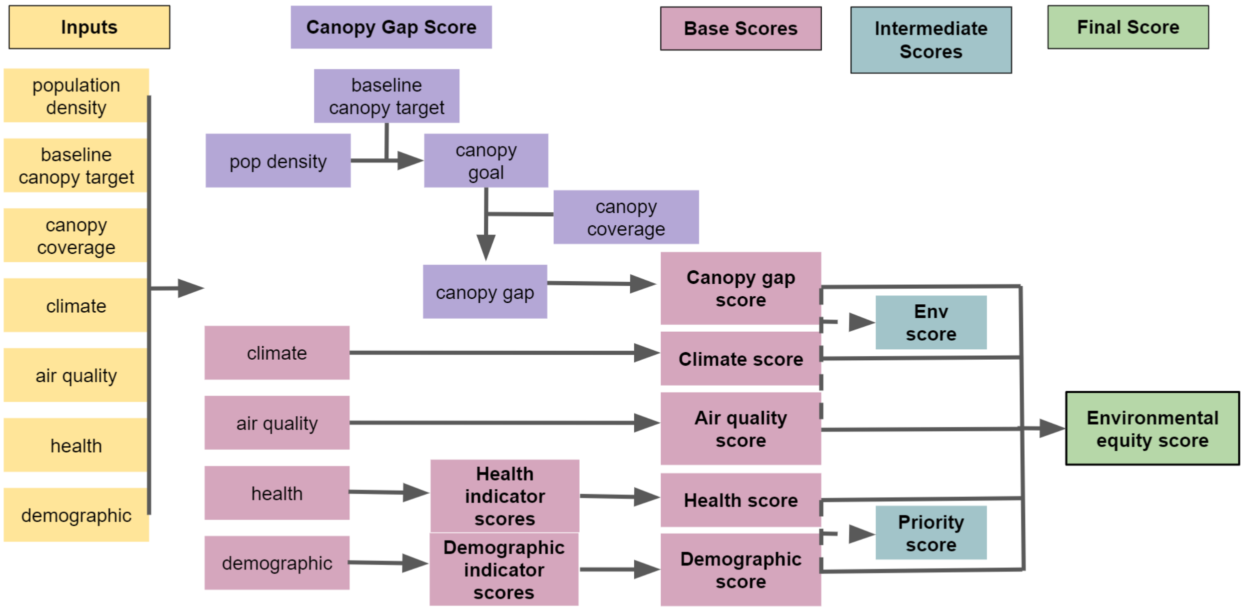

Figure 11. Comprehensive Environmental Equity Model.
The outline shows the basic components of the environmental equity model. Starting from left to right, each color shows a different component. Yellow: Data inputs. Purple: Canopy Gap Score. Pink: Base Scores. Blue: Intermediate Scores. Green: Final Score. Solid lines show all the main steps in our model. The dashed lines show steps to create the intermediate scores, which are additional scores our client can manipulate.

A basic outline of the environmental equity model is shown above. The index is divided into five different components: the inputs, the canopy gap score, the base scores, the intermediate scores, and the final score. While the canopy gap score is also a base score, the steps to calculate it are more complicated than any of the other base scores. Therefore, it deserves its own section.

The solid lines show all main steps in our model. In yellow, the inputs show the datasets we had already calculated or extracted from the data sources. This step also involved cleaning up the data to be put through the index. In purple is the canopy gap score. In pink, the other base scores include the climate, air quality, health, and demographic score. Within the demographic score, demographic indicator scores are also available. The same can be said for the health score.

In blue, the intermediate scores involve the environmental and priority score. These scores are derived through a weighted average of the canopy gap, climate, and air quality score for the former and the health and demographic score for the latter intermediate score. Intermediate scores allow greater flexibility to prioritize different aspects of our model for policymakers, but our client can combine any of the base scores to derive an intermediate score. The dotted lines show that this step is optional to creating the final composite score.

The final score in green is the weighted average of all of the base scores, which results in the environmental equity score. Therefore, our final model has ten outputs: canopy gap, climate, air quality, health, health indicator, demographic, demographic indicator, environmental, priority, and environmental equity score. These outputs are in bold font in the above flowchart.

3.6 Cleaning the Input Data

We retrieved demographic data from the American Community Survey 5-year (2015-2019). The data includes the four demographic indicators, the same indicators as American Forest's tree equity score:

- Income: Percentage of population below 200% of poverty level
- Employment: Percentage of population unemployed 16 years old and above
- Race: Percentage of population who are not white non-Hispanic
- Age: Ratio of seniors above 65 years old and children less than 16 years old to working-age adults

The canopy gap score also required the population density, which was calculated from the same data as the age indicator. In order to get population density, we used the r package "tidycensus." It retrieves the data from ACS through variable codes related to each data table. Table 4 shows the exact data tables and variable codes we retrieved. We were unable to find the exact variables we needed to match our intended indicators, so we also had to transform some of the variables in RStudio.

- Income: Total percentage of population - percentage above 200% of poverty level
- Race: Total percentage of population - percentage that are White alone
- Age: (Percentage of population above 65 years old + percentage below 16 years old) / (Total percentage of population - (percentage above 65 years old + percentage below 16 years old))

Indicator	Block Group Table	Variable	Variable Code
Income	RATIO OF INCOME TO POVERTY LEVEL IN THE PAST 12 MONTHS	Estimate!!Total:!!2.00 and over	C17002_008
		Estimate!!Total	C17002_001
Employment	EMPLOYMENT STATUS FOR THE POPULATION 16 YEARS AND OLDER	Estimate!!Total:!!Not in labor force	B23025_007
Race	HISPANIC OR LATINO ORIGIN BY RACE	Estimate!!Total:!!Hispanic or Latino:!!White alone	B03002_003

		Estimate!!Total	B03002_001
Age	SEX BY AGE	Estimate!!Total*	B01001_001
		Estimate!!Total:Male:!!65 and 66 years	B01001_020
		Estimate!!Total:Male:!!67 to 69 years	B01001_021
		Estimate!!Total:Male:!!70 to 74 years	B01001_022
		Estimate!!Total:Male:!!75 to 79 years	B01001_023
		Estimate!!Total:Male:!!80 to 84 years	B01001_024
		Estimate!!Total:Male:!!85 years and over	B01001_025
		Estimate!!Total:Female:!!65 and 66 years	B01001_044
		Estimate!!Total:Female:!!67 to 69 years	B01001_045
		Estimate!!Total:Female:!!70 to 74 years	B01001_046
		Estimate!!Total:Female:!!75 to 79 years	B01001_047
		Estimate!!Total:Female:!!80 to 84 years	B01001_048
		Estimate!!Total:Female:!!85 years and over	B01001_049
		Estimate!!Total:!!Male:!!Under 5 years	B01001_003
		Estimate!!Total:!!Male:!!5 to 9 years	B01001_004
		Estimate!!Total:!!Male:!!10 to 14 years	B01001_005
		Estimate!!Total:!!Male:!!15 to 17 years	B01001_006
		Estimate!!Total:!!Female:!!Under 5 years	B01001_027
		Estimate!!Total:!!Female:!!5 to 9 years	B01001_028
		Estimate!!Total:!!Female:!!10 to 14 years	B01001_029
		Estimate!!Total:!!Female:!!15 to 17 years	B01001_030

Table 4. ACS 5-year (2015-2019) indicator variables and variable codes for "tidycensus."
This table lists the four demographic indicators (income, employment, race, and age) and identifies the specific block group table, variable, and variable code used to retrieve the data using the R-package "tidycensus.". *The population density for the canopy gap score used the same variable.

After tidying up the indicators, we converted them into a shapefile to be used in our model. All other data inputs did not need to be cleaned. Once we included the air quality, health, climate, and Tacoma boundary shapefiles, we made sure to project everything to the projected coordinate system NAD 1983 UTM Zone 10N. Note that we could only retrieve the data at the county-level and not the city-level, so at this point, all values were for Pierce County. Therefore, we clipped the layer to the Tacoma boundary shapefile from the city of Tacoma's GeoHub (City Boundary (Tacoma)).

3.7 Canopy Gap Score

The second component of the index involved the Canopy Gap Score. This score indicates the additional percent of canopy cover per census block group to reach the city's baseline canopy target. This is the canopy goal across the entire city, which can range from 40-60% canopy coverage within forested states (Nowack & Greenfield, 2018). The scores from this model were based upon a 40% baseline canopy target, which is standard for most cities. A higher score means that there is a larger deficit of trees and is marked as a critical census block group.

Steps:

1. Find the population density in ppl/km^2 , which also requires an additional data transformation. The total population was divided by the shape area. Since the shape area was in meters squared, we multiplied by one million.
2. Reclassify the population density for each census block group into target canopy adjustment factors. This adjusts the canopy target so that the lower the population density, the higher the census block group canopy target. This methodology comes from research by the Nature Conservancy. Lower densities tend to mean more rural areas and more possible planting areas (PPA). Thus the canopy target for those census block groups can be raised. Higher densities tend to be more urban, so the target is lowered (McDonald et al., 2016).

Population Density (ppl/km^2)	Target Canopy Adjustment Factor
Very low (<2k)	1.2
Low (2k-4k)	1.0
Moderate (4k-8k)	0.8
High (>8k)	0.5

Table 5. Target canopy adjustment factors by population density.
This table lists the target canopy adjustment factor based on the population density (ppl/km^2). It assumes more trees can be planted in low-density areas to compensate for more crowded high-density ones

3. Multiply the factor to the city's baseline canopy target, which is adjustable for our client. The results show the idealized canopy goal for each census block group.
4. Subtract the canopy goal by the actual Tacoma tree cover, which came from our client. This shows the canopy gap.
5. Reclassify the canopy gap so that all values below 0, which demonstrates an oversaturation of canopy coverage, would just result in a value of 0.0000001. We are only interested in census block groups with a surplus of canopy coverage. We could not reclassify to just 0 because our normalization tool would not function with 0 as the minimum value. We also could not reclassify to 1 because the normalization tool was used across all indicators, some of which(e.g. air quality) had all values below 1.
6. By normalizing the data on a scale of 0-100, this results in the canopy cover gap score.All normalizations in the model use the same scale.

3.8 Base Scores

The third part of the index involves the other base scores: the Demographic, Air quality, Climate, and Health Score.

This is where the air quality and health data we calculated before is factored into the index model. The demographic and health scores required a few further steps because of the additional indicators within them. Each indicator was normalized in order to find the weighted average, which was then normalized again to get the respective demographic and health score. We included the individual indicator scores in the output since the results were already calculated to get the composite score and could prove useful for our client. This meant the following additional scores:

Demographic:

- Income score
- Employment score
- Race score
- Age score

Health:

- Acute respiratory score
- Asthma score
- Respiratory ER visit score
- Respiratory hospital admissions score

- Cardiovascular hospital admissions score
- Work loss score

For the climate and air quality scores, the values were only normalized to get the base score, as there are no separate indicators within them.

3.9 Intermediate Scores and Final Score

Then weights were added to each base score and the baseline gap score in order to get the final environmental equity score. The weights are customizable for our client. Between the base scores and the final score, intermediate scores can also be included. By finding the weighted average and normalizing the scores between any of the base scores, intermediate scores can be calculated. The two intermediate scores we included are a composite of the following:

- Priority score = health + demographic score
- Environmental score = air quality + canopy gap + climate score

The final environmental equity score is calculated through averaging all the base scores and normalizing again. The final score can be adjusted at any time by changing the baseline canopy target and the weights for each base score.

Results

1. Urban Tree Canopy Distribution

Tree canopy coverage differed widely across neighborhoods in Tacoma; the lowest value recorded was 4% canopy coverage while the highest value was 79 % and average canopy coverage citywide was 20%. Taking a look at different neighborhoods across the city assigned to the 8 sensor locations (Table 6), average tree canopy coverage was lowest (15%) in the census block groups assigned to the 6th and Baker sensor, while the census block groups assigned to the Pointe Woodworth and Tacoma Alexander sensors had the highest average canopy coverage (36%). The variability in canopy coverage within individual census block groups can be viewed in Figure 12.

Purple Air Sensor	Average Percent Canopy Coverage
6th and Baker	15%
Baltimore	20%

Jefferson	19%
Lexington	31%
Pointe Woodworth	36%
South Tacoma	19%
Tacoma Alexander	36%
Titlow	23%

Table 6. Average percent canopy coverage within census block groups assigned to Purple Air Sensors.

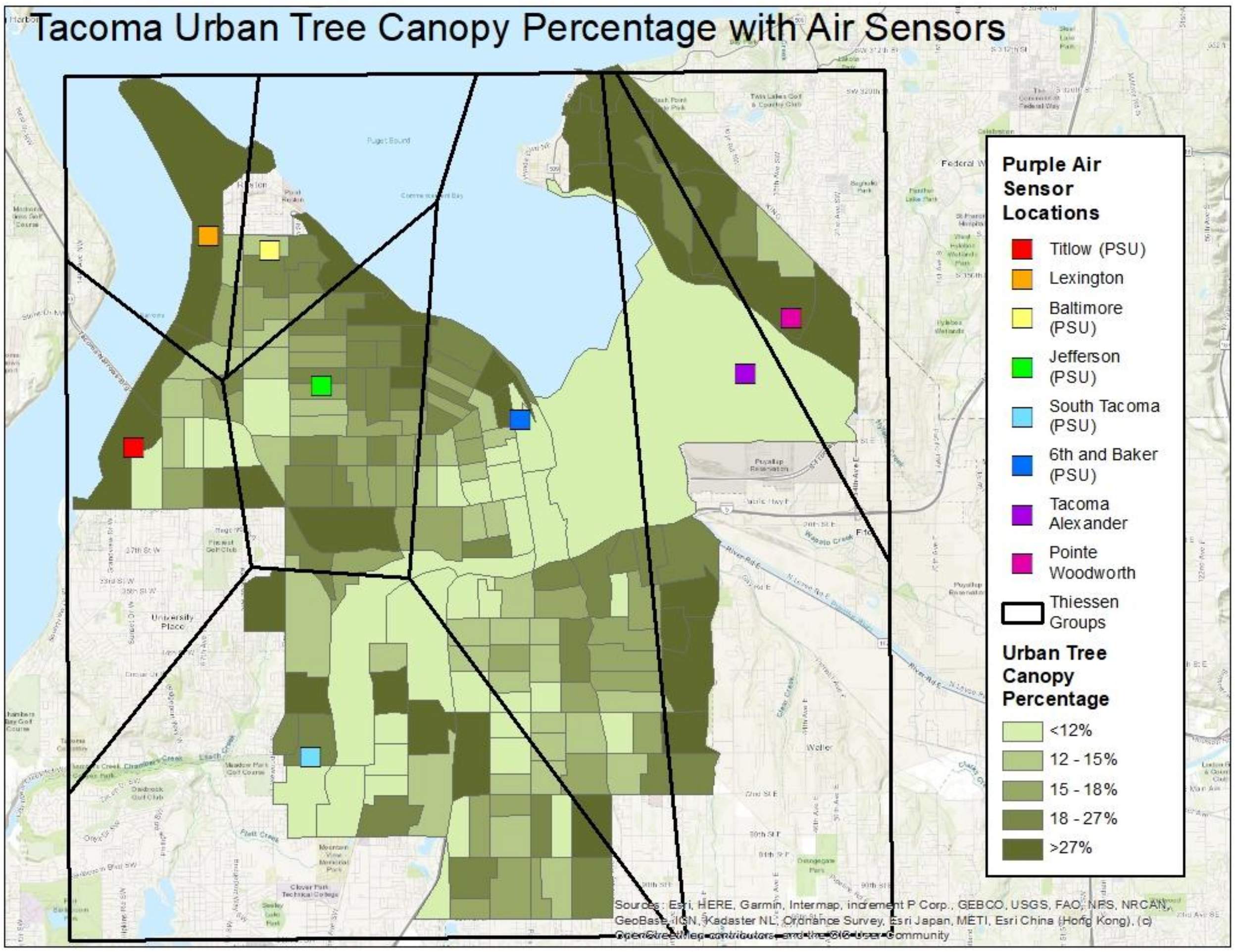

Figure 12. Urban tree canopy cover percentage within census block groups and Purple Air air quality monitor sensor locations. Black lines represent how each census block group was assigned to each Purple Air sensor by thiessen values in ArcGIS. With this, we are able to assess which census block groups experience the highest or lowest canopy coverage compared to $PM_{2.5}$ concentrations recorded at each sensor.

2. Air Pollution Distribution

After extracting the hourly $PM_{2.5}$ data recorded by Purple Air sensors we found that pollution levels vary widely across the city; average hourly $PM_{2.5}$ concentrations across the city ranged from 0.26 µg/m^3 to 133.86 µg/m^3 , and the average citywide was 9.69 µg/m^3. Throughout the year, the Titlow sensor recorded the lowest annual mean $PM_{2.5}$ concentrations per day at 7.5 µg/m^3, while the South Tacoma sensor recorded the highest values citywide at 11.5 µg/m^3, approximately 1.5 times higher than the Titlow sensor. (Table 7, Figure 13). The highest hourly $PM_{2.5}$ concentration recorded during the year was 1,326.03 µg/m^3 on December 11, 2019 at 0:00 and was recorded by the South Tacoma sensor.

Sensor	Mean	Median	Max	SD	SE	Variance
6th and Baker	9.74	6.07	81.61	10.05	0.11	101.05
Baltimore	8.08	5.08	122.54	8.58	0.09	73.69
Jefferson	8.91	5.43	77.54	9.58	0.10	91.79
Lexington	8.06	4.96	233.54	9.64	0.10	92.95
Pointe Woodworth	10.06	6.20	100.99	10.15	0.11	103.02
South Tacoma	11.52	5.72	1326.03	31.81	0.34	1012.11
Tacoma Alexander	9.70	5.39	372.76	11.30	0.12	127.62
Titlow	7.46	4.49	131.92	8.58	0.09	73.58

Table 7. $PM_{2.5}$ concentrations µg/m^3 recorded by Purple Air sensors, Tacoma WA 2019.

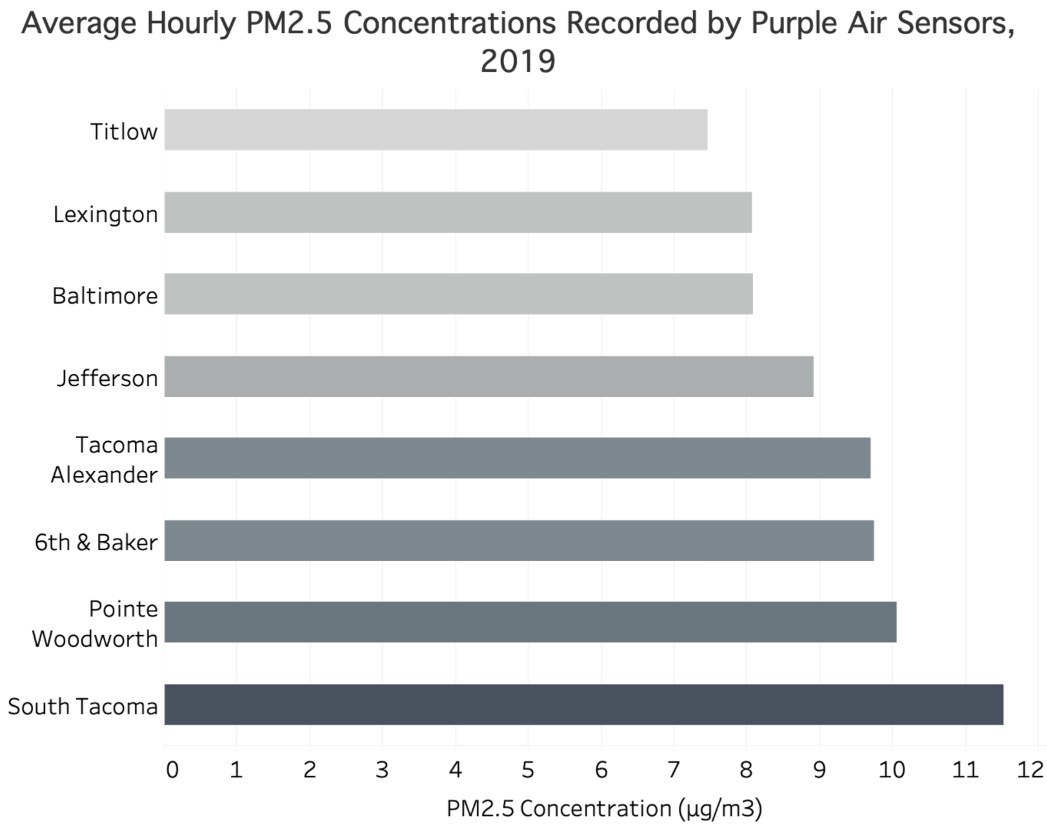

Figure 13. Average Hourly $PM_{2.5}$ Concentrations Recorded by Purple Air Sensors, 2019.

3. Considering Air Quality Standards

In 2016, the EPA updated its air quality standards for fine particle pollution to reflect new research into the acute and prolonged health effects associated with $PM_{2.5}$ exposure and strengthened the annual fine particle standard from 15 µg/m^3 to 12 µg/m^3. The annual fine particle standard is set to protect populations against the health effects associated with long and short term exposure to $PM_{2.5}$. (US EPA, 2016) A city area will meet the standard if a 3-year average of its annual $PM_{2.5}$ concentration is less than or equal to the 12 µg/m^3 level. Since we do not currently have the data for Purple Air sensors for the years prior to or after 2019, it is unknown at this time if the city meets the EPA air quality criteria using the Purple Air data for air quality analysis. However if we were to assume that these years had similar $PM_{2.5}$ levels, the city area would meet these standards.

The EPA also sets a 24-hour fine particle standard at 35 µg/m^3 to account for short-term health effects, such as increased hospital admissions for cardiac and respiratory symptoms, asthma attacks, bronchitis and restricted activity days from high peak $PM_{2.5}$ concentrations. A city will meet the 24-hour standard if the 98th percentile of 24-hour $PM_{2.5}$ concentrations in a year averaged over 3 years is less than or equal to 35 µg/m^3. The highest 24-hour concentration recorded within the 98th percentile in Tacoma was 34.22 µg/m^3. If we were to also assume the additional 2 years stayed within this range the city would meet the 24-hour standard as well.

However, we also wanted to take a look at what was happening in the parts of the city which fell into the 98th - 99th percentiles, and noticed that some city areas experience disproportionately higher occurrences of 24-hour $PM_{2.5}$ concentrations which exceed the EPA air quality standards. (Table 8) Census block groups assigned to the South Tacoma sensor experienced the highest total occurrences, (n = 688) when 24 hour $PM_{2.5}$ concentrations exceeded 35 µg/m^3, while census block groups assigned to the Lexington sensor recorded zero occurrences.

Purple Air Sensor	Total Daily Occurrences Which Exceeded 24-Hour Air Quality Standards
6th and Baker	310
Baltimore	9
Jefferson	114
Lexington	0
Pointe Woodworth	56
South Tacoma	688
Tacoma Alexander	56
Titlow	14

Table 8. Total Occurrences In Which Daily Average $PM_{2.5}$ Concentrations Exceeded EPA 24-Hour Air Quality Standards (35 µg/m3).

Figure 14 also reflects the variability in $PM_{2.5}$ levels distributed across the city at a given time. The chart shows the average $PM_{2.5}$ concentrations recorded by the sensors during the month of January 2019. The graph reflects similar pollution level oscillations across sensor locations throughout days of the month, but there are distinct differences in the quantities of pollution exposure. For example on January 1, 2019, the South Tacoma sensor recorded a daily average of 60.31µg/m^3, while the Lexington sensor recorded an average of 32.80 µg/m3, a difference of

27.51 μg/m^3. Overall, the monthly mean of the South Tacoma sensor area was 1.6 times higher the concentration level of the Lexington sensor area.

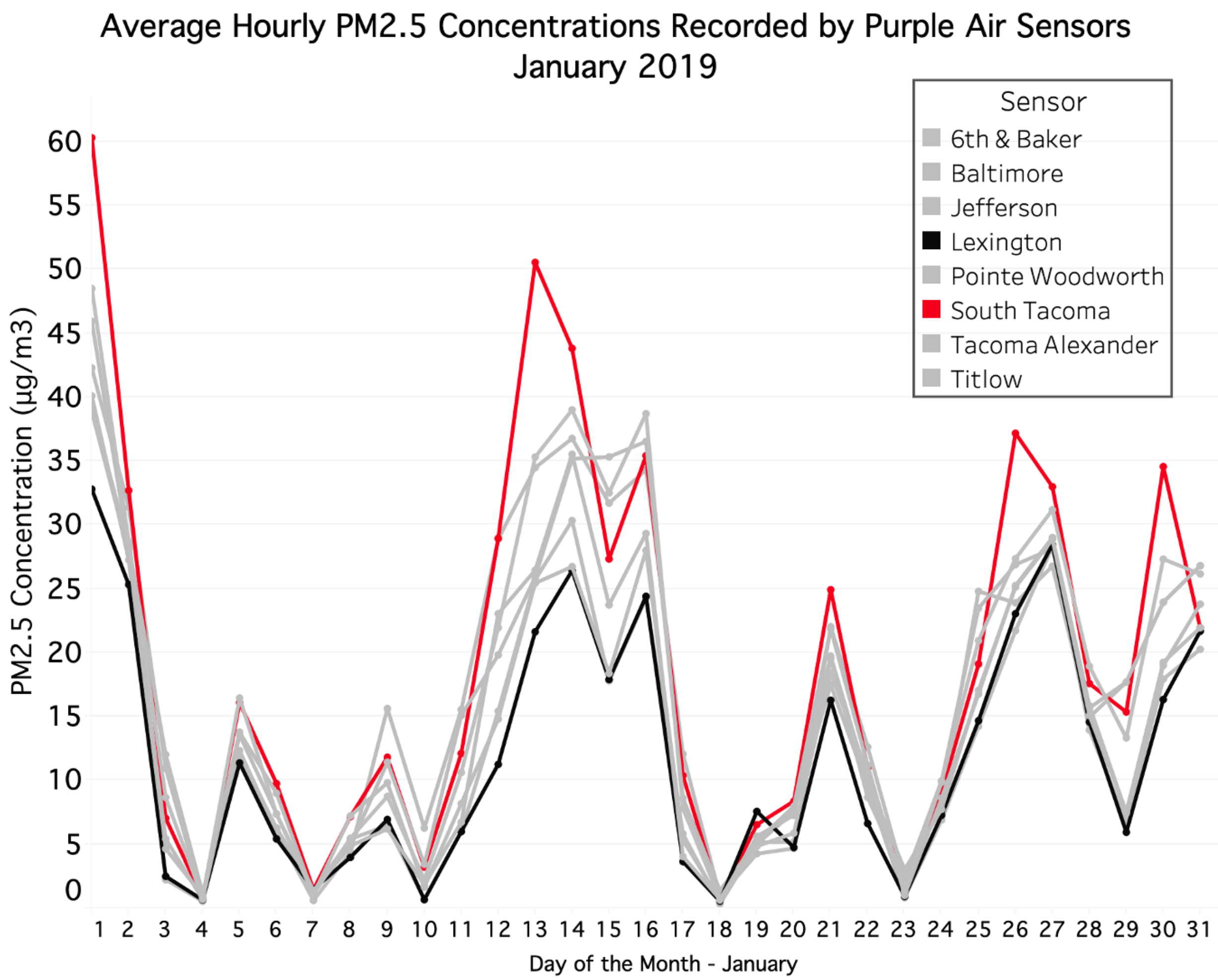

Figure 14. Average hourly $PM_{2.5}$ concentrations, January 2019.

4. Seasonal Variability in $PM_{2.5}$ Concentrations

Average $PM_{2.5}$ concentrations are at their peak levels during the late Autumn and Winter months. Average $PM_{2.5}$ concentrations citywide were 19.18 μg/m^3 in November, 17.03 μg/m^3 in December and 15.47 μg/m^3 in January. Concentrations were lowest in Spring, Summer and early Autumn months, ranging from 4.47 μg/m3 in May, 4.22 μg/m^3 in June, and 4.27 μg/m^3 in September. These seasonal patterns can be seen in Figure 15. Higher pollutant levels occur in Autumn/Winter months due to a combination of atmospheric effects and seasonal weather patterns which lower boundary layer heights. As a result, air pollution is trapped at lower altitudes increasing the risks of human exposure. Denser, colder air also traps smog from industrial, transportation and heating uses. (Liao, et al. 2017)

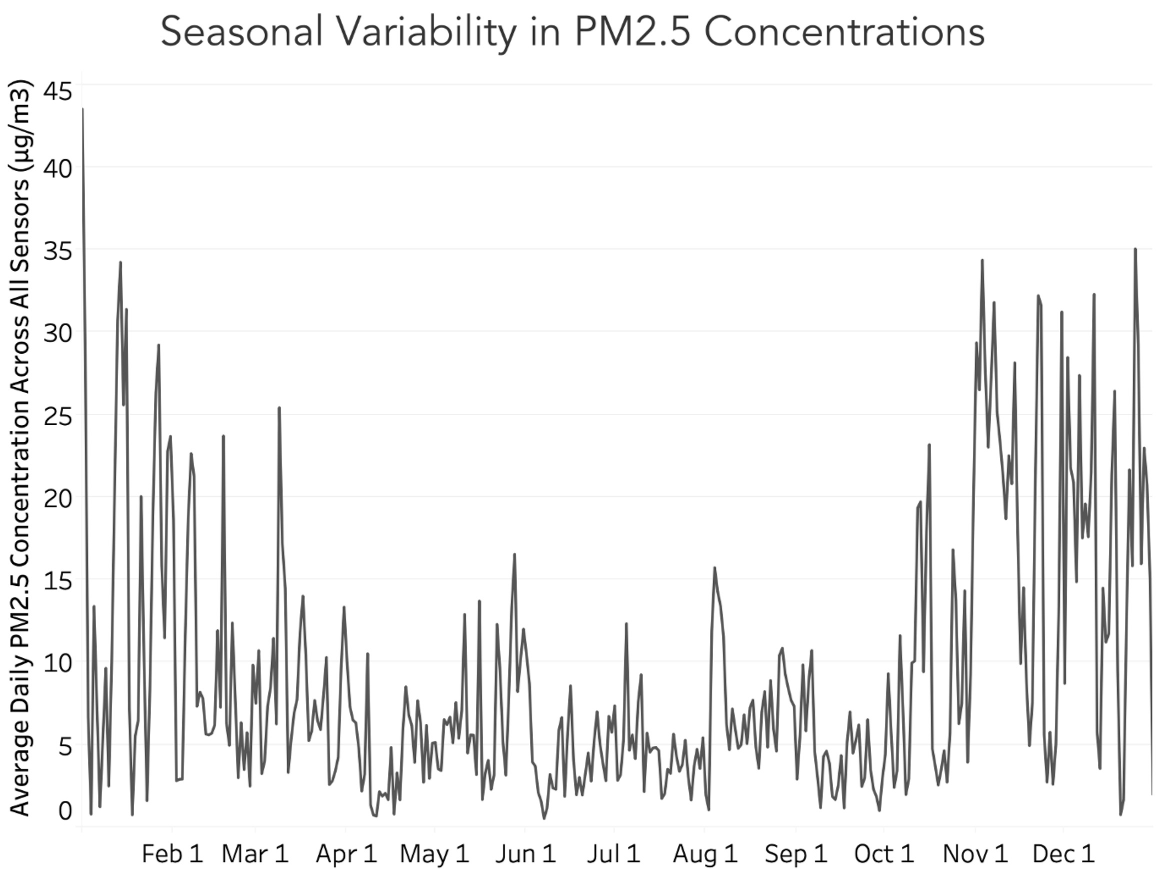

Figure 15. Average daily $PM_{2.5}$ concentrations recorded citywide, 2019.
$PM_{2.5}$ levels peak during the months of January - February, November -December, and lowest during April - September.

5. Daily Pollutant Removal

Hourly air pollutant removal was factored based on tree leaf surface area, average wind speeds (m/s), precipitation and particle resuspension rates. Figure 17 shows the relationships between precipitation, wind speed and pollutant levels which affected hourly pollutant removal throughout the month of December 2019. Pollutant removal increased when pollutant levels and wind speeds increased and decreased when precipitation increased.

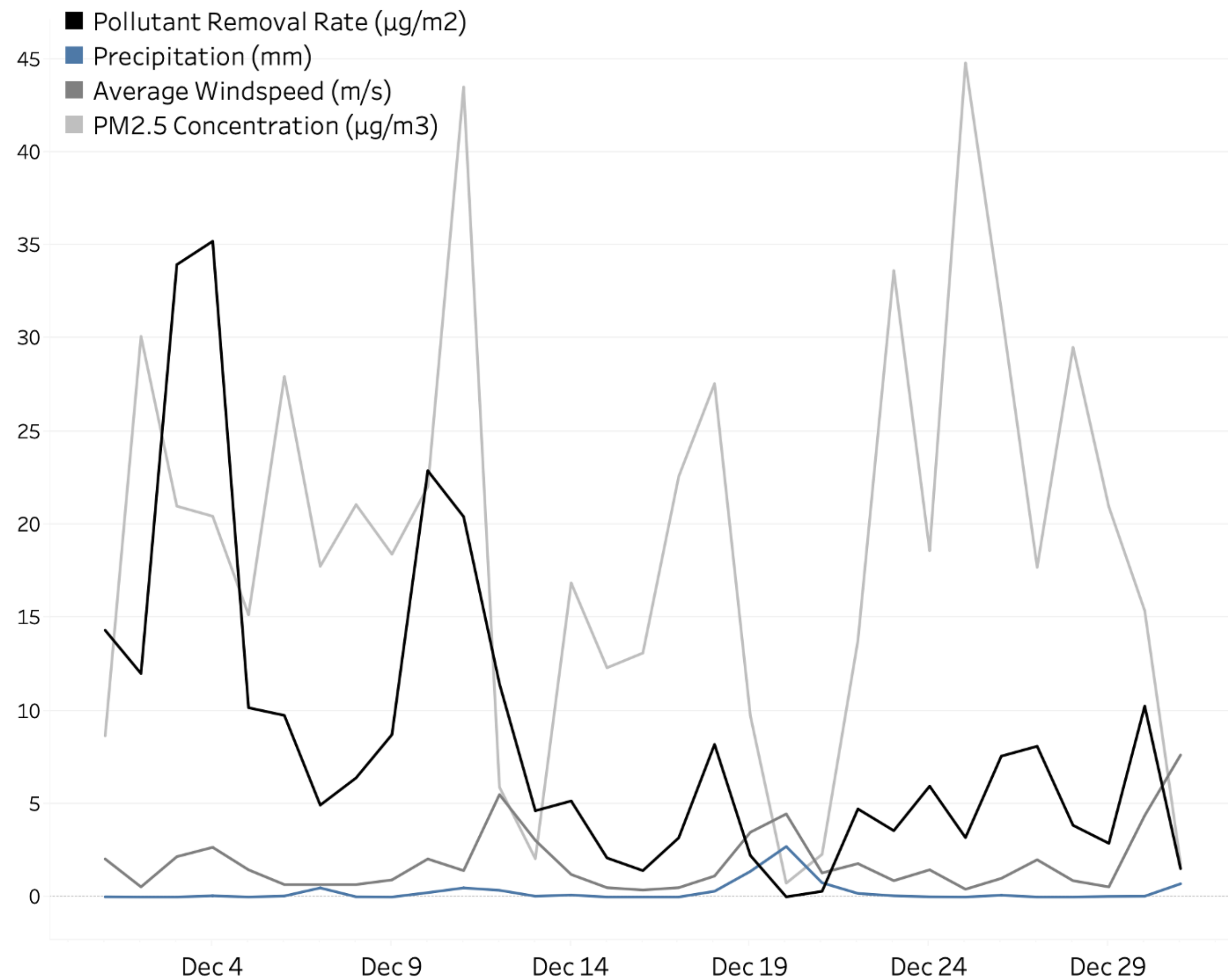

Figure 16. Average hourly pollutant removal rates in relation to precipitation, average wind speed per hour, and pollutant levels in December 2019.
Pollutant removal rates are shown by the black line, precipitation is represented by the blue line, wind speed is shown by the dark grey line, and pollutant levels are represented by the light grey line.

This gives us an estimation for the amount of fine particulate matter which is intercepted by leaf surface area as it mixes with the local atmosphere in urban environments per hour. We factored the minimum, average and maximum pollutant removal values based on the deposition velocity ranges factored by Nowak et. al, 2013 (Table 3). The boxplot in Figure 18 shows the range of hourly pollutant removal µg/m^2 based on the 3 rates of deposition velocity. The median removal amount varied from 10 µg/m2/h for minimum deposition velocity rates, 75 µg/m^2/h for average deposition velocity rates and 151 µg/m^2/h for maximum deposition velocity rates.

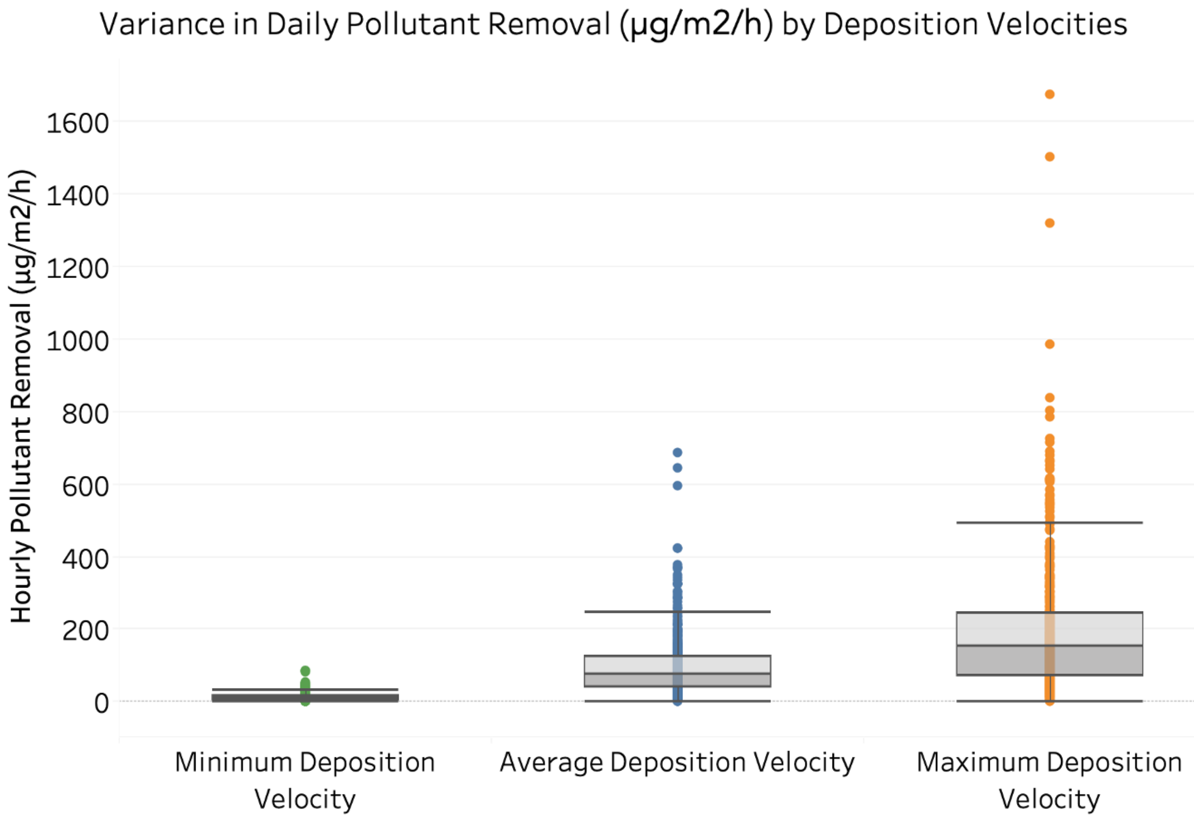

Figure 17. Boxplot showing the range of hourly pollutant removal rates based on deposition velocity. Graph includes values within the 98th percentile.

6. Air Quality Improvement and Concentration Change

Hourly $PM_{2.5}$ concentration change was factored by first finding the hourly air quality improvement; the ratio between the mass of air pollutant removed within the tree canopy coverage area of each census block group and the mass of air pollutant that existed within the area. We factored the hourly air quality improvement for minimum, average and maximum deposition velocities. The median improvement ratio recorded per hour was: 0.08% for minimum deposition velocity values, 0.6% for average deposition velocity values, and 1.17% for maximum deposition velocity values.

Once we factored the hourly air quality improvement, we applied this to the pollutant concentration values to find the total mass of $PM_{2.5}$ removed per hour from leaf surface area interception. Figure 19 shows the range of hourly concentration change; median hourly concentration change 0.006 μg/m^3 for minimum deposition velocity rates, 0.042 μg/m^3 for average deposition velocity rates, and 0.084 μg/m^3 for maximum deposition velocity rates.

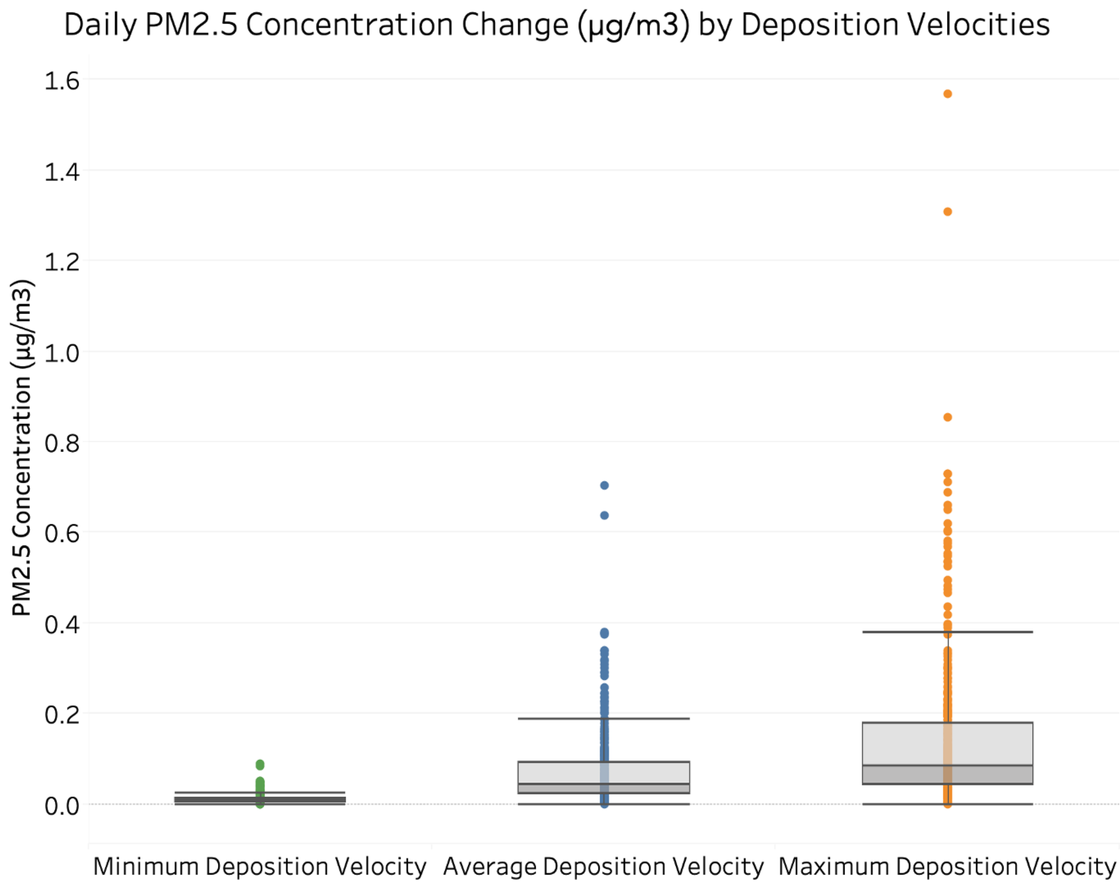

Figure 18. Average concentration change applying minimum, average, and maximum deposition velocity ranges.
Graph includes values within the 98th percentile.

For our analysis quantifying the total annual pollutant removal and hourly concentration change, we used the values factored from the minimum deposition velocity range as these values are comparable to those quantified in Nowak et al. (2013) which found hourly concentration change ranges from 0.006 μg/m^3 to 0.020 μg/m^3 within U.S. cities. Figure 20 shows the distribution of hourly concentration change values using the minimum deposition range. We also felt our approach should incorporate a conservative estimate as other research which applied the UFORE model found that the levels of urban tree uptake of PM2.5 was generally overestimated using this type of deposition-based evaluation. (Nemitz, et al., 2020)

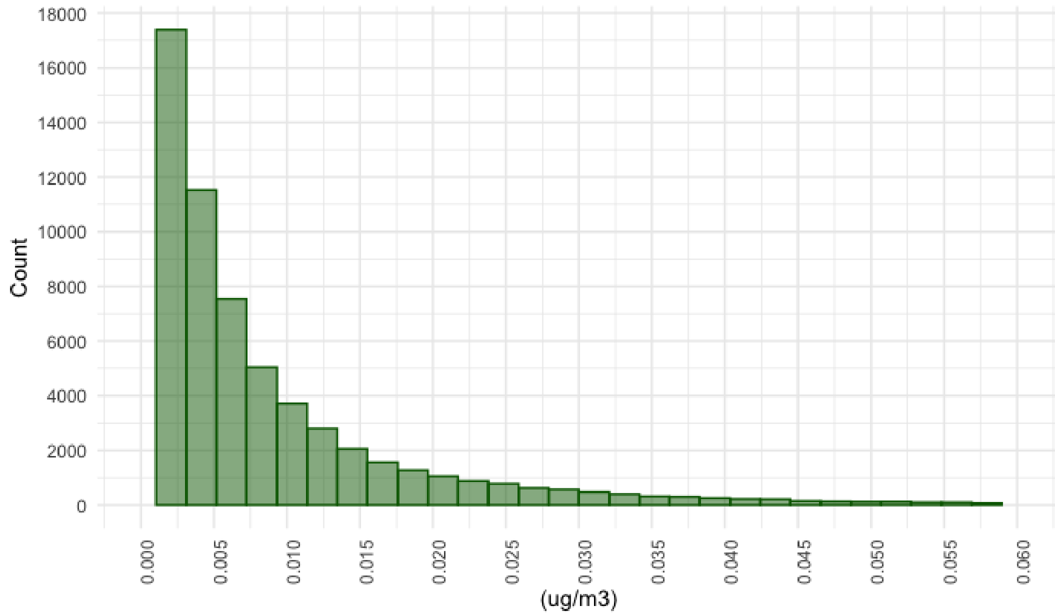

Figure 19. Histogram showing the distribution of hourly concentration change using minimum deposition velocity ranges.
Graph includes values within the 97th percentile.

7. Effects of Tree Canopy Coverage on Pollutant Removal

Hourly concentration change and annual pollutant removal was highest in city areas with the highest tree canopy coverage. Daily concentration change averaged over the year ranged from 0.0044 µg/m^3 for census block groups which had less than 12% tree cover, 0.0069 µg/m^3 for areas with 12% - 15% tree cover, 0.0088 µg/m^3 for areas with 15% - 18% tree cover, 0.010 µg/m^3 for areas with 18% - 27% tree cover, and 0.0198 µg/m^3 for areas with over 27% tree cover. Census block groups that had over 27% tree canopy removed 4.5 times more particulate matter per day compared to census block groups which had the lowest amount of tree canopy below 12%. Census block groups which had the median amount of tree cover between 15% - 18%, removed 1.8 times more particulate matter than areas with the lowest tree canopy areas. These ranges can be viewed in Figure 21 and Table 9.

Annual pollutant removal was calculated as the annual sum of the hourly air pollution removal times the tree cover percent per city area. Annual air pollution removal ranged from 2.4 x 10^{-06} lbs/m^2 for areas with less than 12% tree cover to 1.1x10^{-04} lbs/m^2 for areas with over 27% tree cover. Applied to the average land area m^2 of city areas grouped by the Purple Air sensor locations, this ranges from about 18 lbs (6th and Baker area) to 132 lbs (Lexington area) per year. Areas with the highest tree cover remove 4.6 times more particulate matter per m^2 per year than areas with the lowest canopy, while areas with the median amount of tree canopy removed 2.61 times more particulate matter per m^2.

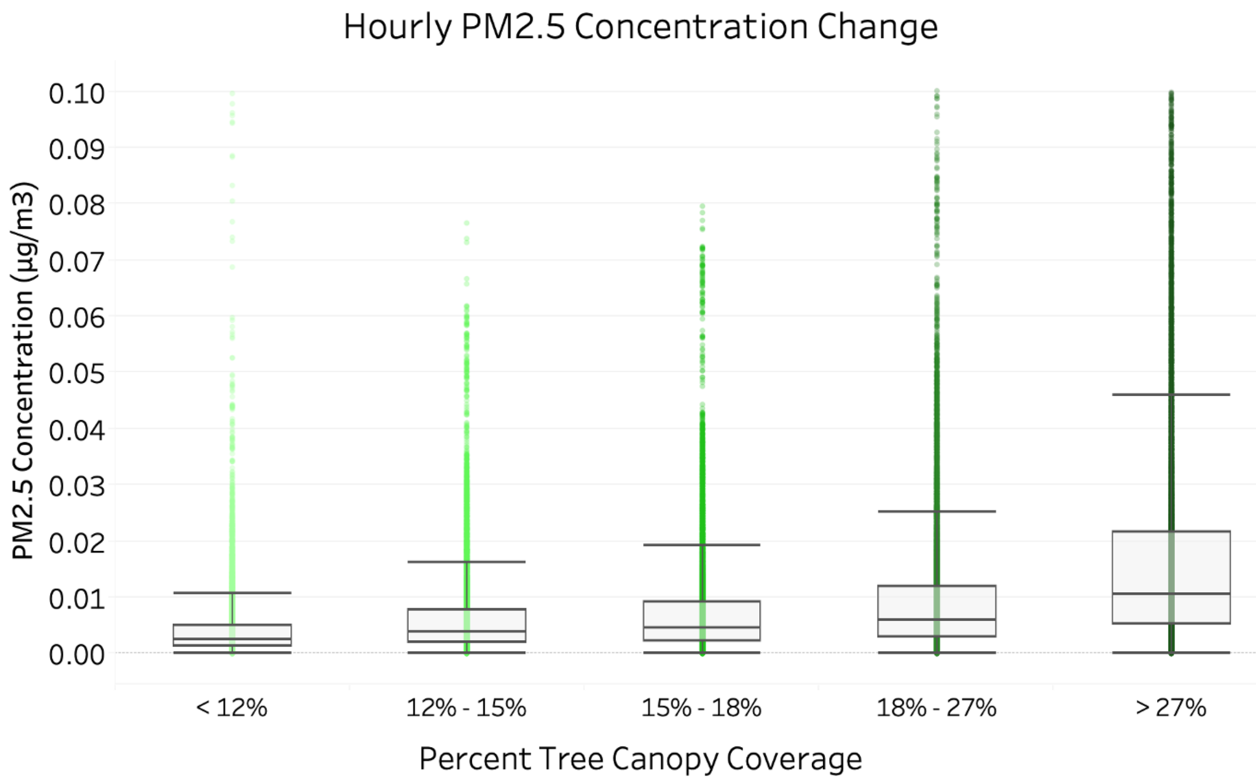

Figure 20. Mean hourly $PM_{2.5}$ concentration removal in relation to percent tree canopy coverage within census block groups.

Tree Canopy Coverage	Hourly $PM_{2.5}$ Concentration (µg/m³)	Hourly $PM_{2.5}$ Concentration Change (µg/m³)	Daily $PM_{2.5}$ Concentration Change (µg/m³)	Annual $PM_{2.5}$Removed (lbs/m²)
<12%	10.28	0.0042	0.0044	2.4x10^-05
12% - 15%	9.55	0.0062	0.0069	3.5x10^-05
15% - 18%	9.46	0.0075	0.0088	4.2x10^-05
18% - 27%	9.58	0.0098	0.01	5.6x10^-05

> 27%	9.56	0.0194	0.0198	1.1x10^-04

Table 9. $PM_{2.5}$ concentration changes by hour, day, and year in relation to tree canopy coverage within census block groups.

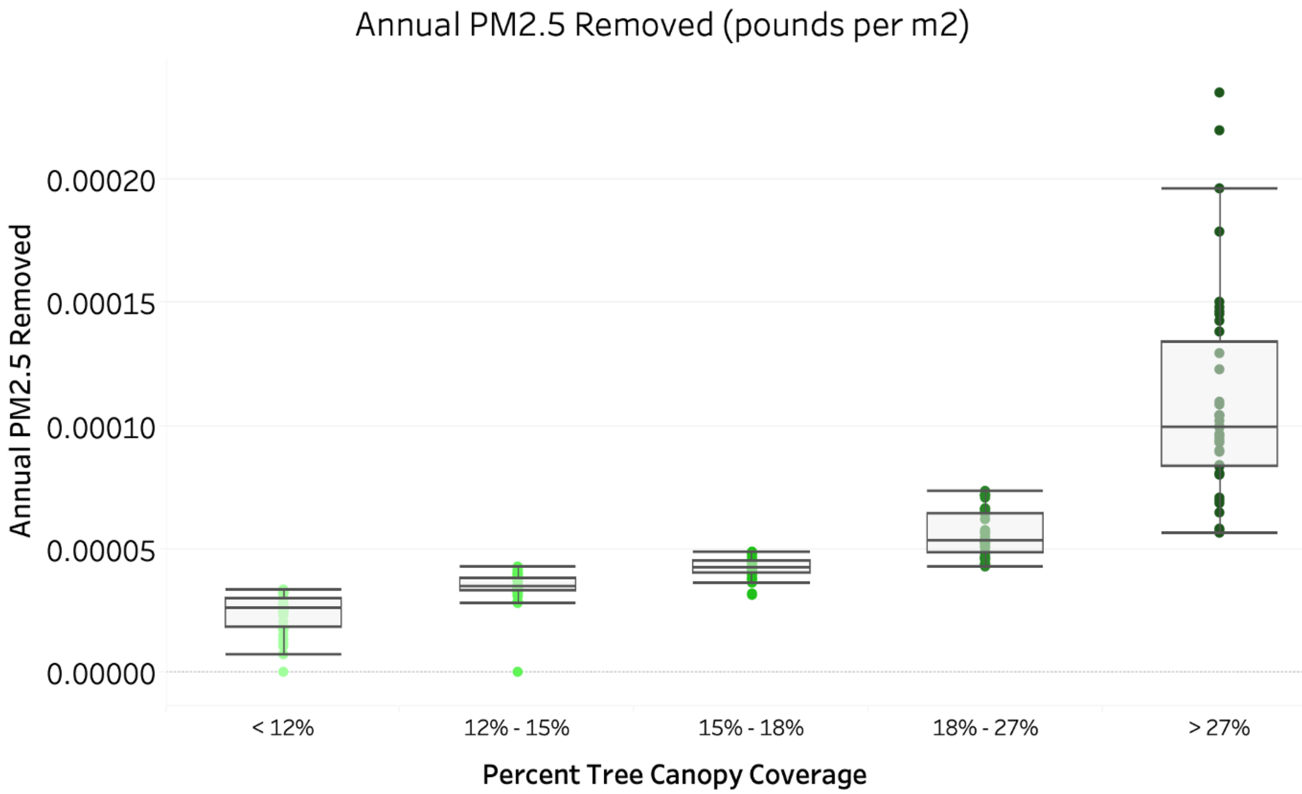

Figure 21. Annual $PM_{2.5}$ Removed (lbs per m^2) by percent tree canopy cover in census block groups

Taking a look at the city areas grouped by the Purple Air sensors they were assigned to, we found that census block groups within the Pointe Woodworth area experienced the most air quality improvement; daily concentration change averaged 0.018 $\mu g/m^3$ over the year and annual particulate matter removed averaged $1.05x10^{-04}$ lbs/m^2. While census block groups within the 6th and Baker area experienced the least air quality improvement; daily concentration change averaged 0.007 $\mu g/m^3$ over the year and annual particulate matter removed $4.16x10^{-05}$ lbs/m^2. Areas within the Pointe Woodworth sensor assignment experienced 2.6 times improved air quality than that of the 6th and Baker area. These ranges are reflected in Figure 23.

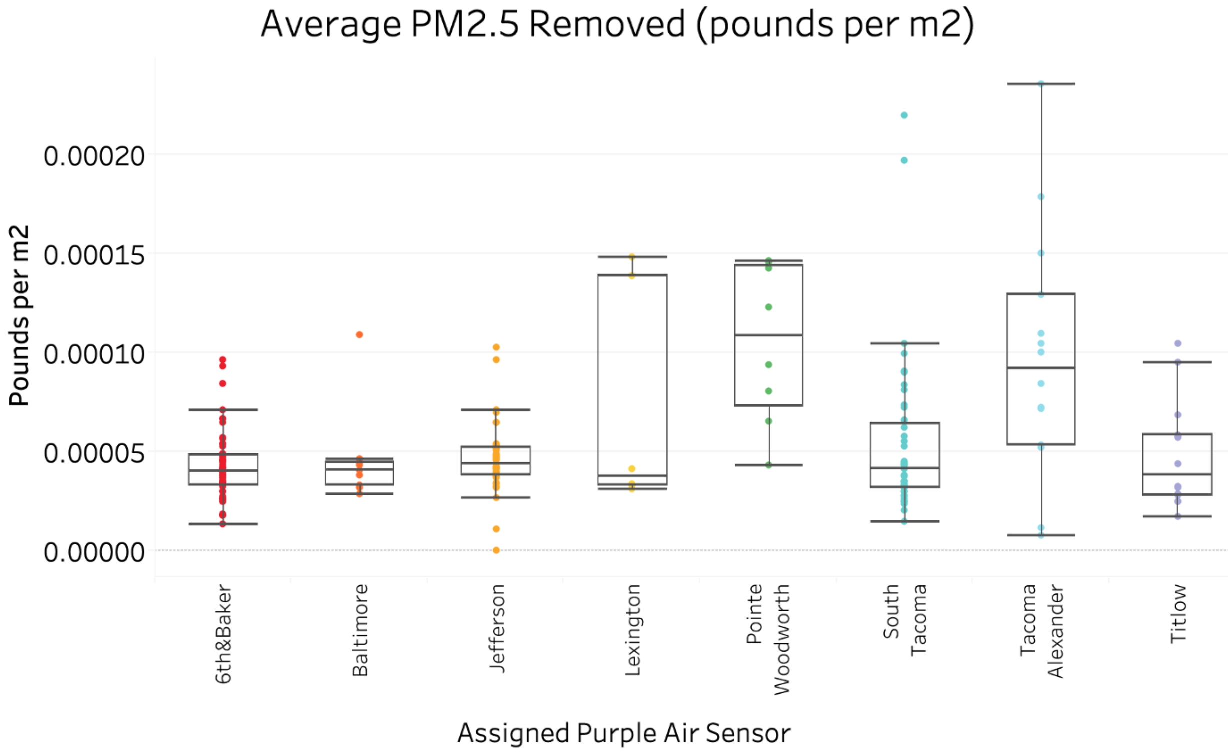

Figure 22. Annual $PM_{2.5}$ removed within each census block group area assigned to Purple Air sensors

8. Effects of Ambient Pollution Levels on Pollutant Removal

We also explored how hourly and annual pollutant removal was influenced by existing ambient air pollution levels prior to leaf surface area deposition. Daily concentration change averaged over the year ranged from 0.003 μg/m^3 for census block groups which recorded the least daily pollution levels of less than 3.17 μg/m^3 over the year, to 0.026 μg/m^3 for census block groups which recorded the highest daily pollution levels of more than 15.03 μg/m^3 over the year. Census block groups that had the highest daily pollution levels removed 8.4 times more particulate matter per day compared to census block groups which had the lowest ambient pollution levels. This reflects the concentration change formula; the more hourly ambient pollution, the more improvement we expect to see since the formula incorporates the ambient pollutant levels minus the ratio of air quality improvement. This range is reflected in Figure 24.

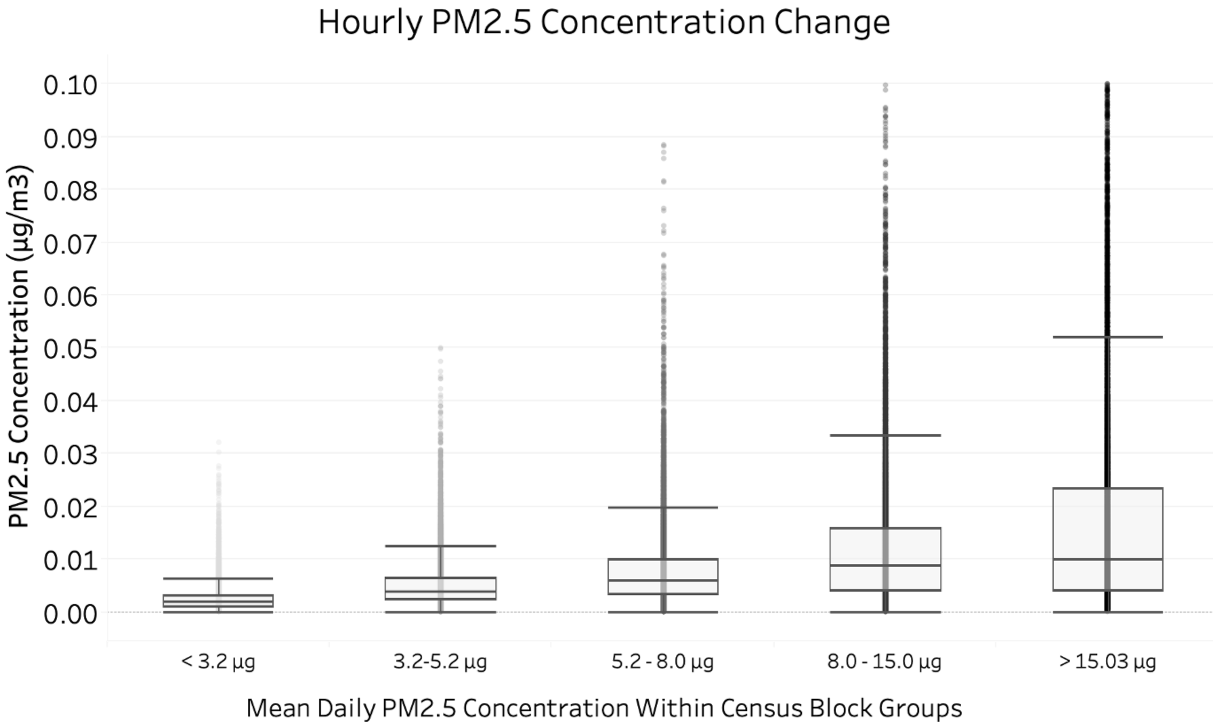

Figure 23. Hourly concentration change within census block groups, grouped by the annual mean of daily $PM_{2.5}$ levels within each census block group area.

In taking a look at the annual removal of particulate matter within these same daily pollutant level classes, (refer to Figure 25) we found that there was no significant relationship (less than a 9.72×10^{-10} difference) between the amount of annual air pollution removal to daily ambient air pollution, which suggests that tree canopy cover is the primary variable affecting pollutant removal in our analysis.

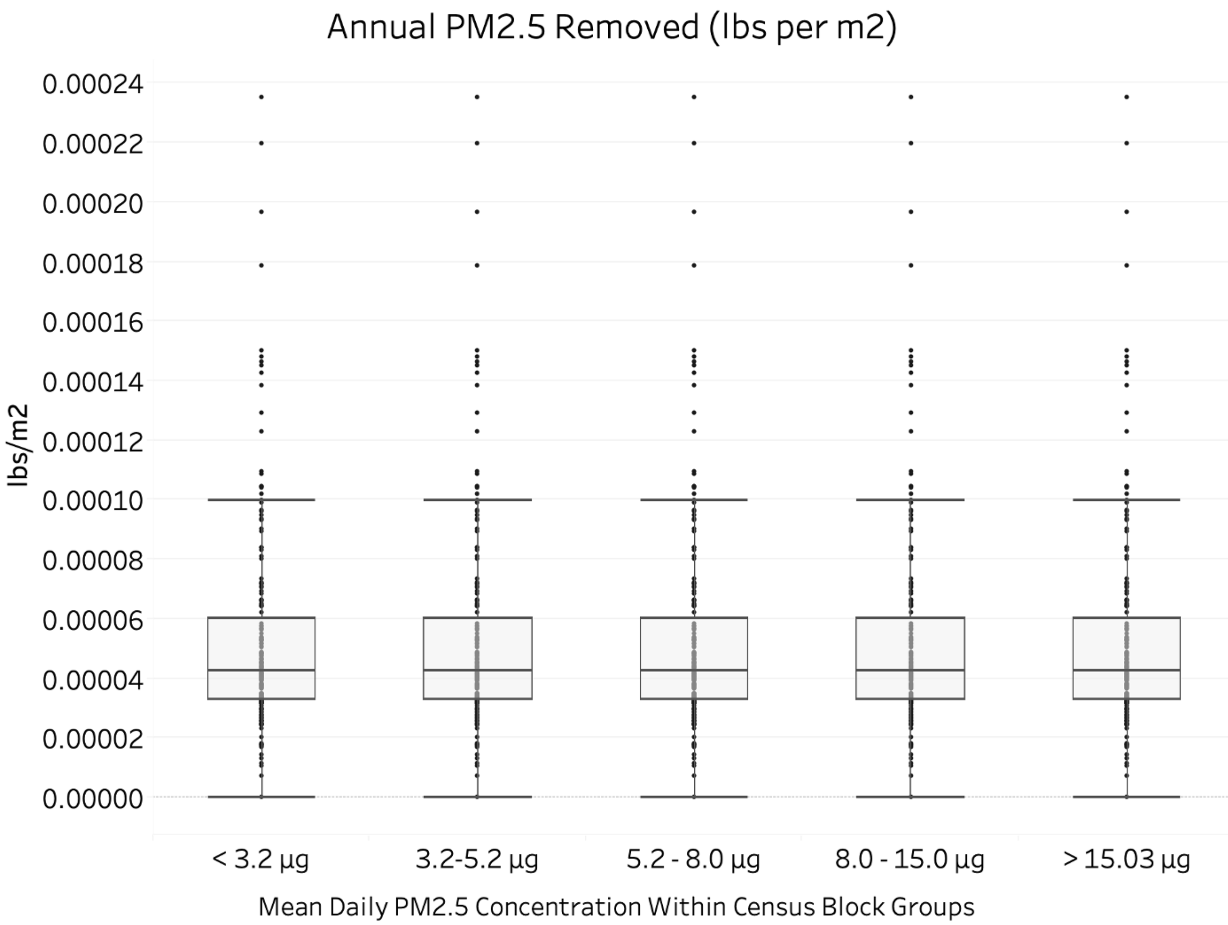

Figure 24. Annual $PM_{2.5}$ removal within census block groups, grouped by the annual mean of daily $PM_{2.5}$ levels within each census block group area.
There was no significant difference between each classification.

The range of total daily and annual air quality improvement within census block groups citywide can be viewed in Figure 26.

Air Quality Maps

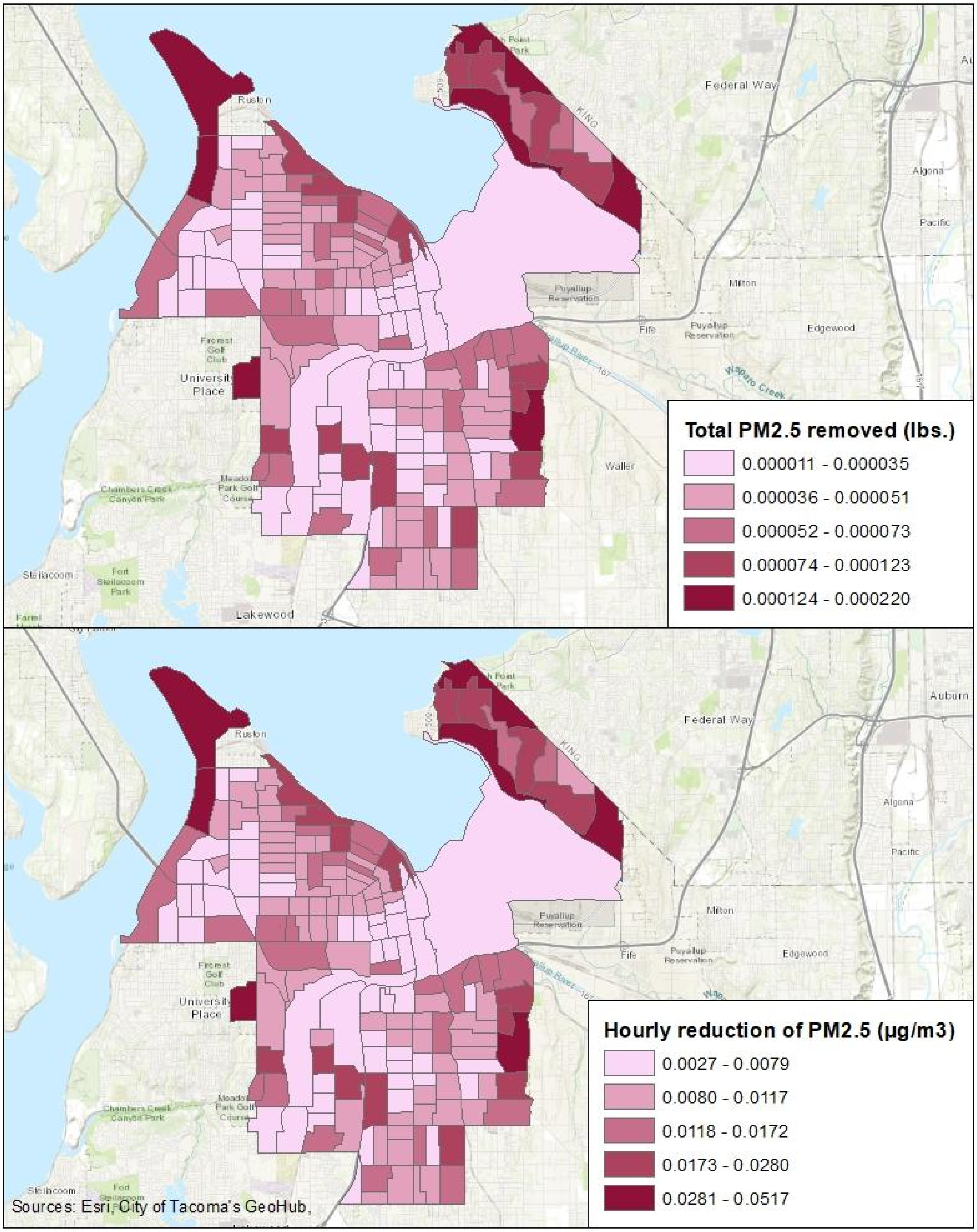

Figure 25. Average particulate matter removed per day and year (m^2) within census block groups.

9. Health Incidence Reductions

We used the annual daily average of ambient $PM_{2.5}$ concentrations per census block group as our baseline scenario, and the annual daily average of air quality improvement (the difference between the daily ambient levels minus the daily concentration change) to find the estimated health incidence reductions using the Benmap program. Health incidences were factored by the population of the affected age groups for each health effect. We found the range of reductions varied across city areas which differed in tree canopy coverage. Refer to Figures 25, 26, and Table 10.

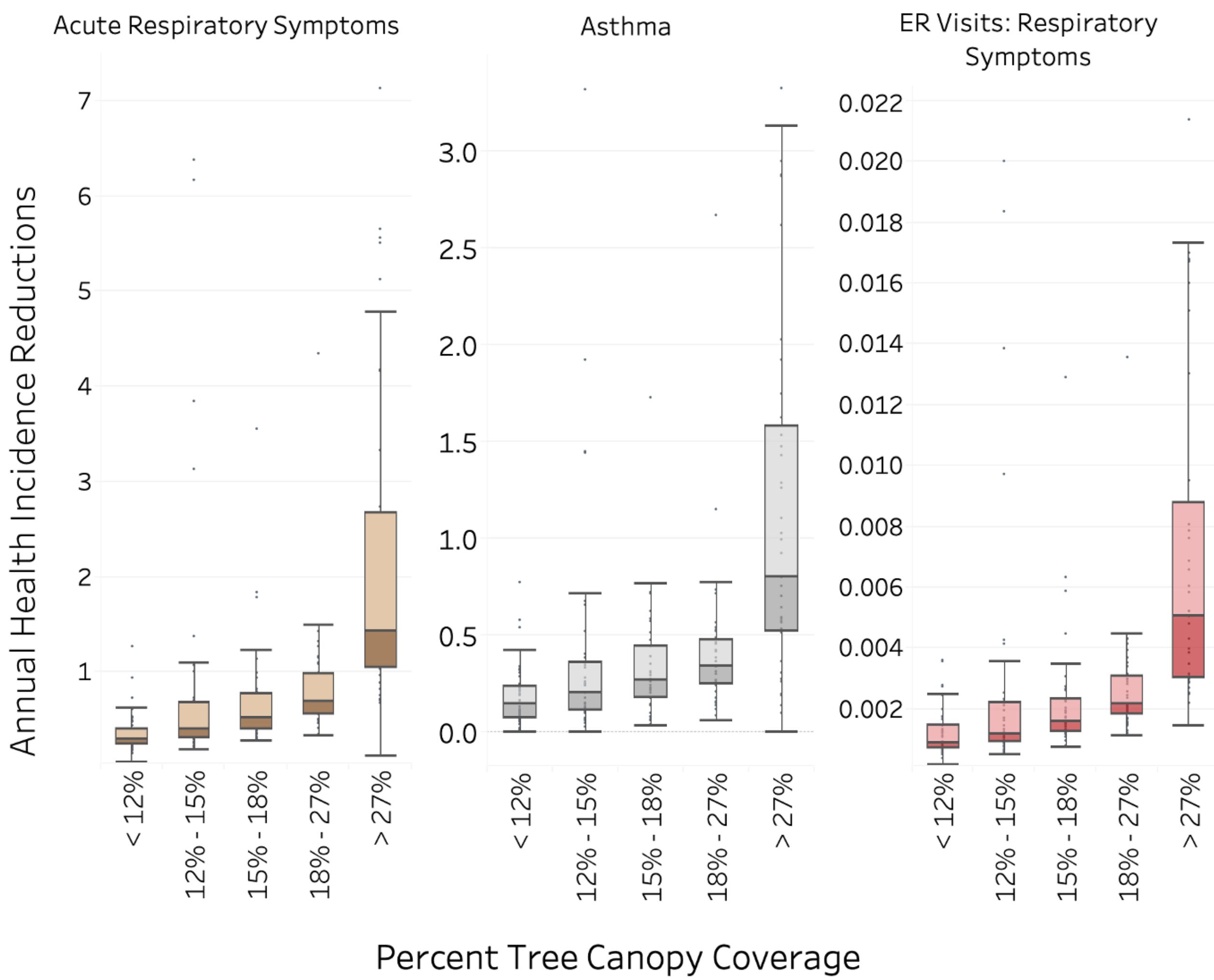

Figure 26. Annual health incidence reductions by tree canopy coverage in census block groups part 1.

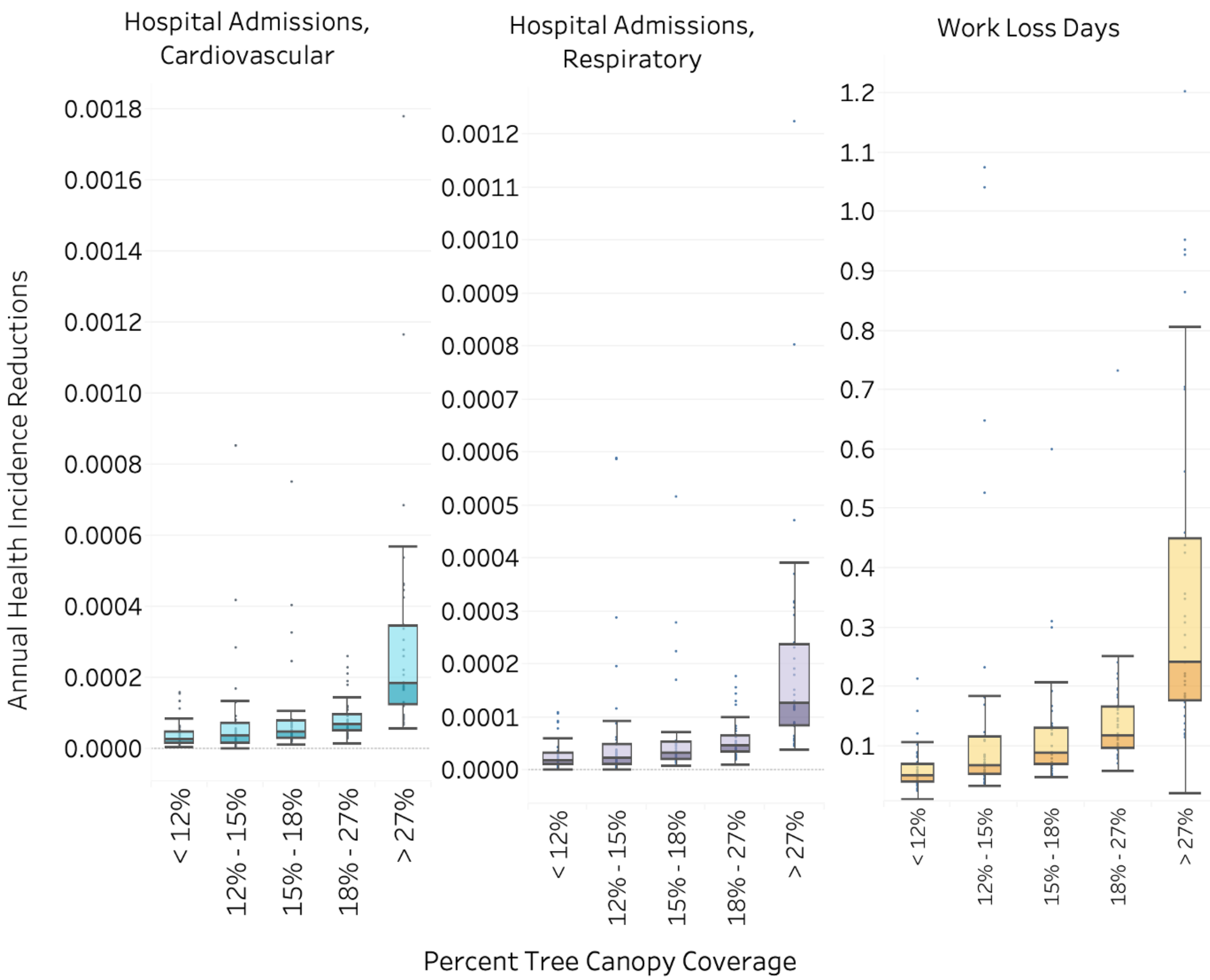

Figure 27. Annual health incidence reductions by tree canopy coverage in census block groups part 2.

The average reduction of acute respiratory symptoms per census block group population per year varied from 0.37 for areas with less than 12% canopy cover, to 2.19 for areas above 27% canopy. The average reduction of asthma symptoms varied from 0.15 to 1.15 per census block group. Average reduction of ER visits for respiratory symptoms ranged from 0.0011 to 0.0073 per census block group. Average hospital admissions for cardiovascular symptoms ranged from 0 to 0.0003. Hospital admissions for respiratory symptoms ranged from 0 to 0.0002. And average reduction of work loss days (days in which the population was ill and could not work due to symptoms caused by $PM_{2.5}$ exposure) ranged from 0.06 to 0.37. City areas that had the highest canopy cover experienced much higher health improvement rates with the lowest canopy cover; approximately 6 - 8 times more reductions in health incidences.

Citywide, the total annual reduction in acute respiratory symptoms was 202.23, total reduction in asthma symptoms was 99.6, ER visits for respiratory symptoms was 0.65, hospital admissions for cardiovascular symptoms was 0.024, hospital admissions was 0.016, and work loss days was 34. These numbers are quite small in comparison to the city population of 260,584 (affecting less than 0.007 of the population on average) and it is unknown how accurate these estimates are in relation to actual public health records.

But our analysis was able to factor how higher amounts of tree canopy cover citywide are more 4.5 times more effective in reducing air pollution levels and 6-8 times more effective in reducing associated health effects than areas with low canopy cover.

Tree Canopy Coverage	Acute Respiratory Symptoms	Asthma	ER Visits: Respiratory Symptoms	Hospital Admissions: Cardio	Hospital Admissions: Respiratory	Work Loss Days
< 12 %	0.37	0.15	0.0011	0.0000	0.0000	0.06
12% - 15%	0.92	0.41	0.0029	0.0001	0.0001	0.15
15% - 18%	0.70	0.34	0.0023	0.0001	0.0001	0.12
18% - 27 %	0.87	0.43	0.0027	0.0001	0.0001	0.15
> 27%	2.19	1.15	0.0073	0.0003	0.0002	0.37

Table 10. Average health impact reductions in relation to tree canopy cover within census block groups.

10. Equity Index Results

The results are divided into the urban tree canopy, base, intermediate, and final scores maps. All the maps were displayed through color gradient with five classifications, but not all the legends are the same. Refer to the table below to determine how to interpret each map.

Map	Color	Interpretation
Urban tree canopy	Light green	Low percentage
	Dark green	High percentage
Base scores and Intermediate scores	Light	Low score (less priority)
	Dark	High score (more priority)
Final score	Green	Low score (less priority)
	Red	High score (more priority)

Table 11. How to interpret the urban tree canopy and each score map.

We compared the results from each score with the urban tree canopy coverage (UTC) map in figure 28. This map shows more exact canopy cover percentages per census block group than figure 12. Generally, the census block groups with the lowest canopy coverage were in the lower half of Tacoma, excluding some of the groups on the edge of the city. These central areas tended to be, or neighbor industrial or commercial areas according to PlanIT Geo's Urban Tree Canopy by Land Use map (LU map)(see figure B1).

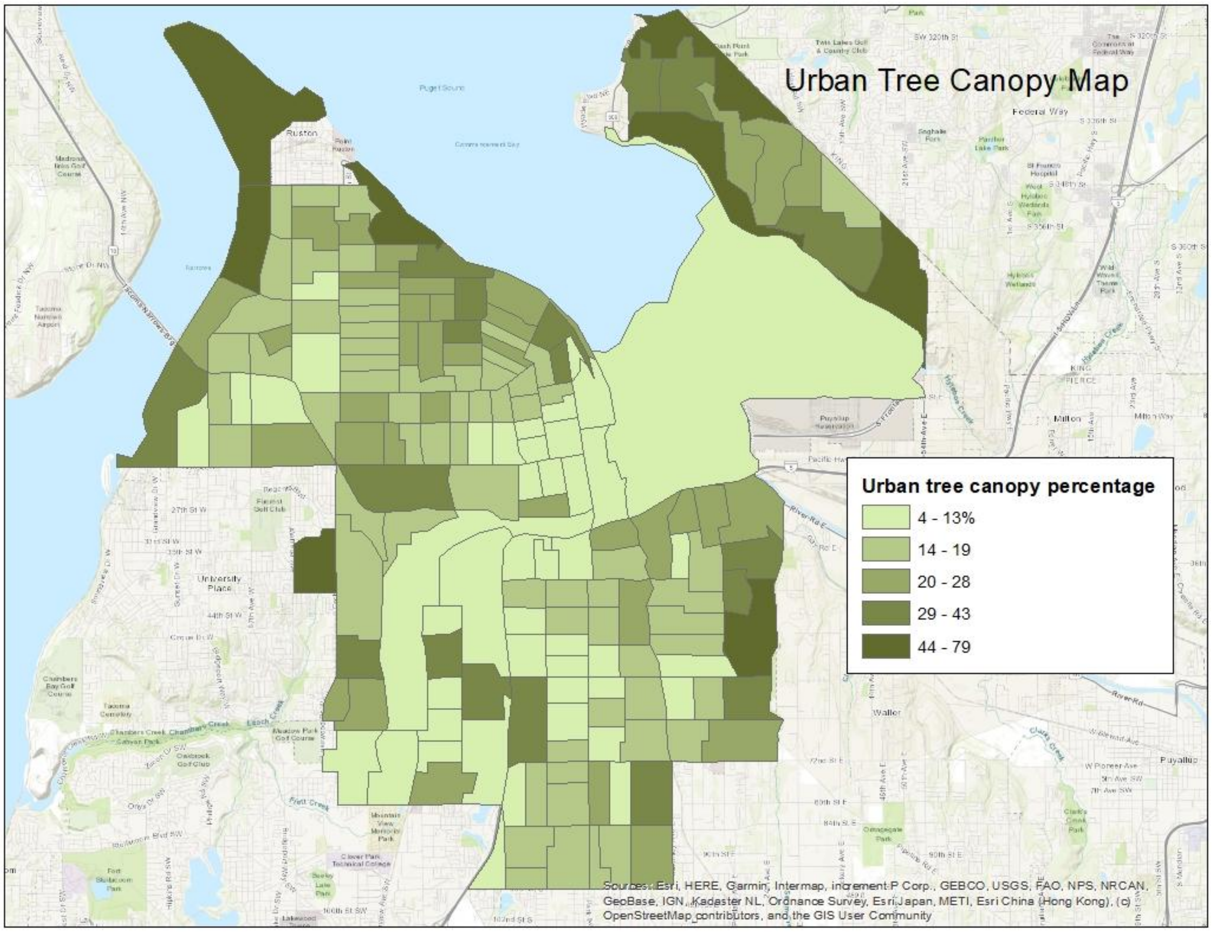

Figure 28. Tacoma urban tree canopy percentage map.
This map shows the urban tree canopy coverage percentage for each census block group based PlanIT Geo's tree canopy assessment report in 2019.

10.1 Canopy Gap Score

The first score to be developed was the canopy gap score, as shown in figure 29. The areas that are darker purple show census block groups which require additional canopy cover to reach the city's canopy baseline target of 40%. Thus, these census block groups have a higher canopy gap. The areas that are dark purple on the canopy gap score map correlate to areas with light green on the UTC map, and the relationship is the same for the light purple and dark green areas. The maps are very similar. After all, high canopy coverage means less of a canopy gap. Any differences between the two maps can be attributed to the canopy adjustment factor and differences in population density between census block groups.

We included the canopy adjustment factor because initially we assumed that low population census block groups would be more rural and have more space for trees. However, we also had to consider the fact that commercial areas would have low population densities but less PPA due to impermeable surfaces. We did not have a Tacoma PPA by census block group dataset to use as an additional indicator to our model.

Therefore, we developed a second map of the canopy gap score that also considered the climate score (figure 30). We used the climate score as a proxy for urbanized areas because higher temperatures tended to mean more heat absorptive and impermeable surfaces, so a higher score meant more less possible planting areas. We first identified the commercial census block groups in Tacoma from the LU map (figure B1). By referencing temperature and population density in those groups, we determined the general range of those attributes through observation. We set a new condition that all census block groups with a population density below 4,000 ppl/km^2 and climate score below 79 would have their canopy target adjusted by 0.5. More than just the scores in commercial areas had shifted; most census block groups in Tacoma now had less of a canopy gap. We tried to determine which map better reflected the UTC map and PlanIT Geo's Urban Tree Canopy, Possible Planting Area and Unsuitable Areas map (figure B2). We assume that figure 29 was more accurate, but it is difficult to determine the correct degree of canopy gap by eye. Still, we decided to use the original canopy gap score for the rest of our analysis.

We conjecture that even if we used statistical analysis instead of observation to capture the average population density and temperature in commercial census block groups, the high degree of variability would still prevent an accurate capture of these areas. This creates a lack of clear distinction between commercial areas and some residential ones, and those residential census block groups also became readjusted. A different indicator than temperature should be chosen to develop a more accurate canopy gap score with commercial areas in mind.

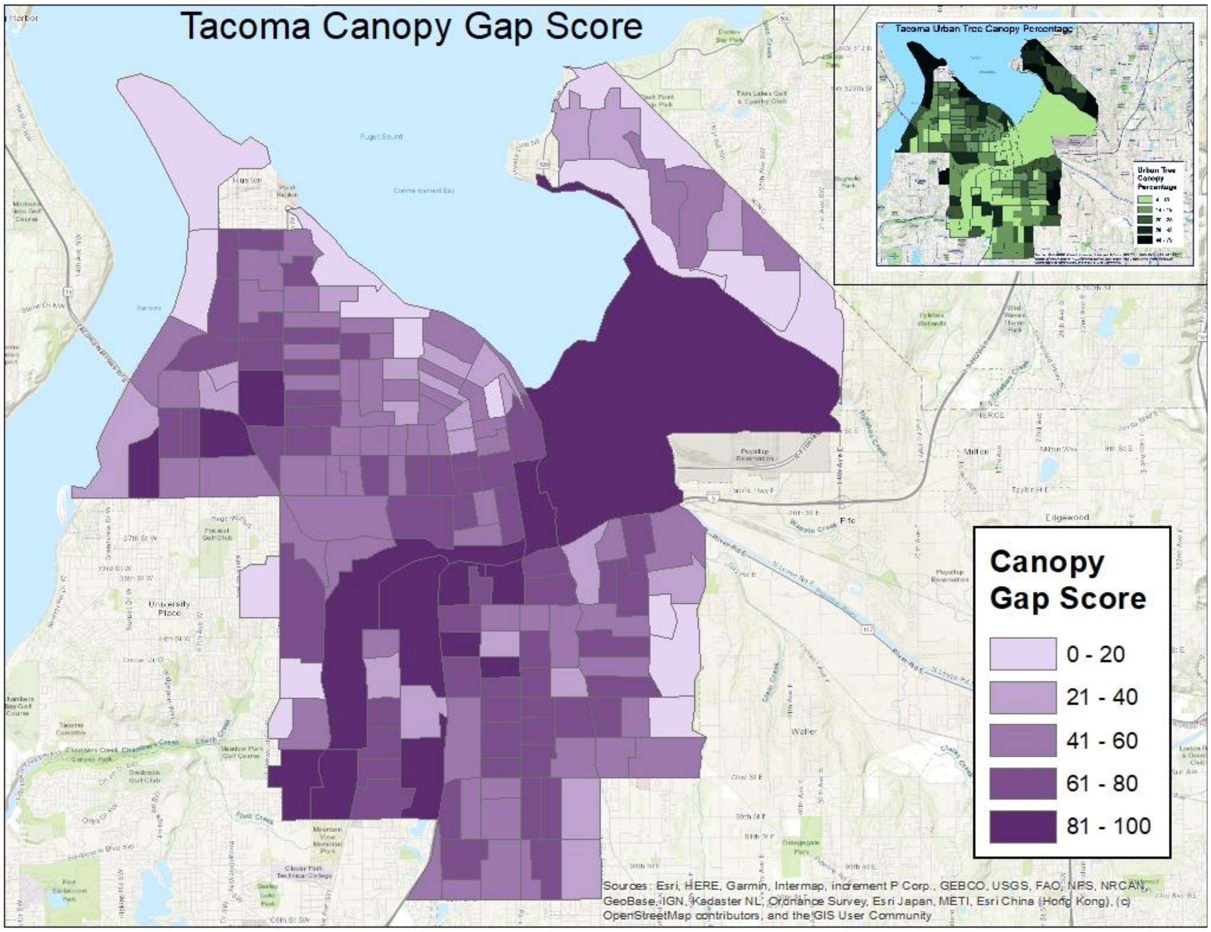

Figure 29. Tacoma Canopy Gap Score map.

Canopy gap scores for each census block group are represented by the purple gradient with reference to the urban canopy percentage map in the upper right-hand corner.

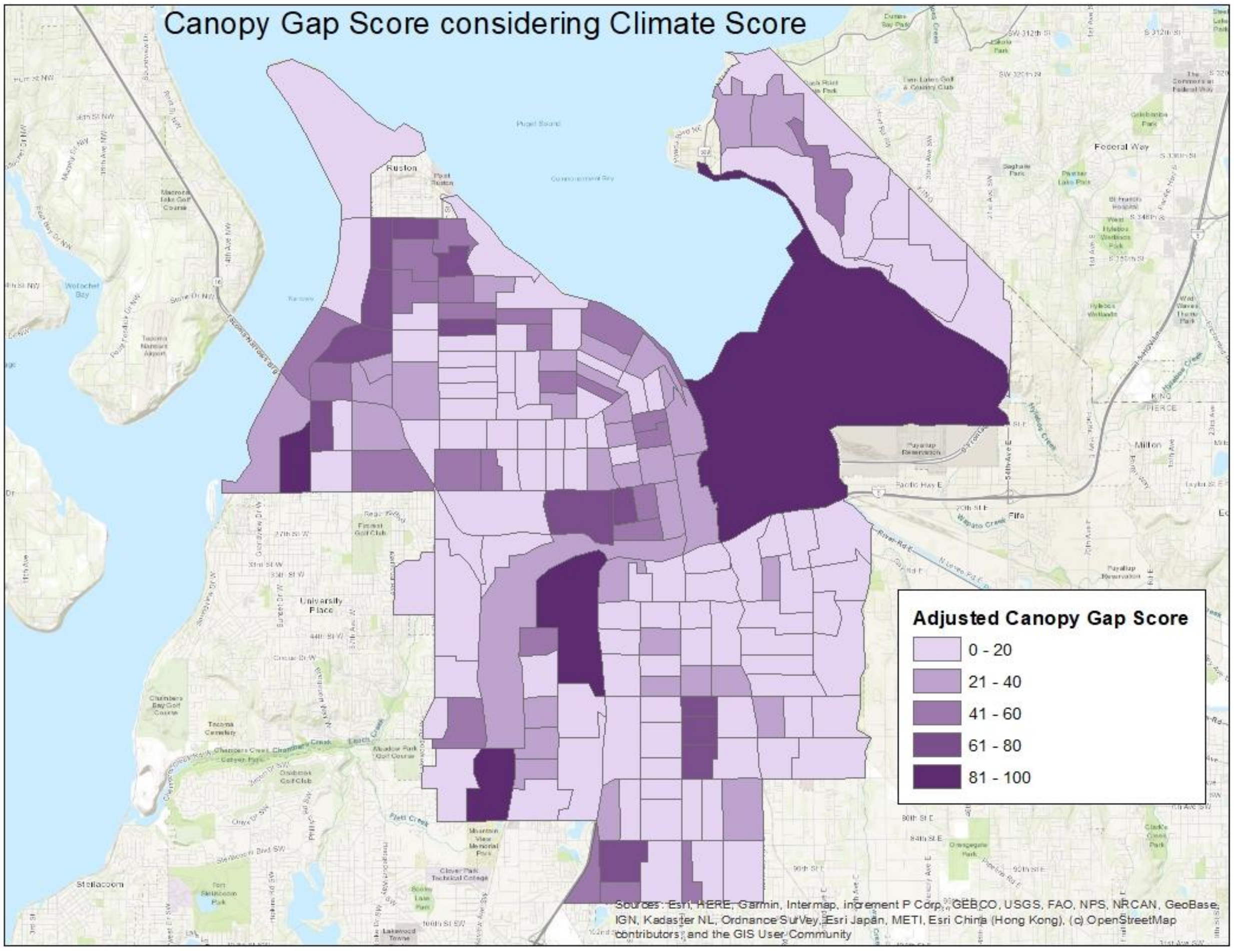

Figure 30. Tacoma Canopy Gap Score with the consideration of the Climate Score (see figure 34).
The canopy gap gap scores for each census block group are represented with a purple gradient. Unlike the canopy gap score map in figure 29, these scores include the addition of the Climate Score to try to account for commercial areas, which have low population densities but low PPA.

10.2 Demographic Score

We then found the scores for each demographic indicator (figure 31) and the overall demographic score (figure 32). Note that while income and race look similar, the other two indicator scores look very different. While natural variation might be responsible for the differences with the unemployment score, the age score looks extremely polarized. The census block group with the highest age score contains the Cross Roads mixed-use development center, which has urban neighborhoods in walking distance to stores, amenities, and transportation. It could be the case that many seniors retire there, which is why that census block also has a high unemployment score and high dependency ratio. More localized information is required to substantiate that hypothesis. Still the final demographic score does not show the polarity of the age score and appears similar to the UTC map.

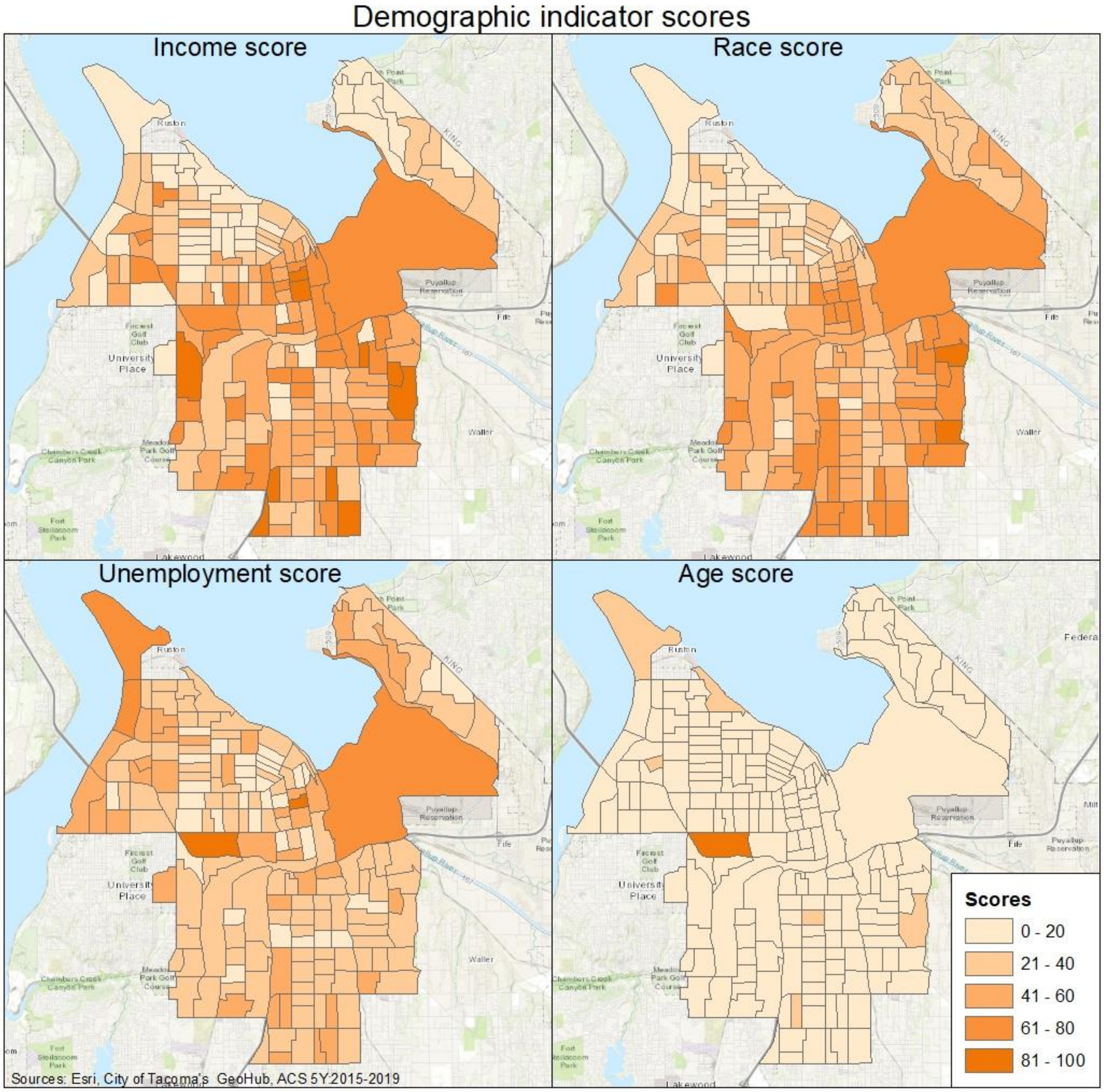

Figure 31. Tacoma Demographic Indicator Scores maps.
This map shows the six demographic indicator scores for each census block group, which are represented with an orange gradient. From left to right, top to bottom: income score, race score, unemployment score, and age score.

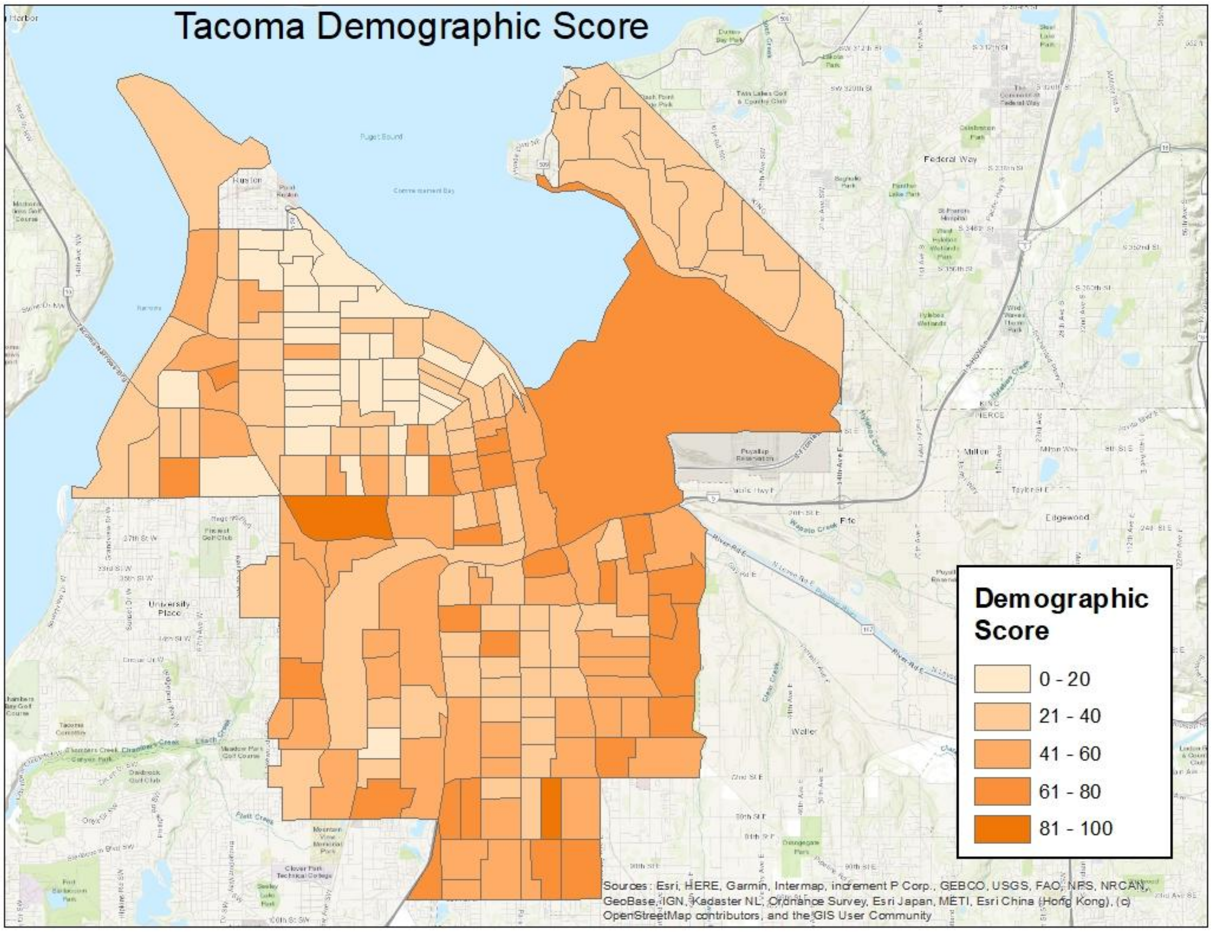

Figure 32. Tacoma Demographic Score map.
The demographic scores for each census block group are represented with an orange gradient. These scores were calculated from the normalized weighted average of the demographic indicator scores.

10.3 Air Quality Score

There was the only indicator for the air quality score (figure 33), so it was quick to see that the score generally reflected the UTC map. It makes sense that this map reflects the UTC map more closely than the demographic score map since a large part of the air quality analysis was built upon canopy coverage.

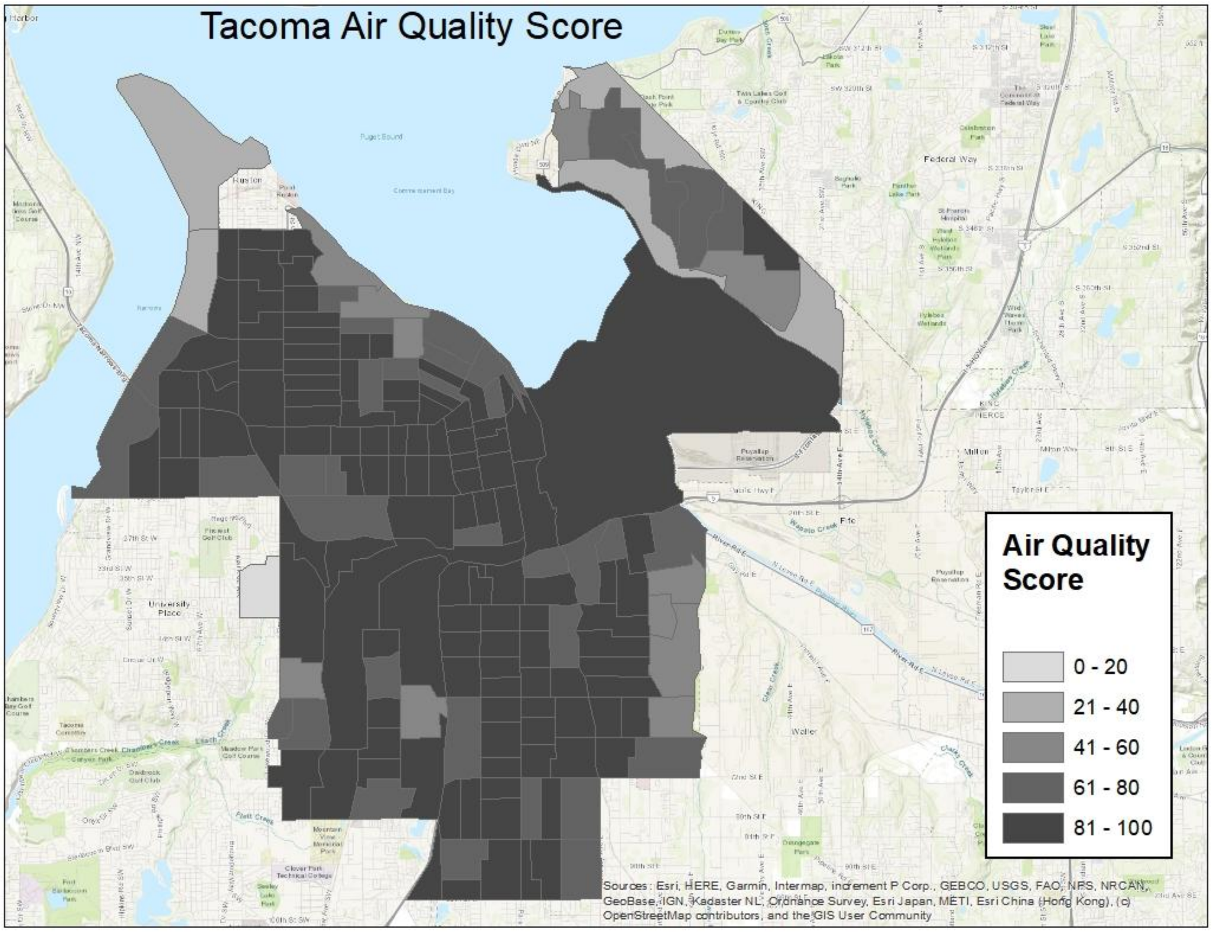

Figure 33. Tacoma Air Quality Score map.
The air quality scores for each census block group are represented with a gray gradient. The only indicator for this score was the annual total removed $PM_{2.5}$ in pounds.

10.4 Climate Score

The climate score only has temperature as an indicator (figure 34), but the map appears similar to the UTC map. Since temperature rises higher with urban infrastructure rather than vegetation surfaces, the relationship follows relatively closely.

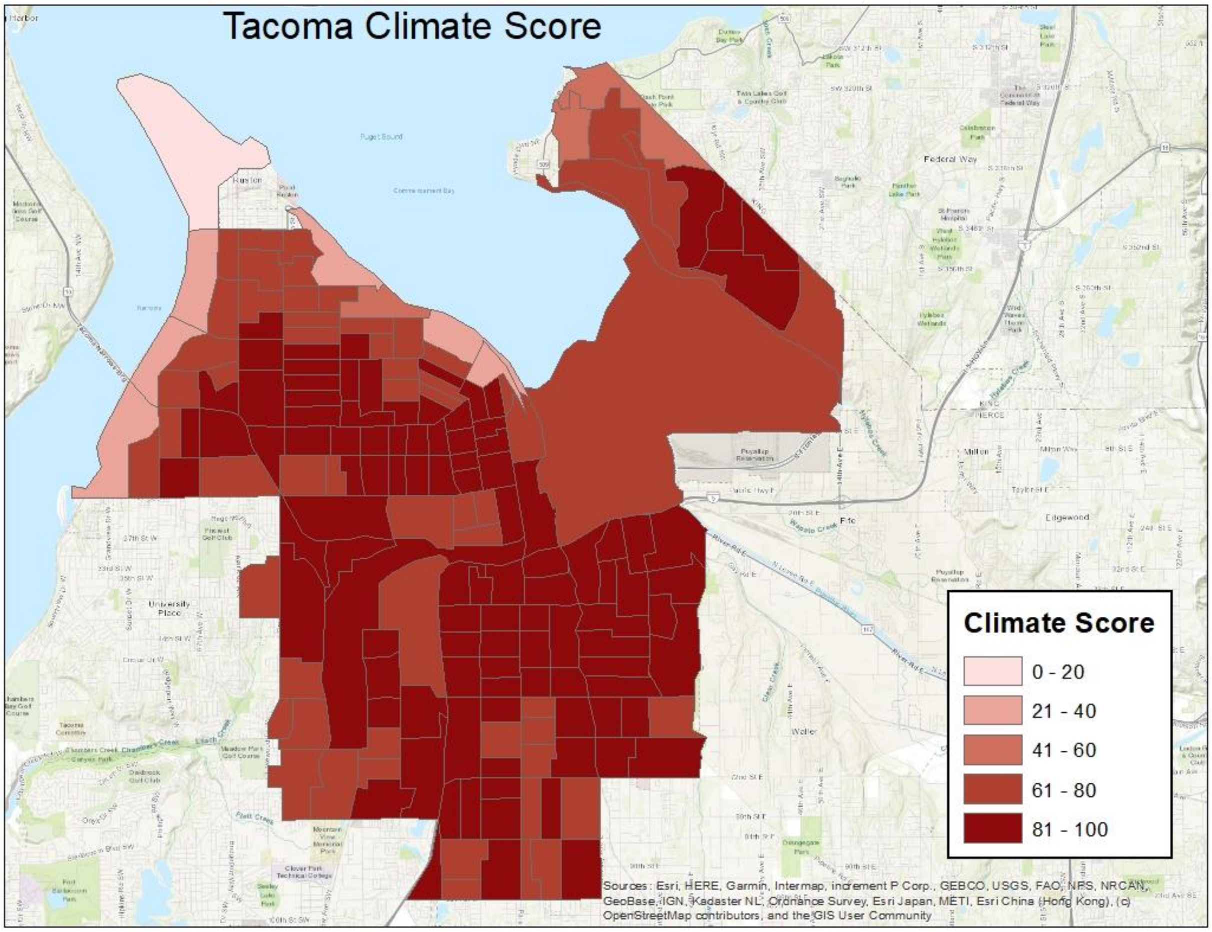

Figure 34. Tacoma Climate Score map.

The climate scores for each census block group are represented with a red gradient. The only indicator for this score was the average temperature during the day on July 25 th , 2018.

10.5 Health Score

Besides few natural variations between census block groups, all of the health indicator scores appear very similar to one another (figure 35). They also reflect a worrying large number of census block groups with high health scores, which means that those areas have less health incident reductions from environmental benefits. However, these scores were developed through using BenMap and do not reflect Tacoma's true public health records. Additionally, these scores had little standard deviation. Even a small increase in one census block group compared to another could lead to much higher scores as a result.

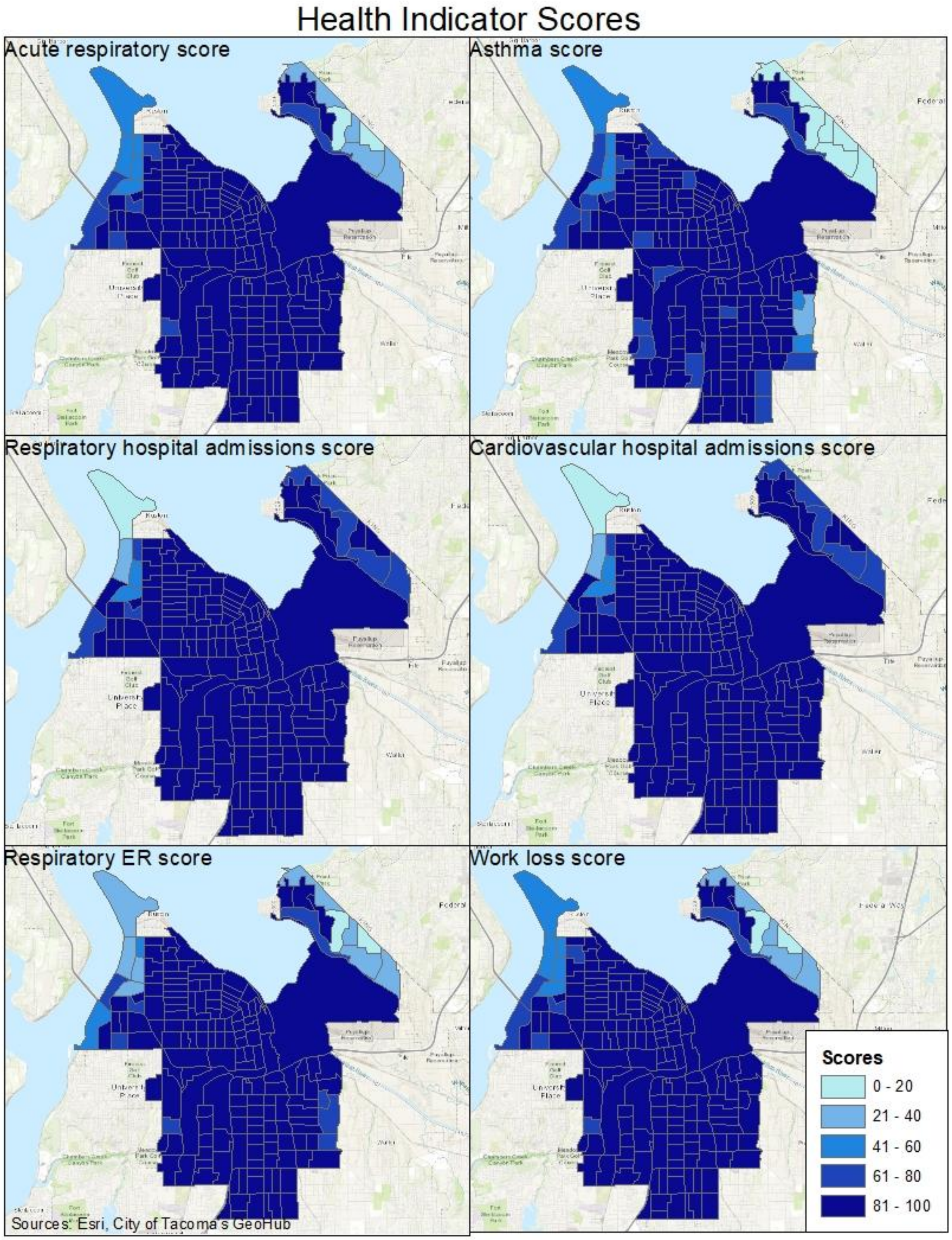

Figure 35. Tacoma Health Indicator Scores maps.

The health indicator scores for each census block group are represented with a blue gradient. From left to right, top to bottom: acute respiratory score, asthma score, respiratory hospital admissions score, cardiovascular hospital admissions score, respiratory ER score, and work loss score.

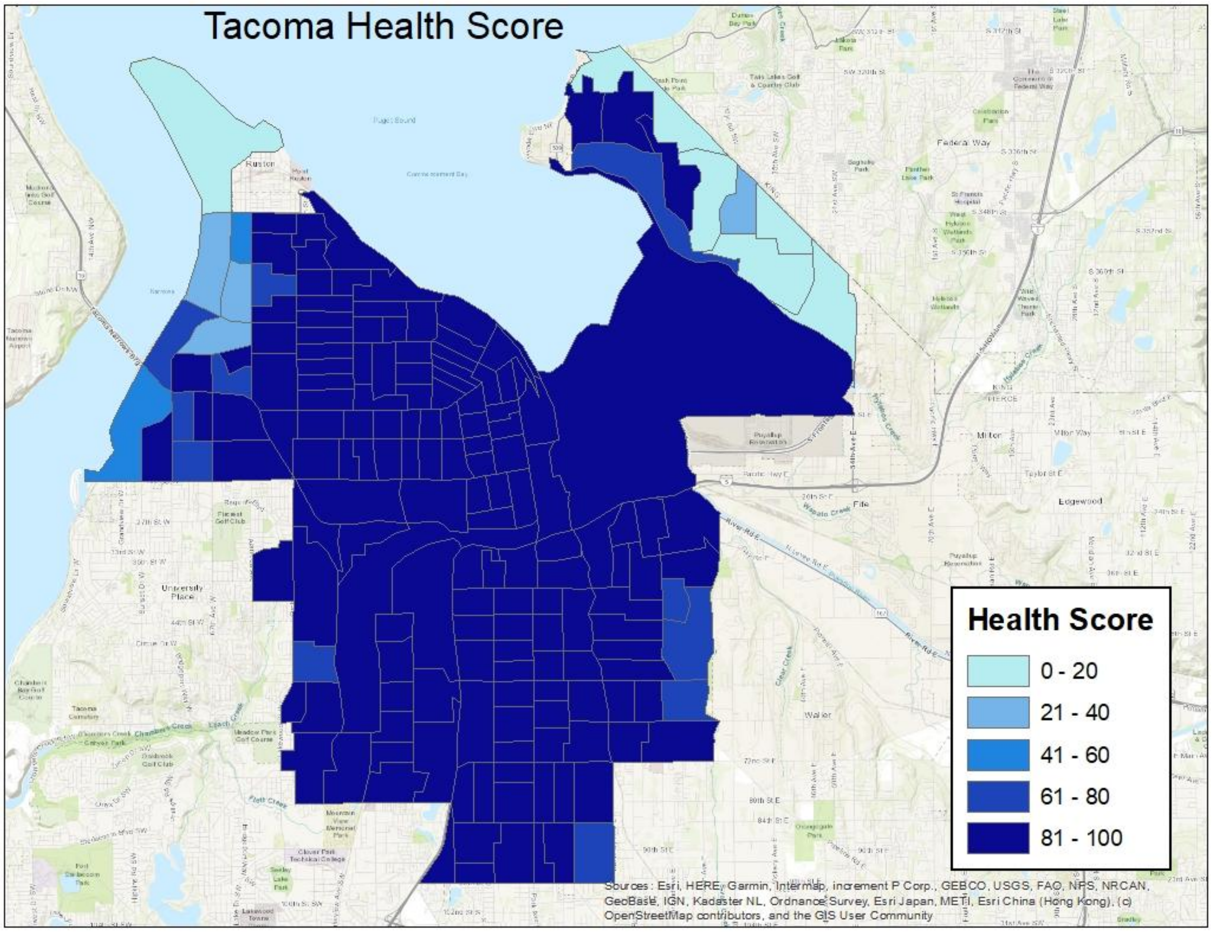

Figure 36. Tacoma Health Score map.
The health scores for each census block group are represented with a blue gradient. These scores were calculated from the normalized weighted average of the health indicator scores.

10.6 Intermediate Scores

Each of these intermediate scores are just examples of possible scores that PlanIT Geo could develop to allow flexibility in reporting desired indicators. They do not contribute to the final score, but they still convey valuable information. Just from comparing the two maps (figure 37), more census block groups have higher environmental scores than priority scores. Therefore, Tacoma policy makers could consider more environmental interventions to address the disproportionate distribution of environmental benefits than health or socio-economic interventions. This is only one possible interpretation of these results.

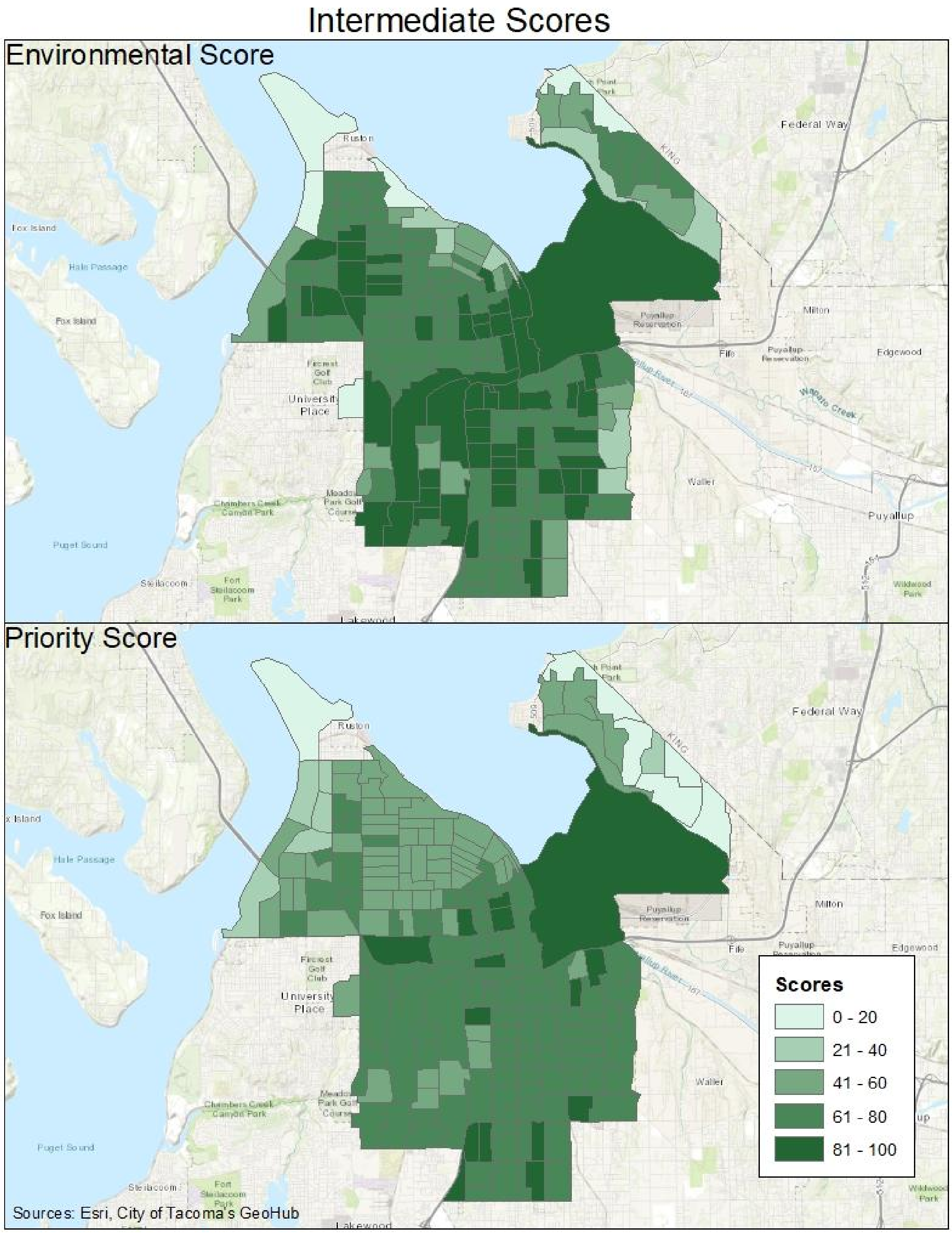

Figure 37. Tacoma Intermediate Scores map.

The intermediate scores for each census block group are represented with a green gradient. Both of these are just possible examples of intermediate scores that can be produced through combination of any of the base scores. Top: Environmental score (canopy gap + air quality + climate scores). Bottom: Priority score (demographic + health scores).

10.7 Environmental Equity Score

Figure 38 shows the final map for the environmental equity score. We determined that 32 out of the 172 census block groups in Tacoma had the most critical scores, 80 and above. While we initially posited that those areas should be prioritized for additional canopy coverage, we acknowledge that many of those areas do not have additional planting space. In section 7.1, we had already determined that using temperature as a proxy for urban space, and thus impermeable surface, proved unreliable. Through visually comparing the environmental equity score map with PlanIT Geo's PPA map (figure B2), we highlighted the five census block groups with the highest score that still have areas for more vegetation.

- Block Group 2, Census Tract 609.03, Pierce County, Washington
- Block Group 3, Census Tract 620, Pierce County, Washington
- Block Group 3, Census Tract 9400.05, Pierce County, Washington
- Block Group 4, Census Tract 609.05, Pierce County, Washington
- Block Group 7, Census Tract 625, Pierce County, Washington

If the environmental equity score could incorporate actual possible plant area scales into the methodology, a better analysis of critical census block groups could be determined.

It is interesting to note that these groups are not localized to a specific region in Tacoma and are all single-family residential areas (see figure B1). However, they are all nearby industrial or commercial areas, and being in a residential area, those groups have higher PPA. The lack of trees and their associated environmental benefits might have increased the environmental equity score in the surrounding census block groups. At this time, it is unclear whether planting in the surrounding residential areas could offset the effect from the lack of trees in those industrial and commercial areas.

Additionally, not every census block group with a high environmental equity score also had low canopy coverage. It is not an exact one to one ratio. Analysing the other indicator did affect which census block groups were the most concerning, even if most groups had the same correlation between canopy coverage and environmental equity score.

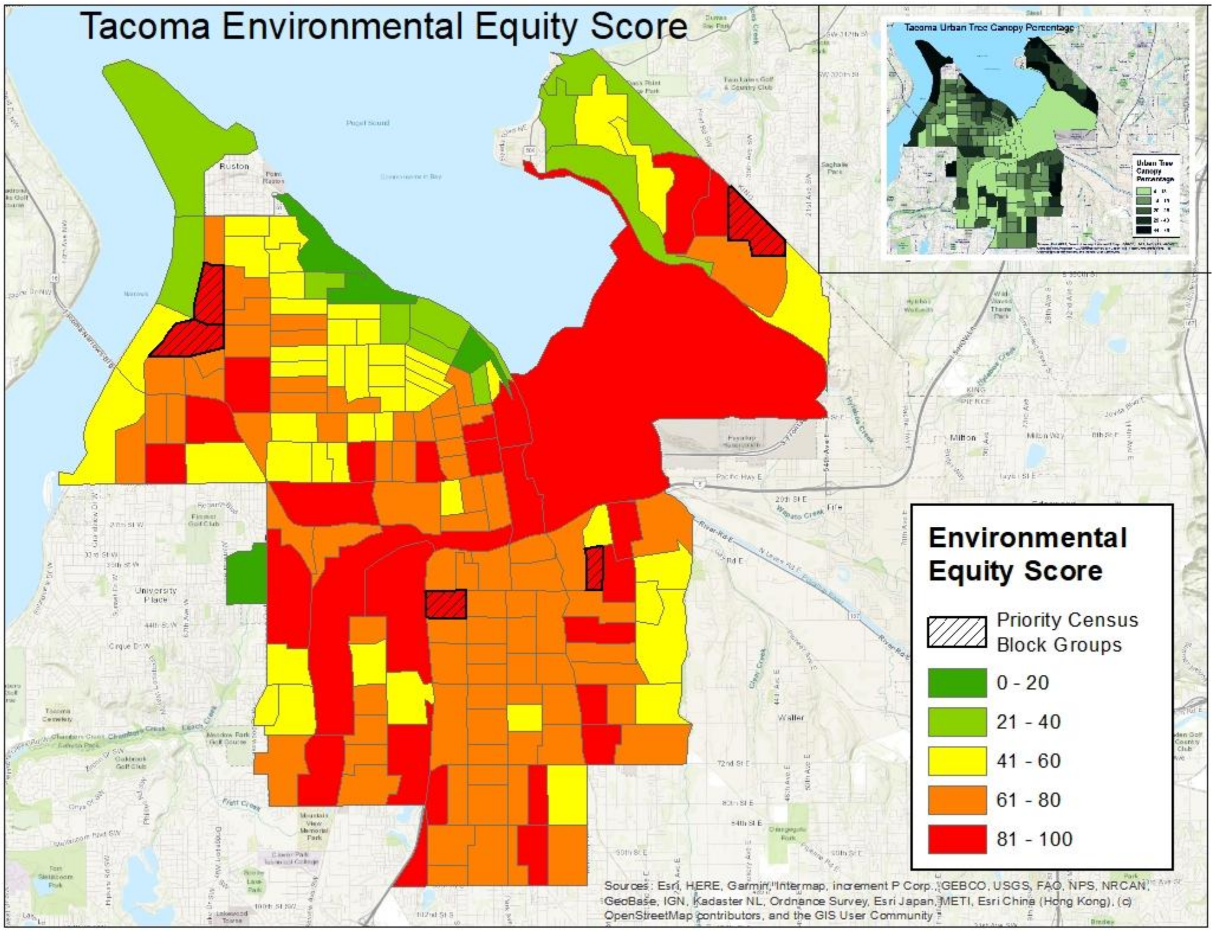

Figure 38. Tacoma Environmental Equity Score map.
The final environmental equity scores for each census block group are represented with a polarized green and red gradient, with green representing the lowest scores and least concerning to red, the highest scores and most concerning. A reference to the urban canopy percentage map is in the upper right-hand corner. The five census block groups with slash marks have some of the highest scores and at least moderate PPA. They are the most viable for improvement through urban forestry intervention.

Discussion

1. Equity in Tacoma

Each of the base scores generally reflected the same relationships as the final environmental equity score, though not to the exact scale. For example, some census block groups almost always had a higher score than others, but the score was not the same across all indicators. There are exclusive factors associated with each indicator, and the interactions of indicators with each other and other elements in the city make parsing out the reason for those differences even more complicated.

However, we did identify trends in the scores. In general, census block groups in the south, called South Tacoma and Eastside, had the highest score. The largest census block group in Tacoma also has a high score, but it contains the Port of Tacoma. This heavy industrial area has many impermeable surfaces and thus, low canopy coverage. However, it also contains no residential areas, so planting more trees in this area is neither a priority nor really possible.

South Tacoma has many residential neighborhoods, nevertheless. Historically, South Tacoma is known to have greater social and economic instability. It has a 18% poverty rate, higher than Washington's 11% poverty rate, and its residents live on average only up to 74 years old, six years less than for other Pierce County residents (Tacoma-Pierce County Health Department). The area also has the highest rates of $PM_{2.5}$ concentrations in the city and receives the least air quality improvement due to the low tree cover. While only two of our priority census block groups lie in this area, they are surrounded by more high-scores than any other group. Considering the fact that additional canopy coverage not only affects the immediate census block group but also the surrounding ones, any urban forestry intervention should begin in this area. More analysis is required to determine how many trees are required to offset the environmental inequity or at least the numbers of trees with the least cost in terms of money and welfare to the city and its residents.

However, we did not perform any statistical analysis and much of our score comparisons were performed visually. We did not screen any other city to compare our final results. While we can say that some neighborhoods in Tacoma have a higher or lower score than others, we can not determine whether they are significantly above or below the average standard of environmental equity for Washington, let alone the national average. However, we can determine that there is unequal distribution of canopy coverage and environmental equity across Tacoma. While the scope of our project cannot recommend exact interventions to affect this distribution, we have determined the five census block groups that would most benefit from planting additional trees in the area. Some census block groups with higher canopy coverage also have low environmental equity scores. The inclusion of the other indicators does contribute to a broader analysis of equity in Tacoma. PlanIT Geo can use these results to demonstrate to its clients how canopy coverage alone does not capture which areas are the most vulnerable in a city.

2. Air Quality

Our air quality analysis was limited to a model which aggregates air pollution reduction based on deposition velocity per tree leaf surface area. These estimates might underestimate the total effects of air quality improvement in census block areas because they do not factor the rate of interception by nearby vegetation which might also play a significant role in $PM_{2.5}$ interception. The model was also limited in that it does not factor other variables such as building density, proximity to air pollutant point sources, or consider tree height and canopy crown density which would affect these estimates. It also did not factor the level of negative health effects caused by trees which produce biogenic volatile organic compounds and can cause respiratory issues such as heightened asthma symptoms, especially during high pollen seasons. (Nowak et al, 2014)

It would also be worthwhile for future analysis to measure the rates of air quality improvement by comparing different proportions of leaf surface area in an urban environment through a sensitivity analysis. We assumed that Tacoma's urban canopy reflected the 76% deciduous and 24% composition recorded by PlanIT Geo's tree inventory, however the city most likely has a total leaf surface area concentration more similar to Seattle's urban forest which is 72% deciduous and 28% evergreen. LAI values might play a significant role in tree particulate interception, as we would expect a higher concentration of evergreen trees would be able to retrieve more particulate matter per year compared to deciduous trees.

This is important to consider when we think of the seasonal effects of air pollution. Referring to figure 39, we can observe the variance in pollutant levels during Winter and Summer months, and the rate of daily PM2.5 concentration reduction. We observed that removal rates citywide reflect the patterns of oscillations of daily pollution concentrations. If we were to assume a higher composition of evergreen trees citywide, we would expect that trees would be more effective in reducing air pollution and we would see more air quality improvement during Winter months when pollutant levels are at their highest. This analysis could also help aid urban foresters and city planners in prioritizing tree type for future tree planting and greenscape proposals. It would also be important to consider the spatial patterns of tree composition in urban environments and model air pollution reduction in areas of the city which may have very differing tree species composition. We would gain more accurate analysis if we could incorporate the specific tree composition within each census block group rather than assuming a uniform composition of tree species.

Air monitor data from Purple Air sensors however did provide us with a more finer scale of air pollutant distribution across neighborhoods in Tacoma than the two EPA Air Quality monitors located in the center of the city (Appendix A.). Future studies may want to consider these types of data in addition to model a finer-grain assessment of pollution in urban areas.

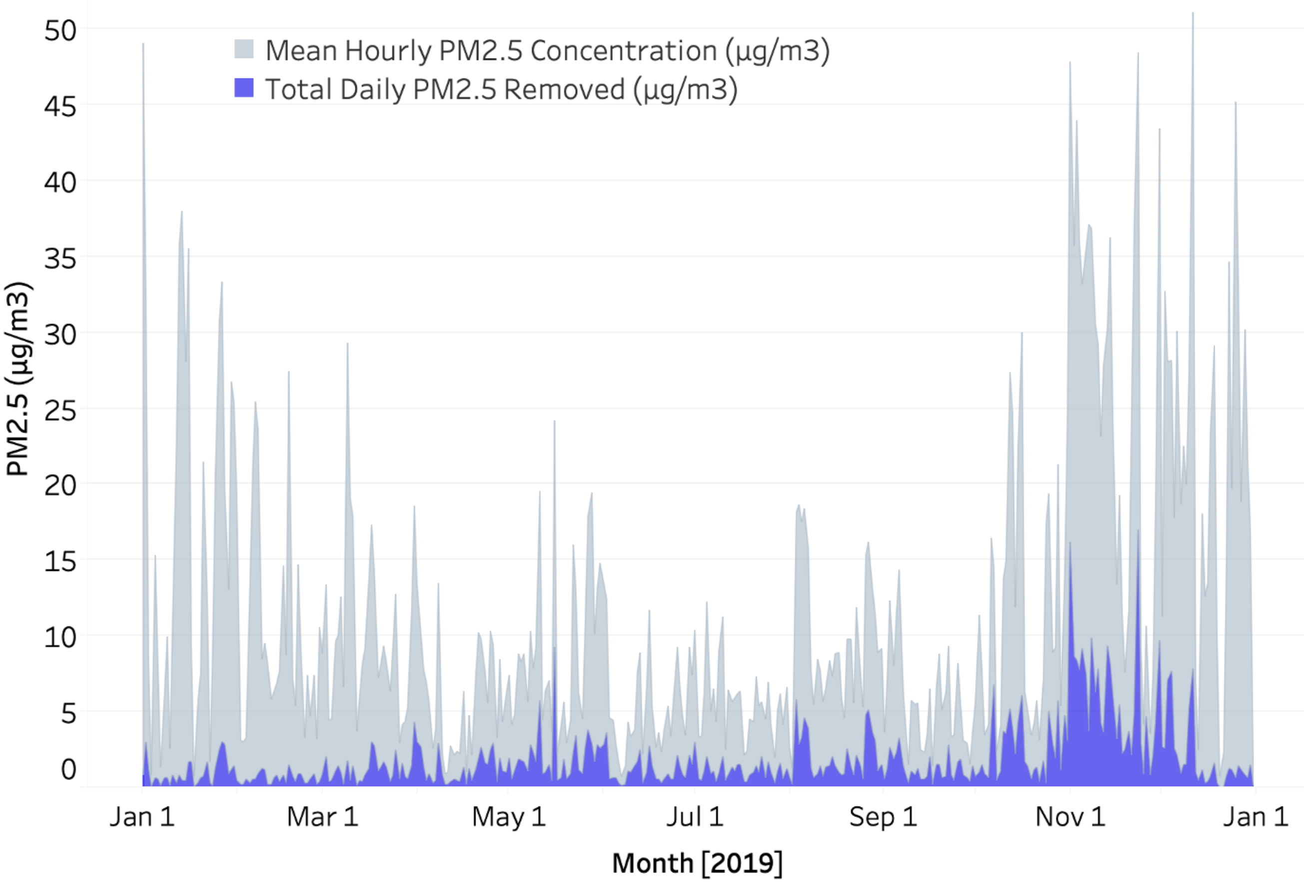

Figure 39. Total daily $PM_{2.5}$ removed in relation to mean annual concentration levels

3. Prospective Client Use

PlanIt Geo, their clients, and any State or city-based urban forest management program throughout the PNW are welcome to use our model to evaluate urban forest equity. Our tool was designed with future clients in mind, and therefore is customizable and able to be applied to other datasets throughout the PNW. As PlanIt Geo partners with many organizations throughout the PNW, we are confident that our tool will be useful to our client in the future. PlanIt Geo and their clients can input their own local data into our model and customize the tool to best fit their overall needs and desired results.

When thinking about the datasets that future users of our model will need, it is important to address some of the shortcomings we encountered throughout the data collection process. First, due to restrictions from COVID-19, we were unable to retrieve state-level public health or hospitalization data, which could have provided an even deeper understanding into how urban trees directly affect human health and incidents of certain illnesses. While Benmap does produce information sufficient for our purposes, future clients may want to make an even stronger claim to the benefits of urban trees on human physical and mental health. In addition, to make the model even more specialized, clients have the ability to calculate actual daily LAI values within their own cities through extensive surveying and creating a comprehensive urban tree inventory.

Finally, the inclusion of the "Intermediate Scores" allows for PlanIt Geo, city planners, and policy makers alike to delve deeper into what the final equity score represents at a finer scale and across different levels. Future users of our model have the ability to stop the model at these intermediate scores and do not have to produce a final equity score if that will not mean as much to whomever the data is being presented to. With this, future clients can report detailed and specific equity scores based on specific aspects of their city that stakeholders may prioritize.

4. Mitigating Harm from Urban Forestry

Despite the myriad benefits of urban forestry, it is also crucial to discuss the potential drawbacks to our proposed methodology. In general, the addition of trees to previously predominantly grey spaces increases shading, aesthetic value, access to green spaces, and ultimately raises property values. While a raise in property value may initially seem beneficial to the overall economy of the city, this phenomenon displaces lower-income communities of color. This phenomenon of urban greening and development resulting in the displacement of low-income communities is called gentrification. Gentrification is historically rooted in the rise of property values that follow urban development and the desire to capture the biogenic services of green infrastructure (Curran, 2012). Therefore, it is crucial to keep this potential phenomenon in mind when participating in urban forestry. More information regarding how to prevent gentrification will be provided in the "Further Recommendations" section of this paper.

Conclusion

Overall, we have found that there is unequal tree canopy distribution in Tacoma, and combined with demographic indicators, the effects correlate to overall unequal environmental equity distribution. We identified the census block groups most in need of urban forestry intervention, though we cannot determine the exact degree in inequity compared to the rest of Washington or the US under the scope of this project. Still, the flexibility of our model will allow our client to focus on different indicators or add additional scores, and the critical census block groups and interventions will be at their discretion. The model has yet to be applied to any other city besides Tacoma, but the model was built so that base scores could be easily added or dropped based on the available input data. Thus, the final composite score would still be valuable for the city of interest. We chose our input data to be as localized to Tacoma as possible, but our client can find different data input sources to more easily compare the final scores across the country. For example, our client can use i-Tree Landscape for air quality data or USGS Earth Explorer for temperature data across the US (*Home—i-Tree Landscape*; *EarthExplorer,* USGS).

We have also determined that there is a necessity to consider urban trees in relation to air pollution and their associated health effects. As seen in our results, a higher concentration of trees in an area is more effective in improving air quality. As there are disparities between low tree-cover and subsequently polluted areas, there is also a disproportionate spread of health benefits. We quantified that city areas with the highest tree cover remove over 4 times more particulate matter than areas with the lowest tree cover, and these areas receive better health benefits. Areas with high tree canopy experience 6 - 8 times fewer health effects such as acute respiratory symptoms, asthma attacks, hospital admissions for respiratory and cardiovascular issues and sick days compared to city areas with the lowest canopy coverage. Urban planners and policy makers must prioritize tree plantings in areas with demographic groups who are historically at higher risk for certain diseases, in addition to in areas experiencing high rates of air pollution as a means to combat these potential negative health effects.

Further Recommendations

1. Data

As previously mentioned, we were unable to acquire all of the specific data we initially aimed to obtain. Future clients should consider getting finer scale health data to replace the use of Benmap as an intermediate step. Once COVID-19 restrictions are lifted and data sharing is more readily available, it should be relatively easy to obtain finer-scale State or city-level public health data, including specific rates of hospitalization for various respiratory and/or cardiac illnesses that can be linked to air pollution and high $PM_{2.5}$ concentrations. Such health data should also likely provide more detailed demographic information, thereby increasing the significance of the final equity score and other intermediate scores due to data better reflecting actual local demographic information.

In addition, future users of our tool should consider calculating a more accurate projection of LAI. Several of the studies that we used when creating our model have explored daily LAI, but few have looked at LAI in the context of urban environments. There are also limitations of using the i-Tree metric for the LAI value in that LAI can be influenced by a variety of issues including the type of tree, land use, urban environments, and tree maturity. A better method to determine LAI, given future clients have the time and resources, would be using field measurements to get a more accurate projection of LAI based on different growing zones in city environments, such as: riparian, greenswale, urban, and traffic corridors. (Klingberg, 2017)

A final consideration future clients can make when using our model is whether or not to include more indicators, if possible. While this does add steps to the modeling process, it also could strengthen a client's argument pertaining to a certain aspect of their city that our model may not currently fully encapsulate within our chosen indicator scores. For example, if a future client wants to show that increasing urban canopy layers in their city results in better physical human health through reduced respiratory problems, the client may want to add an asthma indicator that assesses respiratory illnesses at a more detailed scale than the overall health indicator score would. As we also mentioned with the canopy gap score, our model cannot identify commercial areas with low PPA using just the climate score. If possible, our client can add a PPA percentage per census block group indicator to better capture the canopy gap score.

2. Policy

In building upon our model, future clients should prioritize collaborating with local policy makers to better inform decision-making surrounding urban forestry, environmental justice, and urban development/ infrastructure. In collaborating with our external advisor Mike Carey, the Urban Forest Program Manager for the City of Tacoma Environmental Services, we have seen the potential for how wide-spanning the policy implications can be based on information provided by our tool. Mike specifically mentioned the impact our tool will have on policies prioritizing tree plantings in low income areas, in addition to policies regarding post-planting follow up including education and ensuring that people are not displaced if/when housing prices rise. Future clients can follow in Mike's footsteps and identify top priority areas based on the final Environmental Equity Score to present to policy makers and local government officials for future urban forest management and general city planning.

When considering the effects of green gentrification, previously outlined in the Discussion section of this paper, it is crucial to ensure policy makers not only understand this phenomenon, but do everything they can to prevent the displacement of lower-income community members once property levels inherently rise after more trees are planted in their neighborhoods. Cities using our tool in the future should prioritize partnering with local social justice groups and/or city officials to ensure the prevention of gentrification after trees are planted in lower income communities of color, in addition to ensuring there is continued educational and financial support for these communities once property levels rise.

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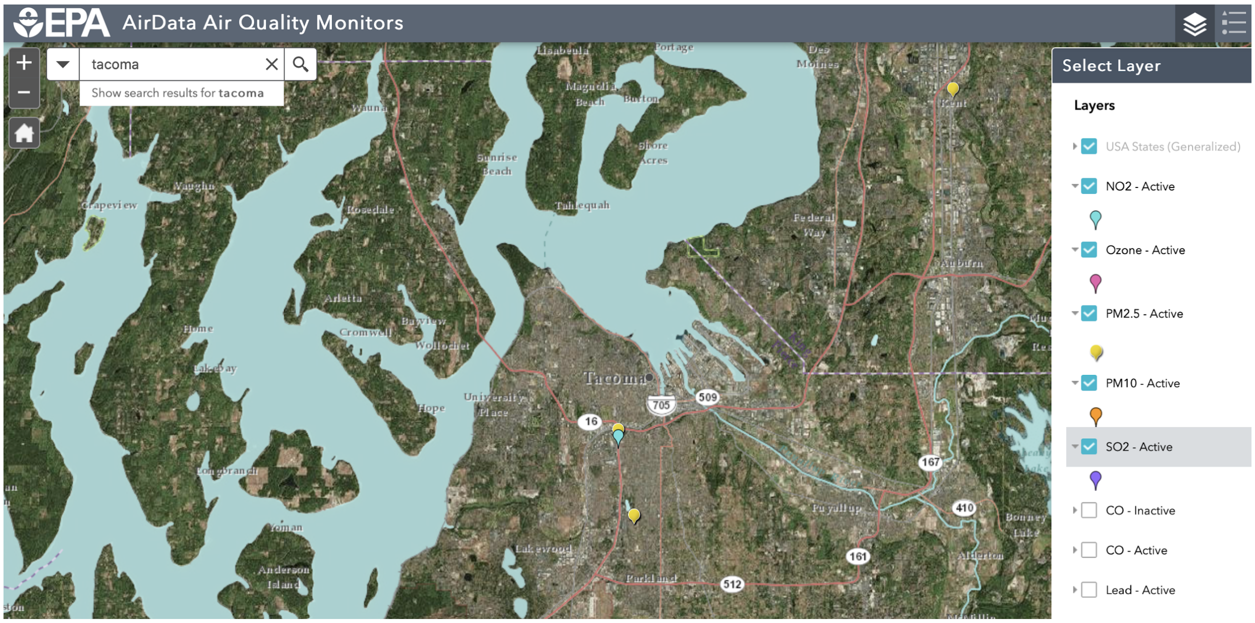
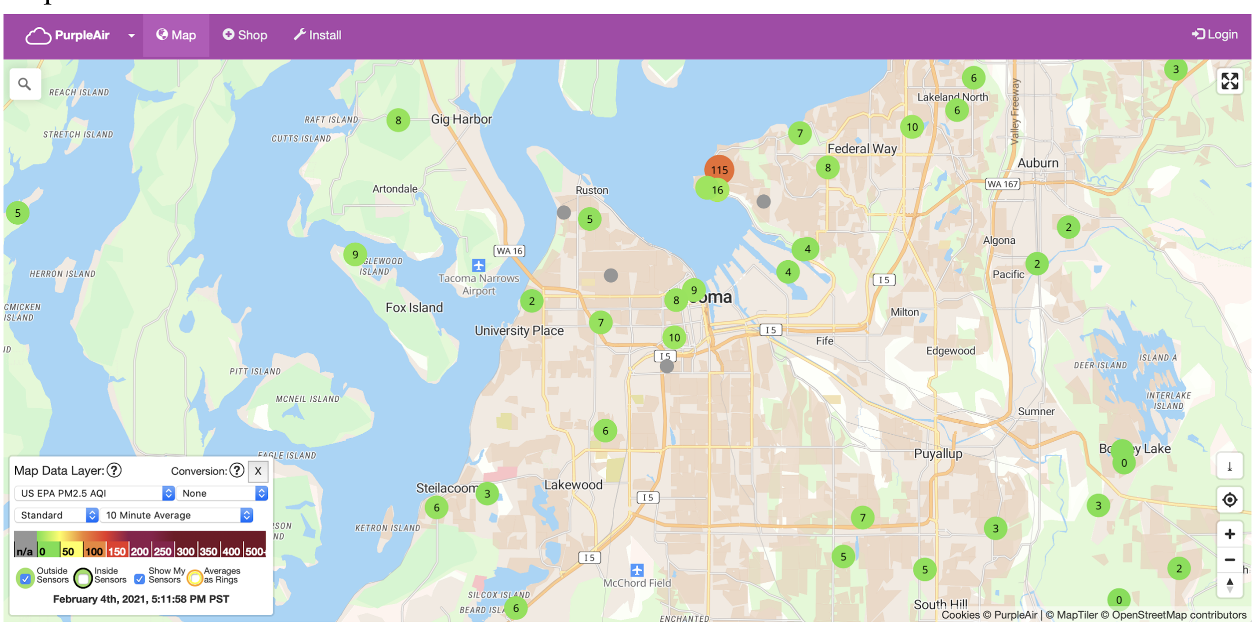
Appendix

Appendix A. Air quality.

EPA air quality monitor sensor distribution in Tacoma



Purple Air sensor distribution



Deposition velocities and percent resuspension by wind speed per unit leaf area - from Nowak et al, 2013.

Deposition velocities and percent resuspension by wind speed per unit leaf area.

Wind speed ($m\ s^{-1}$)	Deposition velocity (V_d) Average ($cm\ s^{-1}$)	Minimum ($cm\ s^{-1}$)	Maximum ($cm\ s^{-1}$)	Resuspension (%)
0	0.00	0.000	0.000	0
1	0.03	0.006	0.042	1.5
2	0.09	0.012	0.163	3
3	0.15	0.018	0.285	4.5
4	0.17	0.022	0.349	6
5	0.19	0.025	0.414	7.5
6	0.20	0.029	0.478	9
7	0.56	0.056	1.506	10
8	0.92	0.082	2.534	11
9	0.92	0.082	2.534	12
10	2.11	0.570	7.367	13
11	2.11	0.570	7.367	16
12	2.11	0.570	7.367	20
13	2.11	0.570	7.367	23

i-Tree data inputs - retrieved 2020

Design/Forecast and US EPA's EnviroAtlas for the conterminous United States

		Model/Process			
		Eco	Eco batch runs for Canopy/ Landscape	Eco batch runs for Design/ Forecast	Eco batch runs for EnviroAtlas
Analysis Domain		Primary/ Secondary/Tertiary partitions	Rural and urban areas in secondary partitions	Rural and urban areas in secondary partitions	Census block group
Year		2005-2013	2010	2010	2008
Air Pollutant		US EPA AQS[a]	US EPA AQS[a]	US EPA AQS[a]	EPA fused[b] ($PM_{2.5}$) US EPA AQS[a] (other pollutants)
Weather		NCDC[c]	NCDC[c]	NCDC[c]	NCDC[c]
Radiosonde		NOAA/ESRL[d]	NOAA/ESRL[d]	NOAA/ESRL[d]	NOAA/ESRL[d]
Forest	LAI	Plot-based estimate	MODIS 2007[e]	0-18 (0.5 increment)	4.5
	Tree Cover (%)	Plot-based estimate	NLCD 2001[f] adjusted[g]	NLCD 2001[f] adjusted[g]	EnviroAtlas-based estimate
	Evergreen (%)	Plot-based estimate	NLCD 2001[f] adjusted[g]	Evergreen 100% or Deciduous 100%	EnviroAtlas-based estimate
Area (m2)		Partition area	Partition area	Partition area	EnviroAtlas-based estimate
Population		2010 Census[h]	2010 Census[h]	2010 Census[h]	2010 Census[h]
Batch Process Completed?		N/A	Yes	Yes	Yes for pilot cities
Lookup Table Created		N/A	_LocationBenefits	_LocationCarbon _LocationPollutant, _LocationPollutantRegression	N/A

Purple Air Sensor channel averages of $PM_{2.5}$

Purple Air Sensor Channel Averages of PM2.5 (µg/m3) - Tacoma, WA 2019								
Sensor/Channel	Mean	Median	Max	Variance	SD	SE	Observations	Missing Data
6th & Baker (PSU) - A	8.12	5.32	81.61	76.66	8.76	0.11	6889	10/15/19 - 12/31/19
6th & Baker (PSU) - B	7.75	4.80	85.63	79.62	8.92	0.11	6889	10/15/19 - 12/31/19
Baltimore (PSU) - A	6.82	4.67	64.98	50.91	7.14	0.09	5920	09/04/19 - 12/31/19
Baltimore (PSU) - B	5.99	4.06	63.82	40.92	6.40	0.08	5920	09/04/19 - 12/31/19
Jefferson (PSU) - A	5.19	3.20	54.05	30.32	5.51	0.06	8760	-
Jefferson (PSU) - B	8.91	5.43	77.54	91.79	9.58	0.10	8760	-
Lexington - A	8.06	4.96	233.54	92.95	9.64	0.10	8760	-
Lexington - B	8.16	4.60	247.59	166.27	12.89	0.14	8760	-
Pointe Woodworth - A	10.44	6.24	141.97	119.60	10.94	0.12	8760	-
Pointe Woodworth - B	10.06	6.20	100.99	103.02	10.15	0.11	8760	-
South Tacoma (PSU) - A	11.57	5.72	1326.03	1030.40	32.10	0.35	8622	1/30/19 - 02/05/19
South Tacoma (PSU) - B	10.36	4.80	1335.07	1014.13	31.85	0.34	8622	1/30/19 - 02/05/19
Tacoma Alexander - A	9.57	5.24	372.76	129.44	11.38	0.13	8037	01/28/19 -02/27/19
Tacoma Alexander - B	10.20	5.68	862.74	226.72	15.06	0.17	8037	01/28/19 -02/27/19
Titlow (PSU) - A	1.89	0.37	901.77	104.41	10.22	0.11	8760	-
Titlow (PSU) - B	7.46	4.49	131.92	73.58	8.58	0.09	8760	-

Purple Air Sensor PM2.5 Concentrations (µg/m3) - Tacoma, WA 2019							
Sensor	Mean	Median	Max	SD	SE	Variance	Location
Titlow (PSU)	7.46	4.49	131.92	8.58	0.09	73.58	47.253452, -122.544228
Lexington	8.06	4.96	233.54	9.64	0.10	92.95	47.2907, -122.524442
Baltimore (PSU)	8.08	5.08	122.54	8.58	0.09	73.69	47.288002, -122.508332
Tacoma Alexander	9.70	5.39	372.76	11.30	0.12	127.62	47.26569, -122.38529
Jefferson (PSU)	8.91	5.43	77.54	9.58	0.10	91.79	47.264218, -122.495192
South Tacoma (PSU)	11.52	5.72	1326.03	31.81	0.34	1012.11	47.198733, -122.498633
6th & Baker (PSU)	9.74	6.07	81.61	10.05	0.11	101.05	47.25804, -122.44368
Pointe Woodworth	10.06	6.20	100.99	10.15	0.11	103.02	47.275444, -122.373175

Appendix B. Urban Tree Canopy Assessment

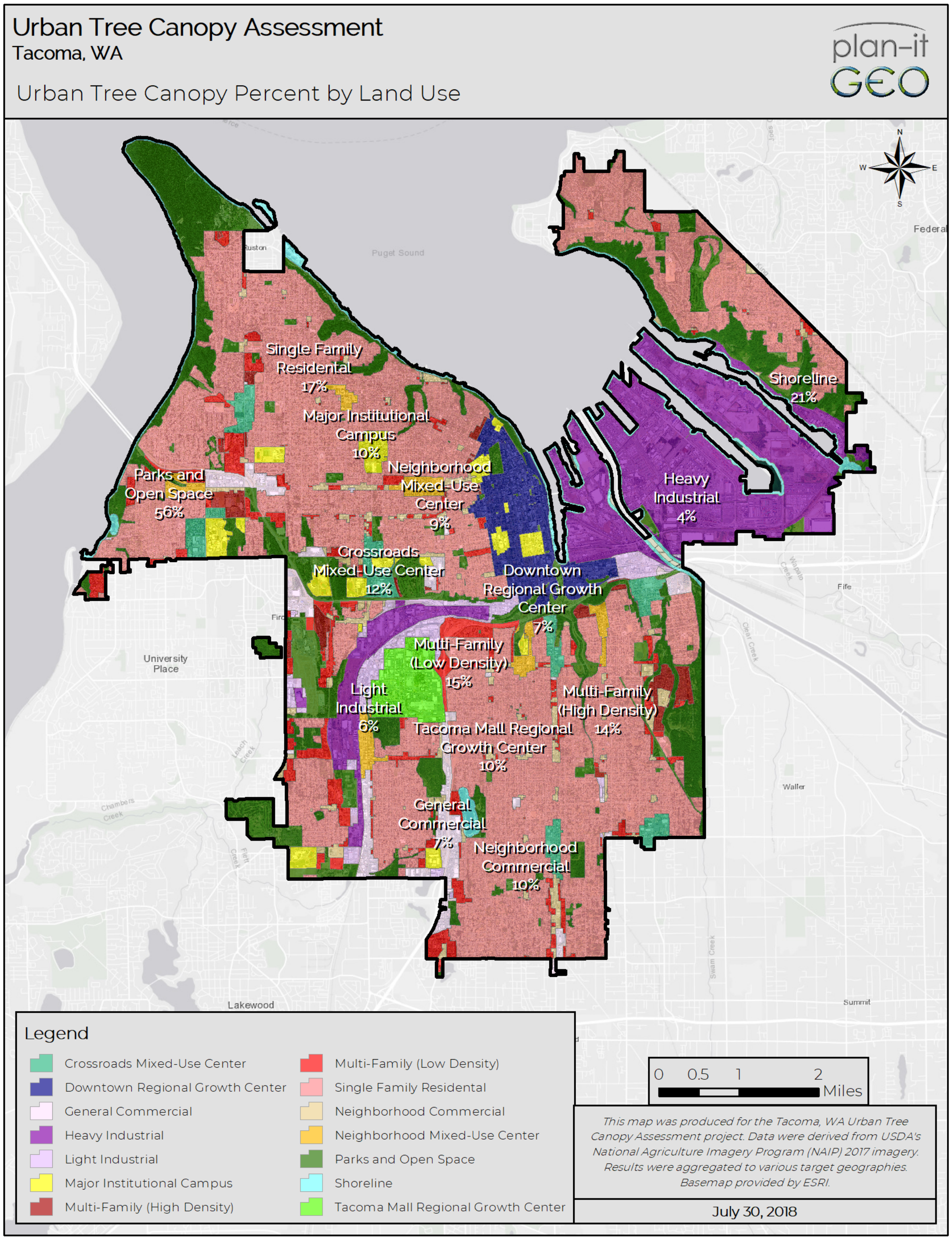


Figure 1. Tacoma Urban Tree Canopy Percent by Land Use.
This map shows the urban canopy percent divided by land use from PlanIT Geo's tree canopy assessment report in 2019.

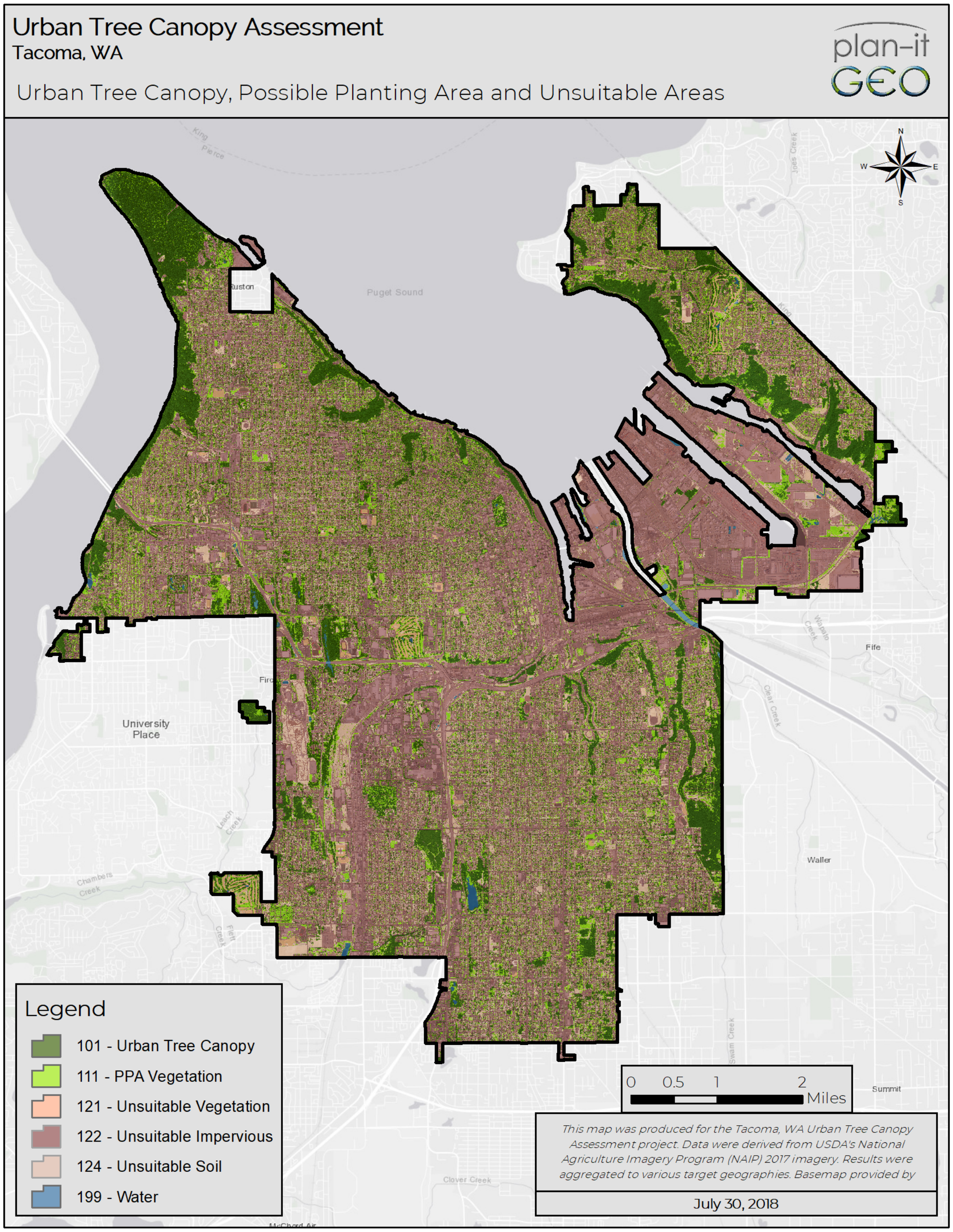


Figure 2. Tacoma Urban Tree Canopy, Possible Planting Area and Unsuitable Areas.
This map shows areas with urban tree canopy in dark green, possible planting areas in light green, and unsuitable areas in pink from PlanIT Geo's tree canopy assessment report in 2019.