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A SPATIAL MULTI-OBJECTIVE APPROACH FOR MODELING THE ECOSYSTEM SERVICES AND BENEFITS OF URBAN TREES

by

Charity Nyelele

A dissertation
submitted in partial fulfillment
of the requirements for the
Doctor of Philosophy Degree
State University of New York
College of Environmental Science and Forestry
Syracuse, New York

June 2020

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ACKNOWLEDGEMENTS

There are many people I would like to thank for this research project. I am particularly indebted to my advisor, Professor Chuck Kroll, for his invaluable guidance, support and encouragement. Special mention goes to my steering committee Drs. Colin M. Beier, David J. Nowak, Lemir Teron and Mary B. Collins for their feedback and support throughout the research process. I am thankful to our collaborative partners from the USDA Forest Service Northern Research Station, Davey Institute, New York City (NYC) Urban Field Station and NYC Parks and Recreation, in particular Dr. Novem Auyeung who helped provide data for some of the analyses. I extend my gratitude to Ethan Bodnaruk, Brenden Covert, Cole Jermyn, Robbie Coville, Robert Hoehn, Alexis Ellis as well as Drs. Reza Abdi, Satoshi Hirabayashi, Jian Lin, Eric Greenfield and the rest of the ESF and i-Tree teams for helping me figure out the i-Tree models and some of the analyses. I would like to acknowledge the Fulbright Program, USDA Forest Service's Urban and Community Forestry Challenge Cost Share Grant Program, and the Environmental Resources Engineering and Environmental Science Departments at ESF for supporting my studies. I greatly appreciate the mentorship of Madodana Sithole and Nkululeko J. Ndiweni; Professors Priscah H. Mugabe, Amon Murwira and Sara B. Feresu as well as Drs. Witness Kozanayi, Munyaradzi D. Shekede and Krasposy K. Kujinga over the years. I also pay tribute to Pat and Auxie Moyo, Shumaila Bhatti, Tyler Lyons, Joseph Makaure, Shiela Chikulo, Onismas Chikorose, Gladys Tutisani, Ropafadzo Diza, Nonhlanhla Ndiweni, Esteri Magaisa, Maakwe Cumanzala, Chiza Mwinde, and Drs. Lindani Moyo, Mbulisi Sibanda, Douglas Caiphus, Tawanda Gara, Timothy Dube, and Youngeun Choi for providing moral support. I am forever grateful to my parents (Machona and Mbaita), siblings (Pretty and Mwembezi Aaron), brother-in-law (Fredrick), nieces (Chantel Tinevimbo and Martha), nephew (Liam Munopaishe), aunt (Suku Muzamba), fiancé (Mziwandile Ndlovu) and the rest of my family for always consistently supporting me in my endeavors, and for their prayers and motivation.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

C. Nyelele. A spatial multi-objective approach for modeling the ecosystem services and benefits of urban trees. 146 pages, 6 tables, 14 figures, 2020. Urban Forestry and Urban Greening journal style guide used.

Trees provide important ecosystem services and benefits, with some, such as air pollutant and heat reductions, being linked to improved human health and well-being. With numerous tree planting initiatives being undertaken in different cities, careful thought needs to be put into considering the placement of trees, their beneficiaries as well as viable alternatives. Using a spatially distributed implementation of the i-Tree suite of ecosystem service models and mapping tools, this research estimated the current and future ecosystem services and benefits of a recent tree planting initiative within each census block group of the Bronx, NY for 2010 and for three 2030 tree cover scenarios (assuming different mortality rates). Results highlight how tree cover and benefits can be enhanced by maintaining existing canopy and ensuring the survival of newly planted trees. Traditional and non-traditional quantitative approaches of assessing environmental equity were used to establish whether there is an equitable distribution of ecosystem services derived from trees among various socio-demographic and socio-economic variables at the census block group level in the Bronx, NY. All ecosystem services and benefits appear to be unequally and inequitably distributed, with disadvantaged socio-demographic and socio-economic block groups receiving disproportionately lower ecosystem services from urban trees. The vast majority of the inequality is explained by variations within each socio-demographic and socio-economic subgroup rather than variations between subgroups. To guide future greening initiatives towards prioritizing planting locations that maximize multiple objectives, as well as the best areas to preserve urban forests and achieve equity, a spatially explicit methodology was used to develop a multi-objective decision support framework which was applied in the Bronx, NY to identify optimal planting locations. Overall, the findings of this research have the potential to guide more local and fine scale decision making regarding where to improve or protect tree cover and maximize the services and benefits of trees.

Keywords: Benefits, Decision support, Ecosystem services, Environmental justice, Equality, Equity, i-Tree, Multi-objective, Optimal, Optimization, Prioritization, Spatially explicit, Urban forestry.

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CHAPTER ONE: INTRODUCTION

1.1 OVERVIEW

More than half of the world's population lives in cities (Dye, 2008) and more than two thirds are expected to live in cities by 2050 (United Nations, 2011). This increase in urban area affects the local climate through the modification of surface albedo, evapotranspiration, and increased aerosols and anthropogenic heat sources, creating elevated urban temperatures and changes in precipitation patterns (Arnfield, 2003; Seto and Shepherd, 2009). In addition to climate impacts, urbanization exacerbates air pollution through increased transportation, heating of buildings, and industrial activities, posing major environmental and public health problems in many cities (McMichael, 2000). The provision of water supply, sanitation, and drainage, and increased impervious surfaces that accompany the urbanization processes affect water resources and can increase storm water quantity and decrease stormwater quality (Griffith et al., 2010; Metsäranta et al., 2005). In addition, the increases in air temperature and decreases in air quality can adversely impact urban inhabitants (Analitis et al., 2018; Hewitt et al., 2020).

Trees can offset some of the negative impacts of urbanization and provide numerous ecosystem services that can improve environmental quality and human health in and around urban areas. However, with rapid urbanization, trees are often lost along with the valuable ecosystem services and benefits they provide (National Research Council, 2013; Nowak et al., 2013). Ecosystem services refer to the conditions and processes through which natural ecosystems sustain and fulfill human life (Daily, 1997), whilst benefits illustrate the final outputs from ecosystems that directly affect human well-being (Haines-Young and Potschin, 2012). Trees provide ecosystem services such as air pollutant removal, carbon storage and sequestration, urban heat island reduction and stormwater runoff reduction which are critical to both environmental quality as well as human health and well-being (Nowak et al., 2007; Salmond et al., 2016). Urban trees also provide a variety of less quantifiable social, economic, psychological, medical, and aesthetic benefits, such as improved aesthetics and increased property values (Dwyer et al., 1992).

Urban tree planting initiatives are being undertaken in many cities around the world to increase tree canopy cover and achieve the many benefits of trees (Battaglia, 2014). In Chicago, trees are being planted to enhance and protect the urban canopy whilst creating and maintaining healthy and vibrant neighborhoods (City of Chicago, 2016). Phoenix is planting trees to primarily create more shade; canopy cover over the desert city is one way to alleviate extreme and prolonged summer heat (City of Phoenix, 2016). Portland is expanding its urban forest to sustainably manage storm water runoff, stop the spread of invasive plants, restore native vegetation, protect sensitive natural areas, and improve water quality and watershed health (City of Portland, 2016). There is a need to assess the extent to which trees provide these ecosystem services, where services are realized, and most importantly to improve methods of determining future planting locations. This research focuses on MillionTreesNYC, an intensive tree planting initiative, that seeks to transform New York City (NYC), NY into a more environmentally sustainable city by increasing tree canopy coverage and providing residents with important health, economic and environmental benefits (MillionTreesNYC, 2016).

Trees can be strategically planted and managed to optimize desired ecosystem services using knowledge of the heterogeneous urban landscape and human demographics. However, optimization models used to identify where to increase tree cover have often been single-variable optimization strategies that direct planners to focus on one ecosystem service (such as air pollutant removal or climate regulation provided by trees), ignoring other services of potential value to humans and the environment (Salmond et al., 2016; Bodnaruk et al., 2017).

This is not surprising considering that often tree plantings are motivated by a specific concern, for example air particulate matter less than 2.5 micrometers in diameter ($PM_{2.5}$) and ozone (United States Environmental Protection Agency (US EPA), 2012). Increasing tree cover has the potential for multiple co-benefits to be realized (Salmond et al., 2016). Individual ecosystem services are elements of an interrelated whole or “bundle” (Cumming and Peterson, 2005), and attempts to optimize a single service often lead to reductions or losses (trade-offs) of other services (Rodriguez et al., 2006, Bodnaruk et al., 2017). Although decision makers are often trying to meet multiple objectives or to get an ‘acceptable’ balance if objectives conflict, assessing how multiple ecosystem services are interconnected and coupled to each other is a major ecosystem service research gap (Carpenter et al., 2009). Few studies have utilized multi-objective optimization in planning tree plantings, although such a comprehensive approach may show the complex interplay of factors and services realized from green spaces at different scales in different urban settings.

Ecosystem services are not homogeneous across landscapes, nor are they static phenomena (Fisher et al., 2009), and urban expansion results in shifts in service patterns (Haas, 2016). The uneven distribution of tree cover in urban areas and subsequently the ecosystem services and benefits it provides has potential implications related to environmental justice, especially if disadvantaged socio-demographic or socio-economic and marginalized communities lack these services and benefits. Environmental justice is increasingly considered in urban forestry and ecosystem service studies. Disparities in tree cover and ecosystem services by urban forests have been investigated in several studies (Escobedo and Nowak, 2009; Kheirbek et al., 2013, Sister et al., 2010; Perkins et al., 2004). There is need for more studies that identify inequity of ecosystem service and benefit distributions across socio-economic and socio-demographic divides that seek to establish how tree planting could be performed to reduce these inequities.

The normative assumption in the literature is that trees in general provide ecosystem services and thus are desirable (Escoboda et al., 2011). However, the complex physiology and ecological functioning of trees mean that efforts to optimize for one service can produce reductions in other services or other undesirable effects such as increased aero-allergens and tree maintenance (Salmond et al., 2016). Despite this, most urban tree optimization approaches do not account for monetary costs associated with tree plantings. In addition, most studies have looked at the supply side of urban forestry benefits (Haase et al., 2014). The inclusion of the demand side, i.e. the corresponding benefits and beneficiaries, is yet to become an integral part of assessments (Serna-Chavez et al., 2014), yet an ecosystem service is only a service if there is a beneficiary (Fisher et al., 2009).

This study uses the i-Tree modeling framework to explore and improve our understanding of the complex interactions, synergies, and trade-offs that occur between urban heat index reduction, $PM_{2.5}$ air pollutant removal, carbon storage and sequestration, and storm water runoff reduction in urban forests. The study focuses on NYC to develop methods for exploring ecosystem service and benefit distributions and distributional equity, and to develop a decision support framework to aid in multi-objective urban forest planning and management. Results of this study are expected to highlight the vital part trees play in urban areas while developing a framework to guide decision making for future tree planting initiatives towards prioritizing planting locations that maximize multiple objectives, as well as the best areas to preserve urban forests while reducing environmental inequities in different cities.

1.2 RESEARCH QUESTIONS

The following research questions and hypotheses are explored in this study.

1) What are the estimates of current and potential future ecosystem services and benefits of NYC's recent planting initiative within each census block group of the Bronx, NY? The null hypothesis being explored is that there are no differences in the ecosystem service and benefit distributions as a result of the new tree plantings in each census block group. It is also hypothesized that there are no spatial and temporal variations in the ecosystem services and monetary benefits across different block groups in the Bronx as tree cover changes over time.
2) Is there an equitable distribution of ecosystem services and benefits derived from trees among various socio-demographic and socio-economic variables at the census block group level in the Bronx, NY? Specifically, are the ecosystem services and the monetary benefits of tree carbon storage and sequestration, and reductions in $PM_{2.5}$ air pollutants, stormwater runoff, and heat index disproportionately distributed based on per capita and median income, percent minorities, population density, percent poverty and total educational attainment characteristics? It is hypothesized that there is an equitable distribution of ecosystem services and benefits provided by urban forests across the Bronx, i.e. there is no environmental injustice related to the distribution of ecosystem services among socio-economic and socio-demographic classes.
3) Can a multi-objective decision support framework identify optimal locations to plant trees in the Bronx considering multiple objectives? Will this approach identify a better allocation of trees that is more equitable than what was planted under MillionTreesNYC? It is hypothesized that the multi-objective decision support framework will not result in an optimal allocation of trees or planting scenarios with greater total benefits and increased equity than what was allocated under MillionTreesNYC.

1.3 ORGANIZATION OF CHAPTERS

This dissertation is organized into five chapters. Chapter 1 serves as an introductory chapter. Chapter 2, which is published in *Urban Forestry and Urban Greening* (Nyelele et al., 2019), uses a suite of i-Tree ecosystem service models and mapping tools in a spatially distributed manner to assess the current and future ecosystem services and benefits of urban tree cover at the census block group level in the Bronx, NY. Chapter 3, another manuscript published in *Urban Forestry and Urban Greening* (Nyelele and Kroll 2020), uses several traditional and non-traditional quantitative approaches to explore whether ecosystem services and benefits are distributed in ways that disproportionately advantage or disadvantage people based on the socio-demographic and socio-economic characteristics of census block groups in the Bronx. Chapter 4, a manuscript in preparation, describes the development of a multi-objective decision support framework in NYC using a spatially explicit methodology within biophysical ecosystem service models to guide future greening initiatives towards prioritizing planting locations that maximize multiple objectives. The concluding chapter (Chapter 5) reflects back on the null hypotheses proposed in Chapter 1 and explores whether there is evidence in the analyses presented in subsequent chapters to reject these null hypotheses. The chapter synthesizes the results of the research to make recommendations for decision-making processes, policy options, management measures, planting scenarios, and generally improved overall urban forest management.

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CHAPTER TWO: PRESENT AND FUTURE ECOSYSTEM SERVICES OF TREES IN THE BRONX, NY

Abstract

Trees provide ecosystem services such as air pollutant removal, carbon storage and sequestration, urban heat island reduction, stormwater runoff reduction as well as other socio-economic benefits. Large-scale tree plantings are occurring in many cities to increase tree canopy coverage as well as the health, economic and environmental benefits that come with trees. Thus, there is a need to assess the extent to which trees provide these ecosystem services, where services are realized, and most importantly to improve methods of determining future planting locations. Using a new spatially distributed implementation of the i-Tree suite of ecosystem service models and mapping tools, we estimate the current and future ecosystem services and benefits of a recent tree planting initiative within each census block group of the Bronx, NY for 2010 and for three 2030 tree cover scenarios (assuming no tree mortality, 4% and 8% annual mortality). Land cover and tree canopy estimates for 2010 are derived from a high-resolution land cover dataset. A grow-out scenario based on urban tree database information and allometric equations is used to predict future canopy cover. Change analysis is carried out at the census block group level to determine the magnitude and direction of change for each service and benefit over time. The monetary value of trees in the Bronx in 2010 is estimated to be $37.6 million, and this value is estimated to range from $40.7 million to $43.9 million in 2030 if the current canopy is maintained and newly planted trees grow to maturity.

Key words: Allometric equations; Benefits; Ecosystem services; Grow-out; i-Tree; Urban forestry

2.1 INTRODUCTION

Urbanization has adverse environmental impacts such as elevated temperatures, increases in air pollution and stormwater quantity, and decreases in stormwater quality, which pose major environmental and public health problems in cities (Seto and Shepherd, 2009). Studies show that increasing tree cover has the potential to provide multiple ecosystem services and benefits including temperature reduction (Livesley et al., 2016; Salmond et al., 2016), air pollutant removal (Nowak, 2002; Nowak et al., 2014), carbon sequestration (Nowak and Crane, 2002; Nowak et al., 2013a), climate regulation (Salmond et al., 2016; Nowak and Crane, 2002) and stormwater improvements (Bolund and Hunhammar, 1999; Livesley et al., 2016). Ecosystem services refer to the conditions and processes through which natural ecosystems sustain and fulfill human life (Daily, 1997), whilst benefits illustrate the final outputs from ecosystems that directly affect human well-being (Haines-Young and Potschin, 2012). Ecosystem services, as the key functions that underpin the potential for well-being, are integral to sustainable development (Wood et al., 2018) and need to be sustained in terms of both quality and quantity for future generations to meet their needs. The relative importance that people assign to benefits provided by ecosystem services is typically represented in monetary units, ratings or ranking schemes (Schmidt et al., 2016).

Many forest management strategies to improve services as well as the health, economic and environmental benefits from trees are being undertaken in different cities. Increasing the number of healthy trees through tree planting is one such strategy, as evidenced by large tree planting initiatives undertaken in New York City (NY), Chicago (IL) and Los Angeles (CA) (MillionTrees NYC, 2017; Chicago Region Trees Initiative, 2018; City Plants, 2018). However, there is uncertainty over the future ecosystem services and benefits of these plantings. Studies that assess the extent to which these tree plantings provide various ecosystem services and also determine where these services are realized, have the potential to inform policy and decision making regarding urban forest management, particularly areas to target for future tree plantings to ensure environmental equity associated with both tree cover and resultant ecosystem services and benefits.

In New York City (NYC), MillionTreesNYC (MTNYC) was launched in 2007 to plant and care for one million new trees throughout the city by 2017 (MillionTrees NYC, 2017). The goal of MTNYC is to increase tree canopy cover to 30% by 2030, based upon Luley and Bond's (2002) analysis and recommendation that increasing urban tree canopy (UTC) in NYC by 10%

was a realistic and achievable canopy cover increase that would also improve ozone related air quality impacts by 3–4%. The NYC metropolitan area has been designated by the United States Environmental Protection Agency (US EPA) as being a non-attainment area for particulate matter less than 2.5 μm ($PM_{2.5}$) and ozone air quality standards (US EPA, 2017a). Both pollutants can be reduced by forests (Nowak et al., 2013b, 2014).

To better understand the spatial and temporal variations in ecosystem services provided by urban forests, we explore a new spatially distributed implementation of the i-Tree (www.itreetools.org) suite of models and mapping tools to estimate the current and potential future ecosystem services and benefits of urban tree cover. Initially focusing on NYC's recent planting initiative at the census block group level in the Bronx, NY, this spatially distributed implementation of i-Tree Tools will in the future be replicated within other cities with different climates, demographic and environmental variables to understand the role of urban forests across diverse urban ecosystems. This work lays the framework to develop a multi-objective decision support tool that guides urban forest decision making by optimizing ecosystem service provision and equity in evaluating urban tree planting locations. Previous studies and assessments that estimate the ecosystem services and benefits of trees in different cities have utilized the publicly available lumped versions of these i-Tree Tools. Lumped models conceptualize and simulate a spatially heterogeneous region as a single unit (e.g., using a mean value from a sample of the trees in a region) to estimate the tree effects on carbon sequestration, energy use, pest infestations, air pollution, stormwater volumes, and water quality (Wang et al., 2005). While this lumped approach provides city-scale information for urban planning, it makes assumptions that simplify the relationships between the structure and function of urban forests and the representation of urban landscapes. In addition, the lumped models do not estimate services and benefits at the fine scales that link tree effects to specific local conditions and residential populations, a scale at which local urban forest planning occurs. Here we make the assumption that the relationship between ecosystem services and tree cover is not simply linear and using spatially distributed inputs and models produces a more accurate estimation of ecosystem services and guides towards better urban forest management.

While the focus of the study is on trees recently planted under MTNYC, the contribution of the entire urban forest to ecosystem services and benefits is also explored. The Bronx was chosen as the initial study site based on: a) the availability of tree planting data (City of New York, 2017a; NYC Parks and Recreation, 2017a, b), b) the air quality, stormwater and urban heat island issues in this borough (Kheirbek et al., 2013; Maantay, 2007; City of New York, 2017b; Rosenzweig et al., 2009; Zahmatkesh et al., 2015), c) the diverse demographics across the borough, and d) the lack of ecosystem services and benefits to some communities in the Bronx (Kremer et al., 2016; Maciejczyk et al., 2004). Two of six Trees for Public Health neighborhoods (Hunts Points and Morrisania), which received special attention during the MTNYC plantings because of their limited tree canopy and relatively high asthma rates, are in the Bronx (MillionTrees NYC, 2017). Of the various air pollutants, this study focuses on $PM_{2.5}$ which poses a high risk to health, since smaller particles can travel more deeply into the lungs, penetrate the lung barrier and enter the blood system causing more harmful effects including cardiovascular and respiratory illnesses (US EPA, 2016).

In this analysis, a spatially distributed implementation of i-Tree Tools is used to characterize and estimate the services and benefits provided by current and future tree cover in the Bronx. These services and benefits include carbon storage and sequestration and reductions in $PM_{2.5}$ modeled using i-Tree Eco (Nowak et al., 2008), air temperature reductions modeled using i-Tree Cool (Yang et al., 2013) and stormwater runoff reduction modeled using i-Tree Hydro

(Wang et al., 2008). These ecosystem services are modeled at the census block level, where demographic data is readily available to estimate ecosystem benefits. In addition to the spatially distributed implementation of i-Tree Tools, another distinguishing feature of this analysis is the use of a grow-out scenario and different management options to explore the potential range of ecosystem services and benefits in the future (2030). Specifically, the study grows out the newly planted trees in the Bronx under varying tree mortality scenarios to simulate future canopy conditions.

2.2 METHODOLOGY

A high resolution (3.2 ft) UTC Assessment (2010) of the Bronx (Figure 2.1) processed by MacFaden et al. (2012) was utilized for this analysis to determine the baseline tree cover distribution. A tree growth model utilizing equations for calculating tree structure (diameter at breast height (DBH), tree height, crown width and crown height) from the i-Tree Forecast model described in Nowak et al. (2013c) is developed and used to simulate the growth of new tree plantings for estimation of canopy conditions in 2030 (the MTNYC target year). To assess the impacts of tree plantings, tree cover from the existing urban forest was assumed to remain stable (i.e., cover losses equaled gains from tree growth and natural regeneration). This assumption appears reasonable since tree cover in NYC remained relatively constant at 20.9% (standard error = 2%) from 1997 to 2010 (NYC Parks and Recreation, 2012; MacFaden et al., 2012). For modeling the growth of planted trees, high, average and low mortality rates are simulated. Estimates of the current (2010) and future (2030) ecosystem services and benefits were made at the census block group level.

2.2.1 Study area

The Bronx (Figure 2.1), one of the five NYC boroughs, is divided into 1132 census block groups (US Census Bureau, 2010). The elevation of the borough ranges from 0 to 320 ft above mean sea level and the area receives mean annual precipitation of 40–52 inches with a frost-free period of 216–234 days. The native soils of the Bronx are predominately sandy loam while the parent material is asphalt over human-transported material (US Department of Agriculture Natural Resources Conservation Service, 2017). Based on a 2010 UTC Assessment, the Bronx had 22.7% tree cover, 16.3% short vegetation, 1.1% bare soil, 1.9% water, and 58% impervious surfaces. Most of the tree cover in the Bronx is found in large groups of trees, primarily urban parks and natural areas owned and managed by the Department of Parks and Recreation. Of the million MTNYC trees, 280,000 were planted in the Bronx, the second highest number after Queens (285,000) (MillionTrees NYC, 2017). The Bronx is known to have air pollution concerns with high levels of carbon monoxide, nitrous oxide, volatile organic compounds, ozone, and fine ($PM_{2.5}$) and coarse particulate emissions (Kheirbek et al., 2013; Maciejczyk et al., 2004). In addition, some communities in the Bronx have been prone to periodic flooding due to high impervious cover which accelerates stormwater runoff (NYC Parks and Recreation, 2017c). Furthermore, South Bronx neighborhoods have among the highest rates of heat illness and death in NYC. In 2010, ten of the twelve community districts in the Bronx had moderate to high Heat Vulnerability Indices (City of New York, 2017b).

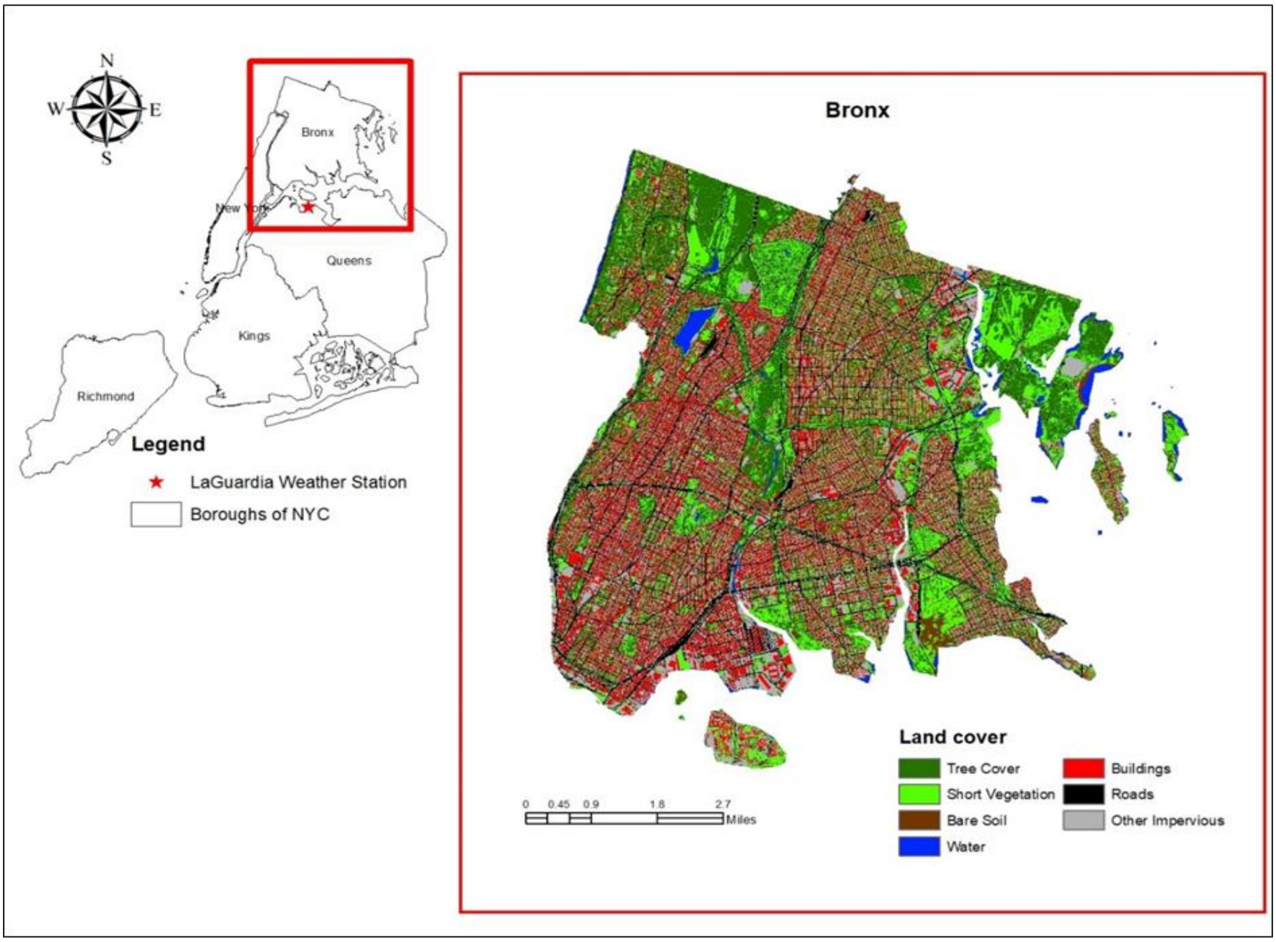

Figure 2.1: Land cover of Bronx, New York from 2010 UTC.

2.2.2 Current and Future Land Cover

Block group land cover estimates for the Bronx are derived from the 2010 land cover dataset (MacFaden et al., 2012). Assuming the Bronx maintains its baseline 2010 tree cover (22.7%), 2030 block group tree cover was estimated by growing out the planted trees' canopies annually from 2010 to 2030. We employed three datasets to determine the new tree plantings in the Bronx. The first was a dataset showing where plantings were made between 2010 and 2017 in restoration areas, including landscaped parks and other natural areas in the Bronx (NYC Parks and Recreation, 2017a). The second was a 2015–2016 Small Parks and Playgrounds (SPaP) inventory of all trees in parks and playgrounds under 6 acres (NYC Parks and Recreation, 2017b). The third was information from the 2015–2016 Street Tree Census (City of New York, 2017a). We assumed all street, park and playground trees with a DBH less than 5 in. were planted after 2010, which is a conservative estimate considering trees are planted at 2.5–3 in. caliper (Stephens, 2010) and generally have an average 0.33 in. annual diameter growth (Nowak et al., 2008).

While the street trees and SPaP data had geographic location, DBH and other tree parameters for each individual tree, the restoration data only had the container size and number of tree seedlings planted in a park or playground. Following a similar methodology to Morani et al. (2011), these seedlings were assumed to take 5 years to reach the minimum i-Tree Eco model diameter of 1 inch and that 20% of the seedlings would die by year 5. As such, these seedlings were added into the growth model 5 years from when they were initially planted. Table 2.1 contains a summary of new trees planted in the Bronx since 2010, including the top five (5) species planted in each location. Singling out specific species or ranking them based on how well they provide certain ecosystem services and benefits is not the focus of the study; we instead look generally at the impact of changes in tree canopy cover.

Table 2.1: Summary of trees planted in the Bronx since 2010.

Location	**Number of Trees**	**Source**	**Top five species**
Small Parks and Playgrounds	300	NYC Parks and Recreation (2017b)	*Prunus, Acer rubrum, Crataegus crus-galli, Quercus palustris, Tilia cordata*
Restoration areas	154,000	NYC Parks and Recreation (2017a)	*Quercus palustris, Quercus rubra, Liriodendron tulipifera, Quercus alba, Liquidambar styraciflua*
Streets	23,000	City of New York (2017a)	*Prunus, Gleditsia triacanthos, Zelkova serrata, Quercus palustris, Tilia cordata*
Total	**177,300**		

Annual per-tree growth of the new tree plantings was simulated to 2030 using species specific equations and parameters from the i-Tree Forecast model. i-Tree Forecast is a separate component of i-Tree Eco that uses structural estimates (e.g., number of trees, species composition), environmental and location variables, and species characteristics along with anticipated growth and mortality rates to simulate future forest structure (e.g., number of trees and sizes) and various ecosystem services based on annual projections of the current forest structure data (Nowak et al., 2013b). Annual tree diameter growth was estimated based on an average DBH growth rate of 0.33 in. per year adjusted for each species to account for variability in competition levels across different urban land types, growing season lengths, tree conditions and current tree height relative to the maximum tree height. Tree height, crown width, crown height, and leaf area were then estimated based on tree diameter each year using species, genus, order, and family specific equations that were derived from measurements from urban tree data (Nowak et al., 2008, 2013b). If no equation exists at the species level, the average over the genus, family, or order level were used as necessary. Different urban tree mortality rates have been documented. Nowak and Aevermann (2019) highlight that the typical residential average mortality rate is 4% although mortality rates will vary among land use classes due to differences in development, management and competition. Lu et al. (2010) estimated young street tree mortality in NYC to be 8.7–26.2% depending on years since planting, figures that translate to an annual mortality rate of 4.4% based on an average annual mortality rate formula from Nowak et al. (2004). Studies in other cities including Syracuse and Baltimore (Nowak, 1986; Nowak et al., 2004) have also documented average mortality rates of 4%. For the new tree plantings, we simulate a low (0%), average (4%) and high (8%) annual mortality rate to provide a best, average and reasonable worst-case scenario in terms of tree loss.

2.2.3 Ecosystem services and benefits

For the various simulations used to estimate block group ecosystem services and benefits of the entire tree population in 2010 and 2030, we assume that the 2030 environmental and climatic conditions and demographics are the same as those in 2010, so that all changes in ecosystem services and benefits are due to the tree plantings of MTNYC. As tree canopy increases from 2010 to 2030, there is an increase in tree cover. This increase in tree cover is overset by a decrease in bare soil; when bare soil is no longer present, this decrease occurs in short vegetation. Impervious surface in 2030 is assumed to be the same as in 2010.

2.2.3.1 $PM_{2.5}$ reduction

A spatially distributed implementation of the i-Tree Eco air pollutant dry deposition model (Hirabayashi et al., 2011) was used to calculate net hourly dry deposition of $PM_{2.5}$ to trees at the block group level for the Bronx. This distributed model applies the lumped i-Tree Eco model to each block group using local estimates of land cover, tree parameters, and environmental variables. i-Tree Eco calculates pollutant flux as the product of deposition velocity (based on Leaf Area Index (LAI), wind speed, and resuspension rate) and pollutant concentration (Nowak et al., 2013b). Hourly meteorological data was obtained from the National Climatic Data Center (https://www.ncdc.noaa.gov/) for 2010 from the LaGuardia Airport weather station located in Queens, NY (for location see Figure 2.1), while $PM_{2.5}$ pollutant concentrations for 2010 were block group specific, obtained from the EPA Fused Air Quality Surfaces Using Downscaling project (US EPA, 2017b). Leaf on and off dates and percent evergreen are also inputs to the model which account for differing seasonal dry deposition rates for deciduous versus evergreen trees. Leaf on and off dates for 2010 were obtained from local frost-free dates from the LaGuardia Airport weather station (https://www.ncdc.noaa.gov). National Land Cover Database (NLCD) 2011 percent evergreen

(Homer et al., 2015) proportions at the block group level were used for 2010 and 2030. LAI at the block group was calculated from the crown height, tree height, and crown width estimates of the MTNYC tree data (NYC Parks and Recreation, 2017a, 2017b; City of New York, 2017a) based on i-Tree methods (Nowak, 1996; Nowak et al., 2008). LAI was calculated for all planted trees in the block group, and an average value estimated for each block group was used in i-Tree Eco. i-Tree Eco was run with estimated 2010 and predicted 2030 land cover to estimate pollutant removal (tons/yr) and yearly monetary benefit ($USD) of pollutant removal for each block group area. Monetary valuation for $PM_{2.5}$ removal in i-Tree Eco is calculated using US EPA's BenMAP model, which estimates the incidence of adverse health effects and associated monetary values resulting from changes in pollutant concentrations for the conterminous US (Hirabayashi, 2014; Nowak et al., 2013b; US EPA, 2017c).

2.2.3.2 Carbon storage and sequestration

Carbon storage and sequestration were calculated using the latest per area of tree canopy cover removal rates for NYC. Carbon sequestration was estimated at 1.7 tons of carbon per acre of tree cover per year while carbon storage is 32.03 tons of carbon per acre of tree cover (Nowak et al., 2018). To estimate the monetary value of carbon storage and sequestration, tree carbon values were multiplied by $129.8 per ton of carbon based on the estimated social costs of carbon for 2015 (Nowak and Greenfield, 2018). These removal rates and monetary values were multiplied by local canopy cover (m^2) to estimate carbon-related ecosystem services and benefits.

2.2.3.4 Stormwater runoff reduction

i-Tree Hydro was used to estimate stormwater runoff reductions by tree cover in 2010 and 2030. The model was first calibrated by minimizing the weekly real-space Nash-Sutcliffe

Efficiency using the un-diverted 38.4 mi^2 of the Bronx River as the contributing area to the US Geological Survey (USGS) gauging station 01302020 at the NY Botanical Garden in the Bronx for the 2010–2012 calendar years. The upper portion of this watershed is diverted for drinking water (NYC Parks and Recreation, 2017c). As the Bronx River watershed stretches beyond the extent of the UTC data, tree cover in adjacent Westchester County, NY was derived from 2011 one-meter digital orthoimages (US Department of Agriculture Farm Service Agency, 2011). The image data were classified into trees, short vegetation, bare soil, water and impervious cover using 250 training polygons randomly distributed across these images within the non-classified area of the watershed. A confusion matrix (Jensen, 2005; Stehman, 1997) using 250 independent assessment polygons (50 per land cover class) randomly selected from the digital orthoimages, was used to evaluate image classification errors and yielded overall classification accuracy of 94%. The overall accuracy represents the proportion of the assessment polygons that were classified correctly during the image classification process.

i-Tree Hydro's calibrated parameters for the Bronx River were applied to model runs for each of the 1132 block groups in the Bronx for 2010 and 2030. Hourly weather data for 2010 was obtained from LaGuardia Airport weather station while LAI, leaf on and leaf off dates and evergreen percent were derived similar to that described for $PM_{2.5}$ reduction. The amount of impervious area directly connected to the stream was calculated from the Sutherland Effective Imperious Area Equations (Sutherland, 2000). Block group land cover data discussed in Section 2.2.2 were used in the model. A 2015 USGS 1 arc-second resolution National Elevation Dataset (NED) (https://viewer.nationalmap.gov) was clipped to each block group boundary to determine local elevation data. This elevation dataset (with an approximate horizontal distribution of 30 m) was selected based on recommendations for i-Tree Hydro which suggest elevation data should have a horizontal resolution of 10–30 m as finer resolution data are more likely to cause complications in modeling in urban areas with bridges and elevated roadways (i-Tree Hydro, 2018). To estimate avoided runoff, an alternative 2010 scenario was created where all tree cover is removed and replaced with either herbaceous cover (for tree canopy over pervious area) or impervious surface (for tree cover over impervious area). i-Tree Hydro was then run for this alternative scenario, as well as the actual 2010 and estimated 2030 scenarios to estimate impervious surface runoff, and the difference in impervious surface runoff between the alternative scenario and the other scenarios was our estimate of avoided runoff. Avoided runoff was valued at the national average of $0.008936/gallon based on the USFS' Community Tree Guide series, which estimates that value regionally based on stormwater treatment and management costs and fees (Hirabayashi, 2013).

2.2.3.5 Air temperature reductions

i-Tree Cool, which is based on the Physically based Analytical Spatial Air Temperature and Humidity model (Yang et al., 2013), was used to simulate the spatial distribution of air temperature for the Bronx for 2010 and 2030. i-Tree Cool calculates spatial solar radiation and heat storage based on semi-empirical functions and generates spatially distributed urban microclimate conditions based on inputs of topography, land cover, and weather data measured at a reference site (Yang et al., 2013). The La Guardia Airport weather station was used as a reference site for air temperature and humidity data for July 2010, the month with the highest temperatures in 2010. The NED, 2010 and 2030 land cover, percent impervious cover and percent tree canopy maps were resampled to a 300-m horizontal resolution and used as input data for this model. Heat index values in degrees Fahrenheit (^{o}F) were calculated for each block group for 2010 and 2030 tree cover scenarios from the hourly 300-m i-Tree Cool air temperature and humidity output for the month of July using the US National Weather Service (US NWS) methodology (US NWS, 2018). The heat index, a human-perceived equivalent temperature, is a measure of how hot it really feels when relative humidity is factored in with the actual air temperature, and is widely used in environmental health research, including studies of air pollution exposures, outdoor temperature exposures, and the development of heat warning systems (Anderson et al., 2013; Rothfusz, 1990). Average reduction in heat index, considered an ecosystem service in this study, was calculated by subtracting the average block group heat index values for 2010 from 2030. This change in heat index was incorporated into a damage function that relates changes in heat index to health and productivity impacts (Voorhees et al., 2011; US EPA, 2017c):

$$\Delta y = y_0 \cdot (e^{\beta \cdot \Delta x} - 1) \cdot \mathrm{Pop} \tag{2.1}$$

where Δy is the change in cardiovascular and respiratory related mortality, y_0 is the baseline incidence rate for the effect, Δx is the change in the heat index, β is a unitless coefficient derived from the relative risk associated with a change in exposure, and Pop is the exposed population. Here y_0 is estimated as 0.02304 based on 2010 cardiovascular and respiratory mortality for the population over 65 years old for the Bronx (Centers for Disease Control and Prevention, 2018). For β we used 0.013867 for the Northeastern US from Basu et al. (2005) based on their study of 1992 mean apparent temperature impacts on cardiovascular and respiratory mortality impacts for ages 65-99 in the 20 largest metropolitan areas of the US. Here Pop (the exposed population) is estimated at the census block group as all people older than 65 years in 2010 (US Census Bureau, 2010). This analysis used a conservative assumption of no change in population in the Bronx between 2010 and 2030 so that all changes in services and benefits are due to trees. To estimate the monetary benefit of reduced mortality we applied the Value of Statistical Life of $8.7 million, which is also used by the EPA in BenMap for changes in air pollution benefits (US EPA, 2017c)

2.3 RESULTS

The aim of this study is to assess the current and future ecosystem services and benefits of urban tree cover at the census block group level in the Bronx, NY. The following sections present the projected 2030 tree cover and the estimated ecosystem services and benefits from this tree cover.

2.3.1 Tree cover

Block group tree cover percentages for the Bronx in 2010 and for the different 2030 tree mortality growth scenarios are illustrated in Figure 2.2. The Bronx had 22.7% tree cover in 2010, and tree cover is estimated to increase to 24.9% in 2030 based on the high tree mortality growth scenario, 26.2% in 2030 using the average mortality growth scenario and 27.4% in 2030 using the low tree mortality growth scenarios (Figure 2.2). Tree cover varies both spatially and temporally at the block group level, with tree cover ranging from 0.18% to 69% in 2010 and from 0.18% to 89% in 2030. The maximum tree cover (89%) is the maximum that can be achieved in that block group without converting impervious surfaces to tree cover.

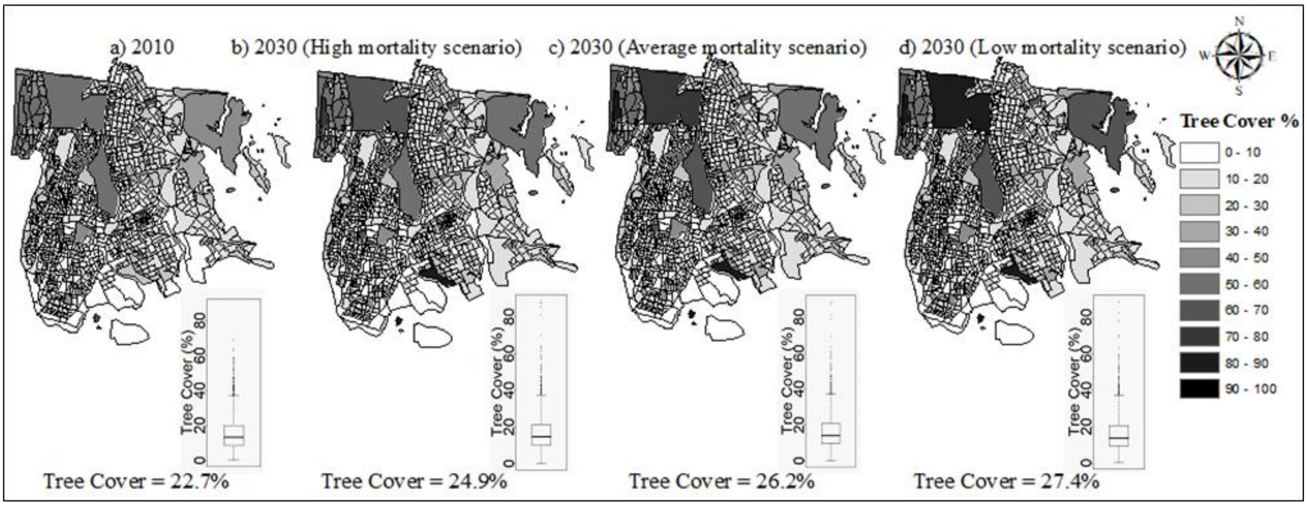

Figure 2.2: Block group tree cover estimates for the Bronx, NY for a) 2010, b) 2030 with high tree mortality, c) 2030 with average tree mortality, and d) 2030 with low tree mortality.

2.3.2 Ecosystem services

All the ecosystem services and benefits (air pollutant removal, carbon storage and sequestration, runoff reduction and air temperature decreases) are estimated at the block group level. There are both spatial and temporal variations ecosystem services and monetary benefits across different block groups in the Bronx as tree cover changes over time.

2.3.2.1 Air pollution removal

The overall monetary benefits of $PM_{2.5}$ removal per acre of tree cover at the block group level for the Bronx in 2010 and the increased benefits of $PM_{2.5}$ removal per acre of tree cover for 2030 are shown in Figure 2.3. In 2010, the Bronx's 2,470 ha of tree cover is estimated to have removed 5.1 tons/yr of $PM_{2.5}$ pollutants, resulting in human health benefits valued at $6.9 million/yr (Figure 2.3). For the 2030 high tree mortality scenario, $PM_{2.5}$ pollutant removal is expected to increase to 5.6 tons/yr ($7.2 million/yr); it will increase to 5.9 tons/yr ($7.3 million/yr) for the average mortality scenario, and increase to 6.2 tons/yr ($7.4 million/yr) for the low mortality scenario. These changes correspond to a 9.8% increase in air pollutant removal for the high mortality scenario, a 15.7% increase for the average mortality scenario, and a 21.6% increase for the low mortality scenario. In 2010, block group $PM_{2.5}$ removal ranged between 0 – 0.8 tons/yr, in 2030 (high mortality) 0–1.1 tons/yr, in 2030 (average mortality) 0–1.2 tons/yr, and in 2030 (low mortality) 0–1.3 tons/yr.

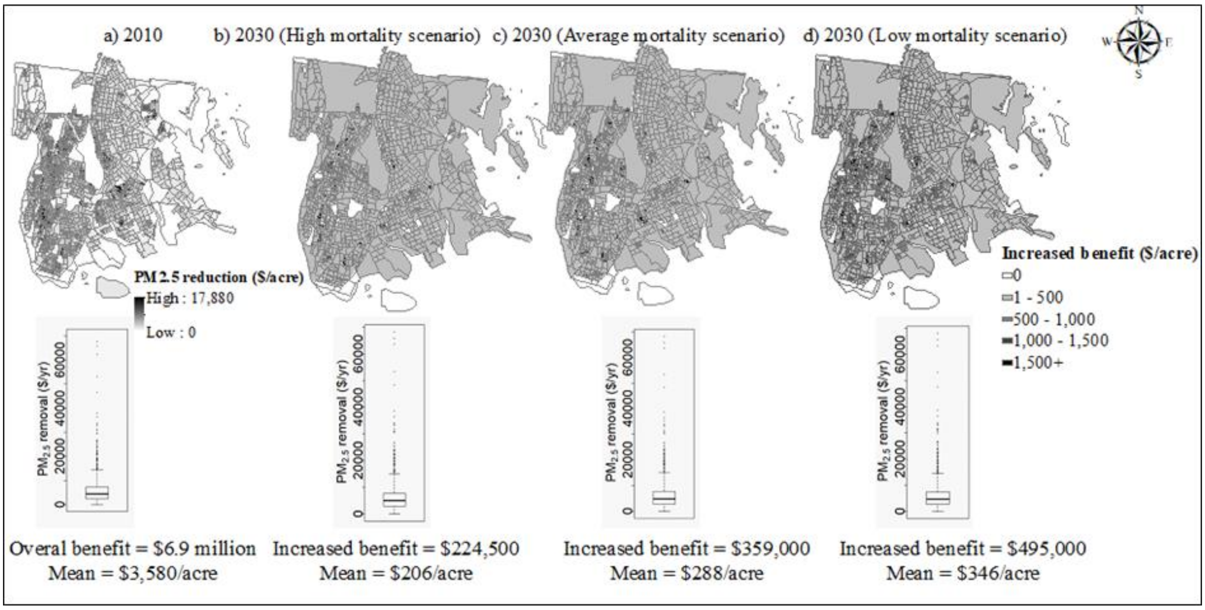

Figure 2.3: a) Estimated 2010 $PM_{2.5}$ removal monetary benefits, increased $PM_{2.5}$ removal monetary benefits in b) 2030 (high mortality), c) 2030 (average mortality), and d) 2030 (low mortality). Box plots illustrate the distribution of $PM_{2.5}$ removal monetary benefits for each analysis scenario.

2.3.2.2 Carbon storage and sequestration

Increases in carbon storage and sequestration services and benefits over time are proportional to tree cover increases. The block group estimates of carbon storage and sequestration benefits per acre of tree cover in the Bronx in 2010 as well as the increase in these benefits for different 2030 scenarios are shown in Figure 2.4. In the individual block groups, carbon storage peaks at 29,900, 37,300, 42,000 and 45,600 tons, with sequestration peaking at 1,600, 2,000, 2,200 and 2,400 tons/yr for 2010, 2030 high tree mortality, 2030 average tree mortality, and 2030 low tree mortality scenarios, respectively. In 2010, total carbon sequestration was 10,300 tons/yr ($1.3 million) and carbon storage was 195,500 tons ($25.4 million). For the 2030 high tree mortality scenario, carbon sequestration is expected to increase to 11,400 tons/yr ($1.5 million/yr) while carbon storage is expected to increase to 215,000 tons ($27.9 million). Carbon sequestration will increase to 12,000 tons/yr ($1.6 million/yr) and carbon storage to 225,600 tons ($29.3 million) for the average mortality scenario, and carbon sequestration is expected to increase to 12,500 tons/yr ($1.6 million/yr) and carbon storage to 237,000 tons

($30.7 million) for the low mortality scenario. These changes from 2010 correspond to a 10% increase for the high mortality scenario, a 16% increase for the average mortality scenario, and a 21% increase for the low mortality scenario.

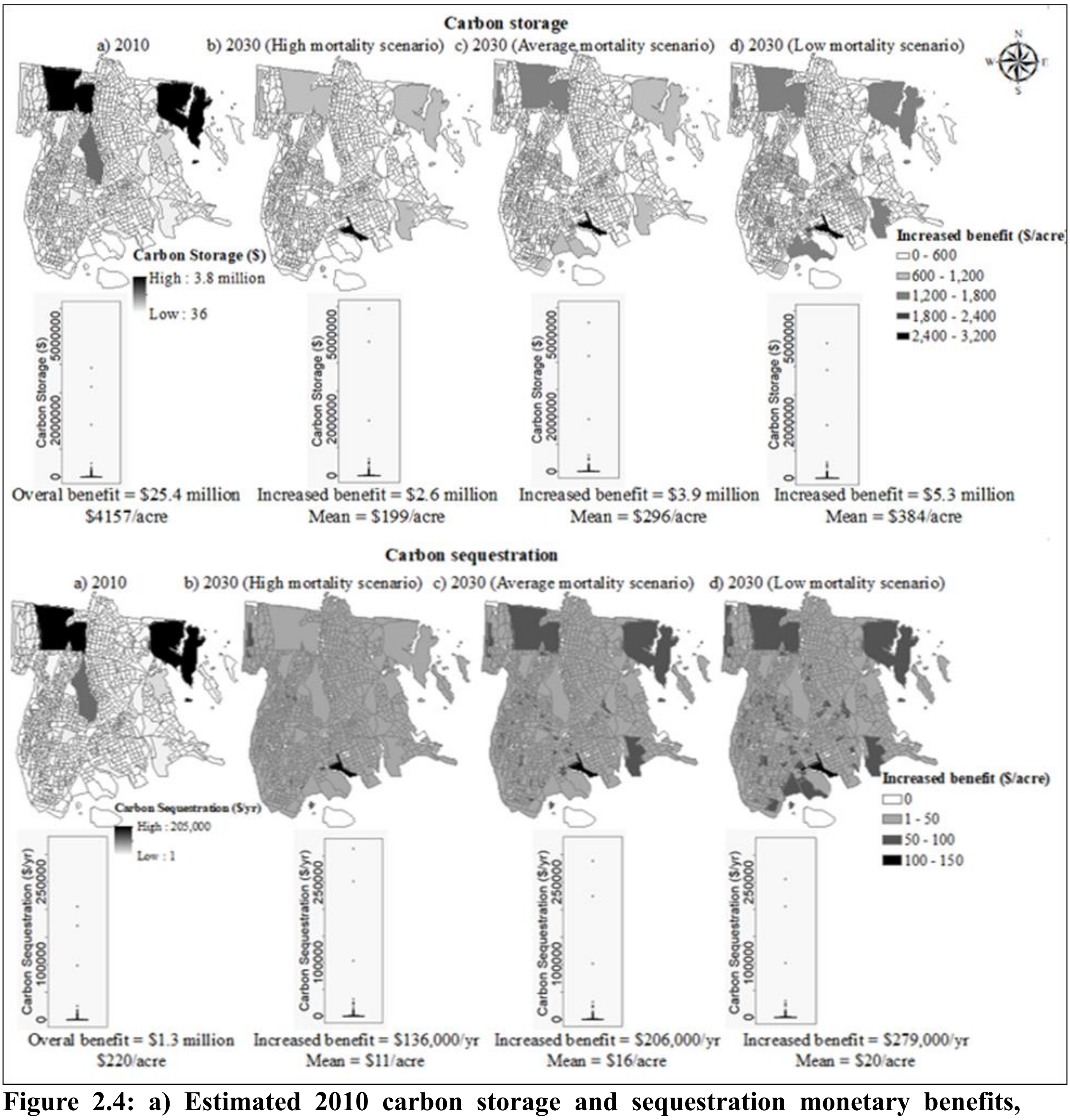

Figure 2.4: a) Estimated 2010 carbon storage and sequestration monetary benefits, increased carbon storage and sequestration monetary benefits in b) 2030 (high mortality), c) 2030 (average mortality), and d) 2030 (low mortality). Box plots illustrate the distribution of carbon storage and sequestration monetary benefits for each analysis scenario.

2.3.2.3 Runoff reduction

Increasing tree cover reduces total surface runoff in the Bronx (Figure 2.5). During the simulation period of 2010–2012, the 2010 tree cover scenario resulted in 2.5 billion ft^3/yr total runoff and 60 million ft^3/yr (9830 ft^3 per acre of tree cover) net avoided runoff by trees (a 2.4% reduction), a service valued at $4 million/yr. Figure 2.5 illustrates avoided runoff reduction monetary benefits for block groups in the Bronx per acre of tree cover in 2010 as well as increases in these benefits for 2030 scenarios. The 2030 tree cover generated from the high tree mortality scenario increases this avoided runoff by 1.2 million ft^3/yr ($82,200/yr). Runoff is reduced by 2 million ft^3/yr ($135,200/yr) based on the 2030 tree cover from the average mortality scenario. Under the 2030 no mortality scenario, runoff is reduced by 3 million ft^3/yr ($197,500/yr). In any given block group, the increase in avoided runoff is a maximum of 184,000 ft^3/yr in 2030 based on the high tree mortality scenario, 303,000 ft^3/yr in 2030 based on the average tree mortality scenario, and a maximum of 391,100 ft^3/yr in 2030 based on the low tree mortality scenario.

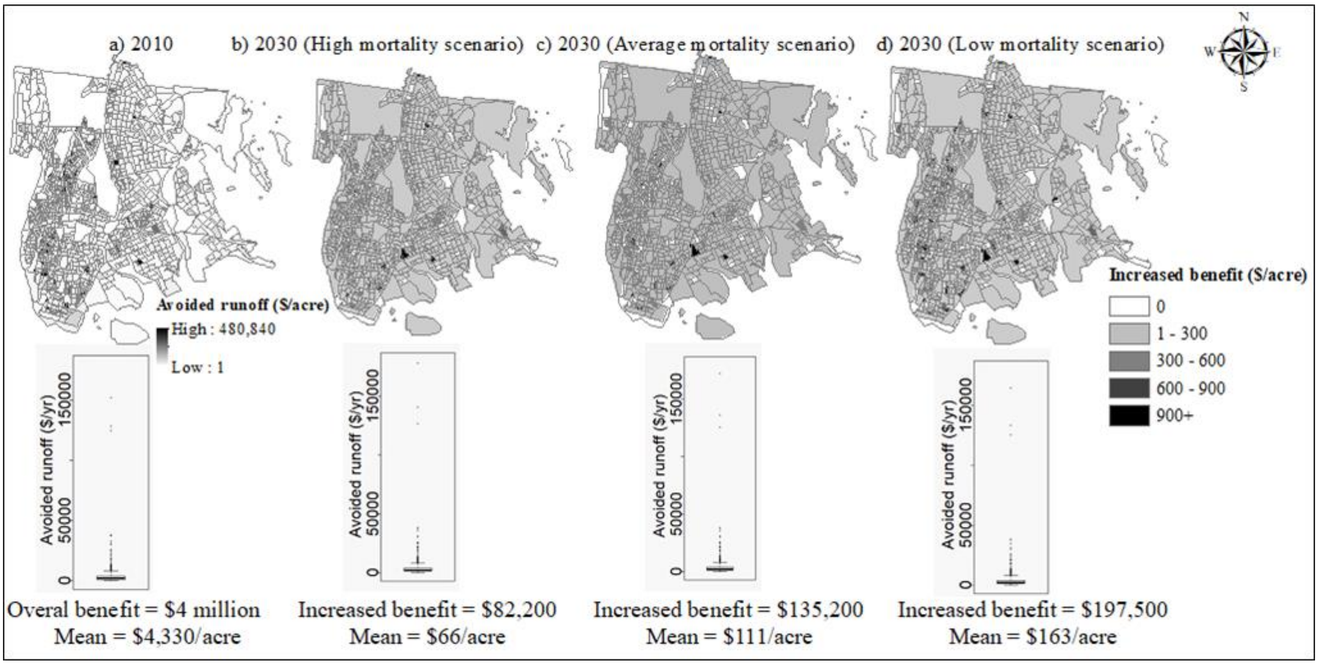

Figure 2.5: a) Estimated 2010 runoff reduction monetary benefits, increased runoff reduction monetary benefits in b) 2030 (high mortality), c) 2030 (average mortality), and d) 2030 (low mortality). The distribution of runoff reduction monetary benefits for each analysis scenario is shown in the box plots.

2.3.2.4 Air temperature reduction

Reductions in heat index values are desirable to reduce heat stress, especially for vulnerable and susceptible populations such as children and the elderly. However, in the Bronx, the estimated 2%–5% increases in tree cover is predicted to have a minimal impact on both air temperature and heat index reduction. Figure 2.6 depicts the block group mean temperature and heat index values in the Bronx in 2010. The average temperature across all scenarios is 87.5°F, while the heat index is 91.1°F. The maximum heat index reduction in any given block group was estimated as 0.06 °F based on the high tree mortality scenario, 0.10°F based on the average tree mortality scenario and 0.17°F under the low tree mortality scenario. Changes in temperature are only observed in 1 block group using the high tree mortality scenario, 2 block groups based on the average tree mortality scenario and 3 block groups using the low tree mortality scenario. Heat index values change in 3 block groups under the high and average tree mortality scenarios and in 4 block groups under the low tree mortality scenarios. In terms of changes in mortality due to reductions in the heat index as a result of increasing tree cover, we did not estimate any reduction in cardiovascular and pulmonary related mortality cases for any tree mortality scenario.

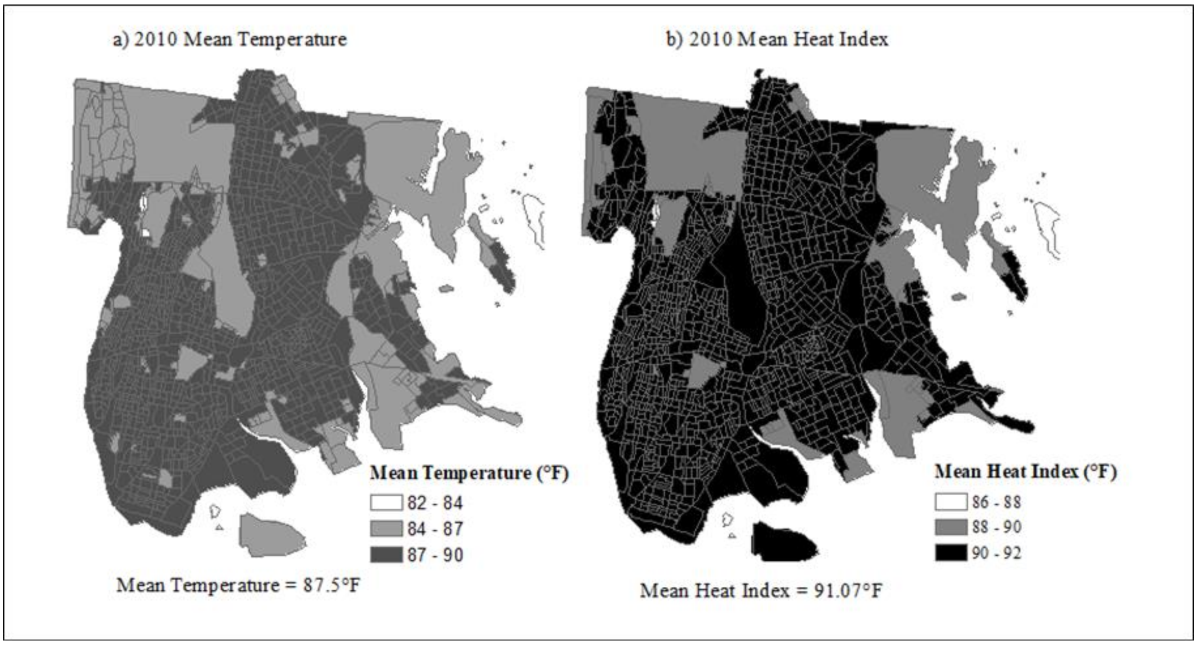

Figure 2.6: a) Estimated 2010 temperature, b) estimated 2010 heat index.

2.4 DISCUSSION

This analysis has illustrated a tree grow-out scenario under varying mortality rates and a spatially distributed implementation of i-Tree tools to estimate current and potential future tree cover and resultant ecosystem services and benefits in the Bronx, NY. Our results show that high amounts of tree cover are expected in large block groups that mostly consist of parks and playgrounds (Figure 2.2). Landscaped parks and other natural areas are also where most of the new trees were planted in the Bronx under MTNYC (NYC Parks and Recreation, 2017a, b). This is not surprising considering that tree planting is usually in areas where there is more plantable space, mostly large properties including urban parks and natural areas owned and managed by the Department of Parks and Recreation. Smaller block groups are typically in commercial districts that are primarily impervious surfaces (e.g. roads and buildings) and have relatively few trees and few opportunities to expand tree canopy (O'Neil-Dunne, 2012). Our projections of future tree cover using the low, average, and high mortality scenarios illustrate how tree mortality affects tree cover and subsequent tree benefits. Numerous factors affect planting, regeneration and mortality through time, so management plans and urban forest monitoring are needed to ensure local management goals are met (Morani et al., 2011). This also has implications for sustainable development discussions with regards to tree cover amounts needed to sustain future populations.

Vegetation improves air quality, but to what level depends on the local situation (Bolund and Hunhammar, 1999). Our results have shown that in general, the greater the tree cover, the greater the pollutant removal; the greater the pollutant removal and population density, the greater the monetary value of this benefit (Nowak et al., 2014). This is evident in the Bronx where pollutant removal across all scenarios varies with block group size and tree cover percentages; parks and forested areas with high tree cover typically have the greatest pollutant removal. In addition to tree cover amounts, removal rates by trees will vary locally based on factors that include pollutant concentration, length of growing season, percent evergreen leaf area and meteorological conditions (Nowak et al., 2014; Hirabayashi and Nowak, 2016). However, due to the minimal spatial variation in the weather and pollutant concentration employed in the Bronx, total tree cover will be the main driving cause of removal rates. Nowak et al. (2014) highlight that due to the limited number of weather and pollutant monitors nationally, use of the closest weather and pollutant data might not be representative of the area being analyzed. While the removal gradients follow a distribution similar to the tree cover distribution (Figure 2.2), the monetary benefit of this service (Figure 2.3) shows a different pattern and is influenced by population demographics. BenMap's economic valuation is driven by modeled air quality changes, population demographics and baseline incidence rates (US EPA, 2017c). It then follows that areas with high population and incidence rates will have a higher monetary benefit from pollutant removal than areas with high tree cover alone. To overcome uncertainties associated with estimating tree LAI, we calculated block group specific averages using data from all the newly planted trees in each block group. Our average LAI is

3.6, a value slightly lower than the 4.8 (standard error = 1) value Nowak and Greenfield (2018) found based on field samples from 34 US cities and urban areas within the conterminous US. The LAI of 3.6 is for newly planted trees, and thus should be smaller than the average LAI in cities across the US.

Carbon storage and sequestration are strongly impacted by the total amount of tree cover (Nowak et al., 2013a). In general, block groups with higher total tree cover will have greater forest carbon storage and sequestration (darker shades in Figure 2.4). Nowak and Crane (2002) argue that urban forests take up a small portion of all annual carbon emissions. They note that while increasing the number of trees can potentially slow the accumulation of atmospheric carbon, tree care practices release carbon back to the atmosphere by fossil-fuel emissions from maintenance equipment. Thus, some of the carbon gains from tree growth are offset by carbon losses to the atmosphere via fossil fuels used in maintenance activities. Our results indicate that trees have some effect, although minimal to offset some of the carbon emissions that contribute to greenhouse gas formation. Numerous studies have quantified carbon sequestration and its economic value. In Hangzhou, China, Zhao et al. (2010) found that sequestration of carbon by urban forests was comparable to carbon emissions from several industrial sectors and offset urban industrial carbon emission by 18%. Morani et al. (2011) estimated that new trees planted in NYC will sequester an average of 7,000 tons of carbon per year. Nowak and Crane (2002) note that after a tree is removed, the tree eventually decomposes, and the carbon stored in that tree is emitted back to the atmosphere, though a fraction of the carbon may be retained in the soil. In addition, all the carbon sequestered by subsequent trees grown on that same site will be offset by carbon emissions due to decomposition of the tree previously on the site. Another important element to consider is the placement of trees; for example, trees strategically located around buildings can reduce building energy use and consequently lower carbon emissions from fossil-fuel-burning power plants (Nowak and Crane, 2002).

Studies have reported stormwater runoff reductions of 2%–7% (Vargas et al., 2008). In Phoenix, AZ, 22,146-acres of tree canopy is estimated to have reduced stormwater runoff by 91.7 million ft^3 (4,140 ft^3 per acre of tree cover), with an estimated value of $6.1 million (Davey Resource Group, 2014). NYC's street trees are estimated to reduce stormwater runoff by 890.6 million gallons annually, with a value of $35.6 million (MillionTrees NYC, 2017). Larger amounts of pervious surfaces such as grass and soil under trees allow water to infiltrate into the ground, unlike impervious surfaces that enhance runoff. In addition, vegetated areas allow water to infiltrate and be held in pore spaces, allowing direct evaporation of this water and transpiration through the vegetation (Bolund and Hunhammar, 1999), as well as increased interception (Freeborn, 2011). Urban trees have the potential to reduce surface water runoff and help motivate greening initiatives in cities to reduce the risk of flooding. For example, NYC dedicated $2.4 billion to increasing and improving urban green infrastructure for stormwater absorption (McPhearson et al., 2014).

Studies have documented reductions in temperature by trees. Scott et al. (1999) found that trees in a Davis, CA parking lot reduced air temperatures by 1–3 °F. Rosenzweig et al. (2009) found that increasing tree cover from 22% in the Fordham neighborhood of the Bronx to 31% by planting in open spaces reduces air temperature by 0.1 °C, while increasing tree cover to 32% by planting street trees reduces it by 0.2 °C. Luley and Bond (2002) report that replacing all urban grass with trees in NYC reduced surface air temperature by up to 1 °C on a summer afternoon. Our result is not surprising considering that the amount of tree cover added is too little to have an impact on temperature. It is also important to consider that the configuration and placement of newly planted trees was not necessarily done in a manner that maximizes the cooling effect of trees. Nowak (2002) highlights that in areas with scattered tree canopies, radiation can reach and heat ground surfaces; at the same time, the canopy may reduce atmospheric mixing such that cooler air is prevented from reaching the area. Previous epidemiologic studies examining the relationship between temperature and mortality report changes in mortality for much higher temperature changes than we are seeing in the Bronx. For example, Basu and Ostro (2008) report a 2.6% percent increase in cardiovascular mortality for each 10°F increase in mean daily heat index. Our finding of no reduced mortality due to a reduction in heat is due to our minimal predicted changes in temperature (about 0.1°F) and the small value of the unitless coefficient β in Equation (2.1) ($\beta = 0.013867$), which was obtained from Basu et al. (2005) for the Northeastern US.

Where our study differs from previous studies and i-Tree assessments is in utilizing a spatially explicit modelling methodology utilizing a growing body of spatial biophysical data and i-Tree Tools as opposed to using traditional lumped models. We also explored a tree grow-out scenario under varying mortality rates to estimate future canopy conditions. While our findings may not be surprising, it is important to note that carbon related services and benefits, avoided runoff benefits and services, and $PM_{2.5}$ removal services differ significantly (at $p = 0.05$) from ecosystem services and benefits estimated obtained from employing lumped versions of i-Tree tools. This was based on a Wilcoxon paired signed rank test, a non-parametric statistical hypothesis test (McCrum-Gardner, 2008; Rosner et al., 2006), which concluded that ecosystem services and benefits estimated from our spatially distributed implementation of i-Tree models are significantly different from those estimated from the lumped implementation of i-Tree models used in i-Tree Landscape. The mean services and benefits from carbon storage and sequestration as well as avoided runoff from the spatially distributed models were greater than those from the lumped model, while $PM_{2.5}$ removal and monetary services from the lumped model were higher than those from the spatially distributed model. These differences have implications on what block groups to target for future plantings.

Future work will build on this work (in the Bronx as well as other cities) and seek to improve on the spatial variability in the data as well as incorporate social and demographic data to highlight inequities and promote tree plantings that are equitable across different socio-demographic populations. This will culminate in a body of work that is applicable at large spatial scales (such as entire cities) and in different locations to inform decision-making processes, policy options and management measures for urban forests.

2.5 CONCLUSION

This study quantifies current and future ecosystem services and benefits provided by trees at the block group level in the Bronx, NY using spatially explicit i-Tree Tools. Results show spatially and temporally varying gradients of different ecosystem services and benefits (pollutant removal, stormwater runoff reduction, air temperature reduction as well as carbon storage and sequestration) due to estimated increases in tree cover from 2010 to 2030. We have shown how cover and benefits can be enhanced by ensuring the long-term survival of newly planted trees (reducing tree mortality). Our results have illustrated how new tree plantings have the potential to increase 2010 ecosystem benefits by $6.3 million if trees are maintained to full maturity (and current policies and planning strategies persist), $4.7 million if new trees are lost at an annual rate of 4%/yr and $3.1 million if new trees are lost at an annual rate of 8%/yr. Management plans should enhance the protection and maintenance of existing trees in addition to planting new trees or natural regeneration. Spatially distributed modeling approaches such as ours provide more spatially refined service and benefit estimates and have the potential to guide more local and fine scale decision making regarding where to improve or protect tree cover and maximize the services and benefits of trees. However, more accurate and spatially distributed weather inputs, pollutant concentrations, and species and age specific mortality rates are needed to develop improved results. Regardless, this analysis develops a methodology to estimate the potential range of ecosystem services and benefits due to increased tree cover in the Bronx in 2030. Clearly trees provide a myriad of services and benefits to urban inhabitants and maintaining and expanding existing canopy cover should be a priority in urban settings.

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CHAPTER THREE: THE EQUITY OF URBAN FOREST ECOSYSTEM SERVICES AND BENEFITS IN THE BRONX, NY

Abstract

Trees provide important ecosystem services and benefits, with some, such as air pollutant and heat reductions, being linked to improved human health and well-being. The uneven distribution of tree cover in urban areas and subsequently the ecosystem services and benefits it provides has potential implications related to environmental justice, especially if disadvantaged socio-demographic or socio-economic and marginalized communities lack these services and benefits. This study explores the distribution of ecosystem services and benefits provided by tree cover in the Bronx, NY. Utilizing census block group specific spatial datasets, we employ a Mann-Kendall trend test and the Sen slope estimator to describe the relationship between median income, per capita income, percent minorities, population density, poverty percent and total educational attainment, and carbon storage and sequestration, stormwater runoff reduction, air pollutant removal and heat index reduction ecosystem services and benefits for 2010 tree cover conditions. We explore the equality in ecosystem service and benefit distributions across socio-demographic and socio-economic subgroups using the Atkinson inequality and Theil entropy indices decomposed into within and between subgroup inequalities for each ecosystem service and benefit. These inequality indices allow us to better assess current inequalities and work to achieve greater equity in the distribution of ecosystem services. Using population and ecosystem service data, all ecosystem services and benefits appear to be unequally and inequitably distributed in the Bronx, with disadvantaged socio-demographic and socio-economic block groups receiving disproportionately lower ecosystem services from urban trees. The vast majority of the inequality is explained by variations within each socio-demographic and socio-economic subgroup rather than variations between subgroups. To reduce this inequity, efforts should be made to strategically increase services and benefits by initially targeting disadvantaged block groups with extremely low tree cover.

Key words: Equity, Equality, Ecosystem services, Benefits, Environmental justice

3.1 INTRODUCTION

Empirical studies have documented the direct and indirect environmental, social, and economic benefits of urban trees including temperature reduction (Livesley et al., 2016; Salmond et al., 2016), air pollutant removal (Nowak, 2002; Nowak et al., 2014), carbon sequestration (Nowak and Crane, 2002; Nowak et al., 2013), climate regulation (Salmond et al., 2016; Nowak and Crane, 2002), stormwater runoff and nutrient pollution reduction (Bolund and Hunhammar, 1999; Livesley et al., 2016); energy savings (Akbari et al., 2001; McPherson and Simpson, 2003); improved human health (physical, mental and social well-being) (Donovan et al., 2013;

Jiang et al., 2016; Tzoulas et al., 2007) and increases in residential property values (Anderson and Cordell, 1988; Tyrväinen and Miettinen, 2000). However, the distribution of urban trees is typically not uniform across cities (Flocks et al., 2011), which can lead to potential environmental injustice issues if the health, well-being, and other documented social benefits of urban forests are inequitably distributed.

Environmental justice refers to both procedural fairness and distributive equity and is concerned with equal rights, equalizing opportunity and benefiting the least advantaged (Pellow, 2000; Schlosberg, 2003; Friedman et al., 2018). Equity, a term used synonymously with fairness or justice, refers to the fair distribution of resources, especially the absence of systematic disparities between more and less advantaged social groups (Reidpath and Allotey, 2007). McDermott et al. (2013) and Friedman et al. (2018) highlight that equity is a multi-dimensional concept of ethical concerns and social justice with distributive, procedural and contextual dimensions. Distributive equity, which this study is centered on, addresses the distribution of benefits and costs while procedural equity alludes to fairness in the political processes that allocate resources. Contextual equity is focused on understanding the pre-existing conditions that limit or facilitate access to decision making procedures, resources and benefits. Inequity is often used to define inequalities (uneven distribution of resources in the population) that are avoidable, unjust or unfair (Asada, 2005; Dahlgren and Whitehead, 1991; Hamann et al., 2018). Measures of inequality, such as the Gini coefficient, generalized entropy measures and Atkinson's class of inequality measures, allow us to better assess current inequalities and work to achieve greater equity in the distribution of ecosystem services (Braveman and Gruskin, 2003; Reidpath and Allotey, 2007).

Traditional environmental justice studies seek to determine if socially disadvantaged demographic and socio-economic groups are disproportionately impacted by environmental burdens such as pollution. However, recent studies have emerged, incorporating environmental justice in the distribution of environmental goods or amenities (such as parks and trees) that have a bearing on both environmental quality and human health (Benra and Nahuelhual, 2019; de la Barrera et al., 2019; Fleischer et al., 2018; Jennings, 2012; Keeler et al., 2019; Laterra et al., 2019; Mullin et al., 2018; Szaboova et al., 2019; Wang and Lan, 2019; Watkins et al., 2017). These studies reveal inequitable distributions of environmental amenities along socio-demographic and socio-economic parameters including wealth, class and race. Racial and ethnic minorities and low-income neighborhoods tend to have lower vegetation cover and associated ecosystem services relative to more affluent areas, yet these areas tend to be the underprivileged and the most vulnerable areas that rely more heavily upon these ecosystem services (Flocks et al., 2011; Escobedo et al., 2015; Jenerette et al., 2011; Soto et al., 2016). Low-income and often minority communities tend to be located within lower quality natural environments, are disproportionately exposed to environmental burdens that threaten their health, and access fewer environmental amenities. In addition, these communities often have inadequate access to health care and are thus more dependent on biodiversity for a wide range of natural resources and ecosystem services essential for their well-being (Billé et al., 2012; Massey, 2004; Millennium Ecosystem Assessment, 2005). Various factors have been used to explain these observed trends in the distribution of tree cover and services including the availability of planting space and funding for maintenance, perceptions and preferences, historical processes such as social stratification, climate and landscape heterogeneity, housing tenure and population density (Wolch et al., 2014; Danford et al., 2014; Landry and Chakraborty, 2009; Mincey et al., 2013; Wei et al., 2017).

Given the links between tree cover benefits and health, some city-wide tree planting initiatives, including the million tree planting initiatives in Los Angeles (CA) and New York City (NY), are addressing environmental inequity in their attempts to increase tree cover and associated benefits. In NYC, the MillionTreesNYC initiative launched in 2007 to plant and care for one million new trees throughout the city by 2017 (MillionTrees NYC, 2018), took an explicit environmental justice approach to address the uneven distribution of urban forests (Campbell et al., 2014). Due to a high correlation between poverty, lack of services, low air quality, and incidences of childhood diseases such as asthma, the initiative prioritized six Trees for Public Health neighborhoods: Morrissania and Hunts Point in the Bronx, East Harlem in Manhattan, Far Rockaway in Queens, East New York in Brooklyn, and Stapleton in Staten Island (Campbell et al., 2014; Locke et al., 2010).

In designing solutions that identify locations to not only increase tree cover but make its distribution more just, some cities (e.g., Portland (OR), Chicago (IL) and Columbia (MO)) have prioritized tree planting based on diverse ecological, social and economic goals and preferences with a special focus on equity (Portland Parks and Recreation, 2018; Chicago Region Trees Initiative, 2019; City of Columbia, 2018). For example, Austin (TX) considers public health and safety, air quality, environmental justice, water quality, forest replenishment, preservation and development, and urban heat island in their urban forest planning and management (Halter, 2015). Arizona's Shade Tree Planting Prioritization identifies underserved cities and communities and considers population density, lack of canopy cover, low-income, traffic proximity, sustainability, air quality, and urban heat effect (Grunberg et al., 2017). This commitment to more equitably distributed environmental services is a key component of urban planning and management. However, it remains to be seen whether these programs have been successful and whether disadvantaged stakeholders have improved access to the important ecosystem services and benefits of tree cover.

Despite the growing relevance of ecosystem services and benefits and the important links to human health and well-being, literature examining the distributional equity of ecosystem services and benefits provided by urban trees is limited (Mullin et al., 2018; Landry and Chakraborty, 2009; Wolch et al., 2014; Escobedo et al., 2015; Flocks et al., 2011; Nesbitt et al., 2019; Geneletti et al., 2020; Garrison, 2018, 2019; Nesbitt et al., 2018; Koo et al., 2019), especially in large cities such as NYC that are undertaking large-scale tree plantings and urban greening initiatives. More research is needed to evaluate the long-term outcomes of different planting strategies to ensure that the environmental benefits of the urban forest are shared more widely and equitably (Garrison, 2019). There is need for more equity assessments that consider: (a) the existing distribution of urban trees, (b) the spatial distribution of ecosystem service and benefit supply and demand, and (c) whether the supply and demand are equitably distributed across urban areas, especially with respect to groups who have been traditionally disadvantaged, marginalized or lack the resources or capacity to overcome a scarcity of environmental benefits. Studies that examine equity issues beyond total inequality and attempt to identify the sources of inequality (within-group and between-group) are necessary to inform urban forestry management and create actionable policy recommendations that prioritize approaches that lead to a fairer and more equitable society.

To address literature gaps regarding the distributional equity of ecosystem services and benefits provided by urban trees, this paper presents an analysis of the relationships between urban forest ecosystem services and socio-demographic and socio-economic variables in the Bronx, NY. The study extends previous research in the field by contributing to ecosystem service and benefit assessment methodology by examining total inequality as well as identifying the sources of that inequality (within-group and between-group) for different ecosystem services and benefits. We seek to establish whether there is an equitable distribution of ecosystem services derived from trees among various socio-demographic and socio-economic variables at the census block group level in the Bronx, NY. Specifically, this paper addresses whether the ecosystem services and the monetary benefits of tree carbon storage and sequestration, reductions in particulate matter less than 2.5 microns ($PM_{2.5}$), heat index reduction, and stormwater runoff are disproportionately distributed based on per capita and median income, percent minorities, population density, percent poverty and total educational attainment characteristics. The Bronx was chosen as the study location because of: (a) air quality, stormwater and urban heat island issues in this borough, (b) its diverse demographics, and (c) the lack of ecosystem services and benefits to some communities (Nyelele et al., 2019).

3.2 RESEARCH METHODOLOGY

The Mann-Kendall trend test and the Sen slope estimator (Mann, 1945; Kendall, 1975; Sen, 1968; Helsel and Hirsch, 2002) were used to describe the relationship between socio-demographic and socio-economic data (per capita income, median income, population density, total educational attainment (sum of the population with at least a high school education), poverty percent (percent of the population below the poverty line) and percent minorities) at the census block group level (a total of 1,132 block groups) and different ecosystem services and benefits derived from trees in the Bronx. Socio-demographic and socio-economic variables were selected from previous studies examining the equity of green spaces, ecosystem services or benefits (Landry and Chakraborty, 2009; Geneletti, 2020; Fleischer et al., 2018; de la Barrera et al., 2019; Danford et al., 2014; Schwarz et al., 2015; Ferguson et al., 2018; Nesbitt and Meitner, 2016; Grove et al., 2014). Ecosystem services refer to the conditions and processes through which natural ecosystems sustain and fulfill human life whilst benefits illustrate the final outputs from ecosystems that directly affect human well-being (Nyelele et al., 2019; Daily, 1997; Haines-Young and Potschin, 2012). In this study, ecosystem services include carbon storage (kgs) and sequestration (kgs/yr), stormwater runoff reduction (m^3/yr), $PM_{2.5}$ air pollutant removal (kgs/yr) and heat index reductions (in degrees Kelvin) for 2010 tree cover conditions. Ecosystem benefits refer to the monetary benefits associated with these services, including the monetary benefit ($/yr) of $PM_{2.5}$ air pollutant removal, monetary benefits of carbon storage ($) and sequestration ($/yr) and the avoided stormwater runoff monetary benefits ($/yr) based on stormwater treatment and management costs and fees. Next, we present Lorenz curves, a common visual aide to observe inequality that was first employed to examine income disparity (Lorenz, 1905). Here the Lorenz curves show the cumulative proportion of ecosystem services against the cumulative proportion of the socio-demographic or socio-economic variables; the Gini coefficient (Gini, 1909), is calculated using areas under the Lorenz curve. The Gini coefficient, though, is not decomposable and thus limits our ability to explore sources of inequality and inequity. We then explore potential environmental inequality in ecosystem services using two common measures of inequality, the Atkinson inequality index (Atkinson, 1970) and the Theil entropy index (Theil, 1972). Both of these indices are decomposable, allowing us to examine inequity both within and between socio-demographic and socio-economic subgroups for each ecosystem service following methods by Lorenzo and Liberati (2006a) and Lasso de la Vega and Urrutia (2003).

3.2.1 Ecosystem service and benefit estimates

Ecosystem services and benefits for 2010 tree cover conditions used in this study were estimated using spatially distributed versions of i-Tree models implemented by Nyelele et al. (2019) at the census block group level in the Bronx. i-Tree is a freely available suite of tools developed by the United States (U.S.) Forest Service designed to assess forest structure, ecosystem services and benefits. The model integrates field data from complete inventories of trees or randomly located plots, U.S. Census data, and readily available databases of environmental (e.g., meteorology and air quality) and land cover variables to develop estimates of forest structure, environmental effects and the value of a given urban forest service (Hirabayashi et al., 2012; Nowak et al., 2013; Nowak, 2018). Specifically, $PM_{2.5}$ air pollutant reductions and the monetary benefits of those reductions (based on estimates of incidences of adverse health effects and associated monetary values resulting from changes in pollutant concentrations) were modeled using i-Tree Eco (Nowak et al., 2008). Stormwater runoff reductions were modeled using i-Tree Hydro (Wang et al., 2008) and the monetary benefits of the runoff reductions were calculated at the national average of $\$2.36/m^3$ based on the USFS' Community Tree Guide series (Hirabayashi, 2013). Carbon storage and sequestration were calculated using the latest per area of tree canopy cover carbon removal rates for NYC (Nowak et al., 2018) while the monetary benefits of carbon storage ($) and sequestration ($/yr) were estimated from the social costs of carbon (Nowak and Greenfield, 2018). One improvement over Nyelele et al.'s methodology was in the estimation of the heat related benefits of trees. In this study we adopt methods detailed in Bodnaruk et al. (2017) and consider the reduction in heat index (in degrees Kelvin) as an ecosystem service. This was obtained by subtracting the average block group heat index values for 2010 tree cover conditions described in Nyelele et al. (2019) from the 2010 heat index of the block group without any tree cover. In the scenario without tree cover all tree cover is removed and replaced with impervious surface. This approach is similar to how i-Tree Hydro estimates avoided stormwater runoff. The heat index values for the scenario without tree cover were calculated following the same methodology detailed in Nyelele et al. (2019) using i-Tree Cool derived air temperature and humidity output for the month of July 2010. i-Tree Cool is based on the Physically based Analytical Spatial Air Temperature and Humidity model (Yang et al., 2013) and generates spatially distributed urban microclimate conditions including air temperature and humidity. This heat index is chosen because it is a human-perceived equivalent temperature, it is a measure of how hot it feels when relative humidity is factored in with air temperature, and it is widely used in environmental health research, including studies of air pollution exposure, outdoor temperature exposure, and the development of heat warning systems (Anderson et al., 2013; Rothfusz, 1990).

3.2.1.1 Trend estimation

The Moran's Index (*I*) statistic (Moran, 1950), a common measure of spatial autocorrelation (feature similarity), was used to determine the magnitude of the spatial relationship between ecosystem service values, socio-demographic as well as socio-economic variables. The spatial autocorrelation tool in Geographic Information System (GIS) software ArcMap® (version 10.3) was used to calculate Moran's *I* statistic for each ecosystem service, socio-demographic and socio-economic variable. Given a set of features and an associated attribute (e.g. ecosystem service), the tool evaluates whether the pattern expressed is clustered, dispersed, or random (Leong and Sung, 2015). To identify the trends and relationships between total block group ecosystem services and block group socio-demographic or socio-economic data from the 2010 census, the non-parametric Mann-Kendall test was used (Pohlert, 2018; Helsel and Hirsch, 2002; Meals et al., 2011). The Mann Kendall was selected based on several factors. The test is a non-parametric test that does not require the data to be normally distributed and is thus applicable even for data with outliers. In addition, the test is applicable in the detection of linear or nonlinear monotonic trends in data (Adarsh and Janga, 2015; Drápela and Drápelová, 2011). This test was used to evaluate whether ecosystem services increase or decrease with different socio-demographic or socio-economic variables, and whether the observed trend was significantly different than zero using a type I error of $\alpha = 0.05$. The Sen slope estimator was used to capture the magnitude of the trend. The Sen slope estimator was selected because it is an unbiased estimator of the true slope in simple linear regression and is a distribution free method (Sen, 1968). Another advantage of this estimator is that it limits the effect of outliers on the slope and is robust and free from restrictive statistical constraints (Kocsis et al., 2017). Combining the Mann-Kendall and the Sen slope estimator in trend analysis has the advantage of showing not only the relationship but proffers a way of visualizing the trend and response of one variable due to changes in the other.

3.2.1.2 Assessing environmental inequality

Several inequality metrics have been used to develop a more nuanced understanding of the distribution of environmental variables, including carbon emissions, resource use and industrial air toxics exposure (Boyce et al., 2014). These metrics include the Gini coefficient, generalized entropy measures such as the Theil entropy index, analysis of variance and the Atkinson index (Cowell, 2011; Bourguignon, 1979; Foster and Shneyerov, 1999; Boyce, et al., 2014; Lopes et al., 2015; De Maio, 2007; Lynch et al., 1998; Fields, 1979). These indices are commonly used to assess inequality in income and were applied to assess the inequality of ecosystem benefits delivered by urban trees. Kawachi and Kennedy (1997) compared six different measures of inequality: the Gini coefficient, the decile ratio, the proportion of income earned by the poorest 50%, 60% and 70% of households, the Robin Hood index, the Atkinson index and the Theil entropy measure and concluded that all measures behaved similarly and were highly correlated. The Theil entropy index and Atkinson index allow for distinguishing the effects of inequalities in different areas of the distribution spectrum, providing more meaningful quantitative assessments of inequalities (De Maio, 2007).

Cowell (2011) and the World Bank Institute (2005) discuss the criteria (population independence, symmetry, scale independence, Pigou-Dalton Transfer sensitivity and decomposability) that make a good measure of inequality. Several measures, including the generalized entropy class of measures of the Theil entropy index and the Atkinson index, satisfy all five criteria (Bourguignon, 1979; Foster and Shneyerov, 1999). The Gini coefficient, despite being a popular measure of inequality, only satisfies the first four criteria and is not easily decomposable or additive across groups. Decomposability means that inequality may be broken down by population groups or other dimensions. For a decomposable index, the total inequality of a population is equal to the sum of the inequality existing within subgroups of the population and the inequality existing between subgroups (Bourguignon, 1979).

In this analysis, the Atkinson inequality index and Theil entropy index were decomposed into within and between socio-demographic or socio-economic subgroup inequality in the distribution of ecosystem services from trees in the Bronx. The within group inequality element captures the inequality due to the variability of ecosystem services within each subgroup, while the between group inequality captures the inequality due to the average variability of ecosystem services across different subgroups. Decomposition helps identify the contribution of each socio-demographic or socio-economic subgroup (classified in this study from per capita income, median income, percent minorities, population density, poverty percent and total educational attainment data) to the total inequality of ecosystem services, considering that inequality may stem from different groups of the population with different intensities (Lorenzo and Liberati, 2006a). Although not decomposable, the Gini coefficient was used to measure the degree of inequality in socio-economic and socio-demographic subgroup ecosystem services and benefits. The Gini coefficient is usually defined based on the Lorenz curve, which shows the cumulative proportion of resources against the cumulative proportion of the population (Lorenzo and Liberati, 2005). On the Lorenz curve, a 45° line represents perfect equality of resources and the Gini coefficient is the ratio of the area between the line of perfect equality and the observed Lorenz curve to the total area under the line of equality. The extent to which the Lorenz curve sags below the line of equality indicates the degree of inequality in the distribution of resources. The Gini coefficient ranges from 0 to 1; the higher the Gini coefficient, the more unequal the distribution (Lorenzo and Liberati, 2006b).

Each socio-demographic and socio-economic variable was sorted from highest to lowest and divided into five equal subgroups created from the 1,132 block groups. The five socio-demographic and socio-economic subgroups were then used to decompose the Theil and Atkinson's indices. According to the World Bank Institute (2005), the simplest way to measure inequality is by dividing the population into five groups, for example from smallest to largest income, and reporting the levels or proportions of income (or expenditure) that accrue within each level. Several studies have decomposed inequality using five subgroups in their analysis (e.g., Yiengprugsawan et al., 2009; Hosseinpoor et al., 2006; Gradín, 2008; Dubois and Muller, 2017; Rahman and Huda, 1992).

Atkinson inequality index

The Atkinson inequality index ranges from 0 to 1, where a value of 1 indicates maximum inequality and 0 indicates minimum inequality (De Maio, 2007). Traditionally the Atkinson index has been used to illustrate the percentage of total income that a given society would have to forego to have more equal shares of income between its citizens (United Nations, 2015). The Atkinson index depends on a weighting parameter, epsilon (ε), which is subjectively determined by the researcher. ε measures the aversion to inequality (De Maio, 2007; Haughton and Khandker, 2009); by varying ε, which can range from 0 (representing indifference about the nature of the ecosystem service distribution) to infinity (showing concern only with the ecosystem service of the very lowest socio-economic or socio-demographic group), the Atkinson index allows for varying the sensitivity to inequalities in different parts of the ecosystem service distribution. Typically, ε values used in the literature are 0.5, 1, 1.5 or 2 (De

Maio, 2007; Jenkins, 1999; Mendoza, 2017); the higher the value, the more sensitive the Atkinson index becomes to inequalities at the bottom of the distribution (De Maio, 2007). Higher ε entails greater social utility or willingness by individuals to accept smaller ecosystem services and benefits in exchange for a more equal distribution (United Nations, 2015).

An important feature of the Atkinson index is that it satisfies the elementary factorial decomposability property, making it is possible to decompose the measure into within and between group inequality (Lasso de la Vega and Urrutia; 2003). Moreover, unlike other indices, it can provide welfare implications of alternative policies and allows the researcher to include some normative content to the analysis. De Maio (2007) highlights that Atkinson values can be used to calculate the proportion of total resources that would be required to achieve an equal level of social welfare if these services were perfectly distributed. The Atkinson index was calculated as:

$$\mathrm{AI} = 1 - \left[\frac{1}{n}\sum_{i=1}^{n}\left[\frac{x_i}{\bar{x}}\right]^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}} \tag{3.1}$$

where AI is the Atkinson index, n is the total population size (in this case total number of block groups in the Bronx), $\bar{x}$ is the population's average value of ecosystem service, x_i is each census block group's value of ecosystem service, and ε represents the degree of concern over inequality (Lasso de la Vega and Urrutia, 2003). For this analysis three ε values (0.5 for a small inequality aversion, 1 for a medium inequality aversion, and 2 for large inequality aversion) were used to assess the impact of ε.

To decompose the Atkinson index into within and between socio-demographic or socio-economic indices for each ecosystem service, a factorial decomposition (Lasso de la Vega and Urrutia 2003), was conducted using the five subgroups calculated from the values of the socio-demographic or socio-economic variable. The between subgroup inequality ($\mathrm{AI_B}$) was defined by:

$$\mathrm{AI_B} = 1 - \frac{\left(\sum \frac{n_1}{n}(\bar{x}_1)^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}} + \left(\sum \frac{n_2}{n}(\bar{x}_2)^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}} + \left(\sum \frac{n_3}{n}(\bar{x}_3)^{1\varepsilon}\right)^{\frac{1}{1-\varepsilon}} + \left(\sum \frac{n_4}{n}(\bar{x}_4)^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}} + \left(\sum \frac{n_5}{n}(\bar{x}_5)^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}}{\bar{x}} \tag{3.2}$$

This index represents the case in which every census block group in the first socio-demographic or socio-economic group has the group 1 mean ecosystem service value ($\bar{x}_1$), every census block group in the second socio-demographic or socio-economic group has the group 2 mean ecosystem service value ($\bar{x}_2$), and so forth. n_i/n represents the population share of each socio-demographic or socio-economic group. The within group inequality ($\mathrm{AI_w}$) was calculated from the overall Atkinson inequality index and between group Atkinson inequality index as:

$$\mathrm{AI_w} = 1 - \left(\frac{1-\mathrm{AI}}{1-\mathrm{AI_B}}\right) \tag{3.3}$$

Theil entropy index

The Theil entropy index is derived from information theory and likens the dispersion of shares across the population to the concept of entropy, a measure of randomness in a given set of information (Lynch et al., 1998). The Theil index measures an entropic distance the population is away from the ideal egalitarian state of everyone having the same income (United States Census Bureau, 2018a). As a member of the generalized entropy class of inequality indices, the Theil index is perfectly decomposable into within and between elements (Lorenzo and Liberati, 2006a), enabling analysis of between and within area effects. Unlike the Atkinson index that ranges between 0 and 1, the values of the Theil index vary between 0 and infinity (or one, if normalized), with zero representing an equal distribution and higher values representing a higher level of inequality (Litchfield, 1999; United Nations, 2015). The Theil index is most sensitive to the middle range of the distribution (Boyce et al., 2016) and was calculated as:

$$\mathrm{T} = \frac{1}{n}\sum_{i}\left(\frac{x_i}{\bar{x}}\right)\ln\left(\frac{x_i}{\bar{x}}\right) \tag{3.4}$$

where T is the Theil index, n is the total population size, x_i is the ecosystem service value of each census block group and $\bar{x}$ is the mean ecosystem service value from the entire population. Using the five subgroups for each socio-demographic and socio-economic variable, the within subgroup inequality was calculated as follows:

$$\mathrm{T_W} = \left(\frac{n_1}{n}\frac{\bar{x}_1}{\bar{x}}\right)\mathrm{T1} + \left(\frac{n_2}{n}\frac{\bar{x}_2}{\bar{x}}\right)\mathrm{T2} + \left(\frac{n_3}{n}\frac{\bar{x}_3}{\bar{x}}\right)\mathrm{T3} + \left(\frac{n_4}{n}\frac{\bar{x}_4}{\bar{x}}\right)\mathrm{T4} + \left(\frac{n_5}{n}\frac{\bar{x}_5}{\bar{x}}\right)\mathrm{T5} \tag{3.5}$$

$\mathrm{T_W}$ is the within subgroup Theil index; T1, T2, T3, T4 and T5 are the Theil indices for each of the five subgroups of the socio-demographic or socio-economic variable in question, respectively; in the brackets are the weights for each group, which include the population share of each socio-demographic or socio-economic subgroup (n_i/n), the relative mean ecosystem service of each socio-demographic or socio-economic subgroup ($\bar{x}_i$) and the average ecosystem service of the population ($\bar{x}$).

The between subgroup Theil inequality was calculated using subgroup means instead of actual ecosystem services as follows:

$$\mathrm{T_B} = \left[\frac{n_1}{n}\left(\frac{\bar{x}_1}{\bar{x}}\right)\ln\left(\frac{\bar{x}_1}{\bar{x}}\right)\right] + \left[\frac{n_2}{n}\left(\frac{\bar{x}_2}{\bar{x}}\right)\ln\left(\frac{\bar{x}_2}{\bar{x}}\right)\right] + \left[\frac{n_3}{n}\left(\frac{\bar{x}_3}{\bar{x}}\right)\ln\left(\frac{\bar{x}_3}{\bar{x}}\right)\right] + \left[\frac{n_4}{n}\left(\frac{\bar{x}_4}{\bar{x}}\right)\ln\left(\frac{\bar{x}_4}{\bar{x}}\right)\right] + \left[\frac{n_5}{n}\left(\frac{\bar{x}_5}{\bar{x}}\right)\ln\left(\frac{\bar{x}_5}{\bar{x}}\right)\right] \tag{3.6}$$

where $\mathrm{T_B}$ is the within subgroup Theil index; n_i/n represents the population shares of each socio-demographic or socio-economic group and $\bar{x}_i/\bar{x}$ is the relative mean ecosystem service of each socio-demographic or socio-economic group.

3.3 RESULTS

3.3.1 Moran's I test

Based on statistically significant p-values and positive z-scores, results of the Moran's *I* test indicate that the spatial distribution for all ecosystem services and benefits (with the exception of avoided runoff which is completely random with $I = -0.003$) as well as socio-demographic and socio-economic variables is more spatially clustered than would be expected if the underlying spatial processes were random. However, on the basis of the Moran's *I* values which are particularly low (ranging between 0.006 and 0.3 across all ecosystem services and benefits and between 0.045 and 0.3 for socio-demographic and socio economic variables), there appears to be limited spatial clustering of the variables associated with the geographic features in the study area indicating some general randomness in the majority of the features. Poverty percentage has a relatively higher Moran's *I* value of 0.5 as evidenced by the presence of high poverty clusters in the southwest parts of the borough as well as some low poverty clusters predominantly in the northern and eastern parts of the Bronx.

3.3.2 Mann-Kendall trend test

Population density, poverty percentage and minority percentages exhibit significant negative relationships with carbon storage and sequestration, $PM_{2.5}$ pollutant removal and heat index reductions (Table 3.1). Significant negative relationships are also observed for poverty percentage and avoided runoff services and monetary benefits. The carbon storage and sequestration services as well as monetary benefits have the same τ and p-values since carbon-related ecosystem services were estimated using per area of tree canopy cover removal and monetary rates. Similarly, avoided runoff services and benefits have the same τ and p-values based on the $2.36/m^3 used to estimate the monetary value of the estimated avoided runoff (see Nyelele et al., 2019 for estimation of ecosystem services and benefits). No significant trends were observed for the avoided runoff services and benefits and minority percent, educational attainment and population density. Significant positive relationships are observed for median and per capita income for carbon storage and sequestration, avoided runoff, heat index reductions and $PM_{2.5}$ pollutant removal ecosystem services as well as for educational attainment with carbon storage and sequestration, $PM_{2.5}$ pollutant removal and heat index reductions.

Table 3.1: Mann-Kendall relationships between socio-demographic variables and ecosystem services.

Socio-demographic or socio-economic variable	Carbon services		Avoided runoff		$PM_{2.5}$ removal (kgs/yr)		$PM_{2.5}$ removal ($/yr)		Heat index reduction (K)	
	τ	*p val*	τ	*p val*	τ	*p val*	τ	*p val*	τ	*p val*
Minority percent	**-0.12**	**0.00**	-0.02	0.30	**-0.12**	**0.00**	**-0.06**	**0.00**	**-0.07**	**0.00**
Median income	**0.24**	**0.00**	**0.05**	**0.01**	**0.25**	**0.00**	**0.18**	**0.00**	**0.24**	**0.00**
Per capita income	**0.28**	**0.00**	**0.04**	**0.04**	**0.29**	**0.00**	**0.22**	**0.00**	**0.26**	**0.00**
Poverty percent	**-0.33**	**0.00**	**-0.04**	**0.05**	**-0.34**	**0.00**	**-0.21**	**0.00**	**-0.33**	**0.00**
Total educational attainment	**0.19**	**0.00**	0.03	0.10	**0.19**	**0.00**	**0.33**	**0.00**	**0.10**	**0.00**
Population density	**-0.54**	**0.00**	-0.03	0.15	**-0.53**	**0.00**	**-0.05**	**0.01**	**-0.36**	**0.00**

τ = Kendall's τ
p val = p-value. p val < 0.05 are in bold.

3.3.3 Sen's estimator of slope

Sen's estimator of slope was used to capture the magnitude of the trend or relationship between ecosystem services and socio-demographic or socio-economic variables. The slope enables a better understanding of how ecosystem services respond to changes in socio-demographic and socio-economic variables. For example, for every $1,000 increase in median income in the

Bronx, there is an increase in the monetary benefit of $140 for carbon storage, $7 for carbon sequestration, $6 for avoided runoff and $40 for $PM_{2.5}$ pollutant removal services. For every 10% increase in the poverty percent in the Bronx, there is a decrease in the monetary benefit of $2,400 in carbon storage, $130 in carbon sequestration, $70 in avoided runoff and $700 in $PM_{2.5}$ pollutant removal services (Table 3.2). For those relationships that are significant based on the Mann-Kendall test, when the slope values are normalized and rescaled between 0 and 1 to enable comparison of the data, results indicate that total educational attainment is an important variable for explaining carbon storage and sequestration, $PM_{2.5}$ pollutant removal services and monetary benefits as well as heat index reductions in the Bronx as it has the greatest slope value. Per capita income is important for explaining avoided runoff services and benefits.

Table 3.2: Sen's slope values for each socio-demographic or socio-economic variable and ecosystem service.

		Carbon storage		Carbon Sequestration		Avoided runoff		$PM_{2.5}$ removal		Heat Index Reduction
		kgs	$	kgs/yr	$/yr	m^3/yr	$/yr	kgs/yr	$/yr	(K)
Minority percent	$\hat{b}_1$	$-6*10^2$	-90	-30	-5.0	-1.2	-3.0	$-1.5*10^{-2}$	-20	$-6*10^{-4}$
Median income	$\hat{b}_1$	1	$1.4*10^{-1}$	$5*10^{-2}$	$7*10^{-3}$	$3*10^{-3}$	$6*10^{-3}$	$3*10^{-5}$	$4*10^{-2}$	$1.8*10^{-6}$
Per capita income	$\hat{b}_1$	2	$3.8*10^{-1}$	0.1	$2*10^{-2}$	$5*10^{-3}$	$1*10^{-2}$	$7*10^{-5}$	$1.3*10^{-1}$	$4.7*10^{-6}$
Poverty percent	$\hat{b}_1$	$-1.5*10^3$	$-2.4*10^2$	80	-13	-3.0	-7.0	$-4*10^{-2}$	-70	$-3*10^{-3}$
Total educational Attainment	$\hat{b}_1$	40	6.7	1.4	0.4	0.1	0.3	$1*10^{-3}$	5.8	$5.1*10^{-5}$
Population density	$\hat{b}_1$	$-1.7*10^6$	$-2.7*10^5$	$-9*10^4$	$-1.4*10^4$	$-1.5*10^3$	$-3.6*10^3$	-50	$-1.4*10^4$	-2.7

3.3.4 Inequality metrics

To better observe inequity in the ecosystem services provided by urban trees in the Bronx, the 1,132 census blocks were divided into 100 subgroups based on the percentage of poverty (group 1 being the group with the highest level of poverty and group 100 having the lowest level of poverty). Figure 3.1a shows a scatter plot of the median $PM_{2.5}$ air pollutant removal services for each subgroup, and Figure 3.1b shows the Lorenz curves developed from these subgroup medians. There is a clear trend in the scatterplot, where the subgroups with the lowest level of poverty have an observable increase in $PM_{2.5}$ air pollutant removal services. The Gini coefficient from the Lorenz curve was 0.41, indicating some inequality in the distribution of $PM_{2.5}$ air pollutant removal services. Figure 3.1c and 3.1d are scatterplots of median $PM_{2.5}$ air pollutant removal services and the Lorenz curve as a function of educational attainment. Again, there appear to be inequality in the delivery of these ecosystem services, though slightly less pronounced than when we examined these services versus poverty percentage. On Figure 3.1c, an unusually high median is observed for one subgroup with low total educational attainment. A closer examination of this subgroup indicated that this subgroup contains census block groups with parks that include Van Cortlandt and Pelham Bay (the two largest parks in the Bronx) as well as Soundview and Ferry Point. Parks are generally associated with more tree cover and leaf area resulting in high air pollutant removal rates.

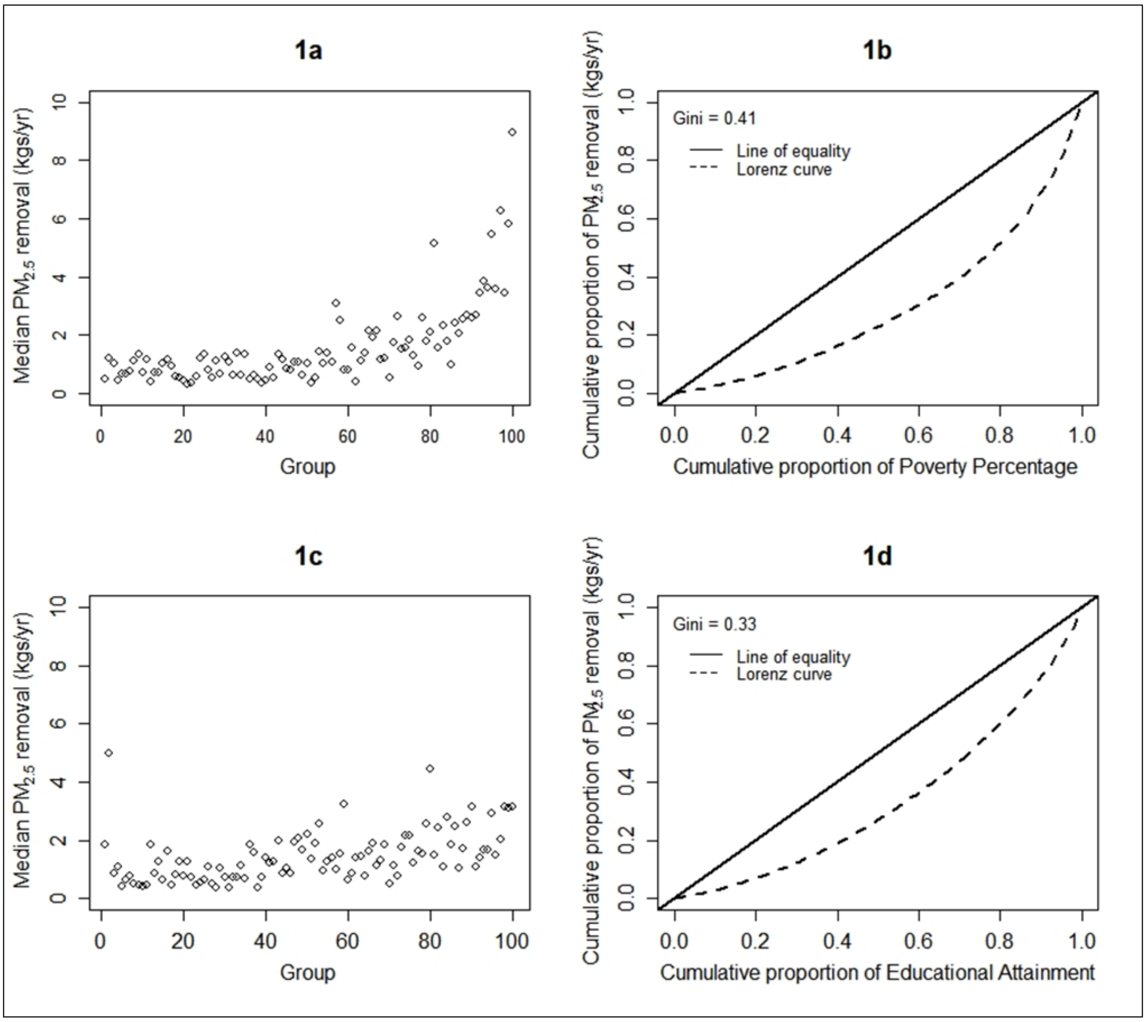

Figure 3.1: Scatter plots and Lorenz curves illustrating the distribution of $PM_{2.5}$ air pollutant removal services for the hundred poverty percent (3.1a and b) and educational attainment (3.1c and d) subgroups.

Figure 3.2 contains the within subgroup (black) and between subgroup (blue) Theil and Atkinson indices for each ecosystem service and benefit examined. Overall, the Theil and Atkinson indices depict inequality in the distribution of ecosystem services in the Bronx. Compared to other services, the level of inequality for heat index reduction benefits and $PM_{2.5}$ monetary benefit distributions are relatively low for the Thiel index and the Atkinson index when $\varepsilon = 0.5$. This is because there is little variability in the spatial distribution of these services, as shown in the box plot in Figure 3.2 for heat index reduction benefits across the census block groups. This result may be due to limitations in the model employed to estimate heat reduction services and the lack of data to describe the spatial distribution of air quality.

Avoided runoff services and monetary benefit also exhibit low Atkinson's index values for ε = 0.5. In addition, most of the inequality in the distribution of ecosystem services across socio-demographic and socio-economic subgroups for all Theil and Atkinson's indices appears to be due to the within group inequality as compared to the between group inequality. Exceptions are observed between population density and carbon related ecosystem services and benefits using Atkinson Index with ε = 1 or 2. These metrics provide us with an understanding of what variables are most important in driving inequality in the distribution of ecosystem services in the Bronx.

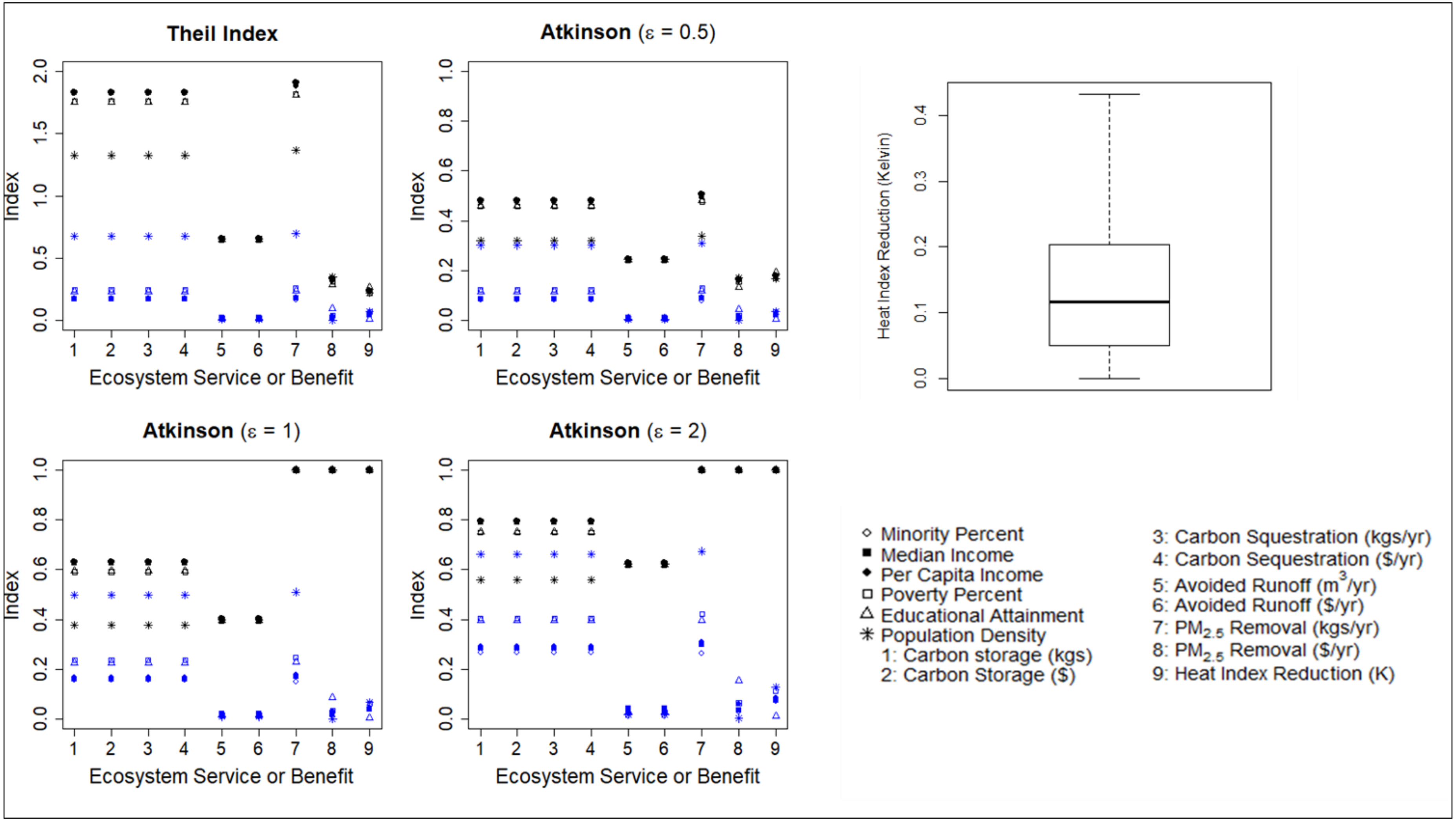

Figure 3.2: Within subgroup (black) and between subgroup (blue) Theil and Atkinson indices for each ecosystem service and benefit. The distribution of the heat index reductions is shown in the box plot.

Looking at the between subgroup inequalities, both metrics highlight that population density drives inequality in carbon storage and sequestration services, heat index reductions as well as $PM_{2.5}$ pollutant removal services, while median income drives inequality related to avoided runoff reduction services. In the Bronx, total educational attainment explains inequalities associated with $PM_{2.5}$ pollutant removal monetary values. As expected, varying ε (0.5, 1 and 2) shows that increasing the value of ε will result in increases in the Atkinson index value for all the ecosystem services across all the socio-demographic and socio-economic variables, indicating less equality between groups.

Note that when the number of subgroups is increased from five (which is standard in the literature) to one hundred (which the Lorenz curves and Gini index presented in Figure 3.1 were based on), results (not presented here) showed that between group variations in the Atkinson and Theil indices were higher than within group variations. As expected, by partitioning the services into more subgroups, the variability in ecosystem services within subgroups decreased. These results showed the drivers of inequality were the same as those shown in Figure 3.2.

3.4 DISCUSSION

This study was framed by environmental justice, focusing on the socio-economic and socio-demographic characteristics of census block groups. The environmental justice hypothesis posits that environmental amenities are inequitably low in disadvantaged socio-economic or socio-demographic communities and predicts these communities experience fewer urban environmental benefits (Watkins and Gerrish, 2018). Low Moran's *I* values obtained from this analysis imply that although there is some spatial clustering of the ecosystem services and benefits as well as socio demographic and socio economic variables associated with the geographic features in the study area, in general these variables are randomly distributed in the majority of the census block groups and the results of the study are not driven by spatial associations between the block groups. The findings in this study show that ecosystem services in the Bronx are related to socio-demographic and socio-economic characteristics of the census block groups. Specifically, the ecosystem services from trees are disproportionately distributed with respect to per capita and median income, poverty percent, population density, minority percent and total educational attainment, with disadvantaged socio-demographic and socio-economic neighborhoods being associated with disproportionately low levels of these services. The Theil and Atkinson's inequality indices also highlight overall inequality in the distribution of carbon storage and sequestration, avoided runoff and $PM_{2.5}$ reduction services across the census block groups of the Bronx. Similar findings of inequity and inequality in the distribution of tree cover and related ecosystem services and benefits have been reported in the literature (Danford et al., 2014; Landry and Chakraborty, 2009; Jenerette et al., 2011; Schwarz et al., 2015; Heynen and Lindsey, 2003; Kendal et al., 2012; Flocks et al., 2011; Wolch et al., 2014; Pham et al., 2012; McPhearson et al., 2013) where more advantaged socio-demographic or socio-economic neighborhoods will have larger amounts of tree cover and services while disadvantaged socio-demographic and socio-economic neighborhoods have minimal coverage.

The observed trends between ecosystem services and the socio-demographic or socio-economic variables can be explained within the context of tree cover distribution. As the amount, type, condition, and distribution of urban forests varies across an urban landscape, so will ecological function and the subsequent provision of ecosystem services by urban trees (Flocks et al., 2011). Thus, many of the ecosystem services from trees, for example air pollutant removal and related health benefits of improved air quality, tend to accrue primarily to those living in the immediate vicinity of trees (Schwarz et al., 2015). McPherson and Rowntree

(1989) also highlight that many of the ecosystem benefits provided by trees are proportional to leaf surface area and that tree canopy cover is a measure related to leaf surface area. For example, among other local conditions (e.g., pollutant concentration, length of growing season, percent evergreen leaf area, meteorological conditions), leaf area will be highly related to the pollutant removal gradients since filtering capacity increases with more leaf area (Givoni, 1991; Nowak et al., 2014; Hirabayashi and Nowak, 2016). The monetary benefit of this service is obtained by modeled air quality changes, population demographics and baseline incidence rates (U.S Environmental Protection Agency, 2017).

Several possible reasons have been brought forward to explain why trees and their ecosystem services are disproportionally distributed, with disadvantaged socio-economic or socio-demographic neighborhoods benefiting less. Firstly, high income earners have been shown to afford and be willing to pay more for properties in neighborhoods with attractive amenities that include greener areas with trees (Heynen and Lindsey, 2003; Hamann et al., 2018; Landry and Chakraborty, 2009). Zhu and Zhang (2008) highlight that urban forests are economic goods and when income increases, the demand will also rise. For every one percent rise in income in U.S. cities with populations greater than 100,000, demand for tree canopy cover increased by 1.76%; for every one percent drop in income, the demand decreased by 1.26% (Zhu and Zhang, 2008). Wealthier households spend more money on environmentally relevant expenditures such as landscaping as a way of investing in the appeal of their own property or neighborhood (Grove et al., 2006; Landry and Chakraborty, 2009). Investing in tree maintenance not only promotes tree health and structural integrity but will result in increased services and benefits from trees.

Grove et al. (2006) further highlight that power and income differences among neighborhoods influence the levels of public investment in green infrastructure; in this regard members of some higher socio-economic groups are better able to attract public investment in local greening initiatives that include tree planting as compared to those in lower socio-economic groups. This is evident in the Bronx, where parks and green spaces in low-income neighborhoods often lack trees and landscaping whilst those in high-income neighborhoods thrive and are often supported by conservancies that raise private money (Kusisto, 2014). The Bronx has the lowest per capita ($18,896) and median ($35,302) income of all NYC boroughs, as well as the highest unemployment rate in NYC (12% in 2016), while 30.7% of the population lives below the poverty line (U.S. Census Bureau, 2018b, 2018d). It is evident that tree planting and landscaping cannot be afforded by some people in the Bronx. Thus, it is commendable that of the half-dozen low-income neighborhoods with particularly poor tree canopy cover that were singled out for plantings under MillionTreesNYC, two are in the Bronx (Morrisania and Hunts Point) (Campbell et al., 2014; MillionTreesNYC, 2018). However, future tree plantings could target more of these low-income neighborhoods, such as those in New York's 15th congressional district, including most of the southern and western neighborhoods of the Bronx, the poorest congressional district in the country (Food Research and Action Center, 2018).

Participation in tree planting in Portland, OR was much lower in neighborhoods with lower high school graduation rates (Donovan and Mills, 2014). A possible explanation could be that trees, especially when young, require more attention (e.g., watering, fertilization), which requires an investment of time and money. Neighborhoods with lower educational attainment tend to have a higher proportion of minority residents and lower median income residents who might not be able to afford this investment. Of the nearly 800,000 people in the Bronx who were at least 25 years old, 71.2% had graduated from high school and 19.1% held a bachelor's or higher college degree (U.S. Census Bureau, 2018d). Census block groups with less educational attainment are sometimes associated with higher rates of crime, and increasing tree cover is sometimes seen as an opportunity for increased crime (Donovan and Mills 2014). Whereas houses nearer to parks in high-income neighborhoods attract higher sale prices, in low-income neighborhoods they have lower prices (Donovan and Mills, 2014; Troy and Grove, 2008; Troy et al., 2012). Block groups with lower educational attainment levels and lower incomes have also been correlated with more renters (Perkins et al., 2004). Given that trees are a long-term investment, renters may not participate in tree planting initiatives because they are unlikely to reap the rewards of increased property values, or they may simply want to avoid gentrification and its outcomes, such as rising rents (Schwarz et al., 2015; Vogt et al., 2015). Studies have also shown that when green infrastructure is incorporated into the design of underserved areas, vulnerable populations may be displaced, an unintended result. For example, Garrison (2018) highlights that large-scale parks may catalyze gentrification; as green infrastructure appears in neighborhoods, neighborhoods become more desirable, rents and housing values rise, and many residents are displaced and priced out of their newly improved neighborhoods. The Bronx has the lowest owner-occupied housing units (19.1%) between 2012 and 2016 in NYC (U.S. Census Bureau, 2018c).

Studies have shown that where minority residents are concentrated, the environment tends to be more degraded and they are more likely to be exposed to the negative impacts of urban environmental hazards such as air pollution and heat stress (Heynen and Lindsey, 2003; Landry and Chakraborty, 2009; Flocks et al., 2011; Wolch et al., 2014). Despite this pattern, racial and ethnic minorities have relatively lower access to parks and green spaces that provide important ecosystem services. Garrison (2018) notes that the history of disinvestment in greenspace in low-income communities of color has always been engrained in New York’s landscape; parks are distributed unequally, with areas with more non-white residents generally having less park space. Despite this, parks were the location of 83% of MillionTreesNYC new trees, creating a significant obstacle to environmental justice. In the Bronx, there is an overrepresentation of racial minorities in low-income communities; for example, African Americans and Hispanics account for 40% and 57% of the South Bronx population, respectively (Statistical Atlas, 2018). Although trees provide many ecosystem services, it is important to also consider that trees can also create disamenities such as increased water demand, maintenance costs, allergies, and perceived safety concerns (Schwarz et al., 2015). What is perceived as an ecosystem service in one location may be seen as a disservice in another, and a lack of inclusive decision-making can produce green spaces that are ill-suited for communities. As such tree planting and other greening activities might be met with resistance from residents who simply do not want trees in front of their houses or in their neighborhoods. Lohr et al. (2004) highlight that in some African-American neighborhoods, residents prefer few trees in public areas because of concerns about safety and crime. Thus, while keeping equity in mind in designing solutions and siting future green spaces that ensure the provision of ecosystem services for everyone, it is imperative for planners to meet the needs and match the values of different locations for ecosystem services while finding ways to deal with people's perceptions and fears.

Our results indicating that ecosystem services from trees decrease as population density increases are consistent with Fei et al. (2016), Meacham et al. (2016) and Eigenbrod et al. (2011). Fei et al. (2016) state that as population density increases, the environment becomes degraded due to the industrial and human activities that result in vegetation fragmentation and land deterioration. The effects of these activities on ecosystems in areas with lower population density are less than those in areas with higher population density, while the different types of ecosystem services decrease as population density increases. While other studies (Schwarz et al., 2015) included population density as a proxy for building density, Grove et al. (2014) highlight that population density has been previously proposed by ecologists to explain variations in the distribution of tree canopy cover (and subsequently the services and benefits it provides). Geneletti (2020) also notes that the distribution of vulnerable individuals is typically proportional to the distribution of population density, i.e. the area with the highest population density are also typically the area with highest number of vulnerable individuals.

Achieving equitable access is difficult because urban forests take space to produce the structure and processes necessary to generate ecosystem services. Population density is presumed to drive vegetation change (and ecosystem service provisioning) through development and the subsequent loss of space for existing trees and growth of new trees (Locke and Grove, 2016). This could be the case in the Bronx where historically the burden of NYC's environmental hazards has been disproportionately imposed on Bronx communities (Pasquel, 2015). For example, street standards and historical development patterns shape the proportion of space that is public versus private property, affecting the availability of tree planting sites (Debats, 2014). Densely populated neighborhoods primarily in the western and southern sections of the borough are characterized by several major highways, nine waste transfer stations (almost one-third of the total number in NYC), and other industrial and polluting land uses, such as Hunts Point Cooperative Market wholesale food distribution center (the largest in the world), power plants, and extremely heavy industrial truck traffic (Spira-Cohen et al., 2011). Debats (2014) notes that in such densely populated and industrial areas it is difficult to plant trees because they have more overhead wires, more driveways, narrower sidewalks, and more hollow sidewalks, all of which consume space that might otherwise have been planted.

While the Mann-Kendall and Sen slope estimator results show lower ecosystem service and benefit provisions in disadvantaged socio-demographic and socio-economic block groups, the Theil and Atkinson inequality indices show that inequality and subsequently inequity are more related to variations within individual subgroups than between the subgroups. Haughton and Khandker (2009) also document similar trends in income inequality studies, where typically over three quarters of inequality is due to within group inequality, and the remainder due to between group differences. This result implies that while some block groups have more ecosystem services, other block groups in the same subgroup and with similar socio-demographic or socio-economic characteristics do not have similar ecosystem services. The data in each subgroup point to demographically and economically mixed block groups, possibly explaining the within subgroup variations. The Bronx is an ethnically diverse borough, with a mixed workforce (blue and white collar) and thus contains both high- and low-income residents (NeighborhoodScout, 2019; DiNapoli and Bleiwas, 2013). Another potential explanation could be the unit of analysis used in the study. Maantay (2002) highlights that many contradictions and discrepancies in environmental justice studies can be traced to the geographic unit of analysis used, and altering the geographic boundaries of the study area can have dramatic implications for the results of the analysis. However, the availability of data is often what dictates the level of aggregation, and in this study the analysis was carried out at the census block level, where demographic data is readily available from the U.S. Census. The trends could also be attributed to the data used in the analysis and how the subgroups were characterized. While the census data came directly from the U.S. Census Bureau, Maantay (2007) notes that the main limitation of census data is the possible undercounting in low-income and immigrant communities. Future studies could supplement census data using data collected by local agencies and community databases were available. Incorporating local knowledge to augment and verify the accuracy of publicly available data sources also allows for direct involvement of the affected people and the incorporation of intimate knowledge of their surroundings. This allows for the development of more detailed, complete, and positionally accurate characterizations of the population subgroups. Although resolving the challenge of inequity will require an in-depth understanding of the local issues that shape it, results of the study show that for increased equality and equity to be achieved, it is important to target new tree plantings in areas with low ecosystem services, particularly within generally disadvantaged socio-demographic and socio-economic groups.

Our Mann-Kendall results do not reveal any significant trends between the avoided runoff services in the Bronx and minority percent, educational attainment and population density These results imply that these services are independent of these socio-demographic and socio-economic variables, and there is a relatively equitable distribution of these services. This result is not surprising since some ecosystem services, for example reductions in storm water runoff, have been shown to benefit a whole city or region. Irrespective of tree planting locations or presence of tree cover, these benefits are experienced by residents in other neighborhoods (Donovan and Mills, 2014). In addition, results of the Theil index and Atkinson index for $\varepsilon = 0.5$ depict low levels of inequality in the distribution of the heat index reduction benefits. While this result could be an artifact of the heat index reduction model and data used in the analysis, this result is not surprising considering both the range and variability of the heat index reduction across the census block groups as depicted by the box plot in Figure 3.2. Results of the analysis show minimal variations in the heat index reductions for the majority of the census block groups in the Bronx. There is a need for more studies to assess the impact of local factors in these areas on ecosystem services as well as studies that seek to improve on the methodology of determining heat index reductions and other tree effects on temperature.-

While our results show that ecosystem services in the Bronx are related to the socio-demographic and socio-economic characteristics of the census block groups, they are not particularly strong in some cases as depicted by the Mann Kendall trend test. For example, minority percent exhibits a weak negative relationship with carbon and air pollutant removal services; median and per capita income have a weak positive relationship with avoided runoff services. The small and significant *p*-values are mostly likely a result of the large sample size (n = 1132 block groups). *p*-values are influenced by sample size in statistical tests (Sullivan and Feinn, 2012), in this case resulting in significant but weak relationships because the sample size is large enough to make a small effect significant. More research is needed to identify the underserved communities and better understand local factors that are likely to affect tree cover distribution and participation in tree-planting programs.

Results have highlighted that ecosystem service inequity should be improved in the Bronx to foster the development of healthier and more resilient urban communities. The methodology used in this study can help identify trends and estimate the rate of change in ecosystem services and benefits across the various socio-demographic and socio-economic variables, but it does not provide insight in attributing a specific trend to a particular cause. Interpreting the cause of a trend and resolving the challenge of urban green inequity will require an in-depth understanding of the local issues since the distribution of urban vegetation is influenced by local environments, development histories, and local governance (Gobster and Westphal, 2004). A limitation of the Atkinson index is that it depends on the degree of society's aversion to inequality (a theoretical parameter, ε, decided by the researcher). To overcome uncertainties associated with the Atkinson index, we varied ε between 0.5, 1 and 2 and compared Atkinson index values between different ε scenarios before drawing conclusions. Our results were consistent with the literature (Lorenzo and Liberati, 2006a; Creedy, 2016) which shows that lower values of ε indicate a more equal distribution than higher values.

Future work will extend this analysis to other cities with different demographics, scales and environmental conditions to explore if similar trends are observed. We will also seek to improve on the socio-demographic and socio-economic data and seek to better understand local factors that are likely to affect tree cover and ecosystem service and benefit distributions.

3.5 CONCLUSIONS

This study provides novel insights into the relationships between socio-demographic and socio-economic variables, ecosystem service and benefit distributions and the concepts of equity, equality and environmental justice in urban systems. Results reveal that ecosystem services in the Bronx are related to a variety of socio-demographic and socio-economic characteristics of the census block groups and therefore support the conclusion that ecosystem services from urban trees are inequitably distributed in the Bronx, and that this inequity is associated with traditional socio-economic and socio-demographic divisions. Results from the decomposition of the inequality measures to identify the sources of the inequality go against the more traditional expectation of between sub-group inequality and show that inequality in the Bronx is mainly due to within sub-group variations likely due to the heterogenous nature of the census block groups in the Bronx and the wide variations in tree cover across census block groups with similar demographics. With numerous tree planting initiatives being undertaken in different cities, environmental inequity studies such as ours illuminate potential environmental justice issues that can be encountered and have the potential to guide more local and fine scale decision making regarding where to increase tree cover and reduce environmental inequities in the distribution of tree cover and related ecosystem services. Although the study is based on a

U.S city and with a particular focus on the Bronx, the methodological and conceptual approaches of this analysis can be used to advance the study of environmental equity of ecosystem services provided by trees as well as for the planning and evaluation of priority tree planting strategies to improve urban green space and ecosystem services provision in cities around the world. The ecosystem service framework adopted in this study links humans and their environment and has implications for urban forest conservation, planning and policy, leading to more equitable and sustainable land-use decisions in different parts of the world. Overall, the study has shown that decision making and management plans should incorporate environmental justice in their programming activities and ensure that tree-planting is a participatory, collective, and local stakeholder-engaged process to achieve more beneficial outcomes from trees, especially for disadvantaged socio-economic and socio-demographic groups and marginalized communities that lack these services and benefits. Addressing this environmental injustice issue could be part of future tree planting initiatives that seek to create cities that are more resilient, sustainable, livable, and just for all people.

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CHAPTER FOUR: A MULTI-OBJECTIVE DECISION SUPPORT FRAMEWORK TO PRIORITIZE TREE PLANTING LOCATIONS IN URBAN AREAS.

Abstract

Trees help mitigate the threats of air pollution, increased temperature and other environmental threats that exacerbate respiratory and heat-related illnesses. With numerous tree planting initiatives being undertaken in different cities to achieve more beneficial outcomes from trees, careful thought needs to be put into the placement of trees, the beneficiaries of the ecosystem services from these trees, and the potential impacts of alternative tree planting schemes. Many cities have explored tree planting prioritization schemes based upon diverse ecological, social and economic goals and preferences. Using a spatially explicit methodology within biophysical ecosystem service models, this research develops a multi-objective decision support framework to guide future greening initiatives towards prioritizing planting locations that maximize multiple objectives. In a case study application of the framework in the Bronx, NY, the analysis utilizes spatially distributed census block group data and optimizes ecosystem service provision, equality and equity in evaluating tree planting locations. While the optimization framework is flexible to handle both linear and nonlinear objectives and constraints, for the case study linear programming is used to identify optimal and equitable planting locations considering increases in tree cover, monetary benefits from storm water runoff reduction, $PM_{2.5}$ air pollutant removal and heat index reduction by trees as well as planting costs associated with plantable pervious and impervious areas. Using a series of different optimization scenarios, the framework identified optimal planting schemes by minimizing planting costs, maximizing increases in tree cover and ecosystem service benefits, and the equity of canopy cover and ecosystem services. We conclude that multi-objective prioritization frameworks can be used to identify optimal locations for greater total benefits from urban greening and that the proposed framework has the potential to inform decision making in different cities.

Key words: Decision support, Multi-objective, Optimal, Prioritization framework, Spatially explicit.

4.1 INTRODUCTION

As human population densities increase, there is growing interest in the services and benefits provided by local ecosystems (Syrbe and Walz, 2012; Aukema et al., 2017; Eigenbrod et al., 2011). Forested ecosystems are a particularly important resource, providing multiple services and benefits (Deal et al., 2017; Brockerhoff et al., 2017; Roeland et al., 2019; Elmqvist et al., 2015). There is an urgent need for decision making bodies to conserve remaining forests and reestablish forest cover in deforested and degraded forest landscapes for the benefit of humans and nature (Chazdon and Guariguata, 2018; Sabogal et al., 2015). With numerous tree planting initiatives being undertaken in different cities for various economic, environmental, social and human health benefits, careful thought needs to be put into considering the placement of trees and their beneficiaries (Salmond et al., 2016). However, constrained resources and lack of adequate space necessary to generate ecosystem services challenge the design of environmental solutions that meet multiple objectives (Almeter et al., 2018).

Studies have shown that greater returns on greening investments occur when considering multiple human health and environmental benefits, particularly in areas of the greatest need (Chazdon and Guariguata, 2018; Millennium Ecosystem Assessment, 2005; Salmond et al., 2016). Prioritization tools are increasingly being used to highlight important synergies and trade-offs that help determine how and where to achieve the most desirable and feasible outcomes from urban trees, including the mitigation of environmental hazards and the provision of ecosystem services to vulnerable and underserved populations (Locke et al., 2010; Halter, 2015; Portland Parks and Recreation, 2018; Almeter et al., 2018; Yoon et al., 2019). Systematic approaches to restoration are increasingly being adopted to identify restoration priority areas which identify land use conflicts, evaluate trade-offs among ecosystem benefits and assess divergent stakeholder needs across a wide range of social, political, economic and ecological dimensions (Almeter et al., 2018; Chazdon and Guariguata, 2018; King et al., 2015).

To incorporate individual and diverse value systems, regional and local governments utilize different prioritization frameworks. New tree plantings for the MillionTrees New York City (NYC) initiative were based on prioritizing neighborhoods with fewer trees to improve local air quality and prevent respiratory illnesses (Campbell et al., 2014; Grove et al., 2006; Garrison, 2019). This NYC initiative was also guided by an Urban Tree Canopy assessment (UTC) prioritization framework using spatial analysis tools and maps for suitability to identify where multiple objectives could be realized (Locke et al., 2010; Campbell et al., 2014). A similar UTC prioritization framework has also been used to identify priority planting areas in Baltimore (MD) (Locke et al., 2013; Campbell et al., 2014). The Chesapeake Bay Communities (Raciti et al., 2006), District of Columbia (District of Columbia, 2013), and Jefferson County, West Virginia (Griffith et al., 2011) used a Priority Planting Index which combines weights of population density, canopy green space and tree canopy cover per capita to identify tree planting areas (Nowak and Greenfield, 2008; Morani et al., 2011). A similar weighting methodology is utilized in i-Tree Landscape (https://landscape.itreetools.org/), i-Tree's spatially distributed modeling system, to prioritize tree planting locations based on land cover, demographics, risk, and ecosystem service and benefit data derived from running county-level lumped versions of i-Tree tools. However, lumped models and coarse scale prioritization tools simplify the relationships between the structure and function of urban forests and the representation of urban landscapes. These methods often fail to capture the spatial heterogeneity of landscapes at the finer scales at which local planning and implementation occurs (Nyelele et al., 2019; Chazdon and Guariguata, 2018). Furthermore, the ranking or weighted scoring approach is subjective as it requires the decision maker to decide on the contribution of each variable to the ultimate goal.

Despite the multiple environmental and human health benefits that can be generated by urban forests, there is limited scientific literature on decision making and tree planting prioritization based on ecosystem benefits. According to Chazdon and Guariguata (2018), few studies incorporate economic analyses to generate planting scenarios based on cost-effectiveness and the total costs of specific restoration interventions. Furthermore, most studies supporting the planning of green spaces with a quantitative basis focus on a single benefit of greening, such as to improve cooling benefits or runoff regulation (Yoon et al., 2019; Werbin et al., 2019).

Bodnaruk et al. (2017) explored priority planting and ecosystem service trade-offs in Baltimore, MD using spatially explicit i-Tree models. Resultant priority planting scenarios optimized a single ecosystem service or benefit related to either air pollution or heat mitigation. The use of single objective optimization methods is not surprising since identifying an optimal spatial pattern subject to multiple benefits is challenging (Brookes, 2001). In the process of maximizing a specific benefit by changing the location and the composition of green spaces, other benefits can be enhanced or diminished because of trade-offs or synergies (Bodnaruk et al., 2017). However, the failure to provide a comprehensive treatment of multiple benefits from urban green spaces has resulted in the failure to meet some stakeholder preferences and achieve regional sustainability (Chen et al., 2015; Hunter et al., 2019).

Most urban forest priority planting frameworks also lack a means to quantify the inequity of tree cover distribution and green infrastructure (Almeter et al., 2018; Nyelele and Kroll, 2020). Given the competition for resources and space in urban settings, strategic investments in green infrastructure require not only accounting for the multiple services potentially generated, but also the intensity of need for those services. Inequality measures such as the Gini coefficient and Atkinson's inequality indices allow us to better assess current inequalities and work to achieve greater equity in the distribution of tree cover (Nyelele and Kroll, 2020). Without considering environmental equity, it is possible that the establishment of tree cover to promote certain goals could exacerbate inequity issues, making susceptible populations more vulnerable to the adverse impacts associated with low canopy cover. There is need for studies that explore trade-offs and synergies between environmental justice and ecosystem services and examine whether tree planting plans increase or decrease tree cover equity. Such an approach could provide city planners, urban foresters, and members of the public with a more comprehensive framework to inform decision-making processes, policy options, management measures and equity tradeoffs between different planting scenarios (Hunter et al., 2019).

This study evaluates the relative benefits provided by increasing tree cover on either plantable pervious (short vegetation or bare soil) or plantable impervious (impervious surfaces that are not buildings or roads) areas. We expect that establishing tree canopy on plantable impervious areas will have a greater impact on net improvements in water quality and summer temperatures (O'Neil-Dunne, 2012), but should incur a higher cost for planting and maintenance. Also, while other studies assume that tree planting resources are unlimited, the framework of the current study ensures that objectives such as minimizing planting costs, maximizing tree cover and benefits, and achieving equity from tree cover increases are met under varying real-world resource constraints.

In this study, we first develop a flexible framework for multi-objective optimization within the context of maximizing the services, benefits and equity of urban forest planting initiatives. Within this framework, we address common resource and implementation constraints that are encountered in practice. We then show how this framework could be implemented using a case study where a spatially explicit modelling methodology at the census block level is used to develop and implement a multi-objective decision support framework. This case study is used to identify priority planting locations in the Bronx, NY by optimizing ecosystem service and benefit provisions related to heat index and storm water runoff reductions, air pollutant removal, tree cover increases and the equity of urban forest cover distributions.

4.2 RESEARCH METHODOLOGY

Here we provide a general optimization framework which can be applied to inform urban greening and restoration interventions in any city if spatially specific data including ecosystem services and benefits per unit area of tree cover can be derived. Such a framework is useful in identifying Pareto optimal locations, where one can assess the tradeoffs and synergies between different objectives. After the general framework is introduced, a case study in the Bronx is presented in Section 4.3 using a spatially specific implementation of i-Tree tools (i-Tree Eco, i-Tree Hydro and i-Tree Cool) to characterize urban forest ecosystem services and benefits.

4.2.1 A theoretical optimization framework

The multi-objective decision support framework could run on any spatial unit; here we propose the census block group level, a scale where census demographic data is readily available in the United States (U.S.). The framework is set up as a general optimization problem which maximizes (or in some instances minimizes) some objective function subject to a series of constraints by changing a set of decision variables. In a general application of this framework, the objective function is to maximize multiple ecosystem services or benefits from increased (or decreased) tree cover as follows:

$$Max \quad \sum_{i=1}^{N} \sum_{j=1}^{M} \left[\left(CI_{i,j} * \Delta TCI_i \right) + \left(CP_{i,j} * \Delta TCP_i \right) \right] \qquad (4.1)$$

Subject to: $g_i(\Delta TCI_i, \Delta TCP_i) \geq, \leq \ or \ = b_i$

where:
- M = the number of services or benefits considered
- N = the number of block groups
- $CI_{i,j}$ = the benefit per unit area increase in impervious tree cover for service or benefit j in block group i
- $CP_{i,j}$ = the benefit per unit area increase in pervious tree cover for service or benefit j in block group i
- ΔTCI_i = change in impervious tree cover in block group i
- ΔTCP_i = change in pervious tree cover in block group i
- g_i = some function of the decision variables (ΔTCI_i and ΔTCP_i)
- b_i = the limit of the available resources or a minimum goal of a specific objective

Decision variables in this case are the increases (or decreases) in tree canopy cover (m^2) on either plantable pervious or impervious areas in each block group. Coefficients in the objective function (CI and CP), indicate the contribution of one m^2 of the corresponding change in tree cover (Chinneck and Ramadan, 2000; Kim, 2018) for each ecosystem service being considered. CI and CP could be constants (assuming a linear response which is plausible over small changes in canopy cover) or a function of the decision variables or other environmental conditions, making the objective function nonlinear. In addition, ΔTCI_i and ΔTCP_i could be disaggregated into species specific plantings (thus facilitating biodiversity and other species-specific objectives); here it is assumed all species are aggregated into these variables. The number of services or benefits to include depends on the problem being addressed and can be related to urban heat island reductions, energy savings, air pollutant removal and aesthetic improvements by trees, among other social, political, economic and ecological benefits.

Multiple objectives can be combined in a single objective function if they can be expressed in commensurate terms, for example monetary units. Considering that some human health (physical and psychological) and aesthetic benefits from trees cannot be adequately captured by monetary terms or quantified in commensurate units, non-commensurate objectives (where units of the coefficients in the objective function vary) can be accommodated in our framework to handle trade-offs between objectives. For non-commensurate objectives or where multiple Pareto optimal solutions exist (i.e. there is no feasible design which improves the value of any of its objective criteria without deteriorating at least one other criterion), the optimization can be executed with one selected objective reflected in the objective function and the other objectives treated as constraints or by treating each objective as a weighted component of the objective function (Brisset and Gillon, 2015; El-Sobky and Abo-Elnaga, 2018). In the weighting option, the objective function is the sum of each component multiplied by a weighting factor reflecting the relative importance of that objective or a scale factor to adjust for non-commensurate objectives (Wurbs, 1991); such a method, though, suffers from the same subjective issues as the Priority Planting Index, discussed previously. In our case study we implement a constraint method for non-commensurate objectives to develop Pareto fronts.

Urban tree canopy goals are most meaningful when tied to specific desired outcomes. As such, constraints can be incorporated as restrictions or limitations on the decision variables or other resources. Constraints can be functions of contractual obligations, planting or implementation costs, budget allocations, available and feasible planting spaces or any resource constraints defined by the user to guide the decision-making process. Depending on the form of the objective function and constraints, the problem can be solved using a variety of optimization techniques that include linear programming (Bertsimas and Tsitsiklis, 1997; Nash and Sofer, 1996; Chandru and Rao, 2010; Vanderbei, 2015; Luenberger and Ye, 1984), dynamic programming (Larsson, 2014; Réveillac, 2015; Carraway, 1990) and nonlinear programming (Sun and Yuan, 2006; Bertsekas, 1997).

4.2.2 Case Study: Bronx, NY

Optimal and equitable tree cover scenarios were explored to expand tree canopy in the Bronx from the baseline 2010 tree canopy cover of 22.7%. The Bronx was chosen as the case study location to test this framework because of a) air quality, storm water and urban heat island issues in this borough, b) its diverse demographics, and c) the lack of ecosystem services and benefits to some communities (Nyelele et al., 2019; Nyelele and Kroll, 2020). Here three ecosystem benefits are considered, improving air quality and reducing the urban heat index and storm water runoff, as well as the inequality and inequity in the distribution of tree cover across census block groups. These were all primary goals of New York City's MillionTreesNYC campaign (Campbell et al., 2014; Locke et al., 2010). To identify areas better suited to meet planting goals, in each block group plantable pervious and plantable impervious areas were defined from 2010 high-resolution UTC land cover imagery (MacFaden et al., 2012). Across the 1,132 census block groups in the Bronx, there were a total of 2,264 decision variables, the increase in plantable pervious and impervious tree cover in each block group. Using 2010 as the baseline, the optimal block groups to target for tree cover increases were then selected based on how best they satisfied the multiple objectives subject to constraints that included a minimum tree cover threshold for each census block group. Figure 4.1 illustrates the distribution of tree cover across census block groups in the baseline scenario.

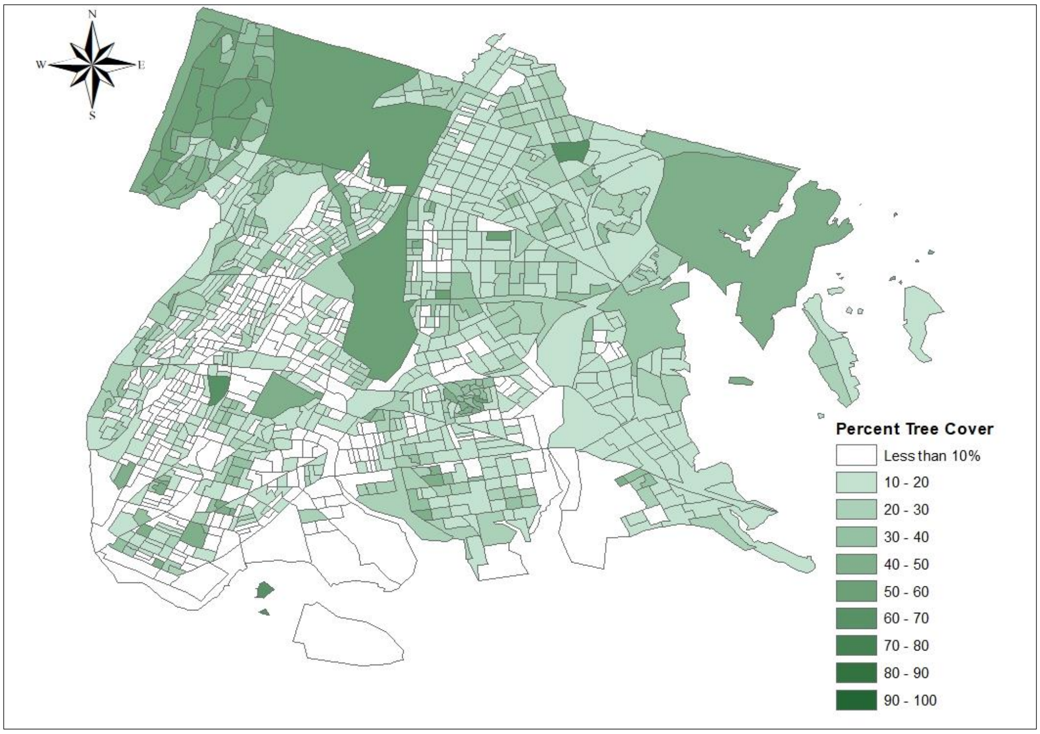

Figure 4.1: 2010 tree cover distribution in the Bronx.

We assumed that all trees planted would grow to maturity and that current tree cover would be maintained. We also assumed planting costs on plantable impervious areas of \$430/m^2 (NYC Parks and Recreation, 2020), or approximately \$2,150 per tree, while the planting costs for increasing tree cover on plantable pervious surfaces were estimated at \$100/m^2 (Central Park

Conservancy, 2020), or approximately $500 per tree. Note that the cost of tree cover could be spatially variable, which is realistic given the value of land typically varies across urban landscapes. A number of different scenarios with varying objectives were explored to examine how different objectives lead to alternative preferred planting schemes. Table 4.1 describes input variables used in the various optimization scenarios considered here. This is followed by a general description of the 13 different optimization scenarios considered in this analysis. Each of these scenarios is explored in a case study in the Bronx.

Table 4.1: Description of variables.

Variable	Description
ΔTCI_i	Change in impervious tree cover in block group i (m^2)
ΔTCP_i	Change in pervious tree cover in block group i (m^2)
$Area_i$	Total area of block group i (m^2)
CG	Total canopy goal for entire borough (m^2)
$CI_{i,HI}$	The heat index reduction benefit per unit area of impervious tree cover in block group i (K/m^2)
$CI_{i,PM}$	The $PM_{2.5}$ air pollutant removal monetary benefit per unit area increase in impervious tree cover for block group i ($\$/m^2$)
$CI_{i,SW}$	The avoided runoff monetary benefit per unit area increase in impervious tree cover for block group i ($\$/m^2$)
$CP_{i,HI}$	The heat index reduction benefit per unit area of pervious tree cover in block group i (K/m^2)
$CP_{i,PM}$	The $PM_{2.5}$ air pollutant removal monetary benefit per unit area increase in pervious tree cover for block group i ($\$/m^2$)
$CP_{i,SW}$	The avoided runoff monetary benefit per unit area increase in pervious tree cover for block group i ($\$/m^2$)
G	Gini coefficient
HI	Total heat index reduction target for the Bronx (K)
MC_i	Minimum canopy threshold across all block groups
$MTCI_i$	Maximum increase of plantable impervious area in block group i (m^2)
$MTCP_i$	Maximum increase of plantable pervious area in block group i (m^2)
N	The number of block groups (1,132 in the Bronx)
PPI_i	Number of people with income below the poverty level in block group i
TB	Total budget available for new plantings ($)
TC_i	Current tree cover in block group i (m^2)

4.2.2.1 Scenario 1: Maximize canopy cover to maintain a specific budget

In line with actual urban greening plans that are created and executed within a certain budget range, the first scenario maximized the total canopy cover utilizing the $400 million initial budget of the MillionTreesNYC initiative (MillionTreesNYC, 2020). This scenario is summarized as follows:

$$Max \sum_{i=1}^{N=1132} [(\Delta TCI_i) + (\Delta TCP_i)] \tag{4.2}$$

Subject to:

1: $\sum_{i=1}^{N=1132}(430 * \Delta TCI_i) + (100 * \Delta TCP_i) \leq TB$ Total Budget
2: $\Delta TCI_i \leq MTCI_i \quad i = 1, \ldots, 1132$ Available Plantable Impervious
3: $\Delta TPI_i \leq MTCP_i \quad i = 1, \ldots, 1132$ Available Plantable Pervious

4.2.2.2 Scenarios 2 to 4: Maximize individual ecosystem services and meet total canopy goal

To illustrate how single ecosystem service benefits can be maximized, three scenarios were analyzed, each maximizing a single benefit related to either $PM_{2.5}$ air pollutant removal monetary benefits, avoided runoff monetary benefits or heat index reduction benefits while meeting a 26% canopy goal. The 26% canopy goal is a midpoint between the current canopy and the 30% ultimate tree canopy goal of the MillionTreesNYC (Elmqvist et al., 2013; Grove et al., 2006; Nyelele et al., 2019). The $400 million initial budget of the MillionTreesNYC initiative was also adopted.

Scenario 2: $$Max \sum_{i=1}^{N=1132} \left[\left(CI_{i,PM} * \Delta TCI_i\right) + \left(CP_{i,PM} * \Delta TCP_i\right)\right] \tag{4.3}$$
Scenario 3: $$Max \sum_{i=1}^{N=1132} \left[\left(CI_{i,SW} * \Delta TCI_i\right) + \left(CP_{i,SW} * \Delta TCP_i\right)\right] \tag{4.4}$$
Scenario 4: $$Max \sum_{i=1}^{N=1132} \left[\left(CI_{i,HI} * \Delta TCI_i\right) + \left(CP_{i,HI} * \Delta TCP_i\right)\right] \tag{4.5}$$

Subject to:

1: $\sum_{i=1}^{N=1132}(430 * \Delta TCI_i) + (100 * \Delta TCP_i) \leq TB$ Total Budget
2: $\Delta TCI_i \leq MTCI_i \quad i = 1, \ldots, 1132$ Available Plantable Impervious
3: $\Delta TPI_i \leq MTCP_i \quad i = 1, \ldots, 1132$ Available Plantable Pervious
4: $\frac{\sum_{i=1}^{N=1132}(TC_i + \Delta TCI_i + \Delta TCP_i)}{\sum_{i=1}^{N=1132}(Area_i)} \geq CG$ Total Canopy Goal

4.2.2.3 Scenario 5: Maximize tree cover, maintain budget and meet minimum tree cover goal

This scenario maximized total canopy cover while meeting a 10% minimum tree canopy threshold in each census block group, which was adopted from canopy cover thresholds from the City of Tallahassee (2018) and the Food and Agriculture Organization (2015). The $400 million planting budget from MillionTreesNYC was also adopted as a constraint.

$$Max \quad \sum_{i=1}^{N=1132}[\Delta TCI_i + \Delta TCP_i] \tag{4.6}$$

Subject to:

1: $\sum_{i=1}^{N=1132}(430 * \Delta TCI_i) + (100 * \Delta TCP_i) \leq TB$ Total Budget

2: $\Delta TCI_i \leq MTCI_i \quad i = 1, \ldots, 1132$ Available Plantable Impervious

3: $\Delta TPI_i \leq MTCP_i \quad i = 1, \ldots, 1132$ Available Plantable Pervious

4: $\frac{(TC_i + \Delta TCI_i + \Delta TCP_i)}{Area_i} \geq MC_i \quad i = 1, \ldots, 1132$ Minimum Canopy Threshold

4.2.2.4 Scenario 6: Maximize tree cover, maintain budget and meet equality target

In this study we used the Gini coefficient as our measure of equality, a commonly used inequality metric (Gini, 1909; Bellù and Liberati, 2005 and 2006; Jenerette et al. 2011; Nyelele and Kroll, 2020). Figure 4.2 presents a visual representation of the Gini coefficient for tree cover across the Bronx in 2010; a plot of the cumulative census block group tree cover percentage versus the cumulative share of block groups from lowest to highest tree cover percentage.

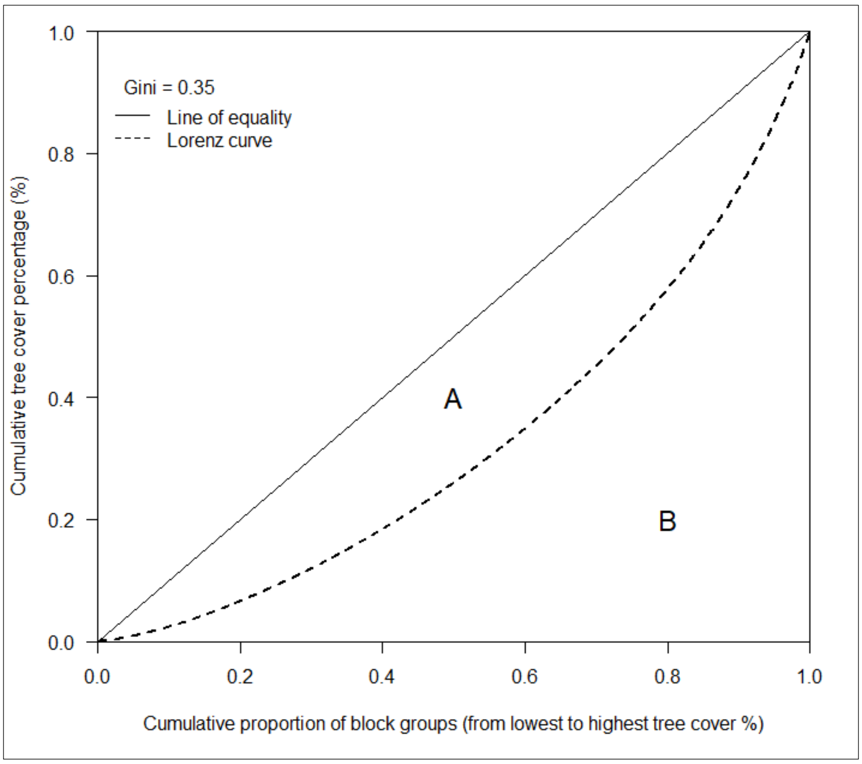

Figure 4.2: The Lorenz curve and Gini coefficient for 2010 tree cover distributions.

If all block groups had the same (average) tree cover percentage, we would obtain the line of equality (45°); the Lorenz curve (dashed line in Figure 4.2) is the line representing the distribution of 2010 tree cover. However, half the block groups with the lowest amount of tree cover in 2010 accounted for less than 30% of the total tree cover in the Bronx. The Gini index, G, is the ratio of the areas, G = A/(A+B). For perfect equality, G = 0; in 2010, G = 0.35, indicating a lack of equality in tree cover across block groups. The Gini coefficient allows us to better assess current inequalities and work to achieve greater equity in the distribution of tree cover. Here we set the threshold for the maximum G for overall tree canopy distribution at 0.25 representing the midpoint between the current G = 0.35 and G = 0.16, the target Gini index from a Green Equity scenario in Boston, MA (Danford et al., 2014). We included a scenario that maximized canopy cover while keeping the Gini index below a specific target. Again the $400 million MillionTreesNYC budget was used.

$$Max \quad \sum_{i=1}^{N=1132}[(\Delta TCI_i) + (\Delta TCP_i)] \tag{4.7}$$

Subject to:

1: $\sum_{i=1}^{N=1132}(430 * \Delta TCI_i) + (100 * \Delta TCP_i) \leq TB$ Total Budget

2: $\Delta TCI_i \leq MTCI_i \quad i = 1, \ldots, 1132$ Available Plantable Impervious

3: $\Delta TPI_i \leq MTCP_i \quad i = 1, \ldots, 1132$ Available Plantable Pervious

4a: $\frac{2 * \sum_{i=1}^{N=1132}\left(i * \left(\mathrm{TC}_{(i)} + \Delta TCI_{(i)} + \Delta TCP_{(i)}\right)/Area_{(i)}\right)}{N * \sum_{i=1}^{N=1132}\left(\mathrm{TC}_{(i)} + \Delta TCI_{(i)} + \Delta TCP_{(i)}\right)/Area_{(i)}} - \frac{N+1}{N} \leq G$ Equality Target

The fourth constraint, the Equality Target, is nonlinear, but can be linearized as:

$$4b: \sum_{i=1}^{N=1132}\left[\frac{(2*i) - N*G - N - 1}{Area_{(i)}}\right] * \left(\mathrm{TC}_{(i)} + \Delta TCI_{(i)} + \Delta TCP_{(i)}\right) \leq 0$$

For this constraint, $\frac{\left(\mathrm{TC}_{(i)} + \Delta TCI_{(i)} + \Delta TCP_{(i)}\right)}{Area_{(i)}}$ represents the percent tree cover for the block group with the i[th] smallest percent tree cover. To maintain this ranking throughout the simulation, an additional constraint is needed:

5: $\frac{\left(\mathrm{TC}_{(i)} + \Delta TCI_{(i)} + \Delta TCP_{(i)}\right)}{Area_{(i)}} \leq \frac{\left(\mathrm{TC}_{(i+1)} + \Delta TCI_{(i+1)} + \Delta TCP_{(i+1)}\right)}{Area_{(i+1)}} \quad i = 1, \ldots, 1131$ Tree Cover Ranking

Without this constraint, a multi-step optimization would be needed, where after tree cover is added to block groups, the block groups would be reranked based on percent tree cover, and the optimization would be rerun based on these new rankings until convergence.

4.2.2.5 Scenario 7: Maximize poverty-weighted tree cover at specific budget.

However, to fully address the issue of equity, i.e. the fair distribution of resources, especially the absence of systematic disparities between more and less advantaged social groups, we should also consider some socio-demographic or socio-economic characteristics of the block groups. In addition, an ecosystem service is only a service if there is a beneficiary (Fisher et al., 2009). Thus, to ensure that the optimization resulted in an optimal and equitable solution that ensures tree cover and resultant ecosystem services reach those that most rely on these services, we modified the above scenario to weight new canopy by the number of people with income below the poverty level in 2010 (U.S. Census Bureau, 2018) in the i^{th} the block group (PPI_i), resulting in the objective function:

$$Max \frac{\sum_{i=1}^{N=1132} PPI_i * (\Delta TCP_i + \Delta TCI_i)}{\sum_{i=1}^{N=1132} PPI_i} \quad (4.8)$$

Subject to:

1: $\sum_{i=1}^{N=1132}(430 * \Delta TCI_i) + (100 * \Delta TCP_i) \leq TB$ Total Budget
2: $\Delta TCI_i \leq MTCI_i$ $i = 1, \ldots, 1132$ Available Plantable Impervious
3: $\Delta TPI_i \leq MTCP_i$ $i = 1, \ldots, 1132$ Available Plantable Pervious

4.2.2.6 Scenario 8: Maximize monetary benefits of air pollutant removal and avoided runoff and meet total canopy goal

Here we maximized the $PM_{2.5}$ air pollutant removal monetary benefits and avoided runoff monetary benefits to meet the 26% canopy goal. The $400 million planting budget from MillionTreesNYC was again employed.

$$Max \sum_{i=1}^{N=1132} \left[\left(CI_{i,SW} + CI_{i,PM}\right) * \Delta TCI_i + * \left(CP_{i,SW} + CP_{i,PM}\right) * \Delta TCP_i \right] \quad (4.9)$$

Subject to:

1: $\sum_{i=1}^{N=1132}(430 * \Delta TCI_i) + (100 * \Delta TCP_i) \leq TB$ Total Budget
2: $\Delta TCI_i \leq MTCI_i$ $i = 1, \ldots, 1132$ Available Plantable Impervious
3: $\Delta TPI_i \leq MTCP_i$ $i = 1, \ldots, 1132$ Available Plantable Pervious
4: $\frac{\sum_{i=1}^{N=1132}(TC_i + \Delta TCI_i + \Delta TCP_i)}{\sum_{i=1}^{N=1132} Area_i} \geq CG$ Total Canopy Goal

4.2.2.7 Scenario 9: Maximize monetary benefits of air pollutant removal and meet equality goals under specified budget

In this scenario we maximized the $PM_{2.5}$ air pollutant removal monetary benefits while not exceeding the $400 million planting budget for MillionTreesNYC while adding an equality constraint to obtain a tree cover distribution with G = 0.25. To explore potential trade-offs between non-commensurate objectives, in this case maximizing $PM_{2.5}$ air pollutant removal benefits (a monetary objective) and achieving equality (a non-monetary objective), we varied the right-hand side of the equality constraint from 0.22 to 0.31. This allowed us to plot the

Pareto front and illustrate how a change in the right-hand side of the equality constraint influences the total $PM_{2.5}$ air pollutant removal monetary benefits obtained.

$$Max\ \sum_{i=1}^{N=1132}\left[\left(CI_{i,PM} * \Delta TCI_i\right) + \left(CP_{i,PM} * \Delta TCP_i\right)\right] \tag{4.10}$$

Subject to:

1: $\sum_{i=1}^{N=1132}(430 * \Delta TCI_i) + (100 * \Delta TCP_i) \leq TB$ Total Budget
2: $\Delta TCI_i \leq MTCI_i \quad i = 1, \ldots, 1132$ Available Plantable Impervious
3: $\Delta TPI_i \leq MTCP_i \quad i = 1, \ldots, 1132$ Available Plantable Pervious
4: $\frac{2*\sum_{i=1}^{N=1132}\left(i*\left(TC_{(i)}+\Delta TCI_{(i)}+\Delta TCP_{(i)}\right)/Area_{(i)}\right)}{N*\sum_{i=1}^{N=1132}\left(TC_{(i)}+\Delta TCI_{(i)}+\Delta TCP_{(i)}\right)/Area_{(i)}} - \frac{N+1}{N} \leq G$ Equality Target
5: $\frac{\left(TC_{(i)}+\Delta TCI_{(i)}+\Delta TCP_{(i)}\right)}{Area_{(i)}} \leq \frac{\left(TC_{(i+1)}+\Delta TCI_{(i+1)}+\Delta TCP_{(i+1)}\right)}{Area_{(i+1)}} \quad i = 1, \ldots, 1131$ Tree Cover Ranking

4.2.2.8 Scenario 10: Maximize poverty-weighted monetary benefits of air pollutant removal and meet equity goals under specified budget

To more fully address equity in the above scenario, we incorporated the population with income below poverty levels into the objective function as follows:

$$Max\ \frac{\sum_{i=1}^{N=1132} PPI_i\left[\left(CI_{i,PM}*\Delta TCI_i\right)+\left(CP_{i,PM}*\Delta TCP_i\right)\right]}{\sum_{i=1}^{N=1132} PPI_i} \tag{4.11}$$

Subject to:

1: $\sum_{i=1}^{N=1132}(430 * \Delta TCI_i) + (100 * \Delta TCP_i) \leq TB$ Total Budget
2: $\Delta TCI_i \leq MTCI_i \quad i = 1, \ldots, 1132$ Available Plantable Impervious
3: $\Delta TPI_i \leq MTCP_i \quad i = 1, \ldots, 1132$ Available Plantable Pervious

4.2.2.9 Scenario 11: Maximize monetary benefits of air pollutant removal and avoided runoff and meet equality and minimum canopy goals under specified budget

We also explored how adding the equality, minimum canopy threshold and budget constraints together influence the maximization of the monetary benefits of $PM_{2.5}$ air pollutant removal and avoided runoff. The $400 million planting budget for MillionTreesNYC was again used.

$$Max\ \sum_{i=1}^{N=1132}\left[\left(CI_{i,SW} + CI_{i,PM}\right) * \Delta TCI_i + \left(CP_{i,SW} + CP_{i,PM}\right) * \Delta TCP_i\right] \tag{4.12}$$

Subject to:

1: $\sum_{i=1}^{N=1132}(430 * \Delta TCI_i) + (100 * \Delta TCP_i) \leq TB$ Total Budget

2: $\Delta TCI_i \leq MTCI_i \quad i = 1, \ldots, 1132$ Available Plantable Impervious

3: $\Delta TPI_i \leq MTCP_i \quad i = 1, \ldots, 1132$ Available Plantable Pervious

4: $\frac{2*\sum_{i=1}^{N=1132}\left(i*\left(\mathrm{TC}_{(i)}+\Delta TCI_{(i)}+\Delta TCP_{(i)}\right)/Area_{(i)}\right)}{N*\sum_{i=1}^{N=1132}\left(\mathrm{TC}_{(i)}+\Delta TCI_{(i)}+\Delta TCP_{(i)}\right)/Area_{(i)}} - \frac{N+1}{N} \leq G$ Equality Target

5: $\frac{\left(\mathrm{TC}_{(i)}+\Delta TCI_{(i)}+\Delta TCP_{(i)}\right)}{Area_{(i)}} \leq \frac{\left(\mathrm{TC}_{(i+1)}+\Delta TCI_{(i+1)}+\Delta TCP_{(i+1)}\right)}{Area_{(i+1)}} \quad i = 1, \ldots, 1131$ Tree Cover Ranking

6: $\frac{(TC_i + \Delta TCI_i + \Delta TCP_i)}{Area_i} \geq MC_i \quad i = 1, \ldots, 1132$ Minimum Canopy Threshold

4.2.2.10 Scenario 12: Maximize poverty-weighted monetary benefits of air pollutant removal and avoided runoff and meet equity and minimum canopy goals under specified budget

To address the issue of equity in the above scenario we modified the objective function and incorporated the population with income below poverty levels so that the optimization resulted in an optimal and equitable solution that ensures tree cover and resultant ecosystem services reach those that rely on these services. The MillionTreesNYC planting budget ($400 million) was used.

$$Max \frac{\sum_{i=1}^{N=1132} PPI_i\left[\left(CI_{i,SW}+CI_{i,PM}\right)*\Delta \mathrm{TCI}_i+\left(CP_{i,SW}+CP_{i,PM}\right)*\Delta \mathrm{TCP}_i\right]}{\sum_{i=1}^{N=1132} PPI_i} \quad (4.13)$$

Subject to:

1: $\sum_{i=1}^{N=1132}(430 * \Delta TCI_i) + (100 * \Delta TCP_i) \leq TB$ Total Budget

2: $\Delta TCI_i \leq MTCI_i \quad i = 1, \ldots, 1132$ Available Plantable Impervious

3: $\Delta TPI_i \leq MTCP_i \quad i = 1, \ldots, 1132$ Available Plantable Pervious

4: $\frac{(TC_i + \Delta TCI_i + \Delta TCP_i)}{Area_i} \geq MC_i \quad i = 1, \ldots, 1132$ Minimum Canopy Threshold

4.2.2.11 Scenario 13: Maximize monetary benefits of air pollutant removal and avoided runoff and non-commensurate heat index reduction and meet total canopy goal

To show how non-commensurate objectives can be included in the same optimization, in this scenario we maximized the monetary benefits of air pollutant removal and avoided runoff in the same objective function and included the heat index reduction benefits as a constraint. Thus, the objective was to maximize the $PM_{2.5}$ air pollutant removal and avoided runoff monetary benefits subject to meeting the heat index reduction constraint. We used the $400 million MillionTreesNYC planting budget.

$$Max \quad \sum_{\mathrm{i=1}}^{\mathrm{N=1132}} \left[\left(CI_{i,SW} + CI_{i,PM}\right) * \Delta\mathrm{TCI_i} + \left(CP_{i,SW} + CP_{i,PM}\right) * \Delta\mathrm{TCP_i}\right] \tag{4.14}$$

Subject to:

1: $\sum_{i=1}^{N=1132}(430 * \Delta TCI_i) + (100 * \Delta TCP_i) \leq TB$ Total Budget
2: $\Delta TCI_i \leq MTCI_i \quad i = 1, \ldots, 1132$ Available Plantable Impervious
3: $\Delta TPI_i \leq MTCP_i \quad i = 1, \ldots, 1132$ Available Plantable Pervious
4: $\sum_{i=1}^{N=1132}\left(CI_{i,HI} * \Delta TCI_i\right) + \left(CP_{i,HI} * \Delta TCP_i\right) \geq HI$ Heat Index Target

While the right-hand side of the heat index reduction constraint (*HI*) can be defined as the desired heat index reduction in each block group, the estimated heat index reduction benefits due to a change in tree cover in this analysis were small in each block group. As such we set *HI* as the total heat index reductions in Kelvins (K) across all block groups (0.2K**N*), where *N* is the number of block groups and 0.2K is the average per block group heat index reduction goal. Such a constraint allows us to maximize heat index reductions where possible to compensate for block groups that cannot achieve the 0.2K reduction on their own.

4.2.3 Estimation of ecosystem service benefits

While the optimization framework presented can utilize data from any ecosystem service and benefit model, per unit area of tree cover services and benefits for this study were estimated for each census block group using spatially distributed i-Tree tools (https://www.itreetools.org/) for 2010 tree cover conditions following the methodology suggested by Nyelele et al. (2019). One improvement over Nyelele et al.'s methodology was in the estimation of block group $PM_{2.5}$ air pollutant concentrations.

Nyelele et al. (2019) used the Environmental Protection Agency's (EPA's) Fused Air Quality Surfaces Using Downscaling output (U.S. EPA, 2017) which had little variability across block groups in the Bronx. Here mean block group air pollutant concentrations derived from twelve New York City Community Air Survey (NYCCAS) short-term monitors for 2010 (New York City Department of Health and Mental Hygiene, 2019) were used to adjust pollutant concentrations using five long-term EPA Air Quality System (AQS) monitors located in the Bronx. Since its inception in 2008, NYCCAS has had at least one monitor in each of the 12 community districts in the Bronx where air pollutant data is collected over 2-week intervals at each location once per season (summer and winter) (Matte et al., 2013). Block group estimates of NYCCAS annual mean $PM_{2.5}$ concentrations ($NYCCAS_{mean}$) for 2010 were derived from an available 300m resolution NYCCAS raster map of mean annual $PM_{2.5}$ concentrations (City of New York, 2020). In the five block groups where the AQS monitors are located, the NYCCAS annual mean pollutant concentration at the AQS station ($AQS\text{-}NYCCAS_{mean}$) was also estimated. For each block group in the Bronx, the nearest AQS monitor was identified and the hourly $PM_{2.5}$ values (Adjusted $PM_{2.5\ hourly}$) for that block group were estimated as the hourly AQS $P.M_{2.5\ hourly}$ values at the nearest monitor scaled by the ratio of $NYCCAS_{mean}$ in that block group to $AQS\text{-}NYCCAS_{mean}$ at the nearest monitor:

$$\text{Adjusted } PM_{2.5\ hourly} = \frac{NYCCAS_{mean}}{AQS-NYCCAS_{mean}} * \text{AQS } PM_{2.5\ hourly} \tag{4.15}$$

To estimate air pollutant removal services, i-Tree Eco does not distinguish between different land cover types and only considers the tree cover percentages in each census block group; thus, in each block group the same per area of tree canopy monetary benefits were used in this analysis to estimate $PM_{2.5}$ air pollutant removal benefits from potential increases over both plantable pervious and impervious areas (CI and CP).

To estimate CI and CP associated with 2010 avoided runoff and July 2010 heat index reductions in each block group, ecosystem services and benefits were first estimated for the 2010 tree cover conditions using i-Tree Hydro and i-Tree Cool following the methodology detailed in Nyelele et al. (2019). The models were then rerun for a scenario where a portion of plantable pervious area was tree cover, and the change in ecosystem service or benefit per unit area increase in canopy cover (CP_i) was estimated for each block group. A similar method of simulating plantable impervious area as tree cover was used to estimate CI_i. In both scenarios, the same amount of tree cover was added in each block group, corresponding to the minimum of either the available plantable impervious or available plantable pervious cover in that block group. For the plantable impervious scenario, increases in tree cover which were assumed to be trees over impervious surfaces, were offset by a decrease in the "other impervious" land cover type from the UTC land cover dataset. In the plantable pervious scenario the increases in tree cover were assumed to be trees over pervious areas and were offset by decreases in bare soil; when bare soil was no longer present, this decrease occurred in short vegetation. The per area of tree canopy avoided runoff benefits for each block group were calculated as the difference between the 2010 tree cover benefits and those from increasing tree cover over plantable pervious areas and plantable impervious areas. Similarly, the per area of tree canopy heat index reduction benefits for each block group were taken as the difference between the 2010 heat index of the block group (baseline) and the heat index obtained from increasing tree cover over plantable pervious areas and plantable impervious areas. Each set of ecosystem service and benefit differences was then divided by the increased tree cover area (m^2) of the block group to estimate the benefits per unit area increase of tree cover. In practice we generally expect CI and CP to vary across a wide range of tree cover. For smaller changes in tree cover, and in this analysis, we assumed CI and CP were constant for a specific block group and thus the benefits and services were linearly related to tree cover. This assumption is implemented in i-Tree Landscape, i-Tree's spatially explicit modeling package.

4.2.4 Solution methodology

In this case study, the objective functions and all constraints except for the equality constraint were linear. As shown in Scenario 6, the equality constraint can be linearized. As such, linear programming was employed as the solution methodology to examine the optimal planting scheme obtained from the above multi-objective optimization problem. In this analysis, linear programming was performed using the package lpSolve in the R statistical computing software (Berkelaar et al., 2019; R Core Team, 2013). If the coefficients in the objective function (CI and CP) were not assumed constant, a nonlinear optimization algorithm would be needed to solve this problem. Linear programming is generally a preferred solution algorithm over nonlinear optimization, as a global optimal should be obtained assuming a convex solution space (Bill, 2015; Griva et al., 2009; Nocedal and Wright, 2006). Linear programming also lends itself to easily interpretable sensitivity analyses due to changes in the right-hand side of constraints, which could be beneficial in some applications of this methodology.

4.3 RESULTS

The optimization framework was implemented in the Bronx and was able to identify the optimal block groups and amount of plantable pervious and impervious areas in each of those block groups for the different optimization scenarios. The following sections present results for the various optimization scenarios explored. For each scenario we show the optimal block groups, tree cover increases, resultant tree cover distributions as well as the costs incurred, and benefits obtained. For ease of reference, we summarize these 13 scenarios in Table 4.2.

Table 4.2: Summary of scenarios explored.

Scenario	Tree cover increases	$PM_{2.5}$ air pollutant removal monetary benefit	Avoided runoff monetary benefit	Heat index reduction target	$400 million total budget	Available plantable area	26% canopy goal	0.25 Gini goal	Minimum 10% canopy threshold	Population below poverty weight
1	OF				C	C				
2		OF			C	C	C			
3			OF		C	C	C			
4				OF	C	C	C			
5	OF				C	C			C	
6	OF				C	C		C		
7	OF				C	C				OF
8		OF	OF		C	C	C			
9		OF			C	C		*C/OF		
10		OF			C	C				OF
11		OF	OF		C	C		C	C	
12		OF	OF		C	C			C	OF
13		OF	OF	C	C	C				

OF = Added in objective function

C = Included as constraint *The right-hand side of this constraint is varied from 0.22 to 0.31 to develop a Pareto front; thus, this constraint is used as part of the objective function

4.3.1 Maximizing tree canopy increases

This section presents results associated with Scenarios 1, 5, 6 and 7 that had the objective of maximizing tree canopy increases under differing constraint conditions. Scenario 1 sought to maximize tree cover increases based on a $400 million planting budget. The optimal solution from this scenario resulted in 4 million m^2 of additional canopy across plantable pervious areas, for a resulting tree canopy cover of 26.3%. Scenario 5 utilized the entire $400 million planting budget from MillionTreesNYC and set a minimum threshold of 10% tree cover in each block group resulting in 2.9 million m^2 of additional cover across plantable pervious areas and 0.26 million m^2 in plantable impervious areas. To reach the minimum tree cover threshold, in some block groups trees were planted on impervious areas. The optimal solution obtained from Scenario 6 indicates that to maximize tree cover increases with $400 million and a goal of achieving a tree cover distribution with a Gini coefficient of 0.25 requires 2.95 million m^2 additional tree cover across plantable pervious areas and 0.25 million m^2 tree cover in plantable impervious areas. Scenario 7, which targets census block groups with larger populations with an income below the poverty level, suggested increasing 3.5 million m^2 across plantable pervious areas and 0.12 million m^2 on plantable impervious areas, resulting in a distributional Gini of 0.35. In general, these results highlight how varying limits on the constraints to the same objective function lead to different optimal solutions being identified, illustrating the trade-offs and synergies that occur when identifying priority planting spaces in real life scenarios. Of the scenarios that do not have the $G \leq 0.25$ equality constraint, results illustrate that maximizing tree cover while maintaining the specified budget and meeting minimum tree cover goal (Scenario 5) leads to a tree cover distribution with improved equality across these scenarios (Gini = 0.27). For these scenarios, Figure 4.3 illustrates the number of block groups identified for increased tree cover; the amount of tree cover increases as well as the potential tree cover distributions from these scenarios. As depicted in Figure 4.3, adding a measure targeting populations below the poverty level (Scenario 7) reduces tree cover increases in large block groups that typically contain parks and playgrounds and have few people living in them.

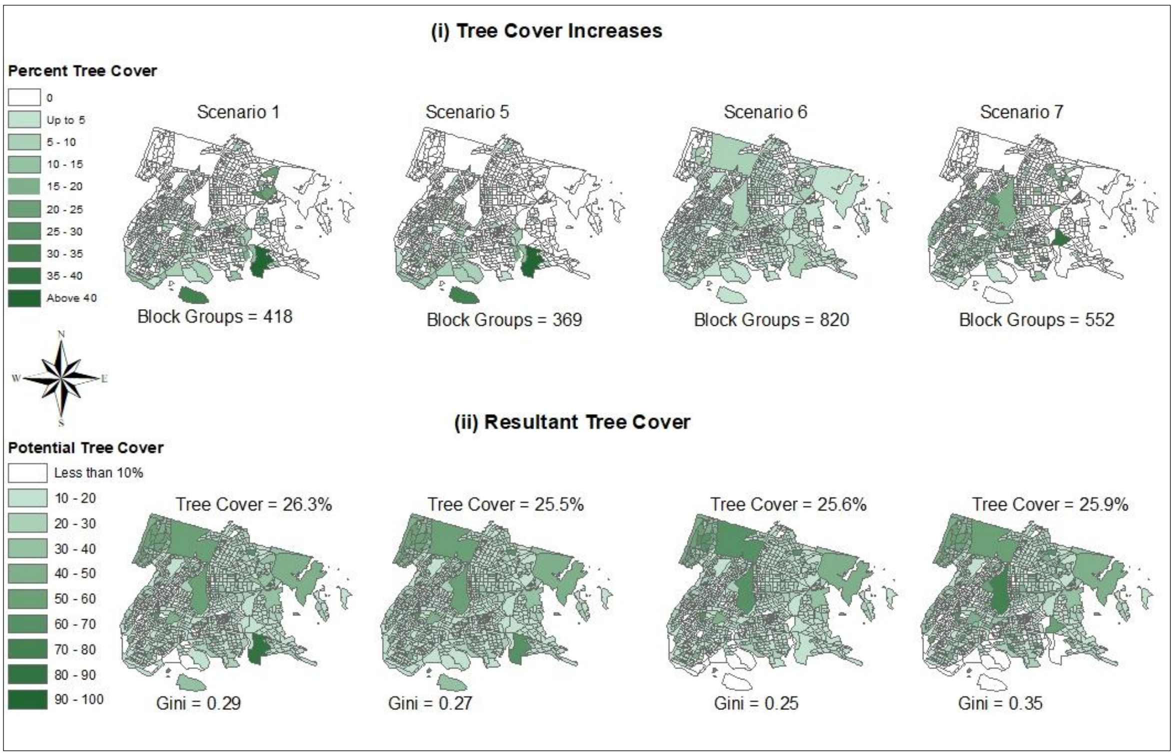

Figure 4.3: Number of optimal block groups, amount of tree cover increases and resultant tree cover tree distributions from scenarios maximizing tree cover increases.

4.3.2 Maximizing ecosystem benefits

This section presents results from scenarios that maximized individual ecosystem service benefits (Scenarios 2, 3, 4, 9 and 10), maximized the monetary benefits from $PM_{2.5}$ air pollutant removal and avoided runoff (Scenarios 8, 11 and 12) and maximized $PM_{2.5}$ air pollutant removal, avoided runoff and heat index reduction benefits simultaneously (Scenario 13) under differing constraints. All scenarios, with the exception of Scenario 8, resulted in tree cover increases over both plantable pervious and impervious areas. In Scenario 8, which maximized the monetary benefits of air pollutant removal and avoided runoff to meet the 26% canopy goal and a $400 planting budget, all the tree cover increases occur over plantable pervious areas. The tree cover increases and implementation costs for each scenario are summarized in Table

4.3. Results indicate that with the same budget of $400 million, different multi-objective approaches can be used to achieve more equal and equitable tree cover distributions with higher $PM_{2.5}$ air pollutant removal, avoided runoff and heat index reduction benefits (Table 4.3). Figure 4.4 shows the number of block groups targeted for tree canopy expansion as well as the amount of additional tree cover in each block group under each scenario. Additionally, most scenarios (particularly Scenario 10) targeting populations below the poverty level, limit tree cover increases in large block groups and instead suggest increasing tree cover in smaller block groups with limited parks and playgrounds.

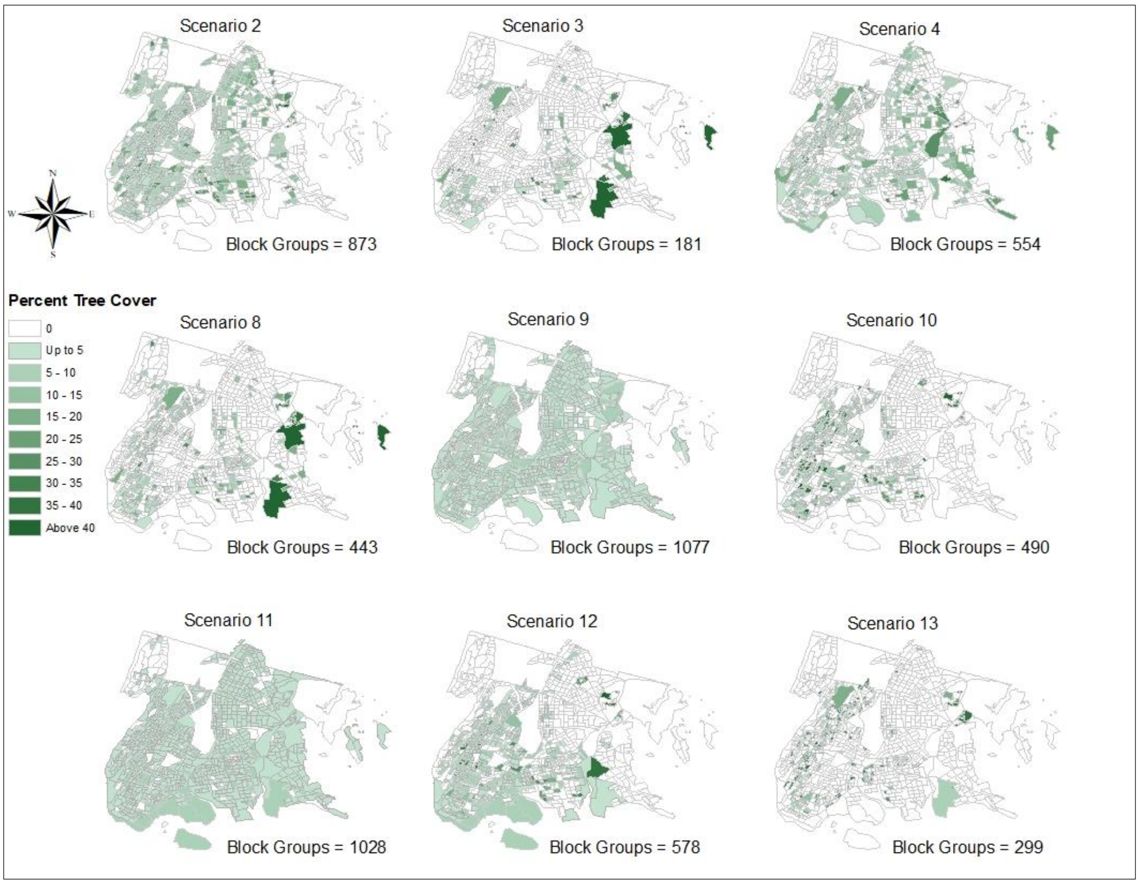

Figure 4.4: Number of optimal block groups and amount of tree cover increases from maximizing different benefits.

The above tree cover increases also result in different tree cover spatial distributions. Figure 4.5 shows resultant spatial distributions of tree cover from each scenario maximizing different ecosystem benefits. As depicted by the Gini coefficient associated with each scenario, there is a reduction in the inequality associated with each resultant tree cover distribution when compared to the 2010 baseline (G = 0.35). Exceptions are observed for Scenarios 3, 8, 10 and 13 whose resultant tree cover scenarios result in Gini coefficients greater than the baseline scenario. Scenario 13, which does not have a tree canopy goal constraint, results in the smallest amount of resultant canopy cover (24%) across all scenarios.

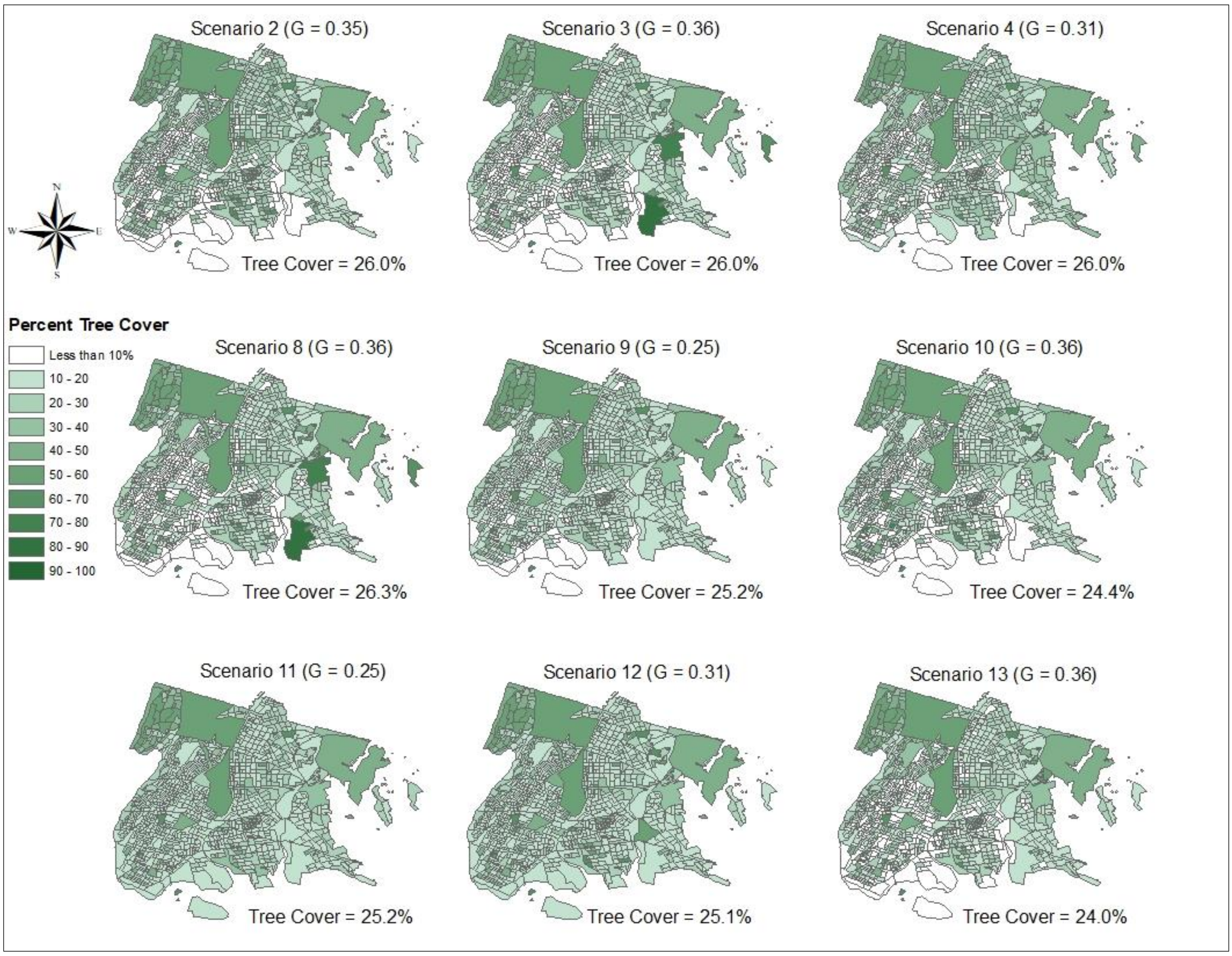

Figure 4.5: Resulting tree cover distributions from maximizing multiple ecosystem service benefits.

In Scenario 9, which maximized the monetary benefits of $PM_{2.5}$ air pollutant removal to meet an equality goal (G = 0.25) utilizing the $400 million planting budget, we also varied G between 0.22 and 0.31 to illustrate potential tradeoffs between optimal solutions. Figure 4.6a shows the Pareto front when the equality goal is relaxed (i.e. G increases) and there is an increase in the monetary benefits realized from the optimal scenario. Additionally, relaxing the equality constraint results in more tree cover increases over plantable pervious areas accompanied by reductions in additional tree cover over plantable impervious areas (Figure 4.6b). As such, when G increases, we observe simultaneous increases in the planting costs associated with adding tree cover in pervious areas and decreases in the amount spent planting over impervious areas (Figure 4.6c). Opposite trends are obtained when G is lowered, and the emphasis is on obtaining more equal tree cover distributions. With lower values of G there is a reduction in the monetary benefits of $PM_{2.5}$ air pollutant removal associated with more tree cover increases over plantable impervious areas and reductions in additional tree cover over plantable pervious areas. The trends in the planting costs also change; with lower G, the money spent increasing tree cover over impervious areas increases while costs of planting over pervious areas simultaneously decreases.

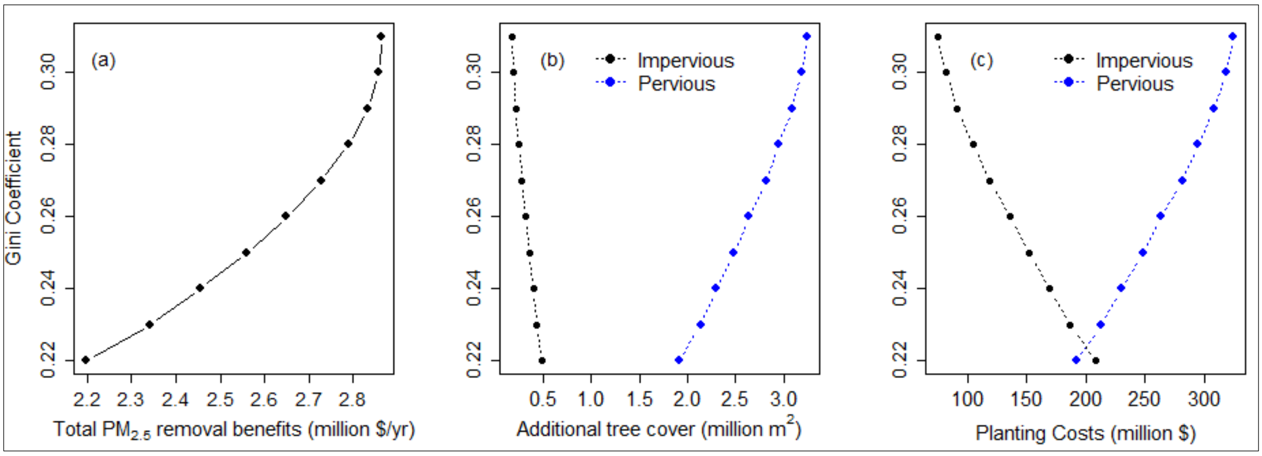

Figure 4.6: Influence of the equity target on: a) $PM_{2.5}$ monetary benefits, b) additional tree cover increases over plantable pervious and impervious surfaces and c) planting costs associated with plantable pervious and impervious areas.

4.3.3 Costs and benefits associated with increased tree cover

In addition to creating different tree cover configurations, the various optimization scenarios also result in different ecosystem service and benefit spatial distributions. Table 4.3 summarizes the total benefits from increased tree cover for each scenario based on aggregating the plantable pervious and impervious canopy benefits across block groups. Ecosystem service benefits from the resultant tree cover scenarios illustrate that even though the optimal locations to increase tree cover from either minimizing costs or maximizing tree cover or other benefits, the resultant tree cover increases will simultaneously lead to increases of different ecosystem services and benefits with potentially improved levels of equality and equity. The costs associated with implementing each scenario are also illustrated in Table 4.3. We also include in parentheses the amount of tree cover (million m^2) increases associated with plantable impervious and pervious areas. Results show that while additional tree cover increases on both pervious and impervious surfaces result in increased benefits, there is a lower cost of implementation for trees planted in plantable pervious areas, and thus most of the tree cover increases occur over plantable pervious areas. As a result, all scenarios, with the exception of Scenarios 10 and 13, identify solutions where a majority of the planting budget is in pervious areas (Table 4.3). Scenarios 10 and 12, which target populations below the poverty level, result in increased amounts of additional tree cover in plantable impervious areas and reduced amounts of additional tree cover over plantable pervious areas when compared to Scenarios 9 and 11 that address equality without any weighting of populations below the poverty level. Additionally, Scenario 10 utilizes the majority of its planting budget by increasing tree cover across plantable impervious areas.

Scenario 2, which maximizes the monetary benefits from $PM_{2.5}$ removal, results in the largest benefit for that service. Scenario 13, which maximizes the monetary benefits of air pollutant removal and avoided runoff in the same objective function and includes the heat index reduction benefits as a constraint, achieves the largest avoided runoff reduction monetary benefits. In general, scenarios that consider all three ecosystem benefits (Scenario 13) or target populations below the poverty level (Scenarios 10 and 12), perform well across all ecosystem service benefits.

Table 4.3: Costs and benefits associated with increasing tree cover in each optimization scenario. Dollars ($) and area ($m^2$) are expressed in millions.

Scenario	$PM_{2.5}$ monetary benefits ($/yr)	Avoided runoff monetary benefits ($/yr)	Blocks with Heat Index reductions	Plantable Pervious Costs ($) (tree cover increases (m^2))	Plantable Impervious Costs ($) (tree cover increases (m^2))	Total Planting Costs ($)
1	1.25	0.28	418	400 (4.00)	0 (0)	400
2	4.92	0.26	873	359 (3.59)	41 (0.01)	400
3	1.25	0.46	181	359 (3.59)	41 (0.01)	400
4	2.21	0.30	554	359 (3.59)	41 (0.01)	400
5	1.22	0.42	369	290 (2.90)	110 (0.26)	400
6	1.82	0.36	820	295 (2.95)	105 (0.25)	400
7	2.79	0.24	552	349 (3.49)	51 (0.12)	400
8	2.30	0.32	443	400 (4.00)	0 (0)	400
9	2.66	0.45	1,077	249 (2.49)	151 (0.35)	400
10	4.48	0.59	490	131 (1.31)	269 (0.63)	400
11	2.06	0.44	1,028	251 (2.51)	149 (0.35)	400
12	3.20	0.46	578	231 (2.31)	169 (0.4)	400
13	3.18	0.77	299	78 (0.78)	322 (0.75)	400

4.4 DISCUSSION

This study presents a spatially explicit decision support framework that determines optimal locations for tree cover increases considering objectives that include the provision of multiple urban forest ecosystem services and benefits, minimizing implementation costs and achieving more equal and equitable tree cover distributions. This analysis was motivated by the lack of studies that recommend areas to increase tree cover by comprehensively considering multiple ecosystem services and benefits from increased tree cover, particularly in areas of greatest need. Also, without a means to quantify the inequity of tree cover distribution and green infrastructure, current frameworks may fail to fully inform decision-making processes of more equitable tree cover distributions, potentially exacerbating environmental injustice concerns. Furthermore, the ranking or weighted scoring approach used in most studies to prioritize planting locations is subjective and often cannot determine optimal options beyond the existing expert's knowledge (Yoon et al., 2019). As such, where and how to increase tree canopy, particularly at fine scales such as the census block group level, remains a problem for decision makers. This study sought to fill this informational gap and improve the decision-making process by creating a framework that could be used to answer critically important restoration questions on where to increase canopy or preserve urban forests.

McPherson (2014) noted that the continued success of tree planting initiatives will depend on strategically selecting and locating new trees. To demonstrate the utility of the framework as a planning tool, we explored thirteen optimization scenarios at the census block group level in the Bronx, NY. Spatial optimization tools that systematically consider a range of scenarios, objectives, constraints, and potentially stakeholder or societal preferences can help decision-makers gain insight into the full spectrum of feasible solutions (Weeks et al., 2014). Thus, in the scenarios explored, we focused on issues of concern to the Bronx (air quality, storm water and urban heat island issues as well as inequality and inequity in the distribution of tree cover) with guidance from the literature and the goals of MillionTreesNYC (Nyelele et al., 2019; Nyelele and Kroll, 2020; Campbell et al., 2014; Locke et al., 2010). In general, results from these different scenarios illustrate how a multi-objective prioritization approach can be used to identify optimal locations for greater total benefits from urban greening. Tools developed to improve science-based decision making in urban forest management often go unused due to highly variable management contexts and changing priorities; Knight et al. (2008) highlight that most tools and models in the literature do not result in management action, primarily because researchers never plan for implementation. To address how the framework can be used to address different objectives, we have shown different scenarios whose results indicate potential greening opportunities in relation to the imposed constraints. We have shown how this framework is flexible to handle a range of urban greening scenarios that can satisfy different environmental, economic, and social requirements of tree planting initiatives in different cities, reducing the gap between scientific assessment and its application.

Many high priority locations identified for the establishment of tree cover from our analysis were in block groups that initially had limited amounts of tree cover. Interestingly, these are low-income neighborhoods, including most of the southern and western neighborhoods of the Bronx. These optimal schemes are different from the plantings undertaken under MillionTreesNYC where most of the new trees were planted in large block groups that mostly consist of parks and playgrounds due to the availability of plantable space, particularly in areas owned and managed by the NYC Department of Parks and Recreation (Nyelele et al., 2019; Garrison, 2019). Increasing tree cover in natural areas, parks and playgrounds makes sense if the goal is to maximize tree cover without consideration of the ecosystem benefits to be realized and the beneficiaries of those services and benefits. However, considering that block groups in the urban core are primarily covered by impervious surfaces and have relatively few existing trees and limited opportunities to expand tree canopy (O'Neil-Dunne, 2012), communities most in need of additional tree cover might not receive it. By defining potential planting areas to include plantable impervious areas, we have increased the potential plantable area across different block groups and shown how different optimal planting schemes across plantable pervious and impervious areas may be identified.

While acknowledging that adding tree cover over plantable impervious areas is important, we also need to consider the costs associated with these conversions since tree planting initiatives are often constrained by available budgets. Our results have shown that when there is a budgetary constraint and planting costs vary between plantable pervious and impervious areas, to minimize implementation costs more tree cover increases will occur in areas with lower implementation costs. As a result, in all the scenarios explored in this study, most tree cover increases were on plantable pervious areas due to the lower implementation cost. This is not surprising, since the high implementation cost of converting plantable impervious surfaces into tree cover has resulted in few studies with prioritization schemes that recommend the conversion of impervious surfaces to tree cover despite the potential increased services and benefits from such areas. However, as pointed out previously, schemes that consider only pervious areas such as bare soil and short vegetation as possible plantable areas will likely identify optimal areas that are typically parks and other natural areas with limited ecosystem service beneficiaries since these areas often have lower population densities.

Strategic placement of trees within the landscape is required to maximize actual benefits (Almeter et al., 2018). To realize increased ecosystem services and benefits, it is imperative to plant on both plantable impervious and pervious areas, especially for services such as heat island and stormwater abatement where reduction in impervious areas generally increase ecosystem benefits (O'Neil-Dunne, 2012). As such, the decision support framework was developed to accommodate different planning and implementation scenarios, and to allow decision makers to consider plantable impervious scenarios if it maximizes their desired ecosystem services and benefits. Our results show that to generate tree cover scenarios with greater overall benefits in the Bronx, we have to maximize multiple benefits simultaneously and plant on both plantable pervious and impervious areas. While cities might focus on a single ecosystem service such as $PM_{2.5}$ air pollutant reductions (Scenario 2), we have shown that considering improving benefits across multiple ecosystem services (Scenario 13) can result in greater improvements in specific benefits without major decreases in other benefits. These results support an assertion by Almeter et al. (2018) that multi-objective designs that consider several benefits simultaneously will generate greater total benefits than single objective designs. Campbell (2014) also indicated that planting plans that quantify, monetize, and promote the urban forest for its multiple benefits are likely to be more successful.

The study has shown how trees can be strategically planted and managed to optimize desired ecosystem services using knowledge of the heterogeneous urban landscape and human demographics. However, some of the outcomes that communities care most about (e.g., social cohesion, quality of place, health and well-being) do not lend themselves to monetization (Almeter et al., 2018). To address this, we have shown how non-monetary objectives can be incorporated in our methodology to propose tree cover increases which provide non-commensurate ecosystem services of interest to the community. Additionally, by incorporating equality and equity constraints while maximizing benefits, our results have illustrated how the framework can be used to explore the tradeoffs in tree plantings schemes that promote equality and distributional equity of tree cover and the resultant ecosystem services and benefits. As shown in the results, although most of the scenarios led to reductions in the Gini coefficient, distributions with improved equality were more pronounced for scenarios that incorporated an equality constraint (Scenarios 6, 9 and 11). These scenarios targeted census block groups previously identified as underserved, particularly those in the south of the Bronx which consist of disadvantaged socio-demographic and socio-economic neighborhoods associated with disproportionately low levels of tree cover (Nyelele and Kroll, 2020). This is important considering that these areas have lower vegetation cover and associated ecosystem services relative to more affluent areas, yet these areas tend to be populated by those who rely more heavily upon these ecosystem services (Flocks et al., 2011; Escobedo et al., 2015; Jenerette et al., 2011; Soto et al., 2016, Nyelele and Kroll 2020). To fully incorporate equity, studies should address both the production and the intended beneficiaries of ecosystem services. By including the number of people with income below the poverty level, we have shown how tree planting prioritization can be carried out to ensure that resources reach the intended beneficiaries or communities that need them most. As illustrated by results from this study, this component of the decision support framework improves on current prioritization schemes that often focus on planting more trees in parks and natural areas with greater existing tree canopy, which often further promotes an inequitable distribution of tree cover (Garrison, 2019).

In our case study we implemented a constraint method for non-commensurate objectives to develop Pareto fronts by changing the right-hand side of the equality constraint (Scenario 9). This allowed us to assess potential tradeoffs between different objectives. Howe et al. (2014) and Halpern et al. (2012) highlight that there are inherent trade-offs between ecosystem services or benefits and equity as well as equality. Identification of potential tradeoffs allows policy makers to better understand the hidden consequences of preferring one objective to another. For example, with $PM_{2.5}$, the greater the tree cover the greater the pollutant removal, and the greater the pollutant removal and population density, the greater the monetary value of this benefit (Nowak et al., 2014, Nyelele et al., 2019). However, due to the minimal spatial variation in the weather and pollutant concentration data used in this study, the primary driver of PM_{25} removal rates was canopy cover, which resulted in increases in canopy cover in pervious areas that are typically parks and natural areas. On the other hand, achieving a more equitable tree cover distribution will result in some tradeoff with $PM_{2.5}$ air pollutant removal benefits since achieving equality requires planting be undertaken in block groups that have limited plantable pervious area. Such an analysis can help planners explore the sensitivity of their tree planting plans to the constraints on their system. Since linear programming was used in this analysis, for each scenario one can easily figure out the marginal change in the objective function due to a change in the right-hand-side of a certain constraint. For example, if the budget is increased or decreased between a certain range of values, one can explore what services and benefits are impacted by the resulting solution.

The optimization framework developed in this study could be important for communicating the impacts of different tree planting scenarios to decision makers. The results from this analysis provide potential guidelines for more detailed implementation plans. For example, in this analysis we did not consider the full range of benefits that trees provide, focusing here on the three primary benefits of interest in the Bronx. We also did not consider that it will take years for the full benefits from newly planted trees to be realized. Chazdon and Guariguata (2018) also highlight that modeling the potential supply of ecosystem services at a given location does not provide information on the temporal trajectory required to reach this potential, which can be critically important for restoration planning. We assumed that benefits are immediate, that current cover will be maintained, and that newly planted trees will reach maturity with no mortality. Future studies can build on this work and explore ecosystem benefit curves under various growth and mortality scenarios as well as the potential effects of alternative policy scenarios developed by incorporating stakeholder consultation to account for different social values and preferences. This may facilitate more accurate and spatially varying data to be used as input to the optimization framework. Weeks et al. (2014) highlight that the accuracy of a spatial optimization model depends critically on the quality of the input data used. While this study uses the i-Tree modeling framework there are other modeling tools available to quantify and commodify the value of the urban forest including SolVES (https://solves.cr.usgs.gov), ARIES (http://aries.integratedmodelling.org/), InVEST (https://www.naturalcapitalproject.org/invest/) and Co$ting Nature (http://www.policysupport.org/costingnature). It must be stressed that the particular focus of this study was to show a methodology which could be used in different cities where spatially varying data can be obtained, and not to necessarily emphasize the data employed in this study. In addition, the successful application of an optimization framework will depend on the complexity of the optimization problem being addressed, including the number of ecosystem services and benefits considered and their spatial interaction (synergies versus tradeoffs) as well as the degree of linearity or non-linearity of the services and benefits considered (Weeks et al., 2014).

The next steps include applying the decision support framework to other cities with different climates, demographics and scales to assess the scalability and functionality of the methodology. This will help determine the applicability and flexibility of the decision support framework to various problems and sites to improve urban forest management and identify potential areas for future tree plantings.

4.5 CONCLUSION

The expansion of urban canopy can provide many environmental and social benefits to urban areas, but planting requires thoughtful decision-making. This study responds to the need for more decision support tools that identify priority planting areas by considering multiple human health and environmental benefits from increased tree cover, particularly in areas of the greatest need. We developed a framework to facilitate decision-making for comprehensive urban greening plans satisfying multiple objectives and applied this framework to a case study in the Bronx, NY to prioritize optimal planting locations for potential tree cover increases. Results of this study have shown the utility of the decision support framework in identifying optimal locations for tree cover increases based on different objectives and resource constraints, as well as how multi-objective prioritization can be used to identify optimal locations that generate greater total benefits from urban greening. While the direct results of this study are important, the significance of this study is in its potential to improve decision making for a range of decision makers that work on urban forest management, as well as individuals and community-based organizations who are advancing tree planting efforts from alternative priorities and objectives such as climate resilience, ecological and environmental health, human health, as well as social and health equity priorities. With numerous tree planting initiatives being undertaken in different cities and with limited space for greening in most urban areas, it is crucial for decision makers to know how to optimize the spatial configuration of greenspaces to get the maximum benefit from increased tree cover. While this framework was specifically tested in the Bronx, it can be applied to other cities seeking to identify optimal locations to increase tree cover given a specified budget or canopy goal using locally derived spatially distributed data and selection criteria. Beyond identifying the best locations to plant trees, this framework can also help cities systematically reach other social, economic, and ecological goals.

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CHAPTER FIVE: THESIS SYNTHESIS

5.1 INTRODUCTION

This dissertation presents research focused on improving both our understanding and the management of urban forestry as well as the ecosystem services and benefits stemming from these complex systems. The ultimate goal of this work is to guide more local and fine scale decision making regarding where to increase or protect tree cover to maximize the services and benefits of trees while addressing potential environmental justice concerns in urban areas. While acknowledging that urban forestry provides numerous ecosystem services and benefits to humans, this research focused on those related to carbon storage and sequestration, stormwater runoff reduction, $PM_{2.5}$ air pollutant removal and heat index reductions by trees. Based on a quantitative analysis focused on New York City (NYC) and specifically the Bronx, using spatially explicit socio-demographic, socio-economic and biophysical data at the census block group level in a spatially distributed implementation of the i-Tree modeling framework and various quantitative approaches this research addresses the following questions:

1. What are the estimates of current and potential future ecosystem services and benefits of NYC's recent planting initiative within each census block group of the Bronx, NY?
2. Is there an equitable distribution of ecosystem services and benefits derived from trees among various socio-demographic and socio-economic variables at the census block group level in the Bronx, NY?
3. Can a multi-objective decision support framework identify optimal locations to plant trees in the Bronx considering multiple objectives? Will this approach identify a better allocation of trees that is more equitable than what was planted under MillionTreesNYC?

5.2 REFLECTIONS ON RESEARCH HYPOTHESES

The background and motivation for this research are discussed in Chapter 1. Also presented in that introductory chapter are the three null hypotheses that this dissertation examined to answer the stated research questions. Here each of the research null hypotheses are presented along with a discussion of whether results obtained in subsequent chapters provide evidence to reject the null hypotheses.

5.2.1 Estimation of current and potential future ecosystem services

By planting one million trees, NYC did not seek to only increase its urban forest but sought to also achieve the many quality-of-life benefits that come with planting trees (MillionTreesNYC, 2016). The first null hypothesis explored in this research was that there are no differences in the ecosystem service and benefit distributions due to the new tree plantings under MillionTreesNYC in each census block group of the Bronx. It was also hypothesized that there are no spatial and temporal variations in the distribution of ecosystem services and monetary benefits across different block groups as tree cover changes over time. The first manuscript (Chapter 2) highlights a spatially distributed implementation of i-Tree ecosystem service models and mapping tools to assess the ecosystem services and benefits (in either biophysical or monetary terms related to $PM_{2.5}$ air pollutant, stormwater runoff and temperature and heat index reductions) of recent plantings at the census block group level in the Bronx. Estimates were made for 2010 baseline tree cover conditions and three futuristic 2030 tree cover scenarios developed from a tree grow-out scenario assuming low, average and high annual tree mortality. When the ecosystem services and benefits for each block group were mapped for the two time periods under review, spatial variations were evident (Figures 2.1 – 2.6). Change analysis for each block group between the baseline 2010 and 2030 scenarios further illustrated gradients of not only tree cover but also the ecosystem services and benefits over time. These results provide sufficient evidence to reject the null hypothesis and instead conclude that recent tree plantings resulted in spatially and temporally varying amounts of tree cover, ecosystem services and benefits across block groups.

5.2.2 Equity of ecosystem services and benefit distributions

While spatial and temporal variations in ecosystem service and benefit distributions are to be expected, results in Chapter 2 highlighted large increases of tree cover in block groups that mostly consist of parks and playgrounds, raising questions of whether tree cover and the services and benefits it provides are equitably distributed and reaching populations that need or rely on them the most. MillionTreesNYC took an explicit environmental justice approach to address the uneven distribution of urban forests (Campbell et al., 2014). Thus, the second hypothesis explored in this research was of an equitable distribution of ecosystem services and benefits provided by urban forests across the Bronx, i.e. there is no environmental injustice related to the distribution of ecosystem services among socio-economic and socio-demographic classes. Particularly focused on distributive equity, the second manuscript (Chapter 3) utilizes census block group specific data and various quantitative approaches of assessing both equality and equity (Mann-Kendall trend test, Lorenz curves, Gini coefficient, Sen slope estimator, Atkinson inequality index and Theil entropy index) to explore this hypothesis. Results show that the ecosystem services and benefits of carbon storage and sequestration, stormwater runoff reduction, air pollutant removal and heat index reduction for 2010 tree cover conditions appear to be unequally and inequitably distributed in the Bronx. Disadvantaged socio-demographic and socio-economic block groups (with respect to median income, per capita income, percent minorities, population density, poverty percent and total educational attainment) receive disproportionately lower ecosystem services from urban trees (Tables 3.2 and 3.3). Decomposing the Atkinson inequality and Theil entropy indices into within and between subgroup inequalities for each ecosystem service and benefit (Figure 3.1) was an important step to gain insights into the sources of these inequalities. Contrary to the more traditional expectation of between sub-group inequality, the vast majority of the inequality in the Bronx is explained by within subgroup variations likely due to the heterogenous nature of the census block groups. Such an analysis is important in highlighting how more efforts should be placed on targeting disadvantaged block groups with extremely low tree cover so as to achieve greater equity in the distribution of the ecosystem services and benefits of trees. Based on disproportionately distributed ecosystem services and benefits across socio-economic and socio-demographic groups, there is evidence to reject the null hypothesis and instead conclude that the ecosystem services and benefits from urban trees are inequitably distributed in the Bronx.

5.2.3 Multi-objective decision support framework for optimal and equitable planting locations

Results from Chapter 2 illustrated the vital role trees play in providing important ecosystem services and benefits, and highlighted the spatial and temporal variations in tree cover distributions and resultant services and benefits. Chapter 3 presented inequities in these ecosystem service and benefit distributions and suggested that to make strides towards addressing environmental injustice concerns across socio-economic divides, future tree plantings should consider underserved communities and seek to create more equitable distributions that foster the development of healthier and more resilient urban communities. Addressing methodological gaps of current prioritization methods, Chapter 4 (Manuscript 3) developed a spatially explicit and flexible multi-objective decision support framework to identify optimal and equitable planting locations while exploring the null hypothesis that a multi-objective approach will not result in an optimal allocation of trees or planting scenarios with greater total benefits and increased equity than what was allocated under

MillionTreesNYC. The multi-objective framework was developed to optimize multiple ecosystem service provisions (e.g., air pollutant removal, storm water runoff reductions and heat index improvements) and the equitable distribution of these provisions in identifying and evaluating tree planting priority locations in urban settings. Thirteen optimization scenarios with varying objective functions and constraints addressing common resource and implementation issues encountered in practice were applied to the Bronx by utilizing spatially distributed census block group data. One of the key distinguishing features of the framework is defining plantable pervious and plantable impervious areas and evaluating the relative benefits from increasing tree cover these surfaces. Each scenario considered identified priority planting locations across plantable pervious or impervious areas. In general, the most optimal areas identified were underserved low-income neighborhoods that initially had limited amounts of tree cover. These priority areas are different from those targeted under MillionTreesNYC, where mostly large block groups containing parks and playgrounds were identified for increases in tree cover. Results from the different scenarios illustrate how a multi-objective prioritization approach can be used to explore different tree plantings schemes that strategically target areas to plant and manage trees to optimize desired ecosystem services and realize greater total benefits while improving the distributional equity of tree cover and resultant ecosystem services and benefits. Results provide evidence to reject the null hypothesis and instead conclude that a multi-objective prioritization framework can identify optimal and equitable locations for greater total benefits from urban greening than what was planted under MillionTreesNYC.

5.3 SIGNIFICANCE AND CONTRIBUTIONS OF THE STUDY

While the direct results of this study are important, the significance of this study is in its potential to improve decision making for a range of agencies and municipalities that work on urban forest management, as well as individuals and community-based organizations who are advancing tree planting efforts from a variety of priorities and objectives. Although the study is focused on the Bronx, the methodological and conceptual approaches presented can be applied to other cities seeking to systematically reach their social, economic, and ecological tree planting goals. Findings and conclusions from this study are significant for global scientific discourse as important scientific knowledge gaps are addressed in this study, both in the themes explored and the methodology used in understanding urban forestry and ecosystem service issues in urban settings. The study links the environment to people, evaluates environmental change, human health, and environmental justice, concepts that can be easily adopted and replicated to understand ecosystem service provision by trees in other parts of the world. Addressing multiple interrelated themes enables a broader appreciation of the complexity of the issues related to urban forestry in urban settings. The study has intellectual merit in that it tracks and maps supply and demand of ecosystem services and benefits, addressing a gap in the ecosystem service literature.

The spatially distributed estimation of ecosystem services and benefits improves on current studies and assessments that often use lumped modeling approaches which are appropriate for city-scale or regional planning, but are not appropriate at the fine scales that link tree effects to specific local conditions and residential populations, a scale at which local urban forest planning typically occurs. Spatially distributed modeling approaches such as the one used in this research are useful to spatially refine service and benefit estimates and illuminate the spatial differences and potential environmental justice concerns needed to guide more local scale decision making. As illustrated in the comparison between ecosystem services and benefits from the lumped implementation of i-Tree models used in i-Tree Landscape and the spatially distributed implementation of the same tools at the census block group level, Chapter

2 illustrated how these services differ significantly (at a p-value of 0.05). These differences may have implication regarding which block groups to target for future plantings. Additionally, the grow-out scenarios used to estimate the growth of newly planted trees under varying mortality scenarios allows for different management options to explore the potential range of ecosystem services and benefits in the future.

This study provides novel insights into the relationships between socio-demographic and socio-economic variables, ecosystem service and benefit distributions, and the concepts of equity, equality and environmental justice in urban systems. This study responds to research and policy that advocates for the inclusion of ecosystem services in decision-making to promote more sustainable development (Secretariat of the Convention on Biological Diversity, 2012). It also adds to the limited literature examining the distributional equity of ecosystem services and benefits provided by urban trees. The ecosystem service framework adopted in this study links humans to their environment and has implications for urban forest conservation, planning and policy, leading to more equitable and sustainable land-use decisions (Secretariat of the Convention on Biological Diversity, 2012; Cortinovis and Geneletti; 2018). Ecological management that considers ecosystem service interactions is likely to produce far better outcomes for societies since increasing tree cover has the potential for significant co-benefits across a range of human health and environmental arenas (Millennium Ecosystem Assessment, 2005; Salmond et al., 2016). Given the competition for resources and space in urban settings, strategic investments in green infrastructure should not only account for the multiple services generated, but also where those services are most needed and the potential beneficiaries of those services. Furthermore, studies such as this one that attempt to identify the sources of inequality (within-group and between-group) are necessary contributions to ecosystem service and benefit assessment methodology that informs urban forestry management and creates actionable policy recommendations that prioritize approaches that lead to a fairer and more equitable distribution of tree cover and the services and benefits they provide.

Many cities are implementing large-scale tree planting programs but have limited guidance on how to optimize plantings to achieve desired benefits and to evaluate the tradeoffs and synergies between competing objectives. As such, where and how to increase tree canopy, particularly at fine scales such as the census block group level, remain to be a problem for decision makers. This study fills this informational gap and developed a decision support framework addressing some of the methodological shortcomings of existing prioritization tools. For example, current prioritization tools fail to comprehensively consider multiple ecosystem services and benefits from increased tree cover, lack the means to quantify inequities of tree cover and ecosystem service distributions, fail to identify schemes that improve areas of greatest need and adopt ranking or weighting approaches that are subjective and dependent on existing expert knowledge. The study demonstrates how publicly available or easily accessible spatial demographic or economic and biophysical data can be better used to prioritize tree planting locations for improved forest management. To address the gap between scientific assessment and its application, this study develops a general decision support framework and then applies this framework in a case study to show how the tool can be used in different cities to addressing varying environmental, economic, and social goals of tree planting initiatives.

5.4 LIMITATIONS OF THE STUDY AND RECOMMENDATIONS FOR FUTURE RESEARCH

While this study has presented insights into the modeling of urban forest ecosystem services and benefits, it has limitations. Exploring these limitations can be useful to inform future research and for evaluating the planting strategies resulting from this analysis.

In Chapter 2, the limitations of the data used in the modeling of ecosystem service and benefit estimates were highlighted. For example, air pollutant removal rates by trees are expected to vary locally based on factors such as pollutant concentration, length of growing season, percent evergreen leaf area and meteorological conditions (Nowak et al., 2014; Hirabayashi and Nowak, 2016). However, due to the minimal spatial variation in the weather and pollutant concentration data in the Bronx, total tree cover was the main driving cause of air pollutant removal rates. This problem is not specific to the Bronx, as Nowak et al. (2014) note that nationally the number of weather and pollutant monitors is limited. In Chapter 4, an improvement was made in the characterization of $PM_{2.5}$ air pollutant concentrations by mean adjusting the data from long-term monitors using concentrations from short-term monitoring sites. Additionally, there are data limitations with regards to LAI estimation at finer scales emphasized in this study (i.e. block group specific data). To overcome this limitation, LAI averages using data from all the newly planted trees in each block group were used. Also, although three annual tree mortality rates were used to provide a best, average and worst-case scenario in terms of tree loss for new plantings, species and age specific mortality rates are needed to develop improved results. Future studies can improve on these methods by obtaining more accurate and spatially distributed weather inputs, pollutant concentrations, and species and age specific mortality rates to develop improved ecosystem service and benefit estimations and to better understand the implications of these variables on the total future benefits.

i-Tree Cool was used to capture the tree effects on air temperature and heat index reductions. Results presented in Chapter 2 and in subsequent analyses highlight minimal variations in temperature and heat index reductions across the Bronx due to increases in tree cover. It may be argued that the amount of tree cover added in each block group in Chapter 2 is too little to have an impact on temperature, heat index and heat related mortality or that the configuration and placement of newly planted trees was not necessarily done in a manner that maximizes the cooling effect of trees. However, results presented in Chapter 3 also depict low levels of inequality in the distribution of the heat index reduction benefits, again raising concerns that this could be an artifact of the heat index reduction model and data used in this analysis. Future studies should assess the impact of local factors and spatial configuration of greenspaces on ecosystem services and improve on the methodology of determining heat index reductions and other tree effects on temperature.

A limitation of the Atkinson index used to assess current inequalities and gain insights into equities in the distribution of ecosystem services in Chapter 3 is that it depends on the degree of society's aversion to inequality (ε) which is chosen by the researcher. To overcome uncertainties associated with the Atkinson index, ε was varied between 0.5 and 2 (based on suggested literature values). Conclusions were drawn from comparisons of different ε scenarios. Additionally, the methodology presented in Chapter 3 can help identify trends to estimate the rate of change in ecosystem services and benefits across various socio-demographic and socio-economic variables. However, this approach is limited in that it does not provide insight in attributing observed trends to a particular cause. Such an analysis requires an in-depth understanding of local issues, since the distribution of urban vegetation is influenced by local environments, development histories, and local governance (Gobster and Westphal, 2004). Further studies could identify underserved communities and seek to better understand local factors that are likely to affect tree cover distribution and local participation in tree-planting programs, which are often critical to the success of forest planting initiatives. This would also help incorporate local knowledge to augment and verify the accuracy of publicly available data, allow for the direct involvement of local citizens, and better incorporate local knowledge to improve the success of urban forest initiatives.

While the decision support tool from Chapter 4 was successful in identifying optimal and equitable planting locations in the Bronx, there is need for studies that assess the uncertainty and tradeoffs of the input and output from this tool. Using a broader range of ecosystem services in cities with different climates, scales, and demographics, one could better assess the effectiveness, efficiency, and robustness of this tool. An important future direction of this research would be to explore how the optimal planting locations identified by the decision support tool match the priority planting locations identified by the responsible municipal agencies in each city. By comparing model predictions against actual management plans and priorities, future studies can address the research implementation gap and prepare for actual implementation of the tool and its integration into existing planning tools such as i-Tree Landscape. Additionally, there is need to explore ecosystem benefit curves under various growth and mortality scenarios and the potential effects of alternative policy scenarios developed by incorporating stakeholder consultation to account for different social values and preferences. This will allow users to not only prioritize specific ecosystem services, but to also examine the social implications of their management plans, and ways to reduce ecosystem inequities among underrepresented communities.

Lastly, the analysis presented here was carried out at the census block group level, the finest unit at which the socio-economic and socio-demographic data needed for the analysis is available. While this was appropriate for the current analysis to link the ecosystem services and benefits to demographic information, this research limited the effect of trees within specific block groups and assumed there is no effect on neighboring block groups. Instead of limiting the biophysical processes through which trees provide ecosystem services and benefits to political rather than biophysical boundaries, future studies should assess interactions between chosen subunits to come up with appropriate biophysical units and demarcations at which ecosystem services and benefit estimations can be made.

5.5 POLICY AND MANAGEMENT RECOMMENDATIONS

Although the study is based on the Bronx, the methods and issues raised in this analysis can be used to improve the maintenance and management of urban forests in different cities. This research has demonstrated that trees provide a myriad of services and benefits to urban inhabitants and that maintaining and expanding existing canopy cover should be a priority in urban settings. As such, management plans should enhance the protection and maintenance of existing trees in addition to planting new trees and promoting natural regeneration. Achieving environmental equity in tree cover and the ecosystem services and benefits it provides should also be a part of management plans in cities seeking to improve their tree cover. Results and conclusions from the study have shown the need for decision making and management plans to incorporate environmental justice in their programming activities to ensure that tree planting is a participatory, collective, and a local stakeholder-engaged process to achieve more beneficial outcomes from trees, especially for disadvantaged socio-economic and socio-demographic groups as well as marginalized communities that lack tree cover and the important ecosystem services and benefits they provide.

Assessment and evaluation of the goals, costs and benefits of tree planting initiatives should be part of all urban forest management plans. While the specific goals of tree planting may vary across cities, planners and decision makers should systematically consider a range of scenarios, objectives, constraints, and stakeholder and societal preferences to gain insight into the full spectrum of feasible solutions. This will help identify the potential tradeoffs between different goals and allow policy makers to better understand the consequences of specific objectives. Results of this study have shown how considering improving benefits across multiple ecosystem services can result in greater improvements in specific benefits without major decreases in other benefits.

5.6 CONCLUSIONS

Overall, this dissertation is comprised of studies which seek to improve the science and management of urban forestry. The study highlights the vital part trees play in urban areas and illuminates inequities associated with tree cover and ecosystem services while developing a framework to guide decision making for future tree planting initiatives.

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