The Role of Vegetative Cover in Enhancing Resilience to Climate Change and Improving Public Health

Anastasia D. Ivanova
University of Massachusetts Amherst

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Anastasia D. Ivanova

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THE ROLE OF VEGETATIVE COVER IN ENHANCING RESILIENCE TO CLIMATE CHANGE AND IMPROVING PUBLIC HEALTH

A Thesis Presented

By

ANASTASIA D. IVANOVA

Submitted to the Graduate School of the University of Massachusetts Amherst in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

February 2021

Environmental Conservation
THE ROLE OF VEGETATIVE COVER IN ENHANCING RESILIENCE TO CLIMATE CHANGE AND IMPROVING PUBLIC HEALTH

A Thesis Presented

By

ANASTASIA D. IVANOVA

Approved as to style and content by:

_______________________________
Timothy Randhir, Chair

_______________________________
David Bloniarz, Member

_______________________________
Raphael Arku, Member

_______________________________
Curtis Griffin, Department Head
Department of Environmental Conservation
DEDICATION

I dedicate my master’s thesis to my loving parents, Olga Tsvetkova and Dmitry Ivanov, and my siblings, Liza Ivanova and Matvey Ivanov.
ACKNOWLEDGEMENTS

I would first of all like to sincerely thank my principal advisor, Professor Timothy Randhir, for providing me the opportunity to work on this incredible project and integrate my interests in health, the environment, and climate change at a master’s level. His valuable guidance and expertise helped me achieve my goals while on an accelerated timeline and prepare for my next professional adventure at Westfield State University where I will be obtaining a Master of Science in Physician Assistance Studies. His creative outlook on the project enabled me to gain a unique and valuable skill set that will help me have a deep understanding of patient contexts under rapid global changes.

I wish to also express my greatest thank you to my committee members, Professor Raphael Arku and Professor David Bloniarz, who worked hard to provide me with resources, knowledge, support, and encouragement during these challenging times of a global pandemic when we had to meet entirely remotely. Their feedback throughout the review process enabled me to constantly improve my work and produce a final product that I am incredibly excited to share.

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At last, I would like to thank my amazing family who has supported me through all of my academic pursuits and made it possible for me to have this opportunity. Thank
you to my incredible mom, dad, sister, and brother for your dedication, patience, understanding, hard work, and never-ending love. I owe it all to you!
ABSTRACT

THE ROLE OF VEGETATIVE COVER IN ENHANCING RESILIENCE TO CLIMATE CHANGE AND IMPROVING PUBLIC HEALTH

FEBRUARY 2021

ANASTASIA D. IVANOVA, B.S., UNIVERSITY OF MASSACHUSETTS AMHERST

M.S. UNIVERSITY OF MASSACHUSETTS AMHERST

Directed by: Professor Timothy O. Randhir

Changing temperature and precipitation patterns are causing degraded soil, water, and air quality which is negatively affecting the safety and health of people, and the productivity of urban and rural communities. However, research shows that implementing urban forests and cover crops into urban and rural landscapes, respectively, can mitigate these effects by providing ecosystem services. As extreme precipitation and heat events continue to intensify, there is a need for comprehensively assessing these ecosystem services under changing climates and for this information to be easily accessible by communities for rapid land-use decision making. Therefore, I investigated the role of urban forests and cover crops in enhancing resilience to climate change through 1. a comprehensive review of the urban forest and cover crop ecosystem services in relation to climate change impacts, 2. modeling ecosystem services in Massachusetts using spatially-explicit techniques for an online decision support tool and 3. a comprehensive review of climate change health impacts in urban communities and the restorative and protective properties of urban forests in relation to these impacts. The
outputs of this thesis inform community members, agencies, city planners, the medical community, and urban forestry project leaders of the benefits and challenges of planting urban trees and cover crops in Massachusetts as a way to improve the productivity of lands and the well-being of people. In addition, the review articles and the decision support tool can be used by communities to guide preparation for and adaptation to the impacts of climate change including medical provider and patient education, optimizing occupational, residential, and educational settings, and resource distribution.
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CHAPTER 1

INTRODUCTION

1.1 Climate change

Climate change refers to local, regional, and global alterations in long-term averages of temperature and precipitation patterns (NASA, 2020). These changes directly affect ecosystems, oceans, weather, air, and water (NASA, 2020). Scientists report human activities as the primary driver of 20th and 21st-century climate change (NASA, 2020). However, as people affect the climate, climate change affects people, diminishing their safety, health, and wellbeing and the productivity of urban and rural landscapes (Luber & McGeehin 2008; Walthall et al. 2013).

As of the 1880s, global temperatures have increased by 1.14°C, with most of this change occurring within the last 40 years (NASA, 2020). Temperature is projected to increase an additional 0.2°C with every decade to come (NASA, 2020). It is also reported that the six hottest years within the last 40 years have occurred since 2014, with 2016 being the hottest year on record (NASA, 2020). A lot of this heat has been absorbed by the world’s oceans resulting in decreasing ice sheets in the Antarctic as well as Greenland and increased sea levels (NASA, 2020).

An intensification of global extreme precipitation events has also been observed. Extreme precipitation events are characterized by increased duration and frequency of rainfall (Dore, 2005, O’Gorman, 2015). Since the 1900s there has been a 2% increase in total global precipitation, however, at local scales, the effects vary from severe periods of droughts to significant rainfall events (Dore, 2005). For example, in the United States, a
5-10% increase in precipitation has been identified, periodically interrupted by periods of severe droughts (Dore, 2005).

Extreme heat events also vary locally and regionally throughout the world. In the United States, for example, extreme heatwaves have intensified by approximately 20% over the past 70 years (Luber & McGeehin, 2008). Extreme heatwaves are characterized by prolonged high minimum night temperatures and hot stagnant air. This meteorological phenomenon causes significant deaths in communities worldwide and has the highest death toll out of any weather-related events in the United States (CDC, 2006; Corburn, 2006; Luber & McGeehin, 2008).

1.2 Impacts of climate change on air, water, and soil quality

The extensive effort on behalf of researchers has enabled the scientific community to identify how these changes in climate are affecting ecosystems. Mainly these impacts include changes to air, water, and soil quality. The air we breathe is already contaminated with pollutants that come from transportation or from natural, agricultural, commercial, industrial, or residential sources (Bernard et al., 2001). Whether it is the use of pesticides, decomposition of vegetation, keeping homes warm, or driving to work each day, the human population is constantly being exposed to air pollutants both inside and outside of their homes (Bernard et al., 2001). Ostro (2004) estimated that in the early 2000s, air pollution accounted for 1.4% of global mortality as well as 0.4% of the total disability-adjusted life years. Climate change adds to these negative effects. Solar radiation and higher temperatures trigger and increase the production of particulate matter air pollution, ground-level ozone, volatile organic compounds, and aeroallergens
by affecting atmospheric processes, emissions from natural sources, and emissions from man-made sources (Bernard et al., 2001; Patella et al., 2018; Wilby, 2007).

Our global population is approaching 8 billion, placing substantial stress on our already limited water supplies (Vorosmarty et al., 2000). Climate change is predicted to negatively impact the hydrological cycle, exacerbating drought conditions in certain parts of the world and increasing flooding conditions in others (Dore, 2005). In regions like parts of Europe, the Mediterranean, South America, and Africa, a change in precipitation patterns have resulted in increased water scarcity affecting access to safe water for consumption and daily activities (Wilby, 2007). However, in a majority of the Eastern and Western coast states of the US, there have been more heavy rainfall events resulting in stormwater flooding (Dore, 2005; Wilby, 2007). As a result, communities are experiencing property damage, emerging contaminants, excess nutrient leaching, and foul water flooding (Paul & Meyer, 2001; Wilby, 2007). A newer field of research is examining personal care products, pharmaceuticals, and insecticides as new forms of water contamination in a quickly urbanizing world (Paul & Meyer, 2001; Talib & Randhir, 2016). Contaminants can have negative effects on the human body, such as the development of cancer or the altering of endocrine functions necessary for good reproductive health (Talib & Randhir, 2016, Talib & Randhir, 2017). In addition, nutrients such as Nitrogen and Phosphorus that leach into surface and groundwater as a result of soil erosion can cause severe environmental stress and public health problems such as acidification of water systems, blood disorders such as methemoglobinemia in newborns, and low levels of vitamin A in the liver (Choudhury et al., 2005; Dosskey et al., 2010; Phupaibul et al., 2002).
Lastly, climate change is predicted to, directly and indirectly, affect soil quality and terrestrial ecosystems (Balser et al., 2010). Due to changing temperature and precipitation patterns, elevated carbon dioxide concentrations, and altered nitrogen availability, terrestrial ecosystems will sustain nutrient imbalances, land cover modifications, and alterations in the abundance of plant species (Balser et al., 2010; Tylianakis et al., 2008). Decisions of which crop species to plants, which patterns of irrigation to use, and which fertilizers to employ will be dictated by changes in temperature and precipitation (Balser et al., 2010; Dixon, 2009). Within the soil reside numerous microbial communities whose metabolic activity can be altered by changes in nutrient availability and climate change disturbance (Balser et al., 2010). As a result, there are expected changes in organic carbon storage, decomposition, and nitrogen mineralization affecting the quality of the soil (Balser et al., 2010; Henry et al., 2005). In addition, as the intensity and duration of precipitation events increase, soil erosion will become an even more prevalent problem in ecosystems (Pruski & Nearing, 2002; Walthall et al., 2013). Soil erosion was found to intensify by up to 1.7% for every 1% increase in the intensity and duration of precipitation (Pruski & Nearing, 2002; Walthall et al., 2013).

1.3 Human modification of land use

Along with climate change, human modification of land use also serves as a stressor to the quality of life of people and the productivity of landscapes (Luber & McGeehin, 2008). Two of the major anthropogenic impacts on the earth’s environment have been urbanization and agriculture. Urbanization is the transformation of natural and rural land to urban land and provides more residential, industrial, and commercial
infrastructure opportunities (McDonald et al., 2013; McDonnell et al., 1997; Weng, 2007). In the 1880s it was identified that approximately 3% of the global population resided in urban communities, however, as of 2018 more than 55% of the world’s population is living in cities (McDonald et al., 2013; UN, 2006). While more opportunities are provided for developing utilities, roads, and businesses through urbanization, urbanization acts as one of the key players in the destruction of ecosystems by changing the interactions between air, soil, and water. (Avelar et al., 2009; Li et al., 2016). Agricultural land, conversely, represents one of the largest man-made ecosystems and currently constitutes half of the world’s habitable land (Ritchie & Roser, 2019). As a result of increasing populations and the subsequent demand for food production, there has been a 466% increase in global agricultural land within the last 300 years (Goldewijk & Ramankutty, 2009). These alterations in land use and cover can significantly impact ecosystem services and put a severe strain on the productivity of urban and rural landscapes (Walthall et al., 2013).

1.4 The impacts of climate change and altered land use on communities

Some of the major effects of shifting land use and changing climates on urban ecosystems include higher temperatures, degraded air and water quality, and disrupted water supplies resulting in urban heat islands, air pollution, negative health outcomes, runoff, droughts, and polluted water supplies (Dore, 2005; Corburn, 2009; Luber & McGreehin, 2008; Wilby, 2007). In rural communities, these effects include runoff, soil erosion, nutrient leaching, degraded soil quality, and degraded water supplies (Dettinger & Earman, 2007; Pruski & Nearing, 2002; Walthall et al., 2013).
As climate change intensifies extreme precipitation and heat events, urban communities will experience disproportional effects in the form of increased stormwater runoff, water supply disruption, urban heat island effects, and degraded air quality (Corburn, 2009; Dore, 2005; Luber & McGreehin, 2008; Wilby, 2007). In cities, stormwater runoff occurs primarily as a result of impervious surfaces that are unable to absorb excess rainfall, resulting in flooding (Hollis, 1988; Wilby, 2007). Urban flooding due to runoff may cause severe property damage and foul water flooding, acting as a significant safety hazard to the human population (Wilby, 2007). Urban heat islands are caused by buildings, roadways, and other infrastructure in cities absorbing and re-radiating solar energy in the form of heat (Corburn, 2009). On average, urban air temperatures are 3-4°C higher than surrounding rural areas (Solecki & Marcotullio, 2013). With climate change, the warming of urban areas is projected to increase an additional 1°C per decade (Corburn, 2009; Voogt, 2002). In addition, as a result of global warming, there have been increased rates of water evaporation which have substantially reduced groundwater recharge which serves as a source of drinking water to cities (Dore, 2005). Finally, as solar radiation combines with city smog, air quality is reduced and instances of respiratory disease increase (Portney & Mullahy, 1990; Ramirez et al., 2017; Wilby, 2007).

In rural communities, climate change and shifting land use are affecting the wellbeing of rural communities by reducing soil quality, disrupting water supplies, increasing runoff, and increasing soil erosion (Dettinger & Earman 2007; Pruski & Nearing, 2002; Walthall et al., 2013). For example. In the United States, agricultural land use has declined 12% as of 1949, from 63% of the country’s area to 51% (Nickerson &
Borchers, 2012). In addition to the stress caused by this major land-use modification, increases in carbon dioxide levels, changes in precipitation patterns, and rising temperatures are further reducing agricultural productivity (Walthall et al., 2013). Agriculture is dependent on good soil quality and the regulation of water quantity and quality (Walthall et al., 2013). Under changing climate, these processes are becoming compromised, affecting crop and livestock production systems that rural communities in part depend on for nutrition and income (Walthall et al., 2013). For many areas, groundwater is a primary water source for irrigation; however, increased temperatures can negatively affect groundwater recharge through enhanced soil water evaporation (Dettinger & Earman 2007; Walthall et al., 2013). In addition, extreme rainfall events can reduce the amount of rainfall that infiltrates into the ground, causing runoff and soil erosion (Pruski & Nearing, 2002; Walthall et al. 2013). As water runs off the land, it picks up fertilizers, herbicides, and pesticides and brings these chemicals into lakes and streams that could be further used for irrigation or as a drinking source (Talib and Randhir 2016, 2017). Specifically, the most common lost nutrient is Nitrogen, which in its inorganic form, can significantly pollute the water (Ulen, 1993).

1.5 Mitigative properties of vegetation

The changes inflicted upon urban and rural landscapes due to climate change affect human safety, health, and quality of life, however, there are two main approaches to incorporating resilience to climate change and shifting land use: the engineering approach and the natural systems approach. The engineering approach uses improved city building and planning designs to counter increases in temperature and precipitation (Wilby, 2007). For example, increasing albedo through the use of reflective materials can
reduce solar radiation that would otherwise be absorbed (Declet-Barreto et al., 2016). Conversely, the natural systems approach uses vegetation as the primary tool for climate change resilience. Urban forests and cover crops can mitigate the effects of climate change in urban and agricultural areas by providing valuable ecosystem services (Millennium Ecosystem Assessment, 2003). Research shows that urban forests can mitigate urban heat island effects, flooding, degraded water supply, and poor air quality by reducing air temperatures, runoff, and pollution (Inkilainen et al. 2013; Middel et al. 2015; Nowak et al. 2014). For every 1% increase in canopy cover, there is an average 0.14°C reduction in air temperature, which can significantly reduce cooling demands and health risks associated with heat stress (Akbari et al., 2001; Middel et al., 2015). Urban forests can also reduce potential stormwater runoff by 9.1-31.07% through canopy interception which can protect the city from flooding and increase groundwater recharge (Inkilainen et al., 2013; Yao et al., 2015). Additionally, urban forests can directly remove air pollutants such as PM$_{10}$, O$_3$, and CO$_2$ via the leaf stomata or the plant surface, improving air quality and thereby reducing respiratory incidents (Hirabayashi & Nowak, 2016; McDonald et al., 2007; Nowak et al., 2014). In the year 2010, trees removed 17.4 million tons of air pollutants in the United States thus preventing 670,000 acute respiratory incidences (Nowak et al., 2014). Similarly, incorporating cover crops into agricultural land use can build resilience to climate change by protecting the water supply, improving soil quality, and reducing runoff and soil erosion. Rainfall that accumulates faster than it can drain will run off into nearby water bodies and pick-up contaminants and waste on the way (Pal et al., 2010; Paul & Meyer 2001; Talib & Randhir, 2016). These water bodies are then used by communities for recreation and
agriculture, affecting the health and wellbeing of people and the environment (Paul & Meyer, 2001; Talib & Randhir, 2017). However, cover crop rooting systems can enhance soil hydraulic conductivity and reduce runoff by up to 80% (Blanco-Canqui et al., 2015; Yu et al., 2016). Similarly, cover crops can protect the soil from soil erosion by acting as a shield against heavy precipitation (Walthall et al., 2013). In parts of the United States, cover crops can reduce soil erosion by up to 11-29% (Basche et al., 2016). In addition, cover crops can improve soil water storage by reducing drainage, lowering the need for pumped water by almost 50% (Delgado et al., 2007; Qi and Helmers, 2009; Wang et al., 2018). Therefore, similarly to urban forests, cover crops can protect the well-being of rural communities and increase the resilience of agricultural landscapes to climate change.

1.6 Research needs, conceptual framework, and objectives

As changes in climate patterns intensify and land use is further modified to support a growing population, there is an urgent need to study how to increase the resilience of landscapes. In order to guide private and public decisions regarding public health and the environment under these impending changes, information regarding climate change, the environment, and health needs to be synthesized, modeled, summarized, and made available for easy access by communities. While much progress has been made in determining the benefits of vegetative cover on landscapes and human health, these studies assess benefits through single coefficients, without investigating potential mitigating effects, and without possible climate change implications. Specifically, studies focus on one or few ecosystem services or health benefits without examining possible co-benefits and interactions with changing climates. Therefore, there
is a need for comprehensively assessing ecosystem services and health benefits of vegetative cover under impending climate change, and for this information to be easily accessible by communities. The impacts of climate change on the safety, health, and wellbeing of communities also warrant a spatially-explicit decision support tool that will integrate information on the restorative capacity of vegetative cover. Therefore, the goal of my research is to investigate and model the role of vegetative cover in enhancing the resilience of landscapes and human health to climate change. Specifically, my objectives are to:

1. Provide a comprehensive review of the urban forest and cover crop ecosystem services that improve resilience properties of landscapes to climate change,

2. Model ecosystem services of urban forests for an online decision support tool to help communities access current benefits of urban forests and predict future urban forest needs and benefits under climate change

3. Provide a comprehensive review of climate change health impacts in urban environments as well as the protective and restorative properties of urban forests in relation to these impacts.

Hypotheses for Objective 1

H₀: There is no certainty in vegetative cover increasing resilience to climate change

Hₐ: There is increasing certainty in vegetative cover increasing resilience to climate change

Hypotheses for Objective 2
H₀: Urban forests have no effect in enhancing ecosystem services and climate resilience

Hₐ: Urban forests contribute to a significant extent in enhancing ecosystem services and climate resilience

Hypotheses for Objective 3

H₀: Urban forests do not contribute to the mitigation of health impacts caused by changing climate patterns

Hₐ: Urban forests contribute to a significant extent in mitigating health impacts caused by changing climate patterns

The results of this study will help guide city planners, urban forestry programs, funders, and healthcare professionals in making land use and healthcare decisions by using temporally- and spatially-accurate information about their communities in relation to changing climate patterns and by using comprehensive reviews and frameworks synthesized through chapters two and four of this thesis. The conceptual framework presented below as Figure 1.1 provides a theoretical foundation for the objectives of this thesis.
1.7 Thesis plan

The following thesis is presented in five chapters consisting of 1. introduction, 2: a review of the ecosystem services of cover crops and urban forests, 3: analysis of ecosystem services of urban forests in Massachusetts for a spatially-explicit decision support tool 4: a review of climate impacts on health and mitigative potential of urban forests, and 5: conclusion. The first chapter introduces the problem and provides background on climate change and changes in land use, as well as their impacts on the environment and people. It aims to address the use of vegetation as a potential mitigation strategy which will lay the foundation for the rest of the thesis. The second chapter will be a review article on the provisional, regulating, supporting and cultural ecosystem services of urban forests and cover crops that can be used by community members to quantify and qualify the role of vegetation in their landscapes as well as provide scientific reasoning for urban forestry and agricultural programs aiming to restore ecosystem services in their landscapes. This chapter will consist of 1. an introduction laying out the
problem and the main objectives to be addressed, 2. a section summarizing the ecosystem services of urban forests organized as provisional, regulating, supporting, and cultural services, 3. A section summarizing the ecosystem services of cover crops as provisional, regulating, or supporting services, 4. a concluding section discussing recommendations.

The third chapter will consist of an introduction, methodology section, results, discussion, and conclusion for modeling of ecosystem services in Massachusetts. The fourth chapter will be a review article on climate impacts on health and the restorative potential of urban forests. It will consist of 1. An introduction explaining the problem and identifying the objectives 2. Sections summarizing empirical research on asthma, cardiovascular diseases, mental health disorders, heat related morbidity and mortality, and skin cancer 3. A section providing recommendations for the medical community, urban design, and researchers. Lastly, the fifth chapter will provide a conclusion to summarize the main results of this thesis and provide guidance for how the outputs of this work can be utilized.
CHAPTER 2
ECOSYSTEM SERVICES OF URBAN FORESTS AND COVER CROPS

2.1 Introduction

2.1.1 Ecosystems and their stressors

Ecosystems are dynamic complexes that consist of the interactions between living species and nonliving aspects of the environment (Millennium Ecosystem Assessment, 2003). Ecosystems provide ecosystem services, benefits that can be obtained from them (Millennium Ecosystem Assessment, 2003). The Millennium Ecosystem Assessment identified four categories of ecosystem services that have been used to gauge the relationship between human and environmental well-being (Millennium Ecosystem Assessment, 2003). These four categories consist of provisional, regulating, supporting, and cultural services and include subcategories such as nutrient cycling, climate regulation, recreational opportunities, and provision of wood, water, and food (Millennium Ecosystem Assessment, 2003). However, recent changes in local, regional, and global climate patterns as well as land use distributions have negatively impacted ecosystems, and thereby, the ecosystem services that they provide.

Climate change has resulted in altered precipitation and temperature patterns worldwide, affecting the wellbeing, safety, health and quality of life of people and the productivity of urban and rural landscapes (Luber & McGeehin, 2008; Walthall et al., 2013). As of the 1880s, global temperatures have increased by 1.14°C, intensifying extreme heat events and their negative impacts (National Aeronautics and Space Administration, 2020). Similarly, there has been a 2% increase in total global
precipitation and an overall intensification of extreme precipitation events (Dore, 2005; O’Gorman, 2015). As a result, communities have been observing degradation of air and soil quality, and altered water quantity and composition which are threatening the health of ecosystems and the ecosystem services they are able to provide (Balser et al., 2010; Bernard et al., 2001; Dore, 2005; Paul & Meyer, 2001; Talib & Randhir, 2016; Wilby, 2007).

Along with climate change, human modification of land use also serves as a stressor to the quality of life of people and the productivity of landscapes (Luber & McGeehin, 2008). Two of the major anthropogenic impacts on the earth’s environment have been urbanization and agriculture. In the 1800s, only 3% of the global population resided in cities, however, over 55% of the global population can be found residing in urban communities as of 2018 (McDonald et al., 2013; United Nations, 2006). As natural and rural land is converted to urban land for residential, industrial, and commercial use, the interactions between air, soil, and water can be altered, making it a greater challenge to extract natural resources (Avelar et al., 2009; Li et al., 2016). Agricultural land is one of the largest man-made ecosystems and currently constitutes half of the world’s habitable land (Ritchie & Roser, 2019). As the global population rapidly approaches 8 billion, there has been an increased demand for food production resulting in nearly a 466% increase in agricultural land within 300 years (Goldewijk & Ramankutty, 2009). These alterations in land use and cover have caused rapid loss of natural processes in human-dominated landscapes, and therefore, it is imperative for communities to begin to explore cost-effective and efficient resilience strategies that can assist in mitigating the effects of climate change and help restore these landscapes.
2.1.2 Impacts on urban and rural communities

The rapid loss of natural process can be observed as urban heat islands, air pollution, negative health outcomes, runoff, droughts, and polluted water supplies in urban communities and runoff, soil erosion, nutrient leaching, degraded soil quality, and degraded water supplies in rural communities (Corburn, 2009; Dettinger & Earman, 2007; Dore, 2005; Luber & McGreehin, 2008; Pruski & Nearing, 2002; Walthall et al., 2013; Wilby, 2007). Urban environments are composed at large of impervious surfaces and built structures such as residential buildings, malls, schools, entertainment centers, and many other businesses and industries (McDonald et al., 2013; McDonnell et al., 2008; Weng, 2007). Impervious surfaces and built environments have low albedo which allows for re-radiation of solar energy into the surrounding atmosphere and the generation of urban heat island effects (Corburn, 2009; Solecki & Marcotullio, 2013). Therefore, urban communities experience temperatures that are 3-4°C higher than surrounding communities putting them at higher risk for heat stress and health complications and increasing demands for cooling resources (Solecki & Marcotullio, 2013). In addition, solar radiation and increased temperatures trigger the production of volatile organic compounds causing degradation of air quality and posing a significant threat to the health of people (Portney and Mullahy, 1990; Ramirez et al., 2017;). In urban communities, extreme precipitation events can lead to an excess stormwater runoff because impervious surfaces are unable to absorb the water (Hollis, 1988; Groisman et al., 1999; Milly et al., 2002; Wilby, 2007). As this water travels to freshwater sources, it can pick up contaminants and toxins and deposit them in bodies of water used for daily activities (Talib & Randhir, 2016; Paul & Meyer, 2011). As this water is consumed or
utilized, people could be exposed to a variety of carcinogens, pharmaceuticals, and pesticides that could be toxic to their health and development (Talib & Randhir, 2016; Talib & Randhir, 2017). In addition, nutrients that leach into surface and groundwater as a result of soil erosion from heavy precipitation events can have substantial negative effects on watersheds conditions and health of people (Choudhury et al., 2005; Dosskey et al., 2010; Phupaibul et al., 2002). Conversely, very dry spells without any precipitation can lead to water scarcity and limited groundwater recharge (Dore, 2005; Milly et al., 2002; Wilby, 2007).

In rural communities, increased intensity and frequency of precipitation events can affect how much water is able to infiltrate, causing runoff and soil erosion (Pruski & Nearing, 2002; Walthall et al., 2013). Researchers find that an increase of 1% in the intensity and duration of rainfall can cause a 1.7% increase in soil erosion (Pruski & Nearing, 2002; Walthall et al., 2013). The water that runs off to nearby water supplies can pick up pesticides, insecticides, and other chemicals that are toxic to the microbial community in the water and to farmers who will use that water to irrigate their crop fields (Talib & Randhir, 2016; Talib & Randhir, 2017; Ulen, 1993). Finally, many farms are dependent on groundwater as their primary source for irrigation, but with increased temperatures causing increased evaporation and poor groundwater recharge, many farms struggle with low water supplies to support their crop production (Dettinger & Earman, 2007; Walthall et al., 2013).

2.1.3 Cover Crops and Urban Forests as resilience tools

As changing climate patterns and changing land use and cover affect the well-being of ecosystems and their inhabitants, it is imperative to investigate possible effective
and cost-efficient resilience strategies. Vegetation has been identified as a potential resilience strategy that can help restore ecosystems, enhance protection from hostile climates, and help mitigate the negative impacts of changing climates and land-use alterations on the environment and people. Urban forests can be implemented into urban environments to assist with mitigating local urban heat island effects and stormwater runoff, and regulating pollutants, water quality and water supplies (Inkilainen et al., 2013; Middel et al., 2015; Nowak et al., 2014). Similarly, cover crops could be implemented into agricultural lands to assist with the protection of water supplies, improvement of soil and water quality, and reduction of soil erosion and stormwater runoff (Blanco-Canqui et al., 2015; Basche et al., 2016; Walthall et al., 2013). Vegetation is able to cause these effects if implemented into urban and rural environments by providing ecosystem services. Vegetative cover is able to act as a shield against rainfall and solar energy which can reduce surface and air temperatures underneath and surrounding the canopy, as well as protect soils from erosion (Akbari et al., 2001; Inkilainen et al., 2013; Middel et al., 2015; Walthall et al., 2013; Yao et al., 2015). Rooting systems of vegetative cover are able to have protective and restorative effects on water supplies and water movement by enhancing hydraulic conductivity, nutrient cycling, and water infiltration (Blanco-Canqui et al. 2015, Yu et al. 2016). In addition, vegetation can directly remove harmful air pollutants from the atmosphere through the plant’s surface or the leaf stomata which can improve local air quality (Hirabayashi & Nowak, 2016; Livesley et al., 2016; McDonald et al., 2007; Nowak et al., 2014).

2.1.4 Research needs and study design
Vegetative cover can assist rural and urban communities in adapting to changing climates through the supplying of valuable ecosystem services. However, a majority of research has focused on investigating ecosystem services as independent entities, focusing on agricultural or urban environments exclusively. Decisions about urban designs, land use and land cover, funding of programs, resource distribution, and climate policies are made not only on local scales but at regional scales such as entire watershed systems, requiring a comprehensive understanding of urban and rural environments as one dynamic landscape. Therefore, this warrants a comprehensive review of empirical research on the ecosystem services provided by urban forests and cover crops that can be used by communities to help identify possible co-benefits of implementing vegetation into their communities and properly allocate funding. This review fills this gap by providing a comprehensive assessment of the ecosystem services provided by urban forests and cover crops that improve the resilience properties of landscapes to rapid environmental changes. Specifically, the objectives of this study were to 1. Assess the role of urban forests in mitigating changing climate patterns through ecosystem services provision, 2. Assess the role of cover crops in mitigating changing climate patterns through ecosystem services provision, and 3. Provide suggestions on how we can encourage communities to implement urban forests and cover crops in their landscapes to extract ecosystem services and help develop resilience to climate change. In addition, each ecosystem service has large implications for human well-being by improving our safety, health, and security. Vegetative cover can provide food security and shade, it can reduce human and biological disease, and nutrients, clean air, and space for healthy recreational activities which all enhance our well-being and bring us closer to adapting to
climate change (Bodnaruk et al., 2017; Clark & Nicholas, 2013; Demir et al., 2019; Soares et al., 2011; Ulmer et al., 2016; Wang et al., 2017, Wen et al., 2017). This relationship is clearly depicted in Figure 2.1 which provides a detailed outline of the contents of the paper. In this review, the sections on urban forest and cover crop ecosystem services are subdivided into ecosystem service categories defined by the Center for Sustainable Systems: provisional, regulating, supporting, and cultural. Recent empirical articles were identified from searches in PubMed, ScienceDirect, Web of Science, and Google Scholar databases using keywords presented below.

Keywords: ecosystem services, urban forests, urban trees, cover crops, soils, benefits, air quality, water quality, runoff, ambient temperature, nutrients, education, recreation, regulation, and soil properties

2.2 Ecosystem services of Urban Forests

2.2.1 Provisional
Emerging empirical research has been focusing attention on the provisional services of urban forests, particularly examining the use of fruit trees and their role in food security in urban communities, as well as examining the benefits of by-products such as leaf litter and firewood (Hurley & Emery, 2017). Recent studies on the provisional services of urban forests have been conducted in various regions of the world, from cities in the United States and Canada to local villages in South Africa under various climatic and sociodemographic conditions. Some researchers like Shackleton et al. (2015) have limited their scope to a few towns while others like Nowak et al (2019) attempted to explore these relationships at larger scales incorporating data for numerous cities. From the work of these researchers, provisional services of urban forests can be separated into two main categories: food provision and raw materials.

2.2.1.1 Food provision

Several recent empirical works have aimed to examine the impacts of planting urban fruit trees on food provision in urban communities, each taking a slightly different approach to investigating this ecosystem service. Clark & Nicholas (2013) conducted a study in Burlington, Vermont with the goal to investigate the role of urban food forestry in provision of food and food security in urban communities by using a modeling approach. First, they identified urban food forest initiatives and master plans using online searches. Then using ArcGIS, they calculated area of open public space and calculated its production capacity if it were planted with apple trees. Finally, they determined the portion of the population with low food security and calculated using an arithmetic equation, the percent of people that could benefit from consuming the produced apples by meeting calorie needs. They found that there was a total of 37 urban food forest
initiatives worldwide and 30 master plans. For Burlington, they found that the total calorie deficit was 833 million kilocalories, however, planting 5% of the available open space with apple trees could help meet the calorie deficit of 7-20% of the population living with very low food security. Planting 50% of open space, could help fully achieve the calorie needs of the population living with low food security if enough mature yield could be achieved (about 50%). Therefore, Clark & Nicholas (2013) concluded that implementing urban food trees in urban communities can help improve food security by providing minimal cost or even free food relatively close to homes. Clark & Nicholas (2013) recommended qualitative and quantitative case studies for a systematic evaluation of all urban food forest initiative programs, ecosystem services and their impacts to determine the values of these programs and help them achieve potential food security and improve urban landscapes.

McLain et al. (2012) took a different approach to investigating food provision of urban fruit trees by conducting a case study in Seattle, Washington with the goal of assessing the underlying framework of projects that aim to help communities extract and collect goods provided by urban forests in the area. McLain et al (2012) reviewed Seattle’s policies, plans, groups and laws in urban forest management and agriculture. They found that fruit harvesting is gaining popularity within these sectors which can assist with food scarcity and can help change the perspective of the landscape to be seen as more agriculture involving and green. However, the idea that forests are providers of goods and foods is limited to a small and relatively private scale, with boundaries set in large forests and wetlands. This can halt the progress in urban sustainability. Therefore,
these researchers recommend stressing the provisional services of urban forests and encouraging gathering and gleaning in all lands.

Colinas et al. (2019) also investigated this ecosystem service by conducting a case study but their main aim was to investigate the socio-environmental impacts of implementing urban fruit trees, including contribution to public knowledge on food and food security. To do so, these researchers focused on a public orchard in the city of Montreal, Quebec and collected information through interviews with users and project developers. The interviews were then further transcribed and analyzed. The fruit trees were planted along a bike path. The interviews revealed that participants of the bike path appreciated the vegetation, attractiveness, socialness, and safety it provided. Some participants were, however, unaware that the trees around the bike path were fruit trees and many were unaware about the project. Those that were aware of the fruit on the trees, had harvested some for eating or turning into jam. They also found that there were several factors that affected the consumption of fruit. These included the taste, the knowledge associated with the fruit, and fear regarding possible insects or contaminants. Therefore, Colinas et al. (2019) recommend that urban planners take into account the location, the nature of the species, and the maintenance of the trees, to encourage people to obtain provisional services from trees.

Shackleton et al. (2015) also conducted interviews for their study in two South African towns but supplemented their approach with household surveys. Their aim was to see how residents from various urban neighborhood types in two South Africa towns, Tzaneen and Bela Bela, valued trees in their landscapes. They selected 150 households randomly in each town and provided household surveys, and conducted life history
interviews, to determine the direct uses of trees and their recognized benefits. The benefits households reported back that they collected included tree fruits and worms (from the Colophospermum mopane tree). These benefits were not only valuable for their nutritional value and role in diet, but also for their economic value.

2.2.1.2 Raw Materials

Several researchers have aimed to examine the impacts of planting urban trees on the provision of raw materials like leaf litter and firewood. Nowak et al. (2019) conducted a study in 28 cities in six different U.S states with the aim to assess the values, savings, and potential uses of waste produced by urban trees in the country. This was done by calculating total leaf biomass and total carbon storage for the urban areas. Data was collected from a previous study that analyzed random plot samples using an i-Tree model. Leaf biomass as well as carbon storage values were then converted using equations and conversion factors to assess wood products and nutrient concentrations. They found that about 28 million tons of leaf litter and 33 million tons of wood were generated by urban trees annually in the U.S. Depending on the product produced (firewood, lumber, pallets, or wood chips) the value of tree wood would be between $86 million and $786 million. The values of nitrogen, phosphorus and potassium in leaf litter was estimated to be $551 million per year. Therefore, utilizing urban waste wood can assist in mitigating climate change by delaying the release of carbon into the atmosphere that would’ve gotten there though decomposition or burning. Nowak et al. (2019) also explain that urban wood waste could be used to create biofuel, firewood, biorefineries, and biochar that can help mitigate the impacts of changing climate patterns by reducing fossil fuel emissions, can provide valuable products such as paper, and can improve soil
fertility. Leaf litter could also be distributed in urban areas to assist with nutrient cycling, water quality, and soil quality by providing nutrients, reducing diseases and pests, and help retain soil moisture. Therefore, urban trees produce valuable urban tree waste that, if implemented correctly, could help mitigate climate change and increase sustainability of urban communities. Nowak et al. (2019) recommend that markets and systems are developed to assist with the removal and utilization of this waste.

Kaoma & Shackleton (2015) conducted a study in South Africa examining the value of non-timber forest products in urban settings. Three townships in the Limpopo and North West provinces were selected. The populations of each town range between 25,000 and 35,000 people. Kaoma & Shackleton (2015) selected 50 random households and interviews were conducted with the inhabitants. In addition, an inventory of the trees for these households were collected. Information regarding use of firewood, wood for house products, fruits, medicine and soil products were collected. Data was analyzed in Microsoft Excel using Statistica 10. They found that 91.3% of the households interviewed used firewood and all households used fruits collected from trees. Finally, merely 20% of all household income came from urban non-timber forest products. Therefore, Kaoma & Shackleton (2015) recommend the urban planners understand the uses of urban tree products and provide space for urban trees in order to enhance urban sustainability.

2.2.2 Regulating

Urban forests interact with the atmosphere which enables them to play an important role in the regulation of air and surface temperatures, air quality, and even water movement (Roeland et al., 2019). Recent empirical works have aimed to better
understand these mechanisms, derive quantitative explanations, and to summarize impacts on the environment and health of people at local and regional scales. Using the results derived from the studies presented in this section, we classified the regulating ecosystem services of urban forests as: regulation of heat, regulation of air pollutants, regulation of runoff, and regulation of disease.

2.2.2.1 Heat

To examine the heat mitigation potential of urban forests, authors of recent empirical studies have used a diversity of methods ranging from using models and tree cover scenarios to quantify the effects of temperature, to examining different urban forest design strategies, generating regression models, and finally quantifying economic returns.

Bodnaruk et al. (2017), Middel et al. (2015) and Ziter et al. (2019) all used a form of modeling such as i-Tree modeling, ENVI-met micro-modeling, or general additive models to quantify heat stress and potential cooling effects of different urban tree scenarios. In the most recent of these studies, Ziter et al. (2019) investigated how tree canopy cover in the United States can affect daytime and nighttime air temperatures in the summer months. Their study area spanned the Upper Midwest United States. To perform this study, Ziter et al. (2019) measured air temperature at 5-meter increments at one second intervals for 10 seven kilometer transects in Madison, Wisconsin using two bicycle-mounted temperature sensors. Canopy cover and impervious cover were determined by a combination of derived and custom raster layers. Further, Ziter et al. (2019) used generalized additive models to gauge the relationship between land cover and air temperatures. Researchers found that daytime air temperatures varied by 3.5°C and decreased nonlinearly with increasing tree coverage. They also found the greatest
cooling effect was when tree coverage exceeded 40% of the urban environment. Ziter et al. (2019) also found that nighttime air temperatures varied an average of 2.1°C and increased as a function of impervious land cover. Ziter et al. (2019) recommend climate change mitigation strategies include modifications to urban vegetation and impervious surfaces and aim to incorporate at least 40% canopy cover into urban neighborhoods. Another group of authors using models to quantify the association between urban trees and climate conducted a study in Phoenix, Arizona with the aim of investigating the cooling effect of urban trees in this area using a microclimate model called ENVI-met. Middel et al. (2015) used eight different tree planting scenarios ranging from having no tree canopy cover to 30% tree canopy cover in combination with different climate scenarios to examine the effect of urban trees and forests on air temperatures. Researchers found that for every percent increase in tree cover, there was an average of 0.14°C cooling of air temperatures (a linear relationship). Middel et al. 2015 also found that a 15% increase (10% to 25%) in current tree cover for the city of Phoenix would result in a 2.0°C decrease in air temperatures. Therefore, Middel et al. 2015 recommend using tree cover as a factor in climate change mitigation policies and strategies with further research being done on the implications of implementing trees.

Lastly, Bodnaruk et al. (2017) attempted to examine the urban heat island mitigation potential in Baltimore, Maryland and the effectivity of pollution removal by using i-Tree models. The city has 24% tree cover and 43.4% impervious surfaces and has a goal to increase tree cover to 40%. They use i-Tree models to calculate removal of pollutants and mitigation of urban heat for current tree cover as well as possible increasing and decreasing tree cover scenarios. Essentially, they determined the optimal
tree cover necessary for effective removal of pollutants and the optimal order of planting to maximize total air pollution and heat mitigation. Bodnaruk et al (2017) found that for the current tree cover, the exceedance heat index was $5.1 \times 10^5$ degrees Celsius. They also found that this value for population-risk was $3.8 \times 10^6$ degrees Celsius. However, they note that if the city was to apply maximum tree cover, these values could be reduced by 4% and 37% respectively which could reduce stress due to heat in this urban community. Bodnaruk et al (2017) recommend that this information is further adapted and applied into a decision support system with consideration of other ecosystem services.

Several researchers like Tan et al. (2016), Rafiee et al. (2016) and Duncan et al. (2019) took it one step further and aimed to investigate different design strategies that bring about the greatest cooling effects. Tan et al (2016) conducted a study in Hong Kong examining different design strategies for urban trees that would bring about the greatest reduction in the urban heat island. The two designs they examined were the sky view factor (SVF) as well as the wind-path approach depending on building layout. They then assessed cooling effects as a result of variation of these designs. With SVF designs implemented in areas with irregular building layouts, having a high SVF (0.8) reduced surface temperatures by 18.7°C. For wind-corridor designs implemented in areas with regular building layouts, air temperature was reduced by 0.6-0.8°C. Therefore, Tan et al (2016) recommend that communities with high density residential land cover implement urban trees in wind corridor format to achieve the greatest cooling effect while less dense communities with more space for planting, could benefit from high SVF designs.
Rafiee et al. (2016) also attempted to investigate different urban design factors by conducting a study in Amsterdam, Netherlands assessing the effect of urban trees on reducing the urban heat island effect. However, for their study they focused on tree canopy volume and urbanization as potential variables affecting the relationship. They were primarily interested in assessing tree crown volume to be able to determine what size of tree and how many trees is necessary to achieve desired results. To assess the different variables that affect urban heat islands, Rafiee et al. (2016) used an ordinary least squares regression analysis. Specifically, they used a multi-linear regression method to examine the effects of the sky view factor, tree volume and degree of urbanization on urban heat island variability. Degree of urbanization was calculated using a land use dataset with extracted green area and 3 km buffers for grid cells. Sky view factor was calculated using a height dataset to generate sky view factor calculations for cells and buffers around observation points. Air temperature was gathered through a thermometer attached to a bicycle that logged temperature and location. Finally, tree volume was calculated using an existing 3D tree model dataset which was derived from LIDAR data. Their major findings showed that tree crown volume had the highest effect on mitigating the urban heat island effect within a 40-meter radius. Urbanization degree affected urban heat island values the most. They also predict that for every 60,000 m³ increase in tree volume within the 40 meter radius, one could expect to see a one degree Celcius reduction in temperature. Rafiee et al. (2016) show that this is equivalent to either 4 large trees, 20 medium sized trees or 90 small trees. Rafiee et al. (2016) recommend that further research investigates how trees can affect urban heat islands during extreme hot days with temperatures above 35°C and they recommend that researchers conduct these
kinds of studies in other cities with different urban configurations. They also recommend that researchers examine the relationship between urban trees and economic benefits such as the cost reduction for electrical use (Rafiee et al. 2016). Finally, they recommend that this knowledge be implemented into a decision support system to help guide decisions.

Lastly, Duncan et al. (2019) did a study in the Perth and Peel Metropolitan Regions of Australia assessing how urban vegetation type, coverage and configuration affects the city’s temperature. To collect data on temperatures, Duncan et al. (2019) used a land surface temperature product from a Moderate Resolution Imaging Spectroradiometer sensor. Data for vegetation height was extracted from an Urban Monitor dataset that was collected via aerial photo-imaging. To measure vegetative coverage, Duncan et al. (2019) used Landsat NDVI data. Precipitation data was also generated using the Climate Hazards Group InfraRed Precipitation with Station data. Finally, Duncan et al. (2019) conducted several regression analysis and Random Forests learning models to explore the relationships between the variables. They found that tree and shrub cover produce a larger cooling effect than grass cover and that a 1 km² increase in tree or shrub cover could reduce land surface temperatures by 5°C and 12°C respectively. Finally, they found that vegetative cover explained 31.84% of variance in summer land surface temperatures, and when tree and shrub cover were removed from the analysis, there was an 89% and 98% reduction in temperature prediction accuracy, respectively. Therefore, Duncan et al. (2019) recommend further research to be done examining the complexity of urban landscapes and how they interact with the atmosphere to decrease temperature in order to have more focused urban planning in relation to changing climate and vegetative strategies.
In two studies published in 2016, Sugawara et al. (2016) and Ballinas & Barradas (2016) attempted to investigate the cooling effect of urban trees by collecting field data. Sugawara et al. (2016) examined the cooling effect of the Shirogane Park located in Tokyo, Japan. Sugawara et al. (2016) collected data during four summers on the air temperature distribution in the park as well as the surrounding town (measured by RTR-52A, T&D thermometer), the temperature within 1.5 km of park, heat flux (collected above the canopy using a sonic anemometer, a radiometer, the eddy covariance method) and wind data at the park boundary (using a sonic anemometer). They further conducted a heat budget analysis. The researchers found the cooling effect of the park extended to a maximum of 450m on the side of the park that was downwind. They also found that the cooling flux was positively correlated with net radiation loss and 83% of the air cooled was due to radiation loss. The average cooling effect of the breeze formed by the park averaged 39 Wm⁻². The park itself, which was 0.2km², had total cooling effect of 7.8 MW which is equivalent to the work of 2600 air conditioners.

Similarly, Ballinas & Barradas (2016) examined the mitigation potential of urban trees in Mexico City through a simple phenomenological model. They selected several trees species (Fraxinus uhdei, Ligustrum lucidum, Eucalyptus camaldulensis, and Liquidambar styraciflua) to focus on in particular because they were interested in seeing if differences in species could substantially influence results. First, they used a simple equation to determine urban energy balance and then used it to develop the phenomenological model and measure the components. Net radiation was determined using a Kipp and Zonen net radiometer CNR1. Speed of the wind, humidity variations and virtual temperature were measured with a 3D sonic anemometer as well as an open-
path infrared gas analyzer. Stomatal conductance was measured using a diffusion porometer and transpiration was measured from sap flow using a metering system. Ballinas & Barradas (2016) found that some tree species are better suited for reduction of the urban heat island effect than others. As an example, in order to see a reduction in air temperature by 1°C, 63 *Eucalyptus camaldulensis* species per hectare would be needed. However, the tree species *Liquidambar styraciflua* could double that affect (reduce air temperature by 2°C) with only 24 of its species per hectare. Therefore, Ballinas & Barradas (2016) recommend taking into consideration tree species in urban planning designs for optimal climate change mitigation.

Lastly, some empirical studies have aimed to not only quantify the mitigation potential of urban forests, but also provide an economic value for this ecosystem service in their study area. Akbari et al. (2001) carried out a study with the aim to examine the benefits and the economic returns from urban heat island mitigation by urban trees and other cool surfaces in Los Angeles, CA. In this city, the maximum temperature has intensified by 2.5°C in the past 100 years and the minimum temperature has intensified 4°C since 1880 which has resulted in an increase of 1-1.5GW in power consumption and a loss of $100 million per year. To assess the impact of vegetation and green surfaces on the mitigation of urban heat islands, the researchers found that studies have used a combination of DOE-2 building-energy simulations, and mesoscale meteorological and photochemical models such as CSUMM and UAM. The researchers found that trees in Los Angeles account for net savings of $270M with $58M due to their contribution to shading. In addition, researchers estimate that mitigation of heat islands in urban areas (using urban trees, cool roofs and cool pavements) can reduce national’s air conditioning
energy use by 20% which can save $10 billion per year. Therefore, Akbari et al. (2001) recommend engaging and receiving support from different members of federal, state and local communities in order to develop programs to plant more trees to help lessen the effects of changing climate patterns and extract economic benefits.

Similarly, McPherson et al. (2016) carried out a study in California, USA with the aim of compiling data for 929,823 urban street trees to examine trends in tree number, density, ecosystem services, and economic returns in 50 cities. There was a total of 49 tree inventories. These inventories were obtained from CAL FIRE and were used along with i-Tree to extract benefits, tree characteristics and functions. McPherson et al. (2016) found that between 1988 and 2014, the total quantity of street trees in this area grew from 5.9 million to 9.1 million, however, density declined by 30%. They found that overall, the total yearly value of all services provided by these trees (interception of rainfall, air pollutant removal, property value benefits, shading and energy conservation) equaled $1.0 billion. Specifically, the 9.1 million trees saved 684 GWh per year of energy due to lower air conditioning needs and 580,152 GJ per year of energy in lower natural gas needs which saved $101.15 million. Combined with the other ecosystem services assessed (property value, air quality and runoff mitigation) that will be discussed further in this paper, McPherson et al. (2016) found that for every $1 spent on a tree, there was a $5.82 return in benefits. Therefore, they recommend that co-benefits of trees be taken into account as communities plan for future greening projects.

2.2.2.2 Air Quality

Carbon monoxide (CO), sulfur dioxide (SO₂), particulate matter smaller than 2.5 μm or 10 μm (PM₂.₅ and PM₁₀, respectively), ozone (O₃), and nitrogen dioxide (NO₂) are all
some of the most common air pollutants affecting the environment and human health (Nowak et al., 2018). Cardiovascular, neurological, and pulmonary diseases all have been linked to increasing air pollutant exposure (Nowak et al., 2018; Pope et al., 2002). Therefore, as changing climates alter atmospheric chemistry and exacerbate the formation of air pollution, it is critical to evaluate effective strategies to reduce air pollutant concentrations and their impact (Portier et al., 2013).

Recent empirical studies have sought to quantify removal of air pollutants by urban trees using i-Tree modeling at local scales and tree inventories. Soares et al. (2011) performed a study in Lisbon, Portugal to calculate the ecosystem services of urban street trees and their economic returns using i-Tree modeling. Data for a total of 3033 Lisbon trees was collected for STRATUM analysis. This included sampling for their names, diameter breast height, overall condition, location of growth, degree of pruning and the requirements for managing the tree’s condition. To evaluate the total annual benefits as well as costs, the researchers followed the protocols layed out for i-Tree STRATUM. They compared tree data with 16 US reference cities and used numerical modeling techniques within the program to make calculations. Researchers found that while expenditure was approximately $1.9 million, total benefits added up to $8,432,779. Researchers also found that services were disproportionally distributed among the various tree species and with five species accounting for 72% of all benefits (Soares et al. 2011). Results for runoff mitigation and property value will be discussed later in this paper. Specific savings for energy were $254,185 for all trees equivalent to $6.16 per (with Plantanus spp. and Populus nigra L. accounting for most benefits). The net annual CO₂ reduction was 1861t which is equivalent to $13,701 in savings (A. negundo, Platanus
spp., *P. nigra*, *Populus x canadensis* and *F. angustifolia* accounted for most reductions and savings). Air pollutants were reduced by 25.6t annually which is equivalent to $5.40 in savings per tree (with *Plantanus spp.*, *C australis*, *F. angustifolia*, *J. mimosifolia* and *P. nigra* providing the greatest savings and benefits). When combining with runoff mitigation and added property values, they found that overall, for every $1 invested into a tree, there was an economic return of $4.48 through the provision of benefits. Soares et al (2011) recommend maintaining the health of tree species for optimal ecosystem services returns as well as increasing efforts to expand species diversity to reduce the risk of losing species that provide substantial percentages of these ecosystem services.

As mentioned previously, Bodnaruk et al. (2017) also used i-Tree models to conduct a study in Maryland with the aim of assessing how trees in the city could assist with removing pollutants and mitigating the urban heat island effect. They calculated removal of pollutants and mitigation of urban heat for current tree cover in addition to possible increasing and decreasing tree cover scenarios. Similarly, to their results on urban heat island mitigation discussed earlier in this paper, pollutants removed under the current tree cover equaled 211 t per year and that produced a health benefit of $8.2 million per year. Increasing cover to 44.4% would provide an extra 173 t/yr pollutants removed which would have a $6.3 million/yr health value. Bodnaruk et al. (2017) also found that when urban tree cover was modified and optimized for the removal of various pollutants, there was an addition benefit of 139 tons of pollutants removed each year. They recommend that this information is also further adapted and applied into a decision support tool to assist with urban planning and climate resilience.
Nyelele et al. (2019) conducted a study in Bronx, NY using the i-Tree software as a mapping tool as well to assess both current and future (2030) benefits of trees planted in the area. Specifically, they were interested in three possible future scenarios: 1. A scenario with low tree mortality, 2. A scenario with 4% tree annual mortality, and lastly 3. A scenario with 8% tree mortality each year. Baseline tree cover information was collected using a UTC Assessment for the area. Future scenarios were generated using tree growth models that used arithmetic equations from the i-Tree Forecast model to calculate for tree characteristics. Nyelele et al. (2019) found that for that year of 2030, air pollutant removal is expected to equal 5.6 tons per year under high mortality and 6.2 tons per year under low mortality. From a 2010 baseline of 195,500 tons, carbon storage could increase to 215,000 tons under high mortality and 237,000 tons under low mortality. Runoff mitigation results will be discussed later in this paper. Nyelele et al. (2019) found that these ecosystem benefits have an equivalent value of 6.3 million dollar in this area and they recommend that management plans include protecting existing trees in addition to planting more trees for climate change mitigation.

Lastly, as previously discussed McPherson et al. (2016) did a study using tree inventories and i-Tree modeling with the aim to compile data for 929,823 urban street trees in the state of California and examine trends in ecosystem services and economic returns provided by these trees. In addition to mitigating heat and reducing energy demands, which was discussed earlier in this paper, these trees also stored 7.78 million metric tons of carbon dioxide and removed 2558 t of air pollutant per year.

One air pollutant, carbon dioxide, has become a significant global threat as levels exceeded 400 ppm in 2013 (NASA, 2020). The alarming predictions for future increases
in carbon dioxide levels have led to a growth in research examining carbon sequestering and storage exclusively.

Nowak (1994) conducted a study in Chicago, Illinois to quantify carbon storage, carbon sequestration and avoided power plant carbon emissions through conservation of energy by urban trees in the area. On 652 plots in the study area, he collected data on the features and characteristics of 8,996 trees. To measure biomass of the trees, Nowak (1994) primarily used allometric equations for tree species and converted to carbon storage. To calculate carbon sequestration, Nowak (1994) used urban tree growth estimates and calculated the difference in the carbon storage between a certain year and the one following it. Next, natural gas consumption was converted to heating energy and the known effect of existing trees on heating energy for the area (0.04%) and the known effect of existing trees on air conditioning energy saving for the area (8.4%) were used to calculate avoided carbon emissions. Nowak (1994) found that for Chicago, trees stored 855,000 metric tons of carbon and that shrubs in this region were only able to store 4% of what trees could store. For the whole United States, Nowak (1994) predicted carbon storage by urban trees to be 400 to 900 million tons. In addition, Nowak (1994) found that larger trees were better at storing carbon than smaller trees (up to 1000 times) and sequestration rates were up to 90% greater. Finally, for the study area (Cook and DuPage Counties), carbon emissions avoided as a result of energy conservation were 12,600 tons. Therefore, Nowak (1994) recommends increasing effort to both plant and maintain trees that have already been planted within communities in order to increase the amount of carbon that can be stored and sequestered, and thereby reduce carbon emission impacts.
For example, if tree cover for this particular region was increased by 4.1%, these trees would store an additional 1.3 million tons of carbon.

Two researchers from the University of Iowa in the United States aimed to develop and apply an approach for quantifying carbon storage and sequestration (Zhao & Sander, 2015). Zhao & Sander (2015) developed approach consisted of using Light Detection and Ranging models and a carbon dioxide emission indicator to map, quantify and proportion carbon storage and sequestration total supplies and needs. They further applied their approach within the Dakota and Ramsey counties in Minnesota, US. When analyzing the supply of the ecosystem service, researchers found that the average carbon stored by the 7,291,140 identified trees in these areas was 1,735.69 million kgC. The average carbon stored per tree was 238.13 kg but ranged anywhere between 103.34 kg and 3402.61 kg. In addition, they found that the net annual carbon sequestration was 33.43 million kgC/year. When comparing this supply to the demand of the study area, they found that the trees offset 1% of human-made carbon emissions. Therefore, researchers show that using an approach that assesses the supply and demand of ecosystem services can help urban environments understand services of their land and its relationship to climate change and use it in policy making for mitigating climate change.

Zhao et al. (2010) conducted a study in Hangzhou, China that aimed to identify how much carbon is stored and sequester by urban forest in that area and pin point energy related carbon emissions of several Hangzhou industries. The researchers conducted a forest inventory for the city and calculated dry-weight biomass for various forests using volume-derived biomass equation. Further, Zhao et al. (2010) quantified carbon storage by dividing tree dry-weight biomass by two, and quantified carbon sequestration using
Zhao et al. (2010) evaluated carbon emissions as a function of the amount of fossil fuel used and carbon emission factors. Zhao et al. (2010) found that the city’s industrial carbon emissions were $7 \times 10^{12}$ g a year, however, the total carbon storage for the city was approximately $1.74 \times 10^{12}$ g indicating urban forests were able to store approximately 1.75 times the quantity of carbon that was being emitted. In addition, Zhao et al. (2010) found that the total carbon sequestered was 1,328,166.55 t for the city. For each hectare of urban forest in the city, the average amount of carbon sequestered was 1.66 t. Therefore, urban forests in Hangzhou were able to offset approximately 18.57% of the industrial carbon emissions. These results indicate to researchers and scientists the importance of evaluating the role of urban forests in reducing carbon emissions, reducing atmospheric carbon dioxide as a result of these emissions, and improving the well-being of cities. Zhao et al (2010) highlight the importance of properly maintaining these trees in order to extract the most benefits in offsetting carbon. They recommend that this would be best done by planting young, low-maintenance trees.

Nowak et al. (2013) formulated and executed a study with the aim to assess carbon sequestration as well as carbon storage of urban trees in the United States to update the national estimates for these factors. The study was done with the intent to provide information on the key role of urban trees in regulating the effects of climate change by reducing carbon dioxide. Nowak et al. (2013) used sampling methods derived by the USDA Forest Service to collected field data for 28 cities and urban areas in the US in six states. Random sampling of 0.04 ha to 0.067 ha plots was conducted in cities and urban areas (respectively) and an i-Tree Eco model was applied. Further, for each tree that was sampled, biomass equations and growth equations were used to estimate carbon
sequestration and carbon storage for the tree. Then, photo-interpretation and ground plot measurements were used to assess tree cover in the sample areas. The data obtained from tree cover and carbon for sample areas were used to determine the total carbon storage and sequestration standardized quantities (in kilograms per meter squared). To estimate state and national values for carbon storage, the standardized quantities were then gathered together in order to determine a standardized average for the whole country. Finally, to estimate carbon sequestration at state levels as well as for the country all together, average sequestration per day was determined for sample cities and states and multiplied by tree cover and the length of the growing season of each state. Nowak et al. (2013) found that for a meter squared of tree cover, tree carbon storage averaged 7.69 kg and carbon sequestration averaged 0.28 kg per year. Nowak et al. (2013) also found that for the United States, the total urban tree carbon stored was approximately 643 million tons which can be valued at approximately $50.5 billion. Similarly, the yearly gross carbon sequestration was found to be 25.6 million tons which has approximately a two billion dollar value. These results indicate that carbon sequestration and carbon storage partake substantial roles in regulating carbon emissions. Nowak et al. (2013) recommend that tree effects on carbon emissions are considered along with their carbon storage and sequestration potentials in order to build a whole representation of the role urban trees play in mitigating climate change.

Myeong et al. (2006) conducted a study in Syracuse, NY with the aim to develop methods to quantify urban tree carbon storage using satellite image time series as well as to apply the methods to an urban area over time to observe the change in carbon storage. Landsat images were used for three different decades for Syracuse, NY to examine
temporal changes. Using the time period of 1985-1999 and Landsat TM imagery, Normalized Difference Vegetation Index was developed. This index was then used as the independent variable of a regression equation that predicts urban forest carbon storage. The dependent variable for the regression were the model estimates of the quantity of carbon storage obtained in 1999. Further, Myeong et al. (2006) estimated the urban tree carbon storage changes in the city. They estimated it to be 146,800 tons for the year 1985, 149,430 tons for the year 1992 and 148,660 tons for the year 1999. Therefore, through this study, Myeong et al (2006) were able to demonstrate how using remote sensing data can produce rapid and reasonable estimates of carbon storage and can show changes in carbon over time. This can assist urban forest management in reducing atmospheric carbon dioxide by rapidly quantifying urban tree carbon storage for use in urban planning designs.

Lastly, Escobedo et al. (2010) executed a study in Florida investigating the success of implementing urban forests to mitigate carbon dioxide levels in urban subtropical environments. Two urban areas, Miami-Dade and Gainesville, were selected. The existing carbon dioxide reduction measures were then used to model carbon storage and sequestration by study area urban trees. Efficacy was determined using the arithmetic mean and median. Field data on 332 random 0.04 ha plots of urban trees throughout the two urban areas was collected and analyzed. Using the Urban Forest Effects model, Escobedo et al. (2010) quantified urban tree carbon storage, carbon sequestration and the effects on building energy. Further, using a combination of plot level carbon dioxide sequestration estimates, geostatistics, block data, and arithmetics, Escobedo et al. (2010) spatially analyzed urban tree carbon dioxide offsets. Escobedo et al. (2010) found that
urban trees offset 1.8 percent of carbon dioxide emissions in Miami-Dade as well as 3.4 percent in Gainesville and Miami-Dade (moderately effective). Escobedo et al. (2010) also found that trees that had higher DBH accounted for more carbon storage. Escodebo et al. (2010) recommend that management takes into consideration the tree type, its maintenance, its growth, and the ecosystem services provided when making decisions about using urban trees in mitigating climate change. They also stressed that maintaining and preserving large trees as well as protecting existing forests during city expansion could be effective in offsetting carbon dioxide emissions and helping combat climate change.

2.2.2.3 Stormwater Runoff

As the intensity and duration of precipitation events increase, researchers are finding it of great importance to investigate how urban forests can mitigating damaging effects on urban communities. Several researchers have aimed to explore the total potential interception versus throughfall of all urban trees in their study area. Inkilainen et al. (2013) conducted a study in Raleigh, North Carolina with the goal of quantifying the amount of rainfall intercepted by vegetation. This was done by measuring throughfall between July and November of the year 2010 on 16 residential yards. There was a total of 206 measuring points within these yards and throughfall and precipitation were measured using buckets. Other factors such as canopy cover, leaf area index, and vertical structural complexity were measured using a spherical densiometer, a Sunfleck PAR Ceptometer, and the Shannon-Weiner equation, respectively. Researchers found that throughfall equalled approximately 78.1 and 88.9% of the total precipitation which indicated to the researchers that urban forests had the potential to reduce runoff between 9.1 and 21.4%.
Therefore, Inkilainen et al. (2013) recommend that researchers continue to examine the role of urban forests in stormwater regulation at different climate zones to build a comprehensive picture. They also recommend that residents contribute by preserving tree cover on their properties and further research examines how societal factors can influence landscape designs.

Similarly, Nyelele et al. (2019) conducted a study in Bronx, NY to assess the current and future (2030) ecosystem benefits of trees planted in the area. Methodology and results for pollution removal were explained earlier in this paper. In addition to those findings, Nyelele et al. (2019) also found that runoff could be reduced by 2 million ft cubed/yr based on average tree mortality scenarios.

In some recent studies, researchers have also aimed to provide an economic value for total runoff mitigation in their study area of interest. McPherson et al. (2016) conducted a study in California, USA, compiling data for 929,823 urban street trees and examining trends in tree numbers, tree density, ecosystem services, and economic returns for 50 cities. As discussed previously in this paper, they found that these trees produced significant economic benefits by mitigating heat, reducing cooling demands, and removing air pollutants. They also found that these trees intercepted 26.19 million cubic meters of rainfall per year which has a value of more than 41 million dollars.

Soares et al. (2011) conducted a study in Portugal with the aim to calculate the total ecosystem services of urban street trees in Lisbon. The methodology is explained earlier in this paper in the air quality section. In addition to reducing air pollutants and carbon dioxide, trees in this area also reduced stormwater runoff. Specifically, Soares et al. (2011) calculated a total reduction of 186,773 cubic meters in stormwater with
Plantanus spp., C. australis, F. angustifolia, P. nigra, and Populus x canadensis accounting for most benefits. This was found to be equivalent to $47.80 of savings per tree.

Yao et al. (2015) conducted a study in Beijing, China with the aim to investigate how urban green space can reduce stormwater runoff. This was done by using GIS software, remote sensing and the Soil Conservation Service Curve Number model. In addition, Yao et al. (2015) also explored a potential future green planning scenario where all green coverage under 40% was increased to 40%. They found that urban green zones (vegetation of more than 60%) constituted only 15.54% of total area, however, it significantly contributed to runoff mitigation. For the year 2012, they found that green space retained 97.9 million m$^3$ of runoff water and adding an additional 11% in tree canopy alone, would increase runoff mitigation by 30% (for a total of 131 million m$^3$). In addition, they found that the economic value of runoff mitigation in 2012 was $0.14 billion and substantially compensated for the cost of investing into green space.

Therefore, Yao et al. (2015) recommend that urban planning implement measures for runoff mitigation that stress the role of urban green space. For example, planting more trees to reduce costs of drainage systems and damage from stormwater runoff. In addition, these measures should be integrated with other compensatory measures such as roof rainwater harvesting.

Lastly, several recent empirical studies have aimed to identify species specific differences in runoff mitigation in order to help better advise urban communities on how to extract the greatest benefit from urban forests. These studies have investigated differences in storage capacity and rainfall interception across species by examining
differences in water uptake, branch angles, stem flow, area index, density, soil properties, and even intensity of storms.

Nytch et al. (2019) aimed to quantify the interception losses by three broadleaf evergreen and three broadleaf deciduous trees that were planted in San Juan, Puerto Rico. They measured canopy throughfall using HOBO RG3-M tipping bucket rain gauges for 13 storms. Data on average storm characteristics was obtained from a micro-meteorological station. For the 13 storms, the total amount of rain that fell was approximately between 2.9 to 72.4 mm depending on the storm lengths. Similarly, the mean throughfall for the trees was 80.4 and the mean interception was 19.6% (for deciduous trees it was 22.7% and for evergreen trees it was 16.7%). Researchers also found that there was a species specific effect that became apparent during low and moderately intense storms (greatest quantity of rainfall was intercepted by the Albizia tree), however, for storms of heavy intensity there was no difference in tree type and the ability to intercept rainfall. Therefore, Nytch et al. (2019) conclude that urban tree canopies can serve as storage reservoirs with varying interception capacity based on micro-meteorological conditions. Nytch et al. (2019) suggest that communities should take into consideration tree type, intensity of common storms, infiltration ability and storage capacity when making decisions regarding stormwater and climate change impacts.

Xiao & McPherson (2016) conducted a study in Davis, California with the aim to obtain characteristics on 20 tree species and determine their capacities to store surface water. The 20 tree species selected depict 77% of all tree species in Davis, CA. Out of these 20 species, eleven were broadleaf deciduous trees, 5 were broadleaf evergreen trees
Xiao & McPherson (2016) measured surface water storage of trees samples (8 samples for each tree type) under different rainfall events. These rainfall events ranged in intensity from 3.6 to 139.7 mm per hectare. To measure surface areas of leaves and stems, an image processing method was used. Finally, the data collected was analyzed through a regression analysis. Xiao & McPherson (2016) found that out of all species, broadleaf trees stored the lowest amount of surface water while conifer trees had both the highest minimum and maximum capabilities and that storage capacities in general varied threefold amongst species. In addition, they found that crown surface storage capacities increased with more intense rain, however the overall effect varied among species. Therefore, Xiao & McPherson (2016) recommend investigating the capacities of different tree species and their components, such as changes in leaf area, in storing rainfall water to better understand and better apply cost-effective tree planting strategies.

Gotsch et al. (2018) conducted a study in Lancaster Pennsylvania with the aim of investigating which tree species are best suited for mitigating stormwater runoff. Specifically, they measured water uptake, branch angle, total sap flow, stemflow and throughfall to investigate differences among nine tree species. To measure sap flow, external and internal sensors containing heat probes were used. Atmospheric data such as rainfall characteristics, humidity, temperature and pressure were measured with a Vaisala WXT520 transmitter. Stemflow and throughfall were measured using gauges. Branch angles and total leaf areas were physically measured. Next, several statistical tests and analysis were conducted including ANOVA testing, linear and mixed models, and likelihood-ratio tests among. Gotsch et al. (2018) found that tree characteristics and
functions had a strong impact on the amount of stormwater they could mitigate. Specifically, trees with large branch angles mitigated more stormwater runoff by directing it to stem flow. Additionally, they found that microclimate affected large and small tree species differently, and there was substantial variation in sap flow for large trees but not much variation in small trees. Gotsch et al. (2018) recommend that underlying characteristics of green vegetation should be explored and incorporated into decision making and urban planning to achieve greatest overall ecosystem services.

Rahman et al. (2019) conducted a study in Munich, Germany with the aim to investigate the infiltration potential of soils under two different tree species common to the area, *Tilia cordata* and *Robinia pseudoacacia*. First, Rahman et al. (2019) collected morphological data for each tree. This included data on tree heights of species, diameter at breast height measurements, the specific surface area, and fine root biomass. Using a Vaisala Weather transmitter, they then collected microclimate data which included air pressure, temperature and humidity. Tree transpiration as well as stem growth (on a daily scale) was measured using thermal dissipation probes and stem radius dendrometers, respectively. Soil characteristics such as moisture and temperature were measured using Tensiomark and soil infiltration was measured using a Decagon mini-disk infiltrometer. Finally, using R, Rahman et al. (2019) conducted a series of statistical tests (ANOVA, t-tests, and Spearman’s rank correlation tests) to test for relationships and significance of variables. Rahman et al. (2019) found that *T. cardata* transpired three times the amount of *R. pseudoacacia*, however, *R. pseudoacacia* had higher soil infiltration (0.42 cm per minute), more annual growth, and more fine root biomass (121 g/m²). Therefore, Rahman
et al. (2019) conclude that tree species that have more fine root biomass and faster growth are better suited for infiltration and runoff mitigation.

Livesley et al. (2014) conducted a study in Victoria, Australia investigating throughfall and stemflow for two tree species (*Eucalyptus nicholii* and *Eucalyptus saligna*) to determine the hydrological benefits of the species. These two tree species have contrasting dark in terms of density and texture. Stemflow was measured using a stemflow helix, throughfall and gross rainfall were collected using a throughfall trough placed in different locations, plant area index was measured using a digital camera and a set of arithmetic equations, and microclimate data was gathered from a climate station. Finally, regression analysis was conducted. Livesley et al. (2014) found that interception and storage capacity varied between the two species. There was less interception capability by both species under large and intense rainfall events. While there was less interception capability by both species under large and intense rainfall events, they found that *E. nicholii*, which had smooth bark and less canopy density, intercepted 44% of the less intense rainfall events defined by being less than 4 mm. This is 15% more than the rainfall intercepted by *E. saligna*. In areas where small rainfall events are common, selecting tree species with the greatest potential to intercept, would provide the greatest benefit in mitigating stormwater runoff. *E. saligna*, however, had more stemflow, even under less intense rainfall conditions, with a funneling ratio of 2.4. This could have positive implications for the hydrological cycle, groundwater recharge and soil quality. Therefore, Livesley et al. (2014) conclude and recommend that using urban tree species can assist in the reduction of runoff and rainfall by almost 20% in this area, if employing suitable tree species.
Baptista et al. (2018) conducted a study in Melbourne, Australia investigating the storage capacity and rainfall interception of three common tree species to the area. The species that were selected for the study were *Ulmus procera*, *Platanus × acerifolia*, and *Corymbia maculate*. Rainfall was simulated using a rainfall simulator and water storage capacity was measured as a change in mass of the tree in rain simulations using a mass balance. Canopy metrics of trees were measured using a ZEB1 laser scanner. Leaf surface area, branch area, total surface area, and stem area data were also calculated. Finally, Baptista et al. (2018) conducted statistical analyses to determine the relationships between interception and tree metrics. Through their calculations, they found that plant surface area, area index, and density correlated with storage capacity of the tree canopy. Out of the three tree species examined at equal plant surface areas and canopy volume, *U. procera*, had the highest storage capacity. Under a 5 mm rainfall simulation, *U. procera* reduced runoff by approximately 26% opposed to the 5% reduction by *C. maculata* and 20% reduction by *P. acerifolia*. Therefore, Baptista et al. (2018) recommend that urban planners and foresters consider canopy metrics of tree species when determining which to plant to increase rainfall interception and reduce stormwater runoff.

### 2.2.2.4 Disease

The increasing public health concern of changing climates and loss of valuable ecosystem services with shifting land use has encouraged more researchers to investigate the benefits of incorporating urban forests into urban environments on human health. Extreme climate conditions such as heat or cold waves, prolonged periods of low precipitation, and periods of abnormally high precipitation have been found to be associated with diverse negative health outcomes through direct and indirect pathways.
Some of these health outcomes are exacerbation of asthma symptoms, elevated stress and anxiety, cardiovascular diseases, and even mortality (Portier et al., 2020). However, forests have been found to have mitigating effects on some of these health outcomes because they are able to limit the impacts of solar radiation and extreme temperatures through shade and transpirational cooling, remove air pollutants, and provide a natural space isolated from noise and view to the city (Lanki et al., 2017; Nowak et al., 2014; Wolf et al., 2020). Some of the recent studies investigating this phenomenon are summarized below.

Reid et al. (2017) conducted a study in New York City, New York to examine the relationship between different forms of urban vegetation and overall health. Reid et al. (2017) sent out a survey to 1549 residents in New York City that asked questions regarding stressors and health. In addition, they implemented a New York City land cover raster file created from 2010 LiDAR data as well as 4-band orthoimagery. Finally, they used regression models to estimate the relationships between vegetation types and amount with self-reported health statistics. They found that individuals living in locations with higher quantitied of tree canopy within a 1000-meter buffer, reported higher for health in the surveys. However, these results did not hold for a 300-buffer size. Therefore, Reid et al. (2017) recommend that further research evaluates health effects of urban forests at different buffers. However, the positive relationship that was observed between urban forests and health effects at a 1000 buffer meter indicates that urban cities could improve their resident’s health through the implementation of trees in the landscape. This would be a very affordable and simple treatment in comparison to medication and other medical interventions.
Several researchers have aimed to investigate the relationship between urban forestry and health by focusing on specific diseases, such as mental health disorders, instead of measures of overall health. Several empirical studies examined the influence of urban forestry on mental health by conducting interviews and surveys, measuring prescription rates, and conducting studies in laboratory environments. For example, Shackleton et al. (2015) conducted a study in two South African towns assessing how residents from urban neighborhood types valued trees in their communities through surveys and interviews. In addition to the provisional services mentioned earlier in this paper, residents also reported back on valuing the benefits trees provide for their health. Specifically, the surveys and interviews that were conducted with members of these neighborhoods revealed that residents valued trees for their promotion of social interactions as well as for their psychological stress reducing effect.

Taylor et al. (2015) took a different approach to investigating the relationship between mental health and urban forestry by measuring anti-depression prescription rates in London, United Kingdom. Anti-depression prescription rates that were obtained from a governmental website. Data on urban street tree coverage was obtained and calculated from Greater London Authority and ArcGIS. Finally, regression analysis was employed to determine the relationship between antidepressant and street trees. They found that overall, locations with lower densities of street trees had higher antidepressant prescription rates. Specifically, for an addition of one tree per kilometer, there was a reduction in 1.38 antidepressant prescriptions for every 1000 people. Taylor et al. (2015) state that while these findings agree with previous research that has examined the mental health benefits of urban trees, more research is needed as this relationship is complex and
there could be other variables contributing to the relationship. This can help expand the role of urban trees specifically in urban planning as well as in policy agendas. The research also hope that these results can help encourage the preservation of existing street trees.

Jiang et al. (2016) conducted a study in four Midwestern urban areas to examine the relationship between human stress and tree density. This was done in a laboratory setting by first generating 6-minute videos of urban neighborhood streets with varying tree density (0-70%). Next they recruited 160 adult participants from the areas. Then, in order to induce psychological stress in participants, Jiang et al. (2016) had them quickly prepare and deliver a speech, followed by a subtraction task in front of viewers. In addition, they told participants they were being recorded and evaluated to increase levels of stress. Lastly, using the Visual Analog Scale, they measured self-reported stress three times throughout the procedure. They found that after controlling for possible confounding variables such as sex and age, there was a positive relationship between tree density and reduction of self-reported stress. Specifically, they found that an increase from 2% to 62% in tree canopy density increased stress recovery by 60%. Jiang et al. (2016) state that future research should apply these methods to urban streets in parks, schools, and other kinds of neighborhoods outside of medium-income, single-family ones in order to build a more comprehensive view of the relationship between urban trees and stress reduction. This can help urban planners justify planting trees and improve the well-being of communities.

Lastly, Beil & Hanes (2013) conducted a study with the aim to access the relationship between stress and different urban environmental settings. First, 15
participants were recruited and screened for eligibility. These participants completed health history forms, and current and previous stress was measured. Participants were further taken to environmental settings where pre and post saliva samples, as well as ratings of perceived stress, were collected. The different kinds of environments were grouped into four categories: 1. A very natural environment, 2. a mostly natural environment, 3. a mostly built environment, and 4. a very built environment. Very natural environments resulted in small change in amylase levels (7.56 U/mL) compared to very built environments were there was an increase in amylase levels by 45.05 U/mL. In addition, there were significant differences found between their environments and perceived restorativeness, with very natural environment scoring the highest. Finally, there was also a higher reduction in subjective stress in very natural settings as compared to mostly built settings. Due to the very small sample size and low power of the study, the results were not enough to fully support the notion that natural settings in urban communities produce beneficial reduction in stress. However, statistical significance is subjective stress reductions suggest that an environment with high levels of urban trees and shrubs can have beneficial effects on stress levels. Beil & Hanes (2013) recommend further studies to help determine how strength and frequency of exposures can affect stress levels, in order to further explore this relationship. Beil & Hanes (2013) state that natural urban environments have the potential to be helpful in creating more sustainable and healthy urban communities.

Several researchers have also aimed to investigate the effects of urban forestry on chronic diseases like asthma, diabetes, obesity, and cardiovascular disease. First, empirical studies examining the effects of urban forests on asthma will be summarized.
Asthma is a noncommunicable respiratory disease that causes inflammation and narrowing of air passages in the lungs (WHO, 2020). It has been identified that trees can remove particulate and gaseous pollutants which trigger wheezing and other asthma symptoms (Domm et al., 2008). However, trees can also emit biogenic volatile organic compounds and aeroallergens which can exacerbate asthma symptoms (Domm et al., 2008).

Nowak et al. (2014) conducted a study in the United States with the aim of accessing avoided health impacts as well as monetary costs of air pollutant removal by trees in the nation for the year 2010. Using computer simulations and environmental data (The National Land Cover Database for 2001, the U.S. EPA Air Quality System national database for 2010, and the U.S EPA BenMap), the researchers were able to determine that 17.4 million ton of air pollutants were removed in 2010 by trees in the United States. The health effect benefits as a result of this were equivalent to a savings of 6.8 billion dollars. For the medical community, this equated to the evasion of more than 850 deaths and 670,000 incidences of acute respiratory symptoms. These health benefits were primarily found in the urban areas (68.1%) as a result of urban trees. However, this analysis came with a set of limitations. Nowak et al. (2014) state that there are limitations when it comes to modeling air pollutants. In addition, the data used for air pollutants was limited as a result of the confined number of pollutant monitors throughout the nation. Therefore, Nowak et al. (2014) recommend that additional research is needed modeling the relationship between urban forests, air pollutants and health to make better estimations.
Lai & Kontokosta (2019) investigated the impacts of urban street trees on respiratory health and the quality of air in the US. To do this, they set out to create a database for urban street trees, respiratory illness rates, and air quality for the city of New York. Data to complete this database was obtained from the NYC Department of Parks & Recreation, the NYC Department of Health & Mental Hygiene, the Department of City Planning’s Primary Land Use Tax Lot Output database, Pollen.com and the US Census. Using the data in the database, the authors then performed a multivariate linear regression model determining the relationship between prevalence of asthma, tree density and prevalence of allergenic tree species. The authors found that of the 652,169 street trees they examined, about 76% of the trees contained allergenic pollen in the spring. 24% of the street trees had severe allergenic pollen making them substantial respiratory health threats. However, Lai & Kontokosta (2019) did also find that the overall density of trees planted along the streets was associated with lower asthma emergency department visits with the exception of the tree species Red Maple, American Linden and Northern Red Oak that were positively associated with asthma emergency department admissions. Therefore, the authors explain that these results indicate that while high urban tree density can have a positive effect on respiratory health, this effect can be reversed if the tree species being planted are allergenic.

Lastly, Lovasi et al. (2008) performed an ecological study to examine the prevalence of pediatric asthma in youth living in urban environments with more street trees. Their main objective was to both identify as well as quantify the association between pediatric asthma and street trees by using asthma prevalence data and asthma hospitalization data for pediatric patients and street tree data obtained from the New York
City Department of Parks and Recreation. The prevalence of asthma data came from a school screening conducted in 1999 on 4 and 5-year old youths in the area by the NYC Department of Health. Asthma hospitalization data was obtained from the NYC Department of Health for 1997 for youth children under the age of 15. In addition, the authors gathered data on the proximity to pollution sources. Using the data, they calculated correlation coefficients and ran a Poisson regression model. The authors found that a 1 standard deviation increase in tree canopy density was associated with an overall lower prevalence of asthma in 4 and 5-year-olds. However, it was not associated with lower hospitalization rates for asthma in children under the age of 15. Specifically, after adjusting for possible confounding variables, the authors estimate that there would be a 29% decrease in the prevalence of asthma in children for a 1 standard deviation increase in tree canopy density.

Another group of chronic disorders found to be linked to urban forestry is cardiovascular diseases. Cardiovascular diseases consist of a group of heart and vessel disorders (WHO, 2017a). Currently, cardiovascular diseases hold the spot as the number one cause of death in the world (WHO, 2017a). Several researchers have aimed to investigate how urban forests can influence the exacerbation of cardiovascular symptoms.

Mao et al. (2012) conducted a study investigating the effects of forest bathing on high blood pressure (hypertension). To do this, the authors recruited 24 elderly participants (aged 60 to 75) with hypertension, split them into two equal sized groups, and sent them to either a broad-leaf evergreen forest or to the city area of Hangzhou. All participants spent 7 days and 7 nights in their location from July 23rd, 2011 to July 30th, 2011. For all participants, mood evaluations were conducted, and blood pressure
indicators and cardiovascular disease factors were detected using morning blood samples and blood pressure monitors. Some of these factors detected were renin, angiotensin II, homocysteine, inflammatory cytokines interleukin-6, and angiotensinogen. Blood serums were then analyzed using radioimmunoassay kits and enzyme-linked immunoassays.

Each day participants would walk a predetermine course for 1.5 hours, rest and eat lunch, and walk 1.5 hours back. Mao et al. (2012) found a reduction in blood pressure (both systolic and diastolic), bio-indicators (endothelin-1, homocysteine, angiotensinogen, angiotensin II and angiotensin I), and negative subscales of mood (anger, depression, fatigue, and confusion) to be lower in participants who were exposed to the forest environment in relation to those exposed to the city environment and baseline conditions. Heart rate was not affected in either of the groups. Therefore, while the sample size is small, there results demonstrate how there could be a significant reduction in high blood pressure from even short-term forest bathing. The authors recommend conducting similar studies on larger samples and in different times of the year.

Lanki et al. (2017) examined short-term changes in cardiovascular health while visiting urban green and built environments in Helsinki, Finland. To do this, the authors recruited 36 adult female participants and had them visit an urban forest, the city center, on an urban park in groups of four in random order. Visits lasted 45 minutes with 15 minutes devoted to viewing and 30 minutes to walking at a steady pace on a designated route for 2 km. During the visits, researchers assessed the blood pressure and heart rate of participants, recorded electrocardiograms using Holter-monitors, and monitored for noise exposure and traffic-related air pollution. Prior to visits, researchers collected baseline cardiovascular data and standardized energy levels by administering the same meal to
participants. Analysis of results was carried out using mixed models. The results of viewing the environments and walking through them were evaluated separately. Lanki et al. (2017) found that heart rate was lower when visiting urban green environments and measures of heart rate variability (such as the standard deviation of normal-to-normal intervals and high frequency power) were higher compared to the city center environment. These effects were found to be stronger for urban forests compared to urban parks. In addition, the authors found that when viewing urban green environments, participants experienced lower blood pressure in comparison to the city center environment. However, there was a slight decline in the associations between cardiovascular health and urban green space when air pollution and noise were included. PM10 was found to be positively associated with both blood pressure as well as heart rate. Environmental noise was found to be associated with decreased indexes of heart rate variability. These results indicate that urban green environments have a beneficial short-term effect on cardiovascular health, however, the authors indicate the importance of also investigating longer-term benefits. In addition, they recommend conducting similar studies with other types of population groups.

Lastly, some researchers have aimed to identify the relationship between urban forestry and the chronic conditions of obesity and diabetes. For example, Ulmer et al. (2016) conducted a study in Sacramento, California with the aim to assess the role of urban tree cover as it relates to health. This was done by using pre-existing datasets. Demographic and socioeconomic information was collected through the California Health Interview Survey which was administered between 2001 and 2011. In this survey, participants self-reported on things such as physical activity, body weight, and physician
diagnosed health conditions. Forest cover data was mapped using LiDAR and imagery data. Finally, regression analyses were conducted to test for relationships between the variables. Ulmer et al. (2016) found that more tree cover was significantly associated with higher odds (13% higher) of reporting a higher health score. Specifically, a 10% increase in forest cover was found to be correlated with a 29% improvement in the score. In addition, more tree cover was correlated with less obesity, less type 2 diabetes and less asthma. Specifically, a 10% increase in forest cover was correlated with a 19% reduction in obesity and overweight conditions, a 19% reduction in type 2 diabetes, a reduction in high blood pressure by 7.4%, and a reduction in asthma by 10.4%. However, Ulmer et al. (2016) state that the relationship between asthma and urban trees is highly complicated and more research is needed controlling and examining other variables such as air pollution.

Similarly, Astell-Burt & Feng (2019) conducted a longitudinal study in Australia to investigate whether various types of urban green space, including tree canopy, were related to lower odds of heart disease, diabetes and hypertension. Diagnosed hypertension, diabetes, as well as heart disease were measured in 46,786 participants. The odds of these outcomes were accessed in relation to green space within 1.6 km buffers. These odds were accessed using multilevel models. The authors found that odds of all three diseases were lower in participants who lived in areas with more than or equal to 30% tree canopy covered. Specifically, the odds of incident heart disease was 0.78, the odds of incident hypertension was 0.83, and the odds of incident diabetes was 0.69 in this group compared to those who had 0-9% tree canopy cover. The odds of prevalence heart disease was 0.85, the odds of prevalent hypertension was 0.87, and the odds of prevalent
diabetes was 0.62 in this group compared to those who lived in an area with 0-9% tree canopy cover.)

2.2.3 Supporting

Urban forests provide critical supporting services that allow the Earth to sustain ecosystems (Center for Sustainable Systems, 2020). These include nutrient cycling and consequent effects on soil quality and soil properties, reduced leaching and subsequent effects on water quality, and lastly oxygen production. Recent studies have aimed to better understand these mechanisms and have been summarized below.

2.2.3.1 Nutrient Cycling

Michopoulos et al. (2007) conducted a study examining the nutrient cycling of 10 elements in an urban forest in Athens, Greece. The study was conducted in 2004 and the elements N, S, Mn, Ca, Mg, K, P, Fe, Zn, and Cu were assessed to establish the well-being and productivity of this urban community. Bulk deposition, throughfall, litterfall collection were completed using collectors and littertraps. Foliar, wood biomass, and bark biomass data were collected and determined using pruning devices and allometric equations. In addition, samples of understory vegetation, forest floor, and mineral soils were collected. Following sample and data collection, the researchers performed chemical analyses for separate elements using ion chromatography, the Kjeldahl distillation method, atomic emission spectrometry and inductively coupled plasma atomic emission spectrometry. Finally, the researchers determined the coefficients of variation for elements and performed a t-test to compare nutrient concentrations. Researchers found that the tree bark stored high amounts of calcium, phosphorus, sulfur, and iron while the tree trunk stored higher amounts of magnesium, potassium, zinc, nitrogen, and lastly,
manganese. The forest floor contained high proportions of zinc as well as copper. The understory vegetation contributed valuable nitrogen, potassium as well as phosphorus and the soil served as the largest sink for all elements. Through their research, these researchers showed how tree canopies act as an important sink for pollutants in the air and how understanding nutrient cycling of trees can help better manage these valuable parts of the ecosystem.

Livesley et al. (2016) conducted a study in southeast Melbourne, Australia investigating C/N ratios and carbon storage of tree canopy opposed to grass and to determine the source of variability in soil properties of trees. Soil carbon to nitrogen ratios are important for healthy soil dynamics and for buffering eutrophication. The study was conducted in Gippsland Plains bioregion in Melbourne, Australia on 13 golf courses in the suburbs. First, Livesley et al. (2016) identified species of each tree in their plots that had diameters greater than 8 cm. Then they measured the exact tree stem diameter and calculated the basal area, stem density and vegetation volume. To sample the soil under each tree canopy, Livesley et al. (2016) used a drop hammer and a stainless steel core sampler up to a depth of 0.3 m. The researchers then conducted carbon and nitrogen concentration analyses using a TrueMac elemental analyzer. Further, using linear mixed models, Livesley et al. (2016) examined the relationships between age of the green space, soil properties and attributes. Researchers found that both soil nitrogen and soil carbon were greater under tree canopy despite the soil having lower bulk density. They also determined that urban trees develop high soil carbon to nitrogen ratios which can play a significant role in improving nutrient buffering capacity of soils. They lastly found that this ratio were associated with the age of the green space.
2.2.3.2 Reduced Nutrient Leaching

Groffman et al. (2009) conducted a study in Baltimore, Maryland assessing NO₃-leaching, N₂O fluxes and CO₂ fluxes of eight forested long-term study plots established in 1998 and four grass plots planted from 1999 and 2001 in the area. The data collection period was between 2001 and 2005 on the Gwynns Falls watershed in Baltimore. Data was collected on soil temperature, moisture and chemistry using HOBO H8 Pro Series Temp/External Temp data loggers, a Soilmoisture Trase System 1, and zero-tension lysimeters respectively. Loss of nutrients through leaching were estimated by multiplying yearly runoff values with annual volume-weighted mean NO₃ concentrations and N₂O fluxes were determined using an in situ chamber design. Researchers found that soil temperatures were consistently lower in forest plots and NO₃-leaching was on average lower in forest plots. Through this study, Groffman et al. (2009) showed how urban forests can perform better in certain aspects than grassland, such as reducing NO₃-leaching and, therefore, evaluation of nutrient cycling needs to be taken into account when making landuse and landcover decisions.

Nidzgorski & Hobbie (2016) conducted a study in Minnesota, USA examining the capacity of urban trees in reducing nutrient leaching to groundwater. Leaching of nitrogen into urban groundwater can cause lower oxygen levels and water quality. For 33 trees and seven turfgrass areas located throughout city parks of Saint Paul, Minnesota, Nidzgorski & Hobbie (2016) estimated nitrogen leaching and water fluxes using lysimeters at a depth of 60 cm and the BROOK90 hydrologic model, respectively. Nidzgorski & Hobbie (2016) also measured soil nutrient pools, canopy characteristics and carbon, nitrogen and phosphorus concentration in leaves, tree litter and roots.
Further, Nidzgorski & Hobbie (2016) conducted ANOVA and quantile regression analysis to test for relationships and differences between variables and vegetation types. The results varied by year by overall Nidzgorski & Hobbie (2016) found that deciduous trees had the lowest nitrogen and phosphorus soil water nutrient concentrations when compared to evergreen trees and turfgrass and evergreen trees had overall lower soil water phosphorus concentration but equal nitrogen concentrations. They also found that in the year 2012, trees had lower leaching of nitrogen than turfgrass but the opposite was true for the following year. Overall, trees had lower phosphorus leaching. They also found that leaching was lower for deciduous trees than evergreen trees. Nidzgorski & Hobbie (2016) also scaled their results to the Capitol Region Watershed and found that for this region, trees reduced phosphorus leaching by 533 kg in 2012 with a value of 2.2 million dollars and 1201 kg in 2013 with a value of 5 million dollars. Therefore, urban trees have the potentially to help reduce nutrient leaching and pollution to groundwater with the most prominent reductions being in phosphorus. Therefore, Nidzgorski & Hobbie (2016) recommend that communities investigate the role of urban trees in helping protect water quality.

Denman et al. (2015) conducted a study examining the role of trees and their soils in urban stormwater runoff nutrient removal. Four street tree species commonly seen in urban landscapes of southeastern Australia were planted in model biofiltration systems. The four tree species that were planted were *Eucalyptus polyanthemos*, *Platanus orientalis*, *Lophostemon confertus*, *Callistemon salignus*. These tree species were planted as a randomized block factorial design and grown in mesocosms. The trees grew in three different soils with different hydraulic conductivity rates. The trees were irrigated weekly
with 4.4 L of either tap water or stormwater with a chemical composition consisting of nitrate, glycine, phosphate, copper and dissolved solids. During the experiment, Denman et al. (2015) collected data on aboveground biomass, and nitrogen and phosphorus concentrations leached over the course of 13 months. They found that all of the tree species performed well in all three soil conditions and they were effective in reducing oxidized nitrogen leaching (2-78%) and filterable reactive phosphorus leaching (70-96%). Therefore, Denman et al. (2015) conclude that there is strong potential of street trees to be effective regulators of nutrients in urban systems and there is no significant difference between the specie types. They recommend further conducting field evaluations of urban biofiltration systems using street trees over a long course of time to further examine the role of trees.

2.2.3.3 Oxygen Production

Guan & Chen (2003) conducted a study in Guangzhou, China with the aim of estimating plant biomass as well as the net primary productivity of urban greenery. They collected 302 plant samples and 93 soil samples in the summers of 1996, 1997, and 1998. The Walkley-Black Method was utilized to quantify organic carbon concentrations. Aboveground and belowground biomass were estimated through a combination of using dimensional analysis, harvest methods, and tree characteristics such as tree trunk volume. They found that urban forests compromised only 37.1% of the urban land, however, it accounted for 76.9% of the biomass. The area for the forests was 33600 hm², the biomass produced was 1909731 t, and the net primary productivity was 355848 t/a. The mean biomass per unit area (hm²) was 56.84 t/hm², and the mean net primary productivity per unit area was 10.59 t/hm². Urban forests also accounted for 78.2% of total carbon content.
for all vegetation types examined. Soil was also found to be the largest carbon storage pool, especially under tree canopy. In total, all urban vegetation fixed 462624 t/a of carbon and produced 1232429 t/a of oxygen which equalled 7.61% and 4.97% of carbon produced and oxygen consumed in the city. While these values are a small contribution, it is a contribution and Guan & Chen 2003 researchers state that with increasing conservation and better management of urban vegetation, carbon storage and oxygen production could be greatly increased and could benefit the population substantially more.

2.2.4 Cultural

Lastly, urban forests provide a variety of cultural ecosystem services that contribute to cultural advancement and development of individuals (Center for Sustainable Systems, 2020). These cultural ecosystem services range from added property value, to contributions to heritage, education, and recreation (Center for Sustainable Systems, 2020). The following section will summarize recent empirical studies investigating urban forest cultural ecosystems throughout the world.

2.2.4.1 Added property value

Escobedo et al. (2015) conducted a study in four urbanized regions of Florida, United States with the aim to generate an approach for and analyze the relationship between urban forests and property values. Random plots within the urban regions were selected and data for each tree regarding structure were collected. Property values of residential areas were measured using assessed values from property tax data. Finally, Escobedo et al. (2015) developed a hedonic model of housing type and urban tree structure. They found that property values went up by $1586 per tree. In addition, they
found that replacing trees with grass lowered property value. Therefore, urban trees add significant value to urban properties and Escobedo et al. (2015) recommend that this information is used to help inform local governments of the benefits of conserving and implementing urban trees in addition to increasing investments in possible urban forestry programs.

In California, McPherson et al. (2016) conducted a study with the aim to compile data for 929,823 urban street trees throughout 50 cities, and examine trends in tree number, density, ecosystem services, and economic returns. Previously in this paper, the benefits extracted for heat mitigation, pollution removal, and runoff mitigation were discussed. In addition to these benefits they also found that these trees increased property values by $838.94 million.

In Portugal, Soares et al. (2011) conducted a study to calculate the ecosystem services provided by urban trees in Lisbon. Methodology was previously described in the air quality section. In addition to finding that these trees reduced air pollutants and runoff, they also found that these trees provided additional value to properties. Specifically, added property benefits equalled $145 per tree for a total of $5.97 million dollars for the area. The species most responsible for these added benefits were Plantanus spp., C. australis, P. nigra, A. negundo and Tilia spp.

2.2.4.2 Heritage and Education

Rudi et al. (2019) conducted a study in Prague with the aim to assess and bring attention to the cultural significance of small and young urban trees in this area. They defined a “culturally significant young tree” as having a diameter at breast height of 80 centimeters of less, an age of 100 years or less, and a history documenting its cultural
value. This cultural significance could stem from historical events, memories of certain people, or even messages. Next, they proceeded to map these trees within the study area by using local data, a direct search, and participation of the public. They found 189 trees total, with 92 trees being planted in memory of a person strongly connected to Prague, 87 planted as symbols of political significance or peace. Therefore, they determine that many trees in this urban environment hold an important cultural significance.

Specifically, these trees were planted to remind people of important messages, symbols, people and events in the area. Therefore, these trees serve as not only important heritage characters, but they can also play a valuable role in the education of the environment and its history. However, Rudi et al. (2019) find that conservation of trees in this area is concentrated primarily elsewhere, so they recommend the identification of these trees as an important step in their protection. They believe that public awareness and conservation could be even further enhanced by implementing information panels or special codes for these trees. Through the protection of these trees, cities can preserve their culture and educate members on it.

Shackleton et al. (2015) conducted a study in two South African towns with the aim to see how residents from three urban neighborhood types valued trees in their landscapes. In addition to residents reporting back on provisional and regulating services that were mentioned earlier in this paper, they also reported back on the cultural services they extracted from their landscapes. Shackleton et al. (2015) found that older township neighborhoods expressed more aesthetic connections to the trees such as their enhancement of landscape beauty and their historical roots within their cultures. Specifically, in the Tzaneen neighborhoods, where more than 80% of households
reported on the aesthetic benefit of trees, there is a rich history involving trees and a culturally significant rain queen, Modjaj.

Hodson & Sander (2017) conducted a study in Minnesota, US, with the aim of establishing the relationship between academic performance and urban land cover such as trees and impervious surfaces. This was done by assessing third grader math and reading examination scores for over 200 schools in the Twin Cities Metropolitan Area. Green and blue spaces assessed were tree canopy cover, impervious surfaces, grass cover, shrub cover and water. These blue and green spaces were calculated using land cover and hydrography datasets, and ArcGIS. Finally, they used regression analysis to determine the relationships between the variables. They found that tree canopy was positively correlated with reading performance. This indicates that urban trees can provide valuable educational services to urban communities. Hodson & Sander (2017) suggest that urban landscape designs take this notion into consideration because daily exposure to urban trees in a school setting can improve reading skills which is a predictor of completing high school and having better well-being.

Colinas et al. (2019) conducted a case study in Montreal, Quebec on the socio-environmental impacts of implementing urban fruit trees, including contribution to public knowledge on food and the environment, and the aesthetic value. As mentioned in the provision section of this paper, these researchers focused on a public orchard in the city and collected information through interviews with users and project developers. These interviews revealed that users appreciated the vegetation, attractiveness, socialness, and safety provided by the fruit trees on the bike path. Many strongly appreciated the beauty the fruit trees provided and stated that the trees helped them connect to nature and
strengthen their relationships to people, feel safe and isolated away from the roads, and educate their children and others. Specifically, educational factors users claimed to extract from the trees included knowledge on food, the environment, and species. In addition, the harvesting of fruit was seen as an enjoyable activity. Therefore, the urban fruit trees provided significant social capital to the interviewed users and carried high aesthetic value. Therefore, Colinas et al. (2019) recommend that urban planners take into account these various factors (aesthetics and educational opportunities) when planting and maintaining urban trees in order to gain highest acceptance by the community and extra the most benefits.

2.2.4.2 Recreation

Wang et al. (2017) conducted a study in China with the aim to investigate how different urban tree understory characteristics affect aesthetic and recreational preferences. Photographic images of landscapes were used that were developed using Photoshop 7.0 software. This allowed researchers the ability to manipulate the understory of the trees. Participants were interviewed in Xuzhou in person. They were first shown the images and asked questions about them, and then they were asked to fill out a questionnaire. These surveys were conducted at various public spaces such as university campuses and commercial centers. They further analyzed their data using SPSS. They found that 99% of the people liked being in land covered with trees: 57% of people said this was due to fresh air, 53% commented on the scenic beauty, and 19% commented on using this space for various activities. In addition, 58% of the participants believed the main purposes of the understory of the trees was to promote health and to make the environment for visually appealing. Finally, after excluding an outlier from their results,
they found a strong positive correlation between recreational and aesthetic preferences. Therefore, the connection between urban woodlands and health can be made like so: people are attracted to urban woodlands for their aesthetic value, and due to the positive correlation between aesthetic preferences and recreation preferences, these individuals could also be motivated to engage in more recreational activities. These activities could connect them with nature and increase their overall health and well-being. Since this research also shows that understory was seen as visually attractive, managing the understory of trees can be important in attracting people to urban woodlands. Specifically, low to medium height understory, and using flowers, could attract more people to these areas to extract higher benefits from it. Balancing this with some cleared understory could also encourage more recreational use. This could then justify to urban planners the necessity of urban forests.

Voigt et al. (2014) conducted a study in Salzburg, Austria and Berlin, Germany with the aim to create an approach for investigating the recreational benefits of urban parks, and then test the approach in six urban parks. They develop a mapping tool that links together data regarding the urban park’s structural diversity and self-reported importance. Structural diversity consists of biotic features such as the trees and ground vegetation, abiotic conditions such as water bodies and topography, and the infrastructure. Voigt et al. (2014) believe that all of these components can affect how people perceive the park and what activities they use it for. Mapping of the urban parks was conducted by collaborators in 2013. Self-reported importance was evaluated by interviews and questionnaires. Voigt et al. (2014) found that there was a range of recreational use of the parks. These included walking, walking animals, physical
exercise, sport activities, sunbathing, hanging out with family members, and reading. Specifically, biotic factors (trees) were greatly appreciated for their provision of shade that enabled visitors to engage and participate in a lot of outdoor activities. Therefore, urban trees and vegetation provide a basis for the cultural services provided by urban parks and infrastructure providing additional recreational value. Voigt et al. (2014) recommend further research investigating the value of biotic, abiotic and infrastructural components in green spaces. This would help validate the benefits and help conserve and maintain these areas.

Lastly, Shanahan et al. (2015) conducted a study in Queensland, Australia to investigate the relationship between tree cover and attraction to an urban park. First, they conducted an online lifestyle survey. They included only the people that have visited the parks (670 respondents). Next, they measured tree cover in parks through a data layer obtained from the Brisbane City Council. This data was produced from LiDAR data. To test whether the number of visits to parks was related with the amount of tree cover, they identified 324 parks visited at least once by the respondents and determined what percent of them fell into different vegetation cover brackets (in ten percent increments). Finally, they concluded by running statistical analyses in R. While they did not find a direct relationship between park visitation rates and tree cover, they did find that people with higher nature relatedness tended to travel longer distances for more vegetated parks. This indicates that this part of the population is more likely to obtain benefits from urban vegetation and enhance their wellbeing. Therefore, Shanahan et al. (2015) state that there needs to be more educational and social practices that help connect people to nature in order to enhance recreational benefits of urban forests. If more people are aware of their
benefits and find value in the vegetation, this can assist in developing and preserving sustainable landscapes.

2.3 Ecosystem services of cover crops

Enhancing cover crop ecosystem services is gaining increasing attention in empirical literature as sustaining agricultural ecosystems under changing climates and land use modifications become more challenging. The following section will summarize recent empirical research on the provisional, regulating, and supporting ecosystem services of cover crops.

2.3.1 Provisional

Researchers around the world have been increasingly interested in the effects of cover crops on crop and biofuel production. These recent studies on provisional services of cover crops have been conducted in different regions of the world, from the United States to Brazil, Turkey, and the United Kingdom. Some researchers like Feyereisen et al. (2013) have aimed to access provisional ecosystems services of cover crops using simulation and modeling techniques in ArcGIS, while others like Crotty & Stoate (2019), Demir et al. (2019), Wang et al. (2009), Crusciol et al. (2015), and Delgado et al. (2007) used field experiments.

2.3.1.1 Food provision

Crotty & Stoate (2019) conducted a study in the United Kingdom with the aim to investigate how three cover crop mixes affected soil chemistry, soil biology, weed suppression, and cash crop yields. The cover crop mixtures contained oats, radish, vetch, phacelia, legumes, and buckwheat. The soil is primarily a heavy clay loam and the management system is a minimum tillage management system. Measurements of soil
chemical properties were done through several analytical procedures including mineral soil analysis, pH analysis, and organic matter content analysis. Physical properties such as soil structure, bulk density, porosity, and moisture were assessed from soil cores and a soil compaction meter. Crotty & Stoate (2019) also measured earthworm abundance, biomass, mesofauna, and cash crop yields. They found that overall, cover crops had positive effects on weed suppression, reduced nutrient leaching, and increased crop yield. Earthworms were higher in radish treatments and there was significant weed suppression under some treatments which caused a significant increase in yield and economic profitability. Therefore, Crotty & Stoate (2019) recommend the use of cover crops for sustainable management of agricultural lands.

Demir et al. (2019) executed a study in Turkey with the aim to investigate how cover crops can alter soil properties and crop yield. They conducted field experiments in an apricot orchard on soil clay using four winter cover crops and one summer cover crops. Soil samples were collected at two different depths ninety-day post cover crops implementation using a corkscrew-shaped soil drill. Soil chemical, biochemical, and physical analyses were then conducted on the samples. In addition to the positive effects cover crops had on soil properties, which will be discussed later on in this paper, cover crops increased yields of the apricot crops, most likely due to the increased organic matter provided by the cover crops. The highest increase was seen for the Vicia pannonica Crants (70%) + Tritikale (30%) treatment, with a mean fruit weight increase of 10.7%.

Wang et al. (2009) conducted a study in Florida with the aim to investigate the impact of summer cover crops as well as the application of organic mulch on tomato
yield and soil quality. The dominant soil type for the study area is Krome and the study was conducted during two crop cycles. The cover crops implemented were velvet bean, cowpea, sunn hemp, and sorghum-sudangrass. Each year, Wang et al. (2009) harvested tomato fruits 3 times contingent on the development stage of the fruit. The soil and aboveground biomass were also sampled and analyzed. Wang et al. (2009) found that overall cover crops and organic matter separately influenced the yield of tomato fruits. The influence of cover crops on yield varied between the cover crop species as well as the growing season. For the 2003-2004 season, sunn hemp had the overall highest marketable yield and extra-large fruit yield. In the 2004-2005 season, sunn hemp also had the highest marketable yield but velvet bean had the highest extra-large fruit yield. Therefore, Wang et al. (2009) conclude that sunn hemp and velvet bean can be excellent summer cover crops to implement because of their ability to increase yield and food productivity.

Palisadegrass, with an African origin, has a deep rooting system that can thrive in environments that most crops can’t, such as dry winters (Crusciol et al. 2015). Research shows that this species can improve soil quality as well as increase the total soil organic matter and improve the quality of the soil. Crusciol et al. (2015) conducted a study in Botucatu, Brazil with the aim to investigate the effect of this species on cash crop yields common to the area. In their field study, they intercropped palisadegrass with corn and assessed subsequent yield for three different crops: soybean, corn, and white oat. The soil was sampled at various depths and soil chemistry was analyzed. Nutrients analyzed included nitrogen, phosphorus, calcium, magnesium, sulfur, and potassium Leaf samples of cash crops were also taken when 50% of the species was fully flowering. These
samples were accessed for nutrient composition. In addition, the cash crops were harvested and analyzed for yield. They found that in treatments intercropped with palisadegrass, soybean grain yield increased 14% during the first growing season and 10.3% during the second growing season. Yields of white oat grain were 24% higher during the first growing season and 14.5% higher in the second season and yields for corn were 12.7% higher with treatments intercropping with palisadegrass. Therefore, they recommend incorporating cover crops such as palisadegrass into farming systems to increase crop production and yield.

Delgado et al. (2007) summarized cover crop research conducted by a multidisciplinary team in south-central Colorado over the last decade. Their first set of studies focused on winter cover crops and results will be discussed further in this paper. There second set of studies which were conducted more recently focused on summer cover crops. They found that summer cover crops were shown to have some positive effects on yields. Specifically, in limited irrigation areas which is common to the Colorado landscape, potato yields were significantly increased (12% to 30%) when sorghum-sudan was used as a summer cover crop.

2.3.1.2 Biofuel

Feyereisen et al. (2013) conducted a study in the United States with the aim to investigate the potential of using winter rye as a biofuel cover crop. Using a plant-soil-atmosphere model called RyeGro, Feyereisen et al. (2013) investigated possible winter rye biomass accumulation post soybean and corn harvest. They selected thirty locations in the United States where soybean and crop production was implemented and that would be suitable for winter rye growth. From the simulations provided by the model, they were
able to develop regression equations for use in ArcGIS. They located 18.4 million acres of continuous corn systems and 78.2 million acres of corn-soybean systems in the U.S. that would allow the growth of winter rye. Feyereisen et al. (2013) estimated that 112-151 Tg of winter rye could be produced on this land area. The energy content of this biomass was estimated to be 2.0-2.6 EJ which could help support part of the building and transportation energy demands in the United States. Combined with the other ecosystem services winter rye could provide such as reduced soil erosion, winter rye could serve as a valuable cover crop that helps enhance agricultural productivity and provide a source of energy for other systems.

2.3.2 Regulating

Cover crops are able to enhance regulating services if integrated into agricultural systems (Blanco-Canqui et al., 2015). Cover crops are able to regulate the movement of water affecting water content, demand for water resources, water storage, and runoff (Alliaume et al., 2014; Delgado et al., 2007; Demir et al., 2019). Cover crops can also regulate the presence and growth of weeds (Tursun et al., 2018). Recent empirical studies have aimed to investigate how regulating ecosystem services of cover crops differ across different cover crop treatments, different tillage practices, varying soil types and level of fertilizer use, degree of irrigation, or amount of organic matter present in the soil.

2.3.2.1 Water Regulation

As discussed earlier in this paper, Demir et al. (2019) conducted a study in Turkey to investigate how cover crops can affect water properties, soil properties, and crop yield. The methodology was described earlier in the provisional services section. Through their analyses, they found that cover crops had a significant effect on saturated hydraulic
conductivity, volumetric and available water content, and basal soil respiration which were all higher with the incorporation of cover crops. Available water content increased between 16.4% to 19.4% among treatments, indicating that the soil was able to retain more water and also, make more water available for plant use. The increase in these properties has positive implications for water quantity and quality.

As mentioned earlier in this paper, Delgado et al. (2007) summarized research on cover crops conducted by a multidisciplinary team in Colorado. Colorado is a semi-arid state with limited water resources for agriculture, so therefore, the multidisciplinary team conducted multiple limited irrigation studies. Between 1993 and 1999, this research primarily focused on winter cover crops. This new set of research studies is focusing on summer cover crops. These studies have demonstrated that summer cover crops can be established and nourished with low irrigation while still producing benefits. They found that some crops such as potatoes, barley, and winter wheat require high irrigation input and that a low input cover crop can help reduce this need for pumped water by 50% and can protect the quality of water due to the low dependence on fertilizers.

Haruna et al. (2018) conducted a study in Northern Missouri with the aim to investigate water infiltration under different cover crop treatments and tillage practices. The study took place at Lincoln University’s Freeman farm which has Waldron silt loam soil. Corn was grown as the main crop and cover crops were planted in the fall of each year. Infiltration was measured using single-ring infiltrometers units. Statistical tests (ANOVA and GLM) were done in the SAS statistical software. They found that the saturated hydraulic conductivity for cover crops was 75-85% greater than for no cover crops. The sorptivity was 82-90% greater for cover crops than no cover crops. In
addition, sorptivity was higher in Till management than no-till management. Therefore, cover crops can successfully increase infiltration with positive implications for soil and water quality. Therefore, Haruna et al. (2018) recommend incorporating cover crops into agricultural land to extract these benefits.

Sullivan et al. (1991) conducted a study in Blacksburg, Virginia examining nitrogen production, nitrogen uptake, and crop yield contribution of vetch and rye cover crops. Small plots of corn were established throughout the region on Hayter cobbly loam soil. Cover crops were planted on the plots either alone or as mixtures. Phosphorus and potassium fertilizers were applied to corn. Finally, biomass produced by cover crops, nitrogen uptake by corn, carbon to nitrogen ratio, and soil moisture were assessed. Two tillage practices were used: disk tillage and no tillage. They found that cover crops with more biomass had higher soil water retention. Results on geochemical cycling will be further discussed in this paper.

Alliaume et al. (2014) conducted a study in Canelones, South Uruguay with the aim to assess how cover crops, tillage practices, and the addition of organic matter affect soil and water properties such as runoff, moisture, and erosion. The soil type of the region is Luvic Phaeozem. They implemented three tillage treatments where cover crops were either left as mulch, used as green manure, or not implemented. They also implemented one conventional tillage treatment as the control. The cropping system selected was a tomato-oat rotation system. Runoff was estimated using a boundary line approach. To assess for soil moisture, the time-domain reflectometer was employed. Soil erosion was estimated using field data collected on soil parameters and arithmetic calculations. Data on crop yields, evapotranspiration, and soil water capture were also collected. Results of
stormwater runoff reduction and soil erosion will be discussed later in this paper. They found that during the dry season, reduced tillage combined with cover crop mulching increased soil water capture and storage by a total of 20% which can have positive implications on water conservation as it relates to climate change. However, they also found that reduced tillage resulted in lower crop yield, most likely due to poor crop establishment and nitrogen immobilization, which they recommend should be further investigated in the research. Despite this, Alliaume et al. (2014) state that a combination of the right tillage practices and cover crop management could be greatly beneficial for water quality.

2.3.2.2 Stormwater runoff

As mentioned earlier in this paper, Alliaume et al. (2014) conducted a study in South Uruguay investigating the role of cover crops, tillage practices, and organic matters of soil and water properties of landscapes. Alliaume et al. (2014) found that tillage methods significantly affected runoff. Treatments with cover crops also reduced runoff, however, it was not statistically significant. Specifically, in the treatment without cover crops, the runoff was 54% and 34% at tomato establishment and at termination of growth, respectively. However, for the treatments with cover crops, the runoff was only 6% for both of those times. Soil loss, as a result, was reduced by more than 98% which was statistically significant. Therefore, the best results for runoff mitigation and reduced soil erosion were seen when the practices were combined (reduced tillage combined with cover crop mulching) for a total reduction of 50%.

Yu et al. (2016) conducted a study to investigate the hydraulic conductivity of cover crops in relation to stormwater runoff mitigation. The study took place in Lower
Austria where the primary soil is classified as Chernozem. Twelve cover crop species were analyzed. Using a soil-core method, root samples were taken and assessed for morphological parameters. Using a tension infiltrometer, infiltration was measured. Rainfall simulations were conducted using a HYDRUS 2D. Finally, SAS software was used to conduct statistical testing. Yu et al. (2016) found that cover crop species with more coarse roots and more root density were more effective in mitigating runoff by enhancing soil hydraulic conductivity. Specifically, soil hydraulic conductivity was found to be dependent on root length and radius: the species with the coarsest roots (Melilotus officinalis and Lathyrus sativus) and the species with the densest roots (Linum usitatissimum) were effective in reducing runoff by 17% during high-intensity rainfall. Therefore, Yu et al. (2016) recommend that individuals take into consideration the root systems of species when deciding which species to incorporate into a field to obtain a specific benefit, such as stormwater flood mitigation.

2.3.2.3 Biological Control

Wen et al. (2017) conducted a study in Illinois with the aim to investigate the role of cover crops in suppressing soilborne diseases. Specifically, they were interested in the relationship between cover crops and the following pathogens: *Rhizoctonia solani* that reduces yield and causes root rot, *Fusarium virguliforme* that causes death of crop, and *Heterodera glycines* that causes cysts. The study was conducted as field trials at four locations in Illinois between the years of 2010 and 2013. The cover crops they implemented included canola, mustard, cereal rye, and rapeseed. Wen et al. (2017) collected soil samples in the springtime during or after soybean plantation. These soil samples were analyzed for suppressiveness qualities, pathogens, and microbials. They
also collected cover crop biomass, incidences of diseases, and cyst counts. Soybean pathogens were quantified using qPCR. Soil microbial composition was analyzed using an automated ribosomal intergenic spacer. Wen et al. (2017) found that cover crops were able to induce soil suppressiveness under certain circumstances. Out of those investigated, cereal rye performed the best in terms of soil suppressiveness. Specifically, cereal rye positively affected soybean crops by enhancing soil suppressiveness qualities towards *R. solani* and *F. virguliforme*. Cereal rye also assisted in improving the yield of soybean when they had root rot and reduced SCN egg counts. Rapeseed also had a positive effect on soybean by reducing root rot severity and egg counts. Wen et al. (2017) state that the lack of consistent effect throughout all cover crops could be a result of other conditions such as poor seed germination, extreme weather, and low glucosinolate concentrations. Therefore, they encourage further research to be done controlling for these variables, and for management practices selecting cover crop genotypes with more glucosinolate. They conclude by stating that along with disease suppression, cover crops such as cereal rye can assist with other things like soil erosion and water infiltration, and therefore, should be strongly considered.

Tursun et al. (2018) conducted a study in Turkey with the aim to investigate the role of cover crops on weed control in apricot plots. The field trials were conducted on clay soil and the following cover crops were implemented: hairy vetch, Hungarian vetch, buckwheat, lacy phacelia, and a mixture (Hungarian vetch and *Triticale*). Weed biomass was assessed by clipping the weeds at ground level and obtaining dry biomass. Finally, the richness and density of the species were evaluated, and statistical tests were conducted to compare cover crop suppression with mechanical weed control and using
glyphosate. Trusan et al. (2018) found that cover crops were successful at reducing the biomass of weeds, their richness, and their total density in either a mowed, soil-incorporated or living form (living form had the lowest efficiency). The highest weed suppression was found for lacy phacelia (75%). The second and third highest weed suppression percentages were found for buckwheat (73%) and hairy vetch (63%). Therefore, Tursun et al. (2018) state that cover crops can be a natural alternative to herbicides if mowed in or soil-incorporated which can lower dependence on chemicals and improve soil conservation.

Mirsky et al. (2013) conducted a study in the Eastern United States with the aim to discuss how cereal rye could be implemented in agriculture in this area to maximize weed suppression. In addition, they provide a discussion on the necessary equipment needed to optimize soybean establishment and manage weeds. This was done by combining experiments done in this area over the past decade on no-till soybean production. Mirsky et al. (2013) address that soils in the eastern side of the US tend to be extremely weathered and have lower fertility and organic matter. They found that biomass production and weed suppression were strongly dependent on soil fertility, seeding rate, seeding method, as well as sowing and termination timing. Biomass of 8,000 kg per hectare was found to be the threshold needed to achieve consistent weed suppression, and the factors mentioned above could be manipulated to meet or exceed this value. In terms of management techniques, they have found that high-residue cultivation was successful in improving weed control. In addition, they state that management timing, row cleaners, type of coulters, and equipment weight can strongly affect factors that could influence biomass, weed suppression, and crop standing.
As discussed earlier in this article, Crotty & Stoate (2019) conducted a study in the UK investigating the effect of cover crops on soil properties, weed suppression, and subsequent yield of cash crops. They found that cover crops played an important role in weed suppression which, in turn, increased crop yields and economic profitability (Crotty & Stoate, 2019).

2.3.3 Supporting

Lastly, cover crops provide fundamental supporting ecosystem services such as geochemical cycling and the subsequent effect on soil properties and soil quality, and reducing leaching of nutrients, thereby protecting water quality. Recent empirical studies have aimed to quantify these ecosystem services using simulations and models, as well as field experiments.

2.3.3.1 Geochemical cycling and soil properties

Basche et al. (2016) conducted a study in Iowa, United States, with the aim of assessing the effect of cover crops on soil carbon, crop yield, soil erosion, and nitrous oxide emissions. Using an Agricultural Production Systems Simulation (APSIM), Basche et al. (2016) simulated soybean and maize production using data obtained from a field site in Iowa. Variables such as soil chemical and physical properties, water balance, soil temperature, soil erosion, and crop yields were also simulated through APSIM. They found that while soil carbon declined in cover crop present and cover crop absent simulations, cover crops were able to substantially offset this decline. Specifically, over the course of 45 years, implementing cover crops would offset loss of soil carbon by 3% compared to a scenario without cover crop cover. In addition, cover crops were successful at reducing soil erosion by approximately 11% to 29% and reducing nitrous
oxide emissions by up to 34%. Therefore, Basche et al. (2016) state that cover crops could be able to assist in slowing down or mitigating some of the negative effects of climate change. In order to fully understand whether or not cover crops could improve conditions under future climates, more research is needed. Therefore, they encourage further modeling studies.

Demir et al. (2019) conducted a study in Turkey assessing the effect of cover crops on soil and crop properties. The methodology was described earlier in this paper in the provisional services section. Through their analyses, they found that cover crops had a significant effect on soil chemical and physical properties. Specifically, levels of soil organic matter and nitrogen and potassium, were all higher with incorporation of cover crops. The increase in these properties have positive implications for soil health and soil respiration. Therefore, Demir et al. (2019) recommend integrating cover crops with soil management practices to enhance the quality of soils.

Veloso et al. (2018) conducted a study in Brazil using a split-plot design to investigate how soil organic carbon storage could be affected by implementing legume cover crops, no-tillage management practices, and nitrogen fertilization. Specifically, the field experiment assessed the following conditions: no-tillage, conventional tillage, legume cover crops, no legume cover crops, and nitrogen-based fertilizer or no fertilizer. The soil in the region is classified as sandy clay loam. Soil organic carbon stocks were assessed using the equivalent soil mass approach. To assess how cover crops contributed to the soil organic carbon, they determined isotopic abundance. Through this, they found that legume cover crops were more efficient at storing soil organic carbon than their nonlegume counterparts. Specifically, they were twice as efficient, converting 1 kg of
residue into 0.15 kg of soil organic carbon. The greatest increase in soil organic carbon was found in the no-tillage scenario with two legume cover crops implemented and nitrogen fertilizer applied. Therefore, Veloso et al. (2018) conclude that this combination could effectively store soil organic carbon and assist with mitigating climate change impacts by offsetting carbon dioxide emissions.

Plaza-Bonilla et al. (2015) conducted a study in France with the aim to investigate the relationship between cover crops and grain legumes on soil organic carbon and nitrogen. The study was carried out as an experimental field study as three 3-year rotations in a conventional tillage system. The following conditions were investigated: no grain legumes, one-grain legume, two-grain legumes, with cover crops, and without cover crops. Cover crops used included mustard, vetch, and a mix of vetch-oat. To determine the effect of different treatments on soil organic carbon and nitrogen, Plaza-Bonilla et al. (2015) collected soil samples using a hydraulic coring device and analyzed for carbon and nitrogen concentrations using a Leco-2000 analyzer and the Dumas combustion method. Data were further analyzed using a mixed linear model. Through this analysis, they found that grain legume treatments decreased soil organic carbon and nitrogen, but this loss was mitigated by cover crops. Specifically, cover crops mitigated 13% and 67% of soil organic carbon loss in one legume and two legume treatments, respectively. Similarly, cover crops mitigated 59% and 88% of the soil organic nitrogen lost in the one legume and two legume treatments, respectively. Plaza-Bonilla et al. (2015) that this effect could be due to the low C:N ratio of these species which enhanced decomposition of organic carbon. In addition, they found that cover crops did not have a significantly negative effect on crop yield or the carbon and nitrogen harvest indexes.
Therefore, they conclude that cover crops can play a valuable role in recycling nitrogen and heightening carbon returned to the soil, thereby, improving both overall soil health as well as field productivity.

As mentioned earlier in this paper, Crusciol et al. (2015) conducted a study in Brazil, investigating the effect of palisadegrass on cash crop yields and soil properties. The methodology of their work is described earlier in this study in the provisional services section. They found that there were higher soil nutrient concentrations and soil chemical properties when palisadegrass was implemented. Specifically, they found that treatments intercropped with palisadegrass had more calcium and magnesium in the upper surface of the soil, and more organic matter, potassium, and sulfate sulfur throughout all layers. In addition, they observed a higher soil pH in the upper part of the soil. Therefore, they state that the nutrient cycling properties that palisadegrass can provide could be very valuable to soil with poor quality.

Buchi et al. (2015) conducted a study in Switzerland with the aim to assess nitrogen fixation and biomass production of 19 legume cover crops. Two field experiments with a 3-month growing period were conducted at two different sites. For each of the legumes, Buchi et al. (2015) calculated the nitrogen derived from atmospheric N\textsubscript{2}. From these values, they calculated the total nitrogen fixed in the aboveground biomass. Finally, in a pot experiment, Buchi et al. (2015) calculated the B values to assess the quantity of plant nitrogen resulting from fixation. They found that the biomass produced varied between species with C. arietinum having 0.75 t/ha and V. faba having 6.86 t/ha. The nitrogen collected in the biomass above the ground was 16 kg per hectare for the C. arietinum species and 186 kg per hectare for the V. faba species. Five species
gained over 100 kg per hectare of nitrogen through fixation: *V. sativa*, *V. faba*, *V. villosa*, *L. sativus* and *P. sativum*. Therefore, the percent of plant nitrogen resulting from fixation depends on the species, as well as on the nitrogen available in the soil (as confirmed by measuring the mineral nitrogen values). Buchi et al. (2015) conclude that some legume cover crops can play an important role in the nitrogen cycle by fixing renewable nitrogen which can support the soil and enhance the performance of succeeding crops. They recommend selection of suitable species to use in crop rotation.

As mentioned earlier in this paper, Delgado et al. (2007) wrote a paper summarizing the cover crop research conducted by a multidisciplinary team in south-central Colorado. They found that of the summer cover crops studied, sorghum-sudan had the highest overall content of zinc, copper, and manganese indicating the ability of this crop to cycle macronutrients.

Haruna & Nkongolo (2019) conducted a study in Missouri, United States, with the aim to assess the effect of cover crops, tillage practices, and crop rotation on soil chemistry. The study took place during the 2011 and 2013 growing seasons on silt-loam soil. Corn and soybean were established on 24 plots, with two tillage conditions (no-till and conventional tillage), 2 different cover crop conditions (cereal rye and absence of cover crops altogether), and 4 rotation types (continuous corn or soybean, soybean/corn, and corn/soybean) (Haruna & Nkongolo, 2019). Soil samples were collected using cylindrical cores for chemical analysis. Statistical testing was conducted using the Statistix software. Haruna & Nkongolo (2019) found that soil organic matter increased 4% under no-till management and 8% with the use of cover crops which has positive implications for soil health and crop productivity. They also found that crop rotation
(opposed to continuous cropping) positively affected soil chemistry. Therefore, they conclude that no-tillage management, crop rotation, and cover crops can improve the properties of soil and can enhance crop productivity. These results provide new knowledge that can help communities decide which factors affect management practices and which are the best to use.

As discussed previously in this paper, Sullivan et al. (1991) conducted a study in Virginia examining nitrogen production, nitrogen uptake, and crop yield contribution of vetch and rye cover crops. They found that nitrogen was mostly produced by hairy vetch or by a mix of hairy and big flower vetch (Sullivan et al., 1991). In addition, when cover crops were left to grow longer in the Spring, additional nitrogen was produced. During the first year, corn biomass produced post cover crops was 8.6 to 18.0 Mg/ha without any additional nitrogen-based fertilizer added. In the second year, corn yields were 15.3 Mg/ha and 16.4 Mg/ha for hairy vetch and hairy-bigflower mixture, respectively. Therefore, this shows that cover crops have the ability to regulate nitrogen which can replace the need for nitrogen-based fertilizers.

**2.3.3.2 Reduced Nutrient Leaching**

As mentioned earlier in this paper, Delgado et al. (2007) summarized cover crop research conducted by a multidisciplinary team in south-central Colorado. Between 1993 and 1999, the multidisciplinary team primarily focused on winter cover crops. Winter cover crops were shown to collect anywhere between 100 to 300 pounds of nitrogen per acre and reduce nitrate-nitrogen leaching by up to 184 lb per acre. Since nitrate-nitrogen is a very mobile element, reducing leaching protects the quality of water. They also found that winter cover crops returned a lot of biomass to the soil that helped improve its
quality. Specifically, there was a return of 3.4 dry weights per acre with the use of winter cover crops.

Qi & Helmers (2010) conducted a study in the Upper Mississippi River Basin with the aim to assess evapotranspiration, soil water storage, and subsurface drainage of winter rye. The study took place in Iowa where the dominant soil type is Nicollet. In mid-October, rye was planted in lysosomes and terminated three years later in June. Temperature and rainfall were measured daily by a meteorological station. Soil moisture was determined using a Theta probe, a PR2 Profile probe, and arithmetic equations. Subsurface drainage at the bottom of the lysimeters was monitored and pumped weekly. Finally, evapotranspiration was measured from the lysimeters using an arithmetic equation. They found that rye reduced subsurface drainage by 9% annually which has the potential to reduce nitrate-nitrogen leaching. Between the months of May and June, rye reduced monthly drainage by 21%. Evapotranspiration was estimated to be 2.4 mm per day which was significantly higher than in the bare lysimeters. Therefore, winter cover crops like rye can play an important role in soil water dynamics.

Malone et al. (2014) conducted a study in Midwestern United States with the aim to examine nitrogen loss patterns of cover crops. A lot of nitrates is lost in agricultural fields of this area and drained into the Mississippi River, causing substantial hypoxia in the Gulf of Mexico. Therefore, to assess how cover crops could mitigate this effect, they used a Root Zone Water Quality Model to simulate treatments (cereal rye), regression analysis to evaluate variables that could affect nitrogen loss at 41 different sites, and ArcGIS to interpolate the results (Malone et al. 2014). Variables inputted included meteorological data, soil and water parameters, and field management. Soil types were
primarily Canisteo and Nicollet. They found that implementing winter rye as a cover crop in the Midwest could lower nitrogen loss by 42.5% (average of 20.1 kg N per hectare). Specifically, this effect was observed from winter rye grown and seeded at maturity, in a corn-soybean system, on tile-drained land, and with no-tillage (Malone et al. 2014). They found that if the cover crops were planted later in the fall, they served less of an effect on reducing nitrate loss. Malone et al. (2014) state that this was due to the lower temperatures of the area at this time. Therefore, they conclude that cover crops could be effective at reducing nitrate loss and that air temperature was the most prominent variable affecting the strength of that relationship. They recommend that future research investigates additional factors pertaining to soil quality to fully understand the potential of cover crops.

Kladivko et al. (2014) conducted a study in the upper midwestern United States examining the effect cover crops have on nitrate leaching and water quality. They were interested in examining how the adoption of cover crops in a corn and soybean system can produce valuable benefits that can help lower nitrate loss to the Mississippi River, and thereby improve water quality. In Ohio, Indiana, Iowa, Minnesota, and Illinois, two counties were selected each. Statistics from the National Agriculture Statistics Service were compiled into ArcGIS to estimate crop rotations and agricultural land. Tillage systems were estimated from tillage data obtained from a 2004 tillage survey. Drained land estimates were made by using the National Land Cover Database and the NRCS State Soil Geographic Database on soils. Nitrate losses were estimated using the Root Zone Water Quality Model. Finally, they conducted a regression analysis and imported all results into ArcGIS for manipulation. They found that winter cover crops planted in
the fall could be adopted on 34-81% of the agricultural land in these areas. These cover crops could reduce nitrate loss by about 20%. Therefore, Kladivko et al. (2014) conclude that cover crops could be effective in helping reduce nitrate leaching into bodies of water if they are using in corn and soybean fields in the Midwestern United States. However, these results are for rye that is established through overseeding on lands run with no-tillage, fall-tillage that could be transitioned to spring-tillage, or just spring-till. Kladivko et al. (2014) point out that these kinds of management practices could be difficult for farmers to achieve. Therefore, they recommend the help of further research and technical assistance to overcome this challenge.

Lacey & Armstrong (2014) conducted a study in Illinois, United States with the aim to study the ability of cover crops to stabilize inorganic nitrogen and reduce leaching. The field experiment consisted of nine plots on silty clay loam soils with continuous corn cropping and nitrogen application. Cover crops biomass was sampled each year in the spring and fall, and dry weight was measured for nitrogen using a combustion analyzer. Soil samples were collected in the spring and analyzed for percent of applied nitrogen as inorganic nitrogen. Lacey & Armstrong (2014) found that cereal rye and tillage radish could absorb 60% to 100% of an equivalent rate of applied nitrogen, respectively. Soil nitrate-nitrogen was reduced by 9% with tillage radish cover and 13% with cereal rye cover at 50-80 cm depth with respect to the control. Overall, cereal rye was the most effective in reducing soil nitrate-nitrogen concentrations in the 20-80 cm depth. Therefore, cover crops can reduce nitrate leaching that can result from fall applied nitrogen and should be considered to improve the quality and efficiency of soil.

2.4 Conclusion
While there are many benefits and services provided by vegetative cover, adoption of cover crops and urban forests into landscapes is relatively low (Bergtold et al., 2012). Many landowners, city planners, environmentalists, citizens, healthcare professionals, and government officials are unaware and lack knowledge on the benefits and best practices for vegetative cover. Specifically, farmers make decisions based on economics and costs and their awareness of the environment and biophysical factors (Bergtold et al., 2010; Sastre et al., 2017). However, poor understanding of climate change and the long-term degradation it could have on their landscapes and the misleading perceptions associated with poor crop yields and economic investments can affect how many farmers chose to incorporate cover crops (Bergtold et al., 2010; Crotty & Stoate, 2019; Seifert et al., 2019). Similarly, a lack of knowledge and understanding of the benefits and management practices for urban forests can affect the rate of adoption. For example, concerns of urban trees emitting volatile organic compounds and acting as respiratory irritants, thereby enhancing allergies, have affected how trees are perceived and valued (Akbari et al. 2001; Reid et al. 2017). Therefore, communities need to consider educational practices, incentives, policy modifications, and decision support tools as strategies to help encourage the use of cover crops and urban forests in landscapes to help communities begin to make plans for adapting to climate change.

2.4.1 Educational Practices

Educational practices should be considered as a tool to help encourage communities to adopt urban forests and cover crops into their landscapes. In a study conducted by Sastre et al. (2017), 62% of farmers surveyed in Central Spain reported back on wanting to participate in trainings related to agricultural practices. Small group
trainings held by experts in the field could allow farmers to learn the values, the costs, and the best strategies for implementing cover crops into their crop rotations. Some aspects that could be included in these agendas could be discussions about how cover crops can reduce fertilizer demands, increase economic profits and reduce water demands (Delgado et al., 2007; Sullivan et al., 1991). They could also include discussions on how this could be best achieved such as by selling or removing cover crop biomass at the end of a growing season cycle which would increase profit and reduce nitrogen leaching (Gabriel et al. 2013). In addition, these small group trainings could give farmers one on one support from experts to help determine the best cover crops for their soil and weather conditions which research show to be critical factors in the productivity of cover crops (Krstic et al. 2018). In addition to trainings, educational tools such as monthly newsletters or pamphlets with information on the best times to plant and terminate growth as well as information on the short term versus long term benefits could help encourage farmers to incorporate cover crops into their landscapes (Haruna & Knongolo, 2019; Krstic et al., 2018). Urban forest management could benefit from similar educational tools. Research shows that individuals with more connectedness to nature are more likely to see its values (Shanahan et al. 2015). Therefore, educational tools like classes enhancing public knowledge of nature and notices encouraging school and workplaces to take their activities and events outdoors, can help connect people with nature and encourage using it as a tool for resilience to climate change.

2.4.2 Incentives

Akbari et al. (2001) mentioned the need to receive support from members of federal, state and local governments in order to aid landowners in choosing to incorporate
vegetative cover in their landscapes. One type of support that federal, state and local
governments can provide for landowners is financial support. For example, these
governments could use incentives such as tax breaks or cost sharing to help reduce the
costs of implementing vegetative cover and encourage its use. By working together with
landowners and providing them economic incentives, government officials of urban and
rural communities would begin to stress how important this matter is, which in turn,
could positively influence the perceptions of landowners and encourage them to adopt
these practices.

2.4.3 Policy

Research shows that existing and developed trees can provide more ecosystem
services than newly planted trees (Nyelele et al., 2019). In addition, research shows that
visual beauty of the tree and its understory can encourage more individuals to attend
urban forest parks and engage in recreational activities valuable to their health (Wang et
al., 2017). Therefore, incorporating the maintenance of trees and preservation of existing
trees into policy management can help increase resilience to climate change.

2.4.4. Decision Support Tool

Several researchers have also addressed the need for a decision support tool to
help communities easily evaluate ecosystem services of urban forests and cover crops and
efficiently incorporate vegetative cover into their landscapes (Bodnaruk et al., 2017;
Rafiee et al., 2016). Specifically, there is a need to be able to evaluate multiple ecosystem
services simultaneously to help receive federal, state and local governmental support in
developing programs that plant more urban trees and cover crops (Akbari et al., 2001;
McPherson et al., 2016). This tool should be easily accessible, easy to work with, and
should be tailored to local communities so they can aggregate benefits for their location. These spatial decision tools could be used not only by those involved in urban and rural design planning, but also by researchers, public health officials and clinicians, and common users. Researchers could use spatial decision tools in order to understand future empirical needs under climate change. The public health sector can use spatial decision tools to better advise patients on preventative health strategies like urban forestry therapy programs. Lastly, common users can use this to better understand, support, and participate in their local environments to help restore and extract ecosystems services.

Since these spatial decision tools rely on the integration of information from multiple disciplines, generating these tools and incorporating them into communities will require many professions to work together.
CHAPTER 3

MODELING ECOSYSTEM SERVICES OF URBAN FORESTS

3.1 Introduction

3.1.1 Loss of ecosystem services

Natural lands and healthy natural resources form the foundation for the well-being of communities in Massachusetts as nature provides multiple ecosystem services defined as benefits (Center for Sustainable Systems, 2020). These benefits that people can extract from ecosystems directly or through indirect pathways include provisional, supporting, regulating, and cultural services (Center for Sustainable Systems, 2020; Millennium Ecosystem Assessment, 2005). Healthy ecosystems provide food, fuel, water, and wood; they support the cycling of nutrients and soil formation; they regulate climate, disease pathways and water movement; and they provide recreational and educational opportunities (Center for Sustainable Systems, 2020). However, one major anthropogenic impact, urbanization, has significantly stressed the health of Massachusetts ecosystems (FIC, 2019). Between the years of 1982 and 2012, 544,000 acres of forested land in Massachusetts have been transformed to developed land (FIC, 2019). Due to the transformation of land for residential, industrial or commercial use, there has been substantial loss of ecosystem services and natural processes (Peng et al., 2017). Urbanization affects the interactions between air, soil and water, and thereby, the quality and quantity of natural resources (Avelar et al. 2009, Li et al. 2016; United States Department of Agriculture [USDA], n.d.). With these rapid losses of natural processes in human dominated landscapes, it is imperative to develop a tool that enables communities
to identify, quantify, and restore areas of high risk to their original ecosystem service potential.

In addition to the stress caused by changing land use, ecosystems have also been damaged by altered precipitation and temperature patterns as a result of climate change (Luber and McGeehin 2008, Walthall et al. 2013). In Massachusetts, there has been a 1.6°C increase in temperature since the early 20th century and several recent water years have been the rainiest years on record for the state (Hall et al. 2002, Runkle et al., 2017; Swasey, 2019). Climate impacts on urban communities include droughts, groundwater depletion, disruption to water supplies, soil loss and erosion, urban heat islands, degraded air quality, and substantial stormwater flooding (Corburn, 2009; Dore, 2005; Luber & McGreehin, 2008; Wilby, 2007). Flooding in cities results from stormwater runoff that occurs because cities are composed at large of impervious surfaces that are cannot uptake the extra rainfall (Hollis 1988; Wilby, 2007). Urban heat islands occur as a result of buildings, roadways and other infrastructure absorbing and reradiating solar energy and are typically observed as a 3-4°C temperature difference between cities and their surrounding communities (Corburn, 2009; Solecki & Marcotullia, 2013). Therefore, there is an increasing need for communities to be able to access areas of high risk for ecosystem services loss and restorative potential with the additional implications of rapid climate change.

3.1.2 Restoration of ecosystem services in urban communities

As mentioned previously, not only do communities need to identify and quantify areas experiencing ecosystem services losses, there is also a need to restore these landscapes and build resilience to climate change and further land use alterations. An
emerging field of research has devoted attention to a natural systems approach of
restoration where vegetation like urban forests are incorporated into urban communities
to enhance resilience. Recent empirical studies find that urban forests can help restore
ecosystem services in urban landscapes (Inkilainen et al., 2013, Middel et al., 2015;
Nowak et al., 2014). Urban forests can be incorporated into urban environments to assist
with mitigating urban heat island effects, reducing runoff from intense precipitation
events, and air pollution, restoring water quality and supplies (Inkilainen et al., 2013;
Middel et al., 2015; Nowak et al., 2014). Researchers have found that vegetative cover
can provide these mitigating effects due to its physical structure and biological buildup.
Vegetative cover with large leaf surface area can act as a shield against solar energy,
reducing surface and air temperatures underneath and surrounding it (Akbari et al., 2001;
Inkilainen et al., 2013; Middel et al. 2015; Walthall et al., 2013; Yao et al. 2015). In
addition, rooting systems of vegetative cover can enhance hydraulic conductivity and
water infiltration, thereby protecting water supplies and reducing stormwater runoff
(Blanco-Canqui et al., 2015; Yu et al., 2016).

3.1.3 Research needs, objectives

Current empirical research investigating these ecosystem services focuses on
single coefficients for ecosystem services and certain characteristics of vegetation
without examining local landscapes as a whole and without having that information
presented in a way that can be easily used and applied by communities. However, under
rapid climate change and urbanization, communities are faced with decisions that require
accurate and timely spatial information regarding their community. There is a need for
town-level information on local ecosystems and their ecosystem services that is
scientifically grounded, integrates adaptation strategies, and is easily accessible. It is imperative that communities understand the impacts that urban forests may have in their communities in order to accurately make decisions regarding land use, forestry, land protection, storm water runoff, water supplies, air and water quality, and cooling systems. In addition, using this information communities will be able to allocate funds based on scientific information, improve urban designs, consult citizens, develop programs, and work closely with other professions to create a healthy and safe community.

In this study, we propose that in order to address specific needs of communities at local scales, we need a careful assessment of the local ecosystem and its ecosystem services using spatial models. To assist Massachusetts communities in making decisions about natural resources at private and public levels, we aimed to use spatially explicit techniques in ArcGIS to model ecosystem services and integrate that information into a decision support system that will be accessible by community members through readily available technology. We supplemented with statistical and neural network models in ArcGIS and JMP in our analysis of the urban heat island. Our main objectives for this study were to 1. Develop a baseline assessment of runoff in Massachusetts landscapes to be able to access flood mitigation potential 2. Model the relationship between urban forests, impervious cover, and summer maximum temperatures to understand the heat island mitigation potential of landscapes in Massachusetts, 3. Make the information readily available as an online decision support tool for use by communities.

3.2 Methodology

3.2.1 Study Area
Massachusetts, a state located in the north eastern part of the United states, is sized at 21,000 km² and includes many forests, ponds, forested hills and valleys (Figure 3.1; Hall et al., 2002, The USGS Land Cover Institute [LCI], 2018). The state’s highest peak, also known at Mount Greylock, is 1,064 meters from the ground (LCI, 2018). Along the coast of Eastern Massachusetts are beautiful bays that give Massachusetts its nickname, “The Bay State” (LCI, 2018). In the 20th century, agricultural land was the most fundamental land to Massachusetts and only 30% of forests exceeded 12.2 min height (Hall et al., 2002). As of 1971, the most common land cover type in Massachusetts is forest cover with over 77% of trees exceeding 12.2 meters in height (FIC, 2019; LCI, 2018). However, there has been rapid conversion of forest land to developed land with urbanization (FIC, 2019). Between the years of 1982 and 2012, 544,000 acres of forested land were transformed for urban purposes, and 93,000 acres of agricultural land were converted to developed land (FIC, 2019). These urbanized areas have become foundational to Massachusetts, especially in Eastern Massachusetts along the coast, where much of the profit is obtained from tourism and seasonal attractions the cities provide (LCI, 2018).
Since the beginning of the 20th century, temperatures in Massachusetts have risen 1.6°C with mean January and July temperatures of -4.5°C and 22.6°C respectively (Hall...
et al., 2002; Runkle et al., 2017). In addition to temperature following an upward trend in Massachusetts, precipitation changes in Massachusetts are also following a slight upward trend (Swasey, 2019). In 2018, 155 cm of rainfall fell on Massachusetts making it the rainiest year on record for the state (Swasey, 2019). Urbanized areas are setting even higher records in increasing temperature and precipitation patterns, creating health and economic challenges for the 97% of the state’s population that resides in urban areas (Runkle et al., 2017; The Henry J. Kaiser Family Foundation [KFF], 2019).

As of 2018, there are roughly 6,902,149 people living in Massachusetts with 58.5% being adults between the ages of 18 and 65 (United States Census Bureau, 2018). This accounts for roughly 839.4 people for every square mile (United States Census Bureau, 2018). Of these individuals, 10% live at or below the poverty line and 42.1% hold a bachelor’s degree (United States Census Bureau, 2018). In addition, there are 2,914,929 housing units in the state with an average of 2.53 persons per household (United States Census Bureau, 2018). While deaths due to diseases such as heart disease, diabetes and Alzheimer’s disease are among some of the lowest in the United States, Massachusetts suffers from above average rates of flu and pneumonia (CDC, 2017).

A large economic component of Massachusetts stems from the development of the 26 Gateway Cities in the state that were developed to offer residents a “gateway” to the American Dream (MassINC, 2007). These mid-sized urban areas were created with the intention to offer good jobs to residents in new developing industries (MassINC, 2007). However, the condition of these urban areas in the present day is distressed as some urban areas like Greater Boston continue to evolve, and some fall behind in the economy (MassINC, 2007). Unlike Boston, many other Gateway Cities are poorly
performing in promised areas such as job creation, education attainment, income and overall manageable quality of life (MassINC, 2007). Additional changes in climate are exacerbating these conditions by increasing energy costs necessary to heat or cool households (MassINC, 2007). Therefore, Greening the Gateway Cities Program has been founded to assist with the reduction of cooling related financial investments and energy demands of these cities (Massachusetts Department of Conservation and Recreation [DCR Massachusetts], 2016). Through this program, trees are planted by DCR Bureau of Forestry Urban & Community Forestry crews hired by the communities and have the potential to reduce cooling demands by 1.9% for every 1% increase in tree canopy cover above the 10% minimum (DCR Massachusetts, 2016).

3.2.2. Conceptual Framework

![Conceptual Framework for modeling ecosystem services in Massachusetts](image)

Figure 3.2: Conceptual Framework for modeling ecosystem services in Massachusetts

3.2.3 Modeling Urban Heat Island
3.2.3.1 Data Preparation and Baseline Massachusetts Heat Island

Temperature data was compiled from the PRISM Climate Group webpage. The PRISM Climate Group gathers climate observations within and outside of the US and develops datasets accessible to users. From their webpage, 30-year average maximum temperature data for June, July and August between 1981 and 2010 was downloaded at 800-meter resolution. The months of June, July, and August represent the summer months of the Northern Hemisphere were maximum temperatures are found to be the highest (Center for International Earth Science Information Network, 2016). The three raster layers were imported into ArcGIS and the raster calculator tool from the ArcGIS Spatial Analyst toolbox was used to generate a mathematical expression averaging the values for each raster cell across the layers. The produced output raster contained the averaged maximum summer temperature between 1981 and 2010 for each 800-meter cell in Massachusetts (Figure 3.3).

Figure 3.3: Produced raster layer of the average maximum summer temperature between 1981 and 2010
A Massachusetts feature polygon layer was obtained from MassGIS (Bureau of Geographic Information). The averaged maximum summer temperature raster layer was reprojected using the Project Raster tool from the ArcGIS Data Management toolbox to match the projection of the Massachusetts polygon. The averaged maximum summer temperature raster layer was then clipped using the Clip Raster tool from the ArcGIS Data Management toolbox to the extent of the Massachusetts polygon. Using the resampling tool from the ArcGIS Data Management toolbox, the clipped averaged maximum summer temperature raster layer was resampled to 100 by 100-meter resolution and the raster layer was converted to a point feature file using the Raster to Point tool from the ArcGIS Conversion toolbox. Interpolation was performed on the point feature file using the Natural Neighbor algorithm available in the ArcGIS Spatial Analyst toolbox and a cell size of 30 was designated (Figure 3.4). Natural neighbor interpolation tool interpolates based on the closest sample points to the query point (Environmental Systems Research Institute [ESRI], 2017). The interpolated data file was once more clipped to the extent of the Massachusetts polygon feature layer using the Clip Raster tool from the ArcGIS Data Management toolbox. The produced raster file showed the 30-year average maximum summer temperature for every 30-meter cell in the state of Massachusetts. This file was used as the baseline Heat Island map where the areas falling in the top quartile were defined as having the highest vulnerability.
1. Averaged summer maximum temperature

2. Convert raster to points

3. Natural neighbors interpolation

4. Clipping by study area

**Figure 3.4:** Preparing an interpolated raster layer of the average maximum summer temperature between 1981 and 2010

The NLCD 2016 USFS Tree Canopy Cover (CONUS) and the NLCD 2016 Percent Developed Imperviousness (CONUS) files downloaded from the Multi-Resolution Land Characteristic Consortium webpage were imported into ArcGIS. Using the Project Raster tool from the ArcGIS Data Management toolbox, both layers were reprojected to match the projection of the MassGIS Massachusetts polygon feature layer. The data was then clipped to the extent of the Massachusetts polygon feature layer using
the Clip Raster tool from the ArcGIS Data Management toolbox (Figure 3.5). The NLCD raster layers had a cell size of 30 meters and did not require resampling techniques to match the cell size to the produced 30-year average maximum summer temperature layer.

![Image of percent tree canopy and percent imperviousness raster layers clipped to study area]

**Figure 3.5:** Percent tree canopy and percent imperviousness raster layers clipped to study area

All layers (Figure 3.7) were then clipped to a shapefile of urban places in Massachusetts (Figure 3.6) obtained from the United States Department of Agriculture Forest Service in order to develop a Massachusetts Urban Areas point file. The Raster to Point conversion tool was applied on the 30-year average maximum summer temperature for every 30-meter cell in the state of Massachusetts raster layer. Extract Values to Points tool from the ArcGIS Spatial Analyst toolbox was used to extract the values from the clipped NLCD 2016 USFS Tree Canopy Cover (CONUS) and NLCD 2016 Percent Developed Imperviousness (CONUS) raster layers to the points (Figure 3.8). Using the editor, all null values were removed from the attribute table and it was exported as a text file for further analysis.
Figure 3.6: Massachusetts urban areas polygon used for clipping
1. Massachusetts wide temperature raster  
2. Clipped temperature raster  
3. Massachusetts wide canopy raster  
4. Clipped canopy raster  
5. Massachusetts wide impervious raster  
6. Clipped impervious raster  

**Figure 3.7:** Clipping baseline raster layers to Massachusetts urban areas
1. Raster to points conversion for urban areas

2. Zoomed in to show points with distance of 100 meters from each other

**Figure 3.8:** Raster to point conversion for urban areas in Massachusetts containing temperature values. Extract values to points was used to extract the values of the percent canopy and imperviousness raster layers to the points

The same process was repeated for each individual Gateway City in Massachusetts as well as Boston, West Springfield, Pittsfield and Cambridge in order to assess the relationship between the dependent variable (average maximum summer temperature) and the independent variables (percent canopy and percent imperviousness) at local/city scales. This study polygon is presented in Figure 3.9. Massachusetts Gateway cities are (in alphabetical order as obtained from MassINC): Attleboro, Barnstable, Brockton, Chelsea, Chicopee, Everett, Fall River, Fitchburg, Holyoke, Haverhill, Lowell, Lynn, Lawrence, Leominster, Malden, Methuen, New Bedford, Northampton, Peabody, Quincy, Revere, Salem, Springfield, Taunton, Westfield and Worcester (MassINC, 2020). Each city was exported from the Massachusetts urban places feature layer as its own polygon and used as the clipping extent. The Massachusetts city point file was clipped by each city and the attribute tables were exported separately.
3.2.3.2 Linear Regression Analysis

The ordinary least squares linear regression algorithm was performed in ArcGIS using the OLS (Ordinary Least Squares) tool in the ArcGIS Spatial Statistics toolbox. OLS provides a linear model for a dependent variable that is to be explained or predicted by one or more explanatory variables. The summary OLS output report file provides the coefficients, intercept, measures of statistical significance, and measures of multicollinearity for each explanatory variable (ESRI, 2018). The OLS diagnostic section provides information on model performance and significance, consistency of the relationship, and model bias (ESRI, 2018). To assess for model fit, the user needs to consider all of these factors and assess the residual spatial autocorrelation using the Spatial Autocorrelation tool in ArcGIS (ESRI, 2018). Coefficients represent the strengths
and directions (negative or positive) of the relationships between each explanatory variable and the dependent variable and would appear in the regression equation. The intercept represents the value that is expected for the dependent variable if all explanatory variables were equal to zero. For this analysis, the city point feature layer was imported, temperature was selected as the dependent variable, and percent canopy and percent imperviousness were selected as the explanatory variables. The same process was repeated for each individual Gateway City dataset and the Boston, West Springfield, Pittsfield, and Cambridge datasets.

3.2.3.3 Non-linear Predictive Relationship

To analyze the non-linear predictive relationship between 30-year average maximum summer temperature and percent imperviousness and percent canopy in Massachusetts cities, the Massachusetts City data was imported into JMP. Neural Networks is a part of the predictive modeling platform in JMP Pro 15 that allows users to build neural networks with hidden nodes in either one or two layers (SAS Institute Inc, 2020). It is a tool that is best used to model data that contains non-linear characteristics or is complex (SAS Institute Inc, 2020). In the Pro version of JMP, the user is able to select either TanH, Linear or Gaussian activation functions for the node while the basic JMP package allows users to only work with the TanH activation function (SAS Institute Inc, 2020). Neural Networks also allows users to choose between the Random Kfold, Holdback and Excluded Rows Holdback validation methods, as well as establish fitting options such as robust fit, transformation of covariates, penalty methods, and the number of tours. The user needs to determine the optimal number of nodes and activation functions based on their knowledge of the data and trial-and-error until they have a model.
that explains the variation well (SAS Institute Inc, 2020). For the Massachusetts City dataset, temperature was selected as the response variables and percent canopy and percent imperviousness were selected as the predictive factors. The KFold validation method was determined to be the most optimal with one layer of 3 TanH nodes (Figure 3.10). The formula notation and neural network script can be found in Tables 3.9 and 3.10, respectively. Robust fit was selected, and all covariates were transformed. The same process was repeated for each individual Gateway City dataset and the Boston, West Springfield, Pittsfield, and Cambridge datasets. The formula notation for each city can be found in Tables 3.11 through 3.40 located in the appendix.

Figure 3.10: Neural network diagram

### 3.2.3.4 Future Massachusetts Heat Island

To develop a cartographic representation of the Heat Island in Massachusetts for the year 2100, future climate data was obtained from the University Corporation for
Atmospheric Research webpage. The data was available as a NetCDF file containing the average monthly projected temperature data between 2006 and 2100 at 4.5km resolution. The average of the ensemble members for the Representative Concentration Pathway (RCP) 4.5 emission scenario was selected. The RCP 4.5 is an intermediate scenario of global greenhouse emissions in which radiative forcing is stabilized at 4.5 W m\(^{-2}\) in 2100 (Thomson et al., 2011). The amounts to 650 ppm of carbon dioxide equivalent (Thomson et al., 2011). This scenario assumes that climate policies are put into effect to limit emissions (Thomson et al., 2011). In order to process the NetCDF file and extract the bands corresponding to June, July and August of 2100, a Python script for ArcGIS version 10.5 was developed. (Appendix, Table 3.8). Python is a programming language that enables users to access geoprocessing tools and create simple or complex multi-function processes (Python Software Foundation, n.d.). Therefore, since the NETCDF file contained bands ranging from 1 to 1141, Python was able to assist in extracting bands 1129 through 1141 (corresponding to the year 2100) and create a processing pathway. The bands corresponding to the year 2100 were extracted and raster layers were generated for each band. The bands were reprojected and resampled to 100 by 100-meter resolution. A study area polygon of Massachusetts obtained from MassGIS was added and transformed to a raster layer with 100-meter resolution. The raster calculator was then used to create a positive study area raster by adding the value “1”. The study area raster was multiplied by the temperature raster files for 2100 months. Only June, July and August temperature files were used in the calculation of future average summer temperatures through an algorithm applied in the raster calculator (Figure 3.11)
3.2.4 Modeling Runoff

3.2.4.1 Assessing runoff using the Curve Number Methods

To assess stormwater flood mitigation, runoff was modeled for each 1-meter raster cell in Massachusetts using the Curve Number Method for a “with tree” scenario (Boughton, 1989). The “with tree” scenario was developed from a 2016 land cover/land use ArcGIS file obtained from MassGIS and a soils layer from StatsGo (Figure 3.12). Cross tabulations were created to find all land use and soil combinations and designate curve numbers (Table 3.1). Curve numbers were determined using the SWAT + 8% (Dudula & Randhir, 2016; Marshall & Randhir, 2008; Randhir and Shriver, 2009; Randhir & Tsvetkova, 2011; Talib & Randhir, 2017)
**Figure 3.12:** Generating a unique raster layer from the combination of soils data and land use

<table>
<thead>
<tr>
<th>Land use</th>
<th>Soil Type</th>
<th>Value</th>
<th>CN (curve number)</th>
</tr>
</thead>
<tbody>
<tr>
<td>N/A</td>
<td>C</td>
<td>1</td>
<td>999</td>
</tr>
<tr>
<td>scrub/shrub</td>
<td>C</td>
<td>2</td>
<td>70</td>
</tr>
<tr>
<td>evergreen forest</td>
<td>C</td>
<td>3</td>
<td>76</td>
</tr>
<tr>
<td>deciduous forest</td>
<td>C</td>
<td>4</td>
<td>76</td>
</tr>
<tr>
<td>developed, high intensity</td>
<td>C</td>
<td>5</td>
<td>97</td>
</tr>
<tr>
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</tr>
</tbody>
</table>

**Table 3.1:** Curve numbers for land use and soil combinations

The Curve Number Method uses an equation that assesses runoff (Q) for each cell in terms of rainfall (P) and the potential maximum retention after runoff begins (S).
Potential maximum retention was calculated as a function of the curve numbers using the raster calculator tool from the ArcGIS Spatial Analyst toolbox. The output raster was then used in the algorithm for runoff which was also run using the raster calculator tool and precipitation data from the Prism Climate Group webpage. The cells were then aggregated by their membership to sub-basins in the state to assess runoff patterns in Massachusetts (Figure 3.14).

\[
Q = \frac{(P - 0.2S)^2}{(P + 0.8S)}
\]

\[
S = \frac{1000}{CN} - 10
\]

- \(Q = \text{Runoff (inches)}\)
- \(P = \text{Rainfall (inches)}\)
- \(S = \text{Potential maximum retention after runoff begins}\)
- \(CN = \text{Curve number value}\)

**Figure 3.13: Equations for the Curve Number Method**
Figure 3.14: Calculation of onsite runoff for each cell using the Curve Number Method and calculation of an accumulated output for the region

3.2.5 Spatial Decision Tool

All output files for heat mitigation potential and runoff reduction potential will be made available on an ArcGIS online server for easy access by community members to assist in program funding, distribution of resources, policy planning, program development, and urban design.

3.2.6 Data

Several datasets were needed for the completion of heat mitigation potential modeling. A Massachusetts study area polygon was retrieved from MassGIS (Bureau of Geographic Information) as an outline shapefile. This polygon represents the boundary of the Commonwealth of Massachusetts. Another study area polygon encompassing the urban locations in Massachusetts was retrieved as a shapefile titled “Places” from the
United States Department of Agriculture Forest Service webpage. The 30-year average temperature files for June, July and August were obtained from the Prism Climate Group webpage. The 30-year normal temperature covers the period between 1981 and 2010. Each file was downloaded as a .bil file at 800-meter resolution. Maximum temperature was selected from the menu options as well as monthly values for June, July and August. Percent canopy data for the United States was obtained from the Multi-Resolution Land Characteristics Consortium webpage as “NLCD 2016 USFS Tree Canopy Cover (CONUS)”. Each 30 meter by 30-meter pixel consists of a value between 1 and 100 representing the proportion of the cell that consists of tree canopy coverage. Similarly, percent developed imperviousness was downloaded from the Multi-Resolution Land Characteristics Consortium webpage as “NLCD 2016 Percent Developed Imperviousness (CONUS)”. Each 30 meter by 30-meter pixel is defined by a value between 1 and 100 representing the percent of developed surface in that pixel. Lastly, National Center for Atmospheric Research future climate projections were obtained from the University Corporation for Atmospheric Research webpage as a NetCDF file containing the statistical downscaled (4.5km) monthly means for air temperatures between 2006 and 2100.

Several datasets were needed to develop the inputs for the modeling of runoff. A landcover/landuse layer was obtained from MassGIS (Bureau of Geographic Information) as “2016 Land Cover/Land Use” dataset. This dataset contains land cover mapping made available from 2016 aerial imagery as well as land use information. Soil data was obtained from the STATSGO2 database. An elevation raster layer was obtained from MassGIS as a digital elevation model. Precipitation data was obtained from the
PRISM Climate Group webpage as annual values for the 30-year period between 1981 and 2010.

3.3 Results and Discussion

3.3.1 Urban Heat Island

3.3.1.1 Baseline Assessment

Spatial analysis of the current heat island effect in Massachusetts communities is presented in Figures 3.15 and Figure 3.16. To determine sites with top 25% vulnerability in Massachusetts, the raster file containing the calculated average maximum summer temperature between 1981 and 2010 was subdivided into 16 quintiles as represented in Figure 3.15. The top four were selected to represent the top quartile of vulnerability in Massachusetts as shown in Figure 3.16. For the time period between 1981 and 2010, communities with the highest heat island effect on the Western side of Massachusetts fall within the Greater Springfield, Hampshire, and Franklin counties. These regions have high percent imperviousness compared to surrounding communities as depicted in Figure 3.5. Similarly, on the Eastern side of Massachusetts, the heat island spans primarily across the Middlesex, Norfolk, Plymouth, Bristol and Suffolk counties with some communities in the Essex and Worcester communities also falling within the top 25%. Compared with Figure 3.5, the communities with top 25% vulnerability have high percent imperviousness and low percent canopy. This can be explained by the reflectivity to absorbance ratios of impervious materials and vegetation. Impervious surfaces absorb and re-radiate solar energy causing an increase in air and surface temperature (Corburn, 2009) On the contrary, tree canopy have an absorbance of 91-95% which minimizes reflectivity and transmittance (Qi et al., 2010)
Figure 3.15: Average maximum summer temperature variability across Massachusetts for the period between 1981 and 2010 split into 16 quintiles. Town boundaries are depicted.
Figure 3.16: Vulnerable areas of Massachusetts falling within the top quartile. Town boundaries are shown.

3.3.1.2 Future Assessment

Spatial analysis of the future heat island effect in Massachusetts is presented in Figure 3.17 and Figure 3.18. To determine sites with top 25% vulnerability in Massachusetts, the raster file containing the average summer temperature for 2100 was subdivided into 16 quintiles as represented in Figure 3.17. As shown in Figure 3.18, the top four were selected to represent the top quartile of vulnerability in Massachusetts for 2100. The future heat island effect is projected to shift South. Figure 3.18 shows that communities with the highest heat island effect on the Western side of Massachusetts will fall predominantly in the Greater Springfield area. Similarly, on the Eastern side of
Massachusetts, the heat island is projected to move away from the upper Middlesex and Worcester counties and strongly affect the Norfolk, Plymouth, Bristol, Barnstable, Dukes, and Suffolk counties with some communities in the Essex community also falling in the sites with top 25% vulnerability.

Figure 3.17: Projected average maximum summer temperature variability across Massachusetts for the year 2100 split into 16 equal quintiles.
Figure 3.18: Projected vulnerable areas of Massachusetts falling within the top quartile

3.3.1.3 Linear Regression Analysis

Ordinary Least Squares was conducted on Massachusetts Urban Areas in ArcGIS (study map presented in Figure 3.6). Results of the OLS assessment show a positive relationship between average maximum summer temperature and percent imperviousness, as well as a negative relationship between average maximum summer temperature and percent canopy cover (Table 3.2). The model could be represented as follows: $Y = 26.300305 + 0.002743X_1 - 0.000099X_2$ where $Y$ represents the temperature in degrees Celsius, $X_1$ represents percent imperviousness and $X_2$ represents percent canopy cover. The probability and robust probability were statistically significant for all
terms (p<0.01). However, the adjusted R-squared for the model was 0.008046. This indicates that the model is only able to explain less than 1% variability in the dependent variable. It is possible that we see these results because temperature is a regional phenomenon rather than a local phenomenon. In addition, site specific differences cannot be detected on a statewide scale. Therefore, we aimed to select 30 Massachusetts cities for intracity analysis. Massachusetts Gateway cities are a big economic component of the Massachusetts network and are a target for many funded projects, including Greening the Gateway Cities Project (MassINC, 2007). Therefore, we selected the 26 Gateway cities in addition to Boston, Chicopee, Cambridge, and West Springfield.

Table 3.2: OLS Summary Results for Massachusetts Urban Areas

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
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<td>0.000000*</td>
<td>0.000000*</td>
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<td>0.000000*</td>
<td>0.000000*</td>
<td>1.446204</td>
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<td>Canopy</td>
<td>-0.000099</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.446204</td>
</tr>
</tbody>
</table>

- Number of observations: 5049243
- Akaike’s Information criterion (AICc) [d]: 13983449.475613
- Adjusted R-squared [d]: 0.008046
- Joint F-statistic [e]: 20478.454773
- Prob(>F), (2,5049240) degrees of freedom: 0.000000*
- Joint Wald Statistic [e]: 49376.744894
- Prob(>chi-squared), (2) degrees of freedom: 0.000000*
- Koenker (BP) statistic [f]: 43001.930344
- Prob(>chi-squared), (2) degrees of freedom: 0.000000*
- Jarque-Bera statistic [g]: 1394737.796662
- Prob(>chi-squared), (2) degrees of freedom: 0.000000*
The OLS results for the individual 30 Massachusetts cities can be found in tables 3.41 through 3.70 located in the appendix. The OLS model results varied substantially across cities. Adjusted R-squared values ranged from 0.002465 for the city of Taunton and 0.505652 for the city of Lynn. These results show that a linear regression model can explain up to 50% of variability in intracity analysis for the state of Massachusetts.

Examining the coefficients for percent imperviousness and percent canopy, there is also a considerable difference across the 30 cities (Table 3.3). The cities Brockton, Everett, Fitchburg, Haverhill, Holyoke, Lawrence, Leominster, Lowell, Malden, Northampton, Pittsfield, Springfield, Westfield, West Springfield, and Worcester have a negative coefficient for percent canopy cover and a positive coefficient for percent imperviousness. However, all other cities either the reverse is true, or show two positive coefficients or two negative coefficients. For the city of Lynn where the adjusted R-squared value was the highest, the coefficient for percent canopy is positive while the coefficient for percent imperviousness is negative.
### Table 3.3: Summary of OLS results for individual Massachusetts cities

<table>
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<th>City Name</th>
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<th>Direction of Canopy Coefficient</th>
<th>Adjusted R-square</th>
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#### 3.3.1.4 Nonlinear Predictive Modeling

To analyze the non-linear predictive relationship between 30-year average maximum summer temperature and percent imperviousness and percent canopy in Massachusetts Urban Areas, a neural network was developed in JMP Pro with one layer of 3 TanH nodes. The results for the Massachusetts Urban Area neural network are
presented in Table 3.4. The prediction and contour profiles for the data are presented in Table 3.5. The $R^2$ for neural network training and validation models was approximately 0.011 indicating that the model was not overfitting the data but could only explain about 1% of the variability in the dependent variable, similarly to the results obtained using a linear regression model. Similarly, to the results obtained from the ordinary least squares conducted in ArcGIS, it is possible that our model explains very low variability because temperature is a regional phenomenon rather than a local phenomenon and because site specific differences cannot be detected on a statewide scale. Therefore, we developed neural networks for at intracity levels for the 26 Gateway cities in Massachusetts and Boston, Cambridge, Chicopee and West Springfield.
### Table 3.4: Neural network model fit results for Massachusetts Urban Areas

<table>
<thead>
<tr>
<th>Model</th>
<th>Rsquare</th>
<th>RMSE</th>
<th>Mean Abs Dev</th>
<th>-LogLikelihood</th>
<th>SSE</th>
<th>Sum Freq</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>0.011257</td>
<td>1.032785</td>
<td>0.7012926</td>
<td>5405991.2</td>
<td>4308599.7</td>
<td>4039395</td>
</tr>
<tr>
<td>Validation</td>
<td>0.0115752</td>
<td>1.0327006</td>
<td>0.7011794</td>
<td>1351333.9</td>
<td>1076973.1</td>
<td>1009848</td>
</tr>
</tbody>
</table>

### Table 3.5: Prediction profilers and contour profilers for Massachusetts Urban Areas (Neural Network Outputs)

<table>
<thead>
<tr>
<th>Massachusetts Urban Areas</th>
<th>Prediction Profiler</th>
<th>Contour Profiler</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><img src="image" alt="Prediction Profiler" /></td>
<td><img src="image" alt="Contour Profiler" /></td>
</tr>
</tbody>
</table>
The model fit results for intracity neural network models are presented in Table 3.6. The prediction profilers and contour profiles for the cities can be found in Table 3.7. The R-squared values for the cities range from 0.0324916 for Taunton to 0.6530902 for Lynn showing there is substantial intracity variability. A non-linear predictive model explains up to 65% variability in individual Massachusetts cities compared to a linear regression model that can explain up to 50% variability in individual Massachusetts cities. In addition, the profiler prediction profilers show substantial variability across the cities. While in some cities, there is a negative relationship between temperature and percent canopy, in other there is a positive relationship. Similarly, in some cities, there is a positive relationship between temperature and impervious, however, in many there is a negative relationship. This indicates that percent canopy cover and percent imperviousness act as mitigating variables, but do not fully on their own explain urban heat island effects. Future studies should aim to include elevation, population density, distance to tree canopy, and other measures of canopy and imperviousness to confirm and refine these results.
Table 3.6: Neural network model fit results for 30 Massachusetts cities

<table>
<thead>
<tr>
<th>City Name</th>
<th>Model</th>
<th>Rsquare</th>
<th>RMSE</th>
<th>Mean Abs Dev</th>
<th>-LogLikelihood</th>
<th>SSE</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Freq</td>
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<td></td>
<td></td>
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<td></td>
</tr>
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<td>-61419.78</td>
<td>459.29235</td>
<td>64729</td>
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<tr>
<td></td>
<td>Validation</td>
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<tr>
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<tr>
<td>Boston</td>
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<td>0.3050818</td>
<td>0.221496</td>
<td>20468.611</td>
<td>10253.785</td>
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<tr>
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<td>Validation</td>
<td>0.3726539</td>
<td>0.3056121</td>
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<tr>
<td></td>
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<td>Holyoke</td>
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<td>0.3095744</td>
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</tbody>
</table>

134
Table 3.7: Prediction profilers and contour profilers for 30 Massachusetts cities (Neural Network Outputs)

<table>
<thead>
<tr>
<th>City Name</th>
<th>Prediction Profiler</th>
<th>Contour Profiler</th>
</tr>
</thead>
<tbody>
<tr>
<td>Attleboro</td>
<td><img src="image" alt="Prediction Profiler" /></td>
<td><img src="image" alt="Contour Profiler" /></td>
</tr>
<tr>
<td>Barnstable</td>
<td><img src="image" alt="Prediction Profiler" /></td>
<td><img src="image" alt="Contour Profiler" /></td>
</tr>
</tbody>
</table>
Holyoke

Lawrence

Leominster
Worcester

<table>
<thead>
<tr>
<th>Temp</th>
<th>Impervious</th>
<th>Canopy</th>
</tr>
</thead>
<tbody>
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Revere

<table>
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<th>Impervious</th>
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Methuen

<table>
<thead>
<tr>
<th>Temp</th>
<th>Impervious</th>
<th>Canopy</th>
</tr>
</thead>
<tbody>
<tr>
<td>26.83218</td>
<td>30.58</td>
<td>36.936</td>
</tr>
</tbody>
</table>
West Springfield
3.3.2 Runoff

Runoff for the state of Massachusetts is presented below in Figure 3.19 with town boundaries. A close-up image of the runoff is presented in Figure 3.20. The results of the baseline runoff assessment show that there is significant runoff in the Berkshire county, as well as significant runoff in areas of the Franklin, Hampden, Middlesex, Barnstable, lower Essex, and center Hampshire counties, as well as along the coast in the Greater Boston region.

Figure 3.19: Runoff for the state of Massachusetts with town boundaries
3.4 Conclusion

The results of this study show that there are many at risk communities in Massachusetts that should be targeted for mitigation strategies under climate change and that it is equally important to consider future climate trends because at risk communities are likely to change. The heat island is expected to spread into the Barnstable county putting citizens in those communities at potential risk for climate-related health complications. These results also show that urban forests can be an effective mitigative strategy, however, the results need further confirmation in future empirical studies. A non-linear predictive model was found to be better suited for explaining the relationship
between temperature as a function of percent canopy and percent imperviousness.

However, the neural network model was able to explain only up to 65% of the variability in predicting temperature, therefore, it is critical that researchers examine other potential moderators including elevation, population density, socioeconomic status, proximity to green space, and other measures of canopy cover and imperviousness. While these results provide an insight on the relationship between temperature, percent canopy and percent imperviousness in Massachusetts urban communities, the explanatory power of our models are low and variability is high indicating warranting further assessments for community application purposes.

Runoff was found to be high in areas of the Franklin, Hampden, Middlesex, Barnstable, lower Essex, and center Hampshire counties, as well as along the cost in the Greater Boston region. Therefore, it is important that these communities are targeted in mitigation efforts. Researchers have identified that climate change can impact many areas of health including respiratory, cardiovascular, and developmental health and can play a substantial role in waterborne and foodborne diseases (Portier et al., 2013). For example, runoff as a result of extreme precipitation events, is most prominent in urban areas where there is high impervious cover and can cause foul water flooding and movement of chemicals and toxins to waterbodies used for daily activities and consumption (Wilby, 2007; CITE).

To provide communities with accessible information on their local ecosystems and their ecosystem services that is scientifically grounded and integrates adaptation strategies, the results of this study will be made available as a spatially-explicit decision support tool on ArcGIS online. Communities will be able to make decisions about natural
resources at private and public levels, using this information to improve urban designs, allocate funds, consult citizens, develop programs and work with the medical community to create healthy and resilient environments.
CHAPTER 4
BRIDGING HUMAN HEALTH, CLIMATE CHANGE, AND URBAN FORESTRY

4.1 Introduction

4.1.1 Climate change in urban communities

Climate change is causing devastating changes in temperature and precipitation patterns worldwide (Luber & McGeehin, 2008, Walthall et al., 2013). Global temperatures have increased 1.14°C as of 1880 and as a result, extreme heat events, also known as heatwaves, have been occurring at increased rates throughout the world (Luber & McGreehin, 2008; National Aeronautics and Space Administration [NASA], 2020). There has also been an overall intensification of global precipitation related events characterized by either an increase in the duration and frequency of rainfall or prolonged periods of drought (Dore, 2005; O’Gorman, 2015).

However, the effects of climate change are not equally spread throughout. With over 55% of the world’s population living in cities, urban communities are experiencing disproportionate effects of climate change (Weng, 2007). Urban communities are largely composed of built environments and impervious surfaces which affects how much solar energy is absorbed and re-radiated and how much rain infiltrates (Groisman et al., 1999; Milly et al., 2002; Weng, 2007; Wilby, 2007). Under changing temperature and precipitation events, this can lead to heat waves and increased stormwater runoff carrying contaminants, foul water, and toxins (Corburn, 2009; Hollis, 1998; Solecki & Marcotullio, 2013; Voogt, 2002; Wilby, 2007). In addition, urban communities generally have high dependence on resources such as groundwater, and high industrial, commercial and residential waste production leading to city smog (Bouton et al., 2015; Dore, 2005).
Researchers have found that as climate change intensifies, air quality worsens in urban areas as a result of solar radiation mixing with city smog (Wilby, 2007). Similarly, as heat events become more frequent and intense and there is more evaporation of groundwater than recharge, urban communities are experiencing depleted water supplies (Dore, 2005).

4.1.2 Impacts of climate change on people

While substantial research has been conducted on the environmental effects of climate change, less attention has been devoted to how climate change is affecting people and their health. The World Health Organization estimated that in the early twenty-first century, 166,000 deaths and 5.5 million disability-adjusted life years could be attributed to changing climate patterns (Campbell-Lendrum et al., 2007). Direct health impacts are as a result of catastrophic events including floods, heat waves, hurricanes, wildfires, and tornados (Patella et al., 2018). These are also identified as extreme weather events and cause the displacement of populations, contamination of water resources, property damage, stress, injuries, and death (Kirch et al., 2005; Portier et al., 2013). Indirect human health impacts include climate change-related diseases (Patella et al., 2018). Portier et al. (2013) aimed to identify 11 direct and indirect categories of climate change consequences on human health critical to further research. These categories as exactly identified by the Portier et al. (2013) publication are as follows:

1. Asthma, respiratory allergies, and airway diseases
2. Cancer
3. Cardiovascular Disease and Stroke
4. Foodborne Diseases and Nutrition
5. Heat-Related Morbidity and Mortality

6. Human Developmental Effects

7. Mental Health and Stress-Related Disorders

8. Neurological Diseases and Disorders

9. Vectorborne and zoonotic diseases

10. Waterborne diseases

11. Weather-related morbidity and mortality

Some of the health consequences of climate change arise from complex interactions between ultraviolet radiation, heat, humidity, precipitation and other aspects of atmospheric chemistry that cause the formation or exacerbation of air pollutants and thereby, worsen air quality (Portier et al., 2013). Some of the common air pollutants that affect human health on a global scale include carbon monoxide (CO), particulate matter less than 2.5 μm or 10 μm (PM$_{2.5}$ and PM$_{10}$, respectively), ozone (O$_3$), sulfur dioxide (SO$_2$) and nitrogen dioxide (NO$_2$) (Nowak et al., 2018). For example, 3.3 million premature global deaths per year have been attributed to PM$_{2.5}$ (Lelieveld et al., 2015; Nowak et al., 2018). The health effects that have been identified as relating to air pollution include cardiovascular, pulmonary and neurological diseases (Nowak et al., 2018; Pope et al., 2002). Some other health consequences arise from the interplay of temperature and precipitation on human physiology (Buckley & Richardson, 2012; D’Amato et al., 2010; Lambert et al., 2002; Lee et al., 2018; Miami and Muhyi, 2019; Xu et al., 2013). For example, it has been reported that high temperatures are associated with reported negative emotions and asthma symptoms such as cough and wheezing (Li et al., 2014; Noelke et al., 2016). Lastly, extreme alterations of temperature and precipitation patterns,
portrayed as extreme weather events, can modify the composition of microbial communities in water or soil and damage food supplies leading to waterborne and foodborne diseases (Paul & Meyer, 2001; Talib & Randhir, 2016;) This can result in nutrient deficiencies and neurological and developmental diseases (Portier et al., 2013).

As climate change intensifies, it is critical to identify, explore, and synthesize these health consequences of climate change in order to 1. help guide the medical community in what patient populations and resource demands to expect, 2. help community members understand what climate conditions can exacerbate their conditions, and 3. help city and program leaders understand what challenges to anticipate in order to properly allocate funds.

4.1.3 Urban forestry as a resilience strategy

As important as it is to understand how climate change affects health, it is equally important to examine the effectiveness of possible resilience strategies for restoring health under climate change. One possible resilience strategy that has received minimal attention by researchers and scientists is the implementation of cost-effective vegetation into urban communities. This natural systems approach would enable communities to not only extract ecosystem services that natural ecosystems provide, but also help restore the health and safety of communities. One form of vegetation found to be aesthetically pleasing and having high economic return is urban forests (Akbari et al., 2001; Shackleton et al., 2015). In an article written by Wolf et al. (2020), major health benefit categories of urban trees were identified and sorted into three main categories: reducing harm, restoring capacities and building capacities. The following subcategories of health outcomes were established by Wolf et al. (2020) and are presented below:
1. Urban tree effects of air pollutants and respiratory conditions (reducing harm)
2. Tree pollen and volatile organic compounds (reducing harm)
3. Ultraviolet radiation (reducing harm)
4. Excess heat and thermal comfort (reducing harm)
5. Crime (reducing harm)
6. Cognition and attention restoration (restoring capacities)
7. Mental health, anxiety, and mood (restoring capacities)
8. Psychophysiological stress (restoring capacities)
9. Clinical outcomes (restoring capacities)
10. Birth outcomes (building capacities)
11. Immune system (building capacities)
12. Active living (building capacities)
13. Weight status (building capacities)
14. Cardiovascular function (building capacities)
15. Social cohesion (building capacities)

It has been found that urban trees mitigate the direct impacts of solar radiation by providing shade and transpirational cooling (Declet-Barreto et al., 2016; Wolf et al., 2020). Therefore, urban trees have the capacity to help address harm from ultraviolet radiation and excess heat (Wolf et al., 2020). In addition, the establishment of urban forests and urban parks in urban communities can enhance quality of life for residents, providing them the ability to engage in recreational activities and extract benefits for their mental, physical and social health (Chawla, 2015; Kondo et al., 2018; Tesler et al., 2018;
Wolf et al., 2020). Urban trees also play an indirect role in human health through the removal or air pollutants such as PM$_{10}$, O$_3$, and CO$_2$ via the leaf stomata or the plant surface, reducing the symptoms of cardiovascular and respiratory complications (Hirabayashi & Nowak 2016; McDonald et al., 2007; Nowak et al., 2014). Due to the urgency of climate change, the health benefits of urban forests as they relate to changing climates warrant further identification, explanation, and synthesis in order to encourage city planners, urban forestry professionals, the medical community, residents, and researchers to work together to prepare for and adapt to the health impacts of climate change.

4.1.4 Research needs and study design

There are abundant gaps in our understanding of how climate change, human health, and the environment are linked (Campbell-Lendrum et al., 2009; Portier et al., 2013). Empirical studies have mainly focused on investigating the underlying mechanisms of one of these elements or at most drawing connections between two. However, climate change, human health, and the environment are not discrete categories, and each are part of a highly complex interconnected system (Figure 4.1). It is critical to understand these multiple pathways in order to be able to advise communities about their health in relation to climate change and the environment, establish empirical evidence behind co-benefits of urban forestry, and determine how we can adapt to and mitigate the impacts of climate change. Despite this urgency, investigating climate change, human health, and the environment as one interconnected framework has not represented high priorities in scientific literature. Therefore, the objectives of this review are to 1. summarize recent empirical research examining climate change impacts on health 2.
identify how health can be restored through the implementation of urban forests 3.

determine research gaps in our understanding of climate-induced diseases and restoration potential of urban forests in relation to these diseases 4. provide a discussion on recommendations for the medical community, city residents, urban forestry programs, and urban planning 5. identify vulnerable populations to help communities anticipate resource demands and enhance preparedness 6. Generate framework models for diseases that communities can use to identify how climate change will affect their local community and how urban forests can assist in enhancing their community’s health.

Using these frameworks and an understanding of the population distribution and climate of their community, city leaders will be able to identify which health impacts are most likely in their city and begin identifying cases, establishing preventative measures, and allocating more resources to urban forestry programs and the medical community.

Figure 4.1: Interconnected framework for the links between climate change, human health, and the environment
Using the health categories established by Wolf et al. (2020) and Portier et al. (2013), five links between human health, climate change and urban forestry were identified and can be found in Figure 4.2. Relevant empirical studies investigating climate change impacts on, and the role of urban forestry in reducing the prevalence of skin cancer, prevalence of mental health disorders, heat-related morbidity and mortality, symptoms of cardiovascular disease and cardiovascular dysfunction, and symptoms of asthma were identified using PubMed, ScienceDirect, Web of Science and Google Scholar.

**Figure 4.2:** Conceptual framework identifying overlapping health categories in climate change, urban forestry and public health research that should be prioritized and will be used to structure this review. The categories were obtained from Portier et al., 2013 and Wolf et al., 2020.
Keywords: climate change, temperature, heat stress, heat morbidity, urban forest, urban trees, forest, air quality, health benefits, impacts, cardiovascular disease, symptoms, air pollution, asthma, prevalence, depression, ultraviolet radiation, blood pressure, anxiety, cancer, and pollution

4.2 Prevalence of Mental Health Disorders

The World Health Organization (WHO, 2019) identifies mental health disorders as those characterized by abnormal thoughts, emotions, perceptions, behaviors, and relationships (WHO, 2019). Some of the major categories of mental health disorders include schizophrenia, bipolar disorder, anxiety and depressive disorders, eating disorders, autism spectrum disorders, attention-deficit/hyperactivity-disorder, conduct disorder, and developmental disorders (James et al., 2018). The burden of mental health disorders is on the rise, affecting not only the health and wellbeing of people, but also economies (WHO, 2019). In 2013, three mental health disorders (depression, anxiety disorders, and schizophrenia) were identified among the top twenty causes of global burden of disease (Lee et al. 2018; Vos et al., 2015). Depression is characterized by disturbance in normal levels of pleasures, interest, sleep, appetite, concentration, and self-worth impairing a person’s ability to function in daily activities and cope with stresses (WHO, 2019). It is estimated that there has been an increase in the number of people diagnosed with depression by 18.4% between 2005 and 2015 (Chen et al., 2019; WHO, 2017). Currently, depression affects 264 million people worldwide (James et al., 2018; WHO, 2019). Schizophrenia is estimated to affect 20 million people worldwide and is characterized by disturbances in emotions, languages, perceptions, thinking and behaviors (James et al., 2018; WHO, 2019). Often those that are diagnosed with
schizophrenia experiences hallucinations and delusions which can greatly affect their ability to successfully execute daily activities (WHO, 2019). The prevalence of anxiety is estimated to be 4648 per 100,000, making anxiety the most prevalent psychiatric disorder (Bandelow et al., 2017; Rehm & Shield, 2019).

Climate is considered an important factor influencing mental health, however, the scientific evidence is limited (Chen et al., 2019). Forests have been found to reduce anxiety and mental stress when people spend time walking and viewing the forest (Park et al., 2011; Zhou et al., 2019). This effect has been termed ‘Shinrin-yoku’ in Japan (Stigsdotter et al., 2017; Zhou et al., 2019). This section will summarize evidence for the climate impact on mental health disorders and the effect of urban forests, parks and trees on restoring mental health (Figure 4.3).

**Figure 4.3:** Framework to be used by communities depicting 1: possible climate pathways affecting the prevalence of mental and behavioral illnesses, 2: urban tree and forest mitigation potential, and 3: recommendations for urban and medical communities.

References for the information going into developing this framework are described extensively in the “impact of climate on mental health disorders” and the “impacts of urban forests on mental health disorders” sections.
4.2.1 Impacts of climate on mental health disorders

Researchers have aimed to explore the relationship between climate change and mental health through a combination of self-reported mental health measures and temperature data. Obradovich et al. (2018) studied the effects of warming temperatures on the prevalence of self-reported mental health distress in 2 million US residents. Obradovich et al. (2018) coupled mental health data from the CDC and Prevention’s Behavioral Risk Factor Surveillance System with meteorological data obtained from PRISM Climate Group and National Centers for Environmental Prediction Reanalysis 2 project to explore impacts of recent meteorological stressors on mental health, long-term effects of warming on mental health, and the effects of direct exposure of tropical cyclones. Investigating short-term exposures, Obradovich et al. (2018) found that maximum temperatures exceeding 30°C resulted in a 1% point increase in the probability of mental health issues. In addition, the authors observed a 2% point increase during months where precipitation exceeded 25 days. Assessing for multiyear warming effects, the authors found a 2% point increase in the prevalence of mental health issues with a 1°C increase in temperature. Lastly, exposure to tropical cyclones resulted in a 4% point increase in the prevalence of mental health issues. It is important to note that this study was conducted in the United States which is a developed nation with fairly sufficient resources. Obradovich et al. (2018) point out that in nations that lack similar access to resources, the observed results could be more severe. In addition, they note that direct impacts of changing temperature and precipitation patterns are only a portion of the total impact of climate change on mental health. The mere concern about climate change could
result in more severe effects. Lastly, the authors mention the limitation of the mental health metric that was used. The metric did not contain information of the type of mental health symptoms or categories and their severity. Therefore, their recommendations for future research include examining the impacts of climate change on specific symptoms of mental health disorders.

Noelke et al. (2016) conducted a study in the US in order to investigate how ambient temperature affects mental well-being of adults in the US and whether adaptation could help mitigate negative effects. The authors used the Gallup G1K dataset that gathers information from a random sample of 1000 Americans via surveys 350 days a year. Using the responses for 1.9 million individuals between 2008 and 2013 and temperature data for the day of each response, they set up an ordinarily least squares regression to investigate the effect of temperature on mental well-being of the participants. Mental well-being was assessed based on participant respondents to questions that fell into the following three categories: positive emotions such as happiness and laughter, negative emotions such as anger and stress, and fatigue. The results showed evidence of reduced mental well-being during increased temperature conditions. Specifically, the authors compared mental well-being at average temperatures of 10°C to 16°C with temperatures above 21°C and found a reduction in positive emotions and an increase in reported negative emotions and fatigue. For days with temperatures that exceeded 32°C, mental well-being was reduced by 4.4% of a standard deviation. In addition, the authors find that very low temperatures (less than -7°C) were associated with an increase in mental well-being by 3.1% of a standard deviation.
Willox et al. (2013) examined the relationship between climate change and mental health through 67 in-depth interviews conducted with members of the Rigolet, Nunatsiavut, Labrador, Canada community between January 2010 and October 2010. The Inuit community reside in Northern Canada and practice a lifestyle that is connected to the natural environment. The authors interviewed as many people as they could during the time period in order to gain a representative sample of demographics and experiences. Each interview was structured to contain 40 open-ended questions that were then analyzed for emerging themes and key codes. Willox et al. (2013) found that changing seasonal weather patterns, ice stability and vegetation were all negatively affecting mental health of the Inuit community members. Specifically, as a result of these changes, community members were feeling a loss of cultural identity and experiencing disruptions in their usual activities causing increased family stress, increased risky behaviors, and an amplification of previous traumas by losing previously established sense of worth. While this study is limited in both scope and generalizability, it shows how communities that are closely tied to nature, can experiencing especially devastating impacts to mental well-being under changing climates and emphasizes the importance of recognizing and studying this phenomenon in communities to help them adapt.

In addition to measuring self-reported mental health, several researchers have also aimed to quantify the effects by examining hospital data and daily temperatures. Wang et al. (2014) examined the association between extreme ambient temperatures and psychiatric emergency visits to the hospital in Toronto, Canada using a time series approach for the period between April of 2002 and March of 2010. National Ambulatory Care Reporting System was used to identify cases, Environment Canada was used to
obtain climate data, and the National Air Pollution System was used to obtain information on air pollution. The authors applied a distributed lag non-linear model with a fitted Poisson regression, adjusting for air pollution as a confounding variable. Then, using the 50\textsuperscript{th} percentile of the average daily temperature as the reference condition, the authors calculated relative risks for mental health disorders and the following subcategories: mood disorders, schizophrenia, neurotic disorders consisting of phobia disorders, and substance abuse related disorders. Their findings showed a strong association for all disorders with temperature in the 99\textsuperscript{th} percentile. Cumulatively the authors found cases to increase by 29\% during the week after high temperature exposure. The strongest association was observed within 0-4 days of exposure. Examining each mental health disorder separately for increased risk during a 7-day period after initial high temperature, they found a 14\% increase for substance abuse related disorders, a 149\% increase for schizophrenia, a 68\% increase for mood disorders, and a 12\% increase for neurotic disorders. In addition, the authors investigated the increased risk of mental health disorders for temperatures in the 1\textsuperscript{st} percentile and found a 9\% increase for neurotic disorders but no increase for other mental health disorder subcategories. Therefore, these results suggest that extreme temperature conditions can have a negative effect on the mental health of patients. Further research is warranted to understand how these results may differ across different locations and to understand the underlying mechanisms of the observed relationships.

A similar study examining the relationship between temperature and mental health emergency visits was conducted by Lee et al. (2018) in South Korea four years later. The authors used a distributed lag non-linear model approach with data collected
from 6 cities in South Korea from 2003 to 2013. Meteorological data was obtained from the Korean Meteorological Administration, air pollution data was obtained from the National Institute of Environmental Research in Korea, and emergency admission data was obtained from the Korean National health Insurance Corporation. The data was then pooled by each city using a multivariate model. Mental diseases were classified and grouped using the ICD 10 diagnosis and risks were calculated for 99th temperature percentile. Similarly to Wang et al. (2014), Lee et al. (2018) found that the strongest associations between 99th percentile temperature and mental health diseases occurred between 0-4 days from exposure. Out of the 166,579 total mental health emergency admissions, 14.6% could be attributed to extreme heat indicating that extreme hot temperatures have a strong impact on emergency visits for mental health. Of all the types of mental health disease examined, anxiety had the highest attributable fraction attributed to extreme heat of 31.6%, dementia had the second highest of 20.5%, schizophrenia had the third highest of 19.2% and depression had the lowest of 11.6%. The relative risks for the categories were as follows: 1.375 for anxiety, 1.213 for dementia, 1.123 for schizophrenia and 1.229 for depression.

Chen et al. (2019) conducted a study in Taiwan to investigate the association between major depressive disorder and exposure to temperature. The authors used a retrospective population-based approach, following subjects identified with major depressive disorder in a national longitudinal health insurance database from 2005. Subjects were followed between 2003 and 2013. Climate data were obtained from weather monitoring stations. The Cox proportional hazard model was implemented to access the relationship between climate variables and major depressive disorder while
controlling for covariates including age and gender. Through the follow-up period, 9723 new cases of major depressive disorder were identified and were found to be non-linearly related to long-term exposure to high temperatures. Both long-term exposure to really low and really high temperatures increased the risk of major depressive disorder. Temperatures that fell between 20 and 23°C were found to have the lowest risk for major depressive disorder.

As mentioned previously, the relationship between climate change and mental health can either be direct or indirect in nature (Obradovich et al., 2018). Specifically, negative effects of climate change on mental health can be due to the simple awareness of climate change, an indirect mechanism (Helm et al., 2018). Worrying about climate change as a potential threat to one-self can cause anxiety, leading to dysregulation of normal mental processes (Barlow, 2002; Clayton & Karazsia, 2020).

Clayton & Karazsia (2020) conducted three studies in the United States with the aim of developing a measure of climate change anxiety in order to address how the mere thoughts about climate change can affect mental health. Through the first study, the authors develop a scale of climate change anxiety and validated it using a sample size of 197 US participants recruited through Amazon’s Mechanical Turk. Four factors were identified for the scale: functional impairment, cognitive-emotional impairment, behavioral engagement, and lastly personal experience. The authors identify cognitive-emotional impairment and functional impairment as subscale of climate change anxiety (Clayton & Karazsia, 2020). Question items were developed or adapted from psychological literature pertaining to the four factors. In the second study, the authors replicated the first study using an additional sample of 199 participants. Finally, the third
study was conducted to examine adaptation to climate change anxiety by investigating the relationship between climate change messages and anxiety scores. Participants were either assigned to an empowering message condition or a powerless message condition and then were asked to complete the climate change anxiety measure. It was found that climate change anxiety was associated with cognitive-emotional and functional impairment, while behavioral engagement was not associated with climate change anxiety. However, all factors were positively correlated with negative feelings as a result of climate change. In addition, through the completion of the third study, the authors found that positive adaptation responses such as thinking about reducing personal contributions to climate change can help maintain mental well-being. Clayton & Karazsia (2020) propose that future research investigates which groups of people are at higher risk of climate change anxiety by exploring more diverse groups of participants and conditions.

Certain research studies have also aimed to identify some of the underlying mechanisms that affect the relationship between mental health and extreme temperatures. One possible explanation is that extreme climates may cause emotional discomfort by forcing people to stay indoors more often, change their schedules unpredictably, and face additional expenditures for regulating indoor temperatures (Deschenes, 2014; Noelke et al., 2016). Second, it has been identified that hot temperatures may cause physical discomfort, triggering anxiety and negative emotions (Lee et al., 2018). It has also been found that neurotransmitters like dopamine and serotonin are associated with thermoregulation and that temperature can affect the bioavailability of these biological chemicals (Lambert et al., 2002; Lee et al., 2018). Therefore, it is possible that an
individual might be more vulnerable to extreme temperatures if neurotransmitters that play a role in thermoregulation also play a role in their mental or behavioral disorder (Bark, 1998; Wang et al., 2014). It is also possible that those with mental and behavioral disorders have decreased cognitive awareness to their surroundings, leading to the inability to take precautions during hot temperatures like drink water and take off extra clothing (Bark, 1998; Hansen et al., 2008; Wang et al., 2014). Lastly, it is possible that medications that are taken for mental and behavioral disorders alter normal thermoregulatory processes (Martin-Latry et al., 2007; Wang et al., 2014).

4.2.2. Impacts of urban forests on mental health disorders

Guan et al. (2017) conducted a study in Northeast China with the aim of investigating the reduction of mental stress and anxiety through visiting urban forests dominated with various tree species. The authors recruited 69 university students majoring in urban horticulture and divided the participants into three equal groups to visit urban forests dominated by either birch, maple or oak trees in the Nanhu Park. The study took place on May 10th, 2017. Participants were asked to first measure forest tree characteristics and then were permitted personal time in the forest for 40 minutes. Twelve question questionnaires were administered before and after forest bathing to investigate stresses associated with school, social interactions and participant’s personal life. They found that anxiety alleviation scores increased after the visit but varied across the three different urban forests in relation to subcategory of anxiety assessed. In the urban forest dominated by birch trees, the authors found anti-anxiety scores to increase for roommate communication, finances, and study interest. Specifically, anti-anxiety scores for roommate communication increased 28%, anti-anxiety scores for study interest increased
17%, and anti-anxiety scores for finances increased 11%. In the urban forest dominated by maple trees, only the anti-anxiety scores for study interest increased by 18%. Lastly, in the urban forest dominated by oak, the anti-anxiety scores increased for campus life, family matters, study interest and lesson satisfaction. Specifically, anti-anxiety scores for family matters increased 8%, scores for campus life increased 11%, scores for lesson satisfaction increased 19%, and scores for study interest increased 15%. Guan et al. (2017) suggest that future work should focus on investigating additional species of trees such as pine and cypress and on identifying the aspects of trees that play an effect in the physiological responses during forest bathing.

Taylor et al. (2015) conducted a study in London, United Kingdom, with the aim of examining the relationship between urban trees and depression. They measured depression as anti-depression prescription rates for their study area that they obtained from a governmental website. Using Greater London Authority and the ArcGIS platform, the authors obtained and synthesized data on urban street tree coverage followed by a regression analysis assessing the relationship between rate of antidepressant prescriptions and street trees. Taylor et al. (2015) found that areas with lower street tree density in general had higher antidepressant prescription rates. Specifically, they found that an addition of one tree per kilometer could reduce antidepressant prescription rates by 1.38 for every 1000 people (Taylor et al., 2015). The authors conclude that these findings agree with previous research that has examined mental health in relation to urban trees, however, they advise that more research is needed because this relationship is complex. They state that there are potential other moderating variables contributing to the relationship that need to be considered. They hope that their results can help expand the
role of urban trees in urban planning and policy agendas and can help preserve existing street trees.

Beil & Hanes (2013) accessed the relationship between stress and different urban environmental settings. They first recruited 15 participants and screened them for eligibility in the study. These then had each of the participants completed health history forms and measured current and previous stress levels. The team then has each of the participants complete pre- and post-saliva sample and rating of perceived stress in one of four environmental settings: 1. A very natural environment, 2. A mostly natural environment, 3. A mostly built environment and, 4. A mostly very built. The authors found that in very natural environments, there was only a very small change in amylase levels (7.56 U/mL) compared to very built environments where there was a substantial increase in amylase levels (by 45.05 U/mL). The authors also found that there were significant differences across the environments and perceived restorativeness. They found that very natural environment received the highest scores for restorativeness. The authors also found a higher reduction in subjective stress in very natural settings compared to mostly built environments. However, due to having a very small sample size of 15 participants and as a result, low power, the results on their own are not enough to fully support the notion that natural settings in urban communities produce beneficial reductions in stress levels. However, they claim that statistical significance of subjective stress reductions suggest that an environment with high levels of urban trees and shrubs can have beneficial effects on stress levels. The authors recommend that further studies aim to determine how strength and frequency of exposures can affect stress levels in
order to better gauge the potential of natural urban environments in creating more sustainable and healthy communities.

Jiang et al. (2016) examined the relationship between tree density and stress in four Midwestern urban areas. In a laboratory setting, they generated 6-minute videos of urban neighborhood streets with varying tree density (0-70%). Next, they recruited 160 adult participants from the four Midwestern urban areas and induced psychological stress by having the participants quickly prepare and deliver a speech, followed by a subtraction task in front of viewers. To add to the stress levels, the researchers also told the participants they were being recorded and evaluated. Lastly, the authors used the Visual Analog Scale to calculate stress reported by participants at three occurrences throughout the procedure. The authors found that there was a positive relationship between tree density and reduction of stress as reported by participants after controlling for confounding variables. Specifically, they found that stress recovery increased 60% for an increase from 2% to 62% in tree canopy density. Jiang et al. (2016) stress the importance of future studies applying their methods to urban streets in parks, schools, and other kinds of neighborhoods outside of medium-income, single-family ones in order to build a more representative and comprehensive view of this relationship and be able to better advise urban planners in planting trees and the benefits of this action on the well-being of communities.

Tesler et al., (2018) investigated the effects of an Urban Forest Health Intervention Program in Israel on aspects of mental and physical health of 76 adolescents. The authors used a nonrandomized controlled study design, administering questionnaires to intervention and control groups, and conducted univariate and multivariable analyses.
The 33-question questionnaire was administered before and after the intervention and consisted of items that asked students to self-report on physical activity, symptoms, satisfaction with their life, cigarette use, and alcohol use. The authors found that physical activity habits and satisfaction with life were higher in the intervention group, while smoking frequency, symptoms, and alcohol consumption were lower. Specifically, participants in the intervention group participated in 0.81 more sessions of at least 60 minutes of exercise each week compared to the control group. Life satisfaction increased by 1.42 in the intervention group but decreased in the control group (-0.29). Smoking frequency reduced by 2.60 to 1.72 in the intervention group but increased in the control group from 3.17 to 3.39. Psychosomatic symptoms decreased by -1.37 in the intervention group and only -0.18 for the control group. Lastly, alcohol consumption decreased by -1.08 in the intervention group while only slightly decreasing for the control group (-0.09). Therefore, the results indicate that an Urban Forest Health Intervention Program can be efficient in improving the mental and physical health of adolescents and reducing risky behavior. It is important to note that the youth participating in the study had dropped out from traditional schooling and may face different challenges than students enrolled in formal school, therefore, these students are considered at-risk youth at risk for physical or mental harm. Lastly, self-report studies are often as risk themselves for social desirability response bias which the authors point out as a limitation of this study.

In Guiyang, Southwest China, Zhou et al. (2019) evaluated the effects of short forest visits to parks located in urban environments and rural environments on anxiety. Forty-three students attending a local university were recruited and split into two groups. On the first day, one group visited an urban forest park while the other visited a rural
forest park. On the second day the groups switched. The students were administered 12 question questionnaires evaluating anxiety before visiting the park and after exiting the park. The questions were split into three categories assessing personal, school, and social life. During their visit participants walked through parts of the forest, played a game, and ate their lunches. Zhou et al. (2019) found that urban forest bathing alleviated anxiety from finances, exams, campus life and personal relationships. Rural forest bathing alleviated anxiety from finances but did not alleviate anxiety from campus experiences. Comparing alleviation from financial anxiety between rural forests (20% increase) and urban forests (18% increase), anti-anxiety scores were not statistically different. However, compared to rural forest, urban forests increased anti-anxiety scores for exam stress by one-fold. Lastly, urban forest visits increased scores by 15% for personal relationships. Therefore, Zhou et al. (2019) recommend that students with personal relationship anxiety pay a visit to urban forests as a way to alleviate the stresses and promote good communication. Lastly, Zhou et al. (2019) recommend that future research continues to examine the differences between forests in rural and urban communities and their effects of health physiology long-term.

Lee et al. (2019) explored the therapeutic effects of an urban forestry program in Seoul, South Korea. The aim was to explore not only how the effects occur but also why these changes happen in their target group: middle-aged women. Nine middle-aged women attended the urban forestry therapy program between May 9th and May 30th of 2017. During their therapy session, the participants were involved in a variety of activities from stretching exercises to meditation. Data on the experience of the participants was collected from focus group interviews. The interviews were further
analyzed using the grounded theory method developed by Glaser and Strauss (2017). Lee et al. (2019) found that participants experienced recovery of their self-identity and self-healing processes through the urban therapy program. In the beginning of the program, many participants reported feeling unfamiliar and strange, but through the activities they began to perceive the urban forest as a restorative environment and felt more peaceful emotions. Specifically, as participants gained knowledge about the forest and began to bond with it, they felt a shift in their perception of it and themselves. Therefore, engagement with urban forests and participation in urban forestry programs can help individuals restore, develop positive attitudes, and feel more connectedness.

Shackleton et al. (2015) conducted a study in two South African towns with the aim of examining how residents from three urban neighborhood types valued trees in their landscapes. The two towns were Tzaneen and Bela Bela. The authors selected 150 households at random in each town and provided the households surveys. In addition, they conducted life history interviews to determine the direct uses of trees and their recognized benefits. Upon examining the results of the surveys and life history interviews, the authors found that participants reported back on a variety of provisional services as well as the benefits trees provide for their health. Specifically, authors found that residents valued trees for their promotion of social interactions. In addition, participants reported on the psychological stress reducing effect of trees.

4.3 Symptoms of Asthma

Asthma is considered a noncommunicable respiratory disease that results from the inflammation and narrowing of air passages in the lungs (WHO, 2020). During
asthmatic episodes, bronchial muscles constrict and airways secret more fluid causing mucosal edema (Miami & Muhyi, 2019). Some of the common respiratory symptoms of asthma include cough, production of phlegm, wheezing, shortness of breath, and chest tightness (Li et al., 2014). It is currently estimated that more than 339 million people are affected by asthma worldwide (Vos et al., 2017; WHO, 2020). Asthma is also found to attribute to one percent of all global disability-adjusted life years lost (Li et al., 2014; Masoli et al., 2004). Several risk factors for asthma have been thoroughly investigated including aeroallergens, tobacco smokes, chemicals, and air pollution (WHO, 2020). However, in a developing branch of research air temperatures have also been identified as a trigger for asthma, yet our knowledge is limited (WHO, 2020).

Urban trees planted as either street trees, parks or forests have the potential to reduce exposure to some of these risk factors. For example, trees are able to remove particulate and gaseous pollutants that can trigger wheezing and other asthma symptoms (Domm et al., 2008). However, it has also been found that trees can emit biogenic volatile organic compounds which contribute to ozone formation, and thereby, can exacerbate asthma symptoms (Domm et al., 2008). This section will summarize recent empirical research on how temperatures affects asthma and will summarize how urban trees can mitigate or contribute to these effects (Figure 4.4).
4.3.1 Impacts of climate on symptoms of asthma

Li et al. (2014) conducted a study in six Australian cities with the aim of identifying the relationship between ambient temperature and respiratory symptoms in youth with asthma. 270 participants ages 7 to 12 were recruited and asked to record daytime and night-time respiratory symptoms for four weeks following the instructions provided at an initial meeting with the research staff. Climate data, including temperature and ozone levels, were obtained from weather monitoring monitors in the region. To compare the effect of ambient temperature of asthma symptoms in youth, a mixed logistic regression model was used. The results of the regression models showed that high ambient temperatures increased the risk of asthma symptoms and lasted for four days.
The relationship between ambient temperature and asthma symptoms was found to be linear. Some of the most prominent symptoms observed included wheezing, chest tightness, cough, and phlegm. In addition, the authors found similar results for minimum temperatures, but the effect estimates were lower than those for average and maximum temperatures.

While some studies show a positive association between temperatures and prevalence of asthma, some studies have observed contradictory results showing a stronger effect for colder temperatures and ultimately an inverse relationship.

Similarly to Li et al. (2014), Miami & Muhyi (2019) examined the impacts of climate variables on pediatric asthma. Specifically, they were interested in investigating how meteorological variables influence pediatric admission to the hospital for asthma and wheezy chest. To do this, Miami & Muhyi (2019) used a retrospective study design for pediatric patients between the ages of 1 and 13 admitted to the Almawani hospital in Basra, Iraq. Data on patients was collected from the hospital registries for the period between January 2014 and December 2016. Meteorological data was gathered from the Iraqi World Meteorological Organization and Seismology and consisted of information on humidity, temperature, wind, rain, dust and storms. Results of the study showed that there were higher monthly admission rates with high humidity, higher levels of precipitation, and increased wind speeds. Contradictory to the results observed by Lie et al. (2014), Miami & Muhyi also found a strong association for lower temperature, showing a seasonal variation for asthma admissions. Dust and thunderstorm were found to not be significantly associated with asthma admissions. Miami & Muhyi (2019) state that these
finding suggest that changing weather condition can increase the prevalence of asthma attacks in the youth population.

Lastly, some researchers have observed both effects of extreme cold and extreme hot temperatures on symptoms of pediatric asthma.

Xu et al. (2013) conducted a study in Brisbane, Australia examining how extreme temperature conditions affect hospital admissions for pediatric asthma. To do this, they used an ecological study design gathering emergency department admission data from Brisbane between January 2003 and December 2009. Information regarding weather was extracted from a meteorological bureau. In addition, they also gathered data regarding air pollutants from the Queensland Department of Environment and Heritage Protection. Using a Poisson linear regression model and a distributed lag non-linear model, they found that both extremes of temperatures (very low or very high) were associated with admissions to the hospital for pediatric asthma. They found seasonal variation for the effect with February, May, June and July having the highest admission rates. They also found that heat waves that lasted at least 3 days with temperatures above the 95th percentile caused significant increases in admissions. In addition, they found that the effects of extreme temperatures occurred on the day of exposure.

Similarly, in a study that took place in North Carolina, USA, Buckley & Richardson (2012) examined how the relationship between temperature and emergency visits for adult asthma varied seasonally. The authors used NC DETECTS to gather information of residents of North Carolina who were over the age of 18 between 2007 and 2008. They also obtained temperature data form the State Climate Office of North Carolina. Then, using a case-crossover study design, they assessed the effects of
temperature on adult admissions for asthma. They found seasonal variation in the admissions for adult asthma with positive linear relationships in the winter and in the summer. Asthma emergency department visits peaked in February. In addition, they calculated the odds ratio between adult hospital visits for asthma and each 5°C increase in daily temperature to be 1.01. The risk for admissions for adult asthma were found to be lowest in the Spring and in September.

Certain research studies have aimed to identify some of the underlying mechanisms that affect the relationship between respiratory health and climate variables. Climate has been found to affect asthma by directly acting on the airways (affecting inflammation pathways), or indirectly by affecting levels of asthma triggers like allergens and pollutants (Buckley & Richardson, 2012; D’Amato et al., 2010; Miami & Muhyi, 2019; Xu et al., 2013). More specifically, high levels of precipitation and humid conditions may cause fragmentation of pollen grains, may increase fungal spore counts, and may increase growth of dust mites (D’Amato et al., 2010; Miami & Muhyi, 2019). Low precipitation levels may cause more dust and particulate pollution (Portier et al., 2013). Similarly, high temperatures can increase the production of indoor allergens, air pollutants, and pollen (Buckley and Richardson, 2012; Weinmayr et al., 2010; Xu et al., 2012; Xu et al., 2013). Cold temperatures were found to influence mucus secretions, accumulation of inflammatory factors, and increase viral and bacterial infections (Kaminsky et al., 2000; Miami & Muhyi, 2019).

4.3.2 Impacts of urban forests on symptoms of asthma
Alcock et al. (2017) quantified the associations between green space density and hospital admissions for asthma through their study conducted in England. In addition, they aimed to access how these associations vary with exposure to various air pollution concentrations. Hospital admissions rates for asthma for residents of England were joined with information on vegetation and pollution and a negative binomial regression model was fitted. Data was obtained from the English Hospital Episode Statistics, Lower-layer Super Output Area percentage of green space and gardens were obtained from the Generalized Land Use Database, and tree density data was gathered from Bluesky International National Tree Map (Alcock et al., 2017). Lastly, pollution data for NO₂, SO₂, and PM₂.₅ was obtained from Pollution Climate Mapping model simulation and modeled in ArcGIS. Alcock et al. (2017) established that decreases in hospital admissions for asthma cases were associated with green space and garden only when air pollutant exposures were low, and reduction in hospital admissions for asthma were associated with tree density only when exposure to pollutants was high (Alcock et al., 2017). The authors also note that trees can serve as producers of allergenic pollen, however, the results obtained from this study do not implicate that this is modifying the relationship between urban trees and hospital visits for asthma. Instead, they claim that the dominating mechanisms affecting the association between urban trees and hospital visits for asthma are dispersion and pollutant removal.

Lai & Kontokosta (2019) conducted a study in the US investigating the impacts of urban street trees on respiratory health and air quality. They created a database for urban street trees, rates of respiratory illness and air quality for the city of New York using data sets regarding parks and recreation, pollen, city planning data, census data and New York
city health data. Lai & Kontokosta (2019) used a multivariate linear regression model to determine the relationship between asthma, tree density, and prevalence of allergenic tree species. Of the 652,169 street trees, 76% were found to have allergenic pollen in the spring and 24% having severe allergenic pollen. Lai & Kontokosta (2019) found that the density of trees located along the streets was associated with lower asthma emergency department visits. However, some tree species such as Red Maple, American Linden and Northern Red Oak were themselves positively associated with asthma emergency department admissions. Therefore, these results show that while high urban tree density can have a positive effect on respiratory health, this effect can be reversed depending on the tree species that is planted and its level of allergenic pollen.

Lovasi et al. (2008) conducted an ecological study examining the prevalence of pediatric asthma in children living in communities with more urban street trees. Their aim was to identify and quantify the association by examining asthma prevalence data and asthma hospitalization data for pediatric patients in relation to street tree data obtained from the New York City Department of Parks and Recreation. Prevalence of asthma data was obtained for 4 and 5-year-olds from a school screening conducted in 1999 by the NYC Department of Health. Asthma hospitalization data for children under the age of 15 were also obtained from the NYC Department of Health for 1997. In addition, the authors gathered data on the proximity to pollution sources. Using the data, they calculated correlation coefficients and ran a Poisson regression model. Lovasi et al. (2008) found that a 1 standard deviation increase in tree canopy density was associated with a lower prevalence of asthma in 4 and 5-year-olds but it was not found to be associated with lower hospitalization rates for asthma in children under the age of 15. Specifically, after
adjusting for possible confounding variables, the authors estimate that there would be a 29% decrease in the prevalence of asthma in children for a 1 standard deviation increase in tree canopy density.

Nowak et al. (2018) aimed to investigate pollution removal by urban forests in 86 Canadian cities in 2010 and the subsequent effect on local air pollution and health. They conducted analyses examining flux of pollutants, pollution removal, and monetary value of changes in pollution. Specifically, the U.S. EPA’s Environmental Benefits Mapping and Analysis Program was used to quantify the health impacts and monetary value of pollution removal. Pollutants examined included NO₂, O₃, PM₂.₅, SO₂, and CO. The authors found that across the 86 cities, the total amount of pollution removed was 16,500 t in 2010 which had a health value of $227.2 million. This monetary value stems in part from the reduction in human mortality, reduction of 21,900 respiratory symptom incidences, and reduction of 16,500 incidences for asthma. In addition, they found that the amount of pollutants removed varied across cities anywhere from 5.38 g/m²/year to 2.14 g/m²/year with air quality improvement between 0.001% AND 0.273% across cities. Lastly, they estimated the per hectare benefit value of tree cover to be $511. The authors state that air quality improvement as a result of pollutant removal can be underestimated because data for the amount of upper air pollution that is being prevented from reaching ground level is not accounted for.

Ulmer et al. (2016) investigated the role urban trees can play in human health by conducting a study in Sacramento, California using pre-existing datasets. The authors collected demographic and socioeconomic information from the California Health Interview Survey which was administered between 2001 and 2011. In this survey,
participants self-reported on physical activity, body weight, and physician diagnosed health conditions which enabled the authors to compare how these measures related to forest cover data that they mapped using LiDAR and imagery data. They did this by conducting a regression analyses and found that more tree cover was significantly associated with 13% higher odds of reporting a better health score. Specifically, they found that a 10% increase in forest cover was correlated with a 29% improvement in the score. They also found that more tree cover was correlated with less obesity, less type 2 diabetes and less asthma. Numerically, a 10% increase in forest cover was correlated with a 19% reduction in obesity and overweight conditions, a 19% reduction in type 2 diabetes, and a reduction in asthma by 10.4%. However, Ulmer et al. (2016) advise that the relationship between asthma and urban trees is highly complicated and therefore, they strongly encourage more research that repeats similar measures by controls for and examines other variables such as air pollution.

Nowak et al. (2014) investigated circumvented health impacts and monetary costs of pollutant removal by trees in the US for the year 2010 using computer simulations and environmental data. All data was collected from The National Land Cover Database, the U.S. EPA Air Quality System national database, and the U.S EPA BenMap. Using computer simulation, the researchers determined that in 2010, trees in the US removed 17.4 million tons of various air pollutants which has a human health effect benefits valued at 6.8 billion dollars. In addition, the removal of air pollution helped avoid more than 850 deaths and 670,000 incidences acute respiratory symptoms. They found that the health benefits were primarily observed in the urban areas (68.1%) due to the contribution of urban trees. However, Nowak et al. (2014) state that there are limitations
associated with the modeling of air pollutants. They claim that the data used for air pollutants is limited as a result of the low number of pollutant monitors throughout the nation. Therefore, they strongly recommend that researchers further model the relationship between urban forests, air pollutants and health to confirm their results and make better estimations.

4.4 Symptoms of cardiovascular disease and dysfunction

Cardiovascular diseases serve as the number one cause of death worldwide (WHO, 2017a). It is estimated that cardiovascular diseases killed approximately 17.9 million people in 2016 (WHO, 2017a). Cardiovascular diseases compromise a group of disorders of heart and blood vessel functionality (WHO, 2017a). Some of the common cardiovascular diseases include hypertension, coronary heart disease, and cerebrovascular disease (WHO, 2017a). Often patients with a cardiovascular disease do not experience any symptoms for their underlying cause (WHO, 2017a). Instead, they might experience a heart attack or stroke as a sign of their underlying condition (WHO, 2017a). Several risk factors have been identified for cardiovascular diseases and among them are environmental factors such as climate conditions and air pollution (Mohammadi & Karimi, 2018). As a strategy to improve cardiovascular health, forest bathing, previously introduced as Skinrin-yoku, has received attention in research for its positive effects on health (Mao et al., 2012; Tsunetsugu et al., 2010). The following section will summarize empirical research on climate-induced cardiovascular diseases and the mitigation potential of urban trees (Figure 4.5).
Figure 4.5: Framework to be used by communities depicting 1: possible climate pathways affecting symptoms of cardiovascular disease and dysfunction, 2: urban tree and forest mitigation potential, and 3: recommendations for urban and medical communities. References for the information going into developing this framework are described extensively in the “impact of climate on cardiovascular health” and the “effects of urban forests on cardiovascular health” sections.

4.4.1 Impacts of climate on cardiovascular health

Mohammadi & Karimi (2018) conducted a study in Kermanshah, Iran with the aim of investigating the association between cardiovascular admissions to the hospital and bioclimatic conditions between 2009 and 2015. To achieve this, the authors used a Levene’s tests, a univariate analysis of variance, and a Scheffe and Games-Howell post hoc tests using climate data from the climate database of Kermanshah’s station and cardiovascular admissions to the Imam Ali Hospital. Some of the climate variables obtained included average temperature, wind speed, humidity, radiation, cloudiness. These climate variables were then used to calculate indices including the PET index, equivalent temperature index, effective temperature, and predicted mean vote index. Mahammadi & Karimi (2018) found that extreme weather conditions were related to
increased cardiovascular disease, but there was variation across indexes. The equivalent
temperature index revealed that there was a significant relationship between
cardiovascular hospital admissions and extreme temperature conditions. However, the
effective temperature index showed an association for warm conditions and hot
conditions only and the predicted mean vote and PET indices showed a stronger
association for cool/cold conditions. Overall, the results were most robust for extremes
(cold and hot). These results show that extreme temperatures are related to increases in
cardiovascular disease.

Yin & Wang (2017) studied cardiovascular disease mortality in relation to heat
waves in Beijing, China with the aim of creating a more accurate heat alert for
communities. The authors applied a generalized additive model to analyze excess
mortality risk percentage for heat waves. Climate data was obtained from 18
meteorological stations in the summers of 2010, 2011 and 2012. Mortality data was
obtained from the Chinese Center for Disease Control and Prevention. Yin & Wang
(2017) found that increasing length of a heat wave is related to increasing cardiovascular
mortality. Specifically, when maximum daily temperatures hit thresholds of 32°C, 33°C,
34°C, and 35°C from the fifth day, the excess mortality risk percentage increased by 16%,
29%, 31% and 51% respectively. They also found a harvesting effect for excess mortality
risk percentage on the seventh day. From the ninth day, when temperatures exceeded
32°C, the excess mortality risk percentage was 81%. Similarly, from the tenth day, when
temperatures exceeded 33°C the excess mortality risk percentage was 87%. These results
confirm how extreme heat conditions can increase cardiovascular mortality however,
cardiovascular mortality is dependent on many factors that were not accessed by the
authors such as socioeconomic factors. In addition, the authors had limited data available for use and did not investigate more detailed causes of cardiovascular disease which should be addressed in further research.

Cui et al. (2019) also conducted a study in China investigating the effects of temperature on cardiovascular hospital admissions. They used daily hospital admission data between July 1st, 2015 and October 31st, 2017 for seven hospitals in the Hefei City region. Meteorological data was obtained from the China Meteorological Science Data Sharing Service. Lastly, the authors also collected air pollution data from the Hefei Environmental Monitoring Station. Using the data, they ran a quasi-Poisson regression with a distributed-lag nonlinear model. Cui et al. (2019) found that cardiovascular hospital admissions can be effects by both hot and cold temperatures. The authors established the 25th and the 75th percentiles of temperature to be 10.3°C and 25.6°C, respectively. For temperatures in the first percentile the cumulative relative risk was 0.616 compared to the 25th percentile. For temperatures in the 10th percentile, the cumulative relative risk was 1.081. The effects of cold temperatures on cardiovascular disease are the most harmful at lags 2-4 days. For temperatures in the 99th percentile, the cumulative relative risk was 1.078 compared to the 75th percentile of temperature. Lastly, for temperatures in the 90th percentile, the cumulative relative risk was 1.015. The effects of hot temperatures on cardiovascular disease are the most harmful at lags 10-17 days. This shows that the relationship between cardiovascular disease and temperature is nonlinear with increased prevalence at both extremes. In addition, the authors ran correlations for hospital admissions and three air pollutants and found that cardiovascular hospital admissions were positively correlated with levels of SO₂, NO₂ and PM₁₀.
had a reinforcing effect, SO2 had a weakening effect, and PM10 did not have an effect at low temperatures. At high temperatures, all pollutants had a strengthening effect.

Zhang et al. (2018) studied mortality as a result of cardiovascular disease in relation to temperature under various future climate change scenarios, changes is population density, and possible adaptation. The study was conducted in Beijing, China using historical data obtained from the Chinese Center for Disease Control and Prevention on cardiovascular mortality between 2007 and 2008. To access future cardiovascular deaths due to temperature in two 20 years periods (2050 and 2070), the authors used future population-change scenarios (SSP1, SSP2 and SSP3), global circulation models, representative concentration pathways (RCP2.6, RCP4.5 and RCP8.5), and socioeconomic pathways. Generalized linear models and distributed-lag non-linear models were then applied to estimate mortality risk due to maximum daily temperature. Zhang et al. (2018) found that cardiovascular disease mortality due to temperature will increase under all scenarios but in varying amounts. Using 2007 and 2008 as the baseline, the authors found that under the three RCP scenarios examined, cardiovascular disease mortality could increase anywhere between 3.5% to 10.2%. When changes in population were also considered, the effect was up to fivefold greater. Specifically, for a combined scenario with RCP8.5 and SSP1, cardiovascular disease mortality would increase more than 60%, while under RCP8.5 and no population change, there would only be an increase of 6%. In addition, they found that adaptation to higher-temperatures could result in increased cold-related cardiovascular deaths and the increase would be larger than the decrease in heat-related cardiovascular deaths.
Basu & Ostro (2008) conducted a study in nine counties in California, USA with the aim to access heat-related mortality and vulnerable groups. The authors employed a time-stratified case-crossover approach using daily mortality data provided by the California Department of Health Services and meteorological data from the National Climatic Data Center. Mortality was categorized using the International Statistical Classification of Diseases and Related Health Problems and included subcategories of cardiovascular disease such as dysrhythmia, stroke and congestive heart failure. In addition, the authors accessed for respiratory comorbidities for deaths with cardiovascular disease as the primary cause including asthma, COPD and bronchitis. Basu & Ostro (2008) identified a total of 231,676 nonaccidental deaths between May 1\textsuperscript{st}, 1999 and September 30\textsuperscript{th}, 2003. Cardiovascular deaths constituted 41\%, respiratory constituted 9\%, cerebrovascular constituted 8\% and diabetes made up 3\%. The authors identified cardiovascular deaths to be significantly associated with temperature. Specifically, for every 10\(^\circ\)F increase in mean daily temperature, there was an increase of 2.6\% in cardiovascular mortality. Examining the specific subcategories, the authors found significant elevated risk for ischemic heart disease. No significant elevation in mortality was found for diabetes and cerebrovascular diseases. There was no elevation observed for stroke and respiratory diseases, however, sufficient data for mortality due to asthma and chronic bronchitis were not available.

Liao et al. (2010) conducted a study in Taiwan to identify the effects of changing climates on cardiovascular diseases and provide an estimated value for economic damage. Data for cardiovascular-related mortality was obtained from the Department of Health, Executive Yuan in Taiwan and data for climate variables was obtained from the
International Research Institute for Climate and Society. Data was compiled for the period between January of 1971 and December of 2006. A case study approach was used to access the effects of climate variables on cardiovascular mortality and a contingent valuation method was employed to evaluate the associated economic impacts. Liao et al. (2010) found that deaths due to cardiovascular disease increase by 0.226% for every 1% increase in temperature variation. The authors also found that deaths due to cardiovascular disease are expected to increase between 1.2% and 4.1% under different IPCSS climate change scenarios. Lastly, the authors found that deaths due to cardiovascular disease is more sensitive to colder temperatures. Therefore, they predict that if the number of cold days increases by 1%, percent of deaths due to cardiovascular disease will subsequently increase by 0.277%. The authors proceeded to evaluate the economic impacts of having a 1.2% to 4.1% increase in cardiovascular deaths due to climate change. They sent out surveys to residents in Taiwan between May 7th and May 25th of 2008 and analyzed 510 eligible samples. They found that a majority of participants either had cardiovascular diseases or knew someone in their family with them. They estimated the total economic damage from cardiovascular diseases due to climate change to be between 0.88 billion to 1.68 billion dollars per year for the whole country of Taiwan or $51 to $97.3 per person. Their survey revealed that residents of Taiwan would be willing to pay that amount in taxes in order to have them take action to reduce the risk.

Certain research studies have also aimed to identify some of the underlying mechanisms that affect the relationship between cardiovascular diseases and climate variables. As discussed previously in this review, mental health has been linked to
climate change. Mental health has also been linked to cardiovascular health where increased stress and worry alter blood pressure, heart rate variability, and pulse (Lanki et al., 2017; Peters et al., 1998; Pieper et al., 2007). It has also been found that high temperatures can lead to higher blood viscosity, higher serum cholesterol levels, increased red cell counts, dilated blood vessels, and increased cardiac output as blood flow shifts from vital organs towards the skin surfaces, putting additional stress on the cardiovascular system and leading to hypotension, dehydration, and impairment of vascular cells (Basu and Ostro, 2008; Cheng and Su, 2010; Keatinge et al., 1986; Michael and McGeehin, 2001; Nawrot et al., 2005; Yin and Wang, 2017). At low temperatures, increased platelet viscosity, vasoconstriction, hypertension, increased heart rate, blood and increased platelet fibrinogen have been observed (Cui et al., 2019; Kawahara et al., 1989; Keatinge et al., 1984; Zhang et al., 2014). Lastly, it has been identified that increased temperatures can indirectly affect cardiovascular diseases by increasing ozone and particulate matter formation, leading to impaired gas exchange, increased cardiac effort, inflammation, dysfunction of blood vessels and cardiac function, thrombosis, and even pulmonary embolisms (Baccarelli et al., 2008; Brook, 2008; Portier et al., 2013; Ren et al., 2008).

4.4.2 Effects of urban forests on cardiovascular health

Astell-Burt & Feng (2019) conducted a longitudinal study in Australia to investigate whether various types of urban green space, including tree canopy, were related to lower odds of heart disease, diabetes and hypertension. Diagnosed hypertension, heart disease and diabetes were determined in 46,786 participants.
Following, the researchers identified the odds of these outcomes in relation to green space using an established 1.6 km buffer. The authors found that odds of all three diseases were lower in participants who lived in areas with more than or equal to 30% tree canopy covered. Specifically, the odds of incident heart disease was 0.78, the odds of incident hypertension was 0.83, and the odds of incident diabetes was 0.69 in this group compared to those who had none to 9% tree canopy cover. The odds of prevalence heart disease was 0.85, the odds of hypertension was 0.87, and the odds of diabetes was 0.62 in this group compared to those who lived in an area with 0-9% tree canopy cover.)

Moreira et al. (2020) conducted a study in Sao Paula, Brazil with the aim of investigating the relationship between hypertension and three measures of green space: number of trees along the street, land cover/use and parks within a 1 km buffer. Participants aged 35 to 74 were selected for a longitudinal health study. Land cover classification was conducted using aerial photography. A logistic regression model was then applied to access the association between the three measures of green space and hypertension, adjusting for sociodemographic variables such as age and gender and cardiovascular risk factors such as smoking, diabetes and physical activity. Moreira et al. (2020) identified an inverse association between the quantity (number) of street trees and number of parks within 1 km and hypertension. Specifically, individuals who lived in areas that had more than one park within 1 km had a lower odds ratio for hypertension (0.87) and planting 10,000 additional trees would be associated with an odds ratio of 0.937. In addition, the authors found that proportion of constructed area was positively associated with hypertension (an odds ratio of 1.011). The authors did not find a
significant correlation for land cover classes and hypertension diagnosis when using a
300-meter buffer.

Lanki et al. (2017) examined short-term changes in cardiovascular health while
visiting urban green and built environments in Helsinki, Finland. To do this, the authors
recruited 36 adult female participants and had them visit an urban forest, the city center,
on an urban park in groups of four in random order. Visits lasted 45 minutes with 15
minutes devoted to viewing and 30 minutes to walking at a steady pace on a designated
route for 2 km. During the visits, researchers assessed the blood pressure and heart rate of
participants, recorded electrocardiograms using Holter-monitors, and monitored for noise
exposure and traffic-related air pollution. Prior to visits, researchers collected baseline
cardiovascular data and standardized energy levels by administering the same meal to
participants. Analysis of results was carried out using mixed models. The results of
viewing the environments and walking through them were evaluated separately. Lanki et
al. (2017) found that heart rate was lower when visiting urban green environments and
measures of heart rate variability (standard deviation of normal-to-normal intervals and
high frequency power) were higher compared to the city center environment. These
effects were found to be stronger for urban forests compared to urban parks. In addition,
the authors found that when viewing urban green environments, participants experienced
lower blood pressure in comparison to the city center environment. However, there was a
slight decline in the associations between cardiovascular health and urban green space
when air pollution and noise were included. PM10 was found to be positively associated
with blood pressure and pulse. Environmental noise was found to be associated with
decreased indexes of heart rate variability. These results indicate that urban green
environments have a beneficial short-term effect on cardiovascular health, however, the authors indicate the importance of also investigating longer-term benefits. In addition, they recommend conducting similar studies with other types of population groups.

As mentioned previously, Ulmer et al. (2016) conducted a study in Sacramento, California assessing the role of urban tree cover in human health. The conducted the study using pre-existing datasets collected through the California Health Interview Survey which was administered between 2001 and 2011. This survey contained self-reported information on physical activity, body weight, and physician diagnosed health conditions that was analyzed in a regression analysis with forest cover data. The authors found that more tree cover was significantly associated with higher odds (13% higher) of reporting a higher health score and they found a 7.4% reduction in high blood pressure.

Mao et al. (2012) conducted a study investigating the effects of forest bathing on high blood pressure. To do this, the authors recruited 24 elderly participants (aged 60 to 75) with hypertension, split them into two equal sized groups, and sent them to either a broad-leaf evergreen forest or to the city area of Hangzhou. All participants spent 7 days and 7 nights in their location from July 23rd, 2011 to July 30th, 2011. For all participants, mood evaluations were conducted, and blood pressure indicators and cardiovascular disease factors were detected using morning blood samples and blood pressure monitors. Some of these factors detected were renin, angiotensin II, homocysteine, inflammatory cytokines interleukin-6, and angiotensinogen. Blood serums were then analyzed using radioimmunoassay kits and enzyme-linked immunoassays. Each day participants would walk a predetermine course for 1.5 hours, rest and eat lunch, and walk 1.5 hours back. Mao et al. (2012) found a reduction in blood pressure (both systolic and diastolic), bio-
indicators (endothelin-1, homocysteine, angiotensinogen, angiotensin II and angiotensin I), and negative subscales of mood (anger, depression, fatigue, and confusion) to be lower in participants who were exposed to the forest environment in relation to those exposed to the city environment and baseline conditions. Heart rate was not affected in either of the groups. Therefore, while the sample size is small, there results demonstrate how there could be a significant reduction in high blood pressure from short-term forest bathing. The authors recommend conducting similar studies on larger samples and in different times of the year.

4.5 Heat Related Morbidity and Mortality

The Center for Disease Control defines heat-related illness as a condition that occurs when the body is exposed to extreme heat and is unable to cool (CDC, n.d.). Some of the symptoms that are experienced include fatigue, headaches, nausea, dizziness, fainting, and muscle cramps (CDC, n.d.). Usually, the body as able to rid of body heat through sweat, but when climate conditions are less than optimal, thermoregulatory processes are halted (CDC, n.d.). If heat exhaustion is not treated immediately heat stroke, a life-threatening condition, may occur leading to high body temperatures, elevated pulses, confusion, and unconsciousness (CDC, n.d.). At high body temperatures, vital organs begin to malfunction or become damaged which can lead to organ failure and death (CDC, n.d.). In areas like the midwestern and northeastern United States the temperatures are typically relatively cool and, therefore, many buildings are not equipped with adequate cooling systems (CDC, n.d.). However, the length and intensity of heat waves is increasing (Graczyk et al., 2019; Li et al., 2018). Therefore, when temperatures
surpass what the population is accustomed too or is able to manage, the risk for heat-related illnesses increases (CDC, n.d.). Air conditioning systems are currently considered the number one preventative strategy against heat-related illness (CDC, n.d.). However, not all people of a community have adequate or equal access to air conditioning, posing a challenge for community leaders to implement strategies that could provide safe spaces for residents during stressed weather conditions (Kawachi & Subramanian, 2014) This section will focus on empirical evidence for heat-related illness and urban trees as a potential mitigation strategy (Figure 4.6).

**Figure 4.6:** Framework to be used by communities depicting 1: possible climate pathways affecting heat-related morbidity and mortality, 2: urban tree and forest mitigation potential, and 3: recommendations for urban and medical communities. References for the information going into developing this framework are described extensively in the “impact of climate on morbidity and mortality” and the “protective effects of urban forests on morbidity and mortality” sections.

### 4.5.1 Impacts of climate on morbidity and mortality
Huber et al. (2020) executed a study in 12 German cities investigating excess mortality as related to climate under different future climate variables. They employed a time-series quasi-Poisson regression with distributed-lag non-linear models using mortality data from German research data centers and average daily temperatures from a German meteorological center. Data was obtained between January of 1993 and December of 2015. Future climate projections were obtained from the second phase of the Inter-Sectoral Impact Model Intercomparison Project. For 4 general circulation models, the authors investigated 4 climate-change scenarios for the periods between 2006 and 2099 (RCP2.6, RCP4.5, RCP6.0, and RCP8.5). The authors also conducted a multivariate meta-regression to determine the most optimal linear unbiased predictors. Huber et al. (2020) found that residence of the 12 German cities can expect an increase in mortality due to temperature for global warming above 2°C. For the period of 1993-2015 a higher percentage of excess mortality was attributed to cold temperatures (5.49%) opposed to high temperatures (0.81%), however, this relationship can be reversed for global warming above 3°C where heat is expected to contribute to more deaths. Global warming above 4°C is expected to have a five-fold increase in mortality due to high temperatures. For global warming of 5°C, excess mortality as a result of temperatures are expected to rise to 9.02%, where hot temperatures contribute excess mortality of 5.75%. In addition, they found that the effects of cold was greatest a couple days after exposure and could last up to 3 weeks, however, the effect from heat occurred at exposure and lasted only a couple days.

Graczyk et al. (2019) conducted a study in 10 Polish cities with the aim of estimating the effect of historical heat waves (1992, 1994, 2006 and 2010) on mortality of
city inhabitants and two risk groups: the elderly (65 years of age or older) and those with cardiovascular deficiencies. Data on mortality for the time period of 1989-2012 was obtained from the Central Statistical Office of Poland. For each of the heat waves, reference periods were established and 7-day moving averages were calculated. Graczyk et al. (2019) found that in some cities, the number of deaths due to heat waves was more than three times the mortality of the corresponding reference period. However, they found that summer was not actually the season with the highest deaths in the 10 cities. The greatest mortality occurred during the winter months and this was true also for the two risk groups accessed. Only during the historic heat waves were the mortality rates in the summer and winter months similar. For some heat waves, summer mortality was higher than winter mortality. During the main heat wave of 1992, the mortality rate was 150% the expected. Those with cardiovascular diseases saw an increase of almost 200% in mortality rate. For the main heat wave event of 1994, the mortality rate increased 63-168% across cities. For those with cardiovascular diseases, the mortality rate was 205-232% the expected. Highest of all was found for the age group 65+ where mortality was 330-431% the expected. For the summer of 2006, the highest increase in mortality ranged from 33% to 115% for the whole population, 55% to 220% for the cardiovascular risk group, and 41% to 134% for the elder risk group. Lastly, for the summer of 2010, the maximum mortality rate ranged from 26% to 142% for the population, 40% to 105% for the cardiovascular risk group, and 24% to 162% for the elder risk group. Overall, the highest increase in mortality occurred when maximum temperatures exceeded 35°C and heat wave lasted more than 4 weeks.
Li et al. (2018) conducted a study in China examining heat-related mortality in 51 urban areas under different future climate change scenarios. Representative Concentration Pathways 2.6, 4.5, and 8.5 were utilized in a damage function approach to quantify mortality due to heat in the 2050s and 2070s. Li et al. (2018) found that mid-century excess heat-related mortality is expected to be 37,800 under RCP8.5, 31,700 under RCP4.5, and 25,100 under RCP2.6 relative to 1970-2000.

Ragettli et al. (2017) investigated the association between extreme heat conditions and mortality in Switzerland. Eight Swiss cities were identified, the time period was identified 1995-2013, and subgroups were selected. Mortality data was obtained from the Federal Office of Statistics and meteorological data was obtained from a meteorology and climatology Federal office. Maximum daily apparent temperature was used as the primary measure of temperature, but maximum, minimum and mean daily temperatures were also investigated. To access the association between extreme heat conditions and mortality, the authors used a quasi-Poisson regression models implemented with non-linear distributed lag functions. Relative risks were generated for temperature increases for the median value to the 98th percentile. In addition, the authors investigated whether recent changes in public health interventions and public awareness affected the mortality risks for 2004-2013 compared to 1995-2002. Ragettli et al. (2017) found that mortality risks were highest during the initial heat waves. They also found significant relative risks for all temperature measures. The relative risk for temperature-mortality using maximum daily apparent temperature was 1.12. The relative risks for temperature-mortality using maximum, mean and minimum daily temperatures were 1.15, 1.16, and 1.23, respectively. In addition, they found a non-significant reduction in heat-related deaths for
the 2004-2013 period compared to the 1995-2002 period due to the implementation of heat warning systems. Lastly, the authors found that mortality risk increased rapidly once temperatures exceeded 31°C and was highest on the day of exposure, especially for the daily minimum temperature.

Anderson & Bell (2011) conducted a study in the United States investigating the association between heat waves (their intensity, duration and timing) and mortality risk in 43 cities between 1987 and 2005. For this study, Anderson & Bell (2011) defined heat waves as temperature above or equal to the 95th percentile that last for 2 days or more. For each city, the authors used generalized linear models to calculate mortality risk for each heat wave event, comparing to the mortality risk on days that were not characterized as a heat wave. The also used Bayesian hierarchical modeling to estimate effects at larger scales. Non-accidental mortality data was obtained from a national data set containing data on morbidity, mortality as well as air pollution. Anderson & Bell (2011) found that at a national level, waves of heat resulted in higher mortality (3.74%) compared to days not classified as heat waves. Investigating how duration and intensity of a heat wave affect mortality risk, Anderson & Bell (2011) found that mortality risk increases about 2.5% and 0.38% for every 1°F increase in intensity and every additional day increase in duration, respectively. In addition, they found that the initial heat wave of the summer season had the greatest impact of heat related mortality similarly to Ragettli et al. (2017). These results show not only that there is a positive association between mortality risk and temperature, but also identifies intensity and duration as factors affecting the strength of this association. Lastly, Anderson & Bell (2011) mention that they do not include air pollution in their model because a previous study conducted by the authors which served
a foundation for this study demonstrated that temperature effects on populations in the US are robust to air pollution.

Gasparrini et al. (2015) accessed the effects of low and high temperatures on mortality for 384 locations worldwide. For each location, a time-series Poisson model was fitted and the association between temperature and death was estimated using a distributed lag non-linear model. Data was pooled for a multivariate meta-regression. Gasparrini et al. (2015) found that on average temperature-related mortality constituted 7.71% of all deaths with a wide variation across countries (lowest observed in Thailand of 3.37% and highest observed in China of 11%). In addition, they found that mortality due to cold temperatures was higher than heat-related mortality. Cold-related mortality constituted 7.29% of temperature-related deaths and heat-related mortality constituted 0.42% of temperature-related deaths. Generally, for cold temperatures, the risk of mortality increased linearly for temperatures that fell below the minimum mortality temperature. For heat temperatures, however, a non-linear relationship was observed. Lastly, Gasparrini et al. (2015) found that extreme temperature conditions were responsible only for 0.86% of mortality and the majority of the effect of temperature on mortality was a result of non-optimal but milder temperatures.

Some research studies have aimed to identify some of the underlying mechanisms of heat-related morbidity and mortality. It is found that heatwaves directly kill people by inducing heat stroke, myocardial infarctions, dehydration, fatigue and even respiratory failure (McMichael & Lindgren, 2011). This is because more cardiovascular effort is required to maintain normal body temperature during heat waves (Anderson & Bell, 2011).
4.5.2 Protective effects of urban forests on morbidity and mortality

Chen et al. (2014) investigated reduction in heat-associated mortality via urban vegetation in Melbourne, Australia. First the authors used a meso-scale urban climate model to assess the effects of various vegetation layouts on climate in 2009, 2030 and 2050. The vegetation schemes consisted of forest, shrub-land, grassland, urban leafy, urban generic, and five variations for the Central Business District (CBD). Then the authors used a building simulation tool, AccuRate, to simulate indoor thermal performance for five local residential buildings. Lastly, using mortality data from 1988 through 2007, the authors estimated reduction in heat-related mortality. Chen et al. (2014) found a reduction of 0.5 and 2.0 °C in average summer temperatures for vegetative suburbs and parklands, respectively. For the CBD areas, the authors found that a 2°C reduction in temperature could be achieved through transforming the area to a forest park land. When investigating the indoor thermal performance of residential buildings, the authors found a fast-growing mortality rate when average indoor temperatures exceeded 28.5°C. Overall, the authors found that increasing vegetation cover, especially forest cover, causes a reduction in excess mortality rate. For example, transforming the CBD area to a forest scheme can reduce excess mortality by 37-99%.

Murage et al. (2020) examined the impacts of urban vegetation, socioeconomic variables, demographics, health status, and housing on heat-related mortality in London. Data on mortality were obtained from the Office for National Statistics for the months of May through September between 2007 and 2016. These 185,397 records were then linked to daily temperatures and land-use and a conditional logistic regression was applied to estimated odds of death. Murage et al. (2020) found that temperatures were highest in
neighborhoods that had less urban vegetation, rented homes, lower income, and non-native speakers. Out of all of these variables, vegetation cover had the greatest effect on heat-related mortality while the socioeconomic factors did not have a significant modifying effect. Specifically, in the quartile with the highest tree cover the odds ratio was 1.033, while in the quartile with the lowest tree cover, the odds ratio was 1.043. The land-use category with the highest odds ratio was areas containing ports and airports. Therefore, these results show that land use characteristics and level of urban vegetation can modify heat-related mortality.

Graham et al. (2016) explored incidence of heat-related morbidity in relation to canopy cover in 544 neighborhoods in Toronto, Canada. To do this, Graham et al. (2016) selected four extreme heat events that occurred between 2001 and 2011 and obtain mean air temperature data. The authors compiled ambulance dispatch data from the Toronto Emergency Medical Services and projected the coordinates of the calls in a geographic information system. Tree canopy data was obtained from a Toronto land cover raster. One-way ANOVA with Tukey’s post hoc analysis was used to examine inter-group differences. Then, statistical and graphical interpretation methods were applied. Graham et al. (2016) found that in general heat-related ambulance calls increased by 12.3% during extreme heat events. They also found that ambulance calls due to extreme heat events were negatively associated with canopy cover but positively associated with impervious cover. Specifically, neighborhoods with less than five percent of tree canopy cover had five times the amount of ambulance calls than neighborhoods with more than five percent tree canopy cover and 15 times the amount of ambulance calls than neighborhoods with more than seventy percent tree canopy cover. Therefore, these
results demonstrate how even a small increase in canopy cover from less than 5% to more than 5% can reduce heat-related emergency calls by approximately 80%.

Declet-Barreto et al. (2016) investigated the role of vegetation in reducing temperatures in Cleveland, Ohio. Tree canopy data was obtained from a local planning commission and geographically weighted regression were run using land surface temperature for 12 differently daytime Landsat Thematic Mapper scenes in 2009, 2010 and 2011 for the months between May and October. Declet-Barreto et al. (2016) found that land surface temperature can be reduced anywhere from 0.5°C to 6.4°C between May and October with increasing tree canopy cover. The authors identify not using vegetation configuration and composition in their models as a limitation because both can affect the temperature reduction potential.

In Phoenix, Arizona, Middel et al. 2015 studied the cooling effect of urban trees in tree planting scenarios ranging from absence of trees to 30% tree canopy cover. To investigate the effect of urban forests on air temperatures in all eight tree planting scenarios, they used a microclimate model called ENVI-met and found a linear relationship between tree canopy and cooling potential: 0.14°C cooling of air temperature for every 1 percent increase in tree canopy. They also found that a 15% increase (from 10% canopy cover to 25% canopy cover) for the city of Phoenix would result in a 2.0°C decrease in air temperatures. Therefore, the authors strongly recommend using tree cover to mitigate local effects of climate change in cities, and having urban trees become integrated in mitigation policies and strategies. In addition, they recommend further research being done on the implications of implementing trees in local communities.
Ziter et al. (2019) investigated how tree canopy cover in the Upper Midwest United States can affect air temperatures (daytime and nighttime) in the summer months of the Northern Hemisphere. They did this by measuring air temperature at 5-meter increments and one second intervals for 10 seven kilometer transects in Madison, Wisconsin. They did this using two bicycle-mounted temperature sensors. In addition, they determined canopy cover and impervious cover using derived and custom raster layers. Lastly, using generalized additive models they evaluated the relationship between land cover and air temperatures and found that daytime air temperatures decreased nonlinearly with increasing tree coverage and varied by 3.5°C. In addition, they found that the greatest cooling effect occurred when tree coverage exceeded 40% of the city. Ziter et al., (2019) also found that nighttime air temperatures varied an average of 2.1°C. For this relationship, they found that temperature increased as a function of impervious land cover. Therefore, the authors recommend that climate change mitigation strategies include modifications to urban vegetation and impervious surfaces. In addition, they strongly encourage the implementation of at least 40% canopy cover into urban neighborhoods.

Akbari et al. (2001) investigated the benefits and the economic returns from urban heat island mitigation by urban trees and other cool surfaces in Los Angeles, CA. To do this, the authors used a combination of DOE-2 building-energy simulations, and mesoscale meteorological and photochemical models such as CSUMM and UAM. Their findings showed that urban trees provided substantial savings. Specifically, trees in Los Angeles account for net savings of $270M with $58M due to their cooling potential and shading ability. In addition, the authors made estimates for urban areas in all of the
United States and found that mitigation of heat islands in urban areas using either urban trees, cool roofs or cool pavements can reduce air conditioning energy use by 20%, saving the nation $10 billion per year. Therefore, the authors strongly encourage applying for and receiving financial support from different members of federal, state and local communities in order to develop programs that plant more trees with the aim of mitigating the urban heat island effect and extracting economic benefits.

Lastly, Duncan et al. (2019) conducted a study in the Perth and Peel Metropolitan Regions of Australia with the aim of assessing how urban vegetation type, coverage and configuration affects the city’s temperature. They used a land surface temperature product from a Moderate Resolution Imaging Spectroradiometer sensor and data for vegetation height extracted from an Urban Monitor dataset collected via aerial photo-imaging. To measure vegetative coverage, they used Landsat NDVI data. Precipitation data was generated using the Climate Hazards Group InfraRed Precipitation with Station data. Using all this information, the authors performed several regression analysis and Random Forests learning models to explore the relationships between the variables. Their results show that tree and shrub cover provide a stronger cooling effect and this effect is stronger than that of grass cover. They find that a 1 km² increase in tree or shrub cover has the potential to reduce land surface temperatures by 5°C and 12°C respectively. Lastly, they identified that vegetative cover can explain 31.84% of variance in summer land surface temperatures and when tree and shrub cover were removed from the analysis, there was an 89% and 98% reduction in temperature prediction accuracy, respectively. Therefore, the authors strongly recommend that researchers examine the complexity of urban landscapes and how they interact with the atmosphere to decrease
temperature in order to have more focused urban planning in relation to changing climate
and vegetative strategies.

4.5 Prevalence of Skin Cancer

Skin is our biggest organ serving to protect our inner body from chemicals and
ultraviolet radiation, providing thermoregulation, synthesizing vitamin D, and enabling us
to sense our environment (Iqbal et al., 2019). In the deeper layers of our skin,
melanocytes produce melanin which plays an important role in producing pigment and
protecting the body from harmful ultraviolet radiation (Konstantakou et al., 2018;
Vaverkova et al., 2020). While some exposure to ultraviolet radiation has a beneficial
effect on the body by enhancing production of Vitamin D, too much ultraviolet radiation
can lead to skin damage (Reichrath, 2007; Vaverkova et al., 2020). In fact, exposure to
sun and a history of sunburns serve as predisposition factors for developing skin cancer
(WHO, n.d.). Approximately one third of all cancers are diagnosed as skin cancers each
year (WHO, n.d.). The World Health organization reports that there is an average of 2 to
3 million non-melanoma related cancers of the skin yearly throughout the world as well
as over 130,000 melanoma skin cancers (WHO, n.d.). Research shows that increasing
temperatures and higher levels of ultraviolet radiation can accelerate skin cancer
carcinogenesis (Lin et al., 2019). Therefore, as temperatures continue to rise and
stratospheric ozone is depleted, the incidence of skin cancer is expected to continue to
increase (Chiabai et al., 2018; Vaverkova et al., 2020; WHO). In order for people to
safely spend more time outdoors under changing climate and atmospheric conditions,
community leaders are faced with the challenging of providing protection to their
residents as they engage in what their communities have to offer. Recent studies show that trees absorb 91-95% of ultraviolet radiation, reflect about 5-9%, and transmit less than 1% and can serve as important mitigation strategies in communities (Qi et al., 2010). Therefore, this section will focus on exploring the influence of climate change on skin cancer prevalence and the mitigation potential of urban trees (Figure 4.7).

Figure 4.7: Framework to be used by communities depicting 1: possible climate pathways affecting the prevalence of skin cancer, 2: urban tree and forest mitigation potential, and 3: recommendations for urban and medical communities. References for the information going into developing the framework are described extensively in the “impact of climate change on the prevalence of skin cancer” and the “effects of urban forests on skin cancer” sections.

4.5.1 Impact of climate on the prevalence of skin cancer

Vaverkova et al. (2020) analyzed the influence of environmental changes on behavior and skin diseases in Brno, Czech Republic. Vaverkova et al. (2010) recruited 1757 participants between the ages of 25 and 65 and interviewed them on their medical history, occupation and lifestyle. The authors performed their analysis based on climate data (average monthly temperatures, number of sunny days and their length, annual
temperatures and UV index values) for the years 2011 through 2019. Vaverkova et al. (2020) found that incidence of skin disease increased during the study period and the main contributors to this effect included exposure to the sun, change in the average age of the population, behavioral patterns, migration, changes in climate, and ozone depletion.

Calapre et al. (2016) examined the effects of heat stress and ultraviolet radiation on primary keratinocyte cultures in cell lines and skin models. Adult epidermal keratinocyte cells were cultured in vitro and twelve NativeSkin models were created from non-exposed skin as controls. Ultraviolet radiation was administered to the adult epidermal keratinocyte cells in a cabinet containing a TL20W/01 RS SLV Narrowband UVB lamp and heat stress was induced in an incubator where a temperature of 39°C was maintained for three hours. To assess for apoptosis or proliferations, immunocytochemistry analyses were conducted. The skin model experiments were not exposed to ultraviolet radiation or heat stress and were considered controls. Lastly, ex vivo gene expression analysis was conducted on isolated RNA and a two-way ANOVA and parametric unpaired t-tests were performed. The authors found persistent DNA damage and reduced apoptosis in keratinocytes exposed to ultraviolet radiation and heat stress. Specifically, they found that keratinocytes exposed to ultraviolet radiation and heat stress had an inactivated p53-mediated stress response, a decrease in acetylated p53, and increased SIRT1 expression.

Kimeswenger et al. (2016) conducted a study investigating how infrared radiation A impacts ultraviolet radiation induced apoptosis as well as DNA repair in melanocyte cells. Human melanocyte cells were obtained from three neonatal donors and exposed to water-filtered infrared radiation A or ultraviolet radiation B. Cell death detection was
performed by a cell death detection ELISA kit and DNA repair was evaluated using a southwestern slot-blot analysis and a shuttle vector assay. Protein expression and activity were assessed using a FC500 flow cytometer. Kimeswenger et al. (2016) found that infrared radiation promoted the survival of cells that carry DNA damage from ultraviolet radiation exposure.

Some research studies have aimed to identify some of the underlying mechanisms affecting the relationship between skin cancer and climate change. While the relationship is still largely unclear, Calapre et al., 2016 found that ultraviolet radiation causes a lessening of heat-mediated apoptosis in keratinocyte cells and a reduction in p53-mediated cell cycle arrest. This causes more damaged cells to survive. Another explanation is that warmer climates have encouraged people to spend more time outdoors, usually with less clothing, and thereby, increase their exposure to ultraviolet radiation (Makin, 2011; Parker, 2020). Lastly, there is a complex relationship between pollutants like volatile organic compounds and ozone on dermal health (Balakrishnan et al., 2015; IARC, 2018; Parker, 2020). These pollutants can penetrate tissues and become absorbed, potentially influencing cutaneous carcinogenesis (Balakrishnan et al., 2015; IARC, 2018; Parker, 2020).

4.5.2 Effects of urban forests on skin cancer

Na et al. (2014) conducted a study in Seoul, Korea with the aim of developing a mathematical model in i-Tree to model the impacts of urban trees on mitigating Ultra-Violet rays and reducing exposure. Data sets for canopy, the Ultra-Violet index, solar zenith angle and hourly cloud cover were obtained and combined with multivariate equations derived from Grant and Heisler (2006). Vegetation data was obtained from a
random sampling of plots in the city and imported into the i-Tree Eco model. UV index was obtained from the Tropospheric Emission Monitoring Internet Service project. Solar zenith angle was calculated for each day at 12:30 pm. Cloud cover was obtained each day at noon as well. Using the equations, the authors predicted UV radiation reductions due to urban trees between May 1st 2010 and August 31st 2010. Na et al. (2014) found that trees produced up to 11.8 UV protection factors (UPF) in the park and cemetery where the quantity of canopy was observed to be the highest. This occurred on a day when the sky was clear and the Ultra-Violet index was 7.2. The average UPF in the park and cemetery land uses was 8.3. The second highest average UPF was observed for vacant and agricultural land uses (7.9). The lowest average UPF was obtained for commercial and transportation land uses (3.0) where the percent canopy is lowest. The lowest UPF value was obtained for commercial and transportation land uses (1.7) on a day with overcast cloud cover and a UV index of 2.6. Residential/multifamily land uses and institutional land uses had an average UPF of 3.4 and 3.2, respectively.

Kumakura et al. (2013) investigated the role of five deciduous tree species in solar shading in Tokyo, Japan. The deciduous tree species that were selected for this study were Platanus acarifolia, Ginkgo biloba, Zelkova serrate, Prunus yedoensis and Liquidambar styraciflua. The authors used an already developed numerical simulation tool to model and predict UV-B levels (through UV-B scalar illuminance), mean radiation temperature, and surface temperatures in the shade for all five deciduous tree species in the summer and winter seasons. Kumakura et al. (2013) found that there was a maximum difference of 5°C in the summer and 10°C in the winter in surface temperatures across the species. The authors note that differences in mean radiation temperature were
due to the way solar radiation was transmitted through the tree crowns. *L. styraciflu* had the smallest mean radiation temperature distribution (35°C) in the summer due to its large crown compared to *G. biloba* which had the highest mean radiation temperature distribution (40°C). The UV-B scalar illuminance varied across the species by as much as a factor of two. The species *P. yedoensis*, despite having a smaller crown size, had the lowest UV-B scalar illuminances due to the crown shape (round and flat) that enabled it to block reflected and sky UV-B radiation. On the other hand, *Z. serrate* was not as effective in blocking sky UV-B radiation due to its wedged crown shape and had two times the UV-B scalar illuminance. Lastly, UV-B scalar illuminance was found to be lowest in the winter months.

4.6 Conclusion

4.6.1 Recommendations for the medical community

4.6.1.1 Preventative care and patient education

Patient education should be prioritized. Wang et al. (2014) mention that many patients may not be aware of extreme temperatures and climate variables as risk factors for their condition. Therefore, patient education should focus on reducing exposure in order to lower risk of hospitalization and should be implemented in outpatient care programs. Similarly, Li et al. (2014) stress the importance of designing training programs based on the recommendations of Menne & Matthies (2009) that allow families to become familiar with and be able to identify heat-related health problems, as well as understand available treatments.

Patient education should also incorporate seasonal variability in order to assist patients in better managing and understanding times at which they are at highest risk. For
example, Buckley & Richardson (2012) found seasonal variability for adult asthma admissions. Similarly, Nowak et al. (2019) found that the greatest effect of urban forests on the removal of $O_3$, $SO_2$, and $NO_2$ was during the in-leaf season, specifically during the day, when trees transpire water. $PM_{2.5}$ removal was found to occur all year long and CO removal was found to occur all year but at lower rates (Nowak et al., 2019). These results demonstrate the importance of considering seasonal variation in policy making and health recommendations for asthma management.

4.6.1.2 Resource distribution and preparedness planning

Yin & Wang (2017) stress the importance of creating more accurate standards for extreme weather alerts such as heat waves. Early warning systems enable hospitals to have the opportunity to prepare for patient fluxes and allocate their resources more optimally. For example, the authors put forward a new proposal for alerting the public for the region of Beijing, China (Yin & Wang, 2017). They propose having governments issue heat alerts and medical facilities prepare for increased demand on medical services when temperatures exceeding $35^\circ C$ reach 4 days, or when temperatures exceeding $32^\circ C$, $33^\circ C$, or $34^\circ C$ reach 5 days. Some of the resources that are expected to be of increased demand during heat waves are hospital beds, oxygen therapy, and intravenous fluids (Yin & Wang, 2017). Currently many warning systems deliver very general messages and last for a short time only (Graczyk et al., 2019). Therefore, having early detection and warning systems to alert the public and healthcare teams of potential risks and understanding which medical resources will be of greatest need, can help communities better prepare and intervene during extreme weather events. Rgettli et al. (2017) recommend that warning systems take into account high minimum temperatures along
with maximum temperatures and pay particular attention to initial heat events of the summer when there is increased risk for heat related morbidity and mortality.

4.6.1.3 Healthcare worker education and relief

Clinicians and public health workers are on the front lines of climate-change induced illness, diseases and disasters. Preparedness planning must include resources and education for these workers (Lee et al., 2018). Staff of the medical community must be equipped with de-escalating hospital procedures, continued education opportunities focusing on understanding these issues and the stresses that can be associated with managing and treating patients of this nature, and hospital rules that provide relief to staff during expected peaks. Willox et al. (2013) found that increased impacts of climate change on the health of the community has negative implications for health care workers by exposing them to intensified working conditions, causing over-worked clinicians. This affects their ability to manage their own health, and therefore, be key players in building resilience to climate change impacts on health. Therefore, it is critical to not only put in place resources and regulations that protect patients, but also for those who take care of patients in the first place.

Similarly, education about climate-induced illness and diseases should be incorporated into healthcare worker programs. Medical and Nursing curriculums should incorporate climate education with a focus in climate-induced illnesses. Climate contexts should be introduced through patient simulations and case studies. Students should be able to become familiar with the interactions between the environment, human health and climate change at an early stage to be able to identify vulnerable populations, fill gaps in their communities, and be involved in interprofessional education teaming up with urban
planners, epidemiologist, and other disciplines to understand the resources available for patients. In addition, students should become familiar with climate as a risk factor for numerous diseases and should have a deep understanding of the pathways that affect patient outcomes in order to make appropriate recommendations to patients.

4.6.2 Recommendations for urban design and urban forestry

4.6.2.1 Restorative programs

In a study conducted by Lee et al. (2019), participants who participated in an urban forest therapy program at first reported the forest environment as strange and unfamiliar. The authors cite unfamiliarity as the reason why individuals who might have full access to urban forests many not engage with them. Therefore, it is important to develop urban forestry health programs for individual to participate in and have the opportunity to learn about and extract health benefits of urban forests. Cities should aim to send out information to residents regarding available urban forestry health programs through mail or email and encourage them to use, support and participate in their local urban forests and parks.

4.6.2.2 Urban designs

Moreira et al., (2020) found that even in communities with low densities of green space that was irregularly distributed, there were reductions in climate-induced complications such as hypertension. Urban parks and forests can be controlled to some extent to include tree features that can have mitigating effects on climate-induced health complications (Zhou et al., 2019). Urban parks and forests should be designed to include tree species that are low emitters of volatile organic compounds and aeroallergens, but
that also have structures that are perceived as restorative (Nowak et al., 2018; Tomao et al., 2018). Guan et al. (2017) identify stem density and color of tree species as factors that influence anxiety alleviation in urban parks and forests. For example, they propose that one possible reason birch trees alleviate more measure of anxiety than maple and oak is because their stem density tends to be lower which might allow more sunlight to pass through the tree canopy and increase white-color perception. White is a color that has been identified to reduce anxiety in mice (Sherwin & Glen 2003). Lanki et al. (2017) found that environmental noise such as traffic can affect the beneficial relationship between urban forests and parks and cardiovascular health. Similarly, Hauru et al. (2012) identified the urban forests have a greater restorative effect if they close off the view to urbanized settings. However, these factors need to be considered in combination with the energy requirements, water demands, and maintenance needs of trees in order to build sustainable designs (Nowak et al., 2018). Nowak et al. (2018) recommend incorporating evergreen species into urban forest designs for leaf off seasons and using trees with large total leaf area and water use for in leaf seasons.

Chen et al. (2019) recommend that adaptive strategies consider all potential impacts of temperature. Similarly, it is important to consider city characteristics and population attributes when establishing adaptive strategies. This would allow urban planners and urban forestry programs to begin to assess optimal designs for urban forests and urban parks to extract co-benefits. For example, Lai & Kontokosta (2019) conclude from their study that effects of urban trees of asthma rates vary by level of city air pollution. Similarly, Nowak et al. (2018) find that the amount of health benefits that be extracted from pollution removal by urban forests depends on the local environment.
characteristics and population attributes that tend to vary across cities. Specifically, Nowak et al. (2018) find that pollution removal is greatest at high pollutant concentrations, large amount of canopy cover, increased growing season, increased precipitation levels leading to more dry deposition, higher percent evergreen leaf area that increases removal in leaf-off seasons, and other meteorological factors that increase deposition velocities. Health benefits that can be extracted depends on local atmospheric mixing, pollutant concentrations, and population size (Nowak et al., 2018). This shows the importance of considering multiple city variables and co-interactions of climatic and environmental factors in urban planning and policymaking. Similarly, in a study published the following year, Nowak et al., (2019) found that that trees can increase pollution rates if they trap pollutants beneath the canopy, if there is less wind limiting the dispersion, and if there is lower atmospheric mixing due to less winds. For example, spending time in forested areas near roadways could limit health benefits due to reduced dispersion of car pollutants. Therefore, Nowak et al. (2019) identify local environmental conditions and their effects on dispersion, as well as understanding where communities spend their time are important factors to consider when determining health benefits. Urban forest designs should aim to maximize the space between people and roadways and consider potential co-benefits to extract maximum health benefits from urban forests (Nowak et al., 2019). However, Murage et al. (2020) identify that urban designers will need to overcome the challenge of meeting the needs of increasing populations while not compromising health of residents.

4.6.2.3 Occupational, educational and residential environments
Murage et al. (2020) identify that there is disproportional excess heat-related mortality among those with high indoor temperatures. Therefore, making improvements to residential buildings and occupational environments to reduce indoor heat exposure should also be prioritized by city planners. One of the strategies proposed by Murage et al. (2020) is to design buildings with shutters. Another strategy to consider is to plant street trees that provide shading and cooling effects and can help reduce air and surface temperatures and thermoregulate buildings (Middel et al., 2015; Ziter et al., 2019). Establishing street trees in existing neighborhoods would require cooperation from residents of those neighborhoods. Therefore, tree planting programs should aim to advertise the benefits of planting street trees by providing residents with statistics for potential savings for cooling demands and savings due to healthcare related costs.

4.6.2.4 Spatial tools

Lai & Kontokosta (2019) find that there are substantial neighborhood health disparities and risk factor differ on a local basis depending on their access to resources and quality healthcare. They recommend generating a mapping dashboard as well as a location-based mobile app that can be used by and inform residents. Making this information readily available can help residents of local neighborhoods understand the ecology of the area they live in and be able to make better decision to manage their underlying conditions. They stress the importance of many disciplines working together to generate this form of accessible data including city planners, experts of the filed, data scientists, and communities themselves.

4.6.3 Identifying vulnerable populations
Adaptation and mitigation strategies should especially target vulnerable populations, ensuring them access to educational resources, preventative measures, restorative programs, and information they may need to understand climate-induced illnesses and how to manage them because not all groups are affected equally. Issues of racial and socioeconomic disparities, as well as environmental justice are prominent issues that affect the relationship between climate change and illness (Basu & Ostro, 2008). They should be prioritized in future climate change research in addition to the following identified vulnerable populations for the five health categories discussed in this review:

1. Climate change impacts on mental health are most prominent in women, adults over the age of 46-60, children and young adolescents between the age of 0 and 14 years of age, and individuals of low socioeconomic status (Noelke et al., 2016; Obradovich et al., 2018; Tesler et al., 2018; Wang et al., 2014).

2. Pediatric patients, especially male youth, have been found to be the most vulnerable population for climate-influenced asthma (Li et al., 2014; Miami and Muhyi, 2019; Xu et al., 2013).

3. It is found that age is the most common risk factor for cardiovascular disease (Lanki et al., 2017). Specifically, Cui et al. (2019) find that males under the age of 65 are at highest risk for cardiovascular dysfunction at low temperatures, while women over the age of 65 are at highest risk at high temperatures.

4. Three main risk factors have been identified for heat related morbidity and mortality: age, gender, and pre-existing conditions (Basu and Ostro, 2008; Cadot et al., 2007; Graczyk et al., 2019; Ragettli et al., 2017). Basu and Ostro (2008)
found that those over the age of 65 or under the age of 1, as well as those with cardiovascular diseases are the most vulnerable subpopulations. Similarly, Graczyk et al. (2019) identify cardiovascular deficiencies and older age as risk factors. Gender differences were noted by Ragettli et al. (2017) and Murage et al. (2020) with woman over the age of 74 being at considerably higher risk than the average population.

5. Lastly, those with elevated sun exposure, a history of sunburns, and fair skin are considered among the most vulnerable for developing skin cancer (WHO, n.d.).

Understanding vulnerable populations can help identify risk areas in communities that would benefit from planting urban trees. For example, streets by nursing homes and primary and secondary educational facilities could be important areas to start. It would be important for leaders of these facilities to provide opportunities for recreational activities outdoors such as offering young scholars regular fieldtrips to urban parks and offering nursing home residents opportunities to eat meals outside with other residents or offer nature walking as an elective activity. Education curriculums could also incorporate integrated coursework branching health and the physical sciences. Students should be provided not only the opportunity to learn about health, climate change and the environment as separate entities, but also as an interconnected web that would enable them to make healthier decisions and understand their own potential impacts in helping mitigate climate change.

4.6.4 Future research needs

Future studies should aim to bridge the relationships between health, climate change, and the environment at local, regional and national scales investigating varying
populations, geographic conditions and climates. This review depicts that there still remain gaps in our understanding of how all three of these components connect as most research focuses on only one of two of the three components. Therefore, these future studies should first aim to quantify health impacts that can be attributed to climate change and then quantify the mitigation potential of urban trees, forests and parks in the area. It is important that future research studies aim to explore these relationships through a multidisciplinary approach where clinicians, researchers, city planners, and urban forestry project leaders work together to identify vulnerable populations in their communities and develop adequate adaptation strategies, policies and recommendations.
CHAPTER 5

CONCLUSION

Broadly, the results of this thesis address the current and future role of vegetative cover in building resilience to changing climates and land use that is affecting the safety and health of people and the productivity of landscapes. These results could be used by communities to identify at risk areas and populations for environmental or public health concerns and devise plans for adaptation and restoration through the use of vegetative cover.

Decisions regarding land protection, land use, storm water, air pollution, and agricultural practices are made at both private and public levels with guidance from local and state laws. Often, these decisions are not based on scientific information and do not take into consideration the dynamic nature of ecosystems as they relate to climate change. The review article on the ecosystem services of vegetation will assist communities in making these decisions by serving as a comprehensive report of current information on urban forests and cover crops that is specific to enhancing resilience to climate change and shifting land use. It will provide a unique insight on how we can encourage the use of urban forests and cover crops by communities, specifically landowners, city planners and local governments, and thereby, increase the amount of cover crops and urban trees planted. These suggestions include implementing incentives such as tax breaks and cost sharing between the government and landowners and implementing educational practices such as pamphlets sent annually to landowners regarding the benefits of vegetative cover and their best practices. This will encourage communities not yet well adapted to the
impacts of climate change to start making plans for resilience. This review will also allow urban foresters, project funders, farmers, and city planners to weigh co-benefits of vegetation and possible economic returns when making decisions to integrate vegetative cover into communities.

The ecosystem service spatial models and the spatially-explicit decision support tool that was produced through the completion of the third chapter will assist communities in making decisions regarding land protection, storm water, cooling efforts, and co-benefits of vegetation. This chapter provides a careful assessment of local ecosystems and ecosystem services in Massachusetts conducted using spatially explicit techniques. This will enable communities to rapidly access town-level information on local landscapes and ecosystem potential that is scientifically grounded and easily accessible. This will allow city planners, environmental project leaders, and government officials to prioritize regions that will benefit the most in terms of combating climate change through urban forests. Through the additional emphasis on Massachusetts Gateway Cities, Greening the Gateway Cities Project leaders will be able to use my results to identify areas in cities that will have significant reduced runoff and reduced heat island effects as a result of urban forest integration. In addition, Greening the Gateway Cities Project leaders will be able to use my results in their information brochures to encourage citizens to agree to have Greening the Gateway City Project foresters plant more trees on their properties.

The review article on climate change health impacts and restorative and protective mechanisms of urban forests in relation to these impacts that was developed through the completion of the fourth chapter will assist communities in making scientifically
grounded decisions about land use and public health under impending climate change. Previous studies have investigated climate change health impacts without considering urban forest as a possible adaptation strategy. Similarly, previous studies have examined health benefits of urban forests without considering which health impacts are related to climate change and should be prioritized in changing climates. Therefore, no review to date has comprehensively examined the relationship between climate change, health effects, and urban forests and provided conceptual frameworks to assist the medical community and city planners in protecting their communities. This review fills this gap by providing a comprehensive report focusing on climate change impacts on health that can be mitigated through implementation or use of urban forests. Health professionals, urban forestry programs, city planners, and citizens will be able to use the conceptual frameworks to identify which health impacts to expect in their community based on climate change impacts on their local temperatures and precipitation, and devise plans for resilience using an aesthetically pleasing, and cost-effective strategy. The results from this analysis will help encourage city planners and environmental project leaders to work with healthcare professionals when making decisions regarding land use, specifically when considering where to plant trees. These results will also encourage healthcare professionals to work with city planners and environmental project leaders when making suggestions to the community through patient meetings and website posting on how to improve health. By working together, more trees can be planted in communities that suffer from increased prevalence of climate induced health diseases and there will be increased awareness of how urban trees can help the medical community combat climate change induced health problems.
APPENDIX

LIST OF FORMULAS NOTATIONS AND OLS SUMMARIES

Table 3.8: Python script for 2100 temperature and precipitation files

# ---------------Functions---------------------

def RemoveFilesInDir(rootDir):
    filelist = [f for f in os.listdir(rootDir) if os.path.isfile(os.path.join(rootDir, f))]
    for f in filelist:
        os.remove(os.path.join(rootDir, f))

# ------------ Main-----------------------

import arcpy, os, shutil
from fnmatch import fnmatch
from arcpy.sa import *

exeDir = os.path.dirname(__file__)
rootDir = exeDir + os.sep + r"Data"
destDir = rootDir + os.sep + r"Regions\Massachusetts\Final"
ncdfFile = rootDir + os.sep + r"NetCDF\tas_Amon_CCSM4_rcp45_ensave_200601_210012_downscaled.nc"
studyPol = rootDir + os.sep + r"Regions\Massachusetts\Massachusetts_NAD83.shp"

# Specify time variable: pptmax, tas
var = "tas"

# Specify bands to extract
bands = []
bands.extend(range(529,541))
bands.extend(range(1129,1141))

arcpy.env.workspace = rootDir
arcpy.env.overwriteOutput = True

print "\n" + "-------------------------------"
print "checking out Spatial Analyst extension: " + arcpy.CheckExtension("spatial")

if arcpy.CheckExtension("spatial") == "Available":
    arcpy.CheckOutExtension("spatial")
else:

raise "LicenseError"

print "\n" + "-----------------------------------------------"
print "\n" + "Spatial Analyst extension has been checked out successfully."

try:

    print "\n" + "-----------------------------------------------"
    print "Processing file ", ncdfFile

# Make netCDF raster layer
ncdfRaster = arcpy.env.workspace + os.sep + "nc_" + var + ".img"
print "\n" + "-----------------------------------------------"
print "Making netCDF layer: " + ncdfRaster + " ..."

    arcpy.MakeNetCDFRasterLayer_md(ncdfFile, var, "lon", "lat", ncdfRaster, "time", ",", "BY_VALUE")

# Convert study polygon to raster
studyAreaRaster = arcpy.env.workspace + os.sep + "studyAreaRaster.img"
print "\n" + "-----------------------------------------------"
print "Converting study area vector polygon to raster: " + studyAreaRaster

    arcpy.PolygonToRaster_conversion(studyPol, "FID", studyAreaRaster, ",CELL_CENTER", "NONE", "100")

# Make a "1" study area raster
studyAreaMaskRaster = arcpy.env.workspace + os.sep + "studyAreaMaskRaster.img"
trueRastExp = Raster(studyAreaRaster) + 1
print "\n" + "-----------------------------------------------"
print "Making a positive study area raster: " + studyAreaMaskRaster

    trueRastExp.save(studyAreaMaskRaster)

for b in bands:

    # Make a raster band
    bandRaster = arcpy.env.workspace + os.sep + var + ".img"
    print "\n" + "-----------------------------------------------"
    print "Making raster layer for band " + str(b) + "..."

    arcpy.MakeRasterLayer_management(ncdfRaster, bandRaster, ",", studyPol, str(b))

# Project band raster and resample
    projectedBandRaster = arcpy.env.workspace + os.sep + var + ".prj.img"
print "n" + "-------------------------------"
print "Projecting raster layer " + projectedBandRaster + "...

arcpy.ProjectRaster_management(bandRaster, projectedBandRaster, studyPol, "NEAREST", "100 100", "WGS_1984_(ITRF00)_To_NAD_1983", ",", studyAreaMaskRaster)

# Convert to inches
#convertedToInchesRaster = arcpy.env.workspace + os.sep + 
"convertedToInchesRaster.img"
#convertRastExp = Raster(projectedBandRaster) / 25.4
#print "n" + "-------------------------------"
#print "Converting raster to inches: " + convertedToInchesRaster
#convertRastExp.save(convertedToInchesRaster)

# Make output raster
finalRaster = arcpy.env.workspace + os.sep + var + ";" + str(b) + "_fnl.img"
pcpStudyAreaExp = Raster(studyAreaMaskRaster) * Raster(projectedBandRaster)
print "n" + "-------------------------------"
print "Multiplying precipitation by study area " + finalRaster + "...

pcpStudyAreaExp.save(finalRaster)

# Move final layer to output directory
regionCode = ""
if "Northampton" in destDir:
    regionCode = "nh"
elif "Springfield" in destDir:
    regionCode = "sp"
else:
    regionCode = "ma"

source = finalRaster
destination = destDir + os.sep + var + ";" + str(b) + "_fnl_" + regionCode + ".img"
dest = shutil.copyfile(source, destination)
print "n" + "-------------------------------"
print "File " + source + " has been moved to the final folder."

# Remove temp files
try:
    RemoveFilesInDir(rootDir)
except:
    print "n" + "-------------------------------"
    print "Error removing temp files in " + rootDir
    continue
print "Success."
arcpy.CheckInExtension("spatial")

except:
  print arcpy.GetMessages()
  print "I do not think it worked."
  arcpy.CheckInExtension("spatial")

**Table 3.9: Formula notation for Massachusetts urban area analysis in Neural Networks**

```python
mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
  {Default Local},
  Name("H1_1_1") = TanH(
    0.613115121295762 + -0.00100896583137695 * Log(
      0.0152518307319821 + Impervious) / (100.112669354026 + -1 * Impervious)
    ) + -0.084238758468759 * Log(
      0.689167562580117 + Canopy) / (94.4455396183757 + -1 * Canopy) + -0.084238758468759 * Log(
      0.689167562580117 + Canopy) / (94.4455396183757 + -1 * Canopy)
  );
  Name("H1_2_1") = TanH(
    -0.86680338643092 + 0.00401513083724125 * Log(
      0.0152518307319821 + Impervious) / (100.112669354026 + -1 * Impervious)
    ) + 0.0672893542025643 * Log(
      0.689167562580117 + Canopy) / (94.4455396183757 + -1 * Canopy) + 0.0672893542025643 * Log(
      0.689167562580117 + Canopy) / (94.4455396183757 + -1 * Canopy)
  );
  Name("H1_3_1") = TanH(
    -0.453959442913791 + -0.199668137972976 * Log(
      0.0152518307319821 + Impervious) / (100.112669354026 + -1 * Impervious)
    ) + -0.189942653498306 * Log(
      0.689167562580117 + Canopy) / (94.4455396183757 + -1 * Canopy) + -0.189942653498306 * Log(
      0.689167562580117 + Canopy) / (94.4455396183757 + -1 * Canopy)
  );
  Name("Predicted Temp_1") = 54.9812405143617 + 38.8754292356055 * H1_1_1 + 70.2340807704462 * H1_2_1 + 0.699609829535306 * H1_3_1;
```

**Table 3.10: Neural Network script for Massachusetts urban area analysis**
New Column( "H1_1_1", 
"Numeric",
Formula( 
    TanH( 
        0.613115121295762 + -0.00100896583137695 * 
        Log( 
            (0.0152518307319821 + :Impervious) / 
            (100.112669354026 + -1 * 
                :Impervious) 
        ) + -0.084238758468759 * Log( 
            (0.689167562580117 + :Canopy) / (94.4455396183757 + -1 * :Canopy) 
        ) 
    ) 
),
Set Property( "Intermediate", 1 )
);
New Column( "H1_2_1", 
"Numeric",
Formula( 
    TanH( 
        (-0.86680338643092) + 0.00401513083724125 * 
        Log( 
            (0.0152518307319821 + :Impervious) / 
            (100.112669354026 + -1 * 
                :Impervious) 
        ) + 0.0672893542025643 * Log( 
            (0.689167562580117 + :Canopy) / (94.4455396183757 + -1 * :Canopy) 
        ) 
    ) 
),
Set Property( "Intermediate", 1 )
);
New Column( "H1_3_1", 
"Numeric",
Formula( 
    TanH( 
        (-0.453959442913791) + -0.199668137972976 * 
        Log( 
            (0.0152518307319821 + :Impervious) / 
            (100.112669354026 + -1 * 
                :Impervious) 
        ) + -0.189942653498306 * Log( 
            (0.689167562580117 + :Canopy) / (94.4455396183757 + -1 * :Canopy) 
        ) 
    ) 
),
Set Property( "Intermediate", 1 )
\[
(0.689167562580117 + :\text{Canopy}) / (94.4455396183757 + -1 * :\text{Canopy})
\]

),

Set Property( "Intermediate", 1 )
);
New Column( "Predicted Temp_1",
"Numeric",
Formula(
54.9812405143617 + 38.8754292356055 * :H1_1_1 + 70.2340807704462 * :H1_2_1
+ 0.699609829535306 * :H1_3_1
),
Set Property( "Predicting", {:\text{Temp}, Creator( "Neural" )} )
);

Table 3.11: Formula notation for Attleboro (Neural Networks)

\[
\text{mp}_1 = \text{New Namespace("Neural - Temp")};
\text{mp}_1:predict = \text{Function}({\text{Name("Canopy")}, \text{Name("Impervious")}}),
\{\text{Default Local},
\text{Name("H1_1")} = \text{TanH}(
0.498878051479887 + -0.0762604119260914 * \text{Impervious} + -0.934495026678967 * 
\text{Log}( (2.09925046988654 + \text{Canopy}) / (93.3524803195409 + -1 * \text{Canopy}) )
);
\text{Name("H1_2")} = \text{TanH}(
(-0.589400976974307) + -0.0583827167039327 * \text{Impervious} + 0.0810527869132644 * 
\text{Log}( (2.09925046988654 + \text{Canopy}) / (93.3524803195409 + -1 * \text{Canopy}) )
);
\text{Name("H1_3")} = \text{TanH}(
(-2.88261104526049) + -0.0698902888934514 * \text{Impervious} + 0.932628968916037 * 
\text{Log}( (2.09925046988654 + \text{Canopy}) / (93.3524803195409 + -1 * \text{Canopy}) )
);
\text{Name("Predicted Temp") = 26.9488958167521 + -0.0192273144185662 * \text{H1}_1 + 0.127059887736482 * \text{H1}_2 + -0.0690220752248616 * \text{H1}_3;}
\]

Table 3.12: Formula notation for Barnstable (Neural Networks)
mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
{Default Local},
Name("H1_1") = TanH(-1.27438534055129) + -0.0580680722743243 * Canopy + 0.269647935645979 * Log( (2204.65820273824 + Impervious) / (110.835151043186 + -1 * Impervious) )
);
Name("H1_2") = TanH(-0.769952132109324) + -0.0606841890835658 * Canopy + 0.16213558673654 * Log( (2204.65820273824 + Impervious) / (110.835151043186 + -1 * Impervious) )
);
Name("H1_3") = TanH(0.00327252647095988 + -0.0647763799803603 * Canopy + -0.0158441396589372 * Log( (2204.65820273824 + Impervious) / (110.835151043186 + -1 * Impervious) )
);
Name("Predicted Temp") = 24.3731143924937 + -0.0525418506387985 * H1_1 + -0.145854917708435 * H1_2 + -0.1502288386282 * H1_3;
);

Table 3.13: Formula notation for Boston (Neural Networks)
Log( (2204.65820273824 + Impervious) / (110.835151043186 + -1 * Impervious) )
);
Name("Predicted Temp") = 25.9881859288433 + -17.2011765336342 * H1_1 + 25.5174798805361 * H1_2 + -9.36218802786592 * H1_3;

Table 3.14: Formula notation for Brockton (Neural Networks)

mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
{Default Local},
Name("H1_1") = TanH(
(-0.792205757293852) + -0.176867710055827 * Log(
(0.988451504598531 + Impervious) / (100.794003480859 + -1 * Impervious)
) + 0.137762916247898 * Log(
(1.33654732782603 + Canopy) / (94.0402338207582 + -1 * Canopy)
)
);
Name("H1_2") = TanH(
(-2.35414017491678) + -0.978300497068481 * Log(
(0.988451504598531 + Impervious) / (100.794003480859 + -1 * Impervious)
) + -0.0455884336275372 * Log(
(1.33654732782603 + Canopy) / (94.0402338207582 + -1 * Canopy)
)
);
Name("H1_3") = TanH(
(-0.933624278826867) + -0.103843438892075 * Log(
(0.988451504598531 + Impervious) / (100.794003480859 + -1 * Impervious)
) + 0.110540618348853 * Log(
(1.33654732782603 + Canopy) / (94.0402338207582 + -1 * Canopy)
)
);
Name("Predicted Temp") = 26.6200431032488 + 0.652159120281847 * H1_1 + -0.07602916247898 * H1_2 + -1.0320074934911 * H1_3;

Table 3.15: Formula notation for Cambridge (Neural Networks)
mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
    {Default Local},
    Name("H1_1") = TanH(
        (-1.5196605155759) + -0.0325251287879997 * Canopy + 0.325791162159604 * 
        Log( (89.4470199643428 + Impervious) / (104.029236638517 + -1 * Impervious)
    )
);
Name("H1_2") = TanH(
    (-1.59034554897832) + -0.00495591962795071 * Canopy + -4.12091177074952 * 
        Log( (89.4470199643428 + Impervious) / (104.029236638517 + -1 * Impervious)
    )
);
Name("H1_3") = TanH(
    0.817303018583941 + 0.00524660398988627 * Canopy + 3.70586798944622 * 
        Log( (89.4470199643428 + Impervious) / (104.029236638517 + -1 * Impervious)
    )
);
Name("Predicted Temp") = 24.2763859302112 + -0.328671477627649 * H1_1 + -
    3.44541636948431 * H1_2 + -1.08016053104692 * H1_3;
);

Table 3.16: Formula notation for Chelsea (Neural Networks)

mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
    {Default Local},
    Name("H1_1") = TanH(
        0.68305356279203 + -0.0936313442832433 * Canopy + -0.0420096780611763 * 
        Log( (51.8151024317147 + Impervious) / (102.408713015181 + -1 * Impervious)
    )
);
Name("H1_2") = TanH(
    1.0496548229525 + 0.0579485290710532 * Canopy + 0.760350847176858 * 
        Log( (51.8151024317147 + Impervious) / (102.408713015181 + -1 * Impervious)
    )
);
Name("H1_3") = TanH(
    0.0355952963347252 + 0.0905039501233041 * Canopy + 1.19850458128324 * 
        Log( (51.8151024317147 + Impervious) / (102.408713015181 + -1 * Impervious)
    )
);
Name("Predicted Temp") = 24.6692146090031 + 0.00921935905838525 * H1_1 +
2.17311908172093 * H1_2 +
-0.535893563975148 * H1_3;
);

Table 3.17: Formula notation for Chicopee (Neural Networks)

mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
{Default Local},
Name("H1_1") = TanH(
(-1.08135639056762) + 0.775282152160526 * ArcSinH(
0.622731794768013 + 0.219848155093006 * Canopy
) + -0.365717757492253 * Log(
(0.0288776352900983 + Impervious) / (100.101828426636 + -1 * Impervious)
)
);
Name("H1_2") = TanH(
(-1.07336674832032) + 0.779891821434734 * ArcSinH(
0.622731794768013 + 0.219848155093006 * Canopy
) + -0.307269429057203 * Log(
(0.0288776352900983 + Impervious) / (100.101828426636 + -1 * Impervious)
)
);
Name("H1_3") = TanH(
1.77821264500929 + -0.0733532276696129 * ArcSinH(
0.622731794768013 + 0.219848155093006 * Canopy
) + 0.00749674121001456 * Log(
(0.0288776352900983 + Impervious) / (100.101828426636 + -1 * Impervious)
)
);
Name("Predicted Temp") = 25.1867682755935 + -0.764688460185967 * H1_1 +
0.837188187452961 * H1_2 +
2.31082147643784 * H1_3;
);

Table 3.18: Formula notation for Everett (Neural Networks)

mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
}.
Table 3.19: Formula notation for Fall River (Neural Networks)

mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
{Default Local},
Name("H1_1") = TanH(
1.17938522133151 + 0.00775508781208609 * Impervious + -
0.0092699130283775 * 
Log( (0.318380125752971 + Canopy) / (93.5649810429028 + -1 * Canopy) )
);
Name("H1_2") = TanH(
6.68130698251073 + 0.160792958844666 * Impervious + 0.868417232396795 * 
Log( (0.318380125752971 + Canopy) / (93.5649810429028 + -1 * Canopy) )
);
Name("H1_3") = TanH(
-4.55378606297991 + -0.102757543464006 * Impervious + 1.91043583126004 * 
Log( (0.318380125752971 + Canopy) / (93.5649810429028 + -1 * Canopy) )
);
Name("Predicted Temp") = 25.5034188652532 + -0.571680230625877 * H1_1 +
1.58992950945975 * H1_2 +
-0.0397173158921198 * H1_3;
);

Table 3.20: Formula notation for Fitchburg (Neural Networks)
mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
{Default Local},
Name("H1_1") = TanH(
  1.61540674183102 + 0.347340052043977 * Impervious + 0.0245584823003348
  * Log((1.16852512034672 + Canopy) / (94.5627661922195 + -1 * Canopy))
);
Name("H1_2") = TanH(
  6.90100443681569 + -0.0855780374807315 * Impervious + -3.33577950579468
 * Log((1.16852512034672 + Canopy) / (94.5627661922195 + -1 * Canopy))
);
Name("H1_3") = TanH(
(-1.9405082529872) + 0.0227459647354569 * Impervious + -
0.148522607625218 *
Log((1.16852512034672 + Canopy) / (94.5627661922195 + -1 * Canopy))
);
Name("Predicted Temp") = 21.4540052073122 + 5.10058375126596 * H1_1 +
0.0762242757383986 * H1_2 +
0.254177043757391 * H1_3;

Table 3.21: Formula notation for Holyoke (Neural Networks)

mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
{Default Local},
Name("H1_1") = TanH(
  1.80910019722308 + -0.0365906668116657 * Impervious + 0.148133028427568
  * Log((0.253297156598557 + Canopy) / (94.5652955725118 + -1 * Canopy))
);
Name("H1_2") = TanH(
(-0.964152600744275) + -0.266713196366518 * Impervious +
0.416226481041469 *
Log((0.253297156598557 + Canopy) / (94.5652955725118 + -1 * Canopy))
);
Name("H1_3") = TanH(
  1.68935618856808 + -0.0227266775213214 * Impervious + 0.175709193738787
 * Log((0.253297156598557 + Canopy) / (94.5652955725118 + -1 * Canopy))
);
Name("Predicted Temp") = 27.0767287417013 + 0.181392728481667 * H1_1 + -
0.208502064009302 * H1_2 +
Table 3.22: Formula notation for Haverhill (Neural Networks)

```
mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
{Default Local},
Name("H1_1") = TanH(
  (-1.19813055583666) + -0.178258821446095 * Impervious +
  0.138682749362665 *
  Log( (0.746127933587131 + Canopy) / (93.4122170819211 + -1 * Canopy) )
);
Name("H1_2") = TanH(
  0.590029980215074 + 0.21835849628527 * Impervious + -0.205303301642663 *
  Log( (0.746127933587131 + Canopy) / (93.4122170819211 + -1 * Canopy) )
);
Name("H1_3") = TanH(
  1.38524676592629 + -0.303520733653412 * Impervious + -0.00433457017781743 *
  Log( (0.746127933587131 + Canopy) / (93.4122170819211 + -1 * Canopy) )
);
Name("Predicted Temp") = 25.2917501100016 + -2.12519360139531 * H1_1 + -
  0.647715208658344 * H1_2 + 0.0156923506316581 * H1_3;
```

Table 3.23: Formula notation for Lawrence (Neural Networks)

```
mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
{Default Local},
Name("H1_1") = TanH(
  1.03315543354177 + -0.00080624109055258 * Canopy + 0.0744797308708346 *
  ArcSinH( (-2279.16031980363) + 21.428266886918 * Impervious )
);
Name("H1_2") = TanH(
  6.71257802605974 + -0.0582863963135569 * Canopy + 0.748183374042795 *
  ArcSinH( (-2279.16031980363) + 21.428266886918 * Impervious )
);
Name("H1_3") = TanH(
  (-0.83093568604374) + -0.377980784753447 * Canopy + -0.170543869070716 *
```
\[
\text{ArcSinH}( (-2279.16031980363) + 21.428266886918 \times \text{Impervious} )
\]

Name("Predicted Temp") = 26.6552563128824 + 0.394988156721346 \times H1_1 + -0.0328727069911184 \times H1_2 + 0.0379648799277129 \times H1_3;

**Table 3.24: Formula notation for Leominster (Neural Networks)**

mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"). Name("Impervious")}, {Default Local},
Name("H1_1") = TanH(
  (1.7790233791961) + -0.250596840936792 \times \text{Impervious} + -0.144531495545173 \times 
  \text{Log}( (0.922275460711951 + \text{Canopy}) / (94.5737023370723 + -1 \times \text{Canopy}) )
);
Name("H1_2") = TanH(
  (3.37506361529487) + 0.0330108717987501 \times \text{Impervious} + -0.43940525676733 \times 
  \text{Log}( (0.922275460711951 + \text{Canopy}) / (94.5737023370723 + -1 \times \text{Canopy}) )
);
Name("H1_3") = TanH(
  (3.06307287552602) + -0.661307606980204 \times \text{Impervious} + 1.54528662576853 \times 
  \text{Log}( (0.922275460711951 + \text{Canopy}) / (94.5737023370723 + -1 \times \text{Canopy}) )
);
Name("Predicted Temp") = 23.4092743427361 + -2.79035409525108 \times H1_1 + 0.0912013789542953 \times H1_2 + -0.527020509541358 \times H1_3;

**Table 3.25: Formula notation for Lowell (Neural Networks)**

mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"). Name("Impervious")},
{Default Local},
Name("H1_1") = TanH(
  1797.88463792292 + -1120.94719686272 \times \text{ArcSinH(}
  2.38422273663371 + 0.00107646159979322 \times \text{Canopy}
  ) + 0.00982232278458535 \times \text{Log(}
  41.6587604877705 + \text{Impervious}) / (102.444646453031 + -1 \times 
  \text{Impervious})
  )
);
Name("H1_2") = TanH(
198.407116644083 + -124.648849798142 * ArcSinH(2.38422273663371 + 0.000107646159979322 * Canopy) + -0.791508476008371 * Log((41.6587604877705 + Impervious) / (102.444646453031 + -1 * Impervious));

Name("H1_3") = TanH(316.820942323446 + -198.040343203169 * ArcSinH(2.38422273663371 + 0.000107646159979322 * Canopy) + -0.807165958882669 * Log((41.6587604877705 + Impervious) / (102.444646453031 + -1 * Impervious));

Name("Predicted Temp") = 28.3316529315762 + 0.0428858947360093 * H1_1 + 1.88143661359863 * H1_2 + -0.620565540366182 * H1_3;

Table 3.26: Formula notation for Lynn (Neural Networks)

mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
{Default Local},
Name("H1_1") = TanH(165.356369090553 + 58.6137363729667 * Log((0.430291150410067 + Impervious) / (100.183447497955 + -1 * Impervious)) + 45.6174879997747 * Log((2.57100483410245 + Canopy) / (91.6503555718578 + -1 * Canopy));

Name("H1_2") = TanH(0.956408142120213 + -0.266281949402699 * Log((0.430291150410067 + Impervious) / (100.183447497955 + -1 * Impervious)) + 0.244412149680862 * Log((2.57100483410245 + Canopy) / (91.6503555718578 + -1 * Canopy));

Name("H1_3") = TanH(41.3877839508257 + 7.38389223911583 * Log((0.430291150410067 + Impervious) / (100.183447497955 + -1 * Impervious)) + 4.01074771004927 * Log(}
(2.57100483410245 + Canopy) / (91.6503555718578 + -1 * Canopy)

Name("Predicted Temp") = 25.8631451769659 + -0.052074843280951 * H1_1 +
0.395315468250168 * H1_2 +
+0.0427781474777823 * H1_3;

Table 3.27: Formula notation for Malden (Neural Networks)

mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
    {Default Local},
    Name("H1_1") = TanH(
        41.0916551122254 + 0.271365107489554 * Canopy + 4.61929581215062 *
        ArcSinH( (-6205.06720789639) + 56.0140738671804 * Impervious )
    );
    Name("H1_2") = TanH(
        -9.95679995216378 + 0.0291840647797566 * Canopy + -1.0984946405025 *
        ArcSinH( (-6205.06720789639) + 56.0140738671804 * Impervious )
    );
    Name("H1_3") = TanH(
        24.8306841062969 + 0.0733457433197304 * Canopy + 2.59141217225025 *
        ArcSinH( (-6205.06720789639) + 56.0140738671804 * Impervious )
    );
    Name("Predicted Temp") = 27.0267752056962 + 0.24352537515382 * H1_1 +
0.0441520378809754 * H1_2 +
-0.795071045736885 * H1_3;

Table 3.28: Formula notation for New Bedford (Neural Networks)

mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
    {Default Local},
    Name("H1_1") = TanH(
        0.0295729045359015 + 0.351736018268936 * Log(
            0.0148029173169817 + Impervious) / (100.175559868637 + -1 *
            Impervious)
    ) + -0.04130516122872 * Log(
        0.281468958370839 + Canopy) / (110.280287207435 + -1 * Canopy)
)

Name("H1_2") = TanH(
    1.36793128930439 + -0.0512406321958627 * Log(
(0.0148029173169817 + Impervious) / (100.175559868637 + -1 * Impervious) 
) + -0.609018521557552 * Log(
(0.281468958370839 + Canopy) / (110.280287207435 + -1 * Canopy)
)

); Name("H1_3") = TanH(
0.346584549873982 + 0.455202860407737 * Log(
(0.0148029173169817 + Impervious) / (100.175559868637 + -1 * Impervious)
) 
) + -0.040063061320076 * Log(
(0.281468958370839 + Canopy) / (110.280287207435 + -1 * Canopy)
)

); Name("Predicted Temp") = 26.3096777973018 + -0.904530247628287 * H1_1 + -0.333998505811815 * H1_2 + 0.674846125160036 * H1_3;

Table 3.29: Formula notation for Northampton (Neural Networks)

mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
{Default Local},
Name("H1_1") = TanH(
0.00660992947077807 + -0.000179766503873587 * Impervious + 
0.00200376831857634 * Log( (4.94219358663414 + Canopy) / (94.4070914494917 + -1 * Canopy) )
)

); Name("H1_2") = TanH((
-3.43174711549667) + -0.175308268808397 * Impervious + 1.28091861225471 * 
Log( (4.94219358663414 + Canopy) / (94.4070914494917 + -1 * Canopy) )
)

); Name("H1_3") = TanH((
-4.12989594426954) + -0.551883588189325 * Impervious + 1.82953615037318 * 
Log( (4.94219358663414 + Canopy) / (94.4070914494917 + -1 * Canopy) )
)

); Name("Predicted Temp") = 27.1496213900565 + -4.48950448363786 * H1_1 + 0.481408890838213 * H1_2 + -0.530035856717926 * H1_3;

Table 3.30: Formula notation for Peabody (Neural Networks)
mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
{Default Local},
Name("H1_1") = TanH(
  10.6235800129961 + 2.25660044872554 * Log(
    (0.54621901135051 + Impervious) / (100.157301181459 + -1 * Impervious)
  )
 + 1.15012566291213 * Log(
    (1.28846726802997 + Canopy) / (91.0704329448589 + -1 * Canopy)
)
);
Name("H1_2") = TanH(
  -2.0839639846208 + 1.61888522508633 * Log(
    (0.54621901135051 + Impervious) / (100.157301181459 + -1 * Impervious)
  )
 + -0.142183913357169 * Log(
    (1.28846726802997 + Canopy) / (91.0704329448589 + -1 * Canopy)
)
);
Name("H1_3") = TanH(
  8.74738112113623 + 2.19841585236164 * Log(
    (0.54621901135051 + Impervious) / (100.157301181459 + -1 * Impervious)
  )
 + 1.57898304190673 * Log(
    (1.28846726802997 + Canopy) / (91.0704329448589 + -1 * Canopy)
)
);
Name("Predicted Temp") = 26.1484200587841 + -0.117170510169498 * H1_1 + -0.14006227173625 * H1_2 + 0.100790122164991 * H1_3;

Table 3.31: Formula notation for Pittsfield (Neural Networks)

mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
{Default Local},
Name("H1_1") = TanH(
  -0.536278791730215 + 0.0648599488034679 * Impervious + - 1.10754248284653 *
    Log((3.8482296262428 + Canopy) / (93.1047772125241 + -1 * Canopy))
);
Name("H1_2") = TanH(
  -1.97054323153367 + 0.0249719135403513 * Impervious + - 0.0547281583259744 *
    Log((3.8482296262428 + Canopy) / (93.1047772125241 + -1 * Canopy))
)
\[ \text{Name("H}_{1}\_3") = \text{Tanh}(\]
\[-4.92771604510085 + 0.0473795902503984 \times \text{Impervious} + 1.65856115278086 \times \]
\[ \log((3.8482296262428 + \text{Canopy}) / (93.1047772125241 + -1 \times \text{Canopy})) \]
\);}

\[ \text{Name("Predicted Temp") = 17.3873899204555 + -0.0732170149437774 \times \text{H}_{1}\_1 + \]
\[ 7.99894080013517 \times \text{H}_{1}\_2 + \]
\[ -0.28910377966457 \times \text{H}_{1}\_3; \]
\]

**Table 3.32: Formula notation for Quincy (Neural Networks)**

\[ \text{mp}_1 = \text{New Namespace("Neural - Temp")}; \]
\[ \text{mp}_1:predict = \text{Function}([\text{Name("Canopy")}, \text{Name("Impervious")}]), \]
\[ \{\text{Default Local}\}, \]
\[ \text{Name("H}_{1}\_1") = \text{Tanh}(\]
\[-0.302467521287278 + 0.127462535308907 \times \log((0.191838638920289 + \text{Impervious}) / (100.468609781071 + -1 \times \text{Impervious})) \]
\[ + -0.200251610877633 \times \log((0.412053616564526 + \text{Canopy}) / (93.5143083164627 + -1 \times \text{Canopy})) \]
\];

\[ \text{Name("H}_{1}\_2") = \text{Tanh}(\]
\[0.493521863862734 + -0.0964727438234541 \times \log((0.191838638920289 + \text{Impervious}) / (100.468609781071 + -1 \times \text{Impervious})) \]
\[ + 0.339389496778563 \times \log((0.412053616564526 + \text{Canopy}) / (93.5143083164627 + -1 \times \text{Canopy})) \]
\];

\[ \text{Name("H}_{1}\_3") = \text{Tanh}(\]
\[-0.281612796065032 + 0.444106910263711 \times \log((0.191838638920289 + \text{Impervious}) / (100.468609781071 + -1 \times \text{Impervious})) \]
\[ + 0.0161886497134837 \times \log((0.412053616564526 + \text{Canopy}) / (93.5143083164627 + -1 \times \text{Canopy})) \]
\];

\[ \text{Name("Predicted Temp") = 26.5732727865503 + 0.943615084803757 \times \text{H}_{1}\_1 + \]
\[ 0.820658889632744 \times \text{H}_{1}\_2 + \]
\[ -0.200588788432527 \times \text{H}_{1}\_3; \]
\]

**Table 3.33: Formula notation for Salem (Neural Networks)**
mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
 {Default Local},
 Name("H1_1") = TanH(
          0.658379828114492 + -0.0507480351289613 * Log(0.402667940285052 + Impervious) / (100.743552560864 + -1 * Impervious)
 + 0.364908613302988 * Log((5.03025343503098 + Canopy) / (91.0693643037475 + -1 * Canopy)
);
)
Name("H1_2") = TanH(
          (-0.64682435054447) + 0.162429708141555 * Log((0.402667940285052 + Impervious) / (100.743552560864 + -1 * Impervious)
 + -0.545025831009272 * Log((5.03025343503098 + Canopy) / (91.0693643037475 + -1 * Canopy)
);
)
Name("H1_3") = TanH(
          (-1.92597644807221) + -0.275887042644977 * Log((0.402667940285052 + Impervious) / (100.743552560864 + -1 * Impervious)
 + -0.545025831009272 * Log((5.03025343503098 + Canopy) / (91.0693643037475 + -1 * Canopy)
);
)
Name("Predicted Temp") = 25.6419678387775 + 2.27193805355145 * H1_1 + 1.26638136714347 * H1_2 + 0.698013002712444 * H1_3;
);

Table 3.34: Formula notation for Springfield (Neural Networks)

mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
 {Default Local},
 Name("H1_1") = TanH(
          (-7.41914562565933) + -1.26228794273847 * Log((0.267473416961002 + Impervious) / (100.394989693102 + -1 * Impervious)
 + 0.1730518893893 * Log((0.930344373983926 + Canopy) / (94.3482972287598 + -1 * Canopy)
);
)
Name("H1_2") = TanH(-8.39057162020027 + -1.15459423832043 * Log(0.267473416961002 + Impervious) / (100.394989693102 + -1 * Impervious) + 0.10461434188611 * Log(0.930344373983926 + Canopy) / (94.3482972287598 + -1 * Canopy))

Name("H1_3") = TanH(-48.7667881676482 + -7.22693136208495 * Log(0.267473416961002 + Impervious) / (100.394989693102 + -1 * Impervious) + 2.7334509584783 * Log(0.930344373983926 + Canopy) / (94.3482972287598 + -1 * Canopy))

Name("Predicted Temp") = 37.6772420553813 + -1.063329536223 * H1_1 + 11.614463045042 * H1_2 + -0.236784922539151 * H1_3;

Table 3.35: Formula notation for Tauton (Neural Networks)

mp_1 = New Namespace("Neural - Temp");
mp_1: predict = Function({Name("Canopy"), Name("Impervious")},
{Default Local},
Name("H1_1") = TanH(-3.4763573549017) + -0.142788700567684 * Impervious + 1.77851716610046 * Log((1.69760640474833 + Canopy) / (93.4625118672083 + -1 * Canopy)));
Name("H1_2") = TanH(-3.63738849861814) + -0.133754013183738 * Impervious + 1.8126381747351 * Log((1.69760640474833 + Canopy) / (93.4625118672083 + -1 * Canopy)));
Name("H1_3") = TanH(10.789451885502 + -0.133294118167718 * Impervious + 2.08118980384266 * Log((1.69760640474833 + Canopy) / (93.4625118672083 + -1 * Canopy)));
Name("Predicted Temp") = 26.9675575649574 + 0.731584680078514 * H1_1 + -0.73793690828741 * H1_2 + -0.00729263301516295 * H1_3;

Table 3.36: Formula notation for Westfield (Neural Networks)
mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
{Default Local},
Name("H1_1") = TanH(
    3.50779385082811 + 1.21340405274722 * Impervious + -1.1227403288712 *
    Log( (0.597524909437589 + Canopy) / (94.4597604878254 + -1 * Canopy) )
);
Name("H1_2") = TanH(
    0.488392306629998 + 0.0172045407048359 * Impervious + 0.149227837004359 *
    Log( (0.597524909437589 + Canopy) / (94.4597604878254 + -1 * Canopy) )
);
Name("H1_3") = TanH(
    (-2.25432272478753) + 2.54436596041747 * Impervious + -0.716638677730411 *
    Log( (0.597524909437589 + Canopy) / (94.4597604878254 + -1 * Canopy) )
);
Name("Predicted Temp") = 26.8987119106972 + 0.260885757011106 * H1_1 +
    0.0567980954330983 * H1_2 + 0.0356916669115071 * H1_3;
);

Table 3.37: Formula notation for Worcester (Neural Networks)

mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")},
{Default Local},
Name("H1_1") = TanH(
    0.0631409561839679 + 0.562987134991372 * Log(0.283430789103519 + Impervious) / (100.396784146525 + -1 *
    Impervious)
) + -0.248200834834899 * Log(0.663023355314391 + Canopy) / (95.095610384719 + -1 * Canopy)
);
Name("H1_2") = TanH(
    0.412448174530612 + 0.456056204011731 * Log(0.283430789103519 + Impervious) / (100.396784146525 + -1 *
    Impervious)
) + -0.248486766206423 * Log(0.663023355314391 + Canopy) / (95.095610384719 + -1 * Canopy)
);
Name("H1_3") = TanH(
    (-1.55413265739832) + -0.0487430496753764 * Log(
\[
\frac{(0.283430789103519 + \text{Impervious})}{(100.396784146525 + -1 \times \text{Impervious})} + 0.141213132624027 \times \log\left(\frac{0.663023355314391 + \text{Canopy}}{(95.095610384719 + -1 \times \text{Canopy})}\right) + 0.141213132624027 \times \log\left(\frac{0.663023355314391 + \text{Canopy}}{(95.095610384719 + -1 \times \text{Canopy})}\right)
\]

\[
\text{Name("Predicted Temp") = 25.000591321708 + 0.249479224696179 \times H1_1 + 0.272816478981451 \times H1_2 + -1.3309185636204 \times H1_3};
\]

**Table 3.38: Formula notation for Revere (Neural Networks)**

| mp_1 = New Namespace("Neural - Temp"); | mp_1:predict = Function({Name("Canopy"), Name("Impervious")}), {Default Local}, Name("H1_1") = TanH(16.6783090218791 + -0.110474716020513 \times \text{Canopy} + 1.26963610704046 \times \text{ArcSinH}((-157624.838627516) + 1509.59108891764 \times \text{Impervious})}; |
| mp_1:predict = Function({Name("Canopy"), Name("Impervious")}), {Default Local}, Name("H1_2") = TanH(9.82073176483573 + 0.0295444770608389 \times \text{Canopy} + 0.807938403208179 \times \text{ArcSinH}((-157624.838627516) + 1509.59108891764 \times \text{Impervious})}; |
| mp_1:predict = Function({Name("Canopy"), Name("Impervious")}), {Default Local}, Name("H1_3") = TanH(-7.51904433126382 + 0.0139838453586435 \times \text{Canopy} + -0.655557129262973 \times \text{ArcSinH}((-157624.838627516) + 1509.59108891764 \times \text{Impervious})}; |
| mp_1:predict = Function({Name("Canopy"), Name("Impervious")}), {Default Local}, Name("Predicted Temp") = 25.6687989403434 + 0.0656594125304098 \times H1_1 + 0.352055942363811 \times H1_2 + 0.25984837714278 \times H1_3}; |

**Table 3.39: Formula notation for Everett (Neural Networks)**

| mp_1 = New Namespace("Neural - Temp"); | mp_1:predict = Function({Name("Canopy"), Name("Impervious")}), {Default Local}, Name("H1_1") = TanH(14.7193252045643 + -0.0755810211911475 \times \log(0.236365180693954 + \text{Impervious}) / (100.105785620336 + -1 \times \text{Impervious})} + 0.25984837714278 \times H1_3}; |
| mp_1:predict = Function({Name("Canopy"), Name("Impervious")}), {Default Local}, Name("H1_2") = TanH(-7.53335724344441 \times \log(0.236365180693954 + \text{Impervious}) / (100.105785620336 + -1 \times \text{Impervious})} + 0.25984837714278 \times H1_3}; |
Name("H1_2") = TanH( 
    (-7.87818690969628) + -1.08149080526664 * Log( 
        (0.236365180693954 + Impervious) / (100.105785620336 + -1 * Impervious) 
    ) + -0.049597068507842 * Log( 
        (1.74530560185795 + Canopy) / (92.3576018374074 + -1 * Canopy) 
    ) 
); 
Name("H1_3") = TanH( 
    (-20.8507622231053) + -1.34453033346362 * Log( 
        (0.236365180693954 + Impervious) / (100.105785620336 + -1 * Impervious) 
    ) + 5.86021782658483 * Log( 
        (1.74530560185795 + Canopy) / (92.3576018374074 + -1 * Canopy) 
    ) 
); 
Name("Predicted Temp") = 26.9466161151728 + -0.0210840910106919 * H1_1 + 0.145262000246125 * H1_2 + -0.051905234624315 * H1_3; 

Table 3.40: Formula notation for West Springfield (Neural Networks)

mp_1 = New Namespace("Neural - Temp");
mp_1:predict = Function({Name("Canopy"), Name("Impervious")}, 
    {Default Local}, 
    Name("H1_1") = TanH( 
        (-11.4416262584727) + -1.99015988954719 * Log( 
            (0.0280549356117075 + Impervious) / (100.111691098499 + -1 * Impervious) 
        ) + -1.3145630944344 * Log( 
            (0.36069616642017 + Canopy) / (94.4195135795362 + -1 * Canopy) 
        ) 
    );
Name("H1_2") = TanH( 
    (-12.0573309897836) + -2.04523842416186 * Log( 
        (0.0280549356117075 + Impervious) / (100.111691098499 + -1 * Impervious) 
    ) + -1.37325649574551 * Log( 
        (0.36069616642017 + Canopy) / (94.4195135795362 + -1 * Canopy) 
    ) 
); 
Name("H1_3") = TanH( 
    2.82506912226868 + -0.522989033173243 * Log( 
    ...
\[(0.280549356117075 + \text{Impervious}) / (100.111691098499 + -1 \times \text{Impervious}) + 1.26913665008225 \times \log\left(\frac{0.36069616642017 + \text{Canopy}}{94.4195135795362 + -1 \times \text{Canopy}}\right)\]

\[\text{Name("Predicted Temp") = 27.4395535256553 + -1.0269358770048 \times H_1_1 + 1.00018428366975 \times H_1_2 + -0.160188967022068 \times H_1_3;}\]

<table>
<thead>
<tr>
<th>Table 3.41: OLS Summary Results for Attleboro</th>
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<tbody>
<tr>
<td>Variable</td>
</tr>
<tr>
<td>----------</td>
</tr>
<tr>
<td>Intercept</td>
</tr>
<tr>
<td>Impervious</td>
</tr>
<tr>
<td>Canopy</td>
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<table>
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<tr>
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<table>
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<tr>
<th>Adjusted R-squared [d]</th>
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<tr>
<th>Prob(F, (2,5049240) degrees of freedom)</th>
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<table>
<thead>
<tr>
<th>Joint Wald Statistic [e]</th>
<th>4946.902376</th>
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</table>

<table>
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<tr>
<th>Prob(&gt;chi-squared), (2) degrees of freedom</th>
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<table>
<thead>
<tr>
<th>Koenker (BP) statistic [f]</th>
<th>286.997280</th>
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<table>
<thead>
<tr>
<th>Jarque-Bera statistic [g]</th>
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<table>
<thead>
<tr>
<th>Table 3.42: OLS Summary Results for Barnstable</th>
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<tbody>
<tr>
<td>Variable</td>
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<td>----------</td>
</tr>
<tr>
<td>Intercept</td>
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<tr>
<td>Impervious</td>
</tr>
<tr>
<td>Canopy</td>
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<tr>
<th>Akaike’s Information criterion (AICc) [d]</th>
<th>-210347.426396</th>
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</table>
Multiple R-squared [d] 0.063945 | Adjusted R-squared [d] 0.063934
Joint F-statistic [e] 5817.668832 | Prob(>F), (2,5049240) degrees of freedom 0.000000*
Joint Wald Statistic [e] 15768.954313 | Prob(>chi-squared), (2) degrees of freedom 0.000000*
Koenker (BP) statistic [f] 3253.311093 | Prob(>chi-squared), (2) degrees of freedom 0.000000*
Jarque-Bera statistic [g] 3201.886456 | Prob(>chi-squared), (2) degrees of freedom 0.000000*

Table 3.43: OLS Summary Results for Boston

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
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<tr>
<td>Intercept</td>
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<td>Impervious</td>
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<tr>
<td>Canopy</td>
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<td>0.000000*</td>
<td>0.000000*</td>
<td>1.424800</td>
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<td>Multiple R-squared [d]</td>
<td>0.173281</td>
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<td></td>
<td>77924.674306</td>
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<tr>
<td>Joint F-statistic [e]</td>
<td>14431.570559</td>
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<tr>
<td>Joint Wald Statistic [e]</td>
<td>47874.671590</td>
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<tr>
<td>Koenker (BP) statistic [f]</td>
<td>8889.044234</td>
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<tr>
<td>Jarque-Bera statistic [g]</td>
<td>12304.653314</td>
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Table 3.44: OLS Summary Results for Brockton

<table>
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<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
</tr>
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<tr>
<td>Intercept</td>
<td>27.003383</td>
<td>0.000000*</td>
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<tr>
<td>Impervious</td>
<td>0.000250</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.463755</td>
</tr>
<tr>
<td>Canopy</td>
<td>-0.000137</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.423755</td>
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</table>
Number of observations | 61917 | Akaike’s Information criterion (AICc) [d] | -13412.822752
Multiple R-squared [d] | 0.016271 | Adjusted R-squared [d] | 0.016239
Joint F-statistic [e] | 512.021137 | Prob(>F), (2,5049240) degrees of freedom | 0.000000*
Joint Wald Statistic [e] | 954.096216 | Prob(>chi-squared), (2) degrees of freedom | 0.000000*
Koenker (BP) statistic [f] | 429.150870 | Prob(>chi-squared), (2) degrees of freedom | 0.000000*
Jarque-Bera statistic [g] | 2662.580910 | Prob(>chi-squared), (2) degrees of freedom | 0.000000*

Table 3.45: OLS Summary Results for Cambridge

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
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<tr>
<td>Intercept</td>
<td>26.857205</td>
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<td>Impervious</td>
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<td>0.000000*</td>
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<tr>
<td>Canopy</td>
<td>0.002612</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.095863</td>
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Number of observations | 20431 | Akaike’s Information criterion (AICc) [d] | -28253.060781
Multiple R-squared [d] | 0.143041 | Adjusted R-squared [d] | 0.142957
Joint F-statistic [e] | 1704.888635 | Prob(>F), (2,5049240) degrees of freedom | 0.000000*
Joint Wald Statistic [e] | 7086.823915 | Prob(>chi-squared), (2) degrees of freedom | 0.000000*
Koenker (BP) statistic [f] | 2358.768882 | Prob(>chi-squared), (2) degrees of freedom | 0.000000*
Jarque-Bera statistic [g] | 1406.679636 | Prob(>chi-squared), (2) degrees of freedom | 0.000000*

Table 3.46: OLS Summary Results for Chelsea

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
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<tr>
<td>Intercept</td>
<td>26.221492</td>
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<tr>
<td>Impervious</td>
<td>0.000451</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.107765</td>
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Table 3.47: OLS Summary Results for Chicopee

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
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<tbody>
<tr>
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<td>27.357280</td>
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<td>Impervious</td>
<td>0.000251</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.214822</td>
</tr>
<tr>
<td>Canopy</td>
<td>0.000059</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.214822</td>
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<table>
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<tr>
<th>Number of observations</th>
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<tr>
<td>Multiple R-squared [d]</td>
<td>0.004241</td>
<td>Adjusted R-squared [d]</td>
<td>0.004212</td>
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<tr>
<td>Joint F-statistic [e]</td>
<td>146.429440</td>
<td>Prob(&gt;F), (2,5049240) degrees of freedom</td>
<td>0.000000*</td>
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<tr>
<td>Joint Wald Statistic [e]</td>
<td>271.553325</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Koenker (BP) statistic [f]</td>
<td>1454.155709</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Jarque-Bera statistic [g]</td>
<td>9596.858418</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
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Table 3.48: OLS Summary Results for Everett

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
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<tr>
<td>Intercept</td>
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<td>Canopy</td>
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<td>0.000000*</td>
<td>0.000000*</td>
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<table>
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<tr>
<td>Multiple R-squared [d]</td>
<td>0.008105</td>
<td>Adjusted R-squared [d]</td>
<td>0.007790</td>
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<td>Joint F-statistic [e]</td>
<td>25.737975</td>
<td>Prob(&gt;F), (2,5049240) degrees of freedom</td>
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<td>Joint Wald Statistic [e]</td>
<td>43.119125</td>
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<tr>
<td>Koenker (BP) statistic [f]</td>
<td>37.147810</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
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<tr>
<td>Jarque-Bera statistic [g]</td>
<td>483.958746</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
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<tr>
<td>Variable</td>
<td>Coefficient [a]</td>
<td>Probability [b]</td>
<td>Robust_pr [b]</td>
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<td>Multiple R-squared [d]</td>
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<td>Adjusted R-squared [d]</td>
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<td>Joint F-statistic [e]</td>
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<td>Joint Wald Statistic [e]</td>
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<td>Koenker (BP) statistic [f]</td>
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Table 3.49: OLS Summary Results for Fall River

Table 3.50: OLS Summary Results for Fitchburg
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<th>Coefficient [a]</th>
<th>Probability [b]</th>
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<td>Canopy</td>
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<td>1.561627</td>
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<td>Adjusted R-squared [d]</td>
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</tr>
<tr>
<td>Joint F-statistic [e]</td>
<td>16630.529590</td>
<td>Prob(&gt;F), (2,5049240) degrees of freedom</td>
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<tr>
<td>Joint Wald Statistic [e]</td>
<td>48394.390410</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
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<tr>
<td>Koenker (BP) statistic [f]</td>
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<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
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<tr>
<td>Jarque-Bera statistic [g]</td>
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<table>
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<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
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<td>Canopy</td>
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<td>0.000000*</td>
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<tr>
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<td>Adjusted R-squared [d]</td>
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<tr>
<td>Joint F-statistic [e]</td>
<td>1359.081100</td>
<td>Prob(&gt;F), (2,5049240) degrees of freedom</td>
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<td>Joint Wald Statistic [e]</td>
<td>3182.016640</td>
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<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Jarque-Bera statistic [g]</td>
<td>2268.259196</td>
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### Table 3.52: OLS Summary Results for Holyoke

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<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
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</thead>
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<tr>
<td>Impervious</td>
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<td>0.000000*</td>
<td>1.530118</td>
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<td>Canopy</td>
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<td>0.000000*</td>
<td>0.000000*</td>
<td>1.530118</td>
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</table>

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<th>Number of observations</th>
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<th>Akaike’s Information criterion (AICc) [d]</th>
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</thead>
<tbody>
<tr>
<td>Multiple R-squared [d]</td>
<td>0.321543</td>
<td>Adjusted R-squared [d]</td>
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</tr>
<tr>
<td>Joint F-statistic [e]</td>
<td>15533.828775</td>
<td>Prob(&gt;F), (2,5049240) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Joint Wald Statistic [e]</td>
<td>37224.883151</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Koenker (BP) statistic [f]</td>
<td>1848.847403</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Jarque-Bera statistic [g]</td>
<td>352.131533</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
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</table>

### Table 3.53: OLS Summary Results for Lawrence

<table>
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<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
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<tr>
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<td>Impervious</td>
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<td>Canopy</td>
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<td>0.000000*</td>
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</table>

<table>
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<tr>
<th>Number of observations</th>
<th>21178</th>
<th>Akaike’s Information criterion (AICc) [d]</th>
<th>-80796.947626</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple R-squared [d]</td>
<td>0.107217</td>
<td>Adjusted R-squared [d]</td>
<td>0.107132</td>
</tr>
<tr>
<td>Joint F-statistic [e]</td>
<td>1271.482053</td>
<td>Prob(&gt;F), (2,5049240) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Joint Wald Statistic [e]</td>
<td>1924.365391</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Koenker (BP) statistic [f]</td>
<td>311.088171</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
</tr>
</tbody>
</table>
### Jarque-Bera statistic

| Jarque-Bera statistic [g] | 2518.982671 | Prob(>chi-squared), (2) degrees of freedom | 0.000000* |

### Table 3.54: OLS Summary Results for Leominster

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>26.537931</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>-</td>
</tr>
<tr>
<td>Impervious</td>
<td>0.006573</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.647795</td>
</tr>
<tr>
<td>Canopy</td>
<td>-0.004113</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.647795</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Number of observations</th>
<th>85254</th>
<th>Akaike’s Information criterion (AICc) [d]</th>
<th>100751.652868</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple R-squared [d]</td>
<td>0.333374</td>
<td>Adjusted R-squared [d]</td>
<td>0.333358</td>
</tr>
<tr>
<td>Joint F-statistic [e]</td>
<td>21316.629157</td>
<td>Prob(&gt;F), (2,5049240) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Joint Wald Statistic [e]</td>
<td>70817.929950</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Koenker (BP) statistic [f]</td>
<td>18213.609575</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Jarque-Bera statistic [g]</td>
<td>2600.829871</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
</tr>
</tbody>
</table>

### Table 3.55: OLS Summary Results for Lowell

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>27.107903</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>-</td>
</tr>
<tr>
<td>Impervious</td>
<td>-0.000269</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.435038</td>
</tr>
<tr>
<td>Canopy</td>
<td>-0.000671</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.435038</td>
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</tbody>
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<table>
<thead>
<tr>
<th>Number of observations</th>
<th>41504</th>
<th>Akaike’s Information criterion (AICc) [d]</th>
<th>-92388.431286</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple R-squared [d]</td>
<td>0.029238</td>
<td>Adjusted R-squared [d]</td>
<td>0.029192</td>
</tr>
<tr>
<td>Joint F-statistic [e]</td>
<td>624.983848</td>
<td>Prob(&gt;F), (2,5049240) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Joint Wald Statistic [e]</td>
<td>1289.128049</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Variable</td>
<td>Coefficient [a]</td>
<td>Probability [b]</td>
<td>Robust_pr [b]</td>
</tr>
<tr>
<td>---------------------</td>
<td>-----------------</td>
<td>----------------</td>
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</tr>
<tr>
<td>Intercept</td>
<td>26.155000</td>
<td>0.000000*</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Impervious</td>
<td>-0.004357</td>
<td>0.000000*</td>
<td>0.000000*</td>
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<tr>
<td>Canopy</td>
<td>0.003021</td>
<td>0.000000*</td>
<td>0.000000*</td>
</tr>
</tbody>
</table>

Number of observations: 32782

Akaike’s Information criterion (AICc) [d]: -7324.891876

Multiple R-squared [d]: 0.505682

Adjusted R-squared [d]: 0.505652

Joint F-statistic [e]: 16766.279717

Prob(>F), (2,5049240) degrees of freedom: 0.000000*

Joint Wald Statistic [e]: 50214.401045

Prob(>chi-squared), (2) degrees of freedom: 0.000000*

Koenker (BP) statistic [f]: 1038.338605

Prob(>chi-squared), (2) degrees of freedom: 0.000000*

Jarque-Bera statistic [g]: 76.504672

Prob(>chi-squared), (2) degrees of freedom: 0.000000*

---

Table 3.57: OLS Summary Results for Malden

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>26.370815</td>
<td>0.000000*</td>
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<tr>
<td>Impervious</td>
<td>0.000380</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.446700</td>
</tr>
<tr>
<td>Canopy</td>
<td>-0.002049</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.446700</td>
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</tbody>
</table>

Number of observations: 14752

Akaike’s Information criterion (AICc) [d]: -18188.422636

Multiple R-squared [d]: 0.071731

Adjusted R-squared [d]: 0.071605

Joint F-statistic [e]: 569.856669

Prob(>F), (2,5049240) degrees of freedom: 0.000000*
<table>
<thead>
<tr>
<th>Joint Wald Statistic</th>
<th>986.603877</th>
<th>Prob(&gt;chi-squared), (2) degrees of freedom</th>
<th>0.000000*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Koenker (BP) statistic</td>
<td>479.564572</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Jarque-Bera statistic</td>
<td>4589.699408</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
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</table>

Table 3.58: OLS Summary Results for Methuen

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>26.850718</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>-</td>
</tr>
<tr>
<td>Impervious</td>
<td>-0.000267</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.391699</td>
</tr>
<tr>
<td>Canopy</td>
<td>-0.000162</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.391699</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Number of observations</th>
<th>63354</th>
<th>Akaike’s Information criterion (AICc) [d]</th>
<th>-162386.108502</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple R-squared [d]</td>
<td>0.010537</td>
<td>Adjusted R-squared [d]</td>
<td>0.010506</td>
</tr>
<tr>
<td>Joint F-statistic [e]</td>
<td>337.313950</td>
<td>Prob(&gt;F), (2,5049240) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Joint Wald Statistic [e]</td>
<td>742.322616</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Koenker (BP) statistic [f]</td>
<td>2973.605376</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Jarque-Bera statistic [g]</td>
<td>442.846954</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
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</table>

Table 3.59: OLS Summary Results for New Bedford

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>26.146113</td>
<td>0.000000*</td>
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<tr>
<td>Impervious</td>
<td>-0.003599</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>2.413159</td>
</tr>
<tr>
<td>Canopy</td>
<td>0.001748</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>2.413159</td>
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<table>
<thead>
<tr>
<th>Number of observations</th>
<th>55407</th>
<th>Akaike’s Information criterion (AICc) [d]</th>
<th>26592.695323</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple R-squared [d]</td>
<td>0.252915</td>
<td>Adjusted R-squared [d]</td>
<td>0.252888</td>
</tr>
</tbody>
</table>
Joint F-statistic [e] | 9378.098542 | Prob(>F), (2,5049240) degrees of freedom | 0.000000*  
Joint Wald Statistic [e] | 20876.070239 | Prob(>chi-squared), (2) degrees of freedom | 0.000000*  
Koenker (BP) statistic [f] | 3655.208336 | Prob(>chi-squared), (2) degrees of freedom | 0.000000*  
Jarque-Bera statistic [g] | 192130.104004 | Prob(>chi-squared), (2) degrees of freedom | 0.000000*  

Table 3.60: OLS Summary Results for Northampton

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>27.161705</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>-</td>
</tr>
<tr>
<td>Impervious</td>
<td>0.002462</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.308591</td>
</tr>
<tr>
<td>Canopy</td>
<td>-0.003131</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.308591</td>
</tr>
</tbody>
</table>

Number of observations | 39165 | Akaike’s Information criterion (AICc) [d] | 14179.483661  
Multiple R-squared [d] | 0.172930 | Adjusted R-squared [d] | 0.172888  
Joint F-statistic [e] | 4094.151159 | Prob(>F), (2,5049240) degrees of freedom | 0.000000*  
Joint Wald Statistic [e] | 12689.031648 | Prob(>chi-squared), (2) degrees of freedom | 0.000000*  
Koenker (BP) statistic [f] | 3060.696693 | Prob(>chi-squared), (2) degrees of freedom | 0.000000*  
Jarque-Bera statistic [g] | 1712.505090 | Prob(>chi-squared), (2) degrees of freedom | 0.000000*  

Table 3.61: OLS Summary Results for Peabody

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>26.156655</td>
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<tr>
<td>Impervious</td>
<td>-0.001186</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.338011</td>
</tr>
<tr>
<td>Canopy</td>
<td>0.001036</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.338011</td>
</tr>
</tbody>
</table>

Number of observations | 48413 | Akaike’s Information criterion (AICc) [d] | 1536.267283  

258
<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>25.520507</td>
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</tr>
<tr>
<td>Impervious</td>
<td>0.001849</td>
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<td>1.396491</td>
</tr>
<tr>
<td>Canopy</td>
<td>-0.003752</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.396491</td>
</tr>
<tr>
<td>Number of observations</td>
<td>121395</td>
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<td>80239.107275</td>
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<tr>
<td>Multiple R-squared [d]</td>
<td>0.172657</td>
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<td>0.172643</td>
</tr>
<tr>
<td>Joint F-statistic [e]</td>
<td>12666.39659</td>
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</tr>
<tr>
<td>Joint Wald Statistic [e]</td>
<td>32559.492809</td>
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<td>0.000000*</td>
</tr>
<tr>
<td>Koenker (BP) statistic [f]</td>
<td>9995.078441</td>
<td></td>
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<tr>
<td>Jarque-Bera statistic [g]</td>
<td>43136.517339</td>
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<td>0.000000*</td>
</tr>
<tr>
<td>Table 3.62: OLS Summary Results for Pittsfield</td>
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</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
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</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>26.477273</td>
<td>0.000000*</td>
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<tr>
<td>Impervious</td>
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<td>2.447621</td>
</tr>
<tr>
<td>Canopy</td>
<td>0.002876</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>2.447621</td>
</tr>
<tr>
<td>Table 3.63: OLS Summary Results for Quincy</td>
<td></td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>
Number of observations | 40551 | Akaike’s Information criterion (AICc) [d] | -10258.951892
--- | --- | --- | ---
Multiple R-squared [d] | 0.140049 | Adjusted R-squared [d] | 0.140007
Joint F-statistic [e] | 3301.763051 | Prob(>F), (2,5049240) degrees of freedom | 0.000000*
Joint Wald Statistic [e] | 8939.327804 | Prob(>chi-squared), (2) degrees of freedom | 0.000000*
Koenker (BP) statistic [f] | 5193.859752 | Prob(>chi-squared), (2) degrees of freedom | 0.000000*
Jarque-Bera statistic [g] | 1110.766783 | Prob(>chi-squared), (2) degrees of freedom | 0.000000*

Table 3.64: OLS Summary Results for Revere

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>25.799248</td>
<td>0.000000*</td>
<td>0.000000*</td>
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</tr>
<tr>
<td>Impervious</td>
<td>0.001014</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.015048</td>
</tr>
<tr>
<td>Canopy</td>
<td>0.004140</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.015048</td>
</tr>
</tbody>
</table>

Number of observations | 16673 | Akaike’s Information criterion (AICc) [d] | -8030.704270
--- | --- | --- | ---
Multiple R-squared [d] | 0.098293 | Adjusted R-squared [d] | 0.098185
Joint F-statistic [e] | 908.579474 | Prob(>F), (2,5049240) degrees of freedom | 0.000000*
Joint Wald Statistic [e] | 1861.378360 | Prob(>chi-squared), (2) degrees of freedom | 0.000000*
Koenker (BP) statistic [f] | 103.959518 | Prob(>chi-squared), (2) degrees of freedom | 0.000000*
Jarque-Bera statistic [g] | 1966.426480 | Prob(>chi-squared), (2) degrees of freedom | 0.000000*

Table 3.65: OLS Summary Results for Salem

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
</tr>
</thead>
<tbody>
<tr>
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</tr>
<tr>
<td>Impervious</td>
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<td>0.000000*</td>
<td>0.000000*</td>
<td>1.505327</td>
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<tr>
<td>Canopy</td>
<td>0.005474</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.505327</td>
</tr>
<tr>
<td>Variable</td>
<td>Coefficient [a]</td>
<td>Probability [b]</td>
<td>Robust_pr [b]</td>
<td>VIF [c]</td>
</tr>
<tr>
<td>---------------------------</td>
<td>-----------------</td>
<td>-----------------</td>
<td>---------------</td>
<td>---------</td>
</tr>
<tr>
<td>Intercept</td>
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</tr>
<tr>
<td>Impervious</td>
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<td>0.000000*</td>
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<td>1.466836</td>
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<td>Canopy</td>
<td>-0.002153</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.466836</td>
</tr>
</tbody>
</table>

| Number of observations    | 23090           | Akaike’s Information criterion (AICc) [d] | 25356.061526 |
| Multiple R-squared [d]    | 0.194906        | Adjusted R-squared [d]                    | 0.194836     |
| Joint F-statistic [e]     | 2794.580401     | Prob(>F), (2,5049240) degrees of freedom  | 0.000000*    |
| Joint Wald Statistic [e]  | 7101.300176     | Prob(>chi-squared), (2) degrees of freedom | 0.000000*    |
| Koenker (BP) statistic [f] | 1504.681583    | Prob(>chi-squared), (2) degrees of freedom | 0.000000*    |
| Jarque-Bera statistic [g] | 874.868247      | Prob(>chi-squared), (2) degrees of freedom | 0.000000*    |

Table 3.66: OLS Summary Results for Springfield

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>26.970256</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>-</td>
</tr>
</tbody>
</table>

| Number of observations    | 59615           | Akaike’s Information criterion (AICc) [d] | -6314.331248 |
| Multiple R-squared [d]    | 0.154312        | Adjusted R-squared [d]                    | 0.154283     |
| Joint F-statistic [e]     | 5438.666391     | Prob(>F), (2,5049240) degrees of freedom  | 0.000000*    |
| Joint Wald Statistic [e]  | 8452.759978     | Prob(>chi-squared), (2) degrees of freedom | 0.000000*    |
| Koenker (BP) statistic [f] | 4605.564796    | Prob(>chi-squared), (2) degrees of freedom | 0.000000*    |
| Jarque-Bera statistic [g] | 332357.911446   | Prob(>chi-squared), (2) degrees of freedom | 0.000000*    |

Table 3.67: OLS Summary Results for Taunton
<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
<th>( \text{Var} ) [d]</th>
<th>( \text{Prob}(F) ) [d]</th>
<th>( \text{Prob}(\text{chi-squared}) ) [e]</th>
<th>( \text{Prob}(\text{chi-squared}) ) [f]</th>
<th>( \text{Prob}(\text{chi-squared}) ) [g]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>27.201817</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Impervious</td>
<td>0.001448</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.201843</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Canopy</td>
<td>-0.001630</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.201843</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3.68: OLS Summary Results for Westfield

<table>
<thead>
<tr>
<th>Variable</th>
<th>Number of observations</th>
<th>Akaike’s Information criterion (AICc) [d]</th>
<th>Adjusted R-squared [d]</th>
<th>( \text{Prob}(\text{chi-squared}) ) [e]</th>
<th>( \text{Prob}(\text{chi-squared}) ) [f]</th>
<th>( \text{Prob}(\text{chi-squared}) ) [g]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impervious</td>
<td>137134</td>
<td>-230722.895789</td>
<td>0.002465</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Canopy</td>
<td>135946</td>
<td>-75047.530102</td>
<td>0.145879</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>0.000000*</td>
</tr>
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</table>

Table 3.69: OLS Summary Results for West Springfield
<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>27.425843</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>-</td>
</tr>
<tr>
<td>Impervious</td>
<td>0.001827</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.413534</td>
</tr>
<tr>
<td>Canopy</td>
<td>-0.002603</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.413534</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Number of observations</th>
<th>50515</th>
<th>Akaike’s Information criterion (AICc) [d]</th>
<th>-40785.611888</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple R-squared [d]</td>
<td>0.371431</td>
<td>Adjusted R-squared [d]</td>
<td>0.371406</td>
</tr>
<tr>
<td>Joint F-statistic [e]</td>
<td>14924.125795</td>
<td>Prob(&gt;F), (2,5049240) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Joint Wald Statistic [e]</td>
<td>34609.604769</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Koenker (BP) statistic [f]</td>
<td>1467.806770</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Jarque-Bera statistic [g]</td>
<td>49.175622</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
</tr>
</tbody>
</table>

Table 3.70: OLS Summary Results for Worcester

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient [a]</th>
<th>Probability [b]</th>
<th>Robust_pr [b]</th>
<th>VIF [c]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>26.166240</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>-</td>
</tr>
<tr>
<td>Impervious</td>
<td>0.000806</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.596878</td>
</tr>
<tr>
<td>Canopy</td>
<td>-0.001617</td>
<td>0.000000*</td>
<td>0.000000*</td>
<td>1.596878</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Number of observations</th>
<th>110469</th>
<th>Akaike’s Information criterion (AICc) [d]</th>
<th>54155.982894</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple R-squared [d]</td>
<td>0.048961</td>
<td>Adjusted R-squared [d]</td>
<td>0.048944</td>
</tr>
<tr>
<td>Joint F-statistic [e]</td>
<td>2843.496409</td>
<td>Prob(&gt;F), (2,5049240) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Joint Wald Statistic [e]</td>
<td>5494.123296</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Koenker (BP) statistic [f]</td>
<td>2225.986908</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
</tr>
<tr>
<td>Jarque-Bera statistic [g]</td>
<td>3050.716141</td>
<td>Prob(&gt;chi-squared), (2) degrees of freedom</td>
<td>0.000000*</td>
</tr>
</tbody>
</table>


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