12-16-2018

Understanding Macro-scale Patterns in Urban Tree Canopy and Inequity across Socio-cultural and Biophysical Regions

Elliott Volin
elliott.volin@uconn.edu

Understanding Macro-scale Patterns in Urban Tree Canopy and Inequity across Socio-cultural and Biophysical Regions

Elliott V. Volin

B.S., B.A., Florida State University, Tallahassee, Florida

A Thesis

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Master of Science

At the

University of Connecticut

2018

Approval Page

Master of Science Thesis

Understanding Macro-scale Patterns in Urban Tree Canopy and Inequity across Socio-cultural and Biophysical Regions

Presented by

Elliott V. Volin, B.S., B.A.

Major Advisor: Dr. Robert Fahey____

Associate Advisor: Dr. Anita Morzillo____

Associate Advisor: Dr. Jason Parent____

University of Connecticut

2018

Acknowledgements

To my amazing family, thank you for the never ending love and support!

Special thanks to my advisor, Dr. Robert Fahey, thank you for all the guidance and wisdom over the past few years

To my committee members, Dr. Anita Morzillo and Dr. Jason Parent, thank you for your patience and insight

Thank you to my funding source, the National Urban and Community Forestry Advisory Council (Grant #15-035) for making this research possible

Table of Contents

Abstract

Urban forests provide a variety of ecosystem services that influence environmental and social welfare within developed areas. Prior studies have evaluated the effects of inequitable distribution of urban tree canopy (UTC) on ecological and social benefits, leading to inequalities within individual cities. However, it is not well established how such relationships vary among urban areas in different biophysical and socio-cultural regions. The objective of our study was to identify regional and continental trends in the relationships of UTC with socioeconomic/ demographic factors and characteristics of urban regions (e.g., development patterns, timing). To address our objective, we utilized iTree Landscape and US Census data to develop a data set of census block group level UTC-related response variables (e.g., percent UTC, inequity in UTC) and socio-economic/demographic predictor variables (e.g., median income, inequality in median income) for forty U.S. cities, spanning several different biophysical and sociocultural regions. We utilized multiple regression analysis in an information-theoretic model selection framework to analyze relationships among UTC, ecosystem benefits, socioeconomic, and demographic predictor variables and then evaluated how these relationships varied among cities within and among ecoregions and socio-cultural regions. Our results illustrated a strong negative correlation between UTC and UTC inequity, as UTC decreases, UTC inequity increases. Patterns in socioeconomic predictors of UTC emerged among biophysical and sociocultural regions, indicating socio-ecological factors influence UTC inequities.

Key Words: urban forestry, macro-scale, socioeconomic variables, biophysical regimes, iTree, urban tree canopy inequity

Chapter 1

Understanding Macro-scale Patterns in Urban Tree Canopy and Inequity across Socio-cultural and Biophysical Regions

Elliott V. Volin

MS Thesis

For Submission to *Landscape and Urban Planning*

1 Introduction

Urban forests provide many ecosystem benefits to metropolitan areas, which impact the environmental and social welfare of an urban area (Kuo 2003, Gómez-Baggethun and Barton 2013). These include ecological benefits such as storm water mitigation, carbon sequestration, air and water quality improvements, energy savings, and wildlife habitat (Dwyer et al. 1992, Nowak 1993). Social benefits of the urban forest include a reduced rate of respiratory illnesses, reduced crime rates, and increased use of neighborhood common spaces (Kuo 2003, Elmqvist et al. 2015). The aesthetic appeal of urban forests add both a social value, by providing psychosocial benefits for the population, such as reduced stress levels (Kaplan 1995, Chiesura 2004), and an economic value, by raising property values (Price 2003). The extents to which these benefits impact the urban area are affected by forest structure, percent of urban tree canopy (UTC), tree health, and the presence of other urban vegetation (grasses, shrubs, etc.; Nowak et al. 2008). Consequently, management of the urban forest through expansion of the overall canopy cover can help amplify the ecological, socioeconomic, and health benefits within cities (Nowak et al. 2001).

Cities function as a part of larger biophysical and socioeconomic systems, which can have lasting legacy effects on the urban tree canopy (Jenerette et al. 2011, Roman et al. 2018). Several studies have shown that bioregional factors, such as the forest ecosystem biome or regional disasters like fire or storm events, can profoundly influence the amount of UTC within a city (Schwarz et al. 2015, Roman et al. 2018). For example, Florida receives many windstorms and hurricanes that damage trees. In response, arborists and urban foresters plant a suite of wind resistant trees to withstand the storms (Duryae et al 2007). Socioeconomic factors, such as neighborhood age and income, have strong impacts on the urban tree canopy as well (Lowry et al. 2012, Schwarz et al. 2015). Urban forest management decisions, such as the planting of monocultures or invasive species, can have lasting effects on the urban tree canopy (Roman et al 2018). These biophysical and socioeconomic drivers can create legacy effects that influence the amount and distribution of UTC within cities for decades (Nowak and Greenfield 2012, Roman et al. 2018).

There is also often an uneven distribution of UTC among communities and neighborhoods within cities and metro regions (Landry and Chakraborty 2009). As a result, inequities exist in the amount of ecosystem benefits received by the population across an urban area (Schwarz et al. 2015). Some members of the population do not receive the same positive impacts and leading to increased health risks (Lovasi et al. 2013, Troy et al. 2012). Socioeconomic and demographic factors, including median income, population density, education levels, and median housing values, have been used as predictor variables for urban tree canopy (Jensen et al. 2004, Heynen and Lindsey 2003). Prior work has illustrated a strong correlation between low tree canopy coverage and the socioeconomic status of a neighborhood (Kendal et al. 2012). Studies from developed countries, including the United States, Australia, and Europe, have found that within cities, disadvantaged neighborhoods often have fewer trees, parks, and other vegetated areas, leading to fewer social and ecological benefits received in these areas of an urban region (Bolund and Hunhammar 1999, Luck et al. 2009, Grove et al. 2014).

The socioeconomic factors affecting UTC could also be influencing spatial distribution of tree canopy cover (Iverson and Cook 2000, O'Neill et al. 2003). Different biophysical and developmental legacies have the potential to affect UTC inequity (Roman et al. 2018). This inequity is likely to vary across the US among different regions (Nowak and Greenfield 2012). Further exploration is necessary to better understand national or regional-scale drivers in variation in UTC and inequity both among and within urban areas. The primary objective of this study was to better understand macro-scale patterns of UTC and UTC inequities among urban areas. I aimed to identify and describe continental and regional patterns of UTC and UTC inequity within and among cities across biophysical and sociocultural regions across the contiguous United States and Hawaii. My specific research questions included:

1) How much UTC inequity exists among neighborhoods within cities and what socioeconomic and demographic factors are related to variation in UTC?

2) To what degree is variation among cities in total UTC and UTC inequity related to differences across macro-scale biophysical and sociocultural regions?

3) Does the strength of the relationship between UTC and socioeconomic predictors and the identity of the most important socioeconomic predictors of UTC patterns vary across cities and regions?

2 Methods

Study cities and classification strategies

The overall approach of this study was to conduct a continental macro-scale analysis across different biophysical and socioeconomic regions. The analysis spanned forty cities spread geographically across the conterminous United States and Hawaii (Figure 1). Only cities with existing fine spatial resolution (1m x 1m) UTC layers were included in this study. The study area for analysis of UTC patterns was limited to city boundaries because most urban regions only have fine-grain UTC for the core city. UTC varied greatly among cities, from a low of 6.72 in El Paso, TX to a high of 46.9 in Charlotte, NC (Table 1). City population ranged from 35,000 in Chelsea, MA, to 8.1 million in New York City.

To identify variation in UTC inequity and socioeconomic predictors across the country, cities were grouped into four different regional and demographic classifications: biophysical, socio-cultural, city population, and population trend (Table 1). First, to assess biophysical patterns, cities were classified based on the United States Geological Survey Physiographic Ecoregions classification system (USGS 2003). The USGS utilizes ecological, hydrological, and climatological indices to divide the continental United States and Hawaii into nine distinct ecoregions (Figure 2). Cities included in this study were located in six ecoregions: Appalachian Highlands (13 cities), Atlantic Plains (5 cities), Interior Plains (7 cities), Intermountain Plateaus (4 cities), Pacific Mountain System (10 cities), and Tropical Forest (1 city) ecoregions (Table 1).

Second, to better understand sociocultural influences on UTC and inequity, cities were classified into four broad geographically based sociocultural regions across the contiguous United States and Hawaii: the Northeast, the Midwest/ Great Lakes, the West, and the Sun Belt (Figure 1). For this, I categorized cities across the country according to regional similarities in demographic, sociological, cultural, and economic factors. For example, the Midwest/ Great Lakes region was based largely on economic factors. The Midwest/ Great Lakes region consists of many industrial and agricultural cities from the Rust Belt and Great Plains (Kahn 1999, Hartley 2013). Industrial cities, such as Pittsburgh, Cleveland, Syracuse, and Utica boomed during the industrial revolution, but have declined economically over the last several decades as major industries, such as steel and coal, wane (Kahn 1999, Hartley 2013). Other regions were divided largely along cultural lines where shared histories and traditions dominate the social identity (Vandello and Cohen 1999).

Third, to evaluate possible relationships between city size and UTC patterns, cities were classified according to population size and divided into three categories: small, medium, and large cities. Only the populations within a city's limits were considered (not the entire metro region). Of the forty cities studied, 17 were categorized as small, 11 medium, and 12 large (Table 1). Using this categorization, I was able to attain similar sample sizes. A city was considered small if it had a population of less than 150,000 (according to the 2010 U.S. Census Bureau data), medium cities had populations between 150,001 and 600,000 people, and any city with a population of over 600,001 people was categorized as large.

Finally, I classified cities according to their population growth trends between 1990 and 2010. Cities were organized into one of three subcategories: increasing, sustaining, or decreasing. Prior studies have considered a city with populations of over 100,000 at their peak, to be 'shrinking' if the population decreased by more than 10% (Oswalt and Rieniets 2007, Hollander et al. 2009). Therefore if a city's population dropped by 10% or more, it was categorized as a decreasing population. Similarly, if a city's population rose by 10% or more, it was categorized as increasing. If a city's population neither increased nor decreased by 10%, it was categorized as a sustaining population. Within the forty cities, 18 were increasing in population, 15 sustaining, and 7 decreasing (Table 1).

Data extraction and variable derivation

Urban tree canopy, socioeconomic, and demographic data were extracted from the iTree Landscape database (iTree 2008) and the US Census Bureau (US Census Bureau 1990, 2010). UTC and socioeconomic and demographic information were extracted and analyzed at the census block group scale within each city. Socioeconomic variables utilized in the analysis included median income, percent poverty (annual income ≤ $22,314, US Census Bureau), and median home values. Socio-demographic variables utilized in the analysis included percent minority, population density, percent of home ownership, percent of the population with college degrees, and average year homes were built.

The level of UTC inequity for each city was quantified using the Gini Coefficient, which gauges the degree of inequity in a factor of interest (Yitzhaki 1979). Traditionally, economists have used this metric to measure the distribution of wealth within a country (Lambert and

Aronson 1993). The Gini Coefficient is a well-established metric of inequity (Yitzhaki 1979, Lambert and Aronson 1993, Beaugrand et al. 2010) and recently it has been adapted to measure the inequitable distribution of ecological factors, including tree canopy cover (Beaugrand et al. 2010, Jenerette et al. 2011). The Gini Coefficient ranges from 0 to 1; higher Gini Coefficients represent higher amounts of inequity. For this study, the Gini Coefficient of tree canopy cover among census block groups was used to characterize inequity in UTC within each city.

To better understand how strongly socioeconomic variables predict UTC across cities, I utilized the overall R^2 from multiple regression analysis of UTC as a function of socioeconomic and demographic factors (see Data Analysis section below) as a Socioeconomic Sensitivity Index (SSI). The index ranges from 0-1; higher numbers represented higher predictability of UTC by the socioeconomic predictor variables. Each city was assigned an SSI value, calculated from census block group scale data based on regression models.

Data Analysis

At the city level, I utilized multiple regression in an information-theoretic model selection framework to evaluate relationships between UTC and the aforementioned eight socioeconomic and sociodemographic predictor variables at the census block group scale. In each city, a set of candidate models was evaluated to determine which variables best predicted UTC within the city and the strength of that prediction. Akaike's Information Criterion (AIC) was used to rank and select models with strong support within the model set based on Akaike weights. All regression and AIC models were conducted in R Studio using several packages, including *lm* and *dredge* from *MuMIn* (Burnham and Anderson 2002, Faraway 2002, Barton 2018). AIC adjusts for the number of parameters in each model and gives a relative goodness of fit for each model. All models ΔAIC of less than 2 as compared to the most highly supported model were considered in further analysis (Table 2). Because AIC is only a relative measurement for goodness of fit, adjusted R^2 values were calculated for the most highly supported model in the model set and used as a metric (SSI) to characterize the strength of the correlation between tree canopy cover and socioeconomic predictor variables in each city. A single top model was selected for each city, based on a relevant Akaike weight and a high-adjusted R^2 value.

Among cities I identified macro-scale patterns in UTC, UTC inequity (as measured by the Gini Coefficient), and importance of socioeconomic predictors of UTC (SSI). Means for UTC, UTC inequity, and SSI were compared across the four regional and demographic classifications (Table 1). Analysis of variance (ANOVA) was conducted to test for significant differences among categories within each classification. If the ANOVA indicated significant differences among categories ($p \leq 0.05$), individual comparisons among categories were made with adjustment for multiple comparisons (Tukey HDS Test). Several package were used in R Studio, including *aov* and *TukeyHSD* (Faraway 2002, Dalgaard 2008), to conduct the ANOVA and Tukey tests.

Finally, to evaluate variation of important socioeconomic predictors of UTC among cities, I evaluated patterns in which socioeconomic predictor variables were included in the most highly supported models. The key variables were consolidated within each of the four different regional classifications. A variable was considered an important predictor within the region if it was present in 75% of the cities. Trends in key predictor variables were evaluated nationally and among the biophysical and socioeconomic regions.

3 Results

Macro-scale variation in UTC among cities and regions

Across all cities, I found a negative correlation between overall level of UTC at the city scale and UTC inequity, as measured by the Gini Coefficient ($r^2 = 0.53$, $p < 0.0001$; Figure 4). Generally, as UTC decreases, the amount of UTC inequity increases (regional variation existed as well, leading to patterns in UTC across the country). Within the biophysical regional analysis (Figure 2), the two most western regions, Intermountain Plateaus and Pacific Mountain System, had significantly less UTC than the three eastern regions ($p = 0.001$, $f = 5.65$, $df = 4$; Figure 5). Among the socioeconomic regions, the West had significantly lower amounts of UTC than the other three regions ($p < 0.0001$, $f = 15.12$, $df = 3$; Figure 6). Additionally, the Northeast had a lower amount of UTC compared to the Sun Belt. Within the population size classification, significant patterns emerge in UTC. Large cities have less UTC ($p = 0.01$, $f = 4.67$, $df = 2$) compared to medium and small cities (Figure 7). Patterns in UTC were also examined within the population trends analysis, however, no significant patterns emerged ($p = 0.48$, $f = 0.74$, $df = 2$).

Inequity patterns and variation across categories

Gini Coefficients ranged from a low of 0.15 in Savannah, GA, indicating low levels of inequity, to a high of 0.47 in Oakland, CA (Table 1). Among the biophysical classification, marginal variations in UTC inequity arose ($p = 0.06$, $f = 2.49$, $df = 4$; Figure 5). Cities in the two western regions also had more inequity than the Interior Plains. Significant variation in UTC inequity emerged among the sociocultural regions ($p = 0.004$, $f = 5.07$, $df = 3$; Figure 6). The West had higher amounts of inequity, compared to the other three regions within the sociocultural classifications. Among the population size classifications, significant inequity patterns also emerged ($p = 0.01$, $f = 5.19$, $df = 2$; Figure 7). Large cities had higher UTC inequity compared to medium and small cities. Within the population trend analysis, no significant patterns emerged ($p = 0.78$, $f = 0.29$, $df = 2$).

Socioeconomic predictors of UTC and inequity

Differences in the predictive strength of UTC by the socioeconomic variables emerged within and among cities. Within cities, SSI ranged from a high of 0.84 in Nampa, ID, to a low of 0.05 in Chelsea, MA. Within the biophysical classification analysis, the two western regions, Intermountain Plateaus and Pacific Mountain System, had significantly stronger UTC predictability (SSI) compared to the central and southern regions ($p = 0.008$, $f = 4.02$, $df = 4$; Figure 5). Among the sociocultural regions, the West had a significantly higher SSI than the Sun Belt ($p = 0.05$, $f = 2.83$, $df = 3$; Figure 6). However, there were no significant differences within either the population size or populations trend classifications (Figure 7).

Important socioeconomic predictor variables differed both within and among cities (Table 2). Population density and home ownership were the top predictors of UTC, appearing in the top model for 82 and 77% of cities respectively (Figure 3). The percent poverty was the least prevalent of the socioeconomic variables, predictive in less than a third of the study cities. Among the biophysical regions, median income and percent college degrees were important predictors within the Pacific Mountain System. The percent of home ownership was a key predictor in the other four biophysical regions, but not the Pacific Mountain System (Table 3). Home value was a significant socioeconomic predictor of UTC in the West, but not the other 3 regions within the socioeconomic analysis. Conversely, home ownership was a significant predictor within the other regions, but not the West (Table 3). Within the population size analysis, home value was important for large cities but not for medium or small cities. In comparison, home ownership was important for both small and medium cities, but not large cities (Table 3). The percent of the population with college degrees was a significant variable for cities with decreasing populations, but not for cities with sustaining or increasing populations (Table 3).

4 Discussion

I found a strong negative relationship between UTC and inequity, as well as significant regional patterns of inequity across the continental US and Hawaii. This study is among the first to investigate UTC inequity at a macro scale among different biophysical and sociocultural regions. The strong predictability of UTC by a suite of socioeconomic variables, including home value, percent poverty, and median income, suggests that income and affluence contribute to the inequitable distribution of UTC. After examining multiple cities, Schwarz et al. (2015) found similar patterns of UTC inequity related to high-income households. My study builds upon this by broadening our understanding of how biophysical regimes and sociocultural regions affect UTC inequity and socioeconomic predictors of UTC across the US. Prior research has found that socioeconomically disadvantaged communities often have less access to quality parks and green spaces, leading to larger environmental justice issues (Wolch et al. 2014). My research supports these findings and expands our understanding of regional socioeconomic predictors of UTC to help highlight those environmental justice issues.

My research suggests that biophysical regimes influence patterns of UTC and UTC inequity across the country. I found lower levels of UTC and a higher degree of inequity in Western regions; possibly due to underlying biophysical regimes (Nowak and Greenfield 2012, Roman et al. 2018). The arid climates in desert regions such as the American Southwest lead to less spontaneous growth of urban trees (Roman et al. 2018). This can lead to further inequity as less affluent neighborhoods often do not have the resources to plant urban trees and there is not spontaneous tree establishment (Perkins et al. 2004, Heynen et al. 2006, Landry & Chakraborty

2009). Planting efforts, directed at less affluent areas, may help expand urban trees canopy in more arid regions, as appropriate (Pataki et al. 2011). These planting efforts should also consider other issues facing these regions, such as drought and fire risks. Proper planning can ensure long terms success of planting efforts. Additionally, several socioeconomic variables associated with affluence ('home value', 'median income', and 'percent of the populations with college degrees') were significant predictors of UTC inequity in the western regions, suggesting that more affluent neighborhoods can afford to plant urban trees (Perkins et al. 2004, Heynen et al. 2006, Landry & Chakraborty 2009). Furthermore, disadvantaged neighborhoods will not receive the benefits of urban trees because of the monetary costs of planting and maintaining those trees (Avolio et al. 2018).

Patterns of UTC and UTC inequity across the country were strongly related to sociocultural factors, such as developmental patterns, growth trends, and economic conditions. These findings support those of Roman et al. (2018) and Bigsby et al. (2014), which have shown that developmental legacies are important drivers of UTC. Within my analysis, I utilized the 'average year homes were built' as a proxy to represent the average time of development for residential areas. Within my population growth trend analysis, the 'average year homes were built' was an important predictor of UTC in 71% of cities with declining populations. This is likely a legacy effect, caused by planting during new development or planting programs initiated several decades ago before the decline when those cities were still growing and economically strong (Boone et al. 2010, Roman et al. 2018). Others report neighborhood age to be an influential variable on the abundance of UTC within a residential area (Lowry et al. 2012). Furthermore, economic and developmental legacies were represented in the population growth trends and sociocultural classifications. Population growth or decline within a city is often a reflection of the economic strength of the city (Rieniets 2009). The sociocultural classifications spanned cities that had similar development patterns. For example, the Midwest/ Great Lakes region contained many of the Rust Belt cities, which grew rapidly during the industrial revolution, but have struggled to expand economically over recent decades (Kahn 1999, Hartley 2013).

A Socioeconomic Sensitivity Index (SSI) was developed to measure and highlight how strongly socioeconomic variables predict UTC patterns and which variables are most important. Some cities had a very low SSI (low predictability), such as Chicago, IL, 0.09, while others a very high predictability, like Nampa, ID, with an SSI of 0.84. Within and among cities with a lower SSI value, the population's socioeconomic and demographic variables are not strong predictors of UTC inequity, suggesting other factors are influencing inequity. Other factors, such as the ecological legacies of the surrounding landscape, contribute to the amount and distribution of UTC (Fahey et al. 2012, Fahey and Casali 2017). Additionally, past socioeconomic legacies, which impact current UTC distribution, are not always reflected in the current socioeconomic census data (Boone et al. 2010). Within cities where the socioeconomic variables are strongly influencing the UTC inequity, managers can utilize socioeconomic data to target planting and maintenance efforts to help stem inequity. This study focused on the socioeconomic predictors within city limits. Future research may include the expansion of socioeconomic predictors past city limits and to the greater metropolitan regions. Expanding the area could help to examine possible differences in socioeconomic predictors and give researchers a better understanding of the relationships between spatial scale and socioeconomic predictors of UTC.

Previous studies have found a strong correlation between tree canopy, UTC inequity, and socioeconomic variables within cities (Iverson and Cook 2000, Landry and Chakraborty 2009, Lowry et al. 2012). My research supports and expands on these findings by identifying national and regional patterns in UTC inequity. Managers with a better understanding of the spatial distribution of UTC can help reduce inequity through planting and tree maintenance efforts. Furthermore, my research has highlighted possible environmental injustice issues related to UTC inequity and socioeconomic status in different regions of the country. This issue varies across the country due to the extent and influence of socioeconomic status related to UTC inequity. To better understand the impacts of UTC inequity, a macro scale analysis could be conducted on the inequity of ecological amenities (e.g. carbon sequestration, air quality, energy saving, etc.). Biophysical regions may influence the amount of inequity within ecological amenities, both within and among cities (Roman et al. 2018). This could help highlight environmental justice issues and improve understanding of the social or health impacts of UTC inequity. Management efforts should also focus on less affluent areas, so that more of the population may benefit from urban trees. Particularly, in the Western regions, it will be important for urban forest managers to develop long-term strategies to both plant and maintain urban trees to help stem the UTC inequity.

Table 1: The forty cities included in the study, with regional classifications, total percent UTC, Gini Coefficient, and SSI (strength of UTC predictability by socioeconomic variables) for each city.

City	State	Biophysical	Socio-cultural	Population Size	Population Trend	Total UTC	Gini Coefficient	SSI
Baltimore	MD	App High	NE	Large	Decreasing	23.3	0.37	0.36
Binghamton	NY	App High	MW/GL	Small	Decreasing	24.7	0.30	0.37
Boise	ID	Inter Plat	W	Medium	Increasing	22.1	0.23	0.59
Bridgeport	CT	App High	NE	Small	Sustaining	21.3	0.34	0.61
Burlington	VT	App High	NE	Small	Sustaining	36.1	0.20	0.32
Charlotte	NC	App High	SB	Large	Increasing	46.9	0.15	0.19
Chelsea	MA	App High	NE	Medium	Increasing	10.8	0.27	0.05
Chicago	IL	Int Plain	MW/GL	Large	Sustaining	19.5	0.23	0.10
Cleveland	OH	Int Plain	MW/GL	Medium	Decreasing	21.0	0.20	0.15
Davenport	IA	Int Plain	MW/GL	Small	Sustaining	26.8	0.22	0.30
Denton	TX	Int Plain	SB	Small	Increasing	34.5	0.25	0.18
Des Moines	IA	Int Plain	MW/GL	Medium	Increasing	32.3	0.18	0.22
El Paso	TX	Inter Plat	W	Large	Increasing	6.7	0.42	0.09
Fresno	CA	Pac Mt S	W	Medium	Increasing	20.3	0.25	0.49
Hartford	CT	App High	NE	Small	Decreasing	23.9	0.26	0.30
Honolulu	HI	Trop For	W	Large	Sustaining	18.4	0.40	0.17
Los Angeles	CA	Pac Mt S	W	Large	Sustaining	11.3	0.38	0.43
Madison	WI	Int Plain	MW/GL	Medium	Increasing	30.0	0.29	0.45
Meridian	ID	Inter Plat	W	Small	Increasing	9.5	0.30	0.73
Nampa	ID	Inter Plat	W	Small	Increasing	12.3	0.30	0.84
New Haven	CT	App High	NE	Small	Sustaining	32.4	0.23	0.19
New York	NY	Atl Plain	NE	Large	Increasing	16.8	0.31	0.09
Oakland	CA	Pac Mt S	W	Medium	Sustaining	12.7	0.47	0.62
Pawtucket	RI	App High	NE	Small	Sustaining	18.8	0.22	0.26
Philadelphia	PA	Atl Plain	NE	Large	Sustaining	17.5	0.37	0.37
Pittsburgh	PA	App High	MW/GL	Medium	Decreasing	37.1	0.25	0.31
Richmond	VA	App High	SB	Medium	Sustaining	22.4	0.34	0.46
Sacramento	CA	Pac Mt S	W	Medium	Increasing	17.7	0.31	0.48
San Diego	CA	Pac Mt S	W	Large	Increasing	12.1	0.37	0.27
San Francisco	CA	Pac Mt S	W	Large	Increasing	14.8	0.34	0.32
San Jose	CA	Pac Mt S	W	Large	Increasing	13.1	0.23	0.37
San Luis Obispo	CA	Pac Mt S	W	Small	Sustaining	14.6	0.27	0.48
Santa Barbara	CA	Pac Mt S	W	Small	Sustaining	23.3	0.27	0.49
Savannah	GA	Atl Plain	SB	Small	Sustaining	42.5	0.15	0.30
Sioux City	IA	Int Plain	MW/GL	Small	Sustaining	28.2	0.19	0.26
Syracuse	NY	App High	MW/GL	Small	Decreasing	32.1	0.20	0.42
Tacoma	WA	Pac Mt S	W	Medium	Increasing	22.9	0.27	0.28
Utica	NY	App High	MW/GL	Small	Decreasing	24.7	0.25	0.54
Virginia Beach	VA	Atl Plain	SB	Medium	Increasing	37.9	0.25	0.23
Washington	DC	Atl Plain	NE	Large	Increasing	26.4	0.22	0.26

Biophysical classification abbreviations: App High = Appalachian Highlands, Atl Plain = Atlantic Plains, Int Plain = Interior Plains, Inter Plat = Interior Plateaus, Pac Mt S = Pacific Mountain System. Socio-cultural classification abbreviations: NE = Northeast, MW/GL = Midwest/ Great Lakes, SB = Sun Belt, W = West.

Table 2: Socioeconomic predictor variables included in most highly supported multiple regression models for each city, see Appendix 1 for results and model coefficients for each individual city.

Cities	% Min	Pop Den	% Pov	Home Own	Med Inc	Col Deg	Yr Home Built	Home Val
Baltimore	X	X	X		X	X		X
Binghamton				X		X	X	
Boise	X	X		X		X	X	X
Bridgeport		X	X	X			X	X
Burlington	X				X		X	
Charlotte					X		X	X
Chelsea		X		X				
Chicago	X	X		X		X	X	X
Cleveland	X	X		X	X	X	X	
Davenport	X	X	X	X				X
Denton						X		
Des Moines		X	X	X				X
El Paso	X	X		X			X	X
Fresno	X	X	X	X	X	X		X
Hartford	X	X		X	X	X	X	X
Honolulu	X	X		X			X	
Los Angeles	X	X		X	X	X		X
Madison	X	X		X	X	X	X	
Meridian		X				X		X
Nampa		X		X	X		X	
New Haven	X			X		X		
New York	X	X		X	X	X		X
Oakland		X	X	X	X	X	X	X
Pawtucket	X	X		X				
Philadelphia	X	X		X	X	X		X
Pittsburgh	X	X		X	X	X		X
Richmond	X	X		X			X	
Sacramento	X	X	X		X	X	X	X
San Diego	X	X			X	X	X	X
San Francisco	X	X	X	X		X		X
San Jose	X	X	X			X		X
San Luis Obispo	X	X		X	X		X	
Santa Barbra		X	X	X	X	X	X	X
Savannah	X			X		X	X	X
Sioux City		X		X				
Syracuse	X	X	X	X		X	X	X
Tacoma	X	X	X		X		X	X
Utica				X	X	X	X	
Virginia Beach	X	X	X	X				
Washington		X			X			X

Socioeconomic predictor variable abbreviations: % Min = Percent Minority, Pop Den = Population Density, % Pov = Percent Poverty, Home Own = Percent of Home Owners, Med Inc = Median Income, Col Deg = Percent of Population with College Degrees, Yr Home Build = Median Year Homes were Built in the City, Home Val = Median Home Value for the City.

Table 3: Socioeconomic predictor variables included in multiple regression models by region and city population classification. A variable was considered to be an important predictor of UTC if it was present in 75% or more of cities within each region, highlighted here in bold font.

	% Min	Pop Den	% Pov	Home Own	Med Inc	Col Deg	Yr Home Built	Home Val
Biophysical Regions								
Appalachian Highlands	62	62	23	**85**	38	54	62	46
Interior Plains	57	**86**	29	**86**	29	57	43	43
Intermountain Plateaus	50	**100**	0	**75**	25	50	**75**	**75**
Pacific Mountain System	**80**	**100**	70	60	**80**	**80**	60	**90**
Atlantic Plains	**80**	**80**	20	**80**	60	60	20	**80**
Socio Cultural Regions								
The Northeast	70	**80**	20	70	60	50	30	60
The West	73	**100**	47	67	60	67	67	**80**
Midwest/ Great Lakes	60	**80**	30	**100**	40	70	60	50
The Sun Belt	60	40	20	**80**	0	40	60	40
City Population Size								
Large	**83**	**92**	25	67	50	67	42	**92**
Medium	**82**	**100**	55	**82**	64	64	64	64
Small	47	65	24	**82**	35	53	59	41
Population Trends								
Increasing	61	**89**	39	61	44	56	44	72
Sustaining	73	**80**	27	**93**	40	47	60	53
Decreasing	71	71	14	**86**	71	**100**	71	57

Socioeconomic predictor variable abbreviations: % Min = Percent Minority, Pop Den = Population Density, % Pov = Percent Poverty, Home Own = Percent of Home Owners, Med Inc = Median Income, Col Deg = Percent of Population with College Degrees, Yr Home Build = Median Year Homes were Built in the City, Home Val = Median Home Value for the City.

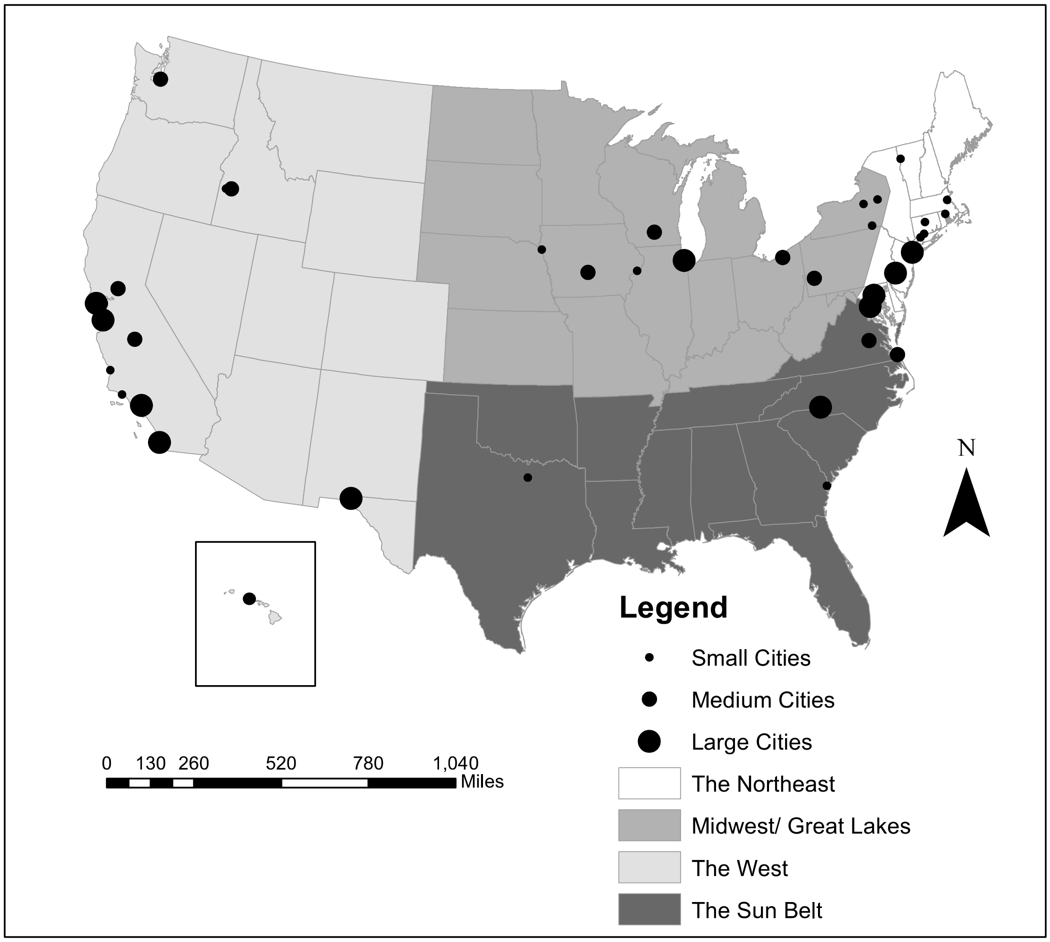

Figure 1: Locations of study cities within the sociocultural regions of the contiguous United States and Hawaii; city population category indicated by city size and total UTC by symbol color.

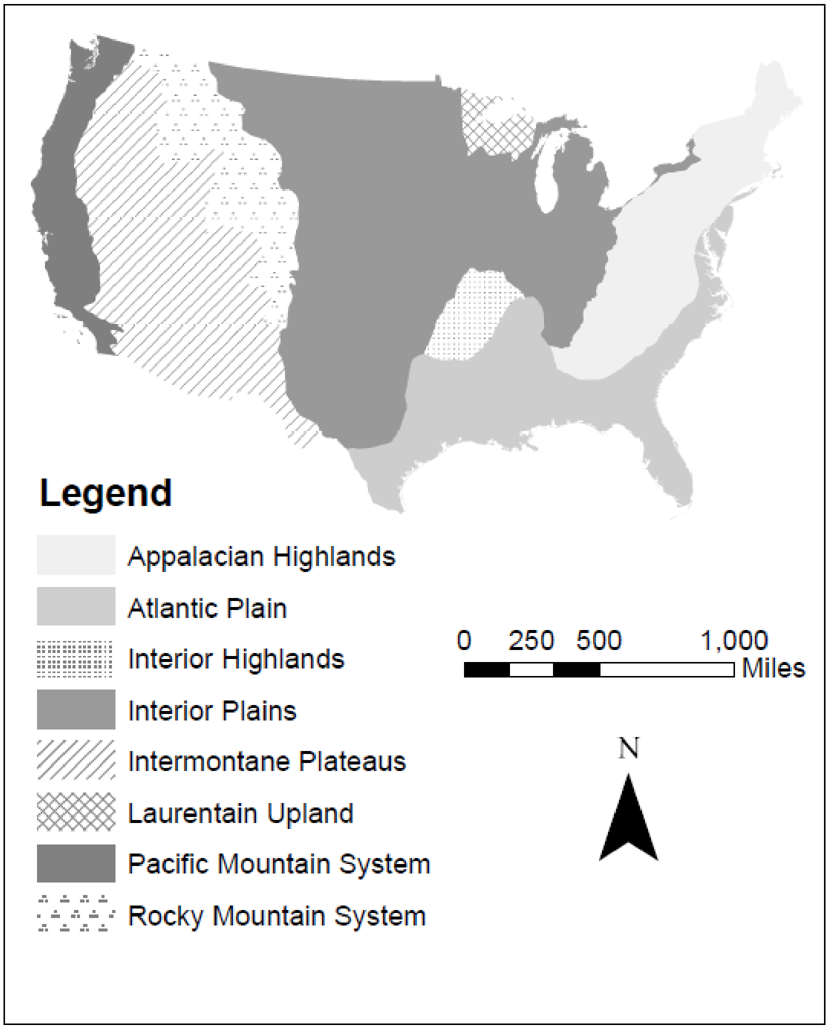

Figure 2: USGS Physiographic Regions used within the biophysical regional analysis.

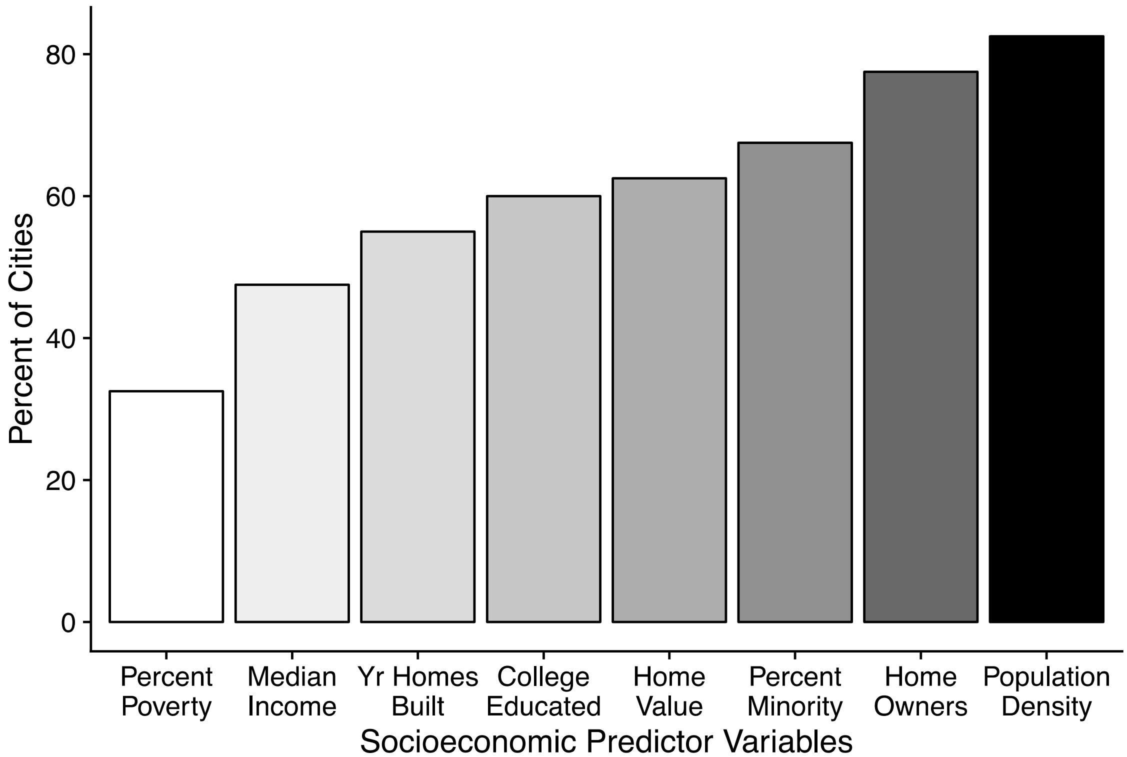

Figure 3: Percent of city-scale multiple regression models relating percent urban tree canopy to socioeconomic predictors that each individual predictor variable entered into.

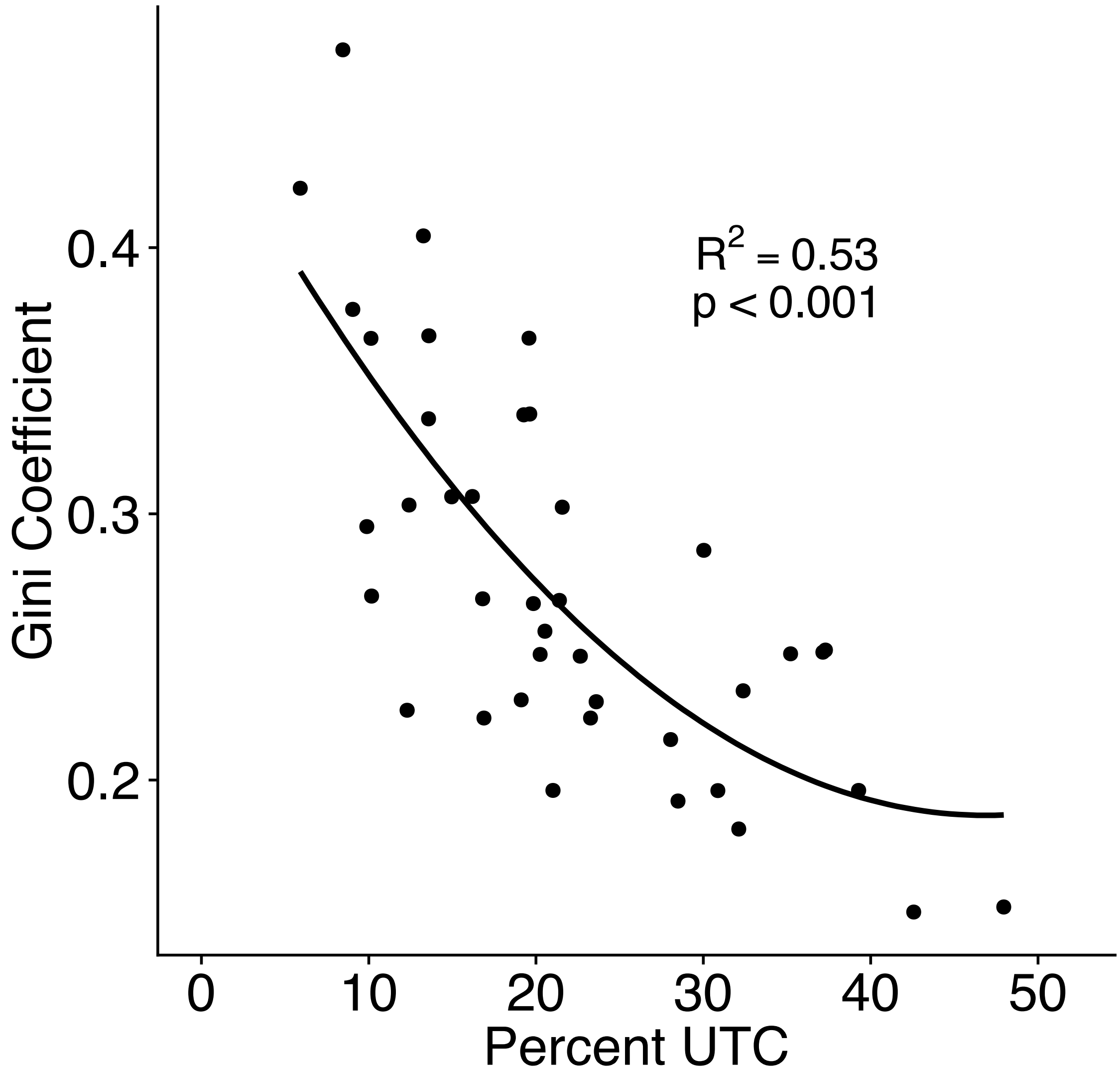

Figure 4: Plot of city scale percent urban tree canopy (UTC) versus inequity in UTC at the CBG scale (as the Gini Coefficient) illustrating a strong negative relationship across cities at the continental scale.

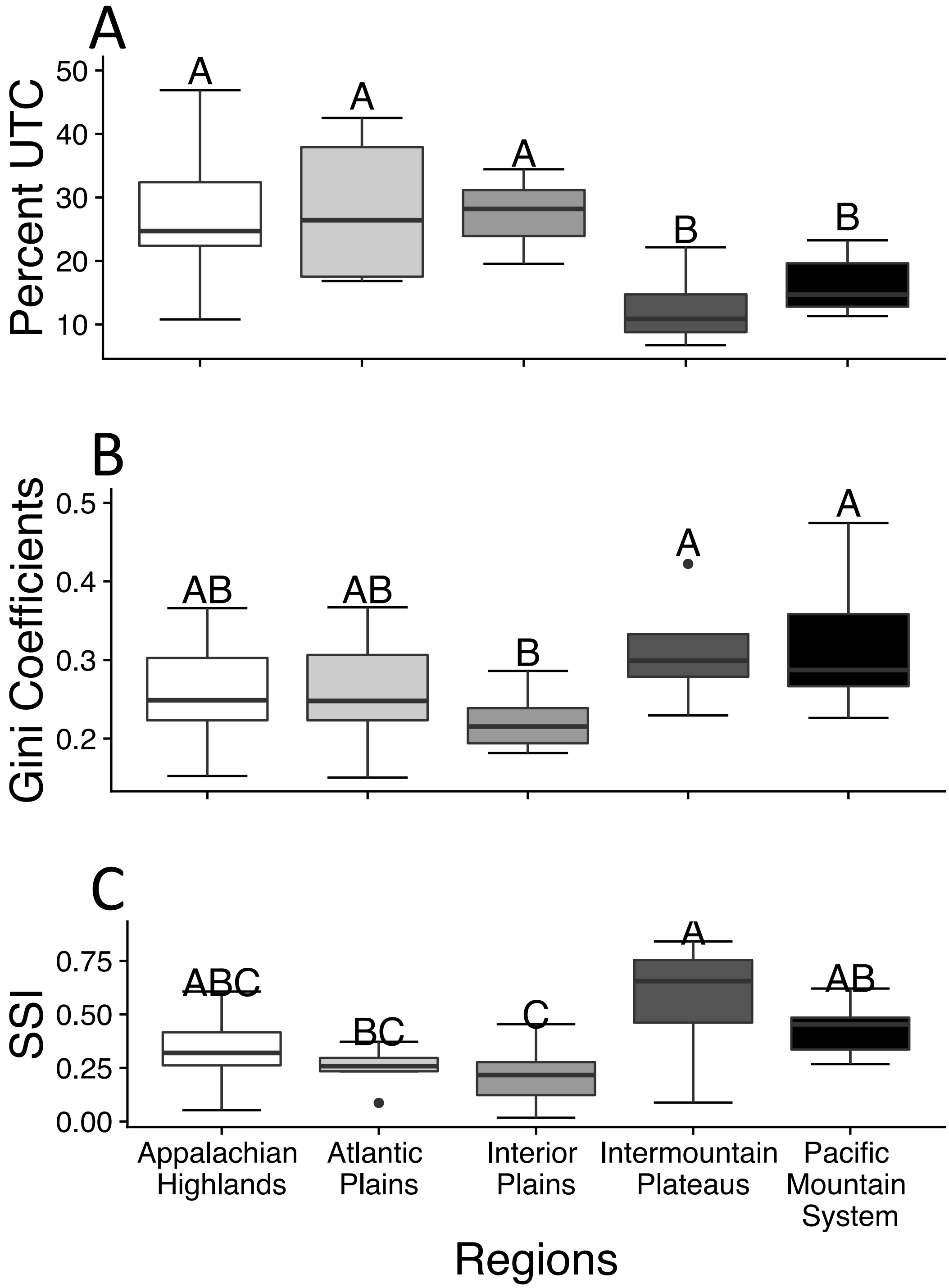

Figure 5: Results of analysis of variance comparing a) urban tree canopy (UTC) percentage, b) UTC inequity (as the Gini Coefficient), and c) the strength of the relationship between UTC and socioeconomic predictors (as the Socioeconomic Sensitivity Index- SSI) among biophysical regions. Results of multiple comparison tests when ANOVA main effects were significant, different letters indicate significant differences among categories.

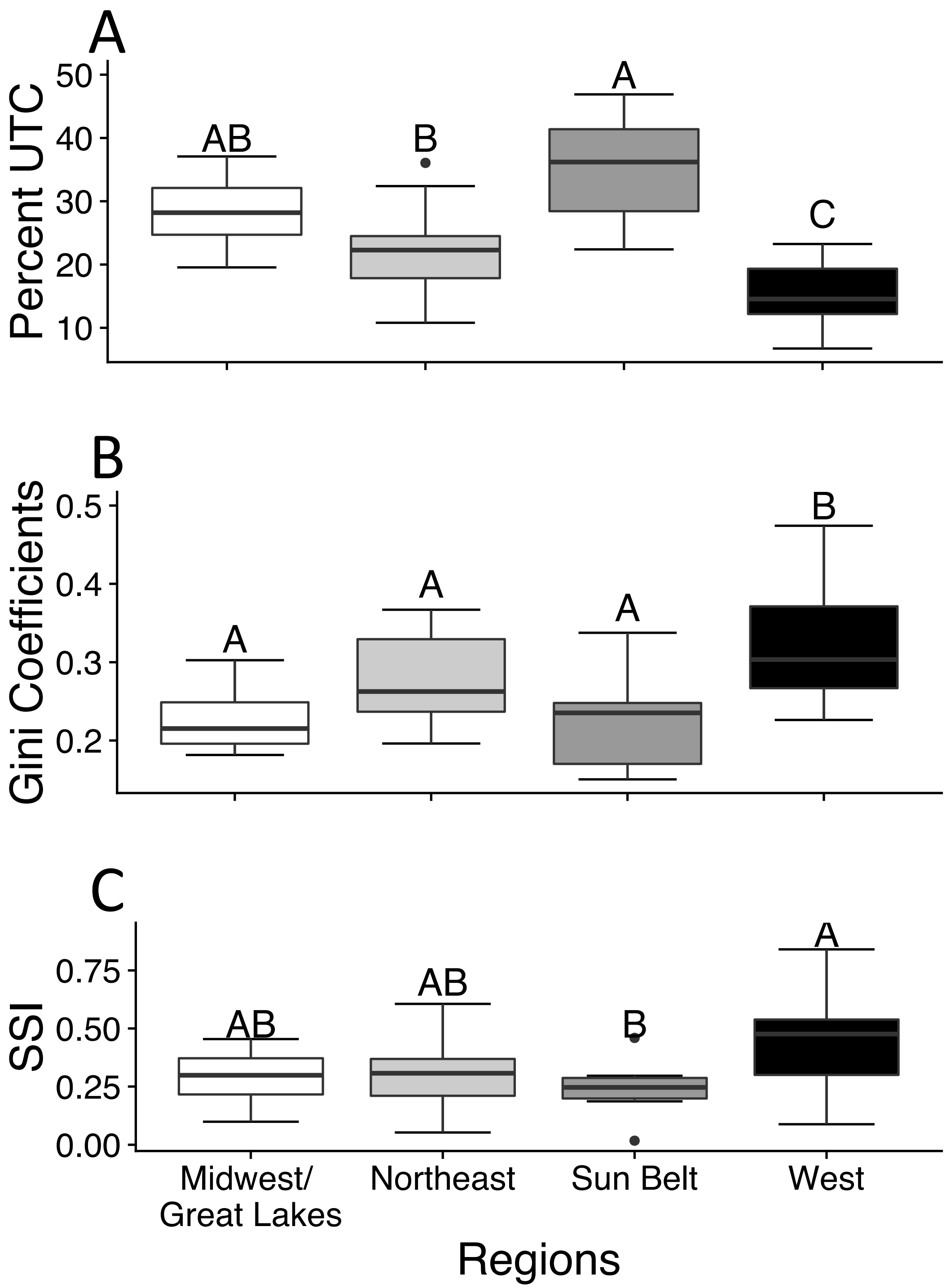

Figure 6: Results of analysis of variance comparing a) urban tree canopy (UTC) percentage, b) UTC inequity (as the Gini Coefficient), and c) the strength of the relationship between UTC and socioeconomic predictors (as the Socioeconomic Sensitivity Index- SSI) among sociocultural regions. Results of multiple comparison tests when ANOVA main effects were significant, different letters indicate significant differences among categories.

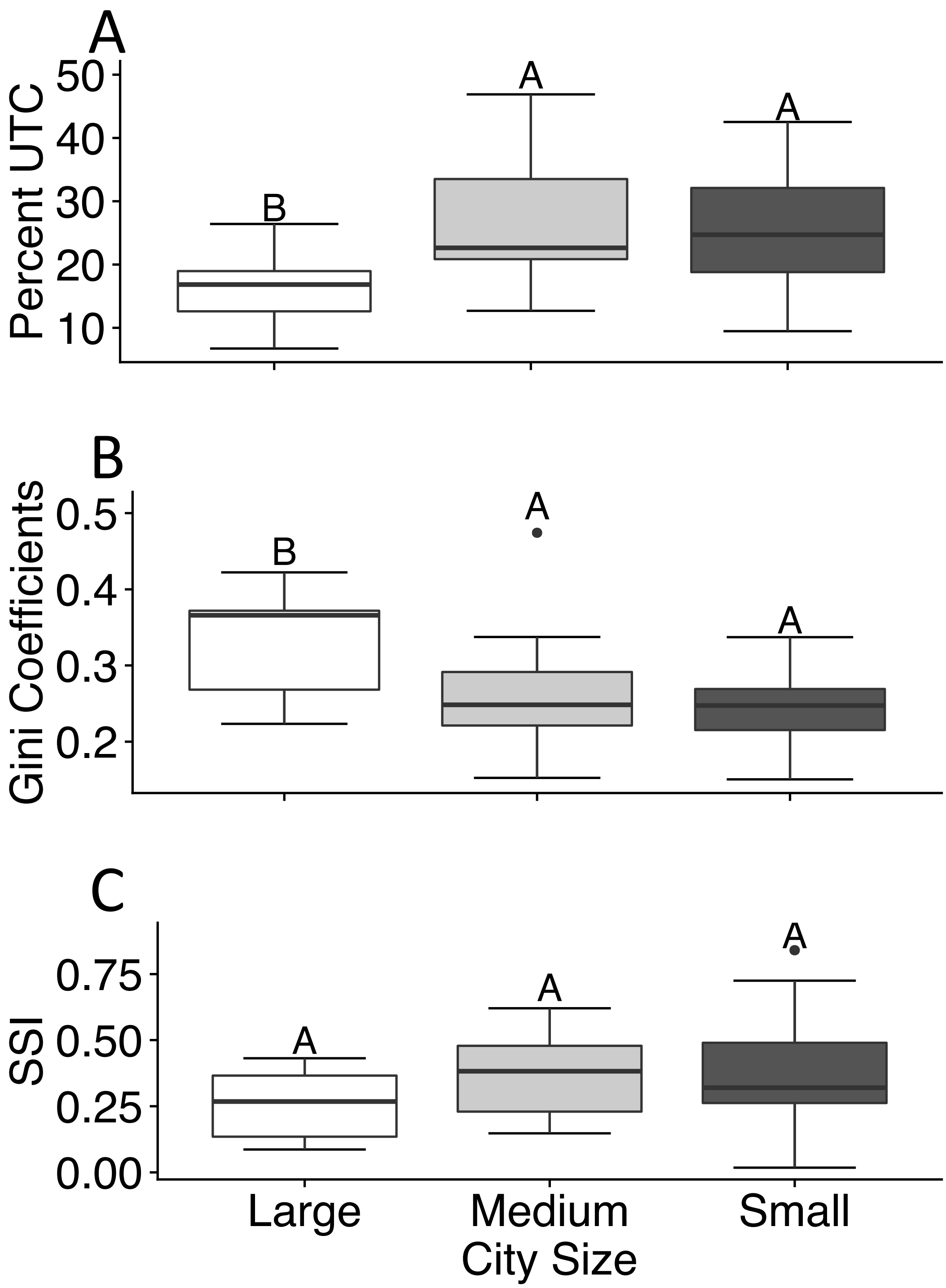

Figure 7: Results of analysis of variance comparing a) urban tree canopy (UTC) percentage, b) UTC inequity (as the Gini Coefficient), and c) the strength of the relationship between UTC and socioeconomic predictors (as the Socioeconomic Sensitivity Index- SSI) among population size categories. Results of multiple comparison tests when ANOVA main effects were significant, different letters indicate significant differences among categories.

References

Barton, K. (2018). Package 'MuMIn'. *R Package Version 1.40.4*

Beaugrand, G., Edwards, M., & Legendre, L. (2010). Marine biodiversity, ecosystem functioning, and carbon cycles. *Proceedings of the National Academy of Sciences*, *107*(22), 10120-10124.

Bolund, P., & Hunhammar, S. (1999). Ecosystem services in urban areas. *Ecological Economics*, *29*(2), 293-301.

Boone, C. G., Cadenasso, M. L., Grove, J. M., Schwarz, K., & Buckley, G. L. (2010). Landscape, vegetation characteristics, and group identity in an urban and suburban watershed: why the 60s matter. *Urban Ecosystems*, *13*(3), 255-271.

Burnham, D.P. & Anderson, D.P. (2002) *Model selection and multimodel inference- a practical information-theoretic approach.* Springer-Verlag, New York, NY.

Chiesura, A. (2004). The role of urban parks for the sustainable city. *Landscape and Urban Planning*, *68*(1), 129-138.

Dalgaard, P. (2008). *Introductory Statistics with R*. Springer- Verlag, New York, NY.

Duryea, M.L., Kampf, E., Littell, R.C. (2007). Hurricanes and the urban forest: 1. effects on southeastern United States coastal plain tree species. *Arboriculture and Urban Forestry*, 33, 83–97.

Dwyer, J. F., McPherson, E. G., Schroeder, H. W., & Rowntree, R. A. (1992). Assessing the benefits and costs of the urban forest. *Journal of Arboriculture*, *18*, 227-234.

Dwyer, M. C., & Miller, R. W. (1999). Using GIS to assess urban tree canopy benefits and surrounding greenspace distributions. *Journal of Arboriculture*, *25*, 102-107.

Elmqvist, T., Setälä, H., Handel, S. N., Van Der Ploeg, S., Aronson, J., Blignaut, J. N., ... & De Groot, R. (2015). Benefits of restoring ecosystem services in urban areas. *Current opinion in environmental sustainability*, *14*, 101-108.

Fahey, R. T., Bowles, M. L., & McBride, J. L. (2012). Origins of the Chicago urban forest: composition and structure in relation to presettlement vegetation and modern land use. *Arboriculture & Urban Forestry*, *38*(5), 181-193.

Fahey, R. T., & Casali, M. (2017). Distribution of forest ecosystems over two centuries in a highly urbanized landscape. *Landscape and Urban Planning*, *164*, 13-24.

Faraway, J.J. (2002). *Practical Regression and Anova using R*. University of Alberta, CA

Gómez-Baggethun, E., & Barton, D. N. (2013). Classifying and valuing ecosystem services for urban planning. *Ecological Economics*, *86*, 235-245.

Grove, J. M., Locke, D. H., & O'Neil-Dunne, J. P. (2014). An ecology of prestige in New York City: Examining the relationships among population density, socio-economic status, group identity, and residential canopy cover. *Environmental Management*, *54*(3), 402-419.

Hartley, D. (2013). Urban decline in rust-belt cities. *Federal Reserve Bank of Cleveland Economic Commentary*, (2013-06).

Heynen, N. C., & Lindsey, G. (2003). Correlates of urban forest canopy cover: implications for local public works. *Public Works Management & Policy*, *8*(1), 33-47.

Heynen, N., Perkins, H. A., & Roy, P. (2006). The political ecology of uneven urban green space: the impact of political economy on race and ethnicity in producing environmental inequality in Milwaukee. *Urban Affairs Review*, *42*(1), 3-25.

Hollander, J. B., Pallagst, K., Schwarz, T., & Popper, F. J. (2009). Planning shrinking cities. *Progress in Planning*, *72*(4), 223-232.

iTree Software Suite User's Manual v2.1 (2008), US Forest Service, Retrieved 10/10/16 from https://www.itreetools.org/resources/manuals/i-Tree%20v2.1%20Users%20Manual.pdf

Iverson, L. R., & Cook, E. A. (2000). Urban forest cover of the Chicago region and its relation to household density and income. *Urban Ecosystems*, *4*(2), 105-124.

Jenerette, G. D., Harlan, S. L., Stefanov, W. L., & Martin, C. A. (2011). Ecosystem services and urban heat riskscape moderation: water, green spaces, and social inequality in Phoenix, USA. *Ecological Applications*, *21*(7), 2637-2651.

Jensen, R., Gatrell, J., Boulton, J., & Harper, B. (2004). Using remote sensing and geographic information systems to study urban quality of life and urban forest amenities. *Ecology and Society*, *9*(5), 5.

Kahn, M. E. (1999). The silver lining of rust belt manufacturing decline. *Journal of Urban Economics*, *46*(3), 360-376.

Kaplan, S. (1995). The restorative benefits of nature: Toward an integrative framework. *Journal of Environmental Psychology*, *15*(3), 169-182.

Kendal, D., Williams, N. S., & Williams, K. J. (2012). Drivers of diversity and tree cover in gardens, parks and streetscapes in an Australian city. *Urban Forestry & Urban Greening*, *11*(3), 257-265.

Kuo, F. E. (2003). Social aspects of urban forestry: The role of arboriculture in a healthy social ecology. *Journal of Arboriculture. 29*(3): 148-155.

Lambert, P. J., & Aronson, J. R. (1993). Inequality decomposition analysis and the Gini coefficient revisited. *The Economic Journal*, *103*(420), 1221-1227.

Landry, S. M., & Chakraborty, J. (2009). Street trees and equity: evaluating the spatial distribution of an urban amenity. *Environment and Planning a*, *41*(11), 2651-2670.

Lovasi, G. S., O'Neil-Dunne, J. P., Lu, J. W., Sheehan, D., Perzanowski, M. S., MacFaden, S. W., ... & Perera, F. P. (2013). Urban tree canopy and asthma, wheeze, rhinitis, and allergic sensitization to tree pollen in a New York City birth cohort. *Environmental Health Perspectives (Online)*, *121*(4), 494.

Lowry, J. H., Baker, M. E., & Ramsey, R. D. (2012). Determinants of urban tree canopy in residential neighborhoods: household characteristics, urban form, and the geophysical landscape. *Urban Ecosystems*, *15*(1), 247-266.

Luck, G. W., Smallbone, L. T., & O'Brien, R. (2009). Socio-economics and vegetation change in urban ecosystems: patterns in space and time. *Ecosystems*, *12*(4), 604.

Nowak, D. J. (1993). Atmospheric carbon reduction by urban trees. *Journal of Environmental Management*, 37,207-217.

Nowak, D. J., Crane, D. E., Stevens, J. C., Hoehn, R. E., Walton, J. T., & Bond, J. (2008). A ground-based method of assessing urban forest structure and ecosystem services. *Aboriculture & Urban Forestry. 34 (6): 347-358.*, *34*(6).

Nowak, D. J., & Greenfield, E. J. (2012). Tree and impervious cover change in US cities. *Urban Forestry & Urban Greening*, *11*(1), 21-30.

Nowak, D. J., Noble, M. H., Sisinni, S. M., & Dwyer, J. F. (2001). People and trees: assessing the US urban forest resource. *Journal of Forestry*, *99*(3), 37-42.

O'Neill, M. S., Jerrett, M., Kawachi, I., Levy, J. I., Cohen, A. J., Gouveia, N., ... & Schwartz, J. (2003). Health, wealth, and air pollution: advancing theory and methods. *Environmental Health Perspectives*, *111*(16), 1861.

Oswalt, P., & Rieniets, T. (2007). Global context. Shrinking cities. *Atlas of Shrinking Cities*.

Perkins, H. A., Heynen, N., & Wilson, J. (2004). Inequitable access to urban reforestation: the impact of urban political economy on housing tenure and urban forests. *Cities*, *21*(4), 291-299.

Price, C. (2003). Quantifying the aesthetic benefits of urban forestry. *Urban Forestry & Urban Greening*, 1(3), 123-133.

Roman, L. A., Pearsall, H., Eisenman, T. S., Conway, T. M., Fahey, R. T., Landry, S., ... & Bardekjian, A. C. (2018). Human and biophysical legacies shape contemporary urban forests: A literature synthesis. *Urban Forestry & Urban Greening*.

Schwarz, K., Fragkias, M., Boone, C. G., Zhou, W., McHale, M., Grove, J. M., ... & Ogden, L. (2015). Trees grow on money: urban tree canopy cover and environmental justice. *PLoS One*, 10(4), e0122051.

Troy, A., Grove, J. M., & O’Neil-Dunne, J. (2012). The relationship between tree canopy and crime rates across an urban–rural gradient in the greater Baltimore region. *Landscape and Urban Planning*, 106(3), 262-270.

United States Census Bureau, US Census 1990-2010, https://www.census.gov/data.html

United States Department of Agriculture, Census of Agriculture Reports, 2012. https://agcensus.usda.gov/Publications/2012/Full_Report/Census_by_State/

United States Geological Survey, 2003. http://ulpeis.anl.gov/documents/dpeis/references/pdfs/USGS_2003.pdf

Vandello, J. A., & Cohen, D. (1999). Patterns of individualism and collectivism across the United States. *Journal of Personality and Social Psychology*, *77*(2), 279.

Yitzhaki, S. (1979). Relative deprivation and the Gini coefficient. *The Quarterly Journal of Economics*, 321-324.