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Assessing macro-scale patterns in urban tree canopy and inequality

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ABSTRACT

Urban forests provide a variety of ecosystem services that influence environmental and social welfare, but variable distribution of urban tree canopy (UTC) within and among urban areas can lead to inequitable provisioning of these benefits. Variation in UTC among and within urban areas is associated with local development patterns and socio-economic factors as well as broad-scale variation in the biophysical and socio-cultural context of urban regions. The objective of this study was to evaluate regional and continental trends in UTC distribution within and among urban areas, including assessing relationships of UTC and UTC inequality with socio-economic/demographic factors and characteristics of urban regions. Remotely-sensed UTC assessments and US Census data were used to derive census block group-level UTC-related response variables (e.g., percent UTC, inequality in UTC) and socio-economic/demographic predictor variables (e.g., median income, population density) for forty U.S. cities spanning several biophysical and socio-cultural regions. Multiple regression analysis was used to analyze relationships of UTC with socio-economic/demographic predictor variables and the strength of these relationships was compared among cities across regions. There was a significant negative relationship ($R^2 = 0.45$) between total UTC and UTC inequality across the 40 cities, as the equality of UTC distribution within cities increased with decreasing total UTC. There was significant variation across biophysical and socio-cultural regions in UTC, UTC inequality, and the strength of the correlation of fine scale UTC with socio-economic/demographic factors. These findings illustrate the important role of broad-scale biophysical and socio-cultural factors as drivers of UTC patterns within and among cities.

1. Introduction

Urban forests provide many ecosystem benefits to metropolitan areas, which impact the environmental and social wellbeing of urban communities (Kuo, 2003). Ecological benefits of urban forests include globally relevant services such as carbon sequestration as well as locally and regionally important factors such as storm water mitigation, air and water quality improvements, and wildlife habitat (Dwyer et al., 1992; Nowak, 1993). Urban forests provide social and health benefits such as reduced rates of respiratory illnesses, reduced crime rates, and increased use of neighborhood common spaces (Kuo, 2003; Elmqvist et al., 2015; Kondo et al., 2017) as well as economic value, such as raising property values (Price, 2003). The extent to which these benefits impact an urban area are affected by forest structure, tree health, species composition, and urban tree canopy (UTC) extent (Nowak et al., 2008). Expansion of overall canopy cover in an urban area can increase the ecological, socio-economic, and health benefits accruing to urban residents (Nowak et al., 2001), although the social and ecological context of different regions and neighborhoods can affect the real and perceived benefits of urban forests (Pataki et al., 2011).

There is also often an uneven distribution of UTC among communities and neighborhoods within cities and metro regions (Landry and Chakraborty, 2009; Schwarz et al., 2015; Riley and Gardiner, 2020). As a result, inequities can exist in the level of urban forest-related ecosystem benefits received by the population across an urban area (Troy et al., 2012; Lovasi et al., 2013; Nesbitt et al., 2018). In such cases,

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purely expanding UTC at a city scale, such as through “Million Tree” campaigns (McPherson et al., 2011), may not benefit those residents that are least well served by this aspect of green infrastructure (Garrison, 2019). Addressing these inequities requires quantifying spatial patterns in UTC at various scales within and among communities and neighborhoods (Grove et al., 2014; Locke et al., 2016) to improve targeting of tree planting and maintenance efforts. However, understanding the underlying socio-ecological factors that drive inequities within and among urban areas will also be essential in resolving this important aspect of environmental justice (Schwarz et al., 2015; Riley and Gardiner, 2020).

Local, neighborhood-scale socio-economic and demographic patterns can be strongly associated with urban forest structure and benefits (Jensen et al., 2004; Kendal et al., 2012; Lowry et al., 2012; Gerrish and Watkins, 2018). Within urban areas, socio-economically disadvantaged neighborhoods often have fewer trees, parks, and other vegetated areas, leading to fewer social and ecological benefits received by residents (Bolund and Hunhammar, 1999; Luck et al., 2009; Grove et al., 2014). Demographic factors, such as the racial or ethnic makeup of neighborhoods, have also been shown to be highly related to levels of UTC (Heynen and Lindsey, 2003; Watkins and Gerrish, 2018). However, neighborhood demographics are not stable over time and legacy effects can obscure these relationships (Boone et al., 2010; Grove et al., 2018), which may be reflected in the finding that neighborhood age can have strong impacts on the urban tree canopy as well (Lowry et al., 2012; Schwarz et al., 2015). Also, political and management decision-making surrounding urban forests, such as the planting of monocultures or implementation of ordinances, can have lasting effects on the urban tree canopy (Roman et al., 2018; Hilbert et al., 2019). These biophysical and socio-economic 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).

Cities function as a part of broader biophysical and socio-economic systems, which can have substantial effects on the structure, make-up, and service provisioning associated with urban forests (Jenerette et al., 2011; Roman et al., 2018; Johnson et al., 2020). Several studies have shown that macro-scale socio-ecological factors, such as the overarching biophysical and ecoregional setting, governance and stewardship patterns, interacting human/natural disturbance regimes, and individual disasters such as fires or storm events, can profoundly influence levels of UTC within urban areas (Schwarz et al., 2015; Berland et al., 2016; Fahey and Casali, 2017; Roman et al., 2018). For example, cities in temperate, mesic areas such as the northeastern US are situated in ecosystems with high pre-development canopy cover and spontaneous establishment of trees, whereas tree canopy in cities in more arid regions is largely intentionally planted and maintained (Nowak et al., 2001; Nowak and Greenfield, 2012). UTC patterns can also have multiple spatial and temporal dimensions; as an example, coastal ecoregions are impacted by frequent and intense windstorms and hurricanes that damage trees and remove canopy (Duryea et al., 2007). Such disturbances then lead to multi-scale management and governance responses (such as species selection and ordinances) that can result in altered local urban forests that may be better able to withstand future storms (Conway and Yip, 2016; Hilbert et al., 2019).

Biophysical setting, socio-economic and demographic conditions, and developmental legacies at a variety of spatial scales, therefore, have the potential to affect the distribution of UTC within and among cities (Nowak et al., 1996; Heynen, 2003; Roman et al., 2018; Johnson et al., 2020). Given that patterns of UTC vary across regions and types of cities (Nowak and Greenfield, 2012), it is likely that the distribution of UTC within a city (and how equal it is) could also vary substantially across cities and regions (Schwarz et al., 2015; Nesbitt et al., 2019; Riley and Gardiner, 2020). The primary objective of this study was to better understand macro-scale patterns of UTC and patterns of unequal distribution of UTC within and among urban areas situated across biophysical and socio-cultural regions spanning the United States. Specific research questions included: *1)* How much inequality in UTC is there among neighborhoods within cities and how is UTC inequality related to total city-scale UTC?; and *2)* Do total UTC, and UTC inequality, and the strength of the relationship between within-city UTC distribution and socio-economic and demographic predictors vary across macro-scale biophysical and socio-cultural regions? The findings of this analysis provide a broader context in which to frame understanding of variability in UTC within and among urban areas.

2. Methods

2.1. Study areas and classification strategies

The analysis spanned forty cities spread geographically across the conterminous United States and Hawaii (Fig. 1), selected based on availability of fine spatial resolution (1m × 1m) UTC data layers derived from remotely sensed imagery and LiDAR data (iTree, 2019). We utilized the i-Tree Landscape database to access UTC data layers, all layers included in this database are required to have documented 90 % or greater accuracy in distinguishing canopy and (further information on characteristics of data layers included in this database can be found at: https://landscape.itreetools.org/hires). Urban tree canopy cover estimates were extracted at the census block group scale (the finest resolution analysis unit available in iTree Landscape) from fine-resolution UTC assessments included in the i-Tree Landscape database (iTree, 2019). Analysis was constrained to the USA in part because this is the area covered by the iTree Landscape database, but also because we were interested in comparing cities across closely aligned geographic regions and avoiding major differences in historical and political development patterns that would affect comparisons with cities in other global regions (such as Europe or Asia). Analysis of UTC patterns was limited to political city boundaries because a large majority of urban regions only had fine-resolution UTC for the core city. City population (based on 2010 Census data) ranged from 42,000 in Burlington, VT to 8.1 million in New York City. The mean number of Census Block Groups included in each city was 557 and varied from 6569 in New York City to 22 in Meridian, ID (Supplemental Material, Table S1). To identify patterns of variation among cities in UTC and inequality, cities were grouped into four different regional and demographic classifications, based on biophysical, socio-cultural, population size, and population trend (Supplemental Material, Table S1).

First, to characterize variation associated with underlying biophysical regime, cities were classified based on the United States Geological Survey Physiographic Ecoregions classification system (Fenneman and Johnson, 1946). This classification system utilizes ecological, hydrological, and climatological indices to divide the continental United States and Hawaii into nine distinct ecoregions (Supplemental Material, Table S1, Fig. S1). 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; Supplemental Material, Table S1).

Second, to better understand broad socio-cultural and developmental influences on UTC and inequality, cities were classified into four geographically-based socio-cultural regions: the Northeast, the Midwest/Great Lakes, the West, and the Sun Belt (Fig. 1). Although there are myriad potential ways of classifying socio-cultural regions, we used broad groupings that focused on regional similarities in demographic, sociological, cultural, and economic factors and that resulted in similar sample sizes of cities across regions. For example, the Midwest/Great Lakes region was based largely on shared economic development patterns, and consisted of industrial and agricultural cities from the Rust Belt and Great Plains (Kahn, 1999; Hartley, 2013). Urban areas making up this region, which includes cities in the northeastern part of the country such as Pittsburgh, Cleveland, Syracuse, and Utica, boomed during the industrial revolution, but have declined economically over

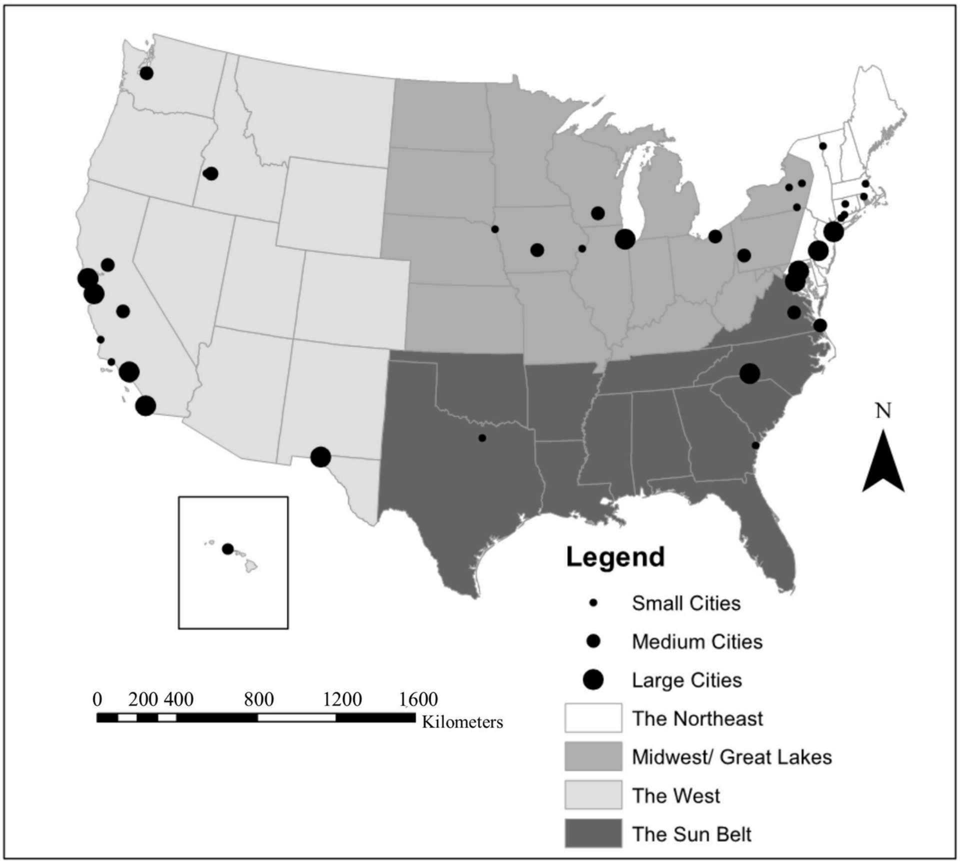

Fig. 1. Locations of study cities within the socio-cultural regions of the contiguous United States and Hawaii; city population category indicated by city size and total UTC by symbol color.

the last several decades along with major industries, such as steel and coal production (Kahn, 1999; Hartley, 2013). Cultural patterns were also factored into delineation of regions, for example in the southern Sun Belt, where shared histories and traditions dominate the social identity (Vandello and Cohen, 1999). See Table S1 in Supplemental Material for complete list of classifications.

Third, to evaluate possible relationships between city size and UTC patterns, cities were classified according to total population using US Census Bureau Data (U.S.Census.Bureau, 2019). To match the geographic availability of the UTC data only populations within city political limits were considered (not the entire metro region) and 2010 Census data were utilized to best match the timing of the majority of the UTC data. A categorization was developed that balanced sample size among groups and matched widely used characterizations of city size. A city was considered small if it had a population of less than 150,000, medium-size cities had populations between 150,000 and 600,000 people, and any city with a population of over 600,000 people was categorized as large. Of the forty cities studied, 17 were categorized as small, 11 medium, and 12 large (Supplemental Material, Table S1).

Finally, cities were classified according to population growth trends between 1990 and 2010 based on US Census Bureau Data (U.S.Census. Bureau, 2019). Cities were organized into one of three subcategories: increasing, sustaining, or decreasing. Prior studies have considered cities with populations of over 100,000 at their peak, to be 'shrinking' if the population decreased by more than 10 % (Hollander et al., 2009). Therefore if population of a city declined by 10 % or more, it was categorized as having a decreasing population. Similarly, if population grew by 10 % or more, the population was categorized as increasing. If population in a city neither increased nor decreased by 10 %, the city was categorized as having a sustaining population. Across the forty cities, 18 had increasing population, 15 sustaining, and 7 decreasing (Supplemental Material, Table S1).

2.2. Data analysis

To address RQ1 UTC and UTC inequality (as measured by the Gini Coefficient) were quantified and simple linear regression was used to evaluate whether UTC inequality was related to total city-scale UTC across the full 40 city data set and within regional and demographic classifications. The level of UTC inequality for each city was quantified using the Gini Coefficient, which is a well-established metric often applied to economic data that gauges the degree of inequality in a factor of interest (Yitzhaki, 1979; Lambert and Aronson, 1993). This metric has recently been more commonly applied to quantify 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, with larger numbers indicating greater levels of inequality. For this study, the Gini Coefficient of tree canopy cover among census block groups was used to characterize inequality in UTC within each city.

To better understand variation across cities and regions in how strongly socio-economic variables predict UTC within cities, we derived a "Socio-Sensitivity Index" (SSI) as the adjusted R^2 for the most highly supported model from a multiple regression analysis for each city. The index ranges from 0 to 1, with higher numbers representing higher predictability of UTC by the socio-economic predictor variables. Socio-economic and demographic data were derived from US Census Bureau information (U.S.Census.Bureau, 2019), also at the census block group scale using 2010 Census Data to match timing of UTC data collection and the Census Block Group designations. Socio-economic variables included in the analysis included median income, percent poverty (annual income $\leq$ \$22,314; U.S.Census.Bureau, 2019), and median home values. Socio-demographic variables used in the analysis included percent minority, population density, percent home ownership, percent of population with college degrees, and average year homes were built. To derive the SSI we used non-spatially weighted multiple regression in an information-theoretic model selection framework to relate UTC and the aforementioned eight socio-economic and demographic predictor variables (RQ2) at the census block group scale. In each city, a set of candidate models was evaluated to assess which combination of variables most effectively predicted variation in UTC within the city (Supplemental Material, Table S2). Akaike's Information Criterion (AIC) was used to rank models within the model set based on Akaike weights (Anderson and Burnham, 2004) and the most highly supported model was used to produce the SSI index. All regression and AIC models were conducted in R Studio using several packages, including *lm* and *dredge* from *MuMIn* (Barton, 2018; R.Studio, 2018).

To address patterns of variation in response variables among regional and demographic classifications (RQ2), means for UTC, UTC inequality, and SSI were compared across the four categories (Table 1) using analysis of variance (ANOVA). Prior to conducting ANOVA assumptions of normality and equal variance were tested for each response variable and all response variables met the assumptions of ANOVA. If the ANOVA test indicated significant differences among categories ($p \leq 0.05$), individual comparisons were made with adjustment for multiple comparisons (Holm-Sidak adjustment). Several packages were used in R Studio, including *aov*, to check data for assumptions of ANOVA, conduct the ANOVA analysis, and complete multiple comparisons tests (R.Studio, 2018).

3. Results

3.1. Patterns in UTC and inequality (RQ1)

UTC varied substantially among cities, from a low of 6.7 % in El Paso, TX to a high of 46.9 % in Charlotte, NC (Supplemental Material, Table S1). UTC inequality based on the Gini Coefficient ranged from a low of 0.15 in Savannah, GA to a high of 0.47 in Oakland, CA (Supplemental Material, Table S1). Across all cities, there was a negative correlation between overall city scale UTC and the level of UTC inequality in the city ($R^2 = 0.45$, $p < 0.001$; Fig. 2). Generally, as overall UTC increased, the amount of UTC inequality declined. The relationship between UTC and inequality varied to some extent, in strength but not direction, across regions as well (Table 1). For example, the relationship between UTC and inequality had an R^2 of 0.92 in the Sun Belt, but only 0.03 in the Midwest, indicating that the city-scale level of UTC was strongly related to inequality in the Sun Belt, but not in the Midwest.

Table 1
Mean values for regions and population categories (see text for details) of city-scale urban tree canopy characteristics including: total percent UTC, UTC Inequality as the Gini Coefficient across Census Block Groups, a Socio-Sensitivity Index reflecting the strength of UTC predictability by socio-economic variables, and the relationship between UTC and UTC inequality across cities within each grouping.

	Count	Total UTC	UTC inequality*	SSI^	UTC vs. Inequality#
Biophysical Region					
Atlantic Plain	5	28.2	0.26	0.25	0.72
App. Highland	13	27.3	0.26	0.34	0.39
Interior Plains	7	27.5	0.22	0.24	0.03
Intermountain	4	12.7	0.31	0.56	0.75
Pacific Mtn.	10	16.3	0.32	0.42	0.22
Socio-cultural Region					
Northeast	10	22.7	0.28	0.28	0.24
Midwest/GL	10	27.6	0.23	0.31	0.03
Sun Belt	5	36.8	0.23	0.27	0.92
West	15	15.5	0.32	0.44	0.28
Population Size					
Large	12	18.9	0.32	0.25	0.51
Medium	12	23.9	0.28	0.36	0.22
Small	16	25.4	0.25	0.41	0.53
Population Trend					
Increasing	18	21.5	0.27	0.34	0.53
Sustaining	15	23.1	0.29	0.36	0.57
Decreasing	7	26.7	0.26	0.35	0.07
Overall	**40**	**23.0**	**0.28**	**0.35**	**0.45**

[*] Based on Gini Coefficient of UTC across all census block groups within each city.
[^] Socio-Sensitivity Index – R^2 value for most highly supported multiple regression model linking socio-economic and demographic variables to the distribution of UTC across all census block groups within the city.
[#] R^2 value for simple linear model comparing city-scale UTC and UTC inequality for each region or population category.

3.2. Variation in UTC, inequality, and predictability among cities and regions (RQ2)

There was substantial variation in mean city-level UTC among socio-cultural regions based on ANOVA ($F_{3,35} = 15.92$, $p < 0.001$), and cities in the West had significantly lower levels of UTC relative to the other three regions (Fig. 3). Mean UTC also varied significantly across biophysical regions ($F_{4,34} = 5.64$, $p = 0.001$), with the two most western regions, Intermountain Plateaus and Pacific Mountain System, exhibiting significantly less UTC than the three eastern regions (Fig. 4). Additionally, cities in the Northeast region also had lower levels of UTC compared to the Sun Belt. There was not a significant difference in UTC among the city population size classes ($F_{2,36} = 1.57$, $p = 0.223$) or among categories in the population trends analysis ($F_{2,36} = 0.734$, $p = 0.487$).

There was significant variation in UTC inequality among socio-cultural regions ($F_{3,35} = 4.21$, $p = 0.012$; Fig. 3). The West had higher levels of inequality, compared to the other three regions. Within the biophysical classification, there was marginally significant variation in UTC inequality ($F_{4,34} = 2.51$, $p = 0.06$; Fig. 4). There was only marginally significant variation in UTC inequality among city population size categories ($F_{2,36} = 2.54$, $p = 0.093$) and no significant difference among population trend categories ($F_{2,36} = 0.110$, $p = 0.896$).

The predictive strength of UTC by the socio-economic and demographic variables, expressed through the SSI metric, varied among cities and across regions. Across the 40 cities, SSI ranged from a high of 0.84 in Nampa, ID, to a low of 0.05 in Chelsea, MA. Predictability of UTC (SSI) varied significantly among socio-cultural regions ($F_{3,35} = 3.35$, $p = 0.03$). Among regions, the West had a significantly greater SSI as compared to the Sun Belt (Fig. 3). SSI also varied among biophysical regions ($F_{4,34} = 3.81$, $p = 0.012$), and was significantly higher in the two

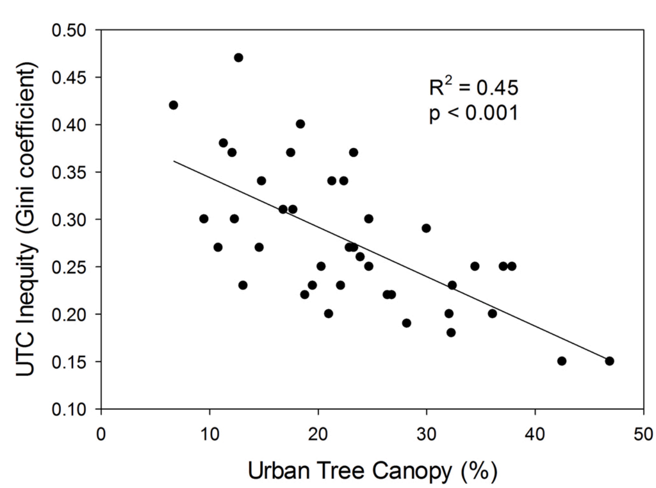

Fig. 2. Plot of city scale percent urban tree canopy (UTC) versus inequality in UTC at the census block group scale (as the Gini Coefficient) illustrating a strong negative relationship across cities at the continental scale.

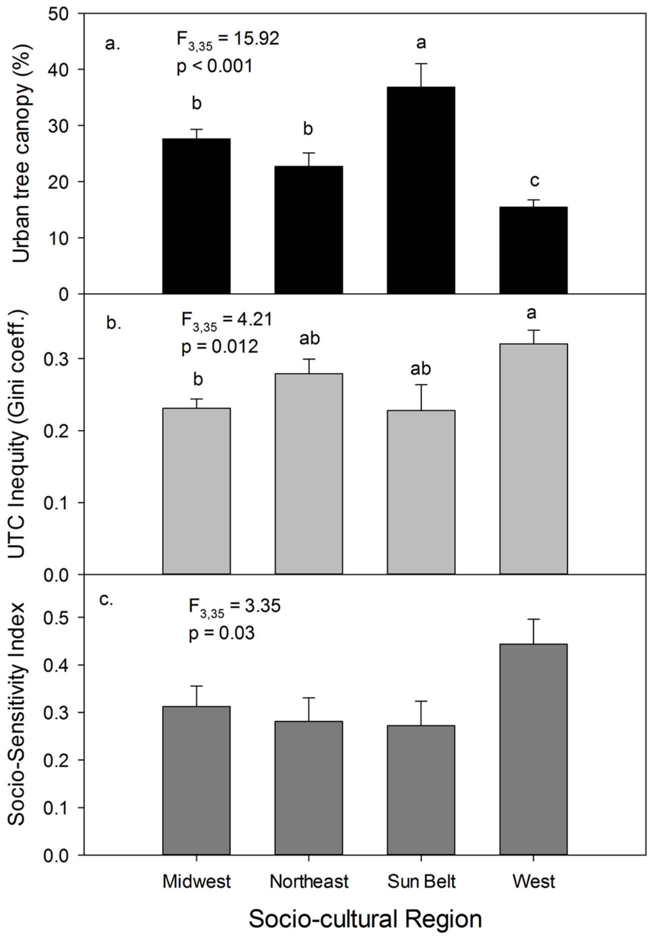

Fig. 3. Results of analysis of variance comparing a) urban tree canopy (UTC) percentage, b) UTC inequality (as the Gini Coefficient), and c) the strength of the relationship between UTC and socio-economic predictors (as the Socio Sensitivity Index- SSI) among biophysical regions. Results of multiple comparison tests when ANOVA main effects were significant, different letters indicate significant differences among categories.

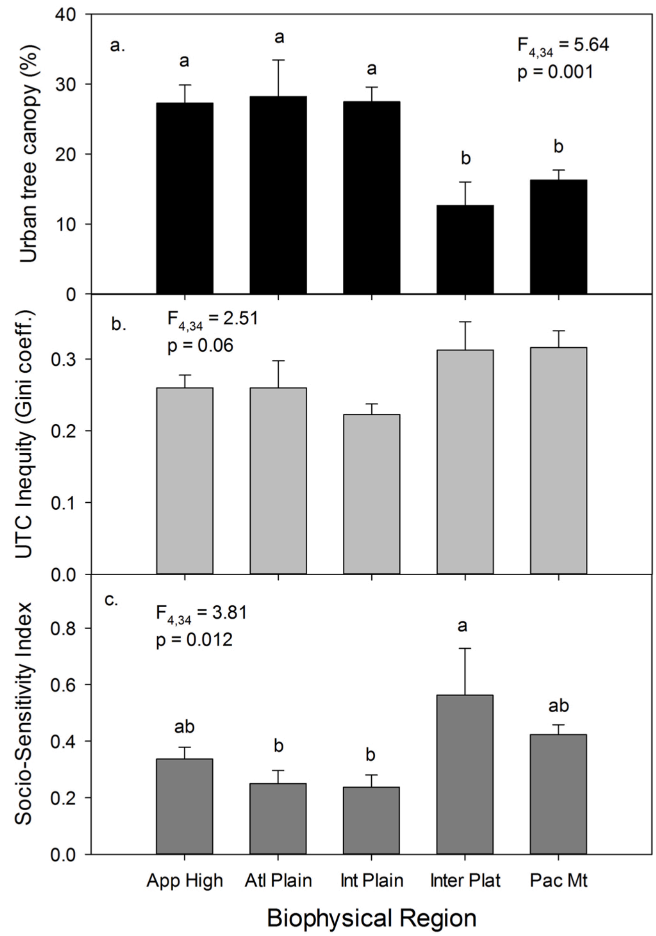

Fig. 4. Results of analysis of variance comparing a) urban tree canopy (UTC) percentage, b) UTC inequality (as the Gini Coefficient), and c) the strength of the relationship between UTC and socio-economic predictors (as the Socio Sensitivity Index- SSI) among socio-cultural regions. Results of multiple comparison tests when ANOVA main effects were significant, different letters indicate significant differences among categories.

western regions, Intermountain Plateaus and Pacific Mountain System, than the central and southern regions (Fig. 4). There was only marginally significant variation in SSI among population size categories ($F_{2,36} = 2.61$, $p = 0.088$), and no significant difference among population trend categories ($F_{2,36} = 0.108$, $p = 0.898$).

4. Discussion

Analysis of the continental scale relationship between city-scale UTC and within-city inequality of UTC distribution demonstrated a relatively strong negative relationship, indicating that the degree of inequality in canopy cover within a city is strongly negatively related to overall canopy cover. Although this finding was not a foregone conclusion (i.e., not an artifact of the analysis and derivation of Gini coefficient-based UTC inequality), it is not surprising given the realities of the spatial dimensions of tree canopy cover and property boundaries (Troy et al., 2007). For example, the less tree canopy cover there is in a city, the more weight that individual high canopy parcels (such as parks) have on overall canopy cover, and these parcels are often encompassed within a single census block or block group. The directionality of the relationship between UTC and UTC inequality was consistent across biophysical and socio-cultural regions and with city characteristics, but the strength of the relationship was highly variable. This finding supports a view that the broad factors governing city-scale inequality may vary with region and city characteristics (Schwarz et al., 2015; Hilbert et al., 2019; Nesbitt et al., 2019). For example, cities with declining population showed very little relationship between overall UTC and inequality, while those with increasing population had a strong negative relationship and also less inequality than expected based on overall UTC levels. This difference could reflect investment, stewardship, and governance impacts on UTC and equity (Perkins et al., 2004; Watkins et al., 2017; Schwarz et al., 2018; Nesbitt et al., 2019), as well as the impact of spontaneous vegetation regrowth in vacant spaces within declining cities in forested regions (Nowak, 2012; Pham et al., 2012; Riley et al., 2018). The strength of the relationship between inequality and total UTC also varied among regions, with very strong relationships evident in the Sun Belt and Atlantic Plain and Intermountain West regions, potentially reflecting the role of rapid recent development.

The deviation of individual cities from the linear relationship illustrated in Fig. 2 could potentially be a valuable indicator for comparing inequality across cities. This residual value indicates which cities have greater inequality in UTC than might be expected based on their overall UTC (values for each city are included in Supplemental Material, Table S1), which can be strongly related to factors such as biophysical setting (Lowry et al., 2012). For example, cities such as Oakland, CA and Honolulu, HI had much greater inequality than expected based on overall UTC, while San Jose, CA and Cleveland, OH had less inequality than expected. These patterns could inform strategies for increasing city-wide UTC in a manner that improves (or at least does not exacerbate) UTC inequality (Ordóñez et al., 2019). For example, cities with high UTC that also have high inequality (e.g., Baltimore, MD and Richmond, VA) may be those that require the most directed/targeted interventions to increase tree canopy (Grove et al., 2018), while cities with low overall UTC and low inequality (e.g., San Jose and San Luis Obispo, CA) may be most appropriate for dispersed city-wide planting efforts (McPherson et al., 2011, 2017). However, planning and implantation of urban tree planting campaigns should take into account issues of "land sparing vs. land sharing" (Stott et al., 2015), variation in amenity value of urban greenspace across neighborhoods (Riley et al., 2018), and social barriers such as community resistance to tree planting (Carmichael and McDonough, 2019). In addition, planting prioritization should be related to possible disservices associated with infrastructure and property damage (Conway and Yip, 2016), and environmental issues, such as water use, drought, and fire risk (Pataki et al., 2011).

Our research supports the notion that the regional setting of a city can have a substantial influence on patterns of UTC (Nowak and Greenfield, 2018) and UTC inequality (Roman et al., 2018; Nesbitt et al., 2019). We found significant variation in levels of UTC across biophysical regions, likely related to a combination of the underlying biophysical setting of the area and the sociological and developmental patterns that have been overlaid on this setting (Hill et al., 2010; Hilbert et al., 2019; Nesbitt et al., 2019). More arid areas found in desert and Mediterranean climate regions have lower urban tree cover because these climates support little natural tree cover and also because they experience less spontaneous growth of urban trees (Lowry et al., 2012; Locke et al., 2017). Across the set of cities analyzed here, there was a slight positive relationship between mean annual precipitation and overall UTC ($R^2 = 0.38$; Supplemental Material, Fig. S2). The lack of spontaneous tree establishment in arid regions (Nowak, 2012) could also exacerbate inequality in UTC distribution, as less affluent neighborhoods often do not have the resources to plant and maintain urban trees (Perkins et al., 2004; Heynen et al., 2006; Landry and Chakraborty, 2009; Roman et al., 2015). Overall there was a weak negative relationship ($R^2 = 0.15$; Supplemental Material, Fig. S2) between UTC inequality and precipitation, which largely coincided with the separation of western cities from those in other regions.

There was also a strong influence of socio-cultural regionality on patterns of both UTC and UTC inequality among cities, supporting the view that both city-scale and regional developmental legacies are important drivers of UTC (Bigsby et al., 2014; Roman et al., 2018). Prior studies have illustrated that the demographic, economic, and sociological characteristics of cities can have an effect on overall UTC and inequality of UTC within cities (Lowry et al., 2012; Schwarz et al., 2015; Berland et al., 2016; Gerrish and Watkins, 2018; Watkins and Gerrish, 2018; Nesbitt et al., 2019). We were interested in whether broad socio-cultural regions that share somewhat similar developmental and cultural histories differed in levels of UTC and inequality. Variability in UTC and inequality among broad socio-cultural regions was substantial, which could reflect variable governance and stewardship patterns across these regions (Berland et al., 2016; Hilbert et al., 2019; Nesbitt et al., 2019), as well as differing regional-scale economic and demographic trends. For example, cities in the Western region generally had low UTC and high inequality, whereas Midwest/Rust Belt cities had very little relationship between UTC and inequality and generally had lower inequality than expected based on overall levels of UTC. This difference could reflect biophysical or developmental legacies in these cities or recent economic changes resulting in land abandonment and spontaneous forest establishment (Heynen et al., 2006; Fahey and Casali, 2017). There is also likely to be an effect of variability in land ownership and land use patterns and urban form (e.g., property sizes and shapes) within cities across cities and regions, as UTC patterns have been linked to private property management (Ossola et al., 2019) as well as the distribution of urban greenspaces (Roman et al., 2018).

Previous studies have found a strong correlation between tree canopy, UTC inequity, and various socio-economic and demographic factors within cities (Iverson and Cook, 2000; Landry and Chakraborty, 2009; Lowry et al., 2012; Locke et al., 2016; Riley and Gardiner, 2020). The distribution of UTC within cities has been related to social stratification (Grove et al., 2014) and, more generally, socio-economically disadvantaged communities often have less access to quality parks and green spaces, leading to larger environmental justice issues (Boone et al., 2009; Grove et al., 2018). In this study, analysis of the Socio Sensitivity Index (SSI) indicated variability among cities and regions in how strongly socio-economic and demographic variables predict UTC patterns (Kendal et al., 2012; Conway and Bourne, 2013; Hilbert et al., 2019). Some cities had a very low predictability of UTC (low SSI), such as Chicago, IL and New York, NY (0.09), while others had very high predictability, like Nampa, ID or Oakland, CA (0.84 and 0.62 respectively). Variation in the strength of this relationship is likely related to a combination of legacy effects and the socio-economic and demographic patterns present in individual cities (Roman et al., 2018).

However, our analysis illustrated that regionality and the biophysical setting of a city can have an effect on the strength of the relationship between UTC and socio-economic and demographic patterns (Fig. 3). For example, the higher SSI found in the western US likely reflects the intentionality of most UTC in arid western cities versus spontaneous tree establishment in the eastern part of the country (Roman et al., 2018; Nesbitt et al., 2019). In areas with spontaneous tree establishment there may be less effect of variation in planting and maintenance effort on total tree cover, although other structural and functional characteristics of the urban forest may still respond to neighborhood sociological characteristics (Pham et al., 2012; Conway and Bourne, 2013; Fan et al., 2019). In some cities there is also likely a legacy effect of pre-urban vegetation patterns on the strength of this relationship. For example, in Chicago (low SSI = 0.10) the variable mosaic of pre-urban vegetation types has been shown to be a strong control on modern canopy cover patterns (Fahey and Casali, 2017), which may to some extent decouple these patterns from socio-economic and demographic patterns. Fine-scale, within-city variation in biophysical conditions may also affect these relationships, and the degree to which these biophysical factors vary within cities is not consistent across cities with different underlying landscape templates (Steele and Wolz, 2019).

Developmental legacies and historical conditions that are not well represented in current socio-economic or demographic data may also limit the strength of the relationship between UTC and current socio-economic and demographic patterns (Boone et al., 2010; Grove et al., 2018). For example, the discriminatory lending practices in the US in the 1930's (known as "redlining") affected investment in some neighborhoods, which could continue to be reflected in the tree cover of those neighborhoods (Ogden et al., 2019). These discrepancies could be especially important in more dynamic urban areas, as neighborhood characteristics at the time of planting may be very different than those present by the time the trees have matured (Boone et al., 2010). Economic and developmental legacies are also represented in differentiation among cities in UTC response variables across population growth trend and socio-cultural classifications. For example, the lack of a relationship between UTC and UTC inequality in the Midwest/Great Lakes region and in cities with declining populations reflects patterns in "Rust Belt" cities. Many of these cities peaked in population and economic vitality several decades ago (Kahn, 1999; Hartley, 2013), and inequality in tree canopy may be reduced where past investments are still reflected in disadvantaged neighborhoods and recent investment is low even in more affluent areas. Therefore, legacy effects can be multi-scale and reflect interactions between local actions, city-level conditions, and broad, regional economic and sociological drivers (Johnson et al., 2020).

5. Conclusions

Our research supports and expands on prior work by identifying cross-regional patterns in UTC inequality and illustrating that broad-scale biophysical and socio-cultural regions may influence levels of inequality in urban ecological amenities such as tree canopy (Roman et al., 2018). This finding could help highlight environmental justice issues and improve understanding of the social or health impacts of UTC inequity, but also indicates that some degree of UTC inequality may be related to underlying ecology or overarching sociological patterns that may not be controlled by local decision-making (Hilbert et al., 2019). Although there can certainly be value in adding tree canopy through large city-scale planting campaigns, our results indicate that cities vary in current UTC equality and some cities may require more targeted interventions than others. Particularly in more arid western regions where urban forest managers will need to both expand the urban canopy as well as develop long-term strategies to both plant and maintain urban trees to help stem UTC inequity. Managers provided with an improved understanding of the spatial distribution of UTC can help reduce inequity through planting and tree maintenance efforts, but having a sense of underlying determinants of these patterns can provide much needed historical and sociological context for these patterns and could help produce more equitable outcomes (Grove et al., 2018; Garrison, 2019). To further understand the impacts of UTC inequality, additional macro-scale analysis should be conducted on the inequity of the provisioning of ecosystem services and benefits associated with UTC, as these factors are not always strongly directly linked to levels of tree cover (Dobbs et al., 2014; Riley et al., 2018). There would be value in expanding these analyses beyond political city limits to evaluate UTC patterns at metropolitan region scales and beyond (Johnson et al., 2020). In addition, from a global perspective expanding to other nations and continents (Graça et al., 2018; Baró et al., 2019; Barona et al., 2020) would provide the opportunity to address questions such as whether the effect of biophysical regionality on urban tree canopy varies across areas with different trajectories and timing of urban development.

CRediT authorship contribution statement

Elliott Volin: Formal analysis, Data curation, Writing - original draft. **Alexis Ellis:** Software, Data curation. **Satoshi Hirabayashi:** Conceptualization, Methodology, Data curation, Funding acquisition. **Scott Maco:** Resources, Funding acquisition. **David J. Nowak:** Conceptualization, Funding acquisition, Supervision, Writing - review & editing. **Jason Parent:** Methodology, Formal analysis, Writing - review & editing. **Robert T. Fahey:** Conceptualization, Methodology, Funding acquisition, Supervision, Writing - review & editing, Project administration.

Declaration of Competing Interest

The authors report no declarations of interest.

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Appendix A. Supplementary data

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