THE RELATIONSHIP BETWEEN URBAN HEAT AND ENVIRONMENTAL JUSTICE IN EUGENE, OREGON

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ACKNOWLEDGEMENTS

I would like to express my sincere thanks and gratitude to the following people:

To my committee advisors, **Dr. Yizhao Yang**, and **Robert Parker, AICP**, for their expert guidance and support throughout this project.

To **Josh Bruce, AICP** for his support, mentorship, and advice during my time at the University of Oregon.

To **Rachel Hiller** for her technical GIS support.

To **Ali Lau** for her design expertise on this project and for her love, drive, and emotional support throughout our time in graduate school.

And finally, to my parents, **Mark Gaskell** and **Catherine Gaskell** for their continued love, support, and understanding, always.

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ABSTRACT

Urban heat is the deadliest natural hazard facing the United States. Extreme heat kills more people in the U.S than all other natural hazards combined. Research shows that extreme heat and heat related illnesses disproportionately affect environmental justice communities. Environmental justice communities in this study are those who are any one of the following indicators: minority population (non-white), low income (less than twice the federal poverty level), low level of education (no high school diploma), very young (under 5), or elderly (over 64). Much research has been conducted on the urban heat island effect, however, there are no studies on the impact of the Urban Heat Island in Eugene, Oregon. This research uses geospatial analysis and a multivariate Ordinary Least Squares (OLS) regression to explore what land use factors are associated with the urban heat island in Eugene and which communities are most affected by urban heat. The regression analysis suggests that medium and high-density land cover are the major drivers of urban heat in Eugene. The very young (under 5 years old) and the elderly (over 64 years old) are most affected by urban heat in Eugene.

CHAPTER 1: INTRODUCTION

Urban heat is one of the most insidious natural hazards facing the United States, especially as climate change continues to cause summer temperatures to rise (Shandas, 2009). Urban heat differs across the city which leads to environmental justice concerns over which communities in cities are most affected by urban heat.

The urban heat island effect describes built up areas that are hotter than nearby rural areas (OAR US EPA, 2014). As the world urbanizes, and as global temperatures in temperate climates (Blanco et al., 2009) continue to rise, the urban heat island effect could increase heat-related illness and mortality, increase air conditioning costs, and contribute to increases in air pollution (OAR US EPA, 2014). On a large scale, it is important to study the urban heat island effect as the total cost to the United States for offsetting the effects of the urban heat island in summer is more than $1billion USD a year (McPherson, 1994).

Research has shown that the effects of the urban heat island are often disproportionately felt by lower-income communities as their neighborhoods lack green space, one of the major mitigating factors of the urban heat island (Wolch, et al., 2014). Access to green space and the public health benefits that green spaces provide is an environmental justice issue (Wolch et al., 2014). Environmental justice issues are often felt in areas known as environmental justice communities. The definition of environmental justice community can vary by place but often includes people who are low income, people of color, the elderly, and the very young (Rowangould, et al., 2016).

A large factor in mitigating the urban heat island effect is tree cover or canopy cover. In a study in Portland, Oregon, Hart and Sailor (2016) found that canopy cover was the most effective factor in mitigating the urban heat island effect. Tree cover is often highest in higher income neighborhoods and lowest in low income neighborhoods. This makes low income neighborhoods more susceptible to the effects of urban heat.

Eugene, Oregon, is located in the fertile Willamette valley and benefits from a temperate climate. Many parts of the City of Eugene are covered with trees and it is known for its greenness, both in its environment and in its commitment to environmental politics. As such, Eugene has been recognized by the Arbor Day Foundation “Tree City USA” Program for 38 consecutive years, the second longest running Tree City in the State of Oregon (Arbor Day Foundation, 2017). That said, according to Altenhoff, Burke, and Kline (2017), Eugene is falling behind in its efforts to maintain the urban forest in Eugene. One reason for this is because the City of Eugene now contracts its tree planting efforts to Friends of Trees, a local nonprofit. While Friends of Trees does great work in the community, it’s model is based on “ask and you shall receive”. This disadvantages those who do not know about the existence of Friends of Trees and does not focus efforts on communities who need the support the most.

Studying the urban heat island effect in Eugene provides interesting data on a city where the effects of the urban heat island are not thought to be as strong as “typical” urban heat communities, such as Los Angeles. Understanding how Urban Heat affects a city like Eugene will have important public health impacts as residents in perceived cool climates are more likely to be susceptible to urban heat. This is because their homes are less likely to have be equipped with air conditioning or other such appliances that combat the effect of urban heat.

1.1 | RESEARCH QUESTION

This project is trying to answer the following question: **What factors affect the Urban Heat Island in Eugene, OR, and how does that impact environmental justice communities?** To answer this question, this research will try to understand the following sub questions

1. Where is the urban heat island located in Eugene, OR?
2. Where are environmental justice communities located in Eugene, OR?
3. What land use factors and environmental justice communities are associated with the urban heat island in Eugene, OR?

1.2 | PROJECT PURPOSE

This research explores the relationship between the Urban Heat Island effect and Environmental Justice issues. This project is located in Eugene, Oregon. Oregon is a state on the west coast of the United States of America, home to 4 million people. Eugene is the third largest city in the state with a population of around 200,000 people. Eugene is located at the southern end of the fertile Willamette Valley, west of the Cascade mountain range and 200 miles south of Portland, the largest city in the state. Figure 1 shows the location of Eugene in relation to the state of Oregon.

Figure 1: Location of Eugene in the State of Oregon

Source: Oliver Gaskell

The study area for this project contains 201,485 people and comprises 137 census block groups. Eugene is a predominantly white city, with 85.70% of the population stating they are white alone according to the 2016 American Community Survey 5-year estimates. The city is also fairly affluent, with 57.60% of the population making over twice the federal poverty level. Eugene is home to the University of Oregon, that largest public university in Oregon. Due to this, only 7.15% of the population have less than a high school education and 36.76% of the population has a bachelor's degree or higher.

Figure 2 provides an overview of key demographic information for Eugene.

Figure 2: Key Demographic Data for Eugene, OR

Indicator	Total	%
Demographics		
Total Population:	201,485	
White Alone	172,665	85.70%
Black or African American Alone	3,332	1.65%
American Indian and Alaska Native Alone	2,025	1.01%
Asian Alone	7,710	3.83%
Native Hawaiian and Other Pacific Islander A	674	0.33%
Some Other Race Alone	5,019	2.49%
Two or More Races	10,060	4.99%
Poverty Status		
Determined	195,440	
Under .50	22,758	11.64%
.50 to .74	-	0.00%
.75 to .99	-	0.00%
1.00 to 1.49	20,844	10.67%
1.50 to 1.99	18,787	9.61%
2.00 and Over	112,575	57.60%
Education		
Population 25 Years and Over:	130,176	
Less than High School	9,309	7.15%
High School Graduate (Includes Equivalency	26,024	19.99%
Some College	46,985	36.09%
Bachelor's Degree or higher	47,858	36.76%
Age		
Total Population:	201,485	
Under 5 Years	9,633	4.78%
5 to 17 Years	26,892	13.35%
18 to 64 Years	134,581	66.79%
65 Years and Over	30,380	15.08%

Source: Social Explorer

1.3 | ORGANIZATION

This report is organized into five chapters. The remainder of this report is organized as follows.

Chapter 2 – Literature Review discusses existing literature on urban heat islands and environmental justice.

Chapter 3 – Methodology discusses the methods used for this project.

Chapter 4 – Findings provides an overview of the findings from the geospatial analysis and regression analysis.

Chapter 5 – Discussion provides a discussion on the interpretation of the findings of the report along with potential recommendations and next steps.

Throughout this report terms will be used that are derived from the U.S census to describe race, income, and education level. These terms are outdated but are used for the sake of clarity when discussing data.

CHAPTER 2 | LITERATURE REVIEW

This literature review will synthesize current understandings of the urban heat island effects, how that pertains to environmental justice, and discuss some of the methods used to determine urban heat islands in cities.

2.1 | URBAN HEAT ISLANDS

The urban heat island effect has been well documented by climatologists since the 1960s (Chandler, 1965; Landsberg, 1981). According to Roth, et al. (1989), there are two factors that determine the urban heat island, the urban canopy layer and the urban boundary layer. The urban canopy layer is the layer below the mean roof level in the city and is the layer that is felt as ambient heat by those living in the city. The urban boundary layer is the layer which sits above the urban canopy layer at a regional scale (Roth et al., 1989). The urban canopy layer has received the most attention as this is the layer which directly affects those who live in cities. Mcpherson (1994) describes these layers in another way, discussing the idea of the urban heat island at both a micro and a mesoscale. A microscale urban heat island could be a parking lot, an area of higher heat felt by individuals through ambient temperature. A mesoscale urban heat island would be the whole urbanized area, which is hotter than the surrounding rural area.

The urban heat island is most apparent during clear, calm, summertime conditions and the differences in temperatures between rural and urban locations are usually greatest in early evening (mcpherson, 1994). It is important to note that the urban heat island is not homogenous and uniform across cities (Huang & Cadenasso, 2016), rather, there are differences in temperature across cities. The differences in temperature across the urban heat island are due to specific land use factors caused by urbanization. Factors that contribute to the urban heat island effect include: building densities, building height to width ratio, the number of roads, the density of traffic using the roads, building and surface materials, green spaces, and the canyon geometry of cities (Hart & Sailor, 2009). The canyon geometry of cities refers to the combination of narrow streets and high buildings which trap hot air and contribute to the urban heat island (Gago, el al., 2013). Stone & Rodgers (2001) elaborate on the factors that cause the urban heat island, stating the asphalt, cement, and roofing have greater heat capacity than forest vegetation. This means the presence of large amounts of asphalt with little green vegetation enhances heat retention by limiting the evapotranspiration of vegetation which is a major cooling factor in urban environments (Stone & Rodgers, 2001).

The importance of the individual factors above vary depending on the location of the city experiencing an urban heat island. For example, Hart and Sailor (2009) found that in Tel Aviv, Israel, the warmest areas of the city were associated with high density urbanism and heavy traffic flow, whilst in Gaborone, Botswana the most important factor was the presence of green space and vegetation. When studying Portland, Oregon, Hart and Sailor (2009) found that Forest Park acts as a cool island, providing a major cooling effect on the neighborhoods around the park.

Given that there are differences in temperature across the urban heat island and therefore across the city itself, there are environmental justice concerns over which communities in cities are most affected by urban heat.

2.2 | ENVIRONMENTAL JUSTICE

According to Robert Bullard, the father of the environmental justice movement, environmental justice is a grassroots movement that addresses the disproportionate burden of environmental risks or hazards borne by people of color and low income communities (Bullard, 1993). Air quality, clean water and open spaces are unequally distributed across cities which is a direct result of historical and contemporary decisions made on the locating of services in cities (Flanagan, 2000). Flanagan goes on to state that “ideas about gender, class, and race have produced an inequitable social relationship to the environment and the control of, or access to, nature” (Flanagan, 2000, p161).

Researchers have found that the disparities in the inequitable social relationship to the environment described by Flanagan manifest themselves in spaces that have higher percentages of impervious surfaces, fewer green spaces, and denser living environments, all hallmark factors that contribute to an urban heat island (Flocks, el al., 2011; Heynen, et al., 2006; Landry & Chakraborty, 2009; Shandas, 2009; Shandas & Voelkel, 2016).

These disparities are important to study because the threat of urban heat has become more insidious than larger disasters such as hurricanes or tornadoes. According to Shandas (2009), more people die of heat waves in the United States than other extreme meteorological events combined. This was demonstrated in Chicago in 1995 when 800 people died during a heat wave, and in Europe in 2003 when 35,000 people died during a summer of heatwaves, including 15,000 in France alone (Heusinkveld, et al., 2014). Researchers are beginning to understand the importance of raising awareness of local consequences of urban heat islands and the need for targeted policies to improve conditions in the hottest neighborhoods (Shandas, 2009).

In a Baltimore study, Huang and Cadenasso (2016) found that there were higher land surface temperatures in low-income neighborhoods. Land surface temperature is a key indicator of the urban heat island. In a Portland study, Shandas (2009) found that the demographic profile of residents living in the hottest parts of Portland were young, low income, renters who lived alone. According to Shandas (2009), this demographic were disproportionately living in the hottest parts of Portland. Additionally, Shandas found that there was a disproportionate number of Hispanic, older adults living alone in smaller homes than average who were affected by harmful air pollutants. Harmful air pollutants often increase with heat and are an important public health indicator of an urban heat island effect (Georgii, 1969).

McPherson (1994) found that increasing vegetated surfaces in communities has a mitigating effect on the urban heat island. Huang, et al., (1987) found that the shade of 3 trees alone around a single-family home reduced annual and peak cooling energy use by 16 and 11 percent respectively. Additionally, in the work by Hart and Sailor (2009) canopy cover was found to be the most important urban characteristic separating warmer from cooler regions. However, access to green space is often highly stratified based on income, racial characteristics, age and gender (Wolch et al., 2014). Mitigation strategies to urban heat island therefore often center around greening of urban spaces, however, Kabisch & Bosch (2017) caution this approach due to the green paradox of gentrification. This paradox refers to the link between green spaces and house prices. When a neighborhood becomes greener, its house prices rise which displaces the people the greening process was targeted at helping (Wolch et al., 2014). While targeted green space improvements are necessary, communities have to be careful to ensure that green strategies provide benefit to the communities disproportionately affected by the urban heat island (Kabisch & Bosch, 2017; Wolch et al., 2014).

The following section of the literature review will synthesize the methods developed to study the urban heat island.

2.3 | METHODS

Throughout the research three major methods of assessing the urban heat island emerge. One method is using satellite data and remote sensing to understand the land surface heat. This is augmented with aerial photography data to assess the land cover across the city (Huang & Cadenasso, 2016). Another method uses vehicles to traverse the city to acquire a more accurate picture of the ambient heat felt by residents of the city (Oke, 1973; 1976). A further method uses a network of fixed point stations around a city to capture data simultaneously in multiple locations (Yow & Carbone, 2006). Each of these data collection methods is backed by differing statistical analyses, usually based around regression models.

3.3.1 | Remote Sensing

Huang & Cadenasso (2016) took remote sensed data in Baltimore. Maryland. and then created a structural equation model and regression analysis to asses four hypotheses. The main aim of this study was to understand the processes and causalities behind the correlation between urban heat island, land cover, and social conditions of neighborhoods. Stone and Rodgers (2001) took remote sensed data from Atlanta, Georgia, and used a regression analysis to examine the relationship between city design and the urban heat island effect. This study ran multiple analysis controlling for tree canopy cover, development year of the buildings, and housing capacity. These regressions were then used to create a path model to analyze the complete interaction between parcel design and thermal emissions (Stone & Rodgers, 2001). Hung, et al. (2006) took remotely sensed satellite data and created a Gaussian approximation to quantify the spatial extents and magnitude of individual urban heat islands in eight Asian mega cities for comparisons.

3.3.2 | City traverse

The majority of city traverses in the research were completed by car, aside from the Heusinkveld et al. (2014) study which completed traverses of Rotterdam by bike. Heusinkveld et al. took their traverse data and performed a regression analysis and created a statistical model to relate the measurements taken on the traverse to urban characteristics such as vegetation cover. In a study of Doha, Qatar, Makido, et al. (2016) paired vehicle traverses with multiple regressions to explore which statistical model best explains the variability of urban heat. Firstly, an Ordinary Least Squares regression was performed, followed by a Regression Tree analysis and a Random Forest Analysis. Finally, Makido et al. (2016) analyzed the root mean square error to find that the random forest technique most accurately predicted surface temperatures. Hart and Sailor (2009) also used a regression tree analysis in their study of Portland, Oregon to determine the most important land use or surface variable in the creation of the Portland urban heat island.

3.3.3 | Fixed Network

Fixed networks of temperature sensors have been used in multiple studies of the urban heat island in cities across the world (Fast, et al., 2005; Todhunter, 1996; Yow & Carbone, 2006). In Orlando, FL, Yow and Carbone (2006) used a network of 29 fixed station sensors across the city, noting that a benefit of a fixed station network is the ability to understand local scale variabilities across a city. In Arizona, Fast et al. (2004) also found that a fixed station network provided a strong understanding of the spatial characteristics of the urban heat island in specific neighborhoods. Fast et al. (2004) also noted the relative inexpensiveness of temperature data loggers which allow for longitudinal studies to occur. However, fixed networks can be problematic if the environmental qualities of sites are not chosen well (Yow & Carbone, 2006).

There are pros and cons to using each method of assessing the urban heat island. Car traverses are time consuming and expensive to run, and can require machine learning or large supercomputers to crunch all of the data generated by multiple traverses of a city (Makido et al., 2016). Remotely sensed data, and fixed networks rely on existing sensors to be well placed (Heusinkveld et al., 2014), and may not provide clarity on what is happening below the roof surface (Roth et al., 1989).

CHAPTER 3: METHODOLOGY

The methodology for this project revolves around understanding the urban heat island effect and environmental justice communities in Eugene. To understand these two factors and their relationship this project focused on temperature, environmental justice indicators, and the existing land use. To analyze this data, a combination of quantitative analysis processes was followed. The quantitative analysis processes used were a geospatial analysis and a multi-variate regression analysis.

All data was gathered at the census block group level. Census block groups are statistical divisions of census tracts, containing between 600 and 3,000 people (U.S. Census, 2010a) This level of data was used for analysis because it is smaller than census tracts which contain between 1,200 and 8,000 people (U.S. Census, 2010b). The smaller size is important because a fine-grained analysis of the City of Eugene demonstrates more precisely which areas of the city are considered environmental justice communities, and which communities are most affected by the urban heat island.

This chapter will outline what data was used, and how each level of quantitative analysis was performed.

3.1 DATA

Data for this project was obtained from a variety of sources. The following section has been divided into three categories for the three aspects of this project: temperature data, environmental justice indicators, and land use data.

3.1.1 | Temperature Data

Temperature data for the City of Eugene was gathered from point source data generated through the website Weather Underground (wunderground.com). Weather Underground provides highly localized weather data through a network of home weather stations (Figure 3). Personal weather stations are linked to the Weather Underground network and users can select the closest station to where they live or work. This provides them with a highly local understanding of the weather outside their window. Once the weather station is linked to the network, Weather Underground stores the data in an archive, allowing users to access historical weather data in the area they live.

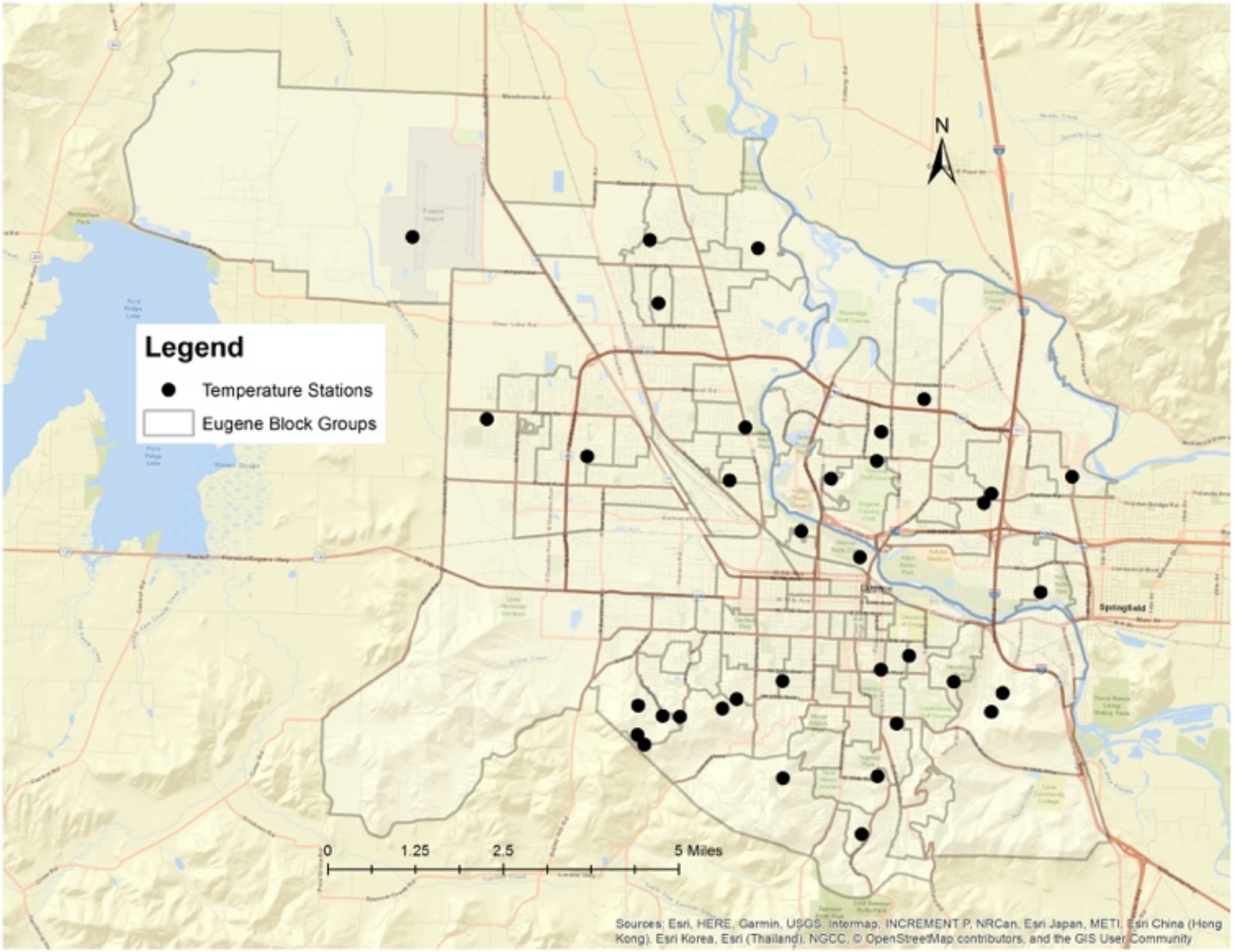
Figure 3: Personal Weather Station

Source: Amazon/Acurite

There are 39 total Weather Underground weather stations located within the City of Eugene. This project collected data from four months of summer in 2017 – June, July, August and September.

Data was cleaned to remove stations that were not functioning on any day during that period. The resulting analysis used temperature data from 35 Weather Underground weather stations for the four months of Summer 2017 (Figure 4)

Figure 4: Map showing Fixed Temperature Stations in Eugene



Source: Oliver Gaskell

Once the data was cleaned, conditional formatting was used to highlight temperatures registered above 90°F. Data for each day of the month was averaged across all stations to provide the highest temperature day for each month. This was then used as the temperature marker for that month in the proceeding analysis.

The hottest day of each month during the study period was:

- June 24th, 2017
- July 31st, 2017
- August 3rd, 2017
- September 3rd, 2017

3.1.2 | Environmental Justice Indicators

To understand the environmental justice indicators data was gathered from the 2016 American Community Survey 5-year averages through the website Social Explorer. Environmental justice communities were identifies using indicators developed by the Environmental Protection Agency (EPA). The EPA identifies six (6) indicators of environmental justice and five (5) of these were used in this project (OA US EPA, 2014). The indicators are:

- Percent Low-Income
  - Percentage of households less than or equal to twice the federal poverty level
- Percent Minority
  - Percentage of non-white individuals and those who identify as multi-racial.
- Education Level
  - Percentage of people over 25 with an education level below a high school diploma
- Individuals under 5
- Individuals over 64
- Linguistic Isolation
  - Percentage of households in which no one over the age of 14 speaks English “very well”

For this project, linguistic isolation was removed from the analysis because data is not available at the census block group level.

For each of the variables, data was downloaded from social explorer and cleaned to correspond with the 137 block groups identified in the City of Eugene.

Figure 5 provides a breakdown of each source used and its corresponding social explorer table

Figure 5: Census Data Used

Variable	2016 ACS 5-year estimates	Table Title	Description
Minority Population	SE:T13	Race	% of total population
Education	SE:T25	Educational Attainment for Population 25 Years and Over	% of total population
Under 5 / Over 64	SE:T7	Age	% of total population
Poverty	SE:T117	Ratio of Income to Poverty Level	% of total population
Building Age	SE:T98	Median Year Structure Built	Median year structure built

Source: Social Explorer

3.1.3 | Land Use Data

To understand the drivers behind the urban heat island in Eugene it was necessary assess the land use in the city. The following land use data was surveyed:

- Percentage Tree Cover
- Percentage Building Cover
- Percentage Land Use Density
    - Developed open space - <20% impervious surfaces.
    - Low Density – 20% - 49% impervious surfaces
    - Medium Density – 50% - 79% impervious surfaces
    - High Density - >80% impervious services
- Percentage of Commercial Land Use
- Building age
- Census block group files

Tree Cover data was provided by the City of Eugene as a GIS layer file. The layer has data on all trees owned or maintained by the City of Eugene. Data was cleaned to remove trees that are dead or damaged.

Building cover data and commercial land use data was provided by Lane Council of Governments (LCOG) through Dr. Yang. The shapefile information contains records of all the buildings in the city including the footprint and area of each building.

Land Use information was downloaded from the Oregon Spatial Data Library. The data is from 2011 and matches well with the more recent building data from LCOG. The data was provided as a raster file that covered the state of Oregon.

Census block group files were downloaded from the Census website TIGER products. Data was downloaded for the state of Oregon and then cleaned to include the 137 block groups that make up the City of Eugene. Each block group has a specific GEOID that denotes the block groups location and was used to link data in the GIS software.

3.2 | GEOSPATIAL ANALYSIS

Once data was obtained, the data was analyzed in ArcMap, a GIS software package. This process was an iterative process that required multiple steps depending on the data type. The geospatial analysis was used to demonstrate a visual correlation between data, and to prepare the data for regression analysis.

3.2.1 | Temperature Data

First, temperature stations were mapped onto the census block group data as points. Temperature data were joined to the station points. To map the temperature data across the space, the IDW tool was used. IDW stands for Inverse Distance Weighted and uses the assumption that data closer to the sampled location has more influence than those further away. The tool creates a raster dataset that smooths the temperature surface across the area defined by the 36 point sources of data. Following the IDW tool, the zonal statistics tool was used to give a temperature value to each block group. This tool calculates statistics for each defined zone in a dataset using values from another dataset. In this case, the defined zone is the block group, and the values come from each temperature point source. Zonal statistics was used to find the average temperature for each block group. This process created a raster file. These data were then converted to an integer and then to a shapefile to allow access to the attribute table. Data was then exported to excel to be cleaned, and then joined by GEOID to the block group file to create a final temperature layer. This data was exported to create a new shapefile with temperature data for that month.

This process was complete four times, once for each month of summer 2017.

3.2.2 | Environmental Justice indicators

For the environmental justice indicators, each dataset was first obtained from the 2016 American Community Survey through Social Explorer and cleaned. The percentages of each indicator were calculated and then each dataset was joined to the Eugene block group file by the GEOID. The data was then exported as a new layer. Each indicator was then visualized through a choropleth map to demonstrate which parts of the city are most affected by each indicator.

3.2.3 | Land Use Polygon Data

For polygon data, the process for cleaning the data was fairly straightforward. For block group data, definition queries were used to narrow down the data just to block groups in Eugene. To assess the percentage of each block group covered by building area the area of each block group was first calculated using the calculate geometry tool. Once the area of each block group was calculated, the area of building cover for each block group was calculated using the identity tool and then the data was exported and cleaned in excel. The clean data was then joined to the block group layer and exported as a new shapefile.

For tree data, a buffer was created around each tree point using the spread of each tree as the buffer. This was done to visualize the extent of tree cover. The spread of a tree corresponds to how wide the canopy is, so this was used as the best measurement of tree cover from the data provided. Data was cleaned from the dataset if the spread was not listed, or if the spread was larger than 80’ because this was deemed unlikely to occur in Eugene and attributed to an error in the data collection. Once the spread was calculated, this figure was used to calculate the percentage of each block group covered by trees. This data was then joined to the block group layer and exported as a new shapefile.

To assess building age, data was downloaded from Social Explorer and cleaned. Median structure age was then subtracted from the current year (2018) to give the age of buildings in each block group.

3.2.4 | Land Use Raster Data

Land use data for the state of Oregon was provided in a raster file. This was clipped to the size of the City of Eugene block groups using the raster clip tool. Zonal statistics were then used to create an attribute table that could allow for the export of data to excel. In excel percentages of developed open space, low, medium, and high density were calculated and then the data was joined to the block group layer and exported as a new shapefile.

The geospatial analysis process allowed for data analysis and for data visualization. Once visualization was complete, each of the different datasets analyzed in GIS were then joined by GEOID to the original block group file and the resulting attribute table was exported to excel. This file contained information for each block group on monthly temperature, percentage of environmental justice indicator and percentage of land use/land cover. This information was then ready to be used in a regression analysis to assess the correlation of each factor to the urban heat island effect.

3.3 | REGRESSION

Once the data was processed through the geospatial analysis, a final table of data was created with data linked to each individual block group. This provided the variables to be used in a multivariate regression analysis. Data was processed in SPSS through an ordinary least squares regression (OLS) and then exported to excel for interpretation. The equation for this regression was:

$$\hat{Y} = b_0 + b_1X_1 + b_2X_2 + \cdots + b_pX_p$$

$\hat{Y}$ is the dependent variable, temperature. The regression was run four times, once for the temperature data in each month.

X_p is the independent variable. In this analysis, the independent variables are the environmental justice indicators and the land use variables (see Figure 57).

b_p is the regression coefficient. The regression coefficient represents the change in the dependent variable relative to a one unit change in the independent variable when holding all other variables constant.

The aim of the regression is to understand the impact of the independent variables on temperature and to see which factors have the most impact on temperature.

3.4 | DATA LIMITATIONS

There are a number of limitations to the data in this study. The temperature data is from point source data which is less reliable than other forms of data such as remote sensing because stationary point source data can be affected by other factors such as car exhausts, or being located in too much shade, or too much sun. In addition, there were only a small number of point source temperature data so the smoothing of the data may have caused some inaccuracies. One major limitation of the study is the availability of temperature data through Weather Underground. The number of point sources of data in the city of Eugene is limited to the number of weather stations owned by people in the city. Weather stations are not cheap, costing between $150 and $1,000 to purchase. This cost barrier means that there were few weather stations located in environmental justice communities, meaning that the data in these areas was less reliable than in non-environmental justice communities.

The tree data only covers trees owned and maintained by the City of Eugene. It therefore does not include privately owned trees or trees owned by businesses or the University of Oregon. This provides a low estimate of tree coverage for Eugene which affects the accuracy of the data.

CHAPTER 4: FINDINGS

As stated in the introduction, the aim of this project is to answer the following question: Is the urban heat island in Eugene OR caused by a lack of trees in environmental justice communities? The findings of this report show that

1. There is an urban heat island effect in Eugene. The hottest parts of the city are in the eastern area of the Bethel Neighborhood, between Highway 99 and N Danebo Avenue, and in the north part of the Cal Young neighborhood, between Delta Highway and Norkenzie road.
2. The location of environmental justice communities in Eugene vary depending on the chosen indicator. Each indicator has block groups with at least 10% of residents who align with that indicator. The highest percentage of residents are those who are Low-income, followed by those who are elderly (over 64). The lowest percentage of residents per block group are residents under 5 years old.
3. According to the regression model, the major land use associated with the urban heat island effect are medium or high-density development. The heat island has strong correlations with the very old and the very young in environmental justice communities.

This chapter will explore the findings discovered through the geospatial analysis and regression analysis. Chapter Five will discuss the findings in depth.

4.1 | TEMPERATURE

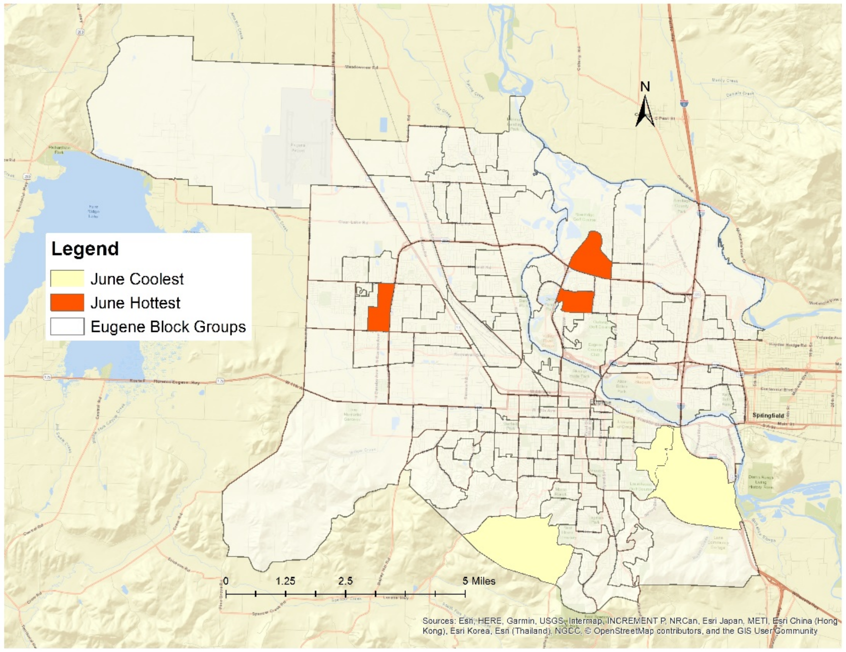
Temperature data was taken in summer 2017 over four months – June, July, August and September. In each of these months the hottest day was chosen to be analyzed and the temperatures were averaged across each block group. The following section provides the temperature findings for each month.

4.1.1 | June 24, 2017

The average temperature in the hottest block group for the June data was 101.25°F. The average temperature in the coolest block group for the June data was 95.00°F. This is a temperature gradient of 6.25°F.

Figure 6 shows the mapped distribution of the hottest and coolest block groups in June. Figure 7 shows the data for the three hottest block groups. There were 6 block groups with an average temperature of 101.00°F in June. Figure 8 shows the data for the three coolest block groups in June.

Figure 6: Hottest and coolest block groups, June 24, 2017



Sources: Esri, HERE, Garmin, USGS, Intermap, INCREMENT P, NRCan, Esri Japan, METI, Esri China (Hong Kong), Esri Korea, Esri (Thailand), NGCC, © OpenStreetMap contributors, and the GIS User Community

Figure 7: Hottest block groups, June 24, 2017

Block Group	AVTEMPJune
410390029032	101.25
410390022012	101.00
410390025033	101.00

Figure 8: Coolest block groups, June 24, 2017

Block Group	AVTEMPJune
410390054003	95.33
410390036003	95.25
410390049001	95.00

4.1.2 | July 31, 2017

The average temperature in the hottest block group for the July data was 97.33°F. The average temperature in the coolest block group for the July data was 90.40°F. This is a temperature gradient of 6.93°F.

Figure 9 shows the mapped distribution of the hottest and coolest block groups in July. Figure 10 shows the data for the three hottest block groups in July. Figure 11 shows the data for the three coolest block groups in July. There were 6 block groups with an average temperature of 90.50°F in July.

Figure 9: Hottest and coolest block groups, July 31, 2017

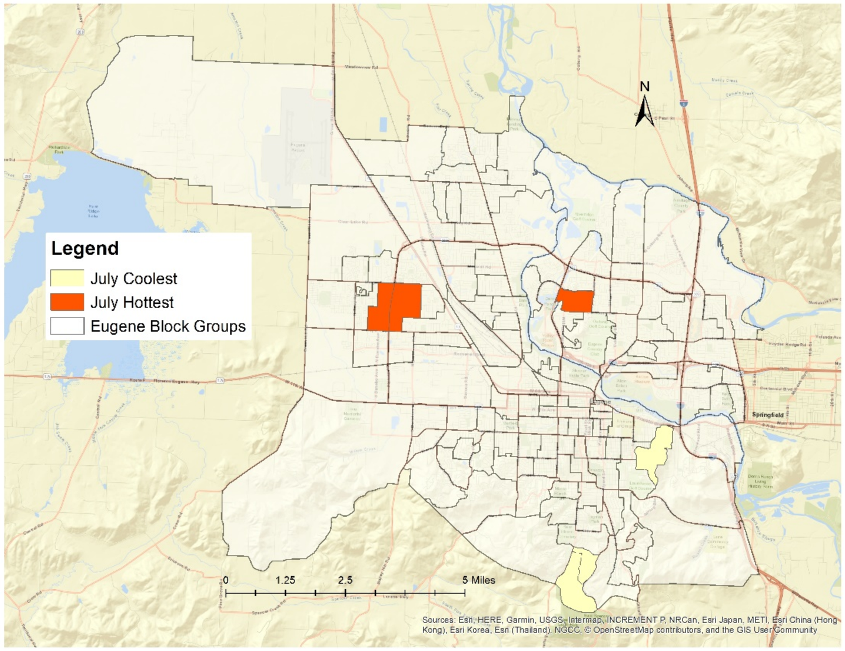


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Figure 10: Hottest block groups, July 31, 2017

Block Group	AVTEMPJuly
410390026003	97.33
410390025033	96.75
410390029032	96.20

Figure 11: Coolest block groups, July 31, 2017

Block Group	AVTEMPJuly
410390054002	90.50
410390054004	90.50
410390049001	90.40

4.1.3 | August 3, 2017

The average temperature in the hottest block group for the August data was 108.20°F. This was the hottest temperature recorded during the study period. The average temperature in the coolest block group for the August data was 99.43°F. This is a temperature gradient of 8.77°F.

Figure 12 shows the mapped distribution of the hottest and coolest block groups in August. Figure 13 shows the data for the three hottest block groups in August. Figure 14 shows the data for the three coolest block groups in August. There were 4 block groups with an average temperature of 99.50°F in August.

Figure 12: Hottest and coolest block groups, August 3, 2017

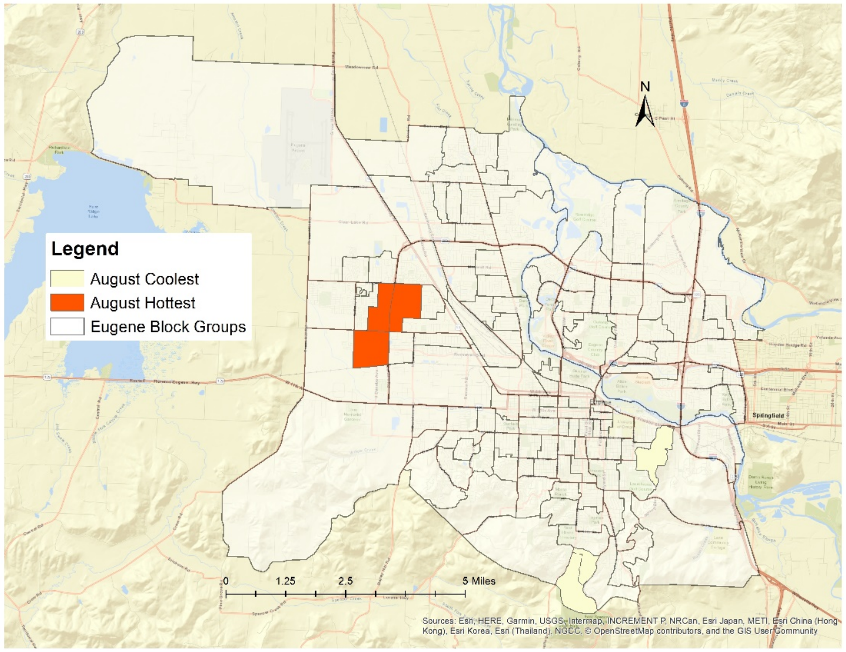

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Figure 13: Hottest block groups, August 3, 2017

Block Group	AVTEMPAug
410390026003	108.20
410390025033	107.75
410390025042	107.00

Figure 14: Coolest block groups, August 3, 2017

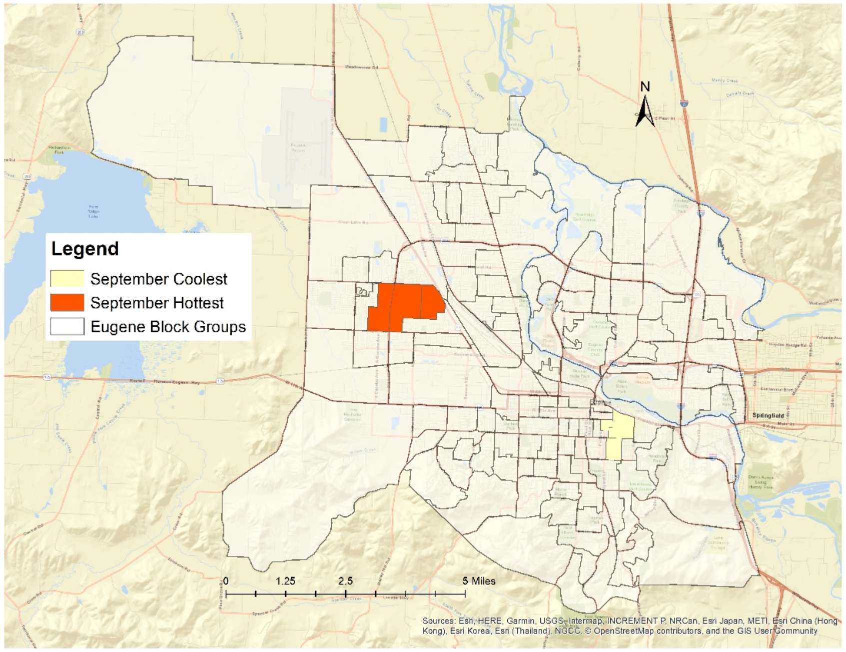
Block Group	AVTEMPAug
410390054002	99.50
410390054004	99.50
410390049001	99.43

4.1.4 | September 3, 2017

The average temperature in the hottest block group for the September data was 101.25°F. The average temperature in the coolest block group for the September data was 90.00°F. This is a temperature gradient of 11.25°F. This was the largest temperature gradient demonstrated during the study period.

Figure 15 shows the mapped distribution of the hottest and coolest block groups in September. Figure 16 shows the data for the three hottest block groups in September. Figure 17 shows the data for the three coolest block groups in September. There were 3 block groups with an average temperature of 90.00°F in September. The next coolest temperature was 90.50°F.

Figure 15: Hottest and coolest block groups, September 3, 2017



Sources: Esri, HERE, Garmin, USGS, Intermap, INCREMENT P, NRCan, Esri Japan, METI, Esri China (Hong Kong), Esri Korea, Esri (Thailand), NGCC, © OpenStreetMap contributors, and the GIS User Community

Figure 16: Hottest block groups, September 3, 2017

Block Group	AVTEMPSep
410390026003	101.25
410390025033	100.75
410390026002	99.50

Figure 17: Coolest block groups, September 3, 2017

Block Group	AVTEMPSep
410390037002	90.00
410390038005	90.00
410390048001	90.00

4.2 | ENVIRONMENTAL JUSTICE INDICATORS

Environmental Justice data was taken from the U.S Census and American Community Survey. The following sections demonstrate the findings from the analysis of the environmental justice indicators.

4.2.1 | Minority

Minority residents refer to those who are not considered “white only” by the U.S Census. This include Hispanic, black, native American, Asian, and Native Hawaiian residents, along with those who are two or more races. In the block group with the highest percentage of minority population, 42.60% of residents are considered minority residents – that is, they are not white. In the block group with the lowest percentage of minority population, 0.00% of residents are considered minority residents.

Figure 18 shows the mapped distribution of block groups with the highest and lowest percentages of minority residents.

Figure 19 shows the three block groups with the highest percentage of minority residents. Figure 20 shows the three block groups with the lowest percentage of minority residents. There is a 42.60% difference between the block group with the most minority residents and the block group with the least minority residents.

Figure 18: Block groups with the highest and lowest percentages of minority residents

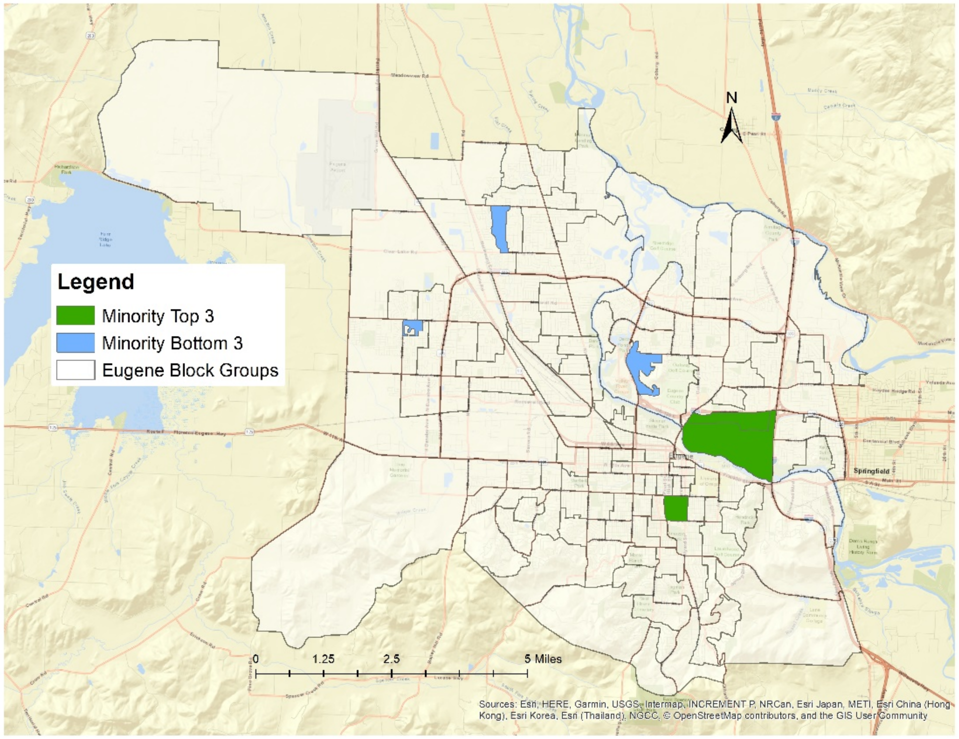


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Figure 19: Block groups with highest percentage minority residents

Block Group	PCT_Minority
410390048003	42.60%
410390031024	39.40%
410390031023	36.90%

Figure 20: Block groups with lowest percentage minority residents

Block Group	PCT_Minority
410390030001	0.00%
410390025034	0.70%
410390024032	2.00%

4.2.2 | Education level

As an environmental justice indicator, education level refers to those residents who did not complete high school and have no other education. In the block group with the highest percentage of residents with no education, 29.70% do not have a high school diploma. In the block group with the lowest percentage of residents with no education, 0.00% do not have a high school diploma. There are 14 block groups in Eugene with 0.00% of residents that do not have a high school diploma.

Figure 21 shows the mapped distribution of block groups with the highest and lowest percentages of residents with no high school diploma.

Figure 22 shows the three block groups with the highest percentage of residents without a high school diploma. Figure 23 shows the three block groups with the lowest percentage of residents that do not have a high school diploma.

Figure 21: Block groups with highest and lowest percentage residents with no high school diploma

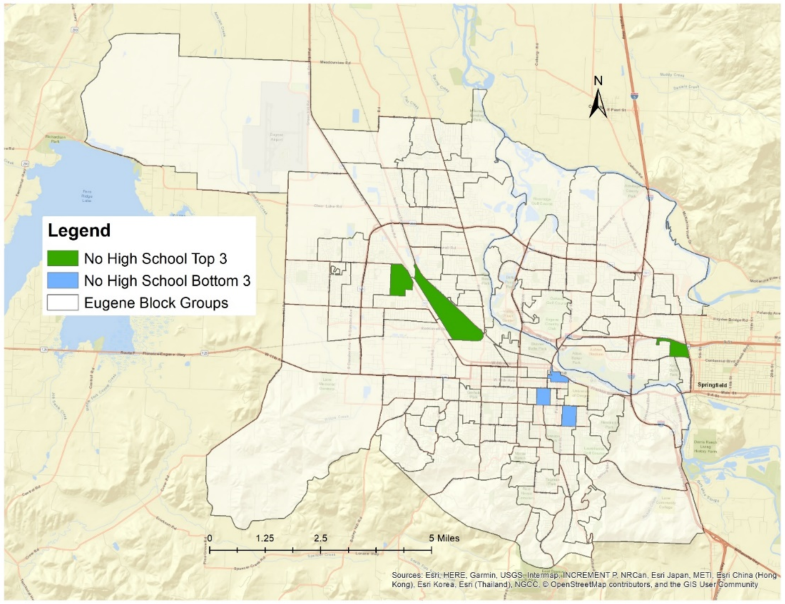

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Figure 22: Block groups with highest percentage residents with no high school diploma

Block Group	PCT_NoHS
410390026002	29.70%
410390032011	26.40%
410390042001	23.30%

Figure 23: Block groups with lowest percentage residents with no high school diploma

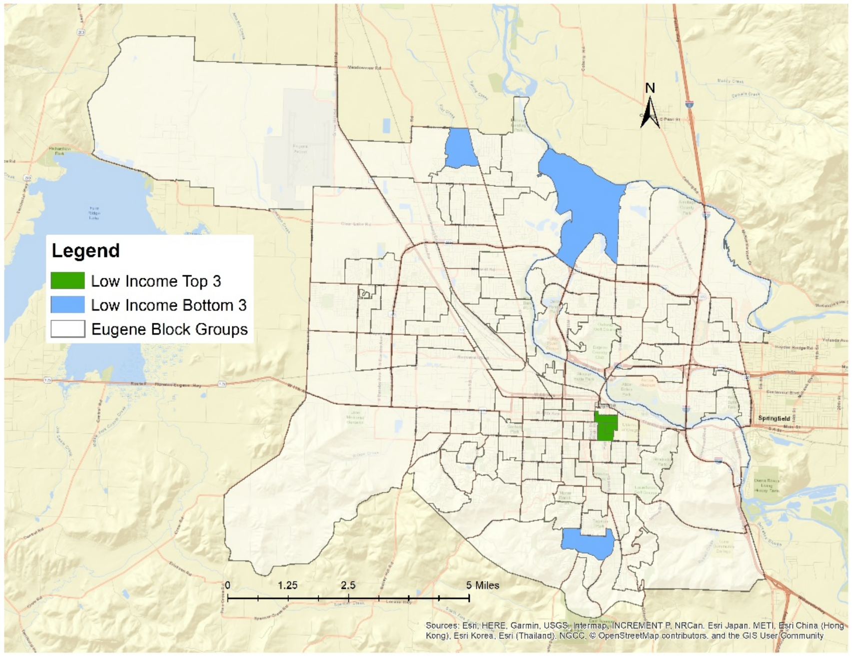
Block Group	PCT_NoHS
410390038003	0.00%
410390038001	0.00%
410390048001	0.00%

4.2.3 | Low-Income

Low-income residents that are considered part of environmental justice communities are those that make less than or equal to twice the federal poverty level. In the block group with the highest percentage of low-income residents, 85.53% are considered low-income. In the block group with the lowest percentage of low-income residents, 5.83% are considered low-income.

Figure 24 shows the mapped distribution of block groups with the highest and lowest percentages of residents who are low income. Figure 25 shows the three block groups with the highest percentage of low-income residents. Figure 26 shows the three block groups with the lowest percentage of low-income residents.

Figure 24: Block groups with the highest and lowest percentages of people who are low-income



Sources: Esri, HERE, Garmin, USGS, Intermap, INCREMENT P, NRCan. Esri Japan. METI, Esri China (Hong Kong), Esri Korea, Esri (Thailand). NGCC, © OpenStreetMap contributors. and the GIS User Community

Figure 25: Block groups with highest percentage of residents who are low income

Block Group	PCT_LowIncome
410390038002	83.53%
410390038005	81.06%
410390038004	76.62%

Figure 26: Block groups with lowest percentage residents who are low income

Block Group	PCT_LowIncome
410390054001	5.83%
410390024012	6.47%
410390022011	6.80%

4.2.4 | Under Five years old

Children under 5 years old are considered members of the environmental justice community due to their higher susceptibility to illness. In the block group with the highest percentage of children under five years, 12.20% are under 5. In the block group with the lowest percentage of children under five years 0.00% are under 5. There are 16 block groups in Eugene with 0.00% of residents under five.

Figure 27 shows the mapped distribution of block groups with the highest and lowest percentages of residents under 5 years old. Figure 28 shows the three block groups with the highest percentage of residents under five years old. Figure 29 shows the three block groups with the lowest percentage of residents under five.

Figure 27: Block groups with the highest and lowest percentages residents under 5 years old

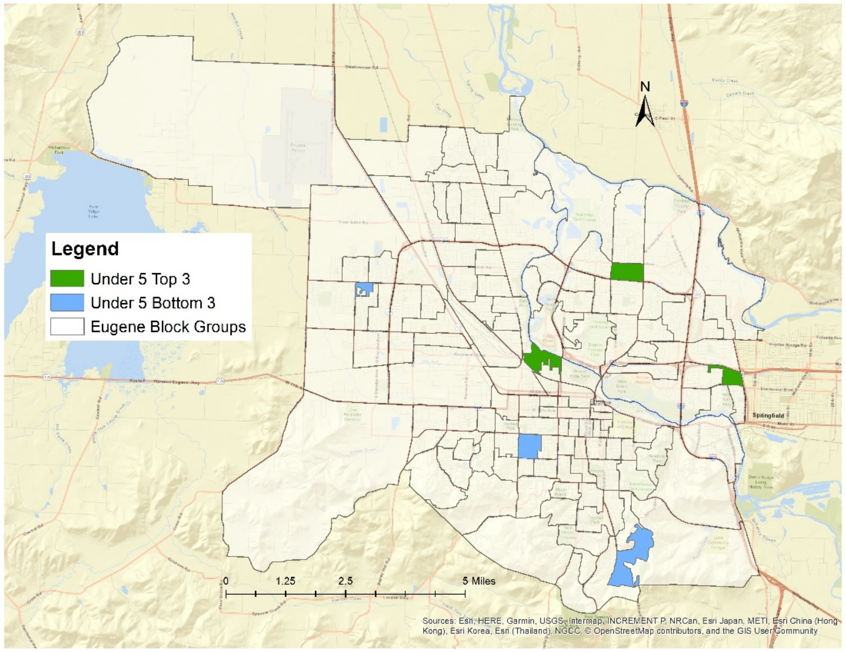


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Figure 28: Block groups with highest percentage residents under 5 years old

Block Group	PCT_UFiveYrs
410390022022	12.20%
410390032011	11.40%
410390040003	11.10%

Figure 29: Block groups with lowest percentage residents under 5 years old

Block Group	PCT_UFiveYrs
410390050004	0.00%
410390046003	0.00%
410390025034	0.00%

4.2.5 | Over Sixty-Four years old

Adults over 64 are considered members of the environmental justice community due to their higher susceptibility to illness. In the block group with the highest percentage of adults over sixty-four years old, 51.30% are over sixty-four. In the block group with the lowest percentage of adults over sixty-four years old, 0.00% are over sixty-four. There are 2 block groups in Eugene that have 0.00% of residents over sixty-four.

Figure 30 shows the mapped distribution of block groups with the highest and lowest percentages of residents over sixty-four. Figure 31 shows the three block groups with the highest percentage of residents over sixty-four years old. Figure 32 shows the three block groups with the lowest percentage of residents over sixty-four.

Figure 30: Block groups with the highest and lowest percentages residents over 64 years old

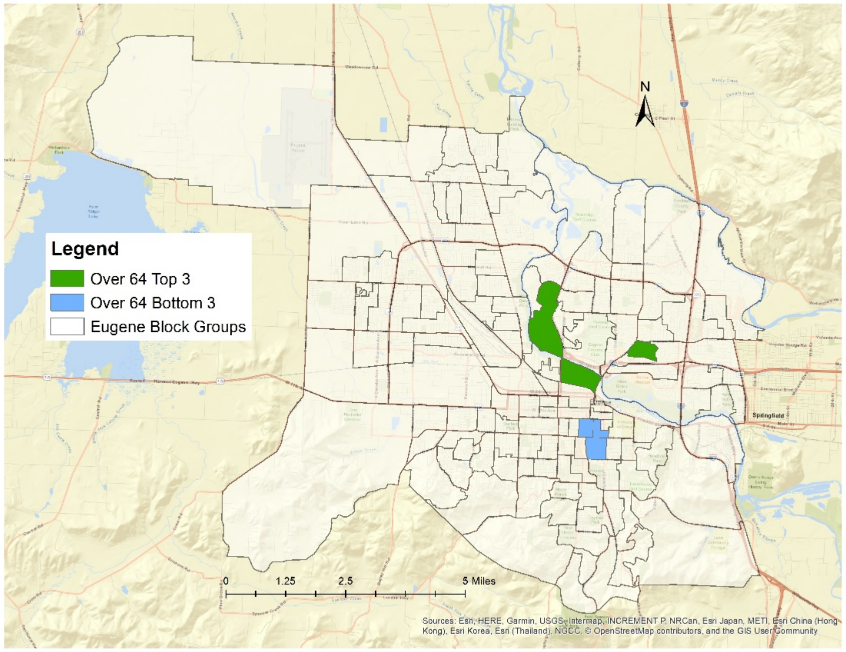

Figure 31: Block groups with highest percentage residents over 64 years old

BlkGrp	PCT_OsixtyFour
410390029041	51.30%
410390040001	47.50%
410390031021	45.60%

Figure 32: Block groups with lowest percentage residents over 64 years old

Block Group	PCT_OsixtyFour
410390038003	0.00%
410390048003	0.00%
410390038004	0.60%

4.3 | LAND USE

Land use data was taken from a variety of government sources including Lane Council of Governments, City of Eugene, and Oregon Spatial Data Library. The following section provides the findings for each land use indicator.

4.3.1 | Tree Cover

Tree cover was calculated through the spread of the trees canopy which gives the diameter of the area covered by the tree. In the block group with the highest percentage of tree cover, 0.44% of the total area of the block group is covered by trees. In the block group with the lowest percentage of tree cover, 0.00% is covered with trees. There are 5 block groups in Eugene that have a percentage tree coverage of 0.00%. There are 10 block groups that did not have any tree data and returned a value of 0. These were not calculated in the tree cover calculations.

Figure 33 shows the mapped distribution of block groups with the highest and lowest percentages of tree cover. Figure 34 shows the three block groups with the highest percentage of tree coverage. Figure 35 shows the three block groups with the lowest percentage of tree coverage.

Figure 33: Block groups with highest and lowest percentage tree cover

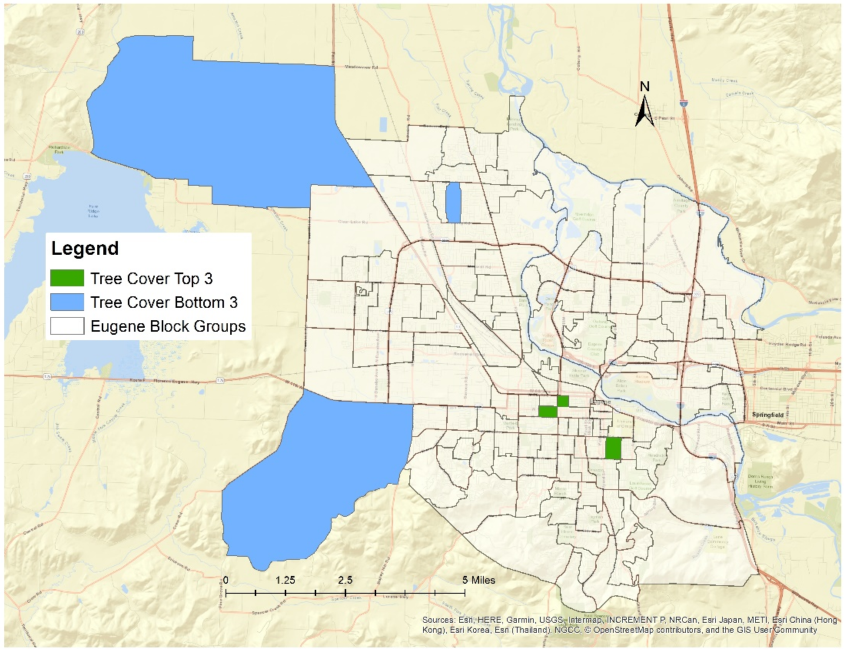

Figure 34: Block groups with highest percentage tree cover

Block Group	PCT_TreeCover
410390045022	0.44%
410390048001	0.43%
410390039003	0.38%

Figure 35: Block groups with lowest percentage tree cover

Block Group	PCT_TreeCover
410390010022	0.00%
410390024033	0.00%
410390010022	0.00%

4.3.2 | Building Cover

Building cover demonstrates the amount of each block group covered by buildings. In the block group with the highest percentage of building cover, 38.23% of the total area of the block group is covered by buildings. In the block group with the lowest percentage of building cover, 0.36% of the total area of the block group is covered by buildings.

Figure 36 shows the mapped distribution of block groups with the highest and lowest percentages of building cover. Figure 37 shows the three block groups with the highest percentage of building cover. Figure 38 shows the three block groups with the lowest percentage of building cover.

Figure 36: Block groups with highest and lowest percentage building cover

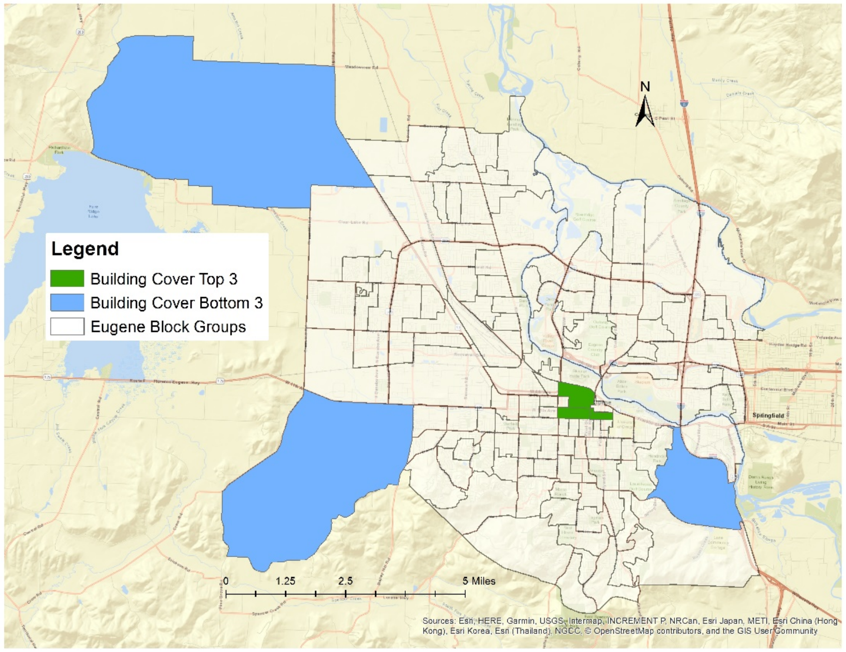

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Figure 37: Block groups with highest percentage building cover

Block Group	PCT_BuildingCover
410390039002	38.23%
410390038002	35.16%
410390039001	32.96%

Figure 38: Block groups with lowest percentage building cover

Block Group	PCT_BuildingCover
410390010012	0.36%
410390010022	0.85%
410390036003	2.10%

4.3.3 | Commercial Land Use

Commercial land use demonstrates the amount of each block group covered by commercial uses. In the block group with the highest percentage of commercial use coverage, 81.55% of the block group is covered by commercial buildings. In the block group with the lowest percentage of commercial use coverage, 0.00% of the block group is covered by commercial buildings. There are 7 block groups in Eugene that have a percentage commercial coverage of 0.00%

Figure 39 shows the mapped distribution of block groups with the highest and lowest percentages of commercial cover. Figure 40 shows the three block groups with the highest percentage of commercial cover. Figure 41 shows the three block groups with the lowest percentage of commercial cover.

Figure 39: Block groups with highest and lowest percentage commercial cover

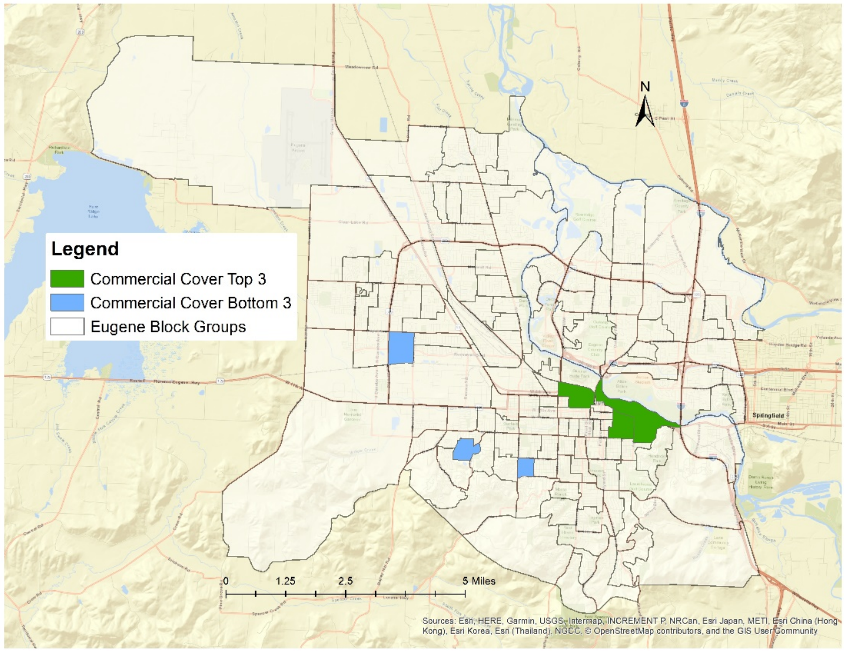

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Figure 40: Block groups with highest percentage commercial cover

Block Group	PCT_Commercial
410390037002	81.55%
410390039001	72.18%
410390037001	63.08%

Figure 41: Block groups with the lowest percentage commercial cover

Block Group	PCT_Commercial
410390044042	0.00%
410390053001	0.00%
410390043003	0.00%

4.3.4 | Land Use Density

Land use density is split into four categories – developed open space, low-density, medium-density, and high-density. Developed open space refers to areas that have less than 20% of surfaces that are impervious. Low-density refers to areas that have between 20% and 49% of surfaces that are impervious. Medium-density refers to areas that have between 50% and 79% of surfaces that are impervious. High-density refers to areas that have over 80% of surfaces that are impervious.

The block group with the highest percentage of a specific land cover is 91.63% covered by low density developments. There are 45 of 137 block groups in Eugene with 0.00% land cover in the high density and developed open space categories. Figure 42, Figure 45, Figure 48, and Figure 51 show the mapped distribution of block groups with the highest and lowest percentages of developed open space, low-density, medium-density, and high-density coverage.

Figure 43, Figure 46, Figure 49, and Figure 52 show the three block groups with the highest percentage of developed open space, low-density, medium-density, and high-density coverage. Figure 44,Figure 47, Figure 50, and Figure 53 show the three block groups with the lowest percentage of developed open space, low-density, medium-density, and high-density coverage.

Figure 42: Block groups with highest and lowest percentage developed open space (<20% impervious surfaces)

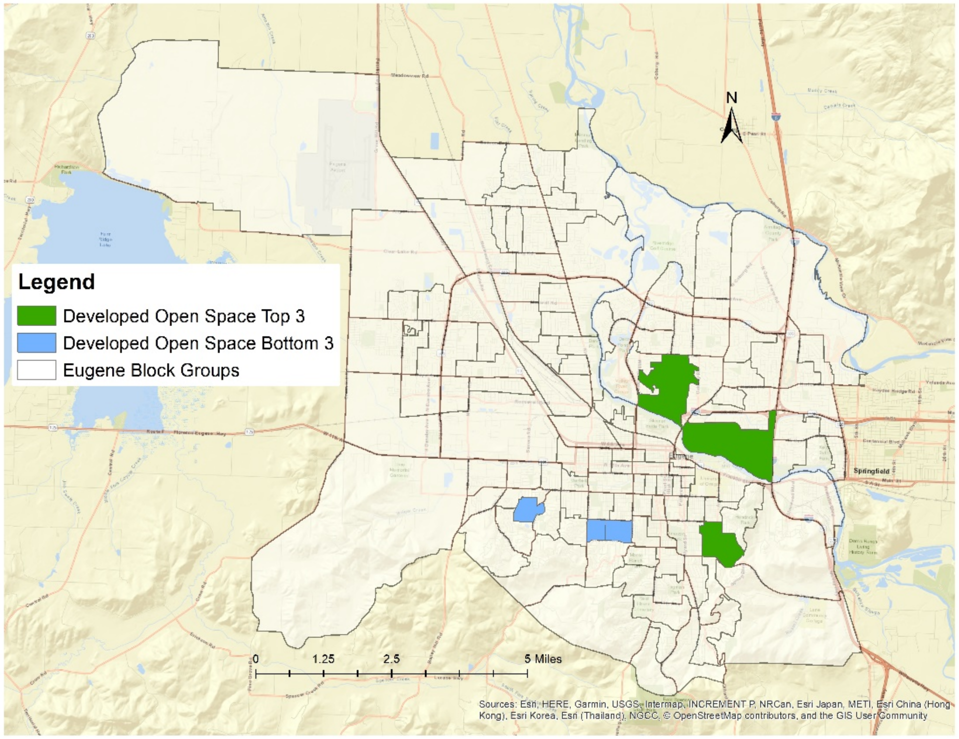

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Figure 43: Block groups with highest percentage developed open space (<20% impervious surfaces)

Block Group	PCT_DevOpenSpace
410390030002	39.51%
410390049003	30.06%
410390031024	27.90%

Figure 44: Block groups with lowest percentage developed open space (<20% impervious surfaces)

Block Group	PCT_DevOpenSpace
410390044042	0.00%
410390046002	0.00%
410390053001	0.00%

Figure 45: Block groups with highest and lowest percentage low density development (20%-49% impervious surfaces)

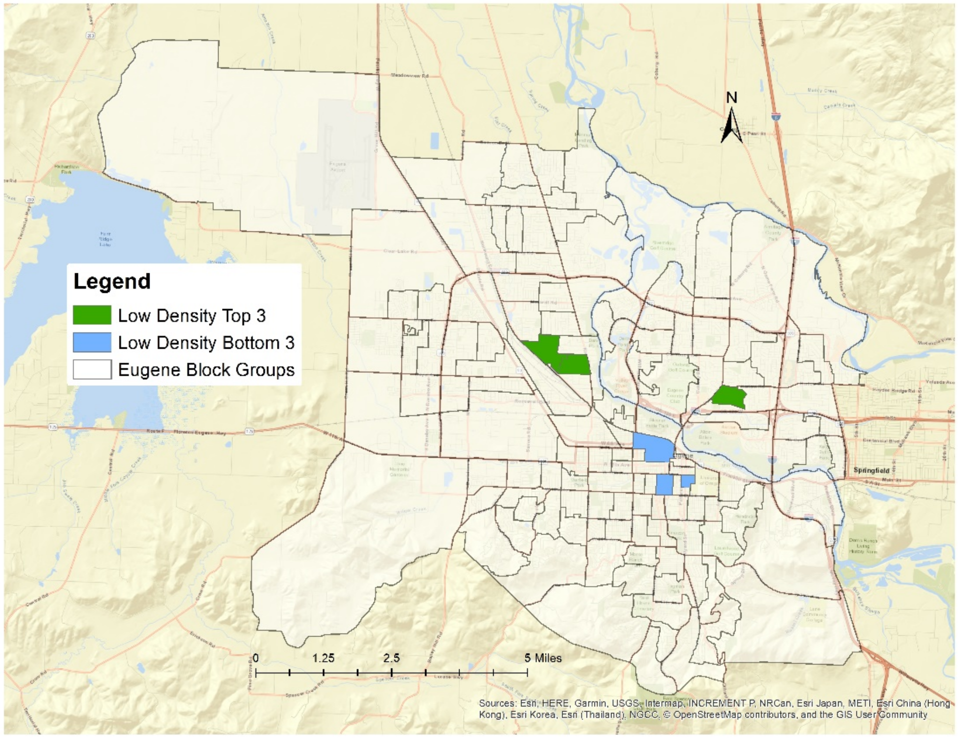

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Figure 46: Block groups with highest percentage low-density development (20%-49% impervious surfaces)

Block Group	PCT_LOWDens
410390041004	91.63%
410390041003	82.30%
410390031021	80.04%

Figure 47: Block groups with lowest percentage low-density development (20%-49% impervious surfaces)

Block Group	PCT_LOWDens
410390038003	1.54%
410390038005	4.05%
410390039001	5.13%

Figure 48: Block groups with highest and lowest percentage medium density development (50%-79% impervious surfaces)

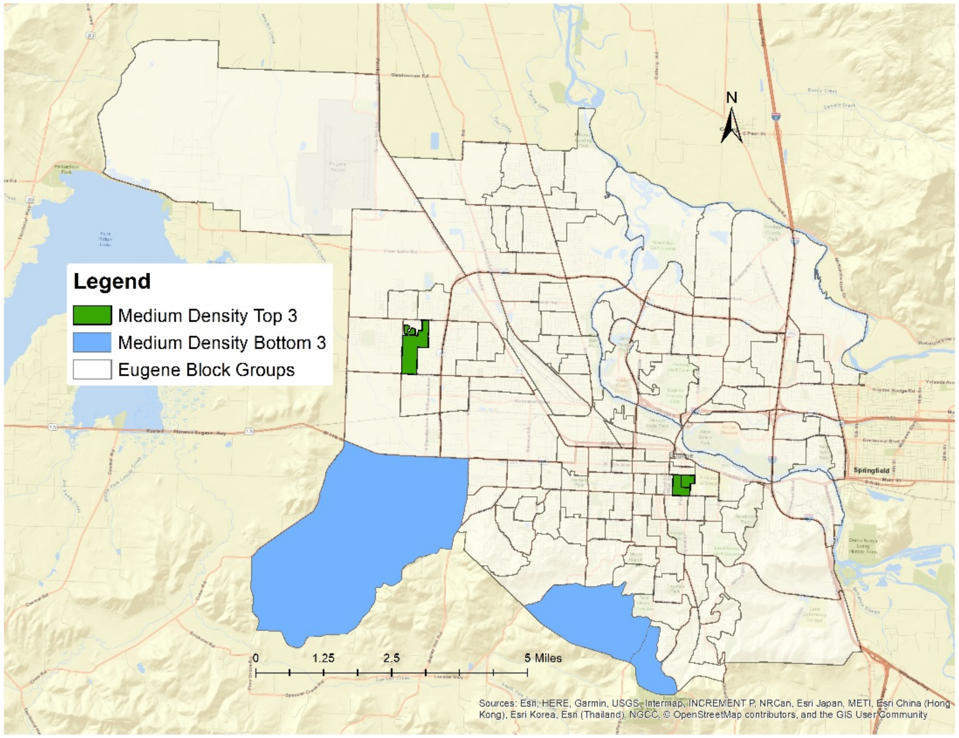

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Figure 49: Block groups with highest percentage medium-density development (50%-79% impervious surfaces)

Block Group	PCT_MEDDens
410390038004	86.02%
410390038005	73.65%
410390025032	69.39%

Figure 50: Block groups with lowest percentage medium-density development (50%-79% impervious surfaces)

Block Group	PCT_MEDDens
410390054004	0.07%
410390054003	1.43%
410390010022	1.96%

Figure 51: Block groups with highest and lowest percentage high-density development (>80% impervious surfaces)

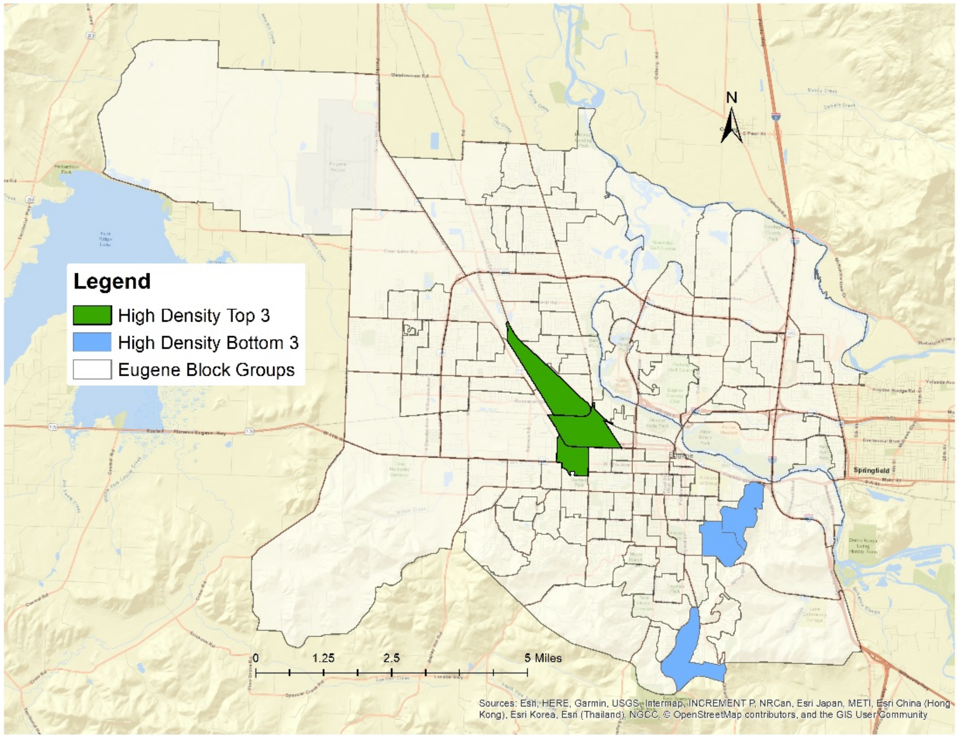

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Figure 52: Block groups with highest percentage high-density development (>80% impervious surfaces)

Block Group	PCT_HIDens
410390044033	65.91%
410390042001	61.71%
410390042002	60.54%

Figure 53: Block groups with lowest percentage high-density development (>80% impervious surfaces)

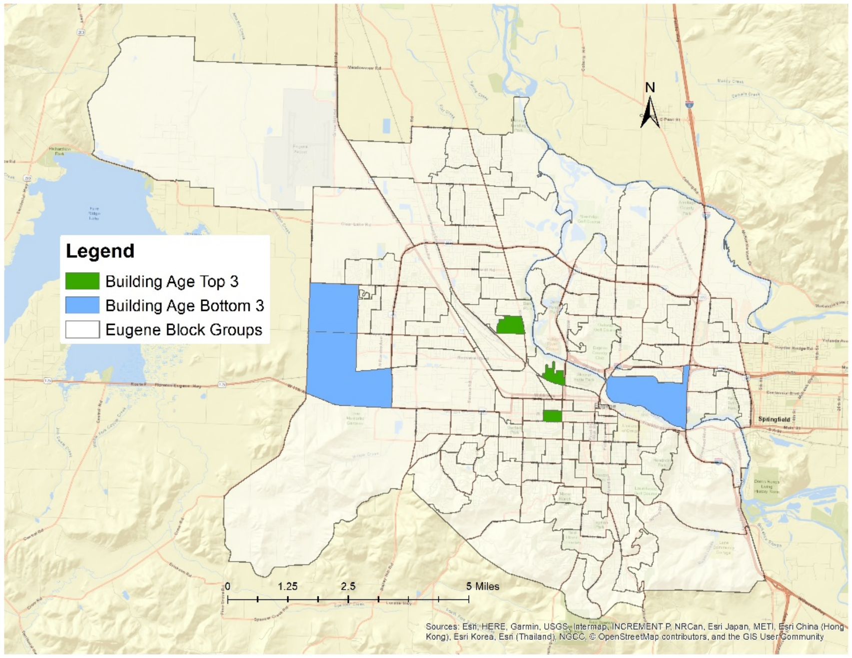
Block Group	PCT_HIDens
410390054004	0.00%
410390049001	0.00%
410390050003	0.00%

4.3.5 | Building Age

Building age describes the age of the building and therefore how long the landscaping surrounding the building has had time to become established. The median age of structures in the block group with the oldest buildings is 79 years. The median age of structures in the block group with the youngest buildings in 15.

Figure 54 shows the mapped distribution of block groups with the oldest and youngest median building age. Figure 55 shows the three block groups with the oldest median age of buildings. Figure 56 shoes the three block groups with the youngest median age of buildings.

Figure 54: Block groups with oldest and youngest median age of buildings



Sources: Esri, HERE, Garmin, USGS, Intermap, INCREMENT P, NRCan, Esri Japan, METI, Esri China (Hong Kong), Esri Korea, Esri (Thailand), NGCC, © OpenStreetMap contributors, and the GIS User Community

Figure 55: Block groups with the oldest median age of buildings

Block Group	Building_Age
410390045022	79
410390041004	71
410390040002	69

Figure 56: Block groups with the youngest median age of buildings

Block Group	Building_Age
410390025041	15
410390025031	16
410390031024	18

4.4 | REGRESSION

In order to understand the relationship between variables and the drivers behind the urban heat island, four multivariate OLS regressions were run in SPSS. Each model had temperature as the dependent variable and each run of the model used a different month as the dependent variable.

Figure 57 shows the independent variables used for each round of regression model. Figure 58 shows the descriptive statistics for the independent variables used in this study.

Figure 57: Independent variables used in regression models

Variables	
Environmental Justice	**Land Use**
	PCT_TreeCover
PCT_Minority	PCT_BuildingCover
PCT_LowIncome	PCT_LOWDens
PCT_UFiveYrs	PCT_MEDDens
PCT_OsixtyFour	PCT_HIDens
PCT_NoHS	PCT_DevOpenSpace
	PCT_Commercial
	Building_Age

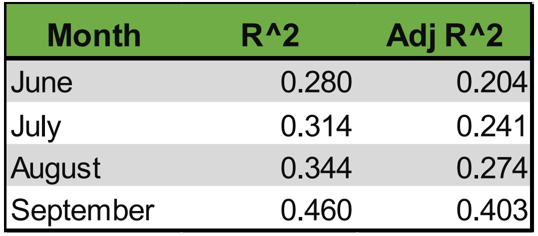
Figure 58: Descriptive Statistics for all variables

Descriptive Statistics					
Indicator	**N**	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
AVTEMPJune	137	95.00	101.00	97.57	1.59
AVTEMPJuly	137	90.00	97.00	93.26	1.64
AVTEMPAug	137	99.40	108.20	102.44	1.89
AVTEMPSep	137	90.00	101.30	94.10	2.11
PCT_Total	137	0.17	0.84	0.41	0.12
PCT_Minority	137	0.00	0.43	0.13	0.08
PCT_LowIncome	137	0.00	0.00	0.00	0.01
PCT_UFiveYrs	137	0.00	0.12	0.05	0.03
PCT_OsixtyFour	137	0.00	0.51	0.16	0.09
PCT_NoHS	137	0.00	0.30	0.07	0.06
PCT_TreeCover	137	0.00	0.00	0.00	0.00
PCT_BuildingCove	137	0.00	0.38	0.16	0.07
PCT_LOWDENS	137	0.02	0.92	0.40	0.20
PCT_MEDDENS	137	0.00	0.86	0.32	0.17
PCT_HIDENS	137	0.00	1.00	0.10	0.14
Valid N (listwise)	137				

4.4.1 | Model Fit

The R-Squared (R^2) coefficient explains the variability of the data. Figure 59 shows the differing R^2 for the data in this project. June has the lowest R^2 of 0.280, meaning that independent variables of the model explain 28% of the variability of the temperature in June. September has the highest R^2 of 0.460. This means that the independent variables of the model explain 46% of the variability of the temperature in September.

Figure 59: R-Squared and Adjusted R-Squared regression results



Month	R^2	Adj R^2
June	0.280	0.204
July	0.314	0.241
August	0.344	0.274
September	0.460	0.403

Each regression model returned an ANOVA table demonstrating the model is statistically significant at the 95% confidence level.

Figure 60, Figure 61, Figure 62, and Figure 63 show the ANOVA tables for each regression model.

Figure 60: June ANOVA table

JUNE - ANOVA[a]					
Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	96.367	13	7.413	3.674	.000[b]
Residual	248.15	123	2.017		
Total	344.517	136			

Figure 61: July ANOVA table

JULY - ANOVA[a]					
Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	113.969	13	8.767	4.324	.000[b]
Residual	249.398	123	2.028		
Total	363.367	136			

Figure 62: August ANOVA Table

AUGUST - ANOVA[a]					
Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	167.292	13	12.869	4.954	.000[b]
Residual	319.532	123	2.598		
Total	486.825	136			

Figure 63: September ANOVA Table

SEPTEMBER - ANOVA[a]					
Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	278.77	13	21.444	8.058	.000[b]
Residual	327.318	123	2.661		
Total	606.088	136			

a – Dependent Variables: AVTemp

b. – Predictors (constant): Building_Age, PCT_UFiveYrs, PCT_MEDDens, PCT_HIDens, PCT_OsixtyFour, PCT_NoHS, PCT_DevOpenSpace, PCT_Minority, PCT_Commercial, PCT_TreeCover, PCT_LOWDens, PCT_LowIncome, PCT_BuildingCover,

4.4.2 | Regression Findings

The regression findings returned both statistically significant results and non-statistically significant results. For every month the following variables returned statistically significant results at the 95% confidence level:

- Percentage of Population Under 5 years old
- Percentage of Land cover that is Low Density
- Percentage of Land Cover that is Medium Density
- Percentage of Land Cover that is High Density

Building Age and Building Cover both have statistically significant results at the 90% and 95% confidence level. The percentage of the population over 64 years old returns statistically significant results at the 95% confidence level in June, July and August, but not in September. The percentage of low income residents and the percentage of those with less than a high school education both return statistically significant results at the 95% level in September only, but not in the other months.

In each case of a statistically significant result, this means that for every 1 unit increase in the independent variable, there is a corresponding change in temperature. For example, in the June model, a one percent increase in the number of children under 5 in a block group is associated with a 12.78^{o}F increase in temperature.

Figure 64 shows the regression model outputs for each month.

Figure 64: Combined monthly regression results

Variable	June	July	August	September
Temperature (Constant)	95.092	90.771	100.419	94.033
PCT_Minority	-1.079	-0.515	-1.228	-2.958
PCT_LowIncome	-0.387	-0.016	-1.13	* -3.732
PCT_UFiveYrs	* 12.776	* 10.71	* 11.627	*10.816
PCT_OsixtyFour	* 4.974	* 5.225	* 4.549	2.642
PCT_NoHS	0.357	0.872	4.051	* 6.483
PCT_TreeCover	116.521	-21.452	3.182	-236.5
PCT_BuildingCover	* -8.985	** -8.084	* -9.99	* -9.755
PCT_LOWDens	* 3.611	* 3.433	*3.629	* 2.452
PCT_MEDDens	* 4.668	*5.389	* 6.209	* 6.508
PCT_HIDens	* 5.478	* 5.185	* 6.291	* 5.151
PCT_DevOpenSpace	3.858	3.525	2.807	1.666
PCT_Commercial	0.153	-0.721	-0.809	-1.718
Building_Age	** -0.023	* -0.026	* -0.032	* -0.028

**- 95% Confidence (0.05)*

*** - 90% Confidence (0.10)*

The following statements describe the results of Figure 64.

The percentage of the population under five years old has a statistically significant impact on temperature at the 95% confidence level. The model indicates that, controlling for all other factors, when there is a one percent increase in those who are under five years old in a block group, this correlates to an **increase** of 12.8°F in June, an **increase** of 10.7°F in July, an **increase** of 11.6°F in August, and an **increase** of 10.8°F in September.

The percentage of the population over sixty-four years old has a statistically significant impact on temperature at the 95 % confidence level. The model indicates that, controlling for all other factors, when there is a one percent increase in those who are over sixty-four years old in a block group, this correlates to an **increase** of 5.0°F in June, an **increase** of 5.2°F in July, and an **increase** of 4.5°F in August.

The percentage of building cover has a statistically significant impact on temperature at the 90% (July) and the 95% confidence levels (June, August, September). The model indicates that, controlling for all other factors, when there is a one percent increase in building cover in a block group, this correlates to a **decrease** of 9.0°F in June, a **decrease** of 8.0°F in July, a **decrease** of 10.0°F in August, and a **decrease** of 9.8°F in September.

The percentage of low density land cover (between 20% and 49% impervious surfaces) has a statistically significant impact on temperature at the 95% confidence level. The model indicates that, controlling for all other factors, when there is a one percent increase in low density land cover, this correlates to an **increase** of 3.6°F in June, an **increase** of 3.4°F in July, an **increase** of .6°F in August, and an **increase** of 10.8°F in September.

The percentage of medium density land cover (between 50% and 79% impervious surfaces) has a statistically significant impact on temperature at the 95% confidence level. The model indicates that, controlling for all other factors, when there is a one percent increase in low density land cover, this correlates to an **increase** of 4.7°F in June, an **increase** of 5.4°F in July, an **increase** of 6.2°F in August, and an **increase** of 6.5°F in September.

The percentage of high density land cover (over 80% impervious surfaces) has a statistically significant impact on temperature at the 95% confidence level. The model indicates that, controlling for all other factors, when there is a one percent increase in low density land cover, this correlates to an **increase** of 5.5°F in June, an **increase** of 5.2°F in July, an **increase** of 6.3°F in August, and an **increase** of 5.2°F in September.

The age of a building has a statistically significant impact on temperature at the 90% (June) and the 95% confidence levels (July, August, September). The model indicates that, controlling for all other factors, when there is a one-year increase in building age, this correlates to a **decrease** of 0.02°F in June, a **decrease** of 0.03°F in July, a **decrease** of 0.03°F in August, and a **decrease** of 0.03°F in September.

In September, the model indicates that the percentage of residents who make equal to or less than twice the federal poverty level (low income residents) has a statistically significant impact on temperature at the 95% confidence level. The model indicates that, controlling for all other factors, when there is a one percent increase in low income residents, this correlates to a 3.7°F **decrease** in temperature.

In September, the model indicates that the percentage of residents who have no high school education has a statistically significant impact on temperature at the 95% confidence level. The model indicates that, controlling for all other factors, when there a one percent increase in residents without a high school education, this correlates to a 6.5°F **increase** in temperature.

The following chapter of this report will provide a discussion of these findings.

CHAPTER 5: DISCUSSION

The key findings from this report are:

1. There is an urban heat island effect in Eugene. The hottest parts of the city are in the eastern area of the Bethel Neighborhood, between Highway 99 and N Danebo Avenue, and in the Cal Young neighborhood, between Delta Highway and Norkenzie road.
2. According to the regression model, the major land use drivers of the urban heat island effect are medium or high-density development.
3. The location of environmental justice communities in Eugene vary depending on the chosen indicator. The heat island has strong correlations with the very old and the very young in environmental justice communities.

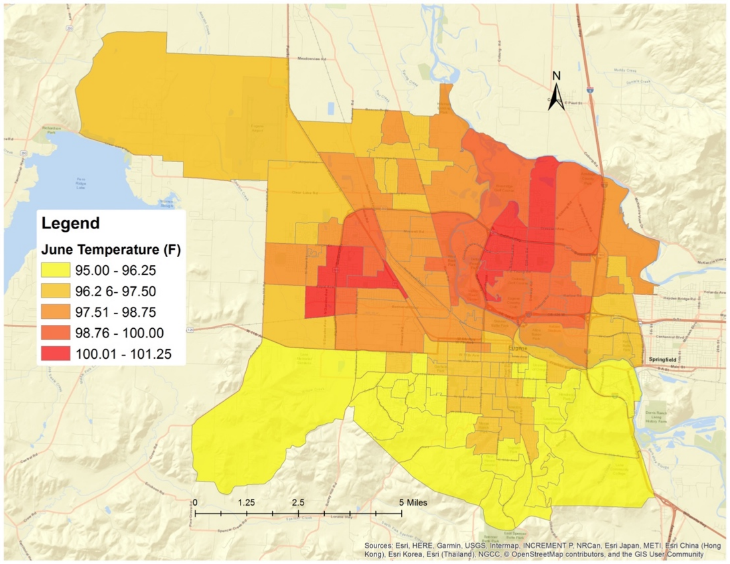
This discussion will explore these statements and posit some reasons behind the findings.

5.1 | URBAN HEAT ISLAND

The urban heat island in Eugene exists predominantly in the eastern area of the Bethel neighborhood and in the Cal Young neighborhood. The heat island migrates through the summer, moving westwards. West of Highway 99 is consistently hot throughout the study period, and the surrounding block groups heat up through the summer. This process can be seen in

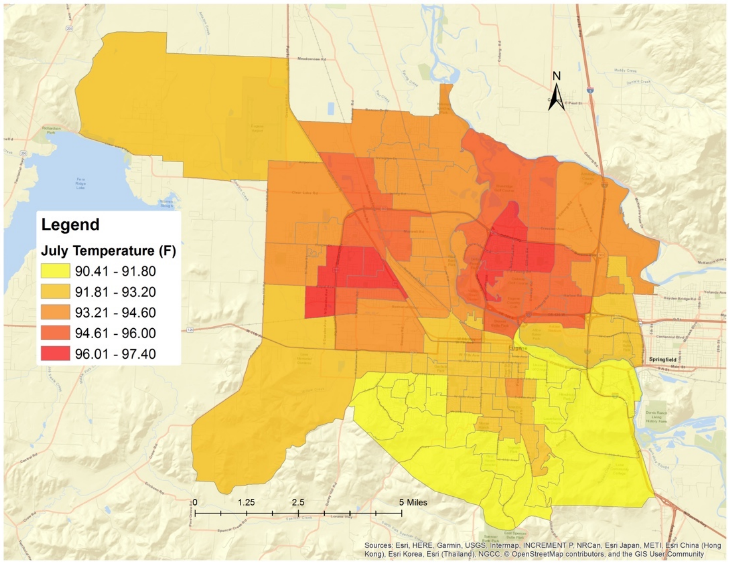
Figure 65 - Figure 68.

Figure 65: Eugene Urban Heat Island, June 2017



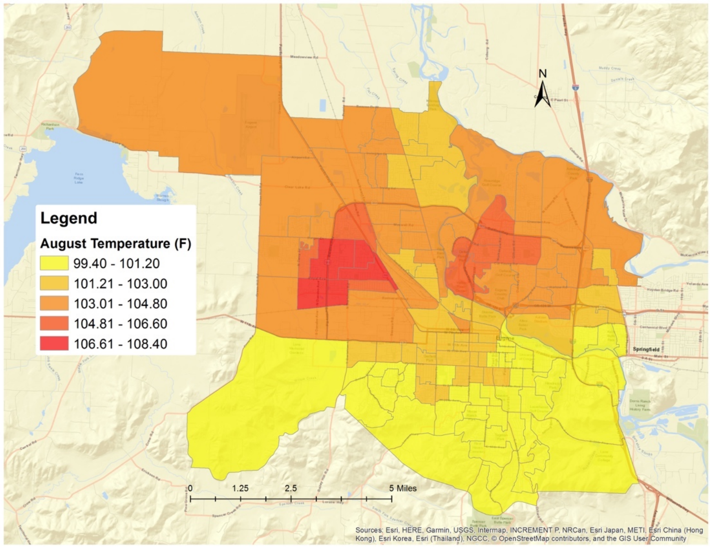
Sources: Esri, HERE, Garmin, USGS, Intermap, INCREMENT P, NRCan, Esri Japan, METI, Esri China (Hong Kong), Esri Korea, Esri (Thailand), NGCC, © OpenStreetMap contributors, and the GIS User Community

Figure 66: Eugene Urban Heat Island, July 2017



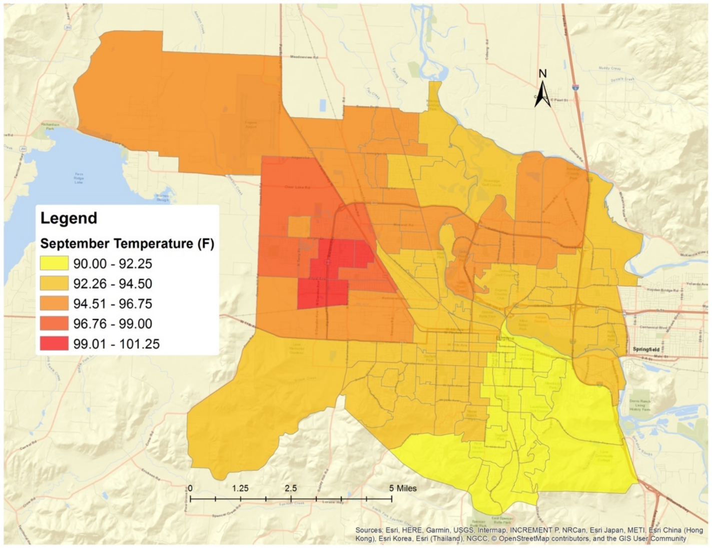
Sources: Esri, HERE, Garmin, USGS, Intermap, INCREMENT P, NRCan, Esri Japan, METI, Esri China (Hong Kong), Esri Korea, Esri (Thailand), NGCC, © OpenStreetMap contributors, and the GIS User Community

Figure 67: Eugene Urban Heat Island, August 2017



Sources: Esri, HERE, Garmin, USGS, Intermap, INCREMENT P, NRCan, Esri Japan, METI, Esri China (Hong Kong), Esri Korea, Esri (Thailand), NGCC, © OpenStreetMap contributors, and the GIS User Community

Figure 68: Eugene Urban Heat Island, September 2017



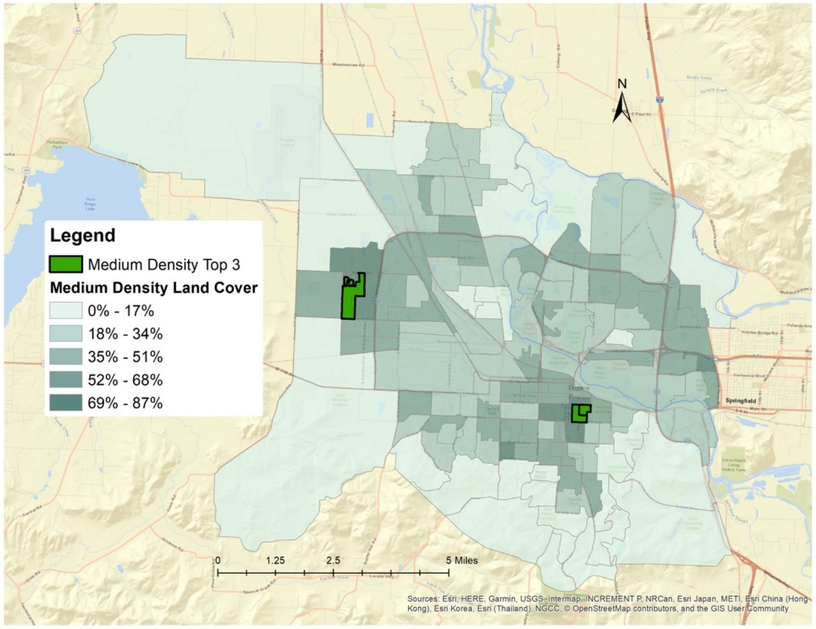
Sources: Esri, HERE, Garmin, USGS, Intermap, INCREMENT P, NRCan, Esri Japan, METI, Esri China (Hong Kong), Esri Korea, Esri (Thailand), NGCC, © OpenStreetMap contributors, and the GIS User Community

5.2 | LAND USE FACTORS

According to the regression model, the major driver of the urban heat island effect in Eugene is shown to be medium and high density land use, that is, areas with more than 50% impervious surfaces.

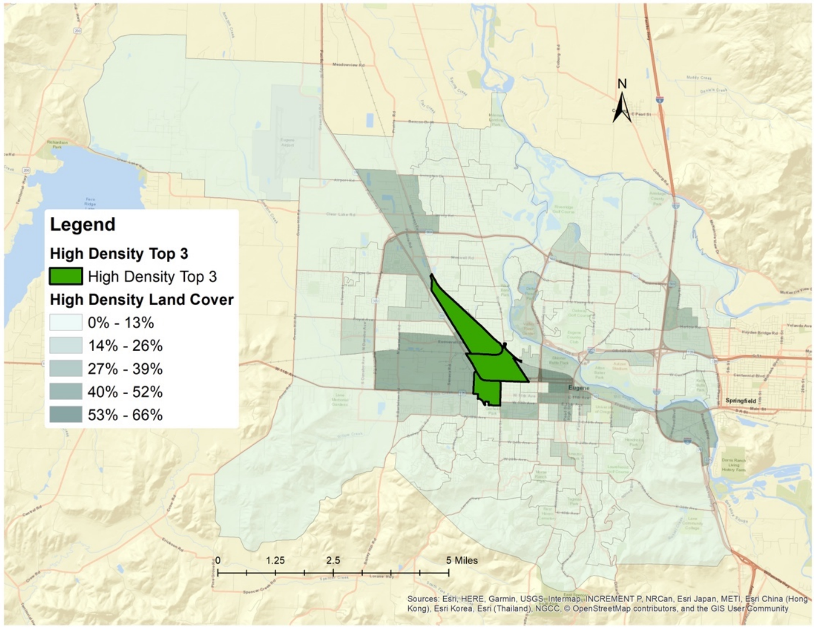
Figure 69 and Figure 70 show that medium and high density land use are concentrated in the north western area of the city. This conforms to literature as impervious surfaces are often dark surfaces, such as roads, which absorb and radiate heat, further increasing the ambient heat felt in an area. Eugene is a mostly low-density community with lots of single family homes. Areas of higher density therefore encourage more impervious surfaces, higher usage rates, and more heat.

Figure 69: Medium Density Land Cover, Eugene, OR



Sources: Esri, HERE, Garmin, USGS, Intermap, INCREMENT P, NRCan, Esri Japan, METI, Esri China (Hong Kong), Esri Korea, Esri (Thailand), NGCC, © OpenStreetMap contributors, and the GIS User Community

Figure 70: High-Density Land Cover, Eugene, OR



Sources: Esri, HERE, Garmin, USGS, Intermap, INCREMENT P, NRCan, Esri Japan, METI, Esri China (Hong Kong), Esri Korea, Esri (Thailand), NGCC, © OpenStreetMap contributors, and the GIS User Community

What is surprising from the regression model is that building cover has a strong negative correlation with the urban heat island effect. It would typically be hypothesized that an increase in building cover would lead to a positive correlation with the urban heat island, that is, that the temperature is likely to increase with an increase in building cover, not decrease. One explanation for this anomaly is that there is an element of covariance between the building density and building cover, meaning that the two variables are measuring similar effects and are cancelling one another out. Further research is required to understand this finding.

Building age returned a statistically significant result in the regression model and has a slight negative correlation with urban heat. This means that older neighborhoods in Eugene are likely to be cooler than newer neighborhoods. One reason for this could be that landscaping in older communities has had more time to mature and provide cover. Conversely, newer buildings have younger landscaping that hasn't reached maturity to provide the canopy cover required to mitigate the urban heat island effect.

According to the literature, tree cover is the most effective mitigating strategy to reducing the urban heat island effect. However, in this study, tree cover did not return a statistically significant result in the regression. One reason for this is the limited data available. For this study, data used was from the City of Eugene. This covers all trees owned and maintained by the City of Eugene, however, it does not include private trees planted by landowners or other private institutions. This study therefore gives a low baseline study of the tree cover in Eugene. Future research should endeavor to obtain more accurate data on tree cover to see whether tree cover is truly a mitigating factor on the urban heat island in Eugene.

5.3 | ENVIRONMENTAL JUSTICE INDICATORS

According to the regression model, the groups most affected by the urban heat island effect in Eugene are the very young (under 5's) and the elderly (Over 64's). This conforms to the literature as urban heat has a high impact on those who are elderly and those who are very young due to their susceptibility to heat related illnesses.

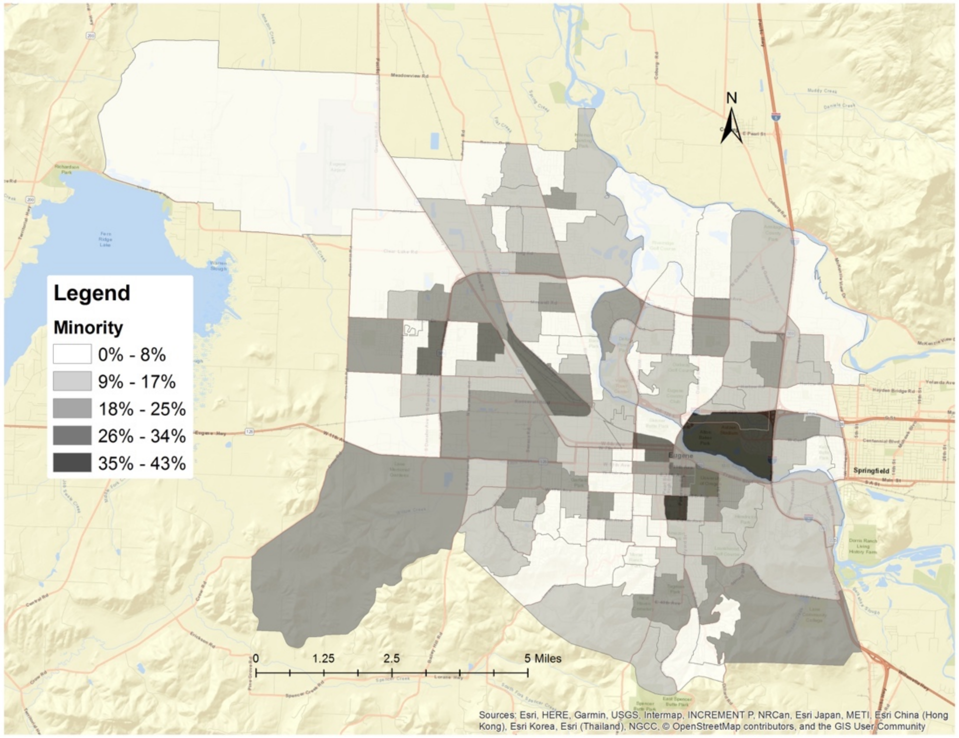
Of all the environmental justice indicators, residents who are under five are the most spread out through the city. The highest concentration of under 5-year old's in a block group is 12% and there are 16 block groups with no residents under 5. Under five-year olds are often clustered near Eugene elementary and pre-schools, and on the outskirts of the city where there are more suburban developments and more traditionally family friendly land use patterns. These areas with newer construction are cheaper and therefore more attractive to families. However, the regression model shows that older communities are cooler and so the areas where families are moving to are more impacted by urban heat than the older, greener parts of the city.

Elderly residents in Eugene also have a strong correlation with the urban heat island. The elderly are often concentrated in retirement communities, such as the Ya Po Ah retirement community at the foot of Skinner Butte. This concentration of elderly residents correlates strongly with the Cal Young concentration of higher temperatures in Eugene.

The regression results from this project are somewhat surprising because they do not show a strong correlation between race and low-income and the urban heat island. This is surprising because the literature shows the communities of color and low-income communities are typically the most impacted by urban heat and environmental justice issues.

When looking at the data on minority groups in Eugene, there are three things that are interesting. Firstly, although Eugene is a very white city (85% white), there are block groups with distinct percentages of people of color. There 6 block groups where minority residents make up more than 30% of the population of the block group and there are 53 block groups where less than 10% of the block group is considered a minority resident. Secondly, these concentrated block groups of people of color correlate more with the location of the University of Oregon than the hottest block groups in the city (Figure 71). The University of Oregon's student body is more diverse than the wider Eugene community and many students live close to the university (University of Oregon, 2016). Finally, when looking at the distribution of communities of color in Eugene, it is evident that the coolest block groups are also the whitest block groups and other communities of color outside of the university live in the hotter, western part of the city.

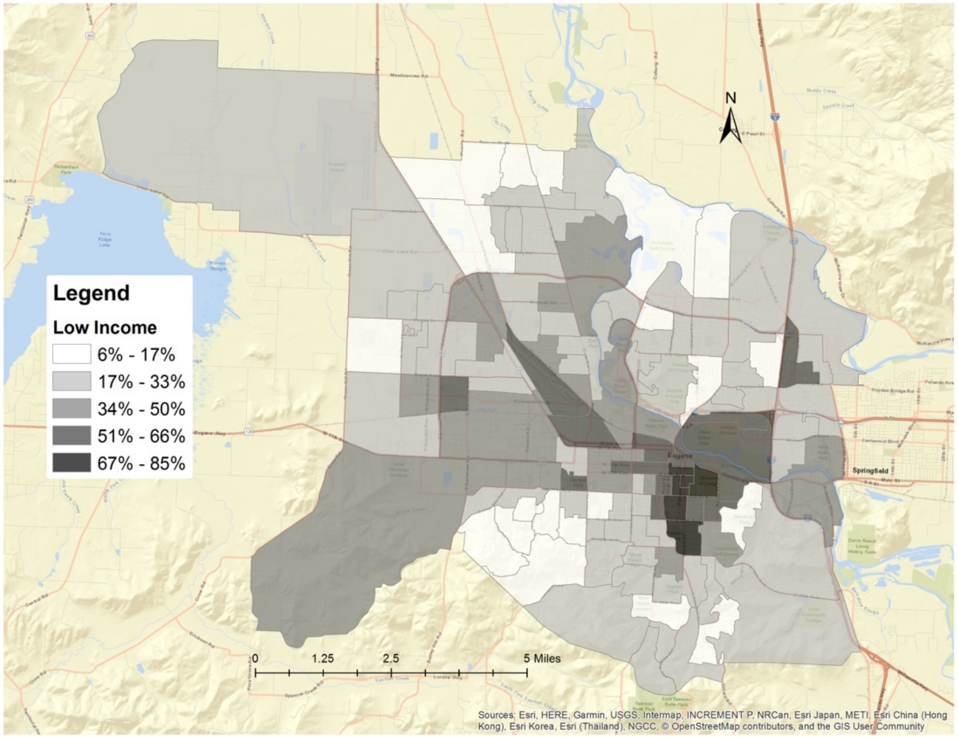
Figure 71: Distribution of minority population in Eugene, OR



Sources: Esri, HERE, Garmin, USGS, Intermap, INCREMENT P, NRCan, Esri Japan, METI, Esri China (Hong Kong), Esri Korea, Esri (Thailand), NGCC, © OpenStreetMap contributors, and the GIS User Community

Eugene is a fairly affluent city, with 57% of the community making more than twice the federal poverty level. However, low income communities do exist in the city. The block groups with the highest percentages of low-income residents are located around the University of Oregon. This is because students are considered low-income. This information skews the data as, although students are considered low income, those who achieve a bachelor's degree are projected to have much higher potential earnings once they graduate than those with less than a bachelor's degree (Carnevale, et al., 2013). Looking at the distribution of low-income communities on a map, it is evident that other low income communities live in the hotter, western part of the city (Figure 72).

Figure 72: Distribution of Low-Income population, Eugene, OR



Sources: Esri, HERE, Garmin, USGS, Intermap, INCREMENT P, NRCan, Esri Japan, METI, Esri China (Hong Kong), Esri Korea, Esri (Thailand), NGCC, © OpenStreetMap contributors, and the GIS User Community

5.4 | CONCLUSION AND FURTHER RESEARCH

This research finds that there is an urban heat island in Eugene, the urban heat island is driven by medium and high-density land cover, and the very young and the elderly are the most at risk from urban heat. In order to mitigate urban heat, provisions should be made for vulnerable groups to enable them to cool down during periods of extreme heat. Short term provisions can include ensuring homes have air conditioning, providing air conditioning units, educating people on the importance of preparing for extreme heat, and providing income assistance for those who may be energy burdened due to increased electricity costs.

Further research should be conducted to understand the true impact of trees on the urban heat island effect in Eugene, and what effect the building form has on urban heat. Further studies should also explore the qualitative side of this research to understand how urban heat effects people and the best way to mitigate urban heat for their community. Finally, further research should explore the impact of the University of Oregon, or control for the impact of the University of Oregon. This is important because students at the University of Oregon who live close to the university have a large impact on demographic data, especially when considering the impact of heat on low-income communities and communities of color.

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