Urban Forestry & Urban Greening 118 (2026) 129349

Contents lists available at ScienceDirect

Urban Forestry & Urban Greening

journal homepage: www.elsevier.com/locate/ufug

Original article

Hyper-local social and ecological factors correlate with public tree distributions across Washington, DC: Implications for equitable ecosystem service provisioning

Jessica Nadler [a,b], Daniel J. Herrera [a,d,1], Gabriela Palomo [a,2], Colleen O'Donnell [a,3], Adam Pekor [a], Zehidul Hussain [a,4], Sharfaa Hussain [c,5], Travis Gallo [a,*,6]

[a] Department of Environmental Science and Technology, College of Agriculture and Natural Resources, University of Maryland, College Park, MD, United States
[b] Department of Geosciences, College of Arts and Sciences, Oberlin College, Oberlin, OH, United States
[c] College of Arts and Science, Trinity Washington University, Washington, DC, United States
[d] North Carolina Museum of Natural Sciences, Raleigh, NC, United States

ARTICLE INFO

Keywords:
Environmental justice
Geographically weighted regression
Green equity
Street trees
Urban tree canopy

ABSTRACT

Urban green infrastructure like public trees can deliver ecosystem services that help cities respond to modern environmental challenges like pollution, climate change, public health, crime, equitability, and biodiversity loss. However, studies have shown that urban trees are inequitably distributed along various socioeconomic variables, translating to inequitable provisioning of ecosystem services. This research aims to explore how street trees are distributed across Washington, DC, USA, as a function of social demographics and urban landscape features. Using data from DC's Urban Forestry Street Trees dataset, we fit a series of both linear and multi-scale geographically weighted regression models to assess patterns in overall tree canopy cover, native species diversity, oak abundance, and recent street tree plantings. Both linear and MGWR models agreed on the direction of correlation between all dependent and independent variables. However, our MGWR models revealed spatial variability in some results. For example, we found that new tree plantings had a positive relationship with the proportion of renters in some localized areas but a negative relationship in other portions of the city, indicating that areas with high renting populations are not equally receiving new trees across the city. We also found a positive relationship with new tree plantings and heat sensitivity index and this relationship was generally uniform across the city, indicating that new tree plantings are being conducted in areas that need them the most. Our analysis can help identify local neighborhoods in which street tree inequalities exist and inform planting efforts that prioritize the equitable distribution of green infrastructure across Washington, DC.

1. Introduction

Sustainable cities must respond to a suite of modern challenges, including pollution, climate change, public health, crime, and equitability. Urban planners increasingly rely on green infrastructure—i.e. trees, green spaces, and wetlands—to deliver ecosystem services that meet these challenges. Green infrastructure can vary widely in scale, ranging from site-specific implementations to landscape-scale networks (Grabowski et al., 2022). Green infrastructure has proven effective at reducing air temperature, pollution, noise, and flooding; providing opportunities for recreation, aesthetics, and connection with nature; and supporting biodiversity through habitat creation in urban settings (Buffam et al., 2022).

Among the components of green infrastructure, public trees are

* Corresponding author.
E-mail address: tgallo@umd.edu (T. Gallo).
1 https://orcid.org/0000-0002-8468-220X
2 https://orcid.org/0000-0002-0661-413X
3 https://orcid.org/0000-0003-0513-6567
4 https://orcid.org/0009-0006-3065-0014
5 https://orcid.org/0000-0003-1317-5259
6 https://orcid.org/0000-0003-2877-9848

https://doi.org/10.1016/j.ufug.2026.129349
Received 6 November 2025; Received in revised form 11 February 2026; Accepted 11 February 2026
Available online 13 February 2026

particularly valued for their ability to provide a range of ecosystem services at a relatively low cost. The shade and evapotranspiration that tree canopies provide are instrumental in reducing the urban heat island effect created by increased heat emission and absorption in developed areas (Gillerot et al., 2024; Parker, 2010; Wang et al., 2021; Yang et al., 2016). Urban areas with low canopy cover experience reduced wind speeds and greater concentrations of heat (Gillerot et al., 2024; Rajagopalan et al., 2014; Ryu and Baik, 2012), which contributes to greater rates of heat-related health conditions and mortality (e.g., major cardiovascular, chronic lower respiratory; Boumans et al., 2014; Wang et al., 2021). Increased tree density, in turn, provides greater shade coverage and drastically reduces regional and local temperatures (Armson et al., 2012; Bowler et al., 2010) and energy costs (Moody et al., 2021). Urban tree planting is thus projected to notably reduce heat-related mortality and morbidity (McDonald et al., 2024).

In addition to contributing to lower air temperatures, street trees also contribute to cleaner air (Nowak et al., 2006). Improved air quality from tree-associated air purification has been linked to lower rates of mortality (Nowak et al., 2013), lung cancer (Wang et al., 2021), and childhood asthma (Lovasi et al., 2008). While the benefits of trees to human physical health are clear, their contributions to human mental health have only recently become appreciated. Urban trees have been correlated with reduced stress (Elsadek et al., 2019; Townsend et al., 2016), better academic performance (Kweon et al., 2017), and better attention (Lin et al., 2014). While these benefits are enjoyed at the individual level, they bear community-level implications. Trees can provide cues that a neighborhood is cared for (Gilstad-Hayden et al., 2015), which has been found to promote social cohesion (Weinstein et al., 2015) and mitigate the psychological precursors to violence (Kuo and Sullivan, 2001). As a result, the correlation between urban canopy cover and reduced crime rates has been demonstrated in numerous US cities, including Chicago (Kuo and Sullivan, 2001; Schusler et al., 2018), Baltimore (Troy et al., 2012), New Haven (Gilstad-Hayden et al., 2015), Cincinnati (Kondo et al., 2017a), Philadelphia (Kondo et al., 2017b), and New York (Lin et al., 2021).

While street trees directly benefit human health by providing air purification, shade, and assisting mental health, they also indirectly benefit society by supporting biodiverse ecosystems. Urban canopies foster biodiversity in cities by providing food, habitat, nesting sites, and movement corridors for wildlife (Bhullar and Majer, 2000; Shackleton, 2016). In the United States, native oaks (*Quercus* spp.) play a disproportionate role in fostering wildlife (Wood and Esaian, 2020). For example, oaks foster especially high *Lepidoptera* (butterfly) species richness (Narango et al., 2020; Piel et al., 2021; Tallamy and Shropshire, 2009), are often preferred by foraging birds (Narango et al., 2017; Wood et al., 2012; Wood and Esaian, 2020) and are an important food source for many native mammals (Tallamy, 2021). Oaks can also be especially disturbance-tolerant, making them prime candidates for disturbance-rich urban environments in a warming climate (Piana et al., 2021; Thomas et al., 2024).

Despite the numerous benefits associated with urban street trees, many studies have shown that urban trees are unequally distributed along various socioeconomic variables (Gerrish and Watkins, 2018; Pham et al., 2017) — especially, race and income (Landry and Chakraborty, 2009; Lin et al., 2021; Watkins et al., 2017) — which translates into an inequitable distribution of ecosystem services for those communities. While these relationships have been observed across several cities, city-specific history and ecology present local nuances that remain uncaptured by sweeping multi-city studies (e.g., Magle et al., 2021). Thus, single-city studies are warranted to capture the social and environmental conditions unique to a locale (Healy et al., 2022; Roman et al., 2021; Smart et al., 2020). Urban planners and decision-makers may rely on these city-specific inferences that reflect their local context to tailor policies that address the challenges unique to their region.

The heterogeneous and dynamic characteristics of urban environments present an opportunity to explore fine-scale social and environmental variables that might give rise to spatial disparities in the distribution of urban public trees. However, the same heterogeneous characteristic may cause significant spatial nonstationary in these data, obscuring our understanding of where ecosystem services are being provisioned. Multiscale geographically weighted regression (MGWR) is an extension of linear regression that allows for the associations between response variables and independent variables to vary both across geographic space and at different spatial scales. MGWR models also offer a more robust understanding of relationships than traditional linear regression (LR) (Xiao et al., 2023), as they are able to capture local variations in the effects of independent variables. Here, we assess the relationships between public tree distribution and social-environmental characteristics of the urban environment in Washington, D.C., USA. We use a MGWR approach to address both spatial heterogeneity and the effects of scale on tree distributions across the city.

The city of Washington, DC, provides an important case study as a proud "city of trees" (Nowak et al., 2006) that has formally prioritized the planting of public street trees to mitigate and expand resiliency to the impacts of climate change (i.e. flooding, urban heat island effect, and pollution) and improve environmental health (i.e. air purification, water filtration, and increased biodiversity) (Department of Energy and the Environment, 2016; Urban Forest Division, 2020). Washington, DC also has a long history of racial and class discrimination (King et al., 2022), and a recent study in Washington, DC, found that median household income was negatively correlated with the health and quality of public street trees (Fang et al., 2023). Here we build on this study to investigate the spatial relationship between social-ecological variables in Washington, DC and four attributes of street trees: overall canopy cover, native species diversity, oak abundance, and the number of trees planted in the last five years. Additionally, we assess an explicit public health component by examining the distribution of public trees in relation to health conditions that can worsen an individual's sensitivity to heat exposure. We hypothesized that each tree metric would be positively correlated with the proportion of residential buildings, the perceived social prestige of an area, and mean building age in an area, and negatively correlated with the proportion of renters and populations that are particularly sensitive to heat exposure. Furthermore, we also hypothesized that these relationships would vary locally across the city in both magnitude and direction. The goal of this study is two-fold: i) to explore the distribution of public trees as they relate to social-ecological variables and ii) to identify location-specific disparities in ecosystem service provisioning that can be addressed through targeted tree plantings. Our analyses can help identify specific neighborhoods in which street tree inequalities exist to prioritize planting efforts that contribute to environmental justice across Washington, DC.

2. Methods

2.1. Study area

We conducted this study in Washington, DC, a city situated at the confluence of the Potomac and Anacostia Rivers in the Mid-Atlantic region of the United States. The city has a terrestrial area of approximately 158 km^2 and is characterized by dense urban development in the center of the city, encircled by a ring of rowhomes and a subsequent ring of single-family homes. The district identifies itself as a "city of trees," which is manifested by a city-wide canopy cover of nearly 37 %, the presence of the United States National Arboretum, and a festival dedicated to non-native cherry trees which attracts over 1.5 million individuals annually (Fang et al., 2023; Nowak et al., 2006; Office of the Mayor of the District of Columbia, 2024). The District of Columbia has formally prioritized the use of public tree plantings to increase shade, stabilize riverbanks, and filter and purify air and water as part of the District's climate change preparedness plans (Department of Energy and the Environment, 2016). To meet these goals, the District of Columbia largely collaborates with a local non-profit, Casey Trees to plant trees on public and private lands and increase the urban canopy to 40 % by 2032 (Buscaino and Schichtel, 2024). Casey Trees plants approximately 5500 trees per year in the District of Columbia (O'Brien, 2023), and in 2024 Casey Trees, the District of Columbia, and other community partners planted 16,000 trees in the District on both public and private lands (Buscaino and Schichtel, 2024). While the area is naturally a beech-oak forested ecosystem, a wide array of other species comprise the city's urban canopy and are maintained by Casey Trees and the city's Urban Forestry Division (Department of Energy and the Environment, 2015; Fang et al., 2023).

Washington is home to approximately 672,000 people across 132 neighborhoods within eight administrative wards (City of Washington, DC, 2007; Census Bureau, 2022a). Although the population is ethnically and socioeconomically diverse, the distribution of these demographics is relatively stratified due to historical redlining and disinvestment practices (King et al., 2022; Logan, 2017). Neighborhoods east of the Anacostia River tend to be low-income (Fig. 1.) and/or Black neighborhoods (e.g., Barry Farm; Fig. 1; King et al. 2022), although Black and middle-income neighborhoods also exist in this portion of the city (e.g., Kenilworth). Conversely, neighborhoods in the western section of the city tend to be both affluent and white (e.g., Georgetown, 16th Street Heights; Fig. 1; King et al., 2022). The northeastern section of the city is more heterogeneous, with neighborhoods forming a patchwork of racial and financial diversity (e.g., Petworth and Brookland; Fig. 1). Fewer residents live in the center of the city (e.g. China Town and Downtown), but neighborhoods tend to be dominated by affluent white families just beyond the city center (e.g., Capitol Hill), before transitioning to primarily middle-class Black neighborhoods further east (e.g., Kingman Park; Fig. 1). Additionally, communities in eastern Washington, DC are more susceptible to heat related illnesses (Fig. 1).

2.2. Urban tree metrics

To assess the spatial distribution of trees across Washington, D.C., we used the Urban Forestry Street Trees database (District of Columbia, 2024a), managed by the District of Columbia Department of Transportation's Urban Forestry Division. The Urban Forestry Street Tree database is a publicly available dataset that includes information for each tree planted in a landscaped public space in Washington, DC (e.g., tree species, year it was planted, health, diameter at breast height). Trees found on federal property, private properties, or non-landscaped public properties are not included in the database. At the time of this analysis, the database contained 213,877 individual street trees across all of Washington, DC. We removed duplicate entries, trees labeled as "dead" or "no tree," and species names left blank or labeled "N/A." After filtering out these records, 187,590 observations remained.

To aggregate the urban street tree data, we superimposed a 550x550m spatial grid over the administrative area of Washington, DC, and removed any cell that did not fall at least 50 % within the city boundaries. Furthermore, we removed any cell in which greater than 25 % of the cell's area was comprised of open water, federal park land, military land, university campuses, or large private properties, since trees in these land use categories are not recorded in the Urban Forestry Street Tree database and their absence would bias our results. We chose a 550x550m grid size because the area of each cell is approximately the mean area of census block groups in Washington, DC, and uniform grid cells ensured that our spatial units were consistent across the landscape, which is not achieved when using census block groups.

Within each remaining gridcell ($n = 526$), we calculated the proportion of overall tree canopy cover, Shannon's diversity index of native trees, the total number of oak trees (*Quercus spp.*), and the number of individual trees planted between 2018 and 2022 (Fig. S1). To calculate canopy cover, we used the Chesapeake Conservancy high-resolution (1-m) land cover database (Chesapeake Bay Program, 2023; Robinson et al., 2019) and calculated the proportion of each land cover class within each grid cell. We then summed the proportions of land cover cells classified as "Forest", "Tree, Other", "Tree Canopy Over Turf Grass", and "Tree Canopy Over Impervious" in each grid cell to obtain a value of total canopy cover. Native tree Shannon's diversity index was calculated using the vegan package (Oksanen et al., 2022) in R version 4.4.0. (R Core Team, 2024). Species were considered native if their native range included Washington, DC, Virginia, or Maryland per the US Department of Agriculture plants database (plants.usda.gov) or the ICUN's listed range for each species (iucnredlist.org). Hybridized species were not included as native. The overall sum of Oak trees in each grid cell was used as oak abundance, and all plantings (regardless of species) conducted between 2018 and 2022 were summed in each grid cell to calculate the number of new plantings. Cells that were removed from the original grid were assigned "NA" values and not included in the statistical analysis. All spatial processing was performed using the 'sf' (Pebesma, 2018) and 'terra' (Hijmans et al., 2024) packages in R version 4.4.0.

2.3. Spatial autocorrelation

Prior to analysis, we investigated the spatial autocorrelation of all dependent variables by calculating Moran's I and plotting local indicators of spatial autocorrelation (LISA; Anselin, 1995).

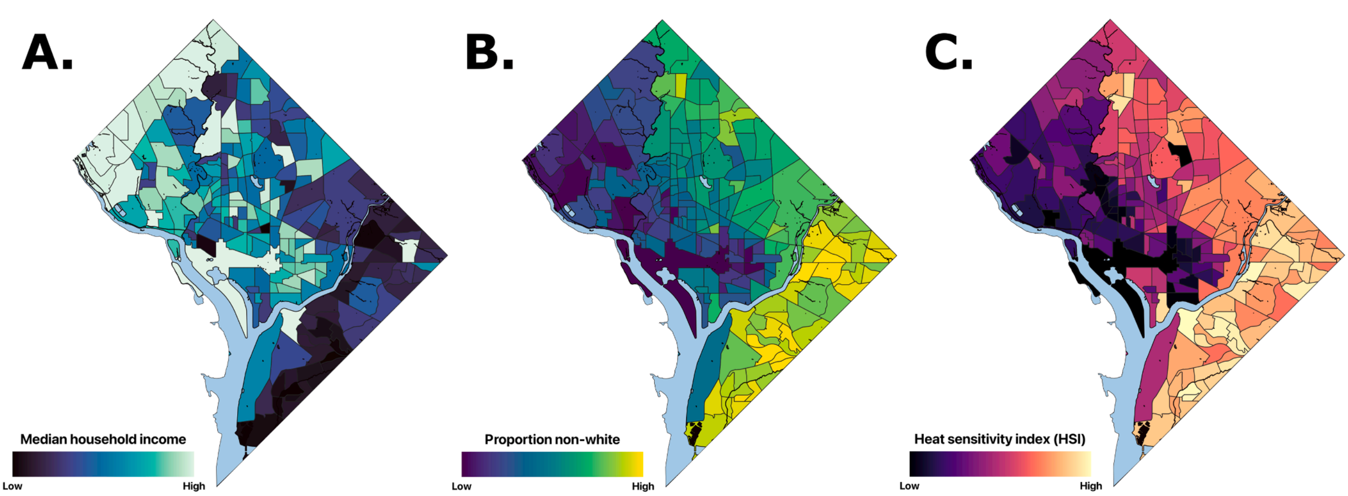

Fig. 1. The distribution of median household income (A), proportion of non-white residents (B) based on the U.S. Census 2023 5-year American Community Survey (U.S. Census Bureau, 2022b), and heat sensitivity index (C) based on (Department of Energy and Environment, 2022) across the city of Washington, DC USA.

2.4. Predictor variables

The aim of this study was to explore how street trees are distributed across the District of Columbia and the implications of this distribution on vulnerable populations. With this in mind, the predictor variables that we used in our study were arranged into two categories: 1) urban landscape characteristics (i.e., mean impervious surface area, proportion of commercial building coverage, proportion of residential building coverage, and mean building age), and 2) socio-demographic characteristics (i.e., proportion of residents that rent, neighborhood prestige, and heat sensitivity).

2.4.1. Impervious cover

To calculate impervious cover, we used the Chesapeake Conservancy high-resolution (1-m) land cover database (Chesapeake Bay Program, 2023; Robinson et al., 2019) and summed the proportions of land cover cells classified as "Impervious Roads", "Impervious Structures", or "Impervious, Other" in each grid cell using the 'terra' package in R.

2.4.2. Residential and commercial building footprints

To calculate residential and commercial building footprints, we first spatially joined the District of Columbia Building Footprints layer (Building Footprints; District of Columbia, 2024b) and the District of Columbia Existing Land Use layer (Existing Land Use; District of Columbia, 2024b). We reclassified buildings labeled as 'Residential' or 'Mixed' to residential buildings and buildings labeled 'Commercial' or 'Industrial' to commercial. We summed the area of each building type within each grid cell and divided by the area of the grid cell to obtain a proportion of coverage by each building type.

2.4.3. Prestige index

As the US capital city, Washington, DC maintains several grand and opulent spaces as symbols of democracy, history, and diplomacy (Schroder, 2021; Witt, 2005). These spaces are revered as points of pride in the city and were thus considered to convey prestige. To quantify prestige across Washington, DC we obtained the Embassies (dataset name: Embassies), federal buildings recognized on the historical register or eligible for the historical register (dataset name: Historic landmarks), monuments and memorials (dataset name: Memorials), museums (dataset name: Museums), University and College Campuses (dataset name: University and college campuses), and parks (dataset names: National parks, Parks and recreation areas) layers publicly available from DC Open Data (District of Columbia, 2024b). Within each grid cell, we summed the number of previously described attributes and log-transformed the data before analysis.

2.4.4. Building age

To calculate mean building age for each grid cell, we calculated the weighted average year a structure was built using the U.S. Census Bureau's 2022 5-year American Community Survey (Census Bureau, 2022b). The average year that structures were built was subtracted from 2024 to get a weighted mean building age for each grid cell.

2.4.5. Proportion of renters

To calculate the proportion of renters in each grid cell, we summed the total population and total renter population from each 2022 5-year American Community Survey census block group that overlapped a grid cell. When a block group did not overlap a grid cell completely, we used an area-weighted crosswalk approach by multiplying the population data by the proportion of the respective census block that was within the grid cell (Goodchild et al., 1993). We then divided the total population by the population of renters to obtain the proportion of renters in each grid cell.

2.4.6. Heat-sensitivity Index

Following the Heat Sensitivity Index methodology prepared by the CADMUS group (Department of Energy and Environment, 2022), we calculated a heat sensitivity index comprised of 9 variables calculated for each 550x550m grid cell in our study area. Using the 5-year American Community Survey (2018–2022) we calculated the following variables for each grid cell: the proportion of people of color that do not identify as white, total population under 5 years of age, total population that was age 65 or over, total population below the 200 % poverty ratio, total population with a disability (calculated at the tract level), and total population who are not proficient in English. All variables were calculated at the census block group scale unless otherwise noted. When Census geometries overlapped the boundaries of a grid cell we used a crosswalk approach and divided the population data by the proportion of the respective census geometry that was within a grid cell (Goodchild et al., 1993). The crude prevalence of obesity, asthma, and coronary heart disease was calculated from the 2023 CDC PLACES Data at census tract scale (Center for Disease Control, 2024). When a grid cell overlapped more than one census tract boundary, we took the mean of each variable.

Each variable was then scaled and indexed using the following aggregation (Department of Energy and Environment, 2022):

$$\textit{Component Index}_i = \left(\frac{\textit{population share}_j - \textit{minimum census tract share}}{\textit{maximum census tract share} - \textit{minimum census tract share}}\right) \times \left(\frac{1}{n}\right),$$

where $i =$ variable, $j =$ grid cell, $n =$ the total number of variables (n = 9). Once scaled and indexed, variables were summed to create the heat sensitivity index (HSI):

$$HSI_j = \sum_{i=1}^{9} \textit{Component Index}_i$$

2.5. Data analysis

For each response variable we fit two models using all four independent variables: a standard linear regression model (LM) and a multiscale geographically weighted regression model (MGWR). Both the LM and MGWR were fit using the 'GWmodel' package (Gollini et al., 2015) using R version 4.4.0. All dependent variables, except proportion of canopy cover, were log-transformed before analysis. The proportion of canopy cover was instead logit transformed – a more appropriate transformation for proportional data. The model assessing new planting rates included all previously described independent variables as additive terms and the existing tree density variable. We included existing tree density as a variable to account for instances where current tree density may lead to decisions not to plant more trees (i.e. there are already enough trees in an area). Here we calculated the existing tree density in each cell by summing the number of existing living street trees in each cell and dividing it by the area of the cell. Models assessing canopy cover, native tree diversity, and oak abundance did not include the existing tree density variable. All independent variables were scaled to have a mean of 0 and a standard deviation of 1. For our MGWR model, we used an adaptive Gaussian kernel to estimate the number of nearest neighbors (bandwidth) and set the backfitting threshold to 0.001

iterations.

While an overall p-value is calculated for each variable using the LM, overall variable-specific significance is not reported for MGWRs as the strength and direction of relationships can vary across space. As a result, a variable can be significant in some grid cells but insignificant in others. With a MGWR model, a variable's t-values can vary spatially, so areas with high t-values indicate stronger evidence that the effect of a variable is locally significant (Fotheringham et al., 2002; Lu et al., 2014). We considered a variable locally significant if the t-value for a respective grid cell was greater than 1.96 (Fotheringham et al., 2002; Lu et al., 2014).

We then visualized the estimated spatially varying regression coefficients for each independent variable in each grid cell using a divergent color palette and added cross-hatching to indicate where a coefficient was not considered locally significant. Visual assessment of these maps allowed us to identify spatial patterns and clustering of results. We also assessed bandwidth values to identify when a variable was locally or globally relevant. Smaller bandwidths indicate that a model used fewer nearest neighbors for the respective variables, indicating more spatial non-conformity, whereas larger bandwidth values indicate greater spatial conformity. Finally, we assessed the adjusted R^2 value for both the LM and MGWR to compare model fit between the two approaches.

3. Results

3.1. Spatial autocorrelation

Local indicators of spatial association (LISA) revealed clusters of spatial autocorrelation in all five of our dependent variables, justifying our use of an MGWR (Fig. 2). Clusters of spatial autocorrelation are indicated by cells with statistically high values bordered by other cells of statistically high values (High-High) or cells of statistically low values bordered by other cells of statistically low values (Low-Low). Across variables, clustering was most prevalent around downtown, areas neighboring the east side of Rock Creek Park, and along the city borders (Fig. 2). Additionally, the analysis also identified regions in which grid cells with statistically low values border grid cells with statistically high values (High-Low), and vice versa (Low-High). These locations of High-Low and Low-High indicate hyper-local anomalies in public tree metrics.

To explore the nuanced relationships between dependent and independent variables across the city, we compared traditional linear regression (LR) models against MGWR models. The MGWR models outperformed LM models for all dependent variables, as indicated by R^2 values (Table 1). Generally speaking, the direction of effect of significant ($p \leq 0.05$) variables in the LM matched the direction of the median estimate of the same variable in the MGWR, indicating that results from the LM and MGWR models complemented each other.

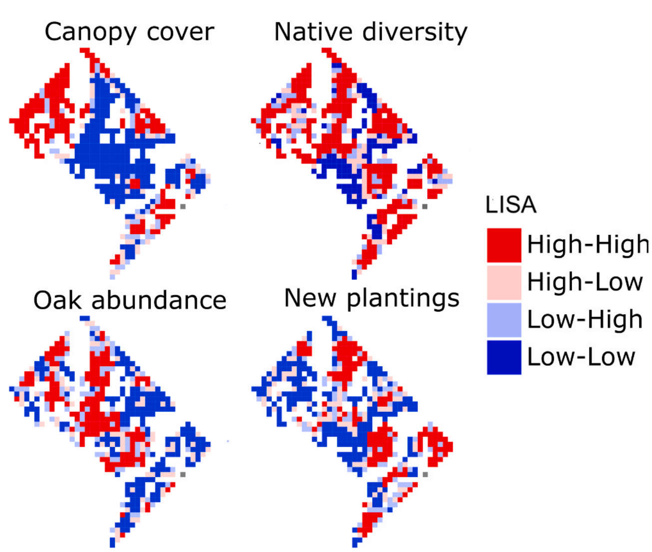

Fig. 2. Visualizations of local indicators of spatial association (LISA) for each dependent variable across sampled grid cells in Washington, DC. Colors indicate the value of each grid cell's dependent variable value in relation to its neighboring cells.

3.2. Canopy cover

Results from our LM indicate a positive correlation between total tree canopy cover and the proportion of residential buildings ($\beta_{LM} = 0.1608$, 95 % CI = 0.1205–0.2011), proportion of renters ($\beta_{LM} = 0.0891$, 95 % CI = 0.0472–0.1310), neighborhood prestige ($\beta_{LM} = 0.0644$, 95 % CI = 0.0285–0.1003), and mean building age ($\beta_{LM} = 0.12892$, 95 % CI = 0.0861–0.1717), and a significant negative correlation with impervious cover ($\beta_{LM} = -0.87760$, 95 % CI = −0.9240 - −0.8312) and heat sensitivity index ($\beta_{LM} = -0.1065$, 95 % CI = −0.1451 - −0.0679). All variables in the MGWR, excluding heat sensitivity index, showed spatial variation in their correlation with tree canopy cover (i.e. low bandwidth; Table 1), including proportion of commercial buildings which was not significant in the LM (Fig. 3). Heat sensitivity was significant in our LM and had a bandwidth of 525 in the MGWR, indicating that the significant negative correlation between tree canopy cover and heat sensitivity index was uniform across the city (Table 1).

3.3. Native tree diversity

Results from our linear model show a negative correlation between native tree diversity and impervious surface ($\beta_{LM} = -0.0928$, 95 % CI = −0.1320 - −0.0537) and a positive correlation with the proportion of residential buildings ($\beta_{LM} = 0.1377$, 95 % CI = 0.1036–0.1717) and commercial buildings ($\beta_{LM} = 0.0553$, 95 % CI =0.0135, 0.0970). While our results from the MGWR model indicated that the correlation between impervious cover and native tree diversity was uniform across the city (bandwidth = 525), the MWGR model indicated that the correlation between both residential and commercial buildings and native tree diversity varied across the city with a bandwidth of 14 and 61, respectively (Fig. 4). Our LM did not find a significant relationship between native tree diversity and mean building age (Table 1). However, we found significant correlations between native tree diversity and mean building age that varied spatially across the city (bandwidth = 42), with some local areas having a significant positive correlation with mean building age and other areas showing a significant negative correlation (Fig. 4).

3.4. Oak abundance

Across our study area, we found an average of 62.5 (sd = 37.5) oak trees per grid cell. For the number of oak trees, we found a significant positive correlation with the proportion of residential ($\beta_{LM} = 0.5224$, 95 % CI = 0.4153–0.6295) and commercial buildings ($\beta_{LM} = 0.1781$, 95 % CI = 0.0467–0.3097) in our LM. However, results from the MWGR model indicated notable spatial variation in local correlations between the number of oak trees and impervious cover (bandwidth = 43), residential buildings (bandwidth = 28), commercial buildings (bandwidth = 230), neighborhood prestige (bandwidth = 59), and mean building age (bandwidth = 312) (Fig. 5). In the case of impervious cover, we found some areas with a significant positive correlation with the number of oaks and other areas with a significant negative correlation (Fig. 5).

3.5. New tree plantings

We found an average of 9.4 trees (sd = 5.6) planted in each grid cell between 2018 and 2022. The linear model for new plantings in the last 5 years, showed a significant negative correlation between impervious

Table 1
Model results for linear and multi-scale geographically weighted regression models used to model the distribution of public street trees in Washington, DC, USA. An asterisk (*) indicates a significant result at a p-value threshold of ≤ 0.05 for the LM results.

Model	Variable	Linear Model Estimate	Linear Model 95 % CI	MGWR Model Median Estimate	MGWR Mean (SD)	MGWR Model Range Estimate	MGWR Bandwidth
Canopy Cover *LM adjR^2 = 0.8684* *MGWR adjR^2 = 0.9210*	% Impervious	-0.87760*	-0.9240, −0.8312	-0.8431	-0.8303 (0.1191)	-1.0968, −0.4248	25
	% Residential	0.1608*	0.1205, 0.2011	0.1084	0.1139 (0.0778)	-0.0740, 0.3064	61
	% Commercial	0.0278	-0.0217, 0.0772	0.0631	0.0772 (0.1163)	-0.1225, 0.3833	90
	% Renter	0.0891*	0.0472, 0.1310	0.0650	0.0647 (0.0624)	-0.1057, 0.2059	433
	Prestige Index	0.0644*	0.0285, 0.1003	0.0702	0.0699 (0.0054)	0.0583, 0.0819	96
	Mean Building Age	0.12892*	0.0861, 0.1717	0.0649	0.0890 (0.1176)	-0.1689, 0.6268	39
	Heat Sensitivity Index	-0.1065*	-0.1451, −0.0679	0.0564	-0.05625 (0.0006)	0.0577, −0.0552	525
Native Shannon's Diversity *LM adjR^2 = 0.1547* *MGWR adjR^2 = 0.6763*	% Impervious	-0.0928*	-0.1320, −0.0537	-0.0116	-0.0209 (0.0198)	-0.0760, −0.0014	525
	% Residential	0.1377*	0.1036, 0.1717	0.0545	0.1094 (0.2271)	-0.1402, 2.0369	14
	% Commercial	0.0553*	0.0135, 0.0970	0.0102	0.0436 (0.1045)	-0.0631, 0.4213	61
	% Renter	-0.0114	-0.0468, 0.0240	0.0069	0.0069 (0.0022)	0.0033, 0.0109	525
	Prestige Index	-0.0109	-0.0194, 0.0412	-0.0087	-0.0086 (0.0029)	-0.0137, −0.0041	525
	Mean Building Age	0.0168	-0.0529, 0.0193	0.0087	0.0037 (0.0738)	0.4212, 0.1905	42
	Heat Sensitivity Index	0.0193	-0.0132, 0.0519	-0.0205	-0.0189 (0.0037)	-0.0228, −0.0126	525
Oak Abundance *LM adjR^2 = 0.1778* *MGWR adjR^2 = 0.5458*	% Impervious	-0.0116	-0.1349, 0.1118	0.1431	0.1529 (0.3741)	-0.7297, 1.1313	43
	% Residential	0.5224*	0.4153, 0.6295	0.2521	0.3155 (0.3479)	-0.2601, 1.9566	28
	% Commercial	0.1781*	0.0467, 0.3097	0.0414	0.0532 (0.1237)	-0.1280, 0.2650	230
	% Renter	0.0126	-0.0987, 0.1240	0.0158	0.0138 (0.0120)	0.0084, 0.0304	525
	Prestige Index	0.0173	-0.0781, 0.1127	-0.1470	-0.5150 (0.8384)	-3.0665, 0.2446	59
	Mean Building Age	-0.0393	-0.1529, 0.07461	0.0165	0.0505 (0.0876)	-0.0482, 0.1973	312
	Heat Sensitivity Index	-0.0664	-0.1690, 0.0362	0.0178	-0.0241 (0.0241)	-0.0616, 0.0063	525
Recent Planting Rate *LM adjR^2 = 0.5172* *MGWR adjR^2 = 0.8033*	% Impervious	-0.1854	-0.2729, −0.0978	-0.0253	-0.0253 (0.0026)	-0.0306, −0.0200	522
	% Residential	0.0882	-0.0019, 0.1784	0.0499	0.0804 (0.1622)	-0.3408, 0.8105	28
	% Commercial	0.1479*	0.0549, 0.2408	0.1303	0.1622 (0.1789)	-0.0844, 0.5904	68
	% Renter	-0.1213*	-0.2001, −0.0425	-0.0303	-0.0084 (0.1538)	-0.4433, 0.6732	45
	Prestige Index	-0.0585	-0.1260, 0.0090	-0.1020	-0.2317 (0.3538)	-1.8688, 0.3454	23
	Mean Building Age	-0.1486*	-0.2294, −0.0677	-0.0872	-0.0863 (0.0032)	-0.0900, −0.0779	525
	Heat Sensitivity Index	0.1720*	0.0994, 0.2446	0.0303	0.02906 (0.0025)	0.0237, 0.0317	525
	Abundance	0.65272*	0.5761, 0.7293	0.5008	0.5771 (0.3186)	0.0967, 2.2873	24

cover (β_{LM} = −0.1854, 95 % CI = −0.2729 - −0.0978), proportion of renters (β_{LM} = −0.1213, 95 % CI = −0.2001, −0.0425), and mean building age (β_{LM} = −0.1486, 95 % CI = −0.2294 - −0.0677), and a significant positive correlation between commercial buildings (β_{LM} = 0.1479, 95 % CI = 0.0549–0.2408), heat sensitivity index (β_{LM} = 0.1720, 95 % CI = 0.0994–0.2446), and current abundance of trees ($\bar{x}$ = 286.5, sd =, 124.4, β_{LM} = 0.65272, 95 % CI = 0.5761–0.7293). Results from our MGWR model indicate spatial variation in the correlation between new plantings and proportion of residential buildings (bandwidth = 28), proportion of commercial buildings (bandwidth = 68), proportion of renters (bandwidth = 45), neighborhood prestige (bandwidth = 23), and abundance (bandwidth = 24). While the proportion of commercial buildings was not significant in our LM, the results of the MGWR indicate that there is significant positive correlation in some local areas (Fig. 6). Additionally, we found local areas of significant negative correlation and other areas of significant positive correlation between the proportion of renters and the number of new plantings (Fig. 6). Finally, bandwidth results from the MGWR model indicate that the correlations between new plantings and impervious cover, building age, and heat sensitivity identified in the LM are fairly uniform across the city (Table 1).

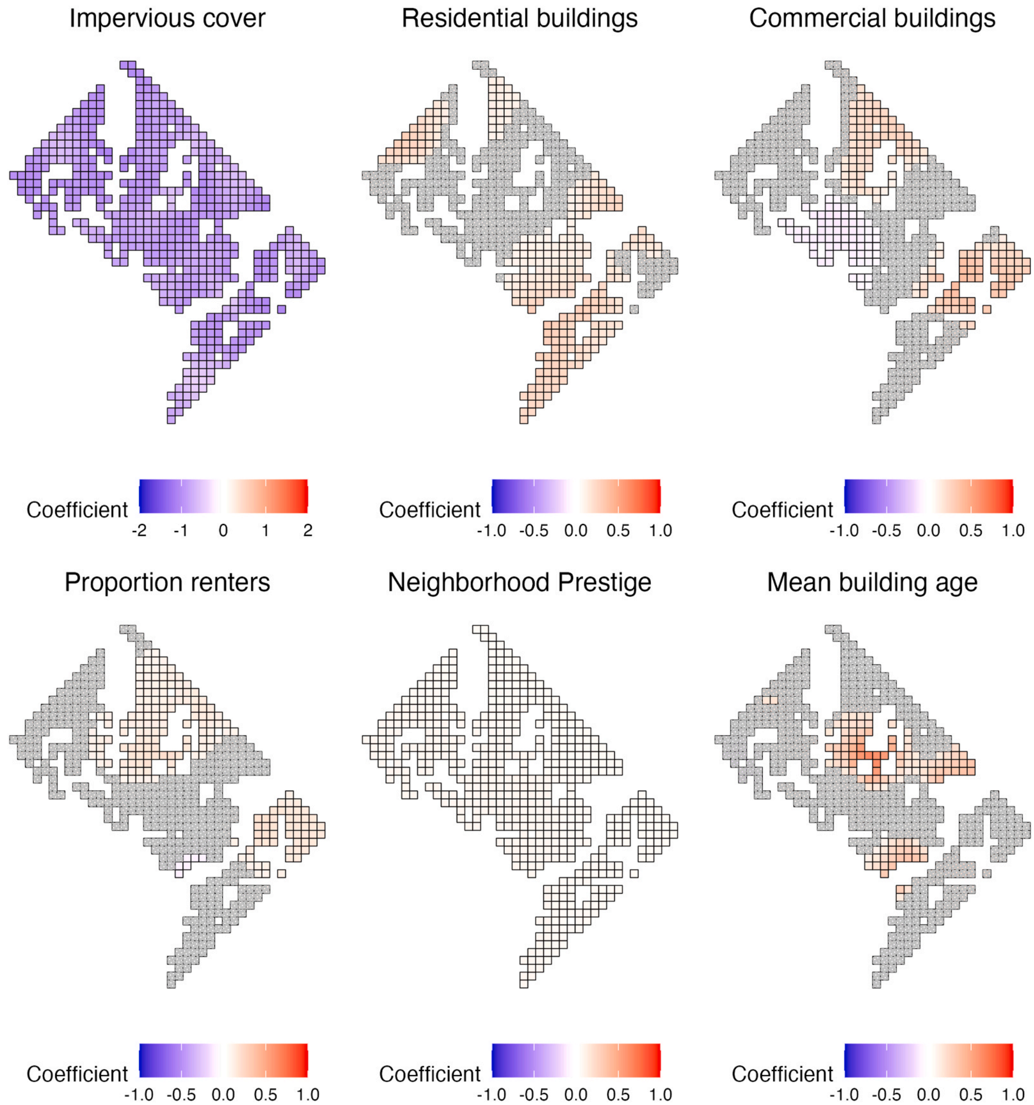

Fig. 3. Visualization of multi-scale geographically weighted regression (MGWR) results for percent canopy cover across Washington, DC. Cool colors indicate a locally negative relationship between the independent variable and canopy cover, while warm colors indicate a locally positive relationship. The relationship was not locally statistically significant in cells with gray cross-hatching.

4. Discussion

Inequities in the distribution of public trees impact neighborhood-level resilience to environmental challenges (e.g., urban heat, pollution, lack of access to nature) and yield inequitable provisioning of ecosystem services to communities. Given the notable societal benefits of street trees, it is essential to ensure that public trees are distributed equitably across cities (Parker and Simpson, 2020). Although the relationship between socio-demographics and urban canopies are well-studied (e.g., Pham et al. 2017; Gerrish and Watkins, 2018; Watkins and Gerrish 2018), our analysis revealed that many of these relationships are not spatially uniform across our focal city, Washington, D.C. Therefore, hyperlocal analyses like ours are needed to identify local trends and inform local management decisions that contribute to social-ecologically resilient cities (Young and Lieberknecht, 2019; Jain and Espey, 2022).

We used a MGWR statistical approach to assess the distribution of street trees across Washington, DC. A MGWR modeling framework allows relationships between dependent and independent variables to vary spatially, providing the ability to identify local differences in highly-heterogenous urban areas. As a result, our findings are neighborhood-specific and uncovered hyper-local relationships that require specific and thoughtful intervention. For example, using a traditional linear regression model, we found that the number of new tree plantings had a significant negative relationship with the proportion of renters in an area, suggesting that trees are being planted less in neighborhoods with more renters. However, when considering spatial non-conformity our MGWR model highlighted that new tree plantings had a significant negative relationship with the proportion of renters in the central and western portions of the city, but a significant positive relationship with the proportion of renters in the northeast and southeastern portions of the city. These results suggest that renter populations in some local areas are not equally receiving new trees, compared to areas with a high renting population elsewhere in the city. This disparity is important because renters tend to have less ability to plant private trees at their residences and may rely more on the ecosystem services provisioned by public trees (Morgan and Ries, 2022; Perkins et al., 2004; Steenberg et al., 2018). These types of results highlight the importance of considering spatial non-conformity in analyzing environmental factors to better address nature equity and environmental justice.

Extreme heat presents a serious public health challenge for urban residents (Kovats and Hajat, 2008; Luber and McGeehin, 2008), and

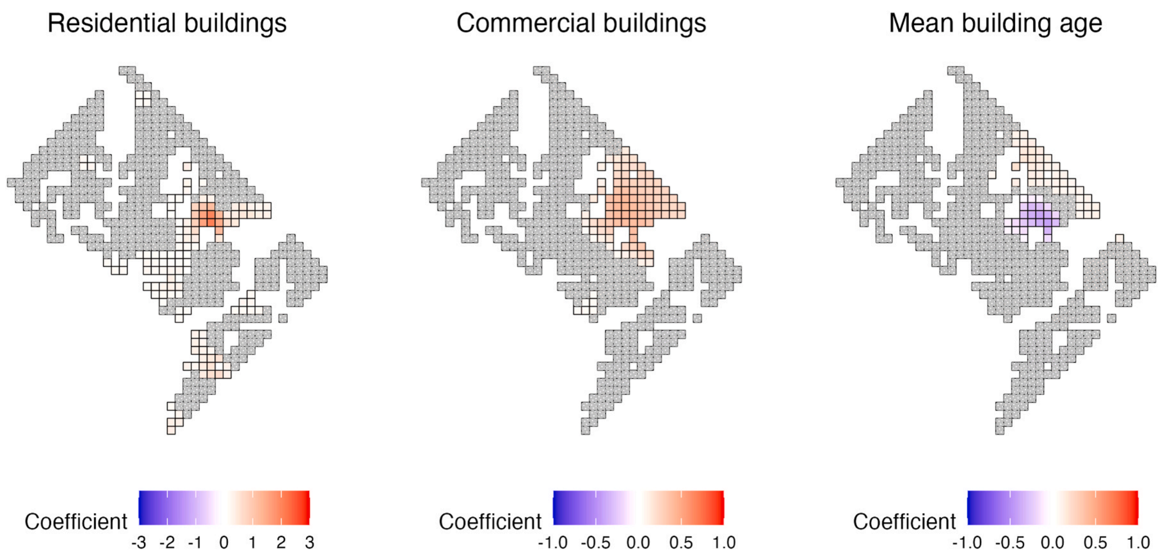

Fig. 4. Visualization of multi-scale geographically weighted regression (MGWR) results for native tree diversity across Washington, DC. Cool colors indicate a locally negative relationship between the independent variable and canopy cover, while warm colors indicate a locally positive relationship. The relationship was not locally statistically significant in cells with gray cross-hatching.

increased tree cover has shown to be a successful mitigation strategy to lower temperatures in urban neighborhoods (Bowler et al., 2010). Ziter et al. (2019) found that during extreme heat events, daytime air temperature was substantially reduced when canopy cover was > 40 % at the scale of a typical city block. Thus, total canopy cover can have serious implications for local areas that have higher populations of heat vulnerable residents. We found that overall tree canopy cover had a negative correlation with the heat sensitivity index of an area, and that the relationship was spatially uniform across Washington, D.C. Thus, in this case, city planners shouldn't prioritize a particular local area but should prioritize planting larger trees that increase shade in areas that have larger populations of heat vulnerable residents across the city. However, increasing the number of large street trees may not always be possible in heavily urbanized neighborhoods due to decreased available planting areas (e.g., smaller sidewalks and sidewalk cutouts). Therefore, urban foresters and community partners should focus on planting larger trees on private residential properties in areas with higher heat sensitivity.

We also found a significant positive relationship and substantial spatial variation in the effect size of all other predictor variables on the proportion of tree canopy cover except for commercial buildings. Instead, we found that commercial buildings have a significant positive relationship in the northern neighborhoods of DC but a significant negative relationship in the downtown core of the city. While it may not be feasible to significantly increase urban canopy cover in the downtown core because of the high density of taller buildings, city managers and planners could prioritize green walls, engineered vegetation coverings, and native green roofs in these areas to increase cooling and other benefits normally provided by trees (Armson 2012, Bowler et al. 2010).

Similarly, we found a significant negative relationship between native tree diversity and impervious cover and this relationship was spatially uniform across the city. As noted, increasing the total tree canopy in highly developed areas may present a challenge, yet increasing the diversity of trees planted in these areas is feasible. Research has shown that higher species diversity can increase human mental wellbeing (Krischke et al., 2025; Southon et al., 2018; Wolf et al., 2020), increase local biodiversity (Anderson et al., 2023; Threlfall et al., 2017; Wood and Esaian, 2020), and provides greater resilience within the urban canopy to environmental disasters (e.g., disease outbreak; Jactel et al., 2017). Focusing on increasing the diversity of native trees planted in highly developed areas will 1) increase the diversity of native trees that people experience, because areas of high impervious cover often correlate with greater human population density and 2) increase the overall tree species pool, and thus increase the resilience of the urban forest by increasing functional and redundant diversity (Petchey and Gaston, 2006; Wood and Dupras, 2021). A key limitation is that not all native species can tolerate harsh urban conditions, such as elevated temperatures and limited growing space. Future research should therefore focus on the adaptability of native tree species to specific urban environments, enabling industry stakeholders (e.g., growers and producers) and urban foresters to draw from a more diverse and resilient species pool (Raupp et al., 2006).

We also found spatially varying correlations between native tree diversity and mean building age. In the areas of northeastern DC, we found a positive correlation between native tree diversity and mean building age, indicating that areas with older housing stock had greater native tree diversity. However, we found a negative correlation in the more central portions of northeast D.C. near the National Arboretum. Thus, increasing the diversity of trees planted around older buildings and homes where native tree diversity is lower in these localized areas will increase tree diversity and the benefits they provide in specific areas where they are currently lacking. These results highlight how city managers can use these localized findings to prioritize hyper-local areas that may be lacking in tree diversity.

Finally, oak trees (*Quercus* sps.) provide a large array of services in urban areas. Their high leaf-area ratio provides shade for urban cooling and captures particulate matter out of the air acting as air filters (Grote et al., 2016; Moss et al., 2019). Oaks also harbor greater biodiversity compared to other commonly used tree species in urban areas (Narango et al., 2020, 2018). Thus, oak trees are a particular asset to urban areas. Results from our LM model indicated a significant relationship between oak abundance and both residential and commercial buildings. However, our MGWR suggests that the magnitude of those positive relationships varied across the city, indicating that oaks could be prioritized in areas that have weaker positive relationships. Additionally, we found varying directions of effects of impervious cover on the number of oak trees. Our results highlight three localized areas where the number of oaks and impervious cover have a positive relationship, but two specific areas in northeast Washington, DC where there is a significant negative relationship. In these specific neighborhoods, oak plantings could be prioritized in more densely developed areas as an opportunity to increase the abundance of oaks in those neighborhoods.

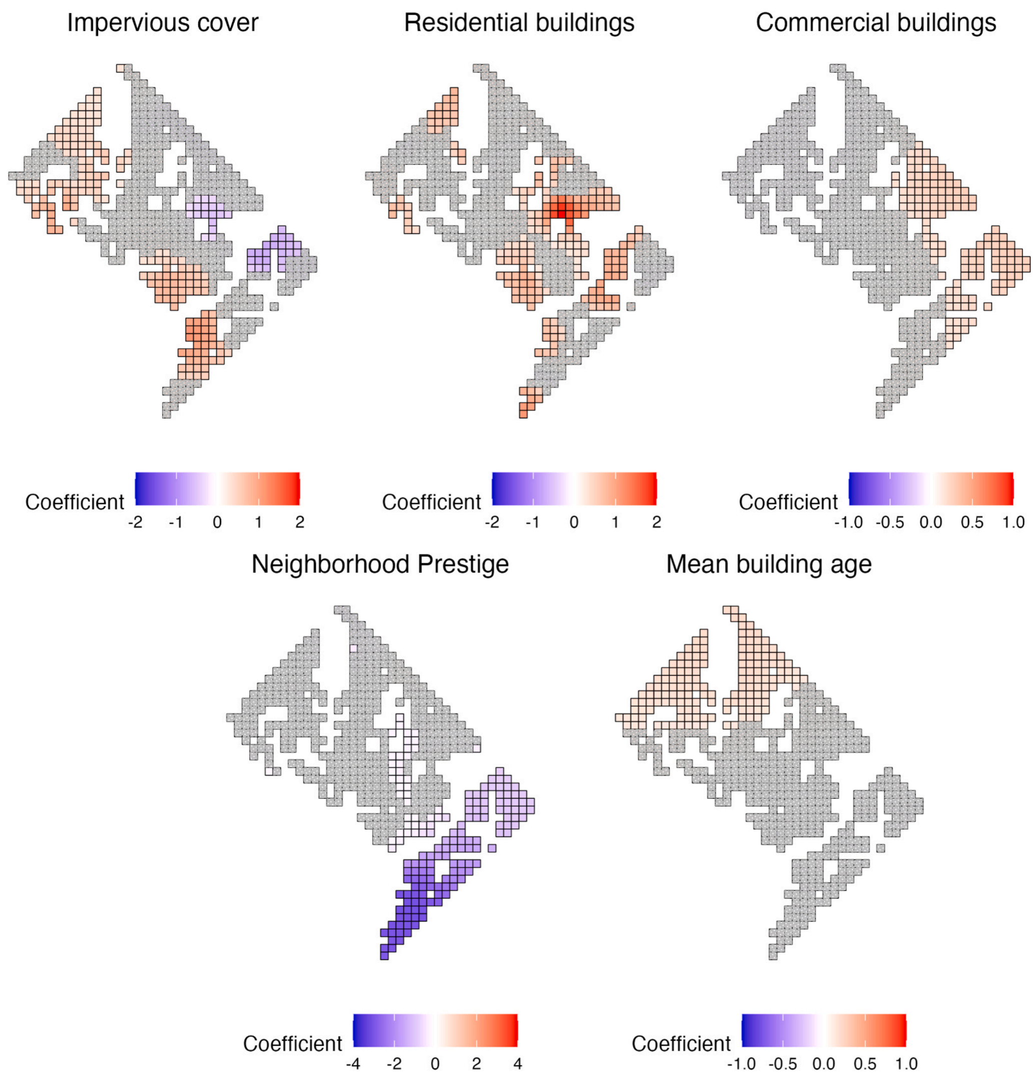

Fig. 5. Visualization of multi-scale geographically weighted regression (MGWR) results for native oak tree abundance across Washington, DC. Cool colors indicate a locally negative relationship between the independent variable and canopy cover, while warm colors indicate a locally positive relationship. The relationship was not locally statistically significant in cells with gray cross-hatching.

While it is important to look at how existing tree metrics correlate with social demographics and the physical characteristics of cities, we felt it was important to also explore where new trees were being planted. New plantings highlight priority locations for urban greening, and it is important to assess whether new plantings are being located equitably, especially as it pertains to historically marginalized populations. We found a significant positive correlation between new plantings and both commercial and residential buildings, but the magnitudes of effect varied across neighborhoods. These results could be following patterns of new development. For example, we found a significant positive relationship with both residential buildings and proportion of renters in a specific area of northeast D.C. (Fig. 6) – an area experiencing high levels of high-density residential development. It is possible that higher planting rates in these areas due to ordinances that require developers to plant trees. If true, these findings would highlight how public policy can increase urban tree canopy and diversity. Notably, we found a positive relationship with new tree plantings and heat sensitivity index and this relationship was generally uniform across the city - indicating that new tree plantings in Washington, D.C. are, on average, being conducted in areas where public health is most benefited.

In our case, the Washington, D.C. Urban Forestry Street Tree database only covers public land managed by the District of Columbia. Therefore, our analysis of native tree diversity, oak abundance, and recent plantings excluded trees on private lands and federally managed lands. Notably, the federal government manages more than 90 % of public parklands in Washington, D.C. (National Capital Planning Commission, 2010), and therefore most of the public greenspaces in Washington, D.C. were excluded from our analysis. To have a more comprehensive understanding of tree distributions in Washington, D.C., future research should prioritize comprehensive urban tree inventories, including both public and private lands. Additionally, while our analysis described how tree species – and thus the ecosystems services they provision – are distributed across Washington, D.C., our analysis did not answer the question of why trees are planted or preserved in specific locales. What, where, and why trees are planted (or preserved) is based on human decisions, and those decisions will vary city to city. Our findings showed where trees are distributed in Washington, D.C. and how their distributions relate to hyper-local social and ecological characteristics, but future studies should focus on the human decisions, public policies, and development patterns that correlate to tree preservation and plantings to better inform equitable tree planting policies and programs.

5. Conclusion

Cities are highly heterogeneous landscapes, and our research

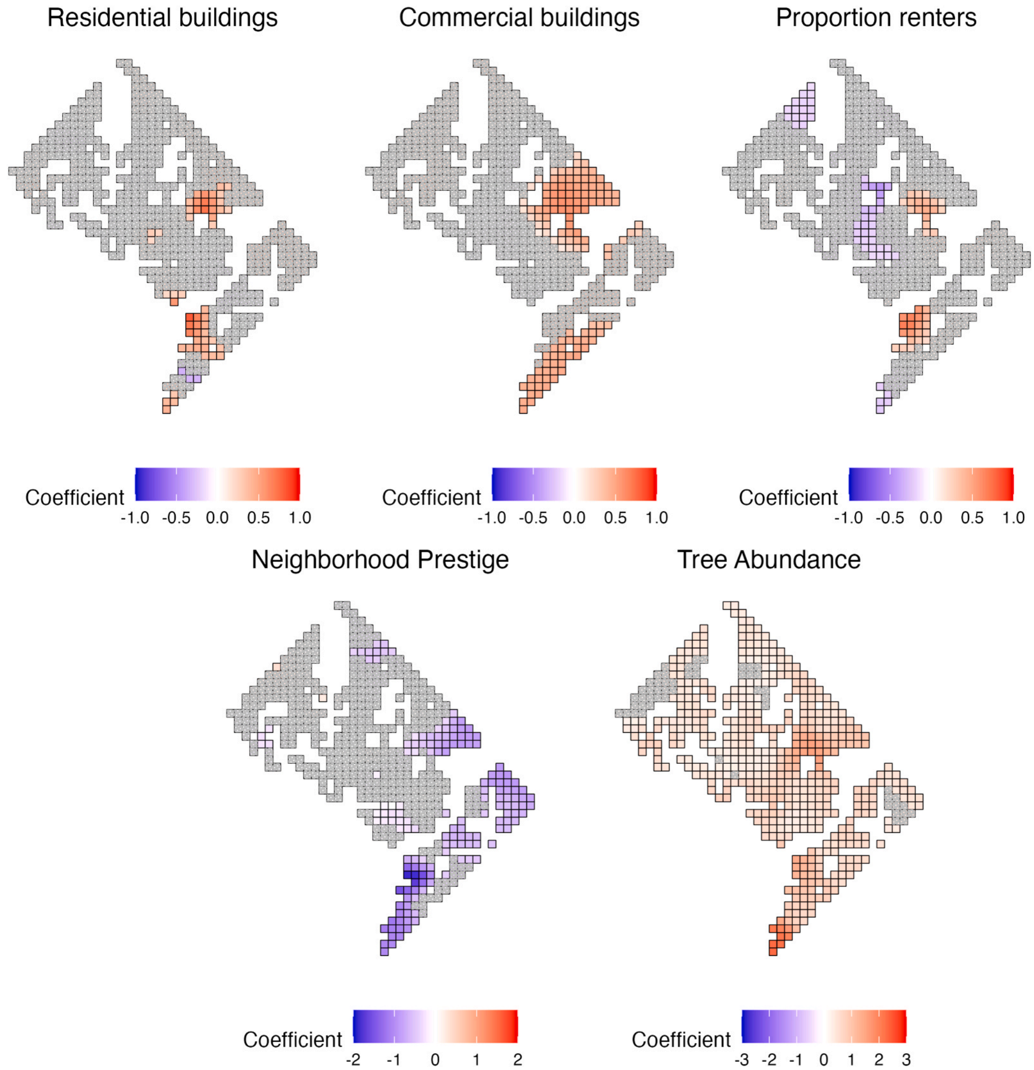

Fig. 6. Visualization of multi-scale geographically weighted regression (MGWR) results for new tree plantings across Washington, DC. Cool colors indicate a locally negative relationship between the independent variable and canopy cover, while warm colors indicate a locally positive relationship. The relationship was not locally statistically significant in cells with gray cross-hatching.

highlights the necessity of integrating spatially explicit models like MGWR into urban ecological studies to account for non-stationarity in environmental relationships. Our analysis found that not all variables associated with public street trees are spatially stationary and we provide spatially explicit insights for urban managers to guide geographically targeted management and tree plantings in Washington, D.C. As suggested by our analysis, this approach may have an unparalleled ability to identify inequities in urban tree coverage and identify geographic areas where targeted tree plantings may lead to healthier communities. Urban tree plantings have become an essential strategy for cities to address environmental and societal challenges. Given the spatially heterogeneous nature of urban areas, city planners should account for spatial nonconformity in their data analysis – as we did – to identify local tree inequities and guide justice-centered tree plantings initiatives.

Funding

JN was funded by the Summer Opportunities in Agricultural Research and the Environment (SOARE) and Strategic Work in Applied Geosciences (SWAG) program at the University of Maryland

CRediT authorship contribution statement

Zehidul Hussain: Writing – review & editing, Formal analysis, Data curation. **Travis Gallo:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Sharfaa Hussain:** Writing – review & editing, Writing – original draft, Conceptualization. **Gabriela Palomo:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **Daniel J. Herrera:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Adam Pekor:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **Colleen O'Donnell:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **Jessica Nadler:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Data curation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGTP and GitHub co-pilot to troubleshoot R code for analysis. After using this tool/

service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Declaration of Competing Interest

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

Acknowledgements

The authors would like to thank the facilities, operational, and administration staff at the University of Maryland as their work behind the scenes is vital to our research. We would also like to thank Mehak Sachdeva for consultation on MGWR models and two anonymous reviewers for thier valuable input that improved the manuscript

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ufug.2026.129349.

References

Anderson, E.C., Locke, D.H., Pickett, S.T.A., LaDeau, S.L., 2023. Just street trees? Street trees increase local biodiversity and biomass in higher income, denser neighborhoods. Ecosphere 14, e4389. https://doi.org/10.1002/ecs2.4389.
Anselin, L., 1995. Local Indicators of Spatial Association—LISA. Geogr. Anal. 27, 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x.
Armson, D., Stringer, P., Ennos, A.R., 2012. The effect of tree shade and grass on surface and globe temperatures in an urban area. Urban For. Urban Green. 11, 245–255. https://doi.org/10.1016/j.ufug.2012.05.002.
Bhullar, S., Majer, J., 2000. Arthropods on street trees: a food resource for wildlife. Pac. Conserv. Biol. 6, 171–173. https://doi.org/10.1071/PC000171.
Boumans, R.J.M., Phillips, D.L., Victery, W., Fontaine, T.D., 2014. Developing a model for effects of climate change on human health and health–environment interactions: heat stress in Austin, Texas. Urban Clim. 8, 78–99. https://doi.org/10.1016/j.uclim.2014.03.001.
Bowler, D.E., Buyung-Ali, L., Knight, T.M., Pullin, A.S., 2010. Urban greening to cool towns and cities: a systematic review of the empirical evidence. Landsc. Urban Plan. 97, 147–155. https://doi.org/10.1016/j.landurbplan.2010.05.006.
Buffam, I., Hagemann, F.A., Emilsson, T., Gamstetter, D., Pálsdóttir, A.M., Randrup, T.B., Yeshitela, K., Ode Sang, Å., 2022. Priorities and barriers for urban ecosystem service provision: a comparison of stakeholder perspectives from three cities. Front. Sustain. Cities 4. https://doi.org/10.3389/frsc.2022.838971.
Buscaino, M., Schichtel, A., 2024. The 17th Annual Tree Report Card: the state of DC's trees (Annual Report). Casey's Trees, Washington, DC.
Census Bureau, U.S., 2022b. Am. Community Surv. 5Year Estim. 20182022.
U.S. Census Bureau, 2022a. 2020 Decennial Census of Population and Housing.
Center for Disease Control, 2024. CDC PLACES.
Chesapeake Bay Program, 2023. Chesapeake Bay land use and land cover (LULC) database 2022 edition. https://doi.org/10.5066/P981GV1L.
City of Washington, DC, 2007. Neighborhood Labels.
R. Core Team, 2024. R: A language and environment for statistical computing.
Department of Energy and Environment, 2022. Heat Sensitivity-Exposure Index Methodology Report. Climate Ready DC. Department of Energy and Environment, Washington DC.
Department of Energy and the Environment, 2016. Climate Ready DC: The District of Columbia's Plan to Adapt to a Changing Climate. Washington, D.C., Washington, DC.
District of Columbia, 2024a. Urban Forestry Street Trees.
District of Columbia, 2024b. Open Data DC catalog.
Department of Energy and the Environment, 2015 District of Columbia Wildlife Action Plan | ddoe 2015 Washington, D.C.
Elsadek, M., Liu, B., Lian, Z., Xie, J., 2019. The influence of urban roadside trees and their physical environment on stress relief measures: a field experiment in Shanghai. Urban For. Urban Green. 42, 51–60. https://doi.org/10.1016/j.ufug.2019.05.007.
Fang, F., Greenlee, A.J., He, Y., Eutsler, E., 2023. Evaluating the quality of street trees in Washington, D.C.: implications for environmental justice. Urban For. Urban Green. 85, 127947. https://doi.org/10.1016/j.ufug.2023.127947.
Fotheringham, A.S., Brunsdon, C., Charlton, M., 2002. Geographically Weighted Regression: The Analysis of Spatially Varying Relationships. ohn Wiley & Sons, Inc, New Jersey, USA.
Gerrish, E., Watkins, S.L., 2018. The relationship between urban forests and income: a meta-analysis. Landsc. Urban Plan. 170, 293–308. https://doi.org/10.1016/j.landurbplan.2017.09.005.
Gillerot, L., Landuyt, D., De Frenne, P., Muys, B., Verheyen, K., 2024. Urban tree canopies drive human heat stress mitigation. Urban For. Urban Green. 92, 128192. https://doi.org/10.1016/j.ufug.2023.128192.
Gilstad-Hayden, K., Wallace, L.R., Carroll-Scott, A., Meyer, S.R., Barbo, S., Murphy-Dunning, C., Ickovics, J.R., 2015. Research note: Greater tree canopy cover is associated with lower rates of both violent and property crime in New Haven, CT. Landsc. Urban Plan. 143, 248–253. https://doi.org/10.1016/j.landurbplan.2015.08.005.
Gollini, I., Lu, B., Charlton, M., Brunsdon, C., Harris, P., 2015. GWmodel: an R package for exploring spatial heterogeneity using geographically weighted models. J. Stat. Softw. 63, 1–50. https://doi.org/10.18637/jss.v063.i17.
Goodchild, M.F., Anselin, L., Deichmann, U., 1993. A framework for the areal interpolation of socioeconomic data. Environ. Plan A 25, 383–397. https://doi.org/10.1068/a250383.
Grabowski, Z.J., McPhearson, T., Matsler, A.M., Groffman, P., Pickett, S.T., 2022. What is green infrastructure? A study of definitions in US city planning. Front. Ecol. Environ. 20, 152–160. https://doi.org/10.1002/fee.2445.
Grote, R., Samson, R., Alonso, R., Amorim, J.H., Cariñanos, P., Churkina, G., Fares, S., Thiec, D.L., Niinemets, Ü., Mikkelsen, T.N., Paoletti, E., Tiwary, A., Calfapietra, C., 2016. Functional traits of urban trees: air pollution mitigation potential. Front. Ecol. Environ. 14, 543–550. https://doi.org/10.1002/fee.1426.
Healy, M., Rogan, J., Roman, L.A., Nix, S., Martin, D.G., Geron, N., 2022. Historical urban tree canopy cover change in two post-industrial cities. Environ. Manag. 70, 16–34. https://doi.org/10.1007/s00267-022-01614-x.
Hijmans, R.J., Bivand, R., Cordano, E., Dyba, K., Pebesma, E., Sumner, M.D., 2024. Terra. Spat. Data Anal.
Jactel, H., Bauhus, J., Boberg, J., Bonal, D., Castagneyrol, B., Gardiner, B., Gonzalez-Olabarria, J.R., Koricheva, J., Meurisse, N., Brockerhoff, E.G., 2017. Tree diversity drives forest stand resistance to natural disturbances. Curr. For. Rep. 3, 223–243. https://doi.org/10.1007/s40725-017-0064-1.
Jain, G., Espey, J., 2022. Lessons from nine urban areas using data to drive local sustainable development. npj Urban Sustain. 2 (7). https://doi.org/10.1038/s42949-022-00050-4.
King, C.J., Buckley, B.O., Maheshwari, R., Griffith, D.M., 2022. Race, Place, And Structural Racism: A Review Of Health And History In Washington, D.C.: Article examines race, place and structural racism in Washington, D.C. Health Affairs 41, 273–280. https://doi.org/10.1377/hlthaff.2021.01805.
Kondo, M.C., Han, S., Donovan, G.H., MacDonald, J.M., 2017a. The association between urban trees and crime: evidence from the spread of the emerald ash borer in Cincinnati. Landsc. Urban Plan. 157, 193–199. https://doi.org/10.1016/j.landurbplan.2016.07.003.
Kondo, M.C., South, E.C., Branas, C.C., Richmond, T.S., Wiebe, D.J., 2017b. The association between urban tree cover and gun assault: a case-control and case-crossover study. Am. J. Epidemiol. 186, 289–296. https://doi.org/10.1093/aje/kwx096.
Kovats, R.S., Hajat, S., 2008. Heat stress and public health: a critical review. Annu. Rev. Public Health. https://doi.org/10.1146/annurev.publhealth.29.020907.090843.
Krischke, J., Beckmann-Wübbelt, A., Glaser, R., Dey, S., Saha, S., 2025. Relationship between urban tree diversity and human well-being: implications for urban planning. Sustain. Cities Soc. 124, 106294. https://doi.org/10.1016/j.scs.2025.106294.
Kuo, F.E., Sullivan, W.C., 2001. Environment and crime in the inner city: does vegetation reduce crime? Environ. Behav. 33, 343–367. https://doi.org/10.1177/0013916501333002.
Kweon, B.-S., Ellis, C.D., Lee, J., Jacobs, K., 2017. The link between school environments and student academic performance. Urban For. Urban Green. 23, 35–43. https://doi.org/10.1016/j.ufug.2017.02.002.
Landry, S.M., Chakraborty, J., 2009. Street trees and equity: evaluating the spatial distribution of an urban amenity. Environ. Plan. a 41, 2651–2670. https://doi.org/10.1068/a41236.
Lin, Y.-H., Tsai, C.-C., Sullivan, W.C., Chang, P.-J., Chang, C.-Y., 2014. Does awareness affect the restorative function and perception of street trees? Front. Psychol. 5. https://doi.org/10.3389/fpsyg.2014.00906.
Lin, J., Wang, Q., Li, X., 2021. Socioeconomic and spatial inequalities of street tree abundance, species diversity, and size structure in New York City. Landsc. Urban Plan. 206, 103992. https://doi.org/10.1016/j.landurbplan.2020.103992.
Logan, J.R., 2017. Racial segregation in postbellum Southern cities: the case of Washington, D.C. Demogr. Res. 36, 1759–1784. https://doi.org/10.4054/DemRes.2017.36.57.
Lovasi, G.S., Quinn, J.W., Neckerman, K.M., Perzanowski, M.S., Rundle, A., 2008. Children living in areas with more street trees have lower prevalence of asthma. J. Epidemiol. Commun. Health 62, 647. https://doi.org/10.1136/jech.2007.071894.
Lu, B., Harris, P., Charlton, M., Brunsdon, C., 2014. The GWmodel R package: further topics for exploring spatial heterogeneity using geographically weighted models. GeoSpat. Inf. Sci. 17, 85–101. https://doi.org/10.1080/10095020.2014.917453.
Luber, G., McGeehin, M., 2008. Climate change and extreme heat events. Am. J. Prev. Med. 35, 429–435. https://doi.org/10.1016/j.amepre.2008.08.021.
Magle, S.B., Fidino, M., Sander, H.A., Rohnke, A.T., Larson, K.L., Gallo, T., Kay, C.A.M., Lehrer, E.W., Murray, M.H., Adalsteinsson, S.A., Ahlers, A.A., Anthonysamy, W.J.B., Gramza, A.R., Green, A.M., Jordan, M.J., Lewis, J.S., Long, R.A., MacDougall, B., Pendergast, M.E., Remine, K., Simon, K.C., St. Clair, C.C., Shier, C.J., Stankowich, T., Stevenson, C.J., Zellmer, A.J., Schell, C.J., 2021. Wealth and urbanization shape medium and large terrestrial mammal communities. Glob. Change Biol. 27, 5446–5459. https://doi.org/10.1111/gcb.15800.
McDonald, R.I., Biswas, T., Chakraborty, T.C., Kroeger, T., Cook-Patton, S.C., Fargione, J. E., 2024. Current inequality and future potential of US urban tree cover for reducing heat-related health impacts. npj Urban Sustain 4, 1–16. https://doi.org/10.1038/s42949-024-00150-3.

Moody, R., Geron, N., Healy, M., Rogan, J., Martin, D., 2021. Modeling the spatial distribution of the current and future ecosystem services of urban tree planting in Chicopee and Fall River, Massachusetts. Urban For. Urban Green. 66, 127403. https://doi.org/10.1016/j.ufug.2021.127403.

Morgan, M., Ries, P.D., 2022. Planting free trees on private property: understanding urban residents' motivations and hesitations. Urban For. Urban Green. 71, 127557. https://doi.org/10.1016/j.ufug.2022.127557.

Moss, J.L., Doick, K.J., Smith, S., Shahrestani, M., 2019. Influence of evaporative cooling by urban forests on cooling demand in cities. Urban For. Urban Green. 37, 65–73. https://doi.org/10.1016/j.ufug.2018.07.023.

Narango, D.L., Tallamy, D.W., Marra, P.P., 2017. Native plants improve breeding and foraging habitat for an insectivorous bird. Biol. Conserv. 213, 42–50. https://doi.org/10.1016/j.biocon.2017.06.029.

Narango, D.L., Tallamy, D.W., Marra, P.P., 2018. Nonnative plants reduce population growth of an insectivorous bird. Proc. Natl. Acad. Sci. 115, 11549–11554. https://doi.org/10.1073/pnas.1809259115.

Narango, D.L., Tallamy, D.W., Shropshire, K.J., 2020. Few keystone plant genera support the majority of Lepidoptera species. Nat. Commun. 11, 5751. https://doi.org/10.1038/s41467-020-19565-4.

National Capital Planning Commission, 2010. CapitalSpace.

Nowak, D.J., Crane, D.E., Stevens, J.C., 2006. Air pollution removal by urban trees and shrubs in the United States. Urban For. Urban Green. 4, 115–123. https://doi.org/10.1016/j.ufug.2006.01.007.

Nowak, D.J., Hirabayashi, S., Bodine, A., Hoehn, R., 2013. Modeled PM2.5 removal by trees in ten U.S. cities and associated health effects. Environ. Pollut. 178, 395–402. https://doi.org/10.1016/j.envpol.2013.03.050.

O'Brien, R., 2023. Casey Trees Sets Tree Planting Record. Hill Rag.

Office of the Mayor of the District of Columbia, 2024. Mayor Bowser and the National Cherry Blossom Festival Announce Estimated 1.6 Million People Attended 2024 Festival, Exceeding 2019 Numbers [WWW Document]. URL ⟨https://dc.gov/release/mayor-bowser-and-national-cherry-blossom-festival-announce-estimated-16-million-people#:~:text=The%202024%20National%20Cherry%20Blossom,of%20stay%20being%203.9%20days⟩. (accessed 10.9.24).

Oksanen, J., Simpson, G.L., Blanchet, F.G., Kindt, R., Legendre, P., Minchin, P.R., O'Hara, R.B., Solymos, P., Stevens, M.H.H., Szoecs, E., Wagner, H., Barbour, M., Bedward, M., Bolker, B., Borcard, D., Carvalho, G., Chirico, M., De Caceres, M., Durand, S., Evangelista, H.B., FitzJohn, R., Friendly, M., Furneaux, B., Hannigan, G., Hill, M.O., Lahti, L., McGlinn, D., Ouellette, M.-H., Ribeiro Cunha, E., Smith, T., Stier, A., Ter Braak, C.J.F., Weedon, J., 2022. Vegan: Community ecology package.

Parker, D.E., 2010. Urban heat island effects on estimates of observed climate change. WIREs Clim. Change 1, 123–133. https://doi.org/10.1002/wcc.21.

Pebesma, E., 2018. Simple features for R: standardized support for spatial vector data. R. J. 10, 439–446. https://doi.org/10.32614/RJ-2018-009.

Perkins, H.A., Heynen, N., Wilson, J., 2004. Inequitable access to urban reforestation: the impact of urban political economy on housing tenure and urban forests. Cities 21, 291–299. https://doi.org/10.1016/j.cities.2004.04.002.

Petchey, O.L., Gaston, K.J., 2006. Functional diversity: back to basics and looking forward. Ecol. Lett. 9, 741–758. https://doi.org/10.1111/j.1461-0248.2006.00924.x.

Pham, T.-T.-H., Apparicio, P., Landry, S., Lewnard, J., 2017. Disentangling the effects of urban form and socio-demographic context on street tree cover: a multi-level analysis from Montréal. Landsc. Urban Plan. 157, 422–433. https://doi.org/10.1016/j.landurbplan.2016.09.001.

Piana, M.R., Hallett, R.A., Johnson, M.L., Sonti, N.F., Brandt, L.A., Aronson, M.F.J., Ashton, M., Blaustein, M., Bloniarz, D., Bowers, A.A., Carr, M.E., D'Amico, V., Dewald, L., Dionne, H., Doroski, D.A., Fahey, R.T., Forgione, H., Forrest, T., Hale, J., Hansen, E., Hayden, L., Hines, S., Hoch, J.M., Ieataka, T., Lerman, S.B., Murphy, C., Nagele, E., Nislow, K., Parker, D., Pregitzer, C.C., Rhodes, L., Schuler, J., Sherman, A., Trammell, T., Wienke, B.M., Witmer, T., Worthley, T., Yesilonis, I., 2021. Climate adaptive silviculture for the City: practitioners and researchers co-create a framework for studying urban oak-dominated mixed hardwood forests. Front. Ecol. Evol. 9. https://doi.org/10.3389/fevo.2021.750495.

Piel, G., Tallamy, D.W., Narango, D.L., 2021. Lepidoptera host records accurately predict tree use by foraging birds. Northeast. Nat. 28. https://doi.org/10.1656/045.028.0410.

Parker, J., Simpson, G.D., 2020. A case study balancing predetermined targets and real-world constraints to guide optimum urban tree canopy cover for Perth, Western Australia. Forests 11, 1128. https://doi.org/10.3390/f11111128.

Rajagopalan, P., Lim, K.C., Jamei, E., 2014. Urban heat island and wind flow characteristics of a tropical city. Sol. Energy 107, 159–170. https://doi.org/10.1016/j.solener.2014.05.042.

Raupp, M.J., Cumming, A.B., Raupp, E.C., 2006. Street tree diversity in eastern north america and its potential for tree loss to exotic borers. Arboric. Urban For. 32, 297–304. https://doi.org/10.48044/jauf.2006.038.

Robinson, C., Hou, L., Malkin, K., Soobitsky, R., Czawlytko, J., Dilkina, B., Jojic, N., 2019. Large scale high-resolution land cover mapping with multi-resolution Data, in: proceedings of. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR).

Roman, L.A., Catton, I.J., Greenfield, E.J., Pearsall, H., Eisenman, T.S., Henning, J.G., 2021. Linking urban tree cover change and local history in a post-industrial city. Land 10, 403. https://doi.org/10.3390/land10040403.

Ryu, Y.-H., Baik, J.-J., 2012. Quantitative Analysis of Factors Contributing to Urban Heat Island Intensity. https://doi.org/10.1175/JAMC-D-11-098.1.

Schroder, I., 2021. L'Enfant's Washington: the figure of the President in the capital of the Republic. Plan. Perspect. 36, 643–666. https://doi.org/10.1080/02665433.2020.1820897.

Schusler, T., Weiss, L., Treering, D., Balderama, E., 2018. Research note: examining the association between tree canopy, parks and crime in Chicago. Landsc. Urban Plan. 170, 309–313. https://doi.org/10.1016/j.landurbplan.2017.07.012.

Shackleton, C., 2016. Do indigenous street trees promote more biodiversity than alien ones? Evidence using mistletoes and birds in South Africa. Forests 7, 134. https://doi.org/10.3390/f7070134.

Smart, N., Eisenman, T.S., Karvonen, A., 2020. Street tree density and distribution: an international analysis of five capital cities. Front. Ecol. Evol. 8. https://doi.org/10.3389/fevo.2020.562646.

Southon, G.E., Jorgensen, A., Dunnett, N., Hoyle, H., Evans, K.L., 2018. Perceived species-richness in urban green spaces: cues, accuracy and well-being impacts. Landsc. Urban Plan. 172, 1–10. https://doi.org/10.1016/j.landurbplan.2017.12.002.

Steenberg, J.W.N., Robinson, P.J., Millward, A.A., 2018. The influence of building renovation and rental housing on urban trees. J. Environ. Plan. Manag. 61, 553–567. https://doi.org/10.1080/09640568.2017.1326883.

Tallamy, D.W., 2021. The Nature of Oaks: The Rich Ecology of Our Most Essential Native Trees. Workman Publishing Co. Inc and Blackstone Publishing, New York.

Tallamy, D.W., Shropshire, K.J., 2009. Ranking lepidopteran use of native versus introduced plants. Conserv. Biol. 23, 941–947. https://doi.org/10.1111/j.1523-1739.2009.01202.x.

Thomas, A.M., Coggeshall, M.V., O'Connor, P.A., Nelson, C.D., 2024. Climate adaptation in white oak (Quercus alba, L.): a forty-year study of growth and phenology. Forests 15, 520. https://doi.org/10.3390/f15030520.

Threlfall, C.G., Mata, L., Mackie, J.A., Hahs, A.K., Stork, N.E., Williams, N.S.G., Livesley, S.J., 2017. Increasing biodiversity in urban green spaces through simple vegetation interventions. J. Appl. Ecol. 54, 1874–1883. https://doi.org/10.1111/1365-2664.12876.

Townsend, J.B., Ilvento, T.W., Barton, S.S., 2016. Exploring the relationship between trees and human stress in the urban environment. Arboric. Urban For. 42, 146–159. https://doi.org/10.48044/jauf.2016.013.

Troy, A., Morgan Grove, J., O'Neil-Dunne, J., 2012. The relationship between tree canopy and crime rates across an urban–rural gradient in the greater Baltimore region. Landsc. Urban Plan. 106, 262–270. https://doi.org/10.1016/j.landurbplan.2012.03.010.

Urban Forest Division, D.D. of T., 2020. District of Columbia State Forest Action Plan: Assessment of Urban Forest Resources and Strategy. Washington, D.C., Washington DC.

Wang, Y., Guo, Z., Han, J., 2021. The relationship between urban heat island and air pollutants and them with influencing factors in the Yangtze River Delta, China. Ecol. Indic. 129, 107976. https://doi.org/10.1016/j.ecolind.2021.107976.

Watkins, S.L., Mincey, S.K., Vogt, J., Sweeney, S.P., 2017. Is planting equitable? An examination of the spatial distribution of nonprofit urban tree-planting programs by canopy cover, income, race, and ethnicity. Environ. Behav. 49, 452–482. https://doi.org/10.1177/0013916516636423.

Weinstein, N., Balmford, A., DeHaan, C.R., Gladwell, V., Bradbury, R.B., Amano, T., 2015. Seeing community for the trees: the links among contact with natural environments, community cohesion, and crime. BioScience 65, 1141–1153. https://doi.org/10.1093/biosci/biv151.

Witt, M.T., 2005. America's Palimpsest: ground-zero democracy and the capitol mall. Public Adm. Rev. 65, 517–533. https://doi.org/10.1111/j.1540-6210.2005.00479.x.

Wolf, K.L., Lam, S.T., McKeen, J.K., Richardson, G.R.A., van den Bosch, M., Bardekjian, A.C., 2020. Urban trees and human health: a scoping review. Int. J. Environ. Res. Public Health 17, 4371. https://doi.org/10.3390/ijerph17124371.

Wood, S.L.R., Dupras, J., 2021. Increasing functional diversity of the urban canopy for climate resilience: potential tradeoffs with ecosystem services? Urban For. Urban Green. 58, 126972. https://doi.org/10.1016/j.ufug.2020.126972.

Wood, E.M., Esaian, S., 2020. The importance of street trees to urban avifauna. Ecol. Appl. 30, e02149. https://doi.org/10.1002/eap.2149.

Wood, E.M., Pidgeon, A.M., Liu, F., Mladenoff, D.J., 2012. Birds see the trees inside the forest: the potential impacts of changes in forest composition on songbirds during spring migration. For. Ecol. Manag. 280, 176–186. https://doi.org/10.1016/j.foreco.2012.05.041.

Watkins, S.L., Gerrish, E., 2018. The relationship between urban forests and race: A meta-analysis. J. Environ. Manage. 209, 152–168. https://doi.org/10.1016/j.jenvman.2017.12.021.

Xiao, G., Wang, T., Luo, Y., Yang, D., 2023. Analysis of port pollutant emission characteristics in United States based on multiscale geographically weighted regression. Front. Mar. Sci. 10. https://doi.org/10.3389/fmars.2023.1131948.

Yang, L., Qian, F., Song, D.-X., Zheng, K.-J., 2016. Research on Urban Heat-Island Effect. Procedia Engineering, Fourth International Conference on Countermeasures to Urban Heat Island, 30-31 May and 1 June 2016 169, 11–18. https://doi.org/10.1016/j.proeng.2016.10.002.

Young, R.F., Lieberknecht, K., 2019. From smart cities to wise cities: ecological wisdom as a basis for sustainable urban development. J. Environ. Plan. Manag. 62, 1675–1692.

Ziter, C.D., Pedersen, E.J., Kucharik, C.J., Turner, M.G., 2019. Scale-dependent interactions between tree canopy cover and impervious surfaces reduce daytime urban heat during summer. Proc. Natl. Acad. Sci. 116, 7575–7580. https://doi.org/10.1073/pnas.1817561116.