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Urban forests and social inequality in the Pacific Northwest

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ABSTRACT

Research has shown there is a positive relationship between urban greenness and the well-being of city residents. But greenness is often unevenly distributed across a city, raising environmental justice issues. In 2011 and 2012 the USDA Forest Service, Forest Inventory and Analysis program installed ground plots in the urbanized areas of Oregon and Washington. We analyze these data for the urban areas west of the Cascade Mountains, linking it with demographic data from the U.S. Census to examine the relationship between greenness and socioeconomic status at a sub-regional scale. To explore some relations between urban forest measures and socioeconomic conditions and measures we developed four models: presence of tree canopy cover with a logistic mixed model, and on a subset of the data, percent tree canopy cover with a linear mixed model and tree count and tree species count with Poisson mixed models. We found that median household income, house value, land use, and years in the Tree City USA program contributed to explaining measures of greenness, such as canopy cover presence, percent canopy cover, tree counts, and tree species counts. This agrees with other studies, but does so at a broad scale covering the most densely populated areas in the Pacific Northwest.

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1. Introduction

Studies conducted in several U.S. cities have shown that urban neighborhoods with higher socioeconomic status (SES) tend to be greener. This finding raises significant environmental justice concerns. Vegetation in the urban environment provides a range of important benefits to local residents, including the removal of air pollutants (Nowak, 1994; Nowak et al., 1996, 2006), moderating air temperatures (Akbari and Taha, 1992; Simpson and McPherson, 1998; Akbari, 2002; Donovan and Butry, 2009), and a green environment has been found to reduce psychological stress and has been linked to better health (Ulrich, 1984; Schroeder and Cannon, 1987; Smardon, 1988; Dwyer et al., 1991, 1992; Donovan et al., 2011; Kardan et al., 2015).

The positive association with human health might be the most potent benefit of natural areas in the urban environment. Jennings and Gaither (2015) report on numerous studies that suggest the active engagement with green spaces is associated with improvements in both physical and psychological well-being. In England, Mitchell and Popham (2008) found lower rates of death due to stress-related illnesses for urban residents with greater exposure to greenness. Access to greenness was also associated with a reduced disparity in human health measures in areas where social inequality existed. Therefore, in addition to a correlation with better health, greenness has been associated with improved health outcomes even where SES indicators are considered low.

Studies that link SES and greenness mainly fall into two categories: those that measure vegetation using remote sensing (e.g., satellite imagery), and those that measure vegetation using a ground-based sampling system such as sample plots. The majority of studies have relied on remote sensing data, for example, Iverson and Cook (2000) used satellite imagery to quantify the relation between land-use, urban development, tree cover, housing density, and household income in the Chicago metropolitan region. They found a positive correlation between the density of canopy cover and neighborhoods with higher levels of income. Gowen and Mellnik (2013) report on a study done in Washington, D.C. that found racial segregation was higher in neighborhoods with higher impervious surface area and lower tree-canopy cover. In a regional-scale study of several metropolitan areas, Jesdale et al. (2013) found a similar relationship within densely populated racially segregated neighborhoods, more impervious surfaces, and less canopy cover. They concluded this puts minority populations living in large cities at a greater risk of heat-related illnesses than non-Hispanic whites living in the same city.

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Although satellite imagery has allowed several authors to identify a relationship between socioeconomic status and the natural environment, satellite resolution of 20–30 m may be too coarse to characterize the natural environment in highly heterogeneous urban areas. For example, satellite imagery provides very limited information on species diversity and density or vertical structure of vegetation. This is important because past research has shown, for example, that taller trees provide more benefits than smaller trees (Nowak et al., 2006; Donovan and Prestemon, 2012). Larger trees of some species are also more cost effective because their life expectancy and, therefore, longevity of ecological, esthetic, and social benefits is greater than that of smaller or faster-maturing trees (Geiger, 2004). Quantifying species diversity can help planners prepare for potential threats. As Boyd et al. (2013) report, the number of invasive tree pests identified in the U.S. is rising dramatically, and since pests often prefer a narrow range of hosts, the resilience of urban forests can be increased by emphasizing genetic or species diversity (Raupp et al., 2006).

Fewer studies have used ground-based vegetation surveys to assess the SES – greenness relationship. Hope et al. (2003) and Kinzig et al. (2005) studied the diversity of plants and birds in the Phoenix, AZ metropolitan area and found a positive correlation between diversity and both income and house value. Szantoi et al. (2012) augmented data from aerial photography and satellite imagery with ground plots in the metropolitan areas of Miami-Dade County, Florida. They reported the amount of neighborhood canopy cover was positively linked with several socioeconomic factors, including income, education, and home ownership. De la Maza et al. (2002) and Escobedo et al. (2008) grouped boroughs (or *comunas*) in Santiago, Chile's metropolitan area into three socioeconomic strata to examine species diversity and the removal of air pollution by trees. Using the Urban Forest Effects Model (UFORE; Nowak and Crane, 2000) to compile tree data collected on ground plots, they found the boroughs in the wealthiest strata had greater species diversity, tree leaf area and subsequent air-quality benefits, than boroughs in the lower-ranked strata. Pedlowski et al. (2002) stratified 10 neighborhoods in Campos dos Goytacazes, Rio de Janeiro, Brazil by wealth and found higher levels of species diversity in street and park trees in wealthier neighborhoods.

Although these studies used ground-based inventory to investigate the SES – greenness relationship, the authors have used a model-based sampling approach where cities were pre-stratified based on land cover or demographic characteristics. In contrast, a design-based approach assumes all areas are of equal importance, plots under the model-based approach are installed to sample each strata for the attributes of interest (e.g., Escobedo et al., 2006). In addition, model-based studies have typically focused on single metropolitan areas and the neighborhoods or suburbs within them. Single-city studies have limited scope of inference; however, a small-scale model-based approach is understandable, given the cost of collecting data and heterogeneous urban land ownership patterns. Nevertheless, the validity of a model-based strategy depends on making the right stratification and modeling assumptions. For example, a model-based study might assume a linear relationship between tree cover and income. A likely sampling strategy would, therefore, concentrate on areas with very high or very low income. If the linearity assumption is correct, then the sampling strategy may reveal more about the relationship between trees and income than a design-based approach with the same sample size. However, if the linearity assumption is incorrect, then the model-based sampling strategy would under sample areas with moderate income, which may result in inefficient or biased coefficient estimates.

The USDA Forest Service, Forest Inventory and Analysis (FIA) inventory is design-based. The sample plots are part of a national grid; their locations are independent of cover, ownership, and land use, so the validity of the sampling inferences does not depend on modeling assumptions (U.S. Department of Agriculture Forest Service, 1992; Bechtold and Patterson, 2005.).

We address the gap in the literature using data from the first regional FIA inventory of urban trees in the U.S. This unique dataset allows us to explore the relationship between neighborhood socioeconomic status, land use, tree cover, tree size, and species diversity across multiple cities in the Pacific Northwest. The sample is also broader than past studies in both geographic area and the number of cities included. We also consider a city's length of membership in the Tree City USA (2013) program as a surrogate for recognizing the benefits of urban trees by having a budget and a plan for promoting urban trees via an urban forestry program. We examined the following questions:

(1) What is the relation between the existence, or presence, of tree canopy cover in urban FIA subplots and neighborhood socio-economic indicators and measures?
(2) What is the relation between tree canopy cover (as measured by percent canopy cover) in urban FIA subplots and neighborhood socio-economic indicators and measures?
(3) What is the relation between tree counts, in subplots with measureable canopy cover, in urban FIA subplots and neighborhood socio-economic indicators?
(4) What is the relation between tree species counts, in subplots with measureable canopy cover, in urban FIA subplots and neighborhood socio-economic indicators and measures?

2. Methods

2.1. Location

The urbanized area (U.S. Department of Commerce Bureau of the Census, 2002) included in this study is located west of the Cascade Mountain Range in Northwest Oregon and Western Washington (Fig. 1). The FIA plots had been installed in areas Census had identified as urbanized, located on a GIS overlay, which included metropolitan areas with a core population of 50,000 or more. Our study area ranged from Eugene, Oregon in the south (44.0519° N Latitude) to Bellingham, Washington, 550 km (335 miles) to the north (48.7502° N Latitude), and located between 122.1633° and 123.2760° West Longitude. The total land area included in the study is roughly 5160 km^2. This encompasses the larger metropolitan areas of Seattle and Portland, and their adjacent suburban cities.

The Köppen climate classification (Kottek et al., 2006) indicates these urban areas reside within a (Csb) zone, characterized by a cool-mild wet winter and dry summer, with warmer summers in the south. Temperatures in this region range from average to winter low of 0 °C in the north to summer highs of 28.2 °C in the south. This area supports two class III ecoregions, as defined by Omernik (1987) and updated by the U.S. Environmental Protection Agency (2013). In Washington, all but the southern portion of the study area is in the Puget Lowland ecoregion, while Vancouver, Washington and all of the study area in Oregon are in the Willamette Valley ecoregion.

2.2. FIA Inventory

The U.S. Department of Agriculture Forest Service, Pacific Northwest Research Station, Resource Monitoring and Assessment (RMA) Program is part of the national FIA effort. The traditional role of FIA is to manage a sampling framework consisting of a set of permanent ground plots on a systematic-random grid that includes all lands in all states (Bechtold and Patterson, 2005). Plots are spaced roughly 5.4 km apart and all plots, prior to 2014, had the same basic design.

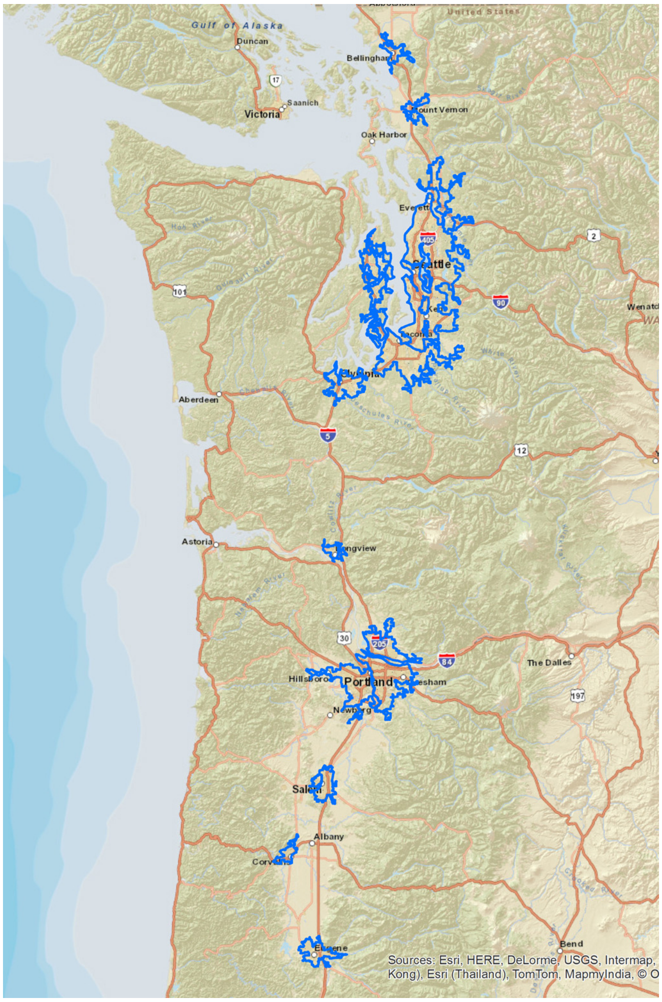

Fig. 1. Study area – urbanized areas of western Washington and Oregon (outlined in blue).

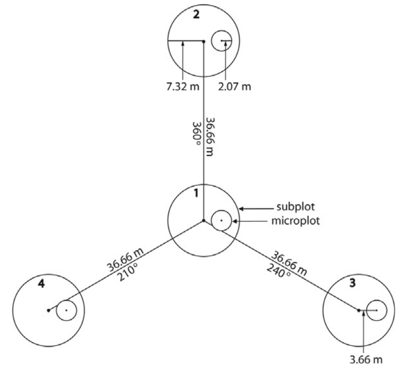

Fig. 2. The urban FIA plot configuration as installed in the Pacific States. Subplots and microplots are numbered 1–4; azimuth and distance are measured from the center of subplot 1.

In forested areas, crews take detailed tree and vegetation measurements from which forest growth, health, and harvest statistics can be calculated and reported at state, region, and national levels. Plots existing in nonforest or developed areas were counted but not visited for the purposes of measurement.

The measurement of plots outside of forested areas is relatively new. The first nonforest pilot inventory was conducted in Maryland in 1999 (Riemann, 2003) followed by projects focused on urban areas in Indiana and Wisconsin (2002), New Jersey (2003), and in Colorado and Tennessee (2005–2009) (Lake et al., 2006; Cumming et al., 2007; Nowak and Dwyer, 2007; Nowak et al., 2011). RMA-FIA installed the Oregon and Washington urban inventories in 2010 and 2011, during the program's urban pilot of the Pacific Coast states. This area included in this study contains 213 of the 1000 plots installed in 5-state pilot effort.

Data was collected in the summer, leaf-on, months. Plots ranged in elevation from 1 to 220 m. Each plot consists of four individual subplots arranged in a triangular pattern that occupies an area 78 m × 69 m (Fig. 2). Each subplot has a radius of 7.3 m and together they sample roughly 0.067 ha. All trees with a diameter at breast height (dbh; 1.4 m) of at least 12.7 cm are sampled on the subplot while within each subplot is a 2.1 m radius microplot for sampling trees with a dbh between 2.54 and 12.7 cm. This protocol comes from the FIA forest inventory (U.S. Department of Agriculture Forest Service, 2012). Our urban study area includes 852 subplots.

The urban protocols were those implemented by FIA in Tennessee and described in Nowak et al. (2011). Variables collected on each subplot include GIS coordinates, land use (among 30 classes), tree-canopy cover, percent ground cover (6 types), the percent of the area subject to regular maintenance such as watering and mowing, and the mapping of any additional land use within the subplot. Tree detail includes species, size, damage, crown-health metrics, and impediments to growth such as overhead power lines or adjacent paved surfaces.

2.3. Demographic data

We compiled demographic data from the American Community Survey (ACS), which are available on the Census Bureau's American Fact Finder website (U.S. Department of Commerce Bureau of the Census, 2013). We queried block group census data collected for years 2007 through 2011.

We selected a pool of candidate SES variables where past research found a correlation with environmental variables (Table 1). These include the number of households in a block group, population density, percent non-Hispanic white, percent of owner-occupied housing, median household income, and median home values. We assumed higher levels of owner occupied housing would reflect greater neighborhood stability and higher home values and

Table 1
Mean block group demographics, comparing data initially included in our models (238) with block groups from the entire urban study area (4387). Only income and home values proved significant.

Variable	Mean (1 SD)	Observations
Block group population	1664 (710) 1456 (639)	238 4387
Race-percent white	81 (14) 78 (16)	238 4387
Number of households	685 (287) 619 (267)	238 4387
Percent households occupied	94 (6) 94 (6)	238 4387
Percent households owner occupied	69 (25) 60 (25)	238 4387
Median household income ($)[a]	73,726 (31,681) 66,575 (29,889)	237 4386
Median home values ($, owner occupied)[a]	351,356 (156,035) 332,071 (152,300)	232 4292

[a] Significant variable.

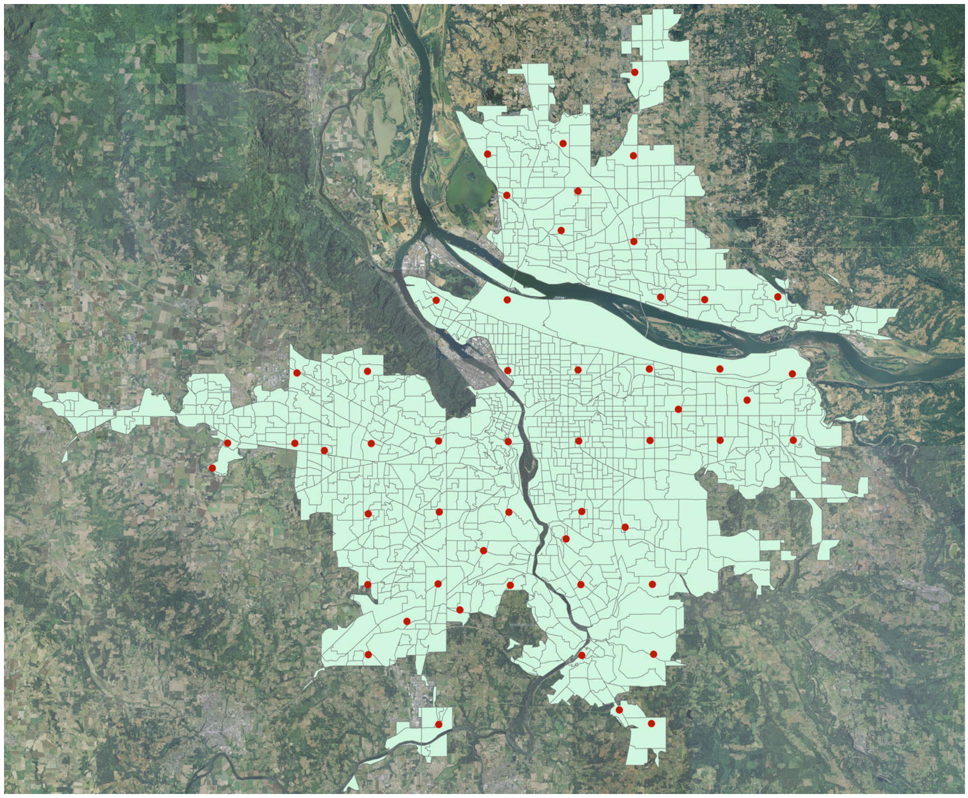

Fig. 3. The urbanized area that includes Portland, OR and Vancouver, WA, showing block group boundaries (polygons) and urban FIA plot locations (points).

higher median household income would indicate greater neighborhood wealth.

To assign SES data to the FIA plots we used a GIS to join the block group coverage (U.S. Department of Commerce Bureau of the Census, 2012), with the FIA plot coverage, and the urbanized area coverage. The urbanized area in our study was composed of 4390 block groups (Fig. 3). The environmental data collected on each subplot was then linked to the demographic data from each intersecting block group.

2.4. Split plots

The subplots that make up each plot create a relatively large footprint. Plot locations were independent of block group boundaries, and twenty-eight of the plots in our study had subplots located in two adjacent block groups (e.g., Fig. 4). Our objective was to link the measured attributes of greenness to the demographic data from the block group where that greenness was measured. Therefore, when a plot straddled two block groups, the plot was split so the subplot data were assigned to the block group where they were measured. In the few cases where a subplot was split between two block groups, the subplot was assigned to the block group that contained the larger portion of the subplot. This process of matching subplots with block groups, rather than whole plots, added 23 additional block groups to the analysis.

Fig. 4. An urban FIA plot where subplot 2 is split from subplots 1, 3, and 4 by a block group boundary (blue line).

2.5. Urban edge effect

The boundaries of Census urbanized areas are drawn to include the population surrounding a central city core. The boundaries themselves often follow a combination of census tract, and block group boundaries, but sometimes cut across less populated areas along the rural–urban interface to capture pockets of denser population. These pockets of population are often the result of city expansion where increasing demand for housing drives the development of forest or agricultural lands. This expansion is often uneven, creating a patchwork of developed and rural land on the edge of suburban areas. It is along this edge that rural land can be included within the urbanized area boundary. Thus, the FIA plots that exist along this urban expansion might sample a mix of land uses, and this is often the case when urban plots are classified as forest or agriculture land use.

Table 2
Condensed land use classes as accounted for on subplots.

Land use summary from all subplots[a]	(%)
Residential	61
Forest	14
Commercial/institutional	13
Agriculture	7
Parks and open space	3
Other	2

[a] Residential includes single and multi-family property, rights-of-way, and vacant lots. Forest includes forestland and timberland. Commercial/Institutional includes industrial, transportation, and utility. Agriculture includes cropland, idle farmland, pasture, and Christmas tree plantation. Open space includes parks, golf courses and cemetery. Other includes wetland and water.

2.6. Missing data

Ground access was denied by landowners for 18 of the 852 subplots located in the study area. We ignored missing subplot data in the model so the net data set consisted of 834 subplots nested in 236 block groups.

2.7. Land use

Crews assigned land use within each subplot based on the classification system used by FIA (U.S. Department of Agriculture Forest Service, 2013). In our study area, there were 21 land use classes recorded among 834 subplots. In terms of area, the 5 most abundant classes were residential, forest, rights-of-way, commercial and industrial use, and institutional land uses. To account for land use in our model, we condensed the individual categories into 6 broader groups (Table 2) and assigned an indicator variable for each category to the subplot based on the classification found at subplot center. Based on experience, the land use found at subplot center was most often the dominant classification on the subplot.

2.8. Subplot cover

Subplot cover was estimated for 7 variables that describe layers occupying the ground surface and above-ground space on each subplot (Table 3). Several cover types can exist in the same vertical space (e.g., permeable surface, shrub, tree canopy), while other layers are mutually exclusive (e.g., herbaceous surface, water, building). The values recorded for all cover types on the subplots ranged from zero to 100 percent. Herbaceous cover (lawn and weeds) was found on 89 percent of the subplots, while shrub and tree canopy cover existed on 61 and 45 percent respectively. Tree canopy was positively correlated with shrub cover and permeable surface cover (bare ground, landscaping material) and negatively correlated with impervious surfaces and buildings, although they are not mutually exclusive.

2.9. Tree data

Tree stems were measured on 300 of the 834 accessible subplots and included 1237 live and 77 dead trees representing 86 species. Native species made up 9 of 10 subplot trees (Table 4). Data collected for each tree includes location on the subplot, species, size, variables associated with crown health and size, and variables associated with damage, predators, and physical impediments to growth. Canopy cover was present on 373 subplots. Canopy is tallied on the subplot for both trees on and any overhanging trees adjacent to the subplot.

Table 3
Average percent cover based on 834 subplots.

Subplot cover (%)	Mean (1 sd)
Tree canopy cover	17 (26)
Shrub cover	15 (25)
Herbaceous	38 (34)
Permeable	27 (30)
Impervious	21 (31)
Building	12 (25)
Water	2 (13)

Table 4
Ten most frequently sampled trees in our study area.

Tree species	Percent
Pseudotsuga menziesii (Mirb.) Franco	23
Alnus rubra Bong.	19
Acer macrophyllum Pursh (Aceraceae)	11
Thuja plicata Donn ex D. Don	10
Prunus avium (L.) L.	3
Tsuga heterophylla (Raf.) Sarg.	2
Arbutus menziesii Pursh (Ericaceae)	2
Populus balsamifera ssp. *Trichocarpa* (Torr. & A. Gray ex Hook.)	2
Betula papyrifera Marsh.	1
Quercus garryana Douglas ex Hook.	1

2.10. Tree City USA

Our Census GIS urban layer included city names associated with the urban polygons (Table 5). In some cases these were individual cities, such as Salem, OR, in other cases they were metropolitan aggregate areas, such as Seattle, which included Bellevue and Tacoma. We include the years (as decades) a city has belonged to the Arbor Day Foundation's Tree City USA (2013) program as an independent variable in our analysis. This is to test the idea that policy associated with the program has a positive relationship with our measures of greenness.

2.11. Modeling

We developed four models to explore the relationship between measures that contribute to describing urban greenness and socioeconomic conditions. We specified the urban forest subplot measurements (presence of tree canopy cover, subplot percentage of tree canopy cover where such cover was present, tree count in the presence of canopy cover, and tree species count in the presence of canopy cover) as response variables for the models. We assumed that the relations between socio-economic conditions and urban forest measurement would hold even when trees were not observed in the subplots, but canopy cover from adjacent trees was measureable. All subplots were included in the analysis for canopy cover presence. For the remaining analyses, we selected for the presence of tree canopy cover in the subplot. We specified the socioeconomic conditions and measures (land-use classes, decades of community participation in the Tree City USA program, median annual household income—in thousands of dollars—and

Table 5
Core cities in study area that belong to the Tree City USA program.

City	Years a Tree City
Bellingham, WA	16
Bremerton, WA	16
Corvallis, OR	11
Eugene, OR	33
Longview, WA – OR	28
Marysville, WA	3
Mount Vernon, WA	17
Olympia – Lacey, WA	20
Portland, OR – WA	35
Salem, OR	36
Seattle, WA	27

average house value—recoded in hundreds-of-thousands of dollars) as explanatory variables. We modeled canopy cover presence with a logistic mixed model, percent tree canopy cover with a linear mixed model, and both tree count and tree species count with Poisson mixed models. In all of the models that we formulated we excluded the indicator for residential housing land use, as that is the dominant land-use class, and is therefore, the default reference class for the specified land-use designations in the presented models. For each of the models, however, we had to exclude additional land-use classes—depending on model behavior and performance – which expanded and generalized the scope of the reference land-use class for those models.

Our tree-inventory data exhibited two nested levels of spatial clustering: subplots were nested within plots, and plots were nested within cities. We also included census block groups as random effects that nest in cities. Because the overlaid block-groups follow a different structure, subplots were also nested within block groups, but this nesting did not necessarily include plots as intermediate nesting structures. To accommodate this data structure, we estimated a hierarchical mixed-effects model. The generalized linear mixed model, from which we developed the logistic mixed, linear mixed, and Poisson mixed models is:

$$Y_{ijkl} = \boldsymbol{\beta}_{ijk[l]}\boldsymbol{X} + Z_i + W_{ij} + U_{ik} + e_{ijkl}$$

where Y_{ijkl} denotes our dependent variable (tree canopy cover present in subplot, percentage of a subplot with canopy cover, trees per subplot, or number of species per subplot) on the lth subplot, on the kth plot, in the jth block group in the ith city, $\boldsymbol{X}$ is a vector of independent fixed-effects socio-economic classes and measures, including a 1 for the intercept, and $\boldsymbol{\beta}_{ijk[l]}$is a vector of fixed-effects coefficients, including the intercept. The random effects include subplot-scale error term e_{ijkl}, which is independently and assumed normally distributed with mean 0 and variance σ^2_{ijkl}, U_{ik} is the plot-scale random effect that is assumed independently and normally distributed with mean 0 and variance σ^2_{ik}, W_{ij} is the block-group-scale random effect that is assumed independently and normally distributed with mean 0 and variance σ^2_{ij}, and Z_i is the city-specific random effect that is assumed independently and normally distributed with mean 0 and variance σ^2_i.

3. Results

We present the results of our four questions in Table 6. The five non-residential land-use classes represent a broad range of land uses. Eliminating explicit reference to residential areas in the modeling allowed us to represent residential areas with the model intercept term. In most cases, however, we eliminated other land-use classes that provided little or no discernable difference in response from models when we determined that they did not provide further clarity in response variables. Our threshold for making this determination was $p = 0.05$.

Where trees were not present in subplots, we recorded tree counts as zeroes. This left about 55% of subplots containing no trees. To proceed with the analysis we decided to perform a two-stage process in which we first developed a model to investigate if the presence of tree canopy cover in a subplot was associated with the available socio-economic indicators and measures. We performed this analysis on all 834 subplots. After that analysis, we focused attention only on those subplots where we had observed the presence of tree canopy cover, developing relations for percentage of subplot that was tree canopy cover, tree counts, and tree species counts.

As a hierarchical model, there are several units of inference, each dependent on the scale at which explanatory measures are associated. For example, Tree City USA tenure is an effect that is associated with the city scale, so units of inference for Tree City USA are the cities in the sample. Likewise, Median Household Income and House Value are block group-scale measures. Land Use classes, are associated with the subunit scale, but might vary at that scale or at other scales, as land-use patterns in urban areas are distributed according to political, historical, commercial, and other means different from the sampling plan for this study. To accommodate this scale ambiguity and accompanying un-even replication we have applied the Kenward-Roger (Kenward and Roger, 1997) method for adjusting degrees of freedom. This method takes into account the imbalances in sample sizes and ambiguities in unit classification. We also included block group as a scale in the hierarchical structure of the model. This addition modified the model structure from a purely nested hierarchical model to a more complicated hierarchical structure with two different nested parts.

There is a moderate amount of collinearity between median household income and median home value at the block group scale. We checked on this in the analysis process, but found no reason for concern, as when the two effects were in contention for inclusion in the model together one or the other of them described insubstantial amounts of variation in the response and was eliminated from inclusion.

Table 6
Model parameter estimates for mixed-effects models to explain variation in Tree Canopy Presence, Tree Canopy Percent Cover, Tree Count, and Tree Species Count in sampled urban areas of the Pacific Northwest (438 subplots, 213 plots, and 11 cities; where lu = land use).

Effect	Parameter Est	DF	*P*-value	Odds ratio
Tree Canopy Presence ($n = 834$)				
Intercept	−2.10	19.09	<0.01	0.12
lu commercial-institutional	−1.14	252.13	<0.01	0.32
lu forest	3.12	655.25	<0.01	22.75
lu agriculture	−1.13	248.51	0.01	0.32
lu other	−2.47	828.00	0.03	0.08
Tree City USA (decades)	0.69	13.63	0.01	2.00
Tree Canopy Percent Cover ($n = 373$)				
Intercept	2.72	49.20	<0.01	
lu parks and open	0.81	182.67	<0.01	
lu forest	0.82	145.77	<0.01	
Household income ($M)	0.004	142.76	0.03	
Tree Count ($n = 367$)				
Intercept	0.59	53.35	<0.01	
lu forest	0.96	177.25	<0.01	
House value ($MM)	0.09	153.72	0.03	
Tree Species Count ($n = 367$)				
Intercept	0.07	27.59	0.63	
House value ($MM)	0.08	186.98	0.01	

(1) Tree Canopy Presence

Our first goal was to determine how well socio-economic indicators and measures describe the presence of tree canopy in urban subplots (Question 1). We used a hierarchical mixed logistic regression model to investigate this question, with subplots nested in plots, plots nested in cities, and block groups nested in cities. We modeled land-use classes as indicator variables, and tenure in the Tree City USA program as a continuous variable at the decade scale. As indicator (0, 1) variables, land-use classes act as adjustments to the intercept, which, as described above, represents subplots located in urban residential areas or (and for the canopy presence model) parks. We found tree canopy presence to be poorly related to standard socioeconomic status measures, but was as an alternative, related to Tree City USA tenure. After adjusting for the length of time that a city has participated in the Tree City USA program, the odds of the presence of tree canopy cover on a subplot is

0.32 times greater in a commercial-institution area than outside this land use. Similarly, the odds of finding tree canopy cover is 22.75 times greater on a subplot if it is in a forest area than if it is not. Measureable tree canopy cover odds are 0.32 times greater in an agricultural subplot as on all other subplots. Measureable tree canopy cover is 0.08 times greater in the catch-all land-use class that we labeled as other than the intercept. In addition, after adjusting for land use, the odds of the existence of tree canopy cover increases by 2 times on a subplot for each additional decade that a city has participated in the Tree City USA program.

(2) Tree Canopy Cover

Our second question asked about the relation of percent tree canopy cover to socio-economic indicators and measures when measureable canopy cover is present. The hierarchical model structure is the same as for presence of tree canopy cover, with the exception that residuals for the canopy cover model were approximately log-normally distributed, rather than the binomial model for canopy cover presence. The model intercept represented subplots that contained residential, commercial institutions, agricultural, and other non-park, non-forest, land use classes. As can be seen in Table 6, parameters for the park and forest land-use classes yielded small increases in the logarithm of expected percent canopy cover, after adjusting for median household income (0.81 for park lands and 0.82 for forest-designated areas). In addition, after adjusting for land use, for every $1000 increase in median household income in a subplot, the logarithm of percent tree canopy cover also increased by about 0.004.

(3) Tree Count

The third question referred to the relation of subplot tree counts to socio-economic conditions. The model uses the same hierarchical structure as previous models, except that we modeled the response in this case as a Poisson random variable.

As above, model details are available in Table 6. As with the rest of the models, we included only subplots with measureable tree canopy cover. Because average house value was not available for block groups where 6 subplots resided, n is equal to 367. The intercept represents the logarithm of the number of trees in a subplot if that subplot was located in areas classified as non-forest. The forest land-use class represents an additive adjustment of 0.96 to the logarithm of the number of trees in a subplot relative to the logarithm of tree counts attributed to residential and other non-forest subplots, as represented by the intercept, after adjusting for median house value. In addition, after adjusting for forest land use and increasing median house value by one-hundred thousand dollars, the logarithm of the number of trees in a subplot will increase by 0.09.

(4) Tree Species Count

The fourth question was about the relation of subplot tree-species counts to socio-economic conditions, given 300 subplots with measureable trees. We again included the 367 subplots where we had data for both canopy cover and home value. We applied the same hierarchical structure to the data as before, and we modeled the species count as a Poisson random variable.

Table 6 contains details for this final model as well. The intercept term represented all land-use classes for this model. Finally, for all land-use classes, a one-hundred thousand dollar change in median house value led to a change of 0.08 in the logarithm of the number of species present in an urban subplot, given that subplot contains measureable tree canopy cover.

4. Discussion

Past studies relating neighborhood measures of wealth to greenness have been either broad, relying on satellite imagery to quantify cover, or focused on individual cities, intensively sampling neighborhoods with ground plots. The broad studies lack information on individual tree numbers, species and size, while the single city studies include tree detail but are limited to smaller areas with focused sampling. We examine the relationship between SES and environmental variables broadly, across multiple cities in the Pacific Northwest. Our study used detailed tree and land use data collected from a set of FIA ground plots that were located independent of SES or cover estimates to test for a positive relationship between neighborhood wealth and neighborhood greenness.

In climates where trees occur naturally, the existence of mature trees in urban areas is an indicator of mid- to long-term land use stability; trees take time to grow and mature whereas land development often requires tree removal or replacement with young trees. Trees also reflect the health of the natural environment in urban settings, a tree in good health requires resources in the way of adequate soil, moisture, and space, and at least a minimal level of protection from damage. The tree itself is a major part of an ecosystem, and the resources that support a tree will support other types of vegetation as well. As our results suggest, the existence of forested areas in urban settings increases the likelihood of trees being present, or near subplots, while land-altering uses, such as commercial, institutional, agricultural, and other uses had a suppressing effect on the likelihood of tree presence in the immediate area. After accounting for land use, increasing the amount of time a community participates in the Tree City USA program coincided with the likelihood of the presence of tree cover on subplots.

We chose percent canopy cover as a dependent variable because cover has been shown to be important in other studies. Unlike the individual tree data, canopy cover is generic in terms of species and tree size; it is simply an estimate of the area of the subplot with canopy overhead, from any tree—either on or off the subplot. Our result is consistent with other studies; subplots had more canopy cover where block groups had higher household incomes. Of note, race was not significant in association with canopy as found by Gowen and Mellnik (2013) or Jesdale et al. (2013). We entered race in the model as the percent of the block group population that identified themselves as non-Hispanic white. Six percent of the block groups in the entire urbanized study area supported a population that Census enumerated to be less than 50 percent white race and our subplots were established in just four of those. Either our sample was too dispersed (not model-based) to establish a correlation with race as other studies found, or there is less correlation between race and trees in the Pacific Northwest due to differences such as climate, which is favorable for tree growth, or culture, meaning few neighborhoods where the majority population is non-white.

Our third question asked if higher tree counts, where measureable canopy cover is present, might be associated with neighborhoods with higher socioeconomic status. The number of trees on a subplot was positively related to home values after accounting for land use. Since block group median home value is based on owner occupied housing, this might be thought of as a surrogate for the rate of home ownership as well as relative wealth associated with the neighborhood. Our result is compatible with Szantoi et al. (2012) who found greater tree counts to be associated with higher home ownership, and with Donovan and Butry (2010), who found that street trees in front of a house for sale, increased the home's selling price.

Whereas tree canopy presence, percent canopy cover, and the count of trees are a measure of the current urban forest, the number of tree species on a subplot can be an indicator of longer-term resiliency. As we said in our introduction, many tree diseases and pests are increasing in number, and since they often thrive on a narrow range of species, neighborhoods with a greater diversity of tree species will likely fare better in the future, in terms of ecosystem services, than those supporting monocultures. This can be an environmental justice issue if there is less tree diversity where SES is lower. The loss of urban trees can have not only a negative impact on property values, as one might expect from our analysis, but Donovan et al. (2013) recently demonstrated a positive correlation existed between the loss of trees to emerald ash borer (*Agrilus planipennis*) and rates of human mortality from respiratory and stress related ailments. Our model result did indicate a positive relationship between species count and median house value. This supports the view that resiliency of the urban forest will be more likely in neighborhoods with a higher SES.

Many communities use Tree City USA standards to enhance urban forest management through improved ordinances to plan for trees, innovative tree planting programs, and increased emphasis on tree care. Though not a traditional measure of SES, our analyses suggests that over time, in terms of the occurrence of tree canopy, these efforts are usually providing benefits. Our particular models did not find this relationship extended to the numbers of trees or the amount of canopy cover, but we can assume there is a positive relationship between the existence of canopy and the existence of trees.

This study agrees with others that have found lower neighborhood SES is associated with fewer neighborhood trees. Greene et al. (2011), and Donovan and Mills (2014) report that citizens in neighborhoods with less affluence are less likely to participate in volunteer tree planting programs. If a city plans to increase total canopy cover to avoid environmental injustice, planners' will want to tailor tree planting programs so they will be more likely to succeed in underserved neighborhoods. Increasing canopy cover in these areas has the potential to provide a larger marginal ecosystem services benefit as compared to planting in neighborhoods that tend to have more, and better maintained, environmental amenities.

5. Conclusions

In the Pacific Northwest, there is a positive correlation between the SES of urban residents and the abundance of the urban forest. These results add to the body of literature that together suggests this relationship exists across multiple metropolitan areas covering a wide range of geographies, climate zones, and demographies. Given our findings, it should be noted that FIA inventory structure is not only robust enough to draw these conclusions but it can provide a mechanism to monitoring this situation over time.

Our study was the first to use urban FIA data for this kind of analysis, but it was limited by density of the plot grid in the urban environment. We think the additional data collected from a denser sampling grid would lead to a more robust model and provide local detail more useful for urban forest officials. Nowak et al. (2008) suggest installing 200 plots of 0.04 ha each in a city to get a reasonable population estimate and standard error associated with the sample. Since 2014, FIA has begun adopting a new strategy for selected urban cities. The plot has been redesigned and the sampling intensity has been increased so 200 plots can be installed in a city's core area. The new design combines subplots into one 14.6 m radius plot that samples the same area (0.067 ha), but as one plot. This design is being used in Baltimore, MD, Providence, RI, Milwaukee and Madison, WI, and Austin and Houston, TX. FIA hopes to continue this effort nationally, on a city-by-city basis. In the longer term, this effort could evolve into a broader urban forest monitoring mission.

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