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Los Angeles, California is prone to extreme climate events—e.g. drought, wildfires, and floods—that are only expected to increase with climate change. The establishment of green infrastructure, including a stable urban forest, is a strategy to improve resilience not only to these events, but also to contribute to other environmental, social, and economic goals. To this end, cities throughout Los Angeles County have tree planting programs and policies aimed to grow and maintain their urban forests. Despite the policy objectives and management goals of such programs, we know surprisingly little about the spatial distribution of the existing urban forest, how and where the canopy has changed over time, or the composition of the population living in places of canopy change. To examine these questions, we conducted an analysis of the Los Angeles Coast based on land cover data derived from high-resolution aerial imagery and LiDAR. In addition to characterizing the overall percentages of existing and possible tree canopy in 2014, we also characterized the change in tree canopy from 2009 to 2014 with five measures of tree canopy and change: total canopy, persistence, loss, gain, and net change. We used market segmentation data to analyze the relationship between tree canopy and the composition of communities. Results indicated that tree canopy covered about 15% of coastal Los Angeles, but this cover was unevenly distributed throughout the study area. The parcel-level analysis of change indicated that while the canopy did not change much from 2009-2014, the changes that did occur were localized and would have been missed at a coarser scale of analysis. Using geodemographic segments, we found that higher-income lifestyle groups tended to have more tree canopy and less loss over time. Change within land uses was consistent with overall change. These high-resolution, high-accuracy data and analyses can support valuable tools to guide decision-making about urban forests, especially as it relates to social equity.

Keywords

Urban forests, tree canopy, land cover analysis, tree canopy change, green infrastructure, geodemographic segmentation, remote sensing

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1. INTRODUCTION

Increasing urban tree canopy is an adaptation strategy that has been recognized for its myriad social, ecological, and economic benefits (see for example two recent reviews of the benefits of urban trees Alliance for Community Trees 2012; MillionTreesNYC 2011). Research has shown that among other services, trees reduce the urban heat island effect (Rosenfeld et al. 1998; Lo et al. 1997; Akbari et al. 2001; Streiling and Matzarakis 2003; Akbari and Konopacki 2005; Elmes et al. 2017) and improve water quality and quantity (Raciti et al. 2006; Bartens et al. 2009). Indeed, urban tree planting initiatives have been developed and implemented across the US and international cities (Table 1).

Table 1. Many urban forestry goals are being actively pursued throughout US and other major cities, some examples of which are shown below. See Literature Cited for references.

City	Initiative and/or lead partner	Goal
Baltimore, USA	Sustainability Plan (2009), TreeBaltimore	double tree canopy by 2037
Boston, USA	Grow Boston Greener (2016)	35% by 2030
Denver, USA	Mile High Million (2006)	1,000,000 by 2025
Houston, USA	One Million + Houston (nd)	1,000,000 in 3-5 years
Los Angeles, USA	Million Trees LA / City Plants (2010)	1,000,000 (date unspecified)
New York, USA	MillionTrees NYC (2008)	1,000,000 in 10 years
Philadelphia, USA	Greenworks Philadelphia (2009), TreePhilly	30% canopy by 2025
Sacramento, USA	5 million trees (2008), Sacramento Tree Foundation	5,000,000 by 2025
Shanghai, China	Roots and Shoots, Millions of Tree Planting Plans (2007)	1,000,000 in 5 years
Seattle, USA	Urban Forest Stewardship Plan (2013)	30% canopy by 2037
Sydney, Australia	Urban Forest Strategy (2013)	23% canopy by 2030

If successful, such policies can be instrumental in increasing the tree canopy cover and thus contribute to achieving urban sustainability goals. However, measuring success of these programs is not necessarily as simple as whether or not a certain number of trees were planted (see Nguyen et al. 2017). It is also necessary to examine factors including, for example, the number of trees that died or were removed, and whether any increases or decreases in tree canopy were equitably distributed. We believe it is important to study the distribution and change in canopy cover as a foundation for evaluating how well urban forestry initiatives meet their goals.

As we describe below, this study was motivated by the idea that there are potential benefits of increasing and maintaining the urban forest, yet meeting tree canopy goals can be challenging in both implementation and evaluation of success. Using data on high-resolution tree canopy and canopy change, geodemographics, and parcel ownership can allow us to assess relationships between tree canopy change and social factors, such as neighborhood demographics and land use. One of our central arguments is that data quality is essential to accurate evaluations. We focused on the urban forest of coastal Los Angeles (LA), USA, and asked three overarching research questions:

1) What is the distribution of tree canopy and canopy change across coastal LA?

2) Who lives in the places with tree canopy, and who lives in places where canopy change occurred?

3) How is the urban forest changing across different land uses?

1.1 Los Angeles Urban Forestry Context

The many benefits of trees have been reported on extensively elsewhere (e.g. Alliance for Community Trees 2012; MillionTreesNYC 2011) and will not be comprehensively reviewed here. These documented benefits of tree canopy have prompted cities around the US to implement programs to plant and maintain their urban forests (Kimball et al. 2014; McGee et al. 2012; Young and McPherson 2013; Table 1). In the Los Angeles region, there are policies and programs to support urban forestry and tree planting. Statewide, the California Department of Forestry and Fire Protection's Urban Forestry Program provides financial and technical assistance “to advance the development of sustainable urban and community forests in California” (CAL-FIRE, nd). Regionally, many municipalities have developed urban forestry plans and tree canopy goals, including the City of Los Angeles with its “MillionTreesLA” initiative (McPherson 2014). Launched in 2005, the program was expected to result in one million new tree plantings between 2006 and 2010. Implementation of the initiative proved challenging (Pincetl 2010), and a follow-up analysis reported that only 91,786 trees were planted from 2006-2010, though that number increased to 407,000 by the time of publication (McPherson 2014). A study of the Million Trees program found there was no identifiable monitoring plan to assess outcomes (Pincetl et al. 2013). In 2013, the program was ended and tree planting activities were transferred to the newly created City Plants, which has the mission “to expand and maintain LA’s green canopy, with particular focus on low-canopy communities” (see www.cityplants.org). The renamed program does not set numeric goals for trees planted, and there is still scant information on metrics for evaluating program outcomes.

To properly monitor and evaluate urban forestry programs requires accurate, current data to understand the existing forest and it changes over time. In the example of the City of Los Angeles, the tree canopy analysis for the Million Trees program (McPherson et al. 2008) was based on aerial imagery from 2000-2005. Thus, an updated analysis of the current spatial distribution of existing tree canopy in the Los Angeles region is needed. In addition, while there is historical information on urban forestry change in Los Angeles (Gillespie et al. 2011), little is known about how this urban forest has changed since more recent tree planting policies and plans were enacted. Understanding tree canopy change and distribution can then inform an assessment of whether the benefits of the urban forest are being equitably distributed. For example, one could examine how variability in canopy may correspond with the socioeconomic and demographic composition of residents in different areas.

Some research has been done to better understand the interplay between the urban forest and society in the Los Angeles region. For example, Avolio and others (2015a) examined how social and environmental variables impact residents' preferences for tree attributes, and found that local environmental factors had as strong an impact as socioeconomic factors in influencing residents' perceptions of the value of trees. A related study on tree diversity in Southern California found that socioeconomic drivers were more tightly linked than biophysical ones (Avolio et al. 2015b). Moreover, Tayyebi and Jenerette (2016) found vegetation and neighborhood income had a positive correlation across all climate zones in metropolitan Los Angeles: coastal, inland, and desert zones. These coupled social and environmental analyses are important to assess questions of equity, to better understand residents' attitudes and behavior towards urban forests, and can contribute to interpretations of how and why the forest changes over time.

1.2 Tree Canopy Distribution & Change

Analyses of high-resolution tree canopy and land cover maps at the parcel and/or approximations of neighborhood scale, such as Census tracts or block groups, are now the industry standard and increasingly common. Examples can be found for Baltimore, MD (Grove et al. 2006a, b Troy et al. 2007, Zhou et al. 2009), Boston, MA (Duncan et al. 2013; Raciti et al. 2014), Cincinnati, OH (Berland et al. 2015), Montreal, ON (Pham et al. 2012a; b), New Haven, CT (Locke and Baine 2014), New York City (Grove, Locke and O'Neil-Dunne; 2014), northern Massachusetts (Giner and Rogan 2012; Giner et al. 2013, 2014; Runfola et al. 2013, 2014; Runfola and Hughes 2014), Philadelphia, PA (Locke et al. 2016), Raleigh, NC (Bigsby et al. 2014), Seattle, WA (Romolini, Grove and Locke 2013), and Tampa, FL (Landry and Chakraborty 2009). Kimball and colleagues (2014) identified 17 distinct uses of high-resolution land cover maps for urban forest planning and land management.

Despite the growing use of high-resolution (<1m) land cover maps for research and practice, there is relatively little research on urban tree canopy change. Tree canopy change occurs at fine scales, when individual trees grow, die or are removed. Random point-based sampling is a technique frequently used to measure canopy and canopy change. The basic method is to randomly distribute points across an area of interest, and then have a human interpreter view aerial imagery and classify the points as tree canopy or other cover types (see Nowak and Greenfield 2010 for a comparison to coarse 30 meter Landsat data, and Nowak and Greenfield 2012 for an example of the technique applied to change detection). Although frequently used, random point sampling has at least three major methodological deficiencies, in addition to operational challenges, that are overcome by using high-resolution (<1m), high-accuracy (≥95%) canopy mapping approaches.

First, the number of points needed to reach a target level of accuracy (e.g. 95% confidence intervals) depends in part on the amount of canopy cover (Parmehr et al. 2016). Areas with less tree canopy cover need fewer points to achieve the same level of accuracy (Parmehr et al. 2016). If the area of tree canopy cover were already known *a priori* then one would not need to conduct random point sampling in the first place. This circuitous problem is often ignored or simply assumed away.

Second, making comparisons across neighborhoods, districts, land uses, or other meaningful categories requires careful considerations of stratified sampling plans (Kaspar et al. 2017). This is because the number of points per strata need to be relatively balanced or the standard errors of the estimates will vary simply based on sampling intensity per category (Kaspar et al. 2017). One will not be able to tell if the differences in canopy cover between two different land uses, for example, are because of the different degree of sampling intensity (e.g. the number of observations), from actual differences in tree canopy cover, or some combination. The initial stratification plan limits from the outset and by design the types of comparisons that can be made from random point sampling and human image interpretation. To overcome this requires increasing the sample size dramatically.

The third deficiency from a data quality perspective is unique to change detection. To detect a 5% change one needs more than 95% confidence (Parmehr et al. 2016). The error from time one, when compared to time two propagates the errors associated with the first two deficiencies of random point sampling described above. A study of Detroit, MI and Atlanta, GA illustrated this problem when measuring change by manually tracing canopy with polygons and with random points. The polygon method showed change for Detroit but not Atlanta, while point-to-point comparisons showed no significant differences at all (Merry et al. 2014). This empirically demonstrates the unreliability of the random point sampling method.

High-resolution (<1m), high-accuracy (≥95%) tree canopy and canopy change maps are needed because 1) this approach's validity does not vary with the amount of canopy in the study area, 2) the method allows for reliable and rigorous *post hoc* comparisons across categories of interest to researchers and practitioners, and 3) can detect small but meaningful changes. For example, a parcel may gain or lose 100% of its canopy, which has important management implications. But because that parcel likely only represents a tiny fraction of a given study area that change would go undetected, and by design, with random point sampling.

In addition to these methodological limitations there are operational limitations. Proponents of the random sampling describe the method as fast and accurate. But often, researchers and practitioners need parcel-scale canopy and canopy change measures because management occurs at the parcel scale. Our study area contained 222,559 parcels. To calculate a confidence interval per parcel, one needs at least three points, although >30 is preferred. (Parmehr et al. 2016 empirically showed that for 3.5% and 30.5% tree canopy cover estimates using random point sampling did not become stable until after 200 points.) That means 667,677 to 6,676,770 human interpretations would have been needed, for 3 or 30 points per parcel, respectively. At the impossibly-fast speed of one interpretation per second, 7.7 to 77.3 days of non-stop interpretation would be needed for 3 to 30 points per parcel. Consider, for example, New York City, which has approximately 1 million parcels. It becomes clear that random point sampling is not fast. See O'Neil-Dunne and colleagues (2012, 2014) for an in-depth discussion of using humans' and machines' strengths in concert. High-resolution (<1m), high-accuracy (≥95%) tree canopy maps are needed for canopy change analyses with realism.

One high-resolution (<1 m), high-accuracy (≥95%) tree canopy change study of Worcester County, MA found a 2% (395 ha) loss from 2008 to 2010. It was estimated that 47% of the total loss was due to high- and low-density urban development. United States Department of Agriculture tree removal for Asian longhorned beetle eradication accounted for 25%, timber harvest (15%) and ice storm damage the remaining 6% (Hostetler et al. 2013). A unique study of high-resolution tree canopy examined change from years 2008, 2010, and 2015. Elmes and colleagues (2017) found an approximately 5.5°C decrease associated with a 100% increase in canopy, and that summer conditions could grow 3.66 to 14.1 days longer in areas that lost canopy. Another high-resolution (<1m), high-accuracy (≥95%) tree canopy change study of Washington, DC found that low-income areas lost more canopy from 2006 to 2011 (as a % and absolute amount) even though higher income areas had more tree canopy in 2006 (Sanders et al. 2015). Most Census block groups experienced a net loss of canopy, and 8% of Census block groups lost between 20 and 30 percent of their entire canopy, which can be qualitatively considered a significant portion of the urban forest (Sanders et al. 2015). A subsequent study of Washington, D.C. analyzed canopy change within Census tracts categorized by income change from year 2000 to 2013 (stable impoverished, decreasing wealth, remained above impoverished, increasing wealth, stable wealthy). Census tracts whose median household income grew (increasing wealth) from year 2000 to 2013 gained tree canopy from year 2006 to 2011, but not as fast as tracts with decreasing incomes (decreasing wealth), and most importantly net changes were negative in tracts of all five income trajectories (Chuang et al. 2017). A unique study of high-resolution (<1m), high-accuracy tree canopy change before and after an earthquake in Christchurch, NZ integrated parcel data. Morgenroth and colleagues (2017) used classification trees and were able to confidently infer removal in more than 80% of cases examined. This paper demonstrates one of the many applications of reliable canopy change data. Landry et al's (2013) assessment of Tampa, FL's urban forest is the most comprehensive known comparison of dot-based random sampling, high-resolution tree canopy change mapping, large pixel image analysis (30 x 30 meter pixels), and field-based methods. The report's high-resolution maps revealed a canopy increase of approximate 3% from 2006 to 2011, compared to only 2% found using point-based and large pixel methods (though not statistically significant), and no change with field methods. Again, point-based sampling is shown to be unreliable relative to other methods. What these papers show is that change often represents a small, albeit extremely important, part of the urban forest and with long-term monitoring and effective policies canopy gain is possible. Further, the spatial distribution of canopy loss may pose environmental justice concerns, if the majority of those changes occur in socially vulnerable areas.

1.3 Geodemographic Segmentation

Geodemographic segmentation encompasses a range of spatial and statistical techniques for classifying areas based on who lives there, and is based on the premise that people who live near each other share demographic, socio-economic, and lifestyle characteristics (Troy 1995). Geodemographic segments are socio-spatial categories that represent different lifestyle groups. A primary use of geodemographic segments is to help characterize consumer behaviors in support of crafting marketing strategies or locating retail centers (Weiss 2000; Holbrook 2001). Geodemography has gained popularity in academic research for assessments of health care service use among different subpopulations (Tao et al. 2013); and in the related area of service planning, social marketing, and benchmarking for public health initiatives (Abbas et al. 2009); as well as evaluation of school performance (Gibbs et al. 2010). Fire incidents were analyzed by geodemographic market segments in South Wales, UK to reveal the types of areas more prone to particular types of fire incidents, false alarms, and hoax calls (Corcoran et al. 2013). The main idea is that categorizing areas based on who lives there, and then examining behaviors in those categories, can help inform sales, service provisioning, and/or program performance across areas comprised of different social groups.

Recent research has shown substantial differences in the amount of tree canopy and the opportunities for additional planting by geodemographic segment in Baltimore, MD (Grove et al. 2006a,b; Troy et al. 2007), Raleigh NC (Bigsby et al. 2014), and NYC (Grove et al. 2014). In Baltimore, for example Troy et al. (2007) found that neighborhoods comprised of more families with children had on average 36% (95% CI [6.7, 64.6]) more tree canopy cover on private residential lands than neighborhoods with similar population densities, occupations and levels of educational attainment but predominated by younger singles or couples without children. Thus, lifestage as an important component of lifestyle relates to urban tree canopy cover on private residential lands. Subsequent research in Washington, D.C. and Baltimore, MD found participation rates in higher-income market segments in different reduced-cost or free tree programs that were ~2 to 6.5 times higher than for other market segments, depending on the program type, and if trees were planted on public (e.g. street trees) or private lands. This was true even though the need was lower in these areas because tree canopy was already well established and more abundant (Locke and Grove 2015; 2016). Alternatively, similar analyses for Philadelphia, PA and New York City found fairly equitable distribution of participation in similar reduced-cost or free tree programs by market segment (Locke et al. 2014; 2015). These differences are likely attributable to how the programs are organized and executed, among other factors (Nguyen et al. 2017). Nevertheless, further investigations in alternative locations are needed to better understand why tree canopy, plantable space, and participation in planting programs are tightly coupled by market segments in some places and not in others.

With this grounding, we conducted multiple analyses to examine our research questions. First, we characterized the changes in tree canopy between 2009 and 2014 using high-resolution (<1m) aerial imagery and LiDAR (O'Neil-Dunne et al. 2015). Then, we used geodemographic market segmentation data to analyze tree canopy and canopy change within market segments. We analyzed tree canopy change at the neighborhood level to understand the relationship between tree canopy change and the social composition of the communities living where the change occurred. Next, parcel-scale analyses describe canopy cover and change within the boundaries of distinct landowners and across land use types.

2. METHODS

Tree canopy and tree canopy change on different land uses may require different types of interventions to meet urban forestry goals. In this study, we use a more recent (2009-2014), spatially explicit assessment of tree canopy change of the Los Angeles coastal region to assess variations in change at three scales: first at the individual tree canopy or "patch" scale, then within Census block groups categorized into market segments, and then within property parcel.

2.1. Study Area

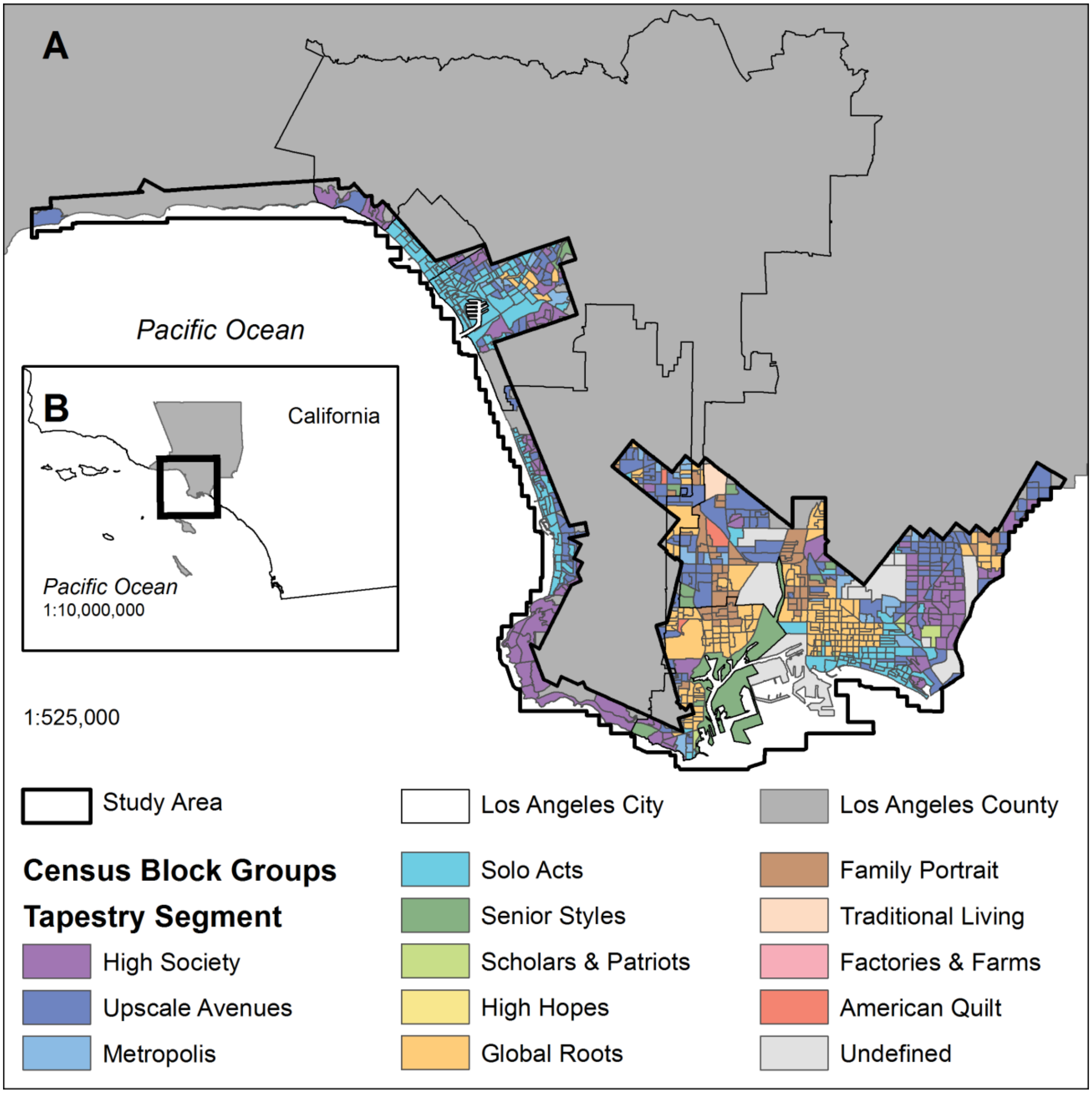

Figure 1. Map of coastal Los Angeles study area and Census Block Groups classified by ESRI Tapestry Segment, located in Coastal Los Angeles County, USA.

This research was conducted in the coastal areas of Los Angeles County, California, which is located in the southwestern United States (Figure 1). The study area boundary was original created by the United States Geological Survey (USGS) to define the extent of California Coastal Conservancy Coastal Lidar Project (see Data section below) whose focus was on topographic mapping to support coastal modeling efforts. It comprises 536 square kilometers. The northern and southern boundaries of the study area are the borders of Los Angeles County, which includes portions of many municipalities, the largest of which are Los Angeles and Long Beach. The western boundary is the Pacific Ocean.

With over 10 million residents in 2015, Los Angeles County is the most populous in the United States (US Census Bureau 2015). As of the 2010 Census, it was also one of the nation's most diverse counties (US Census Bureau 2009). With a semi-arid Mediterranean climate encompassing mountains, deserts, and coastline, the region is vulnerable to extreme heat, droughts, floods, wildfires (Wisner 1999), and other severe weather only expected to become more unpredictable with climate change (Berg and Hall 2015; Bartos and Chester 2014).

2.2 Data

2.2.1 Tree Canopy Change

Tree canopy change within the coastal areas of interest was mapped using a combination of high-resolution imagery and LiDAR data acquired at two different time periods. The LiDAR data was acquired in 2009 by the USGS and distributed by the National Oceanic and Atmospheric Administration (NOAA) as part of the California Coastal Conservancy Coastal LiDAR Project with an average spacing of ~1.5 points per square meter. The imagery was acquired in 2014 as part of the National Agricultural Imagery Program (NAIP) and consisted of 4-band (visible plus NIR) at a resolution of 1 meter. The tree canopy change mapping was accomplished using a semi-automated approach that incorporated elements of automated feature extraction and manual editing. The principal underlying technology used for the automated mapping was Geographic Object-Based Image Analysis (GEOBIA; Hay and Castilla, 2008). GEOBIA works by employing segmentation algorithms to group pixels into objects. These objects can then be classified based on their individual (e.g. spectral reflectance or height) or contextual (e.g. proximity to neighboring objects of a certain class) properties. The object-based system developed for this project was modeled after previous tree canopy mapping projects conducted in urban areas (MacFaden et al. 2012) and included object fate analysis techniques developed by Schöpfer and Lang (2006). The object fate approach ensures that actual tree canopy change was mapped as opposed to change resulting from the spatial inconsistencies that exist between the two datasets. A rule-based expert system using GEOBIA principals was implemented within the eCognition software suite (Trimble Navigation Ltd.). The expert system incorporated segmentation, classification, morphology, and fusion algorithms to map tree canopy change. In general, the process involved creating image objects from the 2009 LiDAR data and 2014 imagery, determining the objects that were tree canopy, and then assigning the object to one of three classes: 1) No Change; 2) Loss; and 3) Gain. The No Change class included tree canopy that persisted between 2009 to 2014. The Loss class comprised tree canopy that was removed. New tree canopy that was established during the period was assigned to the Gain class. Identification of tree canopy within the 2009 LiDAR data relied primarily on the properties of the LiDAR point cloud and surface models, principally that trees were tall and contained a high relative number of LiDAR returns compared to buildings. In the 2014 NAIP the principal characteristics of trees were their high Normalized Difference Vegetation Index (NDVI) values along with their varied texture. The minimum mapping unit for detecting trees was six square meters, and there was no minimum mapping unit imposed on the tree canopy change classes. A team of trained technicians then reviewed the output of the automated approach within ArcGIS (ESRI 2012) at a scale of 1:2,000 making 8,212 corrections. The resultant product was a high-resolution vector GIS layer comprised of polygons classified into three categories: 1) No Change; 2) Loss; and 3) Gain. See O'Neil-Dunne and colleagues (2015) for additional information.

2.2.2 Geodemographic Segments

Year 2010 Census block group data containing ESRI's 2013 Tapestry LifeMode classifications, were acquired from ESRI. This classification system describes populations by clustering demographic, socio-economic, lifestyle characteristics, credit card expenditures, and other data (ESRI 2013; Table 2). Tapestry is therefore an example of geodemographic segmentation data. Not all LifeMode groups are present in our study area, but all are listed for completeness. The tree canopy change dataset did not perfectly align with Census block group boundaries; Census block groups with at least half of their area within the study area were clipped down to the extent of the canopy change layer and included in the analyses. The five measures of canopy and canopy change were analyzed across the ten LifeMode group types found within the study area. As a robustness check the analyses were repeated using only Census block groups completely within the study area boundaries to determine whether the results were substantially different. Since there are only a few Census block groups represented within some LifeMode group types, we restricted the inferential statistics to the five most common LifeMode types which have >=50 Census block groups each. However, for completeness the figures below will show the distribution of canopy and canopy change across all ten LifeMode groups.

2.2.3 Parcels

Parcels were obtained from Los Angeles County (Assessor Parcels – 2015 Tax Roll 2016). Where duplicate polygons occurred, only a single parcel was retained. This was accomplished using the "Delete Identical" tool in ArcGIS with the "Shape" Field specified. Parcels within the study area were selected and clipped down. The extent of the LiDAR did not correspond perfectly to parcel boundaries, so this clipping altered the geometry of some parcels on the edges of the study area. However there are so many parcels (more than 200k) that the effect of this small number of modified parcels is negligible. The parcel dataset left roads and sidewalks (PROW) as undefined negative space. A PROW layer was generated because we are interested in tree canopy and tree canopy change pertaining to street trees. First, the parcel geometries were erased from the study area polygon in ArcGIS. The resulting polygon is the PROW, where street trees are located. Next, that PROW feature was merged back into the original parcel dataset making a complete and spatially exhaustive coverage of the study area. The result is a continuous coverage of the study area depicting land use including the PROW.

Table 2. ESRI's Tapestry Geodemographic segmentation (2013) system's LifeMode classification and brief descriptions. Groups are arrayed from highest income (top) to lowest (bottom).

LifeMode Name	Brief Description
High Society	Affluent, well-educated, married-couple homeowners
Upscale Avenues	Prosperous, married-couple homeowners in different housing
Metropolis	City dwellers in older homes reflecting the diversity of urban culture
Solo Acts	Urban young singles on the move
Senior Styles	Senior lifestyles by income, age, and housing type
Scholars and Patriots	College, military environments
High Hopes	Young households striving for the "American Dream"
Global Roots	Ethnic and culturally diverse families
Family Portrait	Youth, family life, and children
Traditional Living	Middle-aged, middle income—Middle America
Factories and Farms	Hardworking families in small communities, settled near jobs
American Quilt	Households in small towns and rural areas

2.3 Analyses

2.3.1 Change Measures

The tree canopy and tree canopy change layer containing No Change, Loss, and Gain classes were summarized within Census block groups and parcel boundaries. Using the Intersect and Dissolve tools in ArcMap 10.1 (ESRI 2012), we calculated five measures of tree canopy and canopy change: 1) total canopy, 2) persistence, 3) loss, 4) gain, and 5) net change. These are the study's dependent variables. We defined total canopy as the percentage of an area covered by tree canopy at any time during the study period. Total canopy is therefore the sum of No Change, and Gain minus Loss area as a percentage of Census block group or parcel area. Persistence equals the No Change class divided by total canopy, expressed as a percent, and measures areas that had the same canopy cover at the start and end of the study period. Loss and gain were calculated as proportions of the total canopy cover in the same way as persistence, from the Loss and Gain classes in the canopy change layer. Loss and gain measure how much of the canopy cover was lost due to removal and/or death or gained from planting, grow-out, and/or trees that grew spontaneously, between 2009 and 2014, respectively. Net change was calculated as the difference in canopy between 2009 and 2014 divided by the canopy present only in 2009, so that negative values correspond to loss while positive values reflect gain. Total canopy, persistence, loss, and gain can hypothetically vary from zero to one hundred percent, and net change may span from negative one hundred to one hundred percent.

Following our research questions, our analyses were carried out in three phrases. First we describe the tree canopy and canopy change layer across the study area to provide context on overall persistence and change. This step addresses how tree canopy and canopy change were distributed across coastal LA between 2009 and 2014, as classified at the sub-tree canopy scale. Next, we examined the five dependent variables measures within Census block group and then within parcel boundaries; this facilitates analyses by geodemographic segment and by land use, respectively. At the Census block group-level, we analyzed canopy and canopy change by geodemographic segment to better understand the population who lives where the tree canopy and canopy changes occurred, and the types of neighborhoods experiencing change. The five dependent variables did not approximate a normal distribution at the Census block group scale so the Kruskal-Wallis rank sum test was used to investigate differences in canopy and canopy change by LifeMode group instead of analyses of variance. We used the kruskal.test() in the stats package in the R programming language version 3.2.2 “Fire Safety” (R Core Team 2015). Pairwise differences were examined with the Wilcoxon rank sum test using the pairwise.wilcox.test() with the Holm adjustment method for multiple comparisons. Finally, in the third phase, we examined how tree canopy changed across different land uses at the parcel-level. See Locke (2017) for the data and R code for replication.

3 RESULTS

3.1 Canopy Polygon-Level Analyses

Total tree canopy covered 14.49% of the coastal LA study area, meaning that nearly 15% of the region had canopy, lost canopy, or had new canopy between 2009 and 2014. There were nearly three quarters of a million (n = 727,904) canopy polygons in the canopy GIS dataset, the vast majority of which represent persistence (98.25% of patches, 98.06% of area; Table 3). Collectively they cover 14.21% of the study area. There was an order of magnitude more loss than gain at the patch-level; loss polygons also tended to be larger and there were more of them (Table 3). Gains were small and diffuse compared to losses. But loss polygons comprised <2% of the total tree canopy, both as individual patches and by area (Table 3).

Table 3. Descriptive Statistics for tree canopy and canopy change patches.

		Canopy type		
		No change	Loss	Gain
	Number of objects	714,991.00	11,435	1,478
Area ft^2	Total	528,345,269.00	9,867,521.00	575,841.10
	Min.	0.000153	0.0003	0.000388
	Mean	738.95	862.92	389.61
	Max.	9,169,433.00	119,907.10	25,377.66
	Standard Deviation	17,425.06	2,151.45	1,245.47

3.2 CBG-Level Analyses

Generally, higher income Census block groups had more total tree canopy between 2009 and 2014 than their lower income counterparts (Figure 2 I). Specifically, High Society and Upscale Avenues Census block groups had statistically significantly more total canopy cover than Solo Acts, who in turn had statistically significantly more total canopy cover than Global Roots Census block groups, who had statistically significantly more total canopy cover than Family Portrait Census block groups ($p < 0.05$ when adjusting for family wise error rate from multiple comparisons, Figure 2 I). However, major advantage of the market segments is to analyze social groups as defined by many demographic, socioeconomic, and lifestyle characteristics, not just household income summarized to the Census block group. For example, Global Roots Census block groups – comprised of Ethnic and culturally diverse families – tend to have ~12% tree canopy, while High Society – comprised of affluent, well-educated, married-couple homeowners – areas had ~17% tree canopy during the study period (Table 2). Thus, the neighborhoods comprised of higher income households had nearly 42% more canopy than their lower-income counterparts, overall. Higher income market segments also had more stable tree canopy (Figure 2 II), although there were fewer statistically significantly different pairs, than for total canopy. It appears that certain Census block groups in particular – in contrast with groups of Census block groups in a shared market segment – experienced substantial changes, as evidenced by the more abundant outliers in the middle panel (II) than in the top panel (I) of Figure 2. Outliers are defined here as > 1.5 times the interquartile range. Reflecting the canopy-patch specific data, at the Census block group-level the urban forest is mostly persistent too (Figure 2 II); the average No Change per Census block group is 97.77% of the total canopy (median = 98.57, SD = 3.08). Average loss per Census block group was 2.18% of total canopy (median = 1.38, SD = 3.04). Consistent with patch-level data, gain is much less common than loss. The mean gain per Census block group was half a tenth of a percent of total canopy (median = 0.00, SD = 0.33). Twelve Census block groups had gain >1% of total canopy. But when loss is also considered, only seven Census block groups (0.94% of all block groups analyzed) experienced a net increase in tree canopy (Figure 2 III), while nine Census block groups experienced a net loss ≥15% of total canopy.

3.2.1 Robustness Checks

As a robustness check we repeated the analyses above on a smaller dataset using only Census block groups completely within the study area boundaries to see if the results were substantially different. The statistical groupings were largely unchanged, and where there were differences they are likely attributable to the uncertainty associated with smaller sample sizes and multiple comparison tests. The interpretations remain the same; we omit those outputs for brevity.

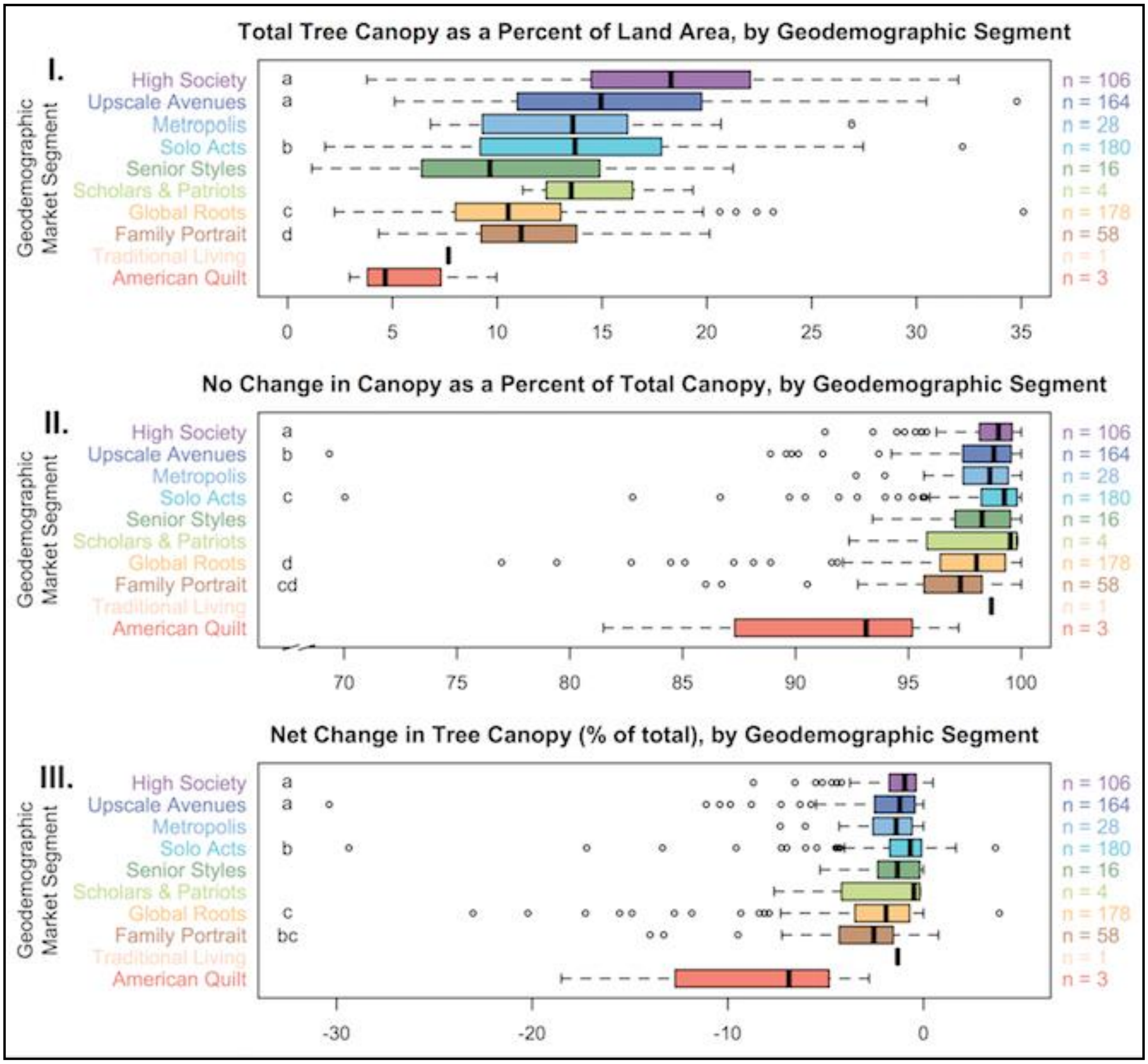

Figure 2. Total tree canopy (I), persistence (II), and net change (III) by geodemographic segment at the Census block group-scale. Segments with the same letters are not statistically significantly different (p <0.05) from each other, per pane, after adjusting for multiple comparisons. All segments are shown for completeness, but only segments with ≥ 50 Census block groups are analyzed statistically to assuage concerns over sample size. Segments are arrayed from highest income (High Society) to lowest income (American Quilt). Note the different x-axes lengths.

A strength of the high-resolution (<1m), high-accuracy (>95%) tree canopy change data is the ability to summarize canopy and change within any boundaries, including individual property parcels. Parcels correspond to distinct land uses and importantly to separable landowners. Parcels link tree canopy – and canopy change – to particular decision makers. Summary statistics for canopy and change are shown in Table 4. Because we derived a PROW polygon, we analyzed canopy change that is specific to street tree management. Total canopy covered 6.997% of the PROW area, of which 97.96% was from the no change category. Loss comprised 2.01% of the total canopy in the public right of way, gain made up 0.03%. Therefore the net change was -1.98% in the PROW. An ~2% loss is consistent with the study area-wide loss (Table 3) and the average loss per Census block group, although net change varied more widely by market segment (Figure 2 III).

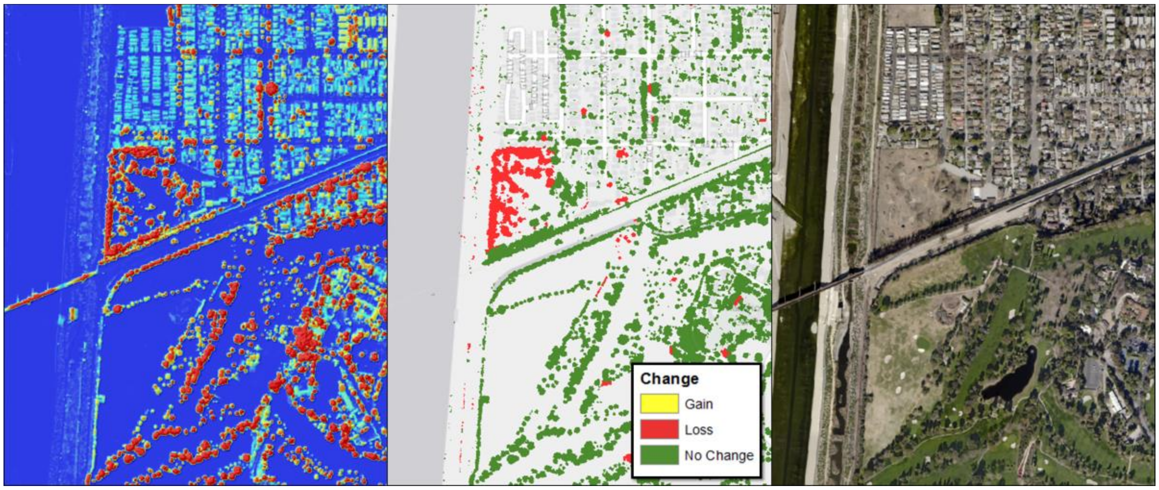

Figure 3. 2009 LiDAR surface model (left), tree canopy change (center), and 2014 imagery (right). The LiDAR surface model represents the height above ground, presenting a clear representation of tall features such as building and tree canopy. Most of the tree canopy is taller (red) then the buildings (cyan and yellow). Tree canopy in the imagery can be discerned by its color, texture, and presence of shadows. There is a large area of tree canopy that was removed in the center-right of the image. In addition to the removal of individual trees scattered throughout the area. Gains in tree canopy are too fine-scaled to be viewed in this graphic but are present throughout the area.

The canopy and canopy change measures encompass the whole range of possible values, or nearly span in the case of gain and net change, when summarized within parcel boundaries (Table 4). The values are also heavily concentrated around extreme values. For example the median no change was a 100% while the median loss, gain and net change are all 0%. This distribution of parcel-scale canopy change is consistent with previous research (Landry 2013). While non-parametric inferential statistics are possible, their utility are limited, as generalizability of canopy and canopy change by land use is not reliable. We instead focus on description over inference.

Table 4. Canopy or canopy change measure as a % of parcel area for all parcels (n = 222,559). Values span generally span the entire hypothetical range and are highly skewed toward extreme values.

	Canopy or Canopy Change Measure as a % of Parcel Area				
	Total Canopy	No change	Loss	Gain	Net Change
Min.	0.00	0.00	0.00	0.00	-100.00
Mean	13.18	91.89	1.21	0.04	-1.09
Median	9.72	100.00	0.00	0.00	0.00
Max.	100.00	100.00	100.00	98.34	98.34
Standard Deviation	12.96	26.40	8.03	1.29	8.13

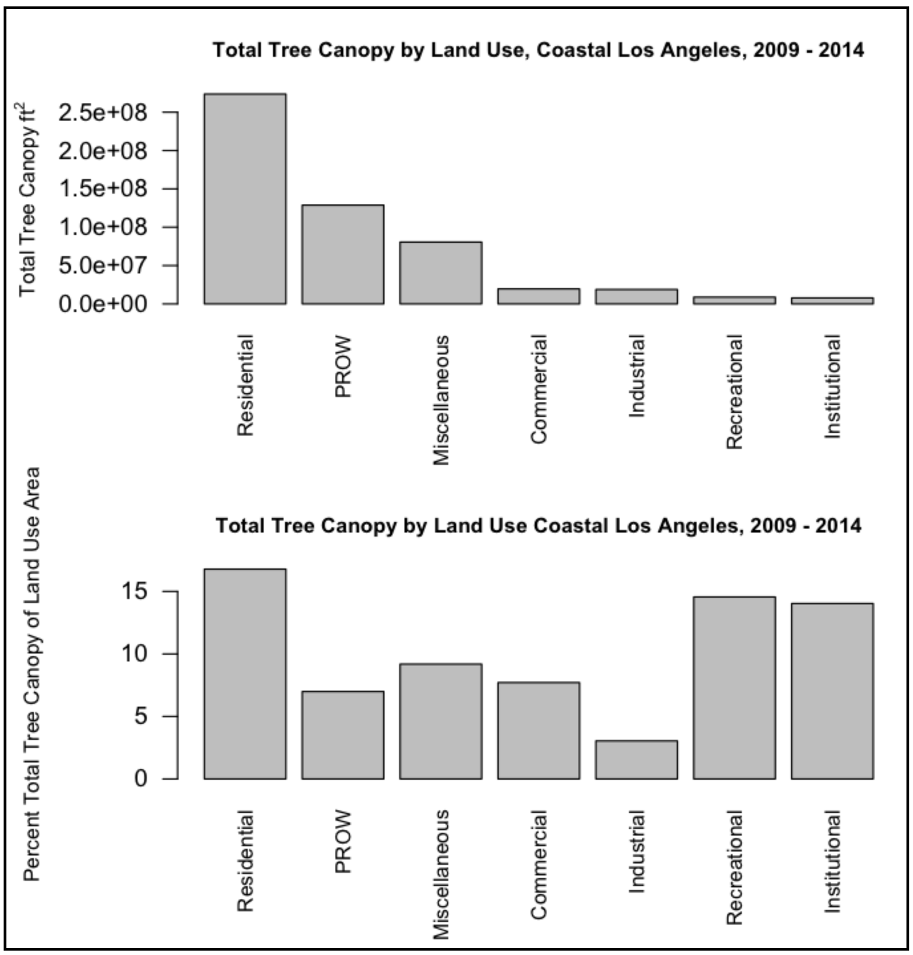

Figure 4. Most of the canopy was on residential lands, by absolute area and as a percent area. Miscellaneous includes Dry Farm, (unavailable), “NA”, and Irrigated Farm.

4. DISCUSSION

How is tree canopy and tree canopy distributed across coastal Los Angeles, which geodemographic markets segments experienced those changes, and how did canopy change across different land uses between 2009 and 2014? We sought to find evidence for three research questions about tree canopy change as it relates to populations and land uses in coastal Los Angeles, California, using both historical and novel data. First, we examined the existing tree canopy cover of coastal Los Angeles, as well as how canopy cover changed between 2009 and 2014. We found existing tree canopy covering approximately 15% of our coastal study region, which is lower than the 20% tree canopy cover found in the City of Los Angeles in the Million Trees LA report (McPherson et al. 2008). We point this out only as a point of comparison, as our study areas were overlapping but not identical, and our methods were different from the 2008 report. Compared to cities across the U.S. recently assessed using our approach, 15% canopy cover is still on the low side. For example, New York City, Des Moines, and Honolulu had tree canopies of 21%, 27%, 20%, respectively (see https://www.nrs.fs.fed.us/urban/utc/pubs for tree canopy reports). In addition, the focus on coastal communities influenced the density of canopy cover as trees become less frequent along liminal regions of the coast.

Tree canopy change is expressed differently across scales. We found very little overall change in tree canopy cover in coastal Los Angeles between 2009 and 2014. For example, the 727,904 tree canopy patches in the study area, 98.25% were classified as no change which represents 98.06% of the total tree canopy area. Persistence was an order of magnitude greater than loss, which in turn was an order of magnitude greater than gain (Table 3). However, canopy change nearly spanned the entire possible range when summarized within parcels (Table 3). The modest decline in tree cover found here is consistent with other similar tree canopy change studies (Hostetler et al. 2013; Landry et al. 2013; Sanders et al. 2015; Chuang et al. 2017; Elmes et al. 2017). In sum, we found that overall canopy in aggregate at the study area-level changed very little, but fine-scale changes indicate that the geographic distribution has shifted over time. This movement of tree canopy within a city has been termed “churn” by previous researchers (Kaspar et al. 2017).

Our second question sought to determine how tree canopy and canopy changes was associated with human population demographics. We found that tree canopy change was most pronounced at the Census block group scale, which can be associated with distinct social groups. Overall higher income Census block groups tended to have more tree canopy, more persistence in that canopy, and lose less tree canopy than lower income areas (Figure 2). These findings are consistent with Tayebbi and Jenerette’s (2016) findings that vegetation and neighborhood income were positively correlated throughout all climate zones in Los Angeles. Our analysis of geodemographic segments revealed that some of the lowest tree canopy was found where the Family Portrait (youth, family life, and children) and Global Roots (ethnically and culturally diverse families) segments lived. This suggests that lower income, non-white families with children are living in areas of lowest tree canopy in the first place, and are also experiencing greater loss of canopy than other areas. This should prompt concerns for equity and environmental justice, and promote the need for data-driven prioritization of future tree plantings.

However, there was considerable range of canopy among Census block groups within the same geodemographic segment, as seen with the wide whiskers in Figure 2, panel I. Average loss per Census block group was 2.18% of total canopy. A similar study of tree canopy change in Washington, D.C. also found that higher income Census block groups both had more canopy and loss less than lower income Census block groups (Sanders et al. 2015). Changes in median household income from year 2000 to 2013 at the Census tract level, were associated less tree canopy in Washington, D.C. (Chuang et al. 2017). Stable homeownership patterns in Sacramento co-occur with residential tree planting survival (Roman, Battles, and McBride 2014). It is therefore possible that residential turnover (Roy Chowdhury et al. 2011) and other socioeconomic changes cause disturbances associated with canopy loss.

Finally, our third research question asked how the urban forest was changing among different land uses. Our results showed that residential, recreational, and institutional land uses had the most tree canopy as a percent of land area, while residential and the public right of way had by far the most tree canopy by total area (Figure 4). Previous studies carried out by the US Forest Service (https://www.nrs.fs.fed.us/urban/utc/pubs/), primarily in the Northeastern United States, show that most tree canopy is on residential land uses, where municipalities lack management jurisdiction. Programs seeking to expand tree canopy increasingly use tree giveaways to reach these private residential lands because they represent an important part of the urban forest, and present great opportunity for increased canopy (Nguyen et al. 2017). Similar to the patch scale, parcel-level canopy was predominantly persistent. Tree canopy change in the public right of way, where municipalities *do* have management jurisdiction, tended to match patch-level changes. For example, in the PROW 97.96% of the total tree canopy area was from the no change category, and net change was approximately a 2% decline. Instead of reflecting urban forest averages, public land managers can lead by example to increase cover and maintain existing cover.

5. CONCLUSIONS & NEXT STEPS

This study adds to the small but growing body of tree canopy change using high-resolution (<1m), high-accuracy (≥95%) tree canopy change data. Our results underscore the value of these methods to assess tree canopy change. Together our three scales of analysis showed that stability was the overall, dominant study area-wide trend, with: uneven overall distribution with limited canopy at the land/water interface; a tendency for higher-income lifestyle groups to have more tree canopy and less loss; the majority of canopy on residential land; and, the most pronounced changes at the parcel-scale. Parcel-scale canopy change spanned the entire range of possible values, signaling a) the importance of high- resolution (<1m), high-accuracy (≥95%) canopy mapping, b) the importance of localized and very meaningful landscape changes that would otherwise be missed at coarser scales. These high- resolution (<1m), high-accuracy (≥95%) data and analyses can support valuable tools to guide decision-making about urban forests, especially as it relates to social equity.

This analysis was instructive in allowing us to apply these methods to a coastal region, which has novel vulnerabilities affiliated with its proximity to a marine ecosystem. According to the NASA Global Rural Urban Map Project, the urban global footprint is just 3% (CIESIN et al. 2011). However, the vast majority of urban settlements are adjacent to large bodies of water. As such, understanding the canopy dynamics of these ecosystems is critical to enhancing the resilience of these communities.

This project is envisioned as longitudinal, both in geographic range and temporal scope. We intend to expand the study, in geography, analysis, and application. The next phase is to extend the study to complete a countywide analysis to examine whether we find similar trends in the inland and desert areas of the Los Angeles region. We intend to continue to study tree canopy, canopy change, and the relationships with other variables of interest. One possibility is to further explore our notion that residential turnover and other socioeconomic changes may have caused disturbances associated with canopy loss. We are also working with local community groups and municipalities to find ways to incorporate the tree canopy data into decision-making about where to plant trees. Such data-driven planning can facilitate identification of priority residential and public parcels for urban forestry improvements.

Understanding the interplay among these variables across an ecosystem as diverse as Los Angeles County will provide a template for investigations of other Mediterranean cities and their associated ecosystems. Incorporating tree canopy analysis into urban planning is a fundamental element of building resilient cities. Our hope is that this project becomes a replicable model for our urban research partners throughout the world and that these data sets provide an open source toolkit for further research efforts.

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