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Sub-parcel scale analysis is needed to capture socially-driven canopy cover change in Baltimore, MD

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HIGHLIGHTS

- Tree canopy area is seldom distributed equitably across social groups, space and time.
- Market segmentation based on lifestyle best predicts residential tree canopy.
- Tree canopy is greater in backyards than front, and the gap varies by social groups.
- Tree canopy change did not vary by segments or front yard versus backyard.
- Long-term tree canopy expectations may consider drivers of gain, loss and persistence.

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ABSTRACT

Urban tree canopy (UTC) cover is rarely distributed equitably across social groups, space, and time. Over the past 20 years, research on the social, spatial, and temporal dynamics of UTC has grown considerably as municipalities adopt ambitious tree canopy cover goals. Yet less is known about how these three dimensions of tree canopy intersect. This paper brings these research areas together by examining i) which sets of social variables–population density, socioeconomic status, or lifestyle–are associated with UTC cover on residential lands, ii) how those relationships vary from front to back yard, and iii) how those relationships are associated with tree canopy cover changes in Baltimore, MD from 2013 to 2018, to more wholistically understand UTC. Socially, population density and social stratification predict tree canopy cover on residential lands, but not as well as lifestyle and life stage factors. More detailed and finer-grain social categories perform best. Spatially, models that explicitly separate front and backyards fit the data better than all-residential statistical models. Ignoring the front yard vs back yard distinction may hinder future theory development, limit the generalizability of empirical research findings, and prevent managers from realizing their canopy goals. Temporally, UTC across residential yards had a positive, though not significant, change likely from the relatively short period (5 y) considered. A fruitful next step could be to model how much planting, maintenance, and loss minimization is needed to achieve the city's 40 % canopy goal with various scenarios for mortality, longevity, and removal over several timesteps.

1. Introduction

Urban tree canopy is rarely distributed equitably across social groups, space, and time. Over the past 20 years, research on the social, spatial, and temporal dynamics of urban tree canopy has developed among a number of dimensions: a) socioeconomic and demographic factors are associated with the inequitable spatial distribution of tree canopy cover (Schwarz et al., 2015; Troy et al., 2007); b) the relationship between socioeconomic and demographic factors and tree canopy covers varies by public versus private lands (i.e. trees in the public right of way and parks in contrast to privately owned trees in residential areas) (Landry & Chakraborty, 2009; Troy et al., 2007); c) within

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residential areas, there can be significant differences in vegetation including tree canopy cover between front and backyards (Locke, Avolio, et al., 2018; Ossola et al., 2019a; b); and d) there are temporal legacies, lags, and contemporary drivers of canopy change (Boone et al., 2010; Locke, Hall, et al., 2021). Finally, and more practically, tracking canopy change in relation to social, economic, and environmental drivers can help cities achieve their urban tree canopy goals and reduce inequity. The purpose of this paper is to bring a number of these research areas together by comprehensively examining 1) social: which sets of social variables–population density, socioeconomic status, and/or lifestyle/lifestage–are associated with tree canopy cover on residential lands, 2) spatial: how those relationships vary from front to back yard, and 3) temporal: how those relationships are associated with contemporary tree canopy cover changes in Baltimore, MD from 2013 to 2018.

We focus on residential land because it is the predominant landuse in most urban areas in the United States and contains most of the existing tree canopy and opportunities for additional tree canopy (Locke, Grove, et al., 2023). Residential lands are substantial, with approximately, 111,053,625 residential yards covering 646,337 km^2 (Lerman et al., 2023) in the United States. We also focus on Baltimore City because out of the 207 jurisdictions in the Chesapeake Bay watershed, only 26 (12.5 %) reported net increase in tree canopy, including Baltimore City (https://chesapeaketrees.net/understand-your-canopy/). The social, spatial, temporal approach (detailed next) in Baltimore could be instructive to other locales in the watershed, or other places with similar dominance of single-family homes with yards of varying size to examine the social and spatial components of UTC change.

1.1. Social: Geodemographic market segments and urban tree canopy (UTC)

Three social theories have been proposed to explain the spatial distribution of tree canopy cover on residential lands: population density, social stratification and the luxury effect, and lifestyle behavior and the ecology of prestige (Grove, Cadenasso, et al., 2006; Grove, Troy, et al., 2006). Population density is presumed to affect the distribution of tree canopy cover based on the assumption that built infrastructure displaces land for trees and other vegetation (Marco et al., 2008; Smith et al., 2005). Social stratification theory and the "luxury effect" have been used to predict tree canopy patterns based upon relative power and income differences among neighborhoods (Gerrish & Watkins, 2018; Watkins & Gerrish, 2018). This relates not only to the ability of different socio-economic groups to invest or attract investment in greening initiatives, but also their ability to move to neighborhoods with more tree canopy cover (Hope et al., 2003; Martin et al., 2004). The third theory is based upon lifestyle behaviors and an "ecology of prestige," which refers to the phenomenon in which household patterns of consumption and expenditure on environmentally relevant goods and services are motivated by group identity and perceptions of social status associated with different lifestyles (Grove et al., 2014; Locke et al., 2016; Troy et al., 2007; Zhou et al., 2009). This theory suggests that a household's land management decisions are influenced by its desire to uphold the prestige of its community and outwardly express its membership in a given lifestyle group (Grove et al., 2014; Locke et al., 2016; Troy et al., 2007; Zhou et al., 2009). Members of different lifestyle groups have additional motivations for different types of management, for example creating play spaces for children.

Although these theories are distinct, they are linked methodologically because measures of population density and income and education are incorporated into empirical characterizations of lifestyle groups with continuous or categorical analyses (Bigsby et al., 2014; Grove et al., 2014; Locke et al., 2016; Locke & Grove, 2016; Troy et al., 2007; Zhou et al., 2009). Many geodemographic segmentations systems like PRIZM and Tapestry (detailed below) are hierarchically organized, with a coarse first level corresponding to urbanization, an intermediate level with more groups corresponding to social stratification, and third and final level with the most segments corresponding to lifestyle/lifestage.

Studies show that statistical models of residential tree canopy cover with population density, and social stratification, that also include lifestyle and lifestage factors fit the data better than those without them in several northeastern cities (Grove et al., 2014; Grove, Cadenasso, et al., 2006; Grove, Troy, et al., 2006; Locke et al., 2016; Troy et al., 2007). However similar analyses of tree canopy in Raleigh, NC suggest urban morphology and parcel-level variables such as parcel size, detached housing, and year built are better correlates of cover than block-group level geodemographic variables (Bigsby et al., 2014). Social groups operationalized via geodemography have also provided insights into the spatial distribution of participation in tree planting programs. Tree planting participation varies by lifestyle categories in Washington, DC, and Baltimore, MD (Locke & Grove, 2016; Nguyen et al., 2017), but not in Philadelphia, PA and New York City (Locke et al., 2013; 2014). Tree canopy change varied by geodemographic market segment in coastal Los Angeles from 2009 to 2014, and higher income areas had more and more stable tree canopy (Locke et al., 2017).

1.2. Spatial: Front and backyards and UTC

Previous research in the US cities indicates the importance of lifestyle-pertinent social norms affecting residential yard care (Chowdhury et al., 2011; Cook et al., 2012; Harris et al., 2013; Robbins, 2012; Robbins et al., 2001; Robbins & Sharp, 2008). Whether motivated by pride and joy of upholding the neighborhood aesthetic (and ecology of prestige) or seeking to avoid negative judgement, shame, and even ostracization in a neighborhood (the moral economy (Robbins, 2012; Robbins et al., 2001; Robbins & Sharp, 2008)), perceived or real pressures for conformity may lead people to change their landscaping. Different neighborhoods may have different social norms, and neighborhoods are comprised of different lifestyle groups. Since backyards are often more secluded than more publicly-visible front yards, researchers have examined the effect of social norms on backyards may also be reduced – if not completely eliminated (Locke, Avolio, et al., 2018; Locke, Roy Chowdhury, et al., 2018). As a consequence, the management actions and associated outcomes like tree canopy cover are hypothesized to be different between front and backyards.

The idea that there may be differences between front yard versus back yard vegetation is not new. Vegetated areas of backyards in Syracuse NY were 1.5–2.4 times larger, and there were 0.9–1.8 times as much tree canopy than front yards (Richards et al., 1984). There were more tree stems in backyards compared to front yards in Shorewood, WI, a suburb of Milwaukee (Dorney et al., 1984). More recently, additional evidence has emerged. Backyards in the greater Boston, MA metropolitan area are larger than front yards, have more tree canopy by area and percent area (Ossola et al., 2019a), and that tree canopy forms larger contiguous blocks that is more connected (Ossola et al., 2019b). In Adelaide, Australia, backyards have almost as much tree canopy cover as public rights of way with street trees, but on a percentage basis they have the most tree canopy cover out of any land use, and cover ~23 % of the entire study area (Ossola et al., 2021).

1.3. Temporal: Time and urban tree canopy

Trees are slow-growing and long-lived organisms. Historical, biophysical and social factors, and their interactions, can shape contemporary tree canopy cover (Roman et al., 2018). Present day-tree canopy have been correlated with historic demographic data (Boone et al., 2010; Clarke et al., 2013; Locke & Baine, 2014; Luck et al., 2009). Past policies and practices can also be associated with current vegetation cover. For instance, racial segregation policies and practices from the 1930 s correspond with vegetation cover (Nardone et al., 2021) and contemporary tree canopy (Hoffman et al., 2020; Locke, Hall, et al., 2021; Nowak et al., 2022).

In addition to long-term time horizons (5–50 years)(Roman et al., 2021), shorter time periods or near-term (5–10 years) have been analyzed predominantly in US cities. The disparities in distributional environmental injustice of tree canopy cover in Philadelphia worsened from 2008 to 2018 (Foster et al., 2022). Similar patterns were found in coastal Los Angeles from 2009 to 2014, where higher income areas had more tree canopy and lost less (Locke et al., 2017). Changes in household income (increases or decreases) corresponded with tree canopy gain in Washington, DC from 2006 to 2011 with consistently high-income areas having more tree canopy and more persistent tree canopy (Chuang et al., 2017). Aside from extreme events like earthquakes (Morgenroth et al., 2016; Staudhammer et al., 2011), development appears to be the largest factor associated with urban tree canopy losses (Croeser et al., 2020; Ellis & Mathews, 2019; Guo et al., 2018; Hostetler et al., 2013; Ossola & Hopton, 2018). It is less clear, however, how urban tree canopy changes—gain, persistence, or loss—varies by social group over near-term time periods (~5–10 years).

In this paper we focus on residential lands because they are the predominant land use in urban areas. Despite what is already known about the social, spatial, and temporal aspects of UTC individually, less is known about how these three domains interact. The purpose is to more comprehensively understand these three domains of UTC together. We examine how tree canopy varies by social groups, across space with front and backyards, and over time from 2013 to 2018, in Baltimore City, MD. This paper asks:

1) **Social:** Which theory: population density (urbanicity), lifemode (social stratification/luxury effect), or lifestyle/lifestage (prestige) best predict the distribution of tree canopy cover on residential lands?
2) **Spatial:** Does resolving parcels into front and backyards improve our ability to predict, and therefore understand, tree canopy cover on residential lands?
3) **Temporal:** How does residential tree canopy change vary by social groups and front and back yard over time?

2. Methods

2.1. Study area

Baltimore City (39.2848101, −76.7030691) is located in the mid-Atlantic region of the United States, and has a temperate climate. Over the past 50 years, the city's population has declined from nearly 1 million to ~570,000 people, while the surrounding counties have grown to ~2.7 million people for the metropolitan region (US Census Bureau, 2023). Recently, the city has experienced a mix of decline, stabilization, and redevelopment among its neighborhoods. Baltimore has a rich history of as a leader in urban ecology (Grove et al., 2015), and has a tree canopy goal of 40 % (Nguyen et al., 2017). There are a number of active urban forestry stewardship groups that vary from large, citywide organizations with full time paid staffs and 501(c)3 tax exemption status, to neighborhood-specific volunteer groups (Sonti et al., 2023). TreeBaltimore (https://www.treebaltimore.org/) is the City's lead, municipal umbrella organization which coordinates among NGOs, volunteers, and agencies at various levels.

2.2. Data

2.2.1. Geodemography and Tapestry

Geodemographic analyses are well-suited to examining nested theories about the distribution of urban tree canopy. Geodemographic market segmentation is a family of spatial and statistical analyses that classifies areas into categories based on who lives in that area, with the underlying premise people within neighborhoods have some common demographic, socioeconomic, and/or lifestyle characteristics (Troy, 1995). PRIZM (the Potential Rating Index for Zipcode Markets) and Environmental Systems Research Institute's (ESRI) Tapestry segmentation are two commonly-used geodemographic datasets, although there are several others, including A Classification of Residential Neighborhoods aka "ACORN" developed in the United Kingdom (Charlton et al., 1985) and city- and use-specific classifications in the UK, Canadian, and US cities (Corcoran et al., 2013; Delmelle, 2015; 2016; Delmelle & Rey, 2021; Tao et al., 2013). The United Kingdom has been a hotbed for geodemography and an early adopter of the family of techniques (R. Harris et al., 2005; Openshaw & Blake, 1995). However geodemographic systems can be found in the Philippines (Ojo et al., 2013), Nigeria (Ojo et al., 2010; Ojo & Ezepue, 2012), and guides for creating local segmentations systems exist (Charlton et al., 1983), and even with particular attention to developing countries (Ojo & Ezepue, 2011).

ESRI's Tapestry geodemographic segmentation uses a non-spatial cluster analysis of spatial data to categorize Census block groups (ESRI, 2015). In other words, the attribute data are subjected to cluster analyses, irrespective of their geographic location. Input data include Census data, labor force participation from the Bureau of Labor Statistics, housing information from the Federal Housings Finance Agency, among others. Tapestry's urbanization levels correspond to population density, LifeMode maps on to social stratification, and the segment level reflects lifestyle/lifestage. Tapestry data have been used in a range of applications including COVID-19 transmission risk modeling (Ozdenerol & Seboly, 2023), carbon footprint estimation (Baiocchi et al., 2022), and assessing the opioid epidemic (Hanson, 2020).

As described above, Tapestry data have successfully been applied in previous urban forestry investigations (Locke et al., 2013; 2014; Locke & Grove, 2016; Nguyen et al., 2017). Conveniently there are three tiers or levels of the categories that neatly match the three theories. The first is urbanicity which corresponds to population density (Fig. 1A, Figure S1 left). The second level is called LifeMode which corresponds to social stratification theory (Figure S1 right). Each LifeMode group is nested within one and only one Urbanicity category. The third level is Segments, which corresponds to lifestyle and lifestage (Figure S2). Thus Tapestry the geodemographic market segmentation operationalizes the three theories investigated here. Each Segment is nested within one and only one Urbanicity class. The classes found within Baltimore City in year 2015, their frequency, and hierarchical layout can be found in Table S1. The Tapestry data used here reflect year 2015, intentionally chosen to occur between 2013 and 2018 to match the land cover data (described below). An additional benefit of categorical data analyses here is that the input variables into a geodemographic segmentation are naturally correlated (e.g. income and education), or correlated by construction (e.g. % of housing units vacant, owner occupied, or rented). By creating social groups first, subsequent statistical analyses are less prone to multicollinearity, and scores of continuous predictors do not consume degrees of freedom in the model. These simpler models may also produce results that are easier to interpret, because they have fewer terms.

2.2.2. Yards

An algorithm created to separate property parcels into front and backyards developed in Boston, MA to examine tree canopy cover (Locke, Ossola, et al., 2021; Ossola et al., 2019a; b) and vegetation-surface temperature relationships during a heat wave in Adelaide, Australia (Ossola et al., 2021), was adapted to work with parcels boundaries in Baltimore City, MD. The geospatial approach identifies the centroid of the largest building footprint per parcel (to exclude garages, sheds, etc.), and finds the shortest distance from that centroid to the street centerline. Finally, a line through the centroid and perpendicular to that first line is drawn to segment the parcel in to two yards. Parcel data represent year 2015 conditions, and buildings year 2017; these are closest in time to each other as is possible and in the middle of the land cover years (2013 and 2018, described below).

Corner yards, which lack a clear front versus back distinction, were assigned to parcels located within 20 m from street intersections. This algorithm resulted 326,191 yards (141,053 backyards, 110,262 front

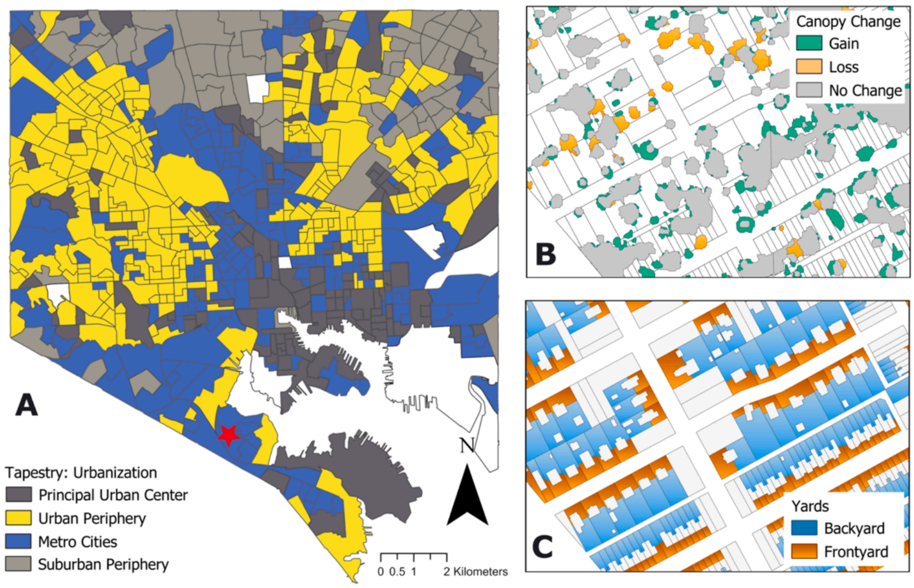

Fig. 1. Tapestry Urbanization categories at the Census block group level (A), residential tree canopy cover change (B), yard-level polygons derived from parcels (C). Panels B and C refer to the location of red star in panel A. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

yards, and 74,876 other yards). Parcels may lack either a front or back yard, so the yards are not all matched pairs. Accuracy of the yard classification algorithm was calculated by visually interpreting 4,000 randomly-selected yards and calculating the percentage of yards correctly classified. The overall accuracy in identifying delimiting Baltimore's backyards and front yards was 99.05 %. Misclassifications occurred when a true front or back yard was within 20 m of an intersection and was classified as a corner yard. A smaller buffer around intersections would have reduced that error but would have resulted in a number of corner yards being wrongly included in the study. The yard polygons are freely available via Ossola and Locke (2024).

2.2.3. Land cover change

Trees do not grow instantaneously and are subject to long-term lags and legacies and the historic aspects of contemporary tree canopy change have been examined elsewhere (Healy et al., 2022; Nix et al., 2023; Roman et al., 2021). We instead focus on near-term contemporary changes that reflect recent land management activities. The Chesapeake Conservancy has created a freely available high-resolution (1 m^2) high-accuracy (Pallai & Wesson, 2017) land cover change dataset for the entire Chesapeake Bay watershed (Chessapeake Bay Program, 2022). The accuracy of land cover classifications across the dataset is 91 %, the accuracy of the tree canopy classes is 98 % (Pallai & Wesson, 2017). The land cover change for Baltimore City, MD, was downloaded from (https://www.chesapeakeconservancy.org/conservation-innovation-center/high-resolution-data/lulc-data-project-2022/) and all tree classes (Tree Canopy, Tree Canopy Over Roads, Tree Canopy Over Impervious Structures, and Tree Canopy over Other Impervious) were combined for each year to create 2013 and 2018 tree canopy cover datasets. The blend of object-based image analysis (OBIA) and manual corrections ensures precision, accuracy, and realism (MacFaden et al., 2012; O'Neil-Dunne et al., 2013; 2014). Importantly, these two years of data were created expressly for the purpose of measuring fine-scale landscape changes using OBIA techniques and manual corrections, so that true changes are detected and not a conflated mix of landscape change and changes in remote sensing techniques. These data represent the most precise and accurate tree canopy change maps produced for this area and for this time period.

2.3. Statistical analyses

Data were analyzed using generalized linear mixed models. The unit of analysis was the census block group, and the response variable was the aggregate proportion of yards covered by canopy in its containing block group. Yards here are the non-building area of a parcel. Because the proportion of tree canopy cover ranges from nearly zero to nearly one, we used a beta error distribution (Geissinger et al., 2022). Some block groups lack front or back yard cover, so a zero-inflated beta distribution was used via the BEINF0() function in the gamlss R package when zeros were present (Rigby et al., 2005). This issue occurred specifically in the models which differentiated between front and backyards (see below).

In the primary analyses, for each of the three levels of the categories of Tapestry segmentation, we fit four models (twelve models in total): A) Residential: an all-residential lands model which aggregates front yard, backyard, and other yards in that block group ($n = 1,256$, each block group appears for 2013 and again for 2018), B) Front/Back data: a model whose outcome is the proportion tree canopy, with rows for either front or back yard in each block group but no front/back term is estimated ($n = 2,506$, some block groups do not have front yards), C) Front vs Back (additive): a model like B that includes a front versus back yard as an additive term, and D) Front vs Back (interaction): a model that includes an interaction between Tapestry segmentation and front versus backyard. This approach builds from simple to complex and allows us to determine if and how tree canopy change relates to social groups on front and back yards. All specifications included year as an additive effect and a block group random intercept to account for the fact that within a block group between canopy cover of front and backyards, and canopy cover between time periods are likely correlated. AIC and RMSE were used to compare the statistical models.

In secondary analyses, once it was seen that models including front and back improved model fit, data were separated into front- and backyard-only subsets. The then three levels of Tapestry segmentation were examined again with six additional models (front or back only and for each of the three levels of Tapestry). The purpose was to assess model fit against the three explanations: population density, social stratification and the luxury effect, and lifestyle behavior and the ecology of prestige for front and back yards separately. Data analyses were conducted in R version 4.3.2 (R Core Team, 2023) in RStudio with the sf package (Pebesma, 2018) and tidyverse *meta*-package (Wickham et al., 2019). Model estimates were derived and extracted using the marginaleffects package (Arel-bundock et al., n.d.).

3. Results

Residential tree canopy cover per block group, which includes back, front and corner yards, per year ranged from 0.615 % to 84.7 % in year 2013, and from 0.709 % to 84.9 % in year 2018 (Table 1). Front yard tree canopy cover per block group also ranged widely from 0.00 % to 89.5 % cover, and back yard cover 0.00 % to 85.4 % in both years 2013 and 2018.The average tree canopy cover was greater in backyards (38.42 % and 37.84 % in 2013 and 2018, respectively) than front yards (26.11 % and 25.2 %). In other words, at the block group level, back yard tree canopy cover is roughly 12 percentage points greater than front yards. Mean and median tree canopy cover changes over time were miniscule; most tree canopy is persistent at this spatial scale (yards aggregated to block groups) and temporal scale (5 years with a single time step).

Across the three Tapestry categorizations, segments (corresponding to lifestyle and lifestage) predicted the tree canopy cover better than urbanization (population density), or the lifemode (social stratification) classifications as indicated by lower AICs (Table 2, Figure S3); model fit statistics (AIC, BIC, RMSE) support the same conclusions. Among the models using Tapestry segments as the predictor, front versus back additive specification fit best (AIC = −2,109.16); the front vs back interaction term with segments resulted in a slightly worse-fitting model (AIC = −2,093.49). The root mean square error was also slightly lower for the front versus back additive specification (0.988) than the front vs back interaction model (RMSE = 0.992).

The secondary front and backyard-only analyses reinforced the primary analyses' findings. The rank-order of the AICs also followed the population density, social stratification, lifestyle/lifestage order, where the lifestyle/lifestage model fits best (Figure S4). Front yard-only models always fit better than backyard-only models. This adds evidence to the idea of fitting into a neighborhood aesthetic, and expressing membership in the lifestyle group.

The best-fitting model (tapestry segments with front and backyards, but no interaction) showed significant differences for front versus back yard and nearly all segment categories (Fig. 2, Table S2). Year was not a significant predictor, indicating that there were no consistent changes in canopy on residential yards within these units of analyses and level of aggregation, although the sign was positive. The model met model assumptions. The residuals were normally distributed, multicollinearity was not an issue because the VIF scores were 1.01, 1.01, and 1, for front vs back, tapestry segment, and year, respectively.

The model selection process helps us consider which explanation about socioeconomic and demographic characteristics correspond best to the social groups. Rare Tapestry segments are included because they still contribute valuable information to front vs back comparisons (Q2: spatial) and over time (Q3: Temporal) questions. Incorporating the additional complexity offered by the Tapestry segment categorization reflecting lifestyle/lifestage, and which contains more categories than either the urbanicity or LifeMode groups, appears to be warranted because the data show substantial variation in the UTC across these groups, both in front and back yards, and the measures of model fit are superior.

Through the model selection process, we learned that there are important differences between front and back yards, and that the additional complexity associated with parsing parcels into front and backyards is also warranted. Prior social theory and empirics suggest front and backyards are distinct portions of the urban forest. Analytically lumping all residential tree canopy together occludes the ability to spatialize social theories about yard care, namely that attitudes and preferences vary from front to back, with associated differences in outcomes like tree canopy cover.

Post-hoc pairwise comparisons of front vs back yards and Tapestry segment resulted in 2,016 hypothesis tests, far too many to list or display; 65.87 % (n = 1,328) of all pairwise tests were significantly different at the $p < 0.05$ level. Examining all 2,016 pairwise differences by their front vs back comparisons, 62.90 % (n = 312) back yard to back yard comparison were significant, 63.33 % (n = 314) front to front were significant, and 68.55 % (n = 702) back to front comparisons were significant. Therefore same-yard location pairs (ie back to back or front to front) were slightly less likely to be significantly different than opposite-yard comparisons (back to front) or all pairs as a whole.

Because each Tapestry segment is nested within a Tapestry urbanization category, pairwise tests can be grouped to the urbanization level. Among the 508 pairwise tests of segments within the same urbanization category (ie. segments in Urban Periphery compared to segments also in Urban Periphery), 57.67 % (n = 293) were significant. Comparisons across urbanization category (ie different urbanization categories) unsurprisingly yielded more significant pairs 68 % (n = 1,035). The majority of within-urbanization segments tests were different, and the vast majority of across-urbanization segment comparisons were more different than chance alone.

Post-hoc tests can also be grouped by yard location (front vs back) and by urbanization category simultaneously. There were 119 back yard to back yard pairs that were also in the same urbanization category, of which 48.73 % (n = 58) were significant. Among the 119 front yard to front yard comparisons of segments also within the same urbanization category 61 (51.26 %) were significantly different. Finally, the 270 back to front comparisons that were also within the same urbanization category yielded 64 % of pairs (n = 174) that were significantly different. In summary, about half of the same-yard (back to back or front to front) were significantly different within and across urbanization categories, while nearly 2/3s of opposite-yard (eg back to front) within the same urbanization category were different.

This modeling approach can further illustrate the importance of differences by lifestyle and lifestage and the utility of geodemographic segmentation. First, we can examine significant differences within an urbanization class. For example, City Strivers and Fresh Ambitions are both in the most-urban group (Fig. 2, top panel) and yet back yards in City Strivers has 21.3 percentage points 95 % CI [17.2, 25.5] more tree

Table 1
Descriptive Statistics: census block group-level summaries of tree canopy cover on residential yards. Residential includes, back yards, front yards, and corner yards. IQR=Interquartile Range.

Location	Year	Mean Tree CanopyCover (%)	StandardDeviation	Median	Minimum	Maximum	IQR
Back	2013	38.42	19.4	37.8	0	89.48	28.38
	2018	37.84	19.7	37.03	0	89.48	28.82
Front	2013	26.11	16.89	25.21	0	85.42	20
	2018	25.2	17.08	24.14	0	85.38	21.2
Residential	2013	35.23	17.13	34.53	0.71	84.89	22.42
	2018	34.56	17.41	33.84	0.62	84.74	22.64

Table 2
Model fit statistics and model comparisons. The letters in the Model Specification column correspond to Figure S3.

Geodemographic segmentation (Tapestry)	Model Specification	AIC	BIC	RMSE	no. obs.	Residual df	Tapestry rank (AIC)
Urbanization	A) Residential	−1102.61	−1071.81	1	1254	1248	3
Urbanization	B) Front/Back data	−1424.78	−1383.99	1	2506	2499	3
Urbanization	C) Front vs Back (additive)	−1677.33	−1630.72	0.99	2506	2498	3
Urbanization	D) Front vs Back (interaction)	−1680.94	−1616.84	1	2506	2495	3
Lifemode	A) Residential	−1231.24	−1154.21	1	1256	1241	2
Lifemode	B) Front/Back data	−1648.97	−1555.72	0.99	2510	2494	2
Lifemode	C) Front vs Back (additive)	−1929.79	−1830.72	0.98	2510	2493	2
Lifemode	D) Front vs Back (interaction)	−1926.87	−1757.85	0.99	2510	2481	2
Segments	A) Residential	−1293.85	−1119.29	1	1254	1220	1
Segments	B) Front/Back data	−1785.9	−1581.98	0.99	2506	2471	1
Segments	C) Front vs Back (additive)	−2092.42	−1882.67	0.99	2506	2470	1
Segments	D) Front vs Back (interaction)	−2078.6	−1688.22	0.99	2506	2439	1

canopy cover than Fresh Ambitions, and 16.5 percentage points 95 % CI [13.3, 19.7] in front yards. Nationally the Fresh Ambitions segment has larger households, more racially diverse neighborhoods, and less educational attainment than the City Strivers segment (Table S3). Second, we can examine segments that are not significantly different despite belonging to different urbanization classes. For example, City Strivers is in the most urban class, and Retirement Communities is in the second least-urban class. Yet their back and front yards have statistically the same amount of tree canopy cover. Multiple factors reflecting urbanization, socioeconomic status, and lifestyle/lifestage can be associated with similarities of tree canopy cover, on front and back yards, which would have gone un-seen with a linear regression approach with scores of predictors.

The temporal change observed was small and statistically insignificant (Table S2), although the trend appears to be net gain (Figure S5). Future tree canopy is tree canopy persistence plus gains from succession, grow out, and planting, minus losses from removal, death from old age, disease, and storm damage (Luley & Bond, 2002). Gain is a slow process whereas loss is often an event. Most tree canopy is persistent at this spatial scale (yards aggregated to block groups) and temporal scale (5 years with a single time step), although individual yards and/or block groups may experience substantial loss or gain. However, today's tree canopy is not guaranteed to be present tomorrow.

4. Discussion

4.1. Research questions

We investigated residential tree canopy cover from three interrelated perspectives: social, spatial, and temporal. We asked (Q1: Social) which categorization of social groups (population density, social stratification, or lifestage/lifestyle) best predicts residential tree canopy cover in order to test the theory of an ecology of prestige (Grove et al., 2014; Grove, Troy, et al., 2006). Population density and social stratification do predict residential tree canopy cover, but the lifestyle/stage categorization associated with an ecology of prestige fits best. This corroborates prior research on the theory of social norms associated with fitting into a neighborhood aesthetic (Robbins, 2012), participation in tree giveaways (Locke & Grove, 2016; Nguyen et al., 2017), and tree canopy change (Locke et al., 2017).

Because social norms are strong motivators of yard care practices (Chowdhury et al., 2011; Cook et al., 2012), and there are frequently differences in yard management between more-visible spaces (front yards) than less-visible backyards (Harris et al., 2013; Locke, Avolio, et al., 2018; Locke, Roy Chowdhury, et al., 2018), we asked if (Q2: Spatial) explicitly separating front and backyards would improve model fit. The empirical inclusion of front and backyard differentiation of this theory-informed expectation (differences between front and backyards) improved model fit. This sub-parcel scale of socio-spatial analysis has often been overlooked or assumed away in urban tree canopy research, potentially due to the computational challenges of spatially resolving front and backyards from parcel data. Yet overlooking sub-parcel variation masks social values and uses (E. M. Harris et al., 2013; Locke, Roy Chowdhury, et al., 2018) and the different contributions of front and backyards to urban residential tree canopy overall. This research demonstrated that lifestage and lifestyle categories (prestige) are the best predictors of urban tree canopy for residential areas overall (Figures S3 and S4, Q1: Social), and that distinguishing between front and backyards further improves the ability to model overall urban tree canopy cover for residential lands (Q2: Spatial). Front yard only models always outperformed backyard only models in the secondary analyses (Figure S4). Additionally, there are differences in canopy cover between front and backyards by social group.

Finally, we investigated how tree canopy change varies by social groups and by front and back yard (Q3: Temporal) to better understand urban forest dynamics. Previous research had examined long-term temporal legacies and lags (30–100 years) on current distributions of urban tree canopy (Healy et al., 2022; Locke, Roman, et al., 2023; Roman et al., 2021; Zhou et al., 2011). Research on near-term temporal changes (5–10 years) has been constrained by the lack of available urban tree canopy data. Our analyses of residential yards found no statistically significant changes over time from 2013 to 2018, although the point estimate sign was positive (Table S2). Thus, there is little urban tree canopy loss or gain in residential yards on average when aggregated to block groups for this near-term time period, so the potential relationships between social groups or front and backyards remain uncertain.

4.2. Implications

These socio-spatial results can have cascading social-ecological implications for residential areas because of the association between trees and ecosystems services for nutrient fluxes, hydrologic flows, heat, and wildlife. Front yard lawns appear to export more nitrogen than backyards (Suchy et al., 2023). Hydrologic flow path lengths and densities within and among backyards may offer greater stormwater absorbing potential than front yards. Backyards may be cooler during extreme heat events due to their vegetative cover (Ossola et al., 2021). The greater extent (Ossola et al., 2019a) and connectivity (Ossola et al., 2019b) of tree canopy cover in backyards may offer more benefits to urban wildlife species.

Social, spatial, and temporal analyses of urban tree canopy cover can have important equity and management implications. Some people experience more ecosystem services from urban tree canopy than others, and it is not by chance alone. Understanding which social groups have more tree canopy cover – and which social groups have more opportunities – may improve efforts to target and reach segments of society that have been ignored or poorly understood and engaged. In other words, it is important to focus on the appropriate combination of messages, markets (social groups), and messengers (Locke & Grove, 2016). Failure to meet people where they are can reduce participation in planting and stewardship, and even catalyze backlash against trees (Battaglia et al., 2014; Carmichael & McDonough, 2018; 2019), further reducing

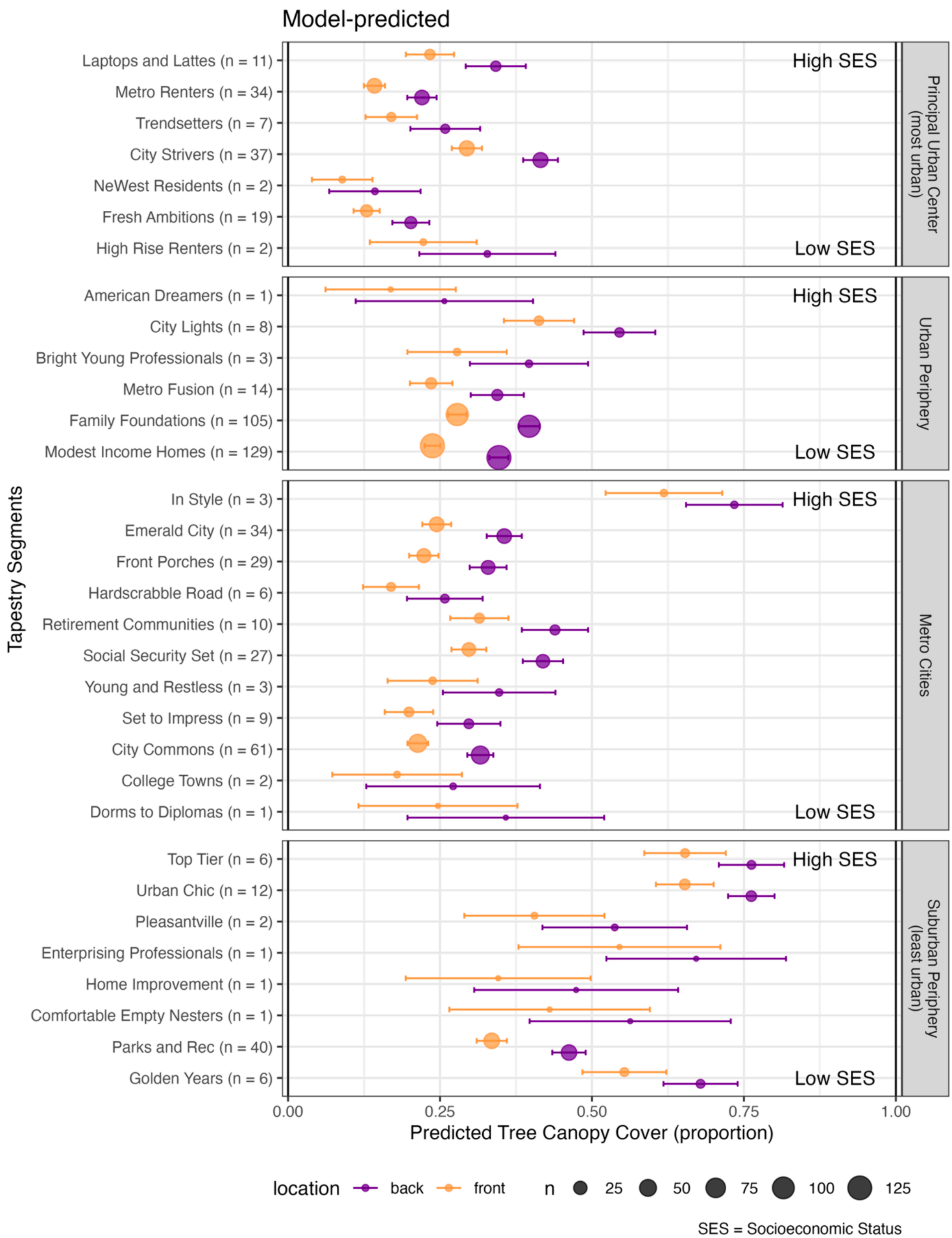

Fig. 2. Predictions from best-fitting model: Tapestry segments (corresponding to lifestyle/life stage), and residential lands parsed by front and back yard, with random effects for block group, and a zero-inflated beta distribution. Panels are arrayed from most urban (top, "Principal Urban Center") to least (bottom, "Suburban Periphery"). Within each panel segments are arrayed from highest (top) socioeconomic status to lowest (bottom). Table S1 provides additional details about the order of Tapestry Segments. Point estimates are sized relative to the number of observations in year 2013; category infrequency is associated with wider confidence intervals.

participation in planting and care. Programs such as the community-based GreenSpace and GreenSkills programs of the Urban Resources Initiative offer one approach to overcome these common pitfalls, while also training urban foresters in a variety of skills (Scanlan et al., 2021).

There are at least two additional management insights from this research. First is the idea that the appropriate combination of markets, messages, and messengers is critical to both planting new trees and retaining existing trees on privately managed land. This research provides empirical support to the idea that different types of neighborhoods, or "markets" corresponding to lifestyle/lifestage categories, have different amounts of existing tree canopy cover, and differences by front and back yard. Messaging may need to vary, tailored to the issues, motivations, and preferences of these different markets, and be delivered through different sources (messengers) for tree planting (Locke & Grove, 2016). Similarly, if the study period were longer, we may also have found variation in tree canopy change by social group, again with varied relationships across front and back yards. Because the extent of urban tree canopy cover depends upon the combination of planting new trees, minimizing loss, and retaining existing urban tree canopy (Luley & Bond, 2002), the combination of markets, messages, and messengers may also be critical to promoting tree care in order to maintain tree health (e.g. watering, pruning, removing vines) and retention of existing urban tree canopy cover. Second, social drivers and potential ecosystem service benefits may vary from front and backyards. Thus, different social engagement practices and planting schemes may be needed for front and backyards for different social groups.

This research raises an important question with regards to the rate to change of tree canopy cover. Policy makers, planners, and managers associated with urban tree planting initiatives would like to demonstrate success. However, what is the appropriate timeframe to assess progress? Given the indeterminant results from this research, urban tree planting initiatives may need to re-evaluate the timeframe for assessing success. Decision makers may also need to develop near- and long-term models for achieving success. Existing urban tree programs essentially focus on establishing a goal and asking how many trees have to be planted to achieve the goal. However, as noted before, an urban tree canopy goal depends upon new tree planting, minimizing loss, and retaining existing urban tree canopy cover. Thus, improved urban tree canopy models would consider growth rates and loss for urban trees in different size classes over time and the relationship between size classes and canopy cover for different species and in different conditions, such as public trees (public rights-of-ways and parks) and private trees (front and backyards).

4.3. Limitations

The front and back yard classification algorithm was not perfect, and some front or backyards may have been inadvertently classified as other yards. As a consequence, a few of these yards may have been dropped, but this is preferred over incorrectly assigning corner yard status to front or backyards. Tapestry's clustering methods are not in the public domain. Additionally, we did not separate out single family homes from other types of residential land uses, though two-family homes and multifamily units may have less real or perceived decision-making control over their yards. The same is true for renters. We focused on residential land uses, because they are the largest, have the most tree canopy cover, the most opportunity for additional cover, and the most land managers. It is important to also consider how tree canopy changes on land managed by municipal agencies such as trees in parks and street trees in the public right of way (Landry & Chakraborty, 2009), but that was beyond the scope of these analyses. This paper focuses on Baltimore City, MD. Results may generalize to other urban areas with similar land use histories, development patterns, and preponderance of single-family homes with decision making power over yards, but care should be taken wen extending to other contexts where yard management permissions might not be granted.

5. Conclusions

High-resolution (1 m^2), high-accuracy (>99 %) tree canopy maps are now industry standard in the United States (Kimball et al., 2014) and other parts of the world (Browning et al., 2024) for research and practice. Equipped with these detailed and flexible data, many municipalities have adopted tree canopy goals (Locke et al., 2017; Nguyen et al., 2017; Young & Mcpherson, 2013). In order to evaluate progress towards achieving canopy cover goals and to promote adaptive management, it is important to assess three inter-related domains of urban tree canopy research: how UTC varies socially, across space, and over time.

This study corroborates prior findings and extends our understanding of urban tree canopy by different social groups, across space, and over time. While population density and social stratification are associated with tree canopy cover on residential lands, lifestyle and lifestage are better predictors. These results have important implications for both social-environmental theory and for UTC policies and practices. For instance, detailed and customized approaches may be needed to engage different social groups. Beta regression models that explicitly distinguish between front and backyards fit the data better than all-residential statistical models. Ignoring the differences between more readily-visible front yards and more secluded backyards hinders our understanding of present-day tree canopy cover, and the ability to craft programs to target these different sub-parcel geographies. This finding suggests new programs may be needed to support tree planting and care for backyards in private residential lands. We observed relatively little change in the canopy over the five-year study period in Baltimore at these spatial scales, corroborating other short term tree canopy studies which show a preponderance of persistence (Chuang et al., 2017; Guo et al., 2019; Hostetler et al., 2013; Locke et al., 2017; Parmehr et al., 2016). Future tree canopy cover is tree canopy persistence plus gain from growth, planting, and success, minus losses to old age, storms, and removals from pests, landowners or agencies (Luley & Bond, 2002). The vast majority of the tree canopy was persistent over the study period, but without adequate protection, that canopy cover cannot be taken for granted. A fruitful next step could be to develop spatially-explicit models that account for how much tree planting, maintenance, and conservation is needed to achieve the city's 40 % canopy goal with various scenarios for mortality, longevity, and removal over several timesteps.

CRediT authorship contribution statement

Dexter H. Locke: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alessandro Ossola:** Writing – review & editing, Visualization, Investigation, Data curation, Conceptualization. **John Paul Schmit:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization. **J. Morgan Grove:** Writing – review & editing, Supervision, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability statement

Yard polygons are available via Ossola and Locke 2024 https://doi.org/10.6084/m9.figshare.26098534.v1. We would be delighted if others used these data and/or code for their own projects. The rest of the data and reproducible code appear in Appendix A.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2024.105187.

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