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Original article

Tree canopy change and neighborhood stability: A comparative analysis of Washington, D.C. and Baltimore, MD

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ABSTRACT

Trees provide important health, ecosystem, and aesthetic services in urban areas, but they are unevenly distributed. Some neighborhoods have abundant tree canopy and others nearly none. We analyzed how neighborhood characteristics and changes in income over time related to the distribution of urban tree canopy in Washington, D.C. and Baltimore, MD. We used stepwise multiple regression analysis to identify strong predictors of UTC, from variables found in neighborhoods with different patterns of wealth-stability over time. We then built spatial lag models to predict variation in UTC cover, using the results of a Principal Component Analysis of the socioeconomic, demographic, and housing characteristics of the two cities. We found that: (1) stable-wealthy neighborhoods were more likely to have more, and more consistent, tree canopy cover than other neighborhood types; (2) decreases *and* increases in income were negatively associated with UTC in Washington, D.C. but not Baltimore, where income stability in both wealthy and impoverished neighborhoods was a significant predictor of UTC; and (3) the association of high socioeconomic status with UTC coverage varied between the two cities.

1. Introduction

Trees provide a variety of ecosystem services and environmental benefits for urban residents. The environmental benefits of urban forests include heat-stress mitigation, carbon sequestration, noise reduction, air and water quality improvement, and stormwater reduction. Tree management is an important sustainability priority for municipalities because trees are an essential component of a well-functioning urban ecosystem and can be important for mitigating natural hazards such as flooding and excessive heat. Many cities have set ambitious goals for increasing tree canopy cover. Our study cities, Washington, D.C. and Baltimore, MD plan to increase tree canopy cover from a current 35% to 40% by 2032 (O'Neil-Dunne, 2009b; District of Columbia Urban Tree Plan, 2013) and from 27% to 40% by 2037, respectively (Baltimore Sustainability Plan, 2009). If the cities are to meet these goals, the majority of tree growth will have to occur on residential property (O'Neil-Dunne, 2009a,b). But tree planting alone does not constitute an effective urban tree canopy (UTC) plan. Such plans also need to take into account how the interactions in social-ecological systems influence current tree distribution and conservation. Trees can survive for decades in cities when they are properly maintained. Therefore, investments to increase tree canopy coverage are long-term investments that are subject to the long-term dynamics of urban environments, which are heterogeneous socio-ecological systems (Grove et al., 2015). To contribute to the understanding of these long-term dynamics as they relate to UTC, we analyzed how changes in neighborhood characteristics (income over time, educational attainment, racial and ethnic composition, age distribution, and residential real-estate development) correlated to tree canopy coverage across census tracts in Washington, D.C. and Baltimore, MD.

Theories about human population density, social stratification, and reference-group behavior have been used to explain tree canopy distribution (Locke and Grove, 2016). One theory holds that human population density drives vegetation change through development, which

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alters land (Smith et al., 2005; Marco et al., 2008; Cook et al., 2012). But variables other than population density influence vegetation cover in an area, and social stratification theory suggests three: 1) wealthier people have more social and spatial mobility than those with lower incomes, and are therefore able to live in neighborhoods that provide attractive amenities, including green spaces (Logan and Molotch, 2007; Roy Chowdhury et al., 2011); 2) the level of public investment in green infrastructure is positively correlated with the socioeconomic status and political power of residents (Grove et al., 2006); and 3) wealthier residents have more disposable income to invest in landscaping and can afford to maintain trees in their yards and neighborhoods (Hope et al., 2002, 2006; Martin et al., 2004). A study of urban trees in six U.S. cities concluded that the more affluent the neighborhood, the more extensive the tree canopy (Schwarz et al., 2015). But wealth differences are not the sole determinant of the uneven distribution of urban trees. In some places, the higher the percentage of racial- and ethnic-minority residents, the lower the tree canopy cover; however, the strength of association varies geographically (Schwarz et al., 2015). Reference-group behavior theory recognizes the influences of population density, mobility, differentiated political power and income, and economic power on land management, but it puts more emphasis on the role of group identity in shaping neighborhood landscapes and maintaining the so-called "ecology of prestige" (Troy et al., 2007; Zhou et al., 2009; Grove et al., 2014). The ecology of prestige theory holds that household vegetation symbolizes membership in a desirable social group. Of course, present-day tree canopy coverage may also reflect inherited landscapes (Luck et al., 2009; Clarke et al., 2013; Locke and Baine, 2015). For example, Boone et al. (2010) found that *past,* rather than present, neighborhood lifestyles and socioeconomic characteristics were better predictors of urban tree canopy cover in Baltimore.

Most studies of UTC have used a single point in time or "snapshots" to compare social and built-environment characteristics with vegetation cover (Landry and Pu, 2010; Pham et al., 2012; Romolini et al., 2013). But tree distribution is determined by complex social-ecological dynamics over time. Therefore, we incorporated changing conditions at the neighborhood scale to evaluate how neighborhood stability influences the extent of canopy cover. Further, we compared two cities in the same geographic area, rather than focusing on just one city or metropolitan area, as most UTC studies have done. While there is clear value in understanding the idiosyncratic role of places and their individual histories, we argue that more comparative analyses are necessary to advance theory in urban ecology (Roy Chowdhury et al., 2011; Cook et al., 2012).

We used time-series social and biophysical data to examine the dynamics of social characteristics and UTC in two cities that occupy a similar biome and have relatively common biophysical constraints and opportunities for vegetation growth: Washington, D.C. and Baltimore, MD. Our study has two parts. First, we quantified the spatial distribution of UTC in the two cities and examined the relationship between changes in income and built-environment characteristics with the amount of tree canopy at a fine scale (defined by an area with 100-m radius). This allowed us to consider whether positive or negative changes in income are related to the distribution of UTC, conditioned by whether a city is growing in terms of population (D.C.) or declining (Baltimore). Second, we compared predictors of urban tree canopy distribution at the census-tract scale for both cities. The methods for this analysis employed a set of socioeconomic and biophysical variables, principal component analysis (PCA) for data reduction, and spatial regression models of the PCA components for each city.

2. Materials and methods

We first tested six hypotheses to identify the relationships among income change, and percentage of UTC at the neighborhood level in both cities. We sorted neighborhoods into five classes by their income change status, and observed UTC in these neighborhoods. Second, we used stepwise regression models to identify significant predictors of UTC. In this second part, we built spatial lag models, using the results of PCA of a set of variables, to predict UTC at the census-tract level for both cities.

2.1. Study areas

Washington, D.C. and Baltimore, MD are located in the mid-Atlantic region of the eastern United States, adjacent to the Chesapeake Bay. Baltimore is about 60 kilometers northeast of Washington, D.C. Both cities are majority African-American and highly segregated (Logan et al., 2014). Baltimore was established in 1729 and Washington, D.C. in 1790, but the majority of urban expansion in both cities occurred in the 20th century, under similar technological regimes dominated by the automobile. Population peaked in both cities in 1950, followed by decades of population decline as surrounding suburbs boomed. The paths of these two cities have diverged more recently. Between 2000 and 2014, the population of Baltimore declined by ~30,000 residents, while Washington grew by nearly 10% (current populations are 622,000 and 660,000, respectively). Median household income is rising faster in Washington, D.C. Gentrification is occurring in some parts of both cities, but the magnitude is greater in Washington and corresponding rents are also higher (US Census ACS 2013; US Census 2000). Washington can be characterized as a "pull" city, drawing people and investment into the city, while Baltimore remains largely a "push" city, with people leaving for the suburbs and other locations (Gottdiener and Hutchison, 2006). Both cities are undergoing change at both the city-wide and neighborhood levels. With their geographic and historical similarities and contrasting recent growth patterns, Baltimore and Washington offer an opportunity to compare how population and socioeconomic change relate to urban tree canopy.

2.2. Data

We analyzed high-resolution tree canopy data for Washington and Baltimore with data from the University of Vermont Spatial Analysis Laboratory. The Washington dataset quantified tree canopy change, including loss, gain, and persistence, from 2006 to 2011. The only available high-resolution information for Baltimore was from a 2007 land-cover raster map. The two datasets were derived from Quickbird, LiDAR, and National Agricultural Imagery Program data. Resolution for the raster data was set at 0.6 m^2. The shapefile for UTC change (loss, gain, no change) had a minimum mapping unit of 8 square meters. The canopy-change shapefile for Washington (Tree Canopy Change, Washington D.C., 2006–2011) and the Baltimore land-cover raster (Land Cover Baltimore 2007) are freely available and distributed under the Creative Commons Share Alike 3.0 license. Our comparative analyses are based on the static state of the tree canopy coverage in relation to income change in the two cities (UTC for Washington, D.C. for 2006 and Baltimore for 2007). In addition, we examined UTC change over time for Washington D.C.

Consistent spatial units are necessary to study socioeconomic, demographic, and building-characteristic change at the neighborhood level. However, geographic boundaries for the U.S Census Bureau can change over time. To make the Census data comparable over time, we aligned historical census information to year 2010 Census boundaries, using the Longitudinal Tract Data Base program. The program uses proportional area weighting to assign census-variable values to the appropriate space (Logan et al., 2014). As of 2013, Washington had 179 Census tracts (including the National Mall and Capitol Hill) and Baltimore had 200. Median household income data in inflation-adjusted dollars were acquired from the year 2000 Census and 2013 American Community Survey (ACS) from the U.S. Census Bureau.

2.3. Study 1: identifying the relationship between income change, the built environment and small area UTC (small area is defined by an area with 100-m radius)

In the first part of the study, we aimed to examine the relationship between income change and extent of tree canopy cover. According to the nature of two different UTC datasets, the hypotheses were categorized into two groups:

I. Existing tree canopy (Washington, D.C. and Baltimore MD):

H1. Neighborhoods that *remain relatively wealthy* will have more tree canopy.

H2. Neighborhoods with *decreasing wealth* will have less existing tree canopy.

H3. Neighborhoods that *remain relatively impoverished* will have less existing tree canopy.

II. Tree canopy change (Washington D.C. only):

H4. Neighborhoods with *increasing wealth* will have increasing tree canopy (*gain*).

H5. Neighborhoods with *decreasing wealth* will have canopy loss and/or low canopy gain.

H6. Neighborhoods that *remain relatively impoverished* will have little to no tree canopy and/or low canopy gain.

The hypotheses are based on social stratification theory, which states that wealthier households: (1) may choose to live in greener neighborhoods, (2) may be more effective in garnering public investment in green infrastructure in their neighborhoods, and (3) may spend more disposable income on landscaping in their yards. We also examined UTC in neighborhoods with increasing and decreasing incomes. Assuming that wealth is a key influence on tree canopy abundance, we expected that increase or decrease in wealth in a given neighborhood would have corresponding changes in tree canopy.

We used stepwise multiple regression models to test hypothesis H1–H3 for both cities. To increase the predictability of the model, we included built-environment variables: land area, number of housing units, and percentage of structures built in each decade from 1930 to 2010. Housing built before 1930 was included in the 1930 decade. The number of houses per unit of land area is a proxy for density of development and physical constraints on tree growth. The percentage (proportion) of structures built in each decade represents characteristics of the built environment that affect tree planting and growth. The examination of H4–H6 were based on the descriptive analysis of the UTC change for only Washington D.C.

2.3.1. Defining neighborhood wealth type

Because Washington and Baltimore have different growth trajectories, we used a relative measure of wealth *within* each city to assign wealth status to neighborhoods. Median household income was standardized to identify a neighborhood's income status in relation to other neighborhoods within each city. We used the standard score, z, a statistical measurement of a variable's relationship to the mean, to characterize the wealth status of neighborhoods. A positive standardized value meant the observation was above the mean (of 0) and a negative value meant the observation was below the mean. Our data yielded five wealth categories (see Fig. 1):

1. *Remained relatively impoverished* (NB1): neighborhoods with a standardized value below −1 between 2000 and 2013. We refer to these neighborhoods as "*stable-impoverished.*"
2. *Decreasing wealth* (NB2): neighborhoods with a standardized value above 0 in 2000 and below 0 in 2013.
3. *Remained above poverty* (NB3): neighborhoods' with standard values that remained below average (0) but above impoverished (-1) between 2000 and 2013.
4. *Increasing wealth* (NB4): Neighborhoods with a standardized value below 0 in 2000 and above 0 in 2013.
5. *Remained relatively wealthy* (NB5): neighborhoods that had standardized values above 0 between 2000 and 2013. We refer to these neighborhoods as "*stable-wealthy.*"

About 44% of the neighborhoods in both cities were in the NB3 category (remained above poverty). NB5 (remained relatively wealthy) was the second most common neighborhood type, making up 30% of Washington's and 33% of Baltimore's neighborhoods. NB5 neighborhoods were distributed on the periphery in both cities (Fig. 2). Neighborhoods with increasing wealth (NB4) were found in Washington's center; in Baltimore, many of the neighborhoods that remained relatively impoverished (NB1) were found in the urban core.

2.3.2. Selecting samples for modeling UTC

We used statistical analysis to examine how well the five neighborhood types predicted existing UTC (static state) in small areas randomly distributed across the two cities. For each city, we generated twice as many random points as the total number of census tracts in the city; each point had a buffer zone of 100 m (i.e., was at least 100 m from any other point). When a buffer zone fell within the borders of two or more census tracts, we treated each portion on a tract as an individual object. Following this procedure, we selected 570 sample areas in Washington and 755 in Baltimore. Theoretically, the spatially random plots would capture the variation in land use proportional to the coverage of those land uses. This method allowed us to examine UTC in a smaller spatial unit than the census tract, to complement the tract-level analysis we conducted in the second part of the study. The sample-selection process maximized the use of the very-high resolution UTC data, and was intended to make our assessment more accurate than it would have been if we had used only aggregate data.

To understand how neighborhood-wealth type correlated with tree canopy, we used IBM SPSS 22 to conduct a stepwise multiple regression with the percent tree canopy cover in each sample area as the dependent variable. This method allowed us to use different combinations of input variables to identify strong predictors of UTC at a very fine scale. While stepwise regression may not be a perfect method for identifying the strongest combination of UTC predictors, it does enable researchers to find models that are explanatory yet parsimonious.

Since our input variables are not normally distributed, according to the Shapiro-Wilk test, we calculated Spearman correlation coefficient to assess relationships among variables. Some building characteristics are associated with each other (the smallest and largest correlation coefficient are between -0.63 and 0.57, $p \leq 0.05$). We further checked for collinearity by calculating the variance inflation factor (VIF) for each independent variable to ensure that there were no issues with multicollinearity in the models. The VIF values from both models were between 1.09 and 1.70, which does not raise concern ("Introduction to SAS", 2016). Moreover, we used F test to examine model fit. The F test of our multiple regression models indicated that including the independent variables significantly improved model fit. In addition, the model residual plots were examined to ensure homoscedasticity and normality of the residuals.

2.4. Study 2: predicting variations in UTC at the census-tract level using spatial lag models

Urban tree distribution is often affected by a combination of current conditions and historical processes. In the second part of the study, principal component analysis (PCA) was used to reduce data from 27 socioeconomic, demographic, and built-environment variables at the census-tract level from year 2013. PCA converts large numbers of variables that might be correlated into a smaller number of "principal" components. We then used the components to first build Ordinary Least

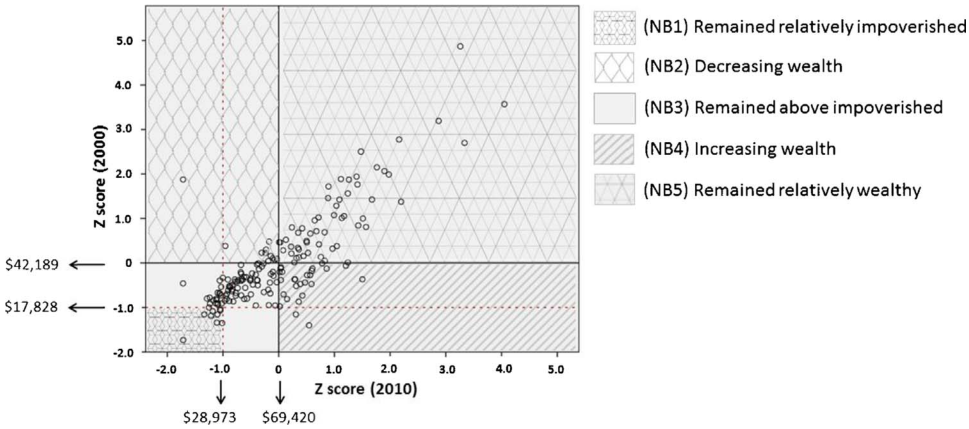

Fig. 1. Distribution of *Z* scores of income data and neighborhood type in Washington, D.C. between 2000 and 2013. (NB1) Remained relatively impoverished; (NB2) Decreasing wealth; (NB3) Remained above impoverished; (NB4) Increasing wealth; (NB5) Remained relatively wealthy.

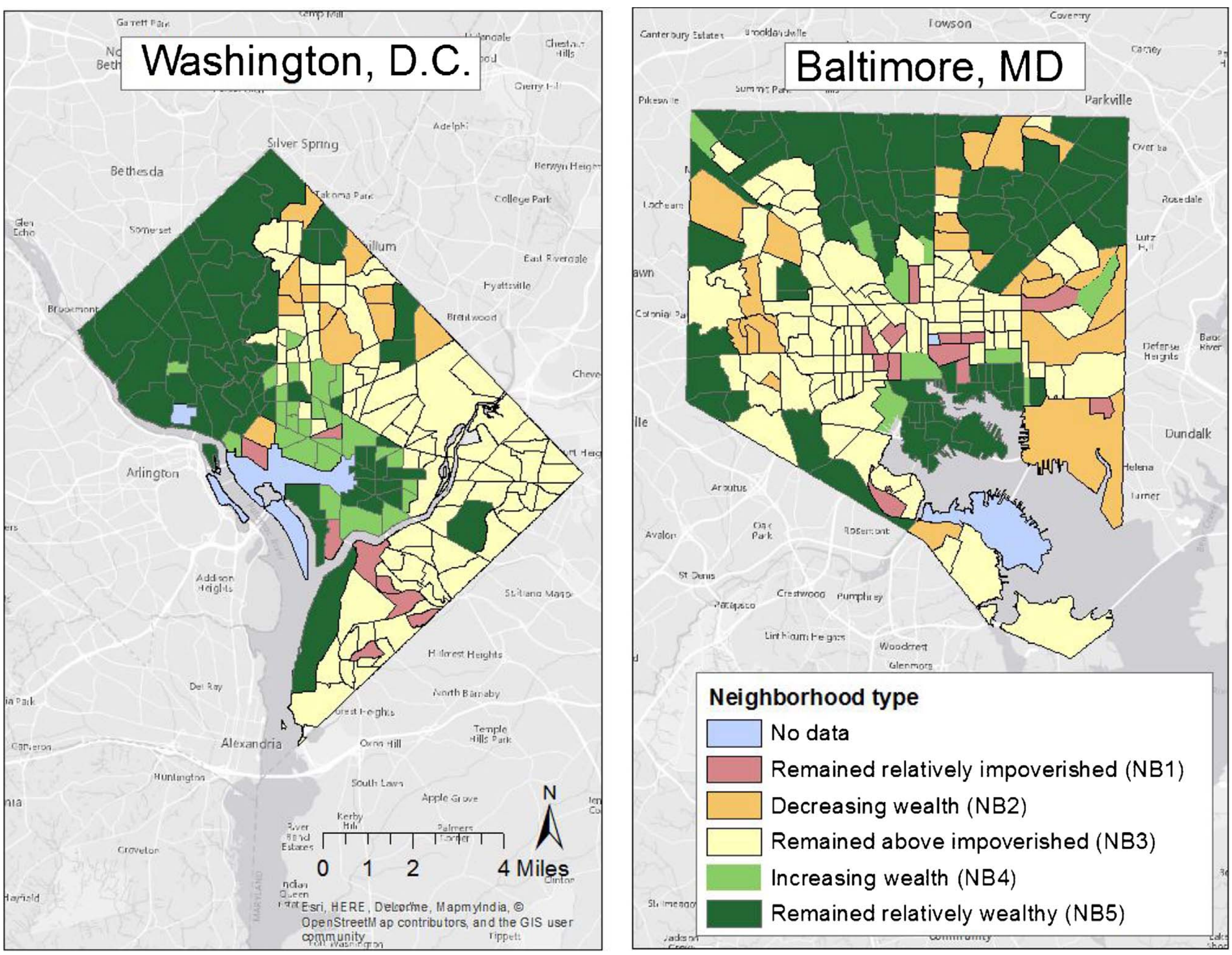

Fig. 2. Spatial distribution of Census tracts in five types of neighborhoods in Washington, D.C. (left) and Baltimore, MD (right).

Square (OLS) models and later spatial autoregressive models that accounted for spatial autocorrelation to estimate the association between the principal components and UTC cover.

The 27 variables (Table 1) reflect the complex interactions between biophysical and social systems, and represent four aspects of a neighborhood:

(1) Socioeconomic status: The proxy variables were median household income and education level. These variables can reflect residents' political power and resources, as well as the disposable income available to invest in landscaping (Grove et al., 2006). It has been suggested that low-income residents might resist tree-planting to avoid gentrification and rising rents (Schwarz et al., 2015).
(2) Race and ethnicity: Research has shown that minorities in urban areas are likely to have fewer environmental amenities than non-Hispanic white populations (e.g., Schwarz et al., 2015). Cultural background has been found to influence the preference for open space; for instance, in Toronto, Canada, Chinese residents did not encourage tree planting in their neighborhoods (Fraser and Kenney, 2000). In some African-American neighborhoods, residents preferred few trees in public areas because of concerns about safety and crime (Lohr et al., 2004).

Table 1
Variables from US Census and their Morna's I for the both cities (Spatial unit: Census tract).

Variable	Description	D.C. Moran's I	Baltimore Moran's I
Wealth			
Median household income (in inflation-adjusted dollars)		0.59	0.57
Education level			
% of population with less than high school education		0.41	0.47
% of population with high school degree		0.75	0.54
% of population with college degree or above		0.71	0.62
Race and ethnicity			
% of non-Hispanic white population		0.83	0.61
% of African American population		0.86	0.64
% of Hispanic White population		0.58	0.50
% of Asian		0.64	0.32
Age			
% of population under 18 years old		0.61	0.29
% of population between 19 and 65 years old		0.60	0.31
% of population 65 years old or above		0.31	0.27
Housing characteristics			
% of owner-occupied housing		0.25	0.45
% of renter-occupied housing		0.33	0.37
% of vacant housing unit		0.31	0.56
Median rent		0.50	0.34
Median home value		0.71	0.55
Age of the building/housing structure		**−0.01**	**0.00**
% housing structure built in that decennial		**0.00**–0.56	**0.01**–0.56
Population density (people/square mile)		0.57	0.33
% of tree canopy coverage		0.67	0.52

Note: all *p-values* ≤ 0.05 except for bolded numbers.

(3) Age: Different age groups may have different attitudes toward tree-planting. For example, Zhang (2007) found that young adults were more willing to contribute money and volunteer time to urban forestry activities than middle-aged and elderly people.
(4) Housing and development characteristics: This category included the variables of housing ownership, vacancy rate, median housing value and rent, population density, median age of built structures, and percent of structures built by decade in each census tract. Housing values, ownership, and built environment can affect UTC coverage. Trees can add value to a home (Battaglia et al., 2014). Population density and building characteristics can reveal the physical constraints on tree planting and growth. Median age of housing was used to account for the fact that trees take time to grow and that current canopy cover reflects previous behaviors and preferences (Troy et al., 2007; Boone et al., 2010; Lowry et al., 2011). Median age of housing also represents the proportion of new development in a place. We viewed this variable as a general indicator of building age in a given neighborhood.

We used the scores of the principal components we derived from PCA as independent variables in spatial models. We applied a Varimax rotation to minimize the number of the original variables that loaded highly on any one component and to increase the variation among them. Six components were retained for Washington D.C. and seven for Baltimore, MD, based on scree plots and examination of eigenvalues. Eigenvalues are the variances of components. In PCA, each variable is standardized and therefore has a variance of 1. Components that have eigenvalues greater than 1 are considered to be principal components worth retaining because their variance is higher than that of the original variables ("Introduction to SPSS: Principal Component Analysis," 2016).

The dependent variable in study 2 was the percentage of UTC in each census tract. Rather than assuming that it was spatially independent, we tested for spatial autocorrelation of UTC. High-resolution tree canopy data were imported into ArcGIS 10.3 and zonal statistics were applied to calculate percentage of tree canopy. The spatial regression models and spatial statistics (Moran's I) that measure spatial autocorrelation were estimated in Geoda version 1.6.7 (Anselin et al., 2006). Moran's I is a weighted correlation coefficient that measures global spatial autocorrelation. The index falls between −1 (dispersed pattern), 0 (complete spatial randomness), and +1 (spatially autocorrelated pattern). We used first-order queen contiguity-based spatial weight matrices, which assign a spatial structure in units of observation according to an area's spatial relation to its neighboring tracts, so that tracts sharing an edge, a corner, or both were defined as neighbors.

3. Results

3.1. Distribution of UTC in different types of neighborhoods

We first examined extent of canopy cover (total coverage) for the two cities. UTC was low in the core of both cities. Washington's average UTC by census tract was 28.63%, about six percentage points higher than Baltimore's (Tables 2 and 3). The difference was statistically significant (Kruskal-Walis test with alpha = 0.05). As was expected, tree canopy was not evenly distributed in either city. The distribution of UTC for both cities was highly spatially autocorrelated, with a Moran's I of 0.52 (p-value < 0.01) for Baltimore and 0.67 (p-value < 0.01) for Washington, D.C. The majority of UTC in both cities was concentrated on the periphery (Fig. 3). In Baltimore, tracts with high UTC cover were located in the western and northern districts; in Washington, D.C. they were located in the western and northwestern parts of the city.

In both cities, census tracts classified as stable-wealthy neighborhoods (NB5) had the highest average UTC, while the stable impoverished tracts (NB1) had the lowest. But there was a statistically significant difference between the cities' stable-impoverished tracts: those in Washington had an average UTC 1.6 times higher than those in Baltimore (21.90% vs. 13.17%). Overall, both poor and wealthy neighborhoods in Washington, D.C. (Fig. 4) had more tree canopy than the corresponding neighborhoods in Baltimore.

We had canopy change data for only Washington, D.C. (Table 2). On average, that city's stable-wealthy neighborhoods (NB5) had the highest percentage of UTC and the least amount of tree canopy gain. A possible explanation is that these stable-wealthy neighborhoods already have a high percentage of tree canopy cover and the space for growth is

Table 2
The change (2006–2011) of tree canopy in five types of neighborhoods in Washington, D.C.

Neighborhood Type[a]	NB1 (n = 8)	NB2 (n = 11)	NB3 (n = 78)	NB4 (n = 26)	NB5 (n = 54)
Average tree canopy remains the same (%)	21.90	24.91	26.90	14.76	38.14
Average gain (%)	0.54	0.69	0.44	0.60	0.34
Average loss (%)	3.88	3.07	3.16	2.31	2.99
Average tree canopy in 2011 (gain + same, %)	22.44	25.60	27.34	15.36	38.48
Net loss/gain (gain-loss %)	−3.34	−2.38	−2.72	−1.71	−2.65

[a] Neighborhood Type: NB1-Stable impoverished; NB2-Decreasing wealth; NB3-Remained above impoverished; NB4-Increasing wealth; NB5-Stable wealthy. The average percentage of tree canopy at census-tract level was 28.63% in 2011.

Table 3
2007 Tree canopy coverage in five types of neighborhoods in Baltimore, MD.

Neighborhood Type[a]	NB1 (n = 12)	NB2 (n = 22)	NB3 (n = 87)	NB4 (n = 11)	NB5 (n = 66)
2007 average tree canopy	13.17%	27.90%	19.55%	14.69%	29.60%

[a] Neighborhood Type: NB1-Stable impoverished; NB2-Decreasing wealth; NB3-Remained above impoverished; NB4-Increasing wealth; NB5-Stable wealthy. The average percentage of tree canopy at census-tract level: 23.00%.

limited. Neighborhoods that remained impoverished (NB1) had the greatest tree canopy loss (3.88%) and an average net loss of −3.34%.

3.2. Study 1: relationship among income change, built characteristics, and small-area UTC

Tables 4 and 5 show the results of the stepwise regression models. The Washington model ($R^2 = 0.31$) explained more variance in the dependent variable than that of the Baltimore model ($R^2 = 0.23$). Stable wealth (NB5) was positively associated with existing UTC in both cities but, interestingly, changes in income were negatively associated with UTC in Washington, D.C., but were not significant UTC predictors in Baltimore. Model results also indicated that stable-impoverished status does not always have a negative relationship with UTC.

3.3. Study 2: predictions of tract-level UTC from spatial lag models

The first six principal components explained 75.31% of the variance in the data from Washington, D.C. (Table 6). The features (the variables with heavy loading) of each component are listed below:

Component 1 was weighted heavily toward median household income, % people with college degree, % of white population, % of Asian, % people aged from 18 to 65, median rent, and median home value. It also has negative and heavy loadings on % people with high school degree and lower, % African American and % population under 18 years old.

Component 2 was weighted heavily on % of renters, % of housing structure built in the 1970s and the 60′s, and median structure age. It also has negative and heavy loadings on median household income, % of owner-occupied structure, and % housing structure built in the 1930s and before.

Component 3 was weighted heavily on % population above 65 years old, and % of housing structure built in the 1950s, 1940s, and 1930s and before.

Component 4 was weighted heavily on % housing structure built between year 2000 and 2010, and median age of housing structure.

Component 5 was weight heavily on % Hispanic population and population density. It also has a heavy and negative loading on vacancy rate.

Component 6 was weighted heavily on % of housing structure built in the 1980s.

For Baltimore, the PCA explained 75.06% of variance and extracted

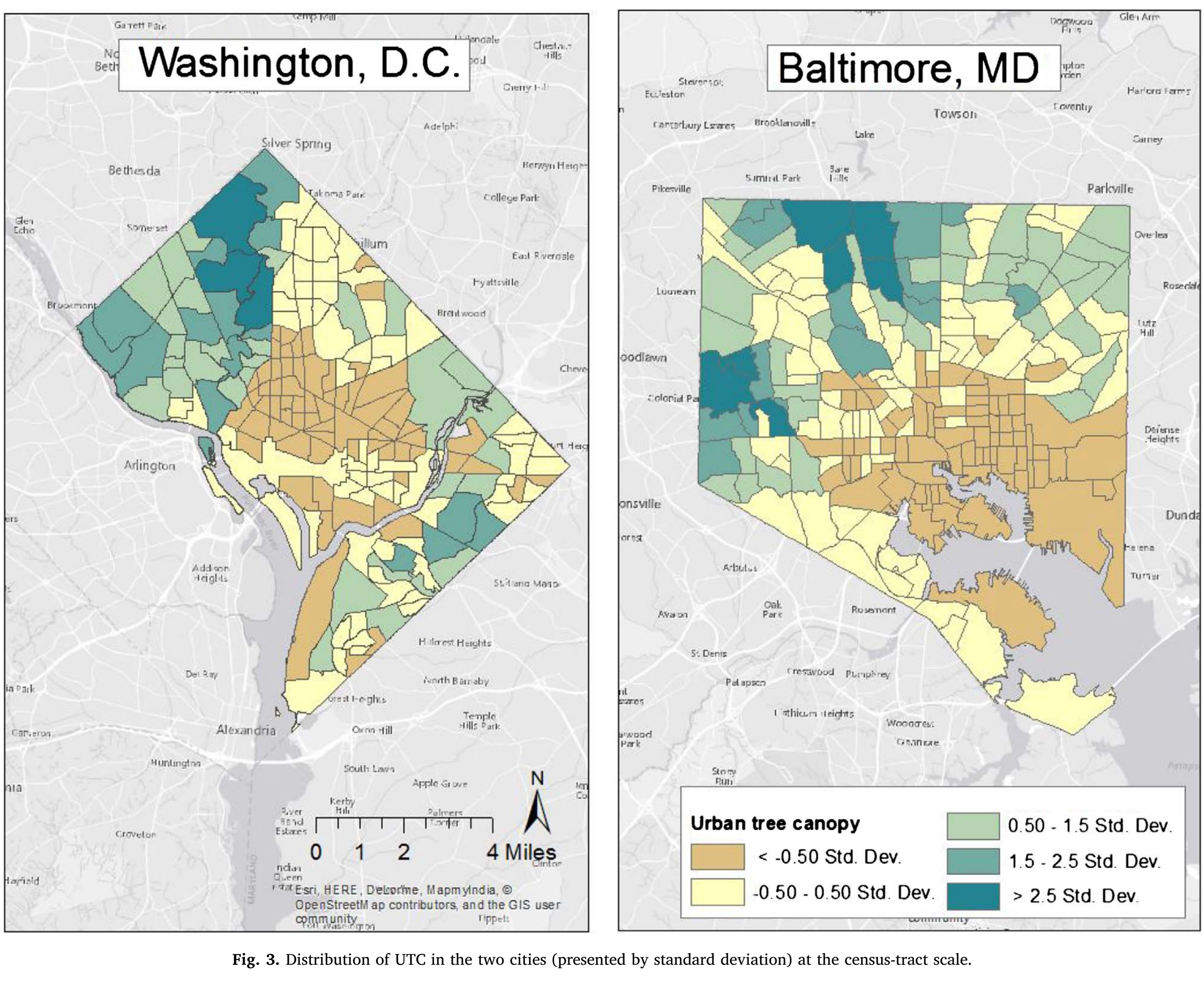

Fig. 3. Distribution of UTC in the two cities (presented by standard deviation) at the census-tract scale.

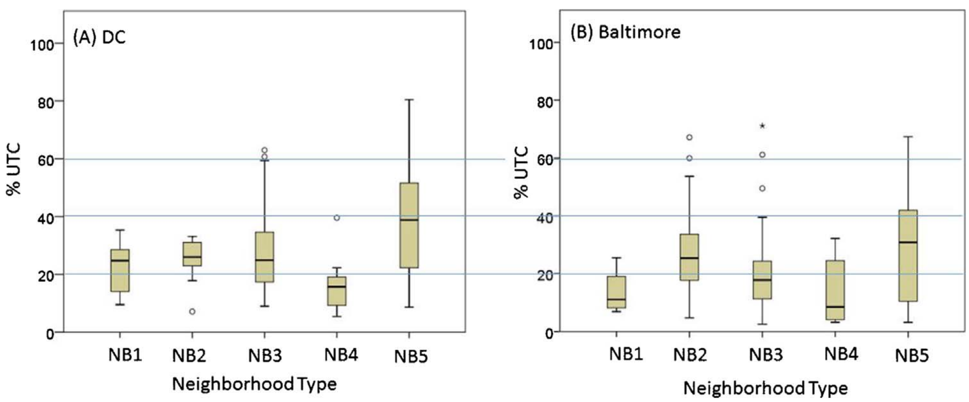

Fig. 4. Tree canopy coverage in five types of neighborhoods in Washington, D.C. (left) and Baltimore (right). Neighborhood Type: NB1-Stable impoverished; NB2-Decreasing wealth; NB3-Remained above impoverished; NB4-Increasing wealth; NB5-Stable wealthy.

Table 4
Stepwise multiple regression analysis: Washington, D.C. (R^2 = 0.31, p = 0.00).

Variables	Unstandardized Coefficients		Standardized Coefficients	*p*-value	VIF
	Estimate	Std. Error			
(Constant)	17.27	3.32		0.00	–
NB5	12.51	2.16	0.25	0.00	1.52
B1950	0.53	0.11	0.21	0.00	1.54
B1990	−1.05	0.21	−0.20	0.00	1.26
Aland	0.00	0.00	0.17	0.00	1.23
HU	0.00	0.00	0.12	0.00	1.18
NB2	−9.48	3.24	−0.11	0.00	1.19
NB4	−8.73	3.12	−0.12	0.01	1.40
B1940	−0.26	0.12	−0.10	0.04	1.70

Variables: B(YEAR): % housing structure built in the decennial; Aland: Area of land; HU: Housing units. NB2: Decreasing wealth; NB4: Increasing wealth; NB5: Remained relatively wealthy.
Note: VIF: variance inflation factor.

Table 5
Stepwise multiple regression analysis: Baltimore, MD (R^2 = 0.23, p = 0.00).

Variables	Unstandardized Coefficients		Standardized Coefficients	*p*-value	VIF
	Estimate	Std. Error			
(Constant)	2.27	1.90		0.23	–
B1950	0.28	0.05	0.20	0.00	1.38
B1970	0.56	0.11	0.20	0.00	1.45
NB5	7.84	1.34	0.21	0.00	1.20
B1940	0.38	0.08	0.19	0.00	1.34
HU	0.00	0.00	0.08	0.02	1.10
NB1	−5.56	2.27	−0.08	0.02	1.10
B1960	0.22	0.09	0.09	0.02	1.54

Variables: B(YEAR): % housing structure built in the decennial; Aland: Area of land; HU: Housing units. NB1: Stable impoverished; NB5: Stable wealthy.
Note: VIF: variance inflation factor.

Table 6
Loadings of components and variance from Principal Component Analysis, and spatial autocorrelation of component scores for Washington D.C.

	Component (Washington, D.C.) 2013					
	1	2	3	4	5	6
Median household income	**0.72**	**−0.55**	−0.04	−0.05	−0.03	0.22
% below high school degree	**−0.79**	0.27	−0.11	0.09	0.22	−0.08
% with high school degree	**−0.88**	0.29	0.05	0.04	−0.21	−0.01
% college degree	**0.92**	−0.31	0.00	−0.06	0.07	0.04
% white population	**0.90**	−0.16	−0.18	−0.07	0.05	0.16
% Black population	**−0.90**	0.13	0.17	0.07	−0.26	−0.10
% Asian	**0.74**	0.19	−0.05	0.23	0.16	0.01
% Hispanic white	0.09	−0.04	−0.04	−0.10	**0.82**	−0.15
% under age 18	**−0.86**	−0.04	−0.01	0.06	−0.07	0.32
% between age 18 and 65	**0.72**	0.24	**−0.40**	0.00	0.18	−0.36
% age above 65	0.10	−0.35	**0.73**	−0.10	−0.21	0.13
% owner-occupied housing	0.21	**−0.84**	0.29	−0.19	−0.12	−0.04
% renter-occupied housing	−0.21	**0.84**	−0.29	0.19	0.12	0.04
Vacancy rate	−0.27	0.39	−0.08	0.00	**−0.57**	−0.23
Median rent	**0.83**	−0.23	−0.10	0.07	0.00	0.09
Median house value	**0.67**	**−0.44**	−0.14	−0.15	0.13	0.33
% structure built 2010 & later	−0.16	−0.07	−0.24	**0.44**	0.06	−0.10
% built between 2000 & 2010	0.12	0.07	−0.10	**0.91**	0.00	−0.05
% built between 1990 & 1999	0.03	0.22	−0.11	**0.48**	−0.21	0.25
% built between 1980 & 1999	0.12	0.30	0.01	0.03	−0.10	**0.71**
% built between 1970 & 1979	−0.14	**0.64**	0.03	0.15	−0.04	0.34
% built between 1960 & 1969	−0.17	**0.69**	0.14	−0.05	−0.26	0.11
% built between 1950 & 1959	−0.27	0.12	**0.74**	−0.16	0.00	−0.07
% built between 1940 & 1949	**−0.42**	−0.08	**0.55**	−0.21	0.13	−0.35
% built before 1940	0.31	**−0.61**	**−0.51**	**−0.45**	0.11	−0.11
Population density	0.18	0.27	**−0.41**	−0.06	**0.60**	−0.14
Structure age	−0.04	**0.50**	0.13	**0.78**	−0.16	0.15
% of Variance	29.50	16.07	8.79	8.79	6.91	5.26
Cumulative %	29.50	45.57	54.35	63.14	70.05	75.31
Moran's I of Component scores	0.76	0.37	0.54	0.35	0.48	0.28

Note 1: Values with a relatively heavy loading are in bold (≥0.4 or < -0.4).
Note 2: All Moran's I *p-values* are ≤0.01.

seven components (Table 7):

Component 1 has high loading on median household income, % of population with college degree, % of while population, % of Asian population, median house value. It also has heavy and negative loadings on % of population with less than or high school degree only and % of housing structure built in the 1940s.

Component 2 has high loading on % of renters; and negative loading on % structure occupied by owner, and % housing structure built in the 1950s.

Component 3 has heavy loading on % of housing structure built in the 1970s, 1960s, and 1950s, and median structure age; and negative loading on vacancy rate, and % housing structure built in the 30 s and before.

Component 4 has heavy loading on % of housing structure built between year 1990 and 2009, and median structure age.

Component 5 has heavy loading on % of Asian population, population age between 18 and 64 years old; and negative loading on % population below age 18.

Component 6 has heavy loading on % of Hispanic population; and

Table 7
Loadings of components and variance from Principal Component Analysis, and spatial autocorrelation of component scores for Baltimore, MD.

	Component (Baltimore 2013)						
	1	2	3	4	5	6	7
Median household income	**0.78**	**−0.52**	−0.08	0.02	0.03	0.03	−0.09
% below high school degree	**−0.62**	0.34	−0.21	−0.04	−0.28	**0.41**	0.11
% with high school degree	**−0.89**	−0.03	0.01	0.02	−0.11	−0.05	−0.05
% college degree	**0.90**	−0.16	0.11	0.01	0.22	−0.18	−0.02
% white population	**0.82**	−0.15	−0.05	0.06	0.15	0.27	0.25
% Black population	**−0.80**	0.09	0.03	−0.05	−0.18	−0.40	−0.24
% Asian	**0.52**	0.31	0.16	0.05	**0.52**	−0.03	0.05
% Hispanic white	0.15	0.05	−0.06	−0.03	−0.04	**0.85**	0.07
% under age 18	**−0.48**	0.10	0.18	−0.02	**−0.65**	0.19	−0.31
% between age 18 and 65	**0.45**	−0.01	−0.25	−0.03	**0.76**	0.15	−0.10
% age above 65	−0.01	−0.14	0.13	0.08	−0.24	**−0.52**	**0.62**
% owner-occupied housing	0.24	**−0.91**	−0.01	−0.16	−0.05	−0.08	0.06
% renter-occupied housing	−0.24	**0.91**	0.01	0.16	0.05	0.08	−0.06
Vacancy rate	**−0.50**	0.23	**−0.61**	−0.08	0.01	−0.12	0.01
Median rent	**0.49**	**−0.44**	−0.26	0.05	0.27	0.04	−0.23
Median house value	**0.87**	−0.03	−0.04	0.03	0.03	−0.01	−0.02
% structure built 2010 & later	0.05	0.09	−0.07	−0.10	0.09	0.18	**0.61**
% built between 2000 & 2010	0.12	0.04	−0.12	**0.88**	0.10	0.03	−0.03
% built between 1990 & 1999	0.05	0.35	0.16	**0.60**	−0.09	−0.06	−0.02
% built between 1980 & 1999	0.18	0.36	0.22	0.21	−0.32	−0.29	0.21
% built between 1970 & 1979	0.23	0.37	**0.59**	0.12	−0.15	−0.28	0.10
% built between 1960 & 1969	−0.01	0.17	**0.79**	−0.15	−0.09	−0.03	−0.08
% built between 1950 & 1959	−0.28	**−0.53**	**0.62**	−0.14	0.08	0.04	−0.03
% built between 1940 & 1949	**−0.62**	−0.31	0.09	−0.14	−0.03	0.06	0.23
% built before 1940	0.25	0.09	**−0.86**	−0.31	0.10	0.11	−0.13
Population density	0.10	0.34	−0.31	−0.27	−0.04	0.14	**−0.45**
Structure age	0.01	0.13	**0.62**	**0.66**	−0.13	−0.11	0.06
% of Variance	24.61	12.56	12.31	7.25	6.60	6.50	5.21
Cumulative %	24.61	37.16	49.49	56.74	63.34	69.85	75.06
Moran's I of Component scores	0.70	0.45	0.55	0.17	0.22	0.51	0.15

Note1: Values with a relatively heavy loading are in bold (≥0.4 or < -0.4).
Note 2: All Moran's I *p-values* are ≤0.01.

negative loading on % population 65 years old and above.

Component 7 has heavy loading on % population age above 65 years old, and housing structure built between 2010 and 2013.

The Lagrange multiplier tests were applied to the ordinary least squares (OLS) regression models, and indicated that the spatial lag specification was more appropriate than the spatial error specification for our study sites (Anselin, 2005). Our spatial autoregressive models, which accounted for spatial autocorrelation and used principal components as independent variables, provided high R^2 values (above 0.7). The Moran's I of the residuals from our spatial lag models indicate that spatial lag specification accounted for the spatial autocorrelation present in the data. Our results also suggest that a principal components approach is effective at capturing the blended nature of socio-ecological variables that may be driving the spatial distribution of tree canopy in our two cities.

In Washington, D.C., the spatial lag model results show three input variables are *negatively* associated with UTC. The observations of these variables are: (1) neighborhoods with a high percentage of renters with low to middle incomes and housing built in the 1960s and 1970s (Component 2), (2) neighborhoods with a high percentage of housing built after 1990 (Component 4), and (3) high-density, Hispanic communities (Component 5). In contrast, two variables were *positively* correlated with UTC: (1) neighborhoods with a high percentage of elderly population and housing structures built in the 1950s (Component 3), and (2) neighborhoods with housing built in the 1980s (Component 6).

The spatial lag model for Baltimore found two components to be *negatively* associated with UTC. First, Component 5, weighted toward population with age between 18 and 65 years old (economically productive group) and Asian, and secondly Component 6, which was weighted toward Hispanics and the population with less than a high school degree. Significant components that were *positively* associated with UTC in Baltimore were neighborhoods weighted toward income, education, economically active groups, and non-Hispanic white population (Component 1); and Component 3 which was weighted toward housing built between 1950 and 1970 and structure age.

Tables 8 and 9 show the coefficient and *p*-value of each independent variable in the spatial lag models. The effects of components on predicting UTC cover varied between the two cities. For instance, we expected that Component 1, which has weights toward education, economically productive populations, would be a significant predictor of UTC, but the model results showed that to be true only in Baltimore. Components with heavy loading toward ethnic minority, such as Baltimore's Component 5 (middle-income, economically active, and Asian communities) and Component 6 (Hispanic working class), and Washington's Component 5 (high-density Hispanic communities) were all negatively associated with UTC. The cities differed in the way housing characteristics were related to UTC. In Baltimore, Component 3 (with

Table 8
Results of spatial lag model for Washington, D.C. (R^2 = 0.70).

Variables	Coefficient
Constant	8.70*
Component 1	0.76
Component 2	−1.66*
Component 3	2.70*
Component 4	−2.44*
Component 5	−1.51*
Component 6	2.78*
Lag Coefficient (Rho) = 0.68*	
Moran's I of residuals = −0.01	

Note: The R^2 and Moran's I of residual of OLS model are 0.43 and 0.38*, respectively.
* $p \le 0.01$.

Table 9
Results of spatial lag model for Baltimore, MD (R^2 = 0.75).

Variables	Coefficient
Constant	5.05*
Component 1	1.49*
Component 2	−1.07
Component 3	1.50*
Component 4	−0.01
Component 5	−1.36*
Component 6	−1.30*
Component 7	0.90
Lag Coefficient (Rho) = 0.77*	
Moran's I of residuals = −0.03	

Note: The R^2 and Moran's I of residual of OLS model are 0.46 and 0.33*, respectively.
* $p \leq 0.01$.

heavy weights on housing built between 1950 and 1970 and structure age) was positively associated with UTC. In Washington, a high percentage of housing built in the1980s was positively correlated with UTC, while a high percentage of housing built after 1990 was negatively correlated.

4. Discussion

Our findings supported Hypothesis 1 (H1), which stated that neighborhoods that remained relatively wealthy would have more tree canopy. The results of our stepwise regression models confirmed that "stable wealthy" (NB5) was significantly and positively associated with UTC. However, income instability had different associations with UTC in the two cities, which have different growth trajectories. We were surprised to find that in Washington D.C., which is in a revival phase, both positive and negative income changes were negatively correlated with the extent of UTC. One could argue that new development and construction in rapidly gentrifying Washington D.C. leads to tree loss, but further investigation is required to substantiate or disprove that argument. Model results also indicated that stable-impoverished status does not always have a negative relationship with UTC. In Washington, a city that has undergone rapid changes in the past decade, stable-impoverished status was not a significant variable at all. But in Baltimore, which has been shrinking in recent decades, income stability, whether remained-wealthy or remained-impoverished, was a significant predictor of the extent of canopy cover. Thus, H2 and H3 were not fully supported.

Hypothesis 4 which stated that increasing wealth occurs with increasing tree canopy, was supported. We did find UTC gains in increasing-wealthy neighborhoods (NB4) in Washington, DC. Surprisingly, we also found that Washington neighborhoods with *decreasing* wealth (NB2) had the *highest* UTC gain, the opposite of Hypothesis 5. This may due to previous planting and care when the neighborhoods were relatively wealthy. However, without proper care, trees can die in over time, which may be part of the reason that the NB2 group had the second highest rate of tree canopy loss of all neighborhood types. A report (O'Neil-Dunne 2009b) on the relationship between UTC and land use reveals that residential areas offer more potential for planting trees than any other type of land use in Washington D.C. Assuming that most of Washington's UTC gain occurred in residential areas, one possible explanation for the correlation between decreasing wealth and UTC is that planting and maintenance efforts in the past have affected present-day UTC. It takes time for trees to grow, and the past investment in growing and maintaining trees may have resulted in high canopy gains in economically declining neighborhoods. This explanation is consistent with the findings of Boone et al. (2010) that *past* social and built-environmental conditions were better predictors of UTC than current conditions.

Hypothesis 5 also unsupported, stated that neighborhoods with decreasing wealth (NB2) would show canopy loss and/or little canopy gain. Indeed, there were relatively large canopy losses in economically declining neighborhoods in Washington D.C. in comparison to the losses in NB4 and NB5. Nevertheless, tree canopy gain was *highest* in neighborhoods with declining wealth. Hypothesis 6 was not supported either. In Washington, stable-impoverished neighborhoods (NB1) had the largest loss of preexisting UTC, but also higher-than-average UTC gain (new planting and growth).

In both cities, a high percentage of structures built in the 1950s was positively associated with UTC. Areas with housing built predominantly in the 1950s may have inherited trees from past residents. During the 1950s, both cities had robust tree-management programs (Merse et al., 2009; Buckley, 2010; Rodier, 2011). Future studies might productively examine past tree-management programs and their relationship to present-day UTC. In Baltimore, UTC was positively associated with high percentages of structures built in the 1950s, 60s, and 70s. It may be that tree canopy is more extensive in older areas simply because the trees in these places have had longer to grow than they have in newer areas.

Our spatial regression models indicated that the combination of ethnic minority and middle or low socioeconomic status was negatively associated with UTC cover. That association bears further study. While much research has explored environmental injustice between white and African American populations, and the history of segregation that limited African Americans' access to environmental goods (e.g., Boone et al., 2009), little attention has been paid to how those issues affect Hispanics and Asians in Baltimore and Washington.

There are several possible explanations for our finding that a high-socioeconomic-status population was not a significant predictor of UTC in Washington D.C. Rapid population growth could be a driver that has led to rapid change and new development that has had adverse effects on tree conservation and new planting. It would be useful to examine whether new urban lifestyles (i.e., compact growth with housing options near jobs, shops, and schools, and reduced dependency on the automobile) will hinder or support UTC plans. A second explanation is that neighborhood change occurs at a faster rate than changes in UTC. Thus, increasing affluence may not manifest in UTC for several decades. More long-term UTC-change data are needed to test this explanation. Future studies to examine the relationship between UTC and variables related to planning, such as land-use change and zoning, could contribute to assessing and developing UTC and municipal UTC plans.

Tree conservation is as important as tree planting. Although we found new planting in some impoverished neighborhoods in D.C., the loss rate of preexisting trees was much faster than the rate of UTC gain (new planting and growth). Low-income neighborhoods may lack resources, knowledge, or incentives to maintain healthy trees. And residents of low-income areas might avoid tree planting to prevent rising rents and gentrification (Schwarz et al., 2015). Research that improves our understanding of the drivers of tree loss can help municipalities in their efforts to develop conservation plans that consider specific neighborhood characteristics and needs.

5. Conclusion

Many urban ecological studies focus on how urban growth impacts ecosystem services. We were specifically interested in how changes in population and economic activity affect the distribution of tree cover. This study is among the first to investigate the relationship between income *dynamics*, an indicator of social change, and the distribution of UTC. Although a recent cross-city study (Schwarz et al., 2015) found that high-income neighborhoods are more likely than low-income neighborhoods to have higher tree canopy cover, our analyses, using a more complex set of time-series data, suggest that income is not the only determinant of tree canopy cover, and that the impacts of income change on tree canopy cover vary between cities. Our study shows that high socioeconomic status is not necessarily a significant predictor of high tree canopy cover in a fast-growing city. Trees take years to grow. Social conditions and structure can change more rapidly than trees can reach maturity.

Our analysis compared two cities with comparable regional climates, population sizes, diversity, and racial history, but different growth patterns over the past 20 years. We found some evidence for associations between neighborhood change and changes in UTC in Washington D.C. over a 5-year period. With longer time frames and more data from Baltimore, we may be able to learn more about the relationships among neighborhood transitions, urban land-cover change, and temporal lags and legacies. Our study can help inform efforts to understand the mechanistic relationships between neighborhood characteristics and UTC change (Grove et al., 2015).

Lack of UTC is an inner-city problem that needs to be considered in municipal sustainability and UTC plans. Spatial and temporal distribution of UTC result from complex interactions in heterogeneous social-ecological systems. The distribution of UTC in the two cities suggests that low-income neighborhoods may lack the resources, capacity, authority, or desire to overcome a scarcity of the benefits that are provided by tree canopy. Stable-impoverished neighborhoods had the lowest UTC cover and largest proportion of tree loss compared with other types of neighborhoods. Although there were new planting efforts in stable-impoverished neighborhoods in Washington, D.C., they were not enough to stem the overall loss of tree canopy in those neighborhoods. Environmental justice is frequently included as one of the objectives of urban tree canopy goals. However, merely increasing the investment in new planting in low-income and low-UTC areas may not produce a lasting increase in tree canopy. Preventing tree loss and providing incentives for planting and maintaining trees in residential areas may be as important as new planting implemented by municipalities.

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