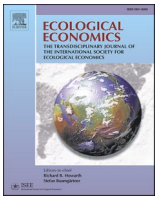
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Capitalization of urban tree cover: An internal meta-analysis

Shyamani D. Siriwardena [a], Kevin J. Boyle [b,*], Thomas P. Holmes [c]

[a] Postdoctoral Researcher, Blackwood Department of Real Estate, 2010 Pamplin Hall (0715), Virginia Tech, Blacksburg, VA 24061, USA
[b] Willis Blackwood Professor, Blackwood Department of Real Estate, 2010 Pamplin Hall (0715), Blacksburg, VA 24061, USA
[c] Emeritus Scientist, USDA Forest Services, Southern Research Station, Research Triangle Park, NC, USA

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ABSTRACT

Hedonic studies of residential tree cover vary spatially due to differences in data and estimation methods, which make it difficult to generalize whether there are differences in preferences, local environmental conditions or differences in data and estimation approaches. We conduct hedonic analyses of tree cover in multiple U.S. cities using consistent spatial data and estimation methods and summarize results via an internal meta-analysis. Study results provide robust evidence for spatially varying preferences for tree cover in urban areas. The results indicate that homeowners place more value on tree cover that is located on properties more than 0.1 km from their homes than tree cover on or near their own properties, within 0.1 km. This poses important community challenges in the public provision of tree cover, which can result in under investment in tree cover at the individual property level. This preference dichotomy can influence community support regarding tree removal and planting policies. The results suggest that areas with more rainfall and higher temperatures are less likely to have positive tree-cover capitalization in property prices. This is an important consideration as climate change brings higher temperatures and more severe storms that pose greater risks of forest fires and falling limbs/trees that can affect residential properties.

1. Introduction

The interest in urban trees as an important asset in healthy and safe communities is a global concern. The United Nations General Assembly declared 2011 the *International Year of Forests* "to bolster efforts that will promote sustainable management, conservation and development of forests worldwide" (United Nations, 2006). Trees in the urban landscape provide a wide range of private and public benefits, such as enhancing stormwater absorption, reducing heat-island effects and mitigating air pollution, which reach beyond enhancing the natural esthetics of communities and protecting natural habitats (e.g., Pataki et al., 2021). Donovan et al. (2022) found that tree planting yields significant public benefits in terms of reducing nonaccidental mortality, including cardiovascular disease, and that this reduction increases as trees age. These benefits, particularly environmental amenities, are capitalized into residential property values and these values, along with the broad public-good benefits can help to justify tree planting and maintenance programs (Plant et al., 2017). Yet tree cover is threatened by increasing urban density along with a changing climate (Burley et al., 2019; Daniel et al., 2016).

A broad view of the academic literature indicates that the interest and concern for community and urban trees is evolving with examples of empirical studies in Norway, Denmark, the Netherlands, Cechia, Portugal, Nigeria, South Africa, New Zealand, Australia, United States and Canada (Alabi and Christian, 2013; Guo et al., 2019; Kovacs et al., 2022; Lautrup et al., 2023; Luttik, 2000; Melichar et al., 2009; Mouratidis, 2019; Pandit et al., 2014; Shackleton et al., 2015; Soares et al., 2011; Thériault et al., 2002). These studies represent the complex interactions between people and urban trees. The studies document how tree cover can reduce urban heat islands temperatures (Alabi and Christian, 2013). And, while tree cover provides a variety of ecosystem services, esthetics is an important driver in the appreciation of tree cover (Guo et al., 2019; Luttik, 2000). There are also mixed results such as increasing tree cover providing an enhanced perception of safety (Mouratidis, 2019) versus a perceived association with crime (Shackleton et al., 2015). While numerous studies have found that tree cover increases property values, Pandit et al. (2014) found that tree cover on or near a property decreases property values, which could be due to the cost of tree maintenance and the risks from falling limbs. Overall, Soares et al. (2011) found that "(f)or every $1 invested in tree

* Corresponding author.
E-mail addresses: shyadil@vt.edu (S.D. Siriwardena), kjboyle@vt.edu (K.J. Boyle), tholmes@fs.fed.us (T.P. Holmes).

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management, residents receive $4.48 in benefits" (p. 69), which is a strong benefit-cost ratio. While this outcome may be true, urban tree cover often occurs on private land and community leaders require incentives to entice property owners to retain and plant trees from the perspective of the public good.

Hedonic studies that show the impacts on property values of urban trees can help local leaders design effective plans for tree retention and planting programs. Previous hedonic property-value studies have shown that a variety of factors, such as tree abundance, canopy cover, landscape composition, risk of forest fire, tree diseases and pest infestations influence property owners' preference for trees in residential areas. For example, homeowners who live in urban areas that are in hotter climates may prefer more tree cover on their properties than those who live in cooler climates or rural areas (Schroeder et al., 2006; Cho et al., 2008). Those who live near forested areas may prefer houses with less trees if the areas are prone to forest fire or invasive species attacks (Holmes et al., 2010; Stetler et al., 2010).

Specifically, the capitalized value of tree cover (the ground surface area covered by tree canopy) varies with distance from properties. For example, trees on properties provide private benefits through shade and privacy but are also associated with risks and costs due to falling limbs. Tree cover within proximity to homes provides public benefits through the provision of landscape amenities. Thus, homeowner valuations of tree canopy cover vary across the landscape (Cho et al., 2011; Price et al., 2010; Sadler et al., 2010; Sander and Haight, 2012; Sander and Zhao, 2015). Kovacs et al. (2022) found that people value off property tree cover more than they value cover on their properties. Siriwardena et al. (2016), while not differentiating between off- and on-property cover, found that 30 % cover near a property maximizes the capitalization in property values while the comparable figure was 38 % at the county level.

The literature suggests there is spatial heterogeneity in the capitalized value of tree canopy cover, and it is logical to ask what can be learned collectively from a variety of hedonic studies conducted at diverse spatial locations. However, such an assessment is challenging as *different measures of trees* have been utilized. For example, some investigators have relied on tree cover measured in terms of percent/proportion of tree cover on property or number of trees on property (Anderson and Cordell, 1988; Dombrow et al., 2000; Morales et al., 1976; Morales, 1980; Mansfield et al., 2005; Holmes et al., 2006; Donovan and Butry, 2010; Netusil et al., 2010; Holmes et al., 2010; Irwin, 2002; Price et al., 2010; Stetler et al., 2010; Sander et al., 2010). Others considered proximity of forests to residential properties (Mansfield et al., 2005; Thorsnes, 2002) or how views of forested areas affected property values (Tyrvainen and Miettinen, 2000). These different measurements provide challenges for obtaining a common unit of measurement for the dependent variable in a meta-analysis because each study's measurement might reflect different components of the value that homeowners place on tree cover.

Kovacs et al. (2022) and Siriwardena et al. (2016) conducted meta-analyses of hedonic studies that included a measure of tree cover as one of the explanatory variables. While insightful, such a meta-analysis faces important challenges as the tree cover variables were measured at various levels of resolution. For example, tree-cover has been measured at resolutions as small as 0.9 m (Drake-McLaughlin and Netusil, 2011) up to 1-acre (Netusil et al., 2010). Further, different approaches have been used to estimate hedonic equations. Studies have specified different functional forms, e.g., linear, log-linear, log-log, and Box-cox specifications. In addition, different approaches to considering spatial heterogeneity have been employed, e.g., spatial lag models, spatial error models (Holmes et al., 2010) and locally weighted regressions (Sander and Zhao, 2015; Cho et al., 2008; Cho et al., 2011; Li and Saphores, 2012). These investigator estimation choices can affect estimates of the capitalized value of tree cover.

External meta-analyses, such as conducted by Kovacs et al. (2022) and Siriwardena et al. (2016), rely on estimation results from diverse studies by adjusting the capitalized value estimates or using regressors to control for differences across studies. An example is the recalculation of reported capitalized values to a common percentage change in tree cover as the dependent variable. Different resolutions in the measurement of tree cover, however, may not be amenable to adjustments in capitalized values nor fully controlled by adding regressors to the hedonic equation that identify different units of measure.

Thus, an alternative is an internal meta-analysis where a common measure of the dependent variable and the key explanatory variables are applied and the estimated capitalized values come from a common estimation process (Banzhaf and Smith, 2007; Klemick et al., 2016; Kuminoff et al., 2010a). An internal meta-analysis relies on multiple studies conducted by the same investigator, or multiple investigators working in collaboration, using common sources of data and estimation approaches, which reduces data and investigator confounds in the estimation of the meta-equation and interpretation of the meta-equation coefficient estimates. Such an "internal" meta-analysis removes the heterogeneity that arises from differences in data availability, variable measurement, and investigator estimation choices across studies.[1]

The current study is an internal meta-analysis of the capitalized value of tree cover that exploits spatially explicit data on tree cover (1 m resolution) to obtain common measures of tree cover as a regressor in the hedonic models, which leads to consistent estimates of capitalized values across the underlying hedonic equations at multiple locations across the United States. In addition, consistent estimation procedures are used to estimate each of the underlying hedonic equations. In this manner, the meta-estimation can focus on spatial differences in the capitalized value of tree cover.

Three measures of tree cover are considered, 0–0.1 km, 0.1–0.5 km, and 0.5–1 km around each property. Tree cover has been evaluated at various threshold distances from homes and the findings are mixed across studies. For example, Cho et al. (2011) found that the capitalized value of tree cover is positive but has diminishing effects up to 1.6 miles from the property. Netusil (2005) concluded that on-property trees reduce sale prices while trees within ¼ mile increase property values. Holmes et al. (2010) found that tree cover on property and within 100 m does not affect property values, but trees within 100 m to 500 m of a property increase values. Such diversity of tree-cover hedonic outcomes is also supported in other studies (Price et al., 2010; Sadler et al., 2010; Sander and Haight, 2012; Sander and Zhao, 2015).

The three buffers help to resolve this diversity of outcomes across differing hedonic studies and provide additional insight. The smallest buffer includes trees on each property and trees on or near properties.[2] The largest buffer considers tree cover in the broad area around properties and likely captures the public-good aspects of tree cover whether located on private or public land. Sander et al. (2010) explored tree cover for buffers of 0.1, 0.25, 0.5, 0.75 and 1.0 km and found significant capitalization in only the 0.1 and 0.25 km buffers. Our three buffers follow the smallest, midpoint, and largest buffers from the Sander study.

Study results provide robust evidence for spatially varying preferences of homeowners for the tree cover in urban residential areas. The results can be used to educate homeowners and communities about the personal financial benefits of tree cover. However, homeowners value

[1] Some investigators have warned of the falsifiability of internal meta-analyses. The analysis reported here satisfies conditions proposed by Vosgerau et al. (2019): all conducted studies were included, there is one estimate for each study design point, and decisions on the exclusion of study locations were made before any of the original analyses were conducted.

[2] The sales data identified property locations by longitude/latitude and street address and did not provide property boundary pixels. Secondary data, such as from property tax assessment records that have been available for specific city case studies in the literature, were not consistent and always available across study areas. Therefore, we were not able to have property-specific tree cover and the smallest buffer, with a radius of 0.1 km, is based on buffers used for previous studies in the literature and this buffer likely includes tree cover on neighboring properties.

tree cover that is not on their properties more than on or near their own properties, which presents tension between the private and public benefits of tree cover that may result in less tree cover than socially and environmentally optimal. This provides insight for planners and foresters on how they can approach community planning and action programs to gain support for maintaining and enhancing urban tree cover.

2. Conceptual model

For a given housing market, the hedonic model is specified as the sale prices of residential properties (*sp*) as a function of structural characteristics of house (*SC*) (e.g., size of living area), property characteristics (*PC*) (e.g., lot size), location characteristics (*LC*) (e.g., proximity to different types of land cover), and environmental characteristics (*EC*) (e.g., tree cover), and a random error (*e*):

$$ln(sp_{is}) = f(SC_{is}, PC_{is}, LC_{is}, EC_{is} : \beta) + e_{is} \quad (1)$$

where β is a vector of coefficients to be estimated, *i* denotes observations and *s* denotes study locations. A log linear relationship is applied as the existing hedonic literature indicates that the marginal values of property characteristics are not linear.

We then consider the capitalized value, or implicit value, for a 1 % increase in tree cover (*TC*) which is computed as:

$$MV_{isb}^{+1\%} = \widehat{PV}_{isb}^{+1\%} - \widehat{PV}_{isb}^{cTC} \quad (2)$$

where $\widehat{PV}$ ia the estimated property value for a 1 % increase in tree cover ($+1\%$) and the current tree cover (*cTC*). Property-level (*i*) estimates of the marginal value of a 1 % increase in tree cover, $MV_{isb}^{+1\%}$, for each buffer (*b*) within each housing market (*s*) are recovered for comparisons of outcome across buffers and markets and as the dependent variable for the internal meta-analysis. The meta-equation is then specified as a function of the tree-cover (TC_{is}) that varies by property and housing market, and can be written as:

$$MV_{isb}^{+1\%} = f(TC_{isb}, C_{is}, N_s, : \gamma) + \varepsilon_{isb} \quad (3)$$

where C_s is a vector of climate variables, N_s is a vector of study-area fixed effects, γ is a vector of coefficients to be estimated, and ε is an error term.

3. Internal meta-analysis

As noted above, estimating similar hedonic models to investigate spatial variability in the capitalization of tree cover removes variability across studies that can potentially confound the outcome of an external meta-analysis. In this study, similar data and methods are applied across study locations to estimate hedonics. The commonalities are as follows:

- Tree cover is computed as the *percentage* of ground surface area covered by the tree canopy.
- Tree cover is recorded at three buffer distances, 0–0.1 km, 0.1–0.5 km, and 0.5–1 km, around each property.
- Property sale and characteristics, land cover types, and climate data were obtained from the same sources at the same resolution.
- The semi-log functional form was used to estimate all hedonics, and a common set of property characteristics and spatial fixed effects were used as regressors.

Noteworthy, the semi-log specification allows for variation in changes in the capitalization of tree cover across properties within study areas as well as across study areas. A linear specification would yield a constant value of tree cover across properties in each study area with a one-unit increase in tree cover resulting in the same increment of value for properties with different base levels of tree cover.

4. Data

The hedonic models were estimated for nine cities across the U.S. (Durham, NC; Phoenix, AZ; Fresno, CA; Portland, OR; Pittsburgh, PA; New Bedford, MA; Milwaukee, WI; Patterson, NJ; Tampa, FL) (Fig. 1).[1, 2, 3, 4, 5, 6 and 7] These communities were selected due to the availability of high resolution GIS data (1 m) on land cover types, including tree cover, from the U.S. Environmental Protection Agency's (2025) EnviroAtlas data base. The EnviroAtlas polygons may extend beyond the geopolitical boundaries of the named cities. We retain the community names to designate these areas that are focused in and around these communities.

The study areas are geographically spread across the U.S. and represent differences in market areas and environmental conditions, as well as tree cover and types of trees. Each city boundary was defined based on GIS community boundary layers in the EnviroAtlas data, which is based on the U.S. Census Bureau's (2025) (http://www.census.gov/2010census/) definition of urban statistical areas. In addition, some cities overlap with the study locations of existing hedonic studies (see Siriwardena et al., 2016).

4.1. Property sale data

Single-family property-sale data were obtained from multiple-listings sales for the period from 2005 through 2014. The data includes sale prices, size of living area, lot size, number of bathrooms and bedrooms, year built, as well as sale dates and property locations (address and latitude/longitude) (Table 1). The data were cleaned for incorrect spatial location of properties, duplicates, missing values, and incongruous data.[5] The final data set includes 757,858 property sales. The average sale prices range from $151,959 to $293,394 (2010 dollars).[6] Residential properties in Portland sold at the highest price followed by those in Patterson and New Bedford. Durham has larger houses on larger lots sold at higher prices. In densely populated cities such as Patterson, Fresno, Portland and Phoenix, larger houses on small lots sold at higher prices.

4.2. Tree cover and other land cover data

The high resolution (1 m) EnviroAtlas data of land cover types obtained for each city includes ten land cover types; trees and forests, impervious surface, water bodies, agricultural lands, grass and herbaceous lands, soil and barren lands, shrub land, orchards, woody wetlands, and emergent wetlands. The "trees and forests" category was used to derive the measures of tree cover within each of the three buffers around a property. The geolocation of each property along with the respective buffers was overlaid with the land-cover data to compute

[3] Data were available for three other cities that were dropped from the analysis. These study areas were excluded due to a small sample of sales (92 observations in Woodbine, IA), lack of data on property characteristics (Green Bay, WI), and under-representation of the housing market (observations from Portland, ME were restricted to a sub-area of the city).

[4] Properties within each city were only included when their largest buffers did not extend beyond the city boundary; thereby, avoiding a boundary effect that could artificially reduce the percentage of tree cover.

[5] Point location of each property was identified via latitude and longitude information and located within the respective study area boundary. All single-parcel transactions, including repeated sales, were included in the data while multiple-parcel transactions, REO sales (repossessed properties) and foreclosures were excluded. Further trimming was done using the upper and lower 5 % of price per square foot of living area. For several cities, information on number of bathrooms and number of bedrooms was not available. Therefore, these two variables were not considered in the final models to retain consistency of the model specification across study locations.

[6] Converted to 2010 dollars using the seasonally adjusted quarterly House Price Index from the Federal Housing Finance Agency (nd).

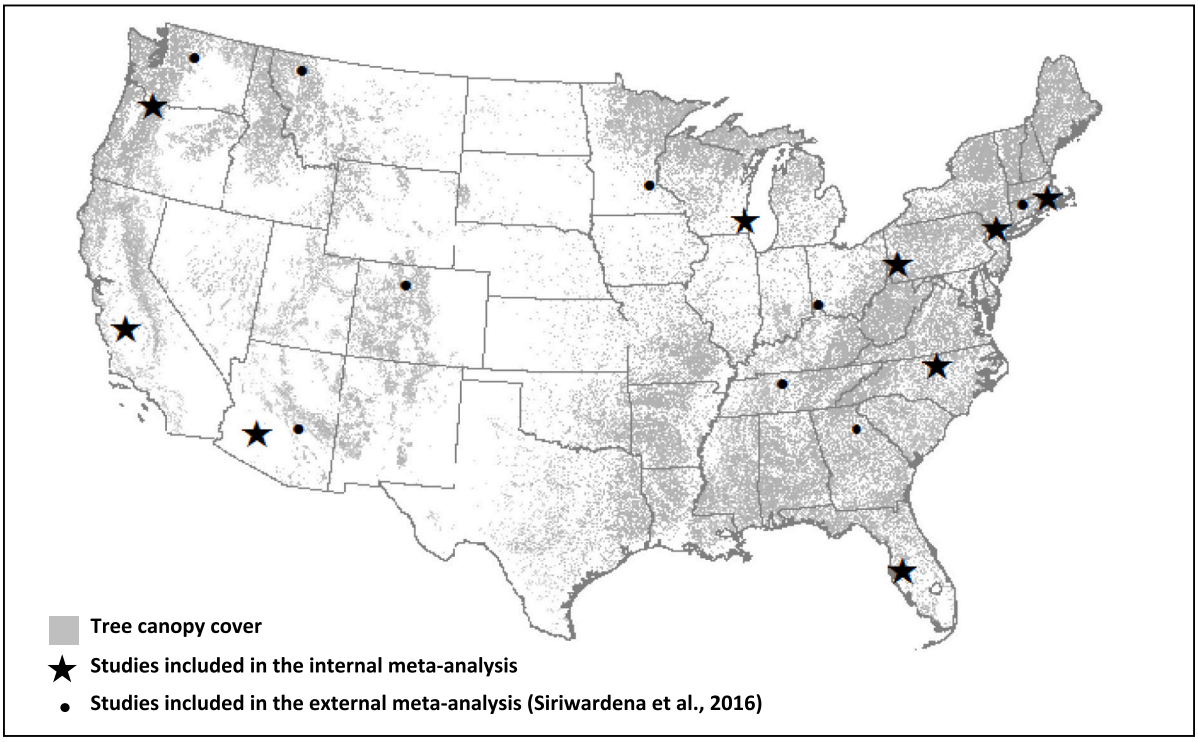


Fig. 1. Geographical Distribution of Hedonic Study Locations.

Table 1
Property characteristics.

Property Characteristics[a]		Cities (Study Areas)								
		Durham	Fresno[b]	Milwaukee	New Bedford	Patterson[b]	Phoenix	Pittsburgh	Portland	Tampa
		(NC)	(CA)	(WI)	(MA)	(NJ)	(AZ)	(PA)	(OR)	(FL)
sp (2010 $s)	mean	237,691	207,263	168,692	241,387	257,533	203,357	151,959	293,394	164,980
	min	27,847	25,187	19,530	42,697	37,065	20,050	18,570	41,752	11,912
	max	1,698,562	2,355,814	1,449,786	1,862,814	772,607	3,743,675	1,915,400	2,617,822	3,200,000
living_sqft	mean	2090	1901	1501	1548	2026	2056	1678	1921	1869
	min	540	504	512	538	528	500	500	500	500
	max	10,340	10,102	11,009	9038	6116	14,042	12,824	11,269	11,382
lot_acres	mean	0.35	0.22	0.26	0.34	0.09	0.22	0.31	0.19	0.25
	min	0.02	0.01	0.02	0.02	0.01	0.02	0.01	0.02	0.02
	max	20.04	19.66	14	18.68	0.8	13.49	19.01	18.73	18.99
age[b]	mean	21	.	54	60	.	16.72	59	38	24
	min	0	.	0	0	.	0	0	0	1
	max	258	.	177	289	.	122	214	155	125
n		30,592	50,659	40,466	6343	5396	250,726	75,894	152,362	145,420
blocks		185	403	1060	930	128	2260	1099	1148	106

[a] Variable definition: *sp* = sale price of property (converted to $2010 dollars using the seasonally adjusted quarterly HPI index from the Federal Housing Finance agency), *living_sqft* = square feet of living area, *lot_acres* = lot size (acres), *age* = age of residence (years), and *blocks* = number of census blocks in each city.
[b] Age of structures was not available.

percentages of areas covered by each land cover. Researchers have modeled the impact of environmental factors like tree cover on property values using adjacency, distance, and buffers (Mazzotta et al., 2014). Adjacency and distance are appropriate for considering the value of a natural area or forest where adjacency to or distance from the areas would be reasonable regressors in the hedonic model. However, it is necessary to define buffers around a property to compute tree-cover that is property specific, which is confirmed by the tree-cover hedonic studies that form the basis for the Siriwardena et al. (2016) and Kovacs et al. (2022) meta-analyses. There is no guidance on the appropriate choice of buffer size and the best available information is the buffer sizes used in previous research. The selected buffers represent tree cover on or adjacent to properties (0.0–0.1 km), in proximity, common walking distance, around a property, (0.1–0.5 km) and the general area around properties where people drive to work, shop, and participate in other activities (0.5–1.0 km).[4, 5 and 6] Kaplan (2001) notes "that having natural elements or settings in the view from the window contributes substantially to residents' satisfaction with their neighborhood" (p.507). This suggests that people consider more than what is on their own property and tree cover would be one of the natural elements of the

neighborhood.[7] The centroid of the buffers was the longitude and latitude assigned to each property.[8]

Tree cover varies across communities and across buffers within communities (Table 2). For example, eastern cities (e.g., Durham and Pittsburgh) are highly forested, with percentage tree cover exceeding 40 %. Tree cover also varies across the three buffers within these two cities; tree cover is the lowest in the immediate vicinity of properties (within 0.1 km) and increases with the distance from the property (the larger two buffers). In contrast, in Fresno and Phoenix where the overall tree cover is less abundant, more trees are maintained in the immediate vicinity of the properties. These differences may arise due to important regional differences. In the east, homeowners may have sufficient shade and want to limit tree cover to reduce having to clean up tree litter and risk of property damages from falling trees and limbs. In the west, with less tree cover and higher temperatures, trees near a property can provide important shade for cooling. This variation in the distribution of tree cover within and across the cities allows the meta-analysis to capture the differential effect of trees on property values.

When considering differences in tree cover across cities, it is important to recognize that local regulations relating to the management of trees vary by community. For example, in Portland, Oregon a permit is required to remove street trees and private trees, and the conditions for street tree removal are stricter than for the removal of private trees (Portland.gov, nd). The city also has approved lists of trees for replanting. In contrast, the city of Milwaukee, Wisconsin has a simpler statement that "Forest Services maintains and services trees and plants that are located in the public right-of-way" (City of Milwaukee, 2025). Tree removal regulations may also vary by state (Friends of Urban Forests, 2025). Thus, differences in tree cover can be driven by climate, individual landowner actions and collective community preferences as reflected in public policies and regulations. It is not possible to control these differences across communities and states in the meta-analysis, but these differences should be kept in mind when interpreting the estimation results. Observed heterogeneity in coefficient estimates can be driven by local conditions informed by collective preferences for tree cover and individual homeowner preferences for tree cover.

4.3. Climate data

Climate data on precipitation and temperature were used in the internal-meta-analysis to identify how these variables influence the value households attach to tree cover. Annual precipitation and maximum summer temperature data were obtained for each city from the National Oceanic and Atmospheric Administration (2025) (Table 2). For Patterson and New Bedford, no city level data were available, therefore county level climate data were obtained for these locations.

5. Empirical models

5.1. Hedonic-price function

The dependent variable is the natural log of sale price in 2010 dollars ($\ln(sp)$), and specified as a function of structural characteristics, tree cover and other property characteristics for each property (i) in each study area (s):

$$\begin{aligned} ln(sp_{is}) = \beta_{0s} + \sum_{h=1}^{3}\left(\beta_{1sh}CH_{ih} + \beta_{2sh}CH_{ih}^{2}\right) + \sum_{b=1}^{3}\left(\beta_{3sb}treecover_{isb}\right. \\ \left. + \beta_{4sb}treecover_{isb}^{2}\right) + \sum_{k=1}^{8}\sum_{b=1}^{3}\left(\beta_{5sbk}ENV_{isbk} + \beta_{6sb}ENV_{isb}^{2}\right) \\ + \rho_{s}block_{is} + \sigma_{s}saleyear_{is} + \epsilon_{is} \end{aligned} \quad (4)$$

where CH are property characteristics (h), b denotes each of the three spatial buffers around properties, ENV is land-cover variables (k) (excluding *treecover*) and ϵ is a random error term. The fixed effects are *block*, which is a vector of census block group identifiers for property locations, and *saleyear* that identifies the year each property sold.

Structural characteristics include the size of living area, lot size and the age of the residential structure. Each of these attributes is expected to have positive but diminishing effects on the sale value of properties (Netusil, 2005; Saphores and Li, 2012; Price et al., 2010). Property prices and tree cover have been found to have a non-linear relationship (Netusil et al., 2010; Stetler et al., 2010; Sander et al., 2010; Sander and Haight, 2012). A similar relationship was investigated for the other land cover variables. Bishop et al. (2020) state in their peer-reviewed "Best Practices" for hedonic models that "the price function should be assumed to be nonlinear" (p. 269).[9] Therefore, squared arguments for these variables are included in the model.

Proximity to the city centers, roads, retail settings, and water bodies may raise property values, while agricultural fields and wetlands may reduce the property values (Cho et al., 2011). To capture these effects, land-cover variables beyond *treecover* are included, e.g., impervious surface, water, grasslands, wetlands, etc. Like the *treecover* variables, these variables are measured in percentages and nonlinear effects are allowed within the three buffer areas.

Omitted variables, such as "neighborhood amenities," may be correlated with the tree cover and, if correlated, could result in biased coefficient estimates. Here we use spatial fixed effects[10] at the census block level to control unobserved heterogeneity in the data. If the

[7] Kovacs et al. (2022) distinguish between on-property and off-property tree cover in their meta-analysis. On-property tree cover requires careful consideration because the tree cover can arise from trees located on the property and from trees on abutting properties. Identifying on-property trees at a large spatial scale is challenging because it may require site visits. Further, while a property owner may benefit from the shade and other amenities provided by neighbor's trees they also share in the maintenance and risks associated with the trees, e.g., leaves and limbs falling in their yards. These benefits and costs are reciprocal for all neighbors, and none have control of the trees on their neighbors' land. Due to these considerations, we model the smallest buffer at 0.1 km to account for trees within the proximity of homes, which is about 330 ft from the centroid of the smallest buffer. This aligns with Kaplan's results regarding environmental amenities that can be observed from the window of a home.

[8] Calculating zonal statistics of GIS data to create these variables is computer-processing intensive, so we restricted the largest buffer to 1 km. The choice of this threshold was also determined by availability of EnviroAtlas GIS data to calculate land cover type variables for each property. When land cover data were not available for a property within a buffer we excluded that property from the analysis. In addition, when a property's' largest buffer extended beyond the city limits it was excluded from the analysis to avoid edge effects. More than 90 % of property locations had adequate land-cover within 1 km of properties.

[9] Bishop et al. (2022) also explain that nonlinearity "is consistent with Ekeland, Heckman, and Nesheim (2004), who prove that transactions between heterogeneous buyers and sellers yield an equilibrium price function that is 'generically' nonlinear. In addition, Cropper, Deck, and McConnell (1988) show that flexible nonlinear specifications for the price function provide more accurate estimates of average MWTP for housing characteristics than simpler linear and log-linear specifications when omitted-variable bias is not a concern. Moreover, Kuminoff, Parmeter, and Pope (2010) find that flexible nonlinear models continue to outperform linear models even when spatial dummy variables are used to reduce omitted-variable bias" (p. 269).

[10] Spatial fixed effects have been widely used in hedonic property models applied to value open space amenities. These include census tracts/blocks (Kuminoff et al., 2010b; Tuttle and Heintzelman, 2015; Pope, 2008), School districts (McMillen, 2010), Subdivisions (Abbott and Kaliber, 2011), city/county/municipality (Kovacs et al., 2011), submarkets (Sander et al., 2010), and tax districts (Pope, 2008). When the spatial fixed effects areas are large (e.g., tax district dummies) the marginal price is overstated and when the fixed effect areas are smaller (e.g., census tracts or blocks) the estimates begin to converge towards the quasi-random experiment estimates (Pope, 2008).

Table 2
Tree Cover and Climate Variables.

Variables[a]		Cities (Study Areas)								
		Durham (NC)	Fresno (CA)	Milwaukee (WI)	New Bedford (MA)	Patterson (NJ)	Pittsburgh (PA)	Phoenix (AZ)	Portland (OR)	Tampa (FL)
					0.0–0.1 km Buffer					
	mean	50	12	41	26	29	39	10	38	15
	min	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.9
	max	100	83	100	100	94	100	56	100	70
					0.1–0.5 km Buffer					
treecover	mean	58	12	47	28	30	39	9	34	16
	min	17	0.0	3.7	1.7	1.4	0.6	0.0	4.9	5.7
	max	98	42	96	98	83	88	34	84	55
					0.5–1.0 km Buffer					
	mean	60	11	49	28	29	40	8	32	18
	min	23	0.2	8.2	0.0	2.6	1.0	0.0	7.2	81
	max	92	9	94	98	75	79	27	74	44
precip	mean	44.5	9.8	34.7	52.8	51.0	38.6	6.5	37.0	48.7
temp	mean	89.7	96.6	80.8	80.6	82.3	81.6	105.2	78.9	91.0

[a] Variable definition: *treecover* = percent tree canopy cover within the defined buffers surrounding properties, *precip* = annual precipitation in the city/county (inches), *temp* = maximum summer temperature in the city/county (°F).

unobservable variables are constant across observations within a census block and only vary across census blocks, the fixed effects will control for the effects of the missing variables (Palmquist, 2006; Kuminoff et al., 2010b; McMillen, 2010; Abbott and Kaliber, 2011). In addition, sale year fixed effects (base case is 2005) capture inter-annual variation not reflected by the included regressors.

All the variables included in the hedonic and their descriptions are given in Table 3.

5.2. Internal meta-equation

The dependent variable in the meta-equation is the estimated marginal value of a 1 % change in tree cover that varies by property, study area and buffer. These pooled data were used to estimate the meta-equation, specified as:

$$MV_{isb}^{+1\%} = \gamma_0 + \gamma_1 B0.5_{is} + \gamma_2 B1.0_{is} + \theta C_{is} + \delta N_s + \omega_{isb}. \quad (5)$$

Binary variables are included to represent the tree-cover buffers where *B0.5* and *B1.0* represent tree cover within 0.1–0.5 km and 0.5–1.0 km of properties, respectively, and the 0–0.1 km buffer is the omitted category. *C* is a vector of climate variables, *N* is a vector of study area indicator variables and ω is a random error. Each property has three observations in the meta-data, one for each of the tree cover buffers.

Variation in hedonic study outcomes suggests that homeowners' preference for tree cover varies across study locations depending on the location-specific factors. As noted in the Introduction, homeowners who live in hotter climates may hold higher marginal values for tree cover than those who live in cooler climates or those who live near forested areas may prefer properties with less tree cover if the areas are prone to forest fires or forest pests and diseases. Therefore, location specific characteristics including study locations and climate are considered in the estimated meta-equation. Fixed effects are included for study areas (Durham is the omitted area).[11] Two climate variables, annual precipitation (*precip*) and maximum summer temperature (*temp*), are also considered. The fixed effects vary across study areas while *precip* and *temp* vary across study areas and time of sale.

All the variables included in the meta-equation and their descriptions are given in Table 3.

6. Results

6.1. Hedonic model estimation

Overall, the coefficient estimates for *treecover* and *treecoversq* are significant across cities and buffers; there is only one instance where both are insignificant, Patterson for the 0.5–1.0 buffer (Table 4). *Treecover* is significant in all but three instances, 0.0–0.1 buffer for Paterson and Pittsburg, and 0.5–1.0 buffer for Patterson. *Treecoversq* is insignificant in eight instances (0.0–0.1 buffer – Portland; 0.1–0.5 buffer Milwaukee, Pittsburg, and Tampa; 0.5–1.0 buffer – Milwaukee, New Bedford, Patterson, and Pittsburg). Given these significance findings, we tested the joint hypothesis of $H_0 : \beta_3 = \beta_4 = 0$, and this null hypothesis could not be rejected for all city/buffer combinations. This supports the nonlinear relationship between sale prices and tree cover.

Coefficient estimates for other control variables in the hedonic are reported in Appendix Tables A and B1-B3 for parsimony in reporting since they are not core to the theme of this article. Most coefficient estimates are significant at the 10 % level and the qualitative results are consistent across cities.

For the 0.0–0.1 buffer, three communities have negative *treecover* coefficients and positive *treecoversq* coefficients (Durham, Fresno, and Tampa) (Table 4). This pattern of results indicates that property value capitalization of tree cover first decreases as tree cover increases and then increases at higher levels of tree cover. All other community coefficients in this buffer are positive for *treecover* and *treecoversq*, indicating that capitalization increases at an increasing rate as tree cover increases.

Results for the 0.1–0.5 buffer are more mixed (Table 4). The *treecover* and *treecoversq* coefficients are negative and positive, respectively, for Fresno and both coefficients are significant for New Bedford, Patterson, Pittsburg, and Portland. The pattern for Durham, Milwaukee, Phoenix, and Tampa is a positive coefficient for *treecover* and negative coefficient for *treecoversq*, which indicates that tree cover increases capitalization up until a point and then decreases capitalization beyond that point.

In the 0.5–1.0 buffer, the *treecover* coefficients are positive while the *treecoversq* coefficients are negative for five communities, and both coefficients are positive for the other four communities (Table 4).

Since *treecover* and *treecoversq* both influence the capitalization of tree cover in property values, marginal-value summary statistics tell a

[11] Socio-economic variables such as age, education, income, and the family size (Netusil et al., 2010; Saphores and Li, 2012; Sander and Zhao, 2015) and neighborhood characteristics such as population density (Saphores and Li, 2012) and residential vacancy rates (Ottensmann et al., 2008) can also influence how homeowners value tree cover. In the meta-equation, a suite of socio-demographic variables at the census block level were considered to control for these household and neighborhood characteristics. However, these variables were excluded from the final model as they were highly correlated with the study area fixed effects.

Table 3
Hedonic and Internal Meta-analyses Equations.

Variable	Variable definitions	Hedonic equation	Meta-equation
Dependent variables			
ln(sp)	Log of sale price of property (2010 $s)	X	.
MV	Property level marginal value estimate for a 1 % increase in tree cover	.	X
Property characteristics			
sp	Sale price of property (2010 $s)	X	X
living_sqft	Size of living area of house (square feet)	X	.
living_sqftsq	Squared living area	X	.
lot_acres	Lot size (acres)	X	.
lot_acressq	Squared lot size	X	.
age	Age of residence (years)	X	.
agesq	Squared age	X	.
Property characteristics			
treecover1	Percent of tree cover within 0–0.1 km buffer	X	.
treecover1sq	*treecover1* squared	X	.
treecover2	Percent of tree cover within 0.1–0.5 km buffer	X	.
treecover2sq	*treecover2* squared	X	.
treecover3	Percent of tree cover within 0.5–1 km buffer	X	.
treecover3sq	treecover3 squared	X	.
ENV [a]	Percent of k^{th} land cover within h^{th} buffer (m = 8, d = 3)	X	.
ENVsq	Squared percent of k^{th} land cover within h^{th} buffer (m = 8, d = 3)	X	.
Fixed effects			
saleyear	Sale year, 2005–2014 (2005 is the excluded year)	X	X
block	Vector of indicator variables for census blocks	X	.
B	Binary variables for the 0.1–0.5 km, and 0.5–1 km buffers (0–0.1 km is the excluded buffer)	.	X
N	City dummy variables (Durham is the excluded city)	.	X
Climate variables			
precip	Annual precipitation in the city or county (inches)	.	X
temp	Maximum summer temperature in the city or county (°F)	.	X

[a] This vector includes impervious surface, water bodies, agricultural lands, grass and herbaceous lands, shrub land, orchards, woody wetlands, and emergent wetlands. These environmental amenities along with the tree cover and soil and barren lands contribute to the total land cover within each buffer. Barren land is the excluded land cover in the analyses. For detailed descriptions of these variables, see: https://www.epa.gov/enviroatlas.

more straightforward story than is obvious from viewing the hedonic coefficient estimates. Property-level effects Marginal values for a 1 % increase in tree cover are positive or negative depending on the signs and magnitudes of β_3, β_4, and the tree cover within each buffer for a property ($treecover_{isb}$). The marginal values are averaged by study area and by buffer.

Overall, mean marginal values are positive, and 90 % of the marginal values across the nine study areas are positive (Table 5), suggesting that tree cover on adjacent and near properties adds value to residential properties. However, there are exceptions, the percentage is much less than 90 % for Fresno (0.0–0.1 buffer), Paterson (0.5–1.0 buffer) and Phoenix (0.0–0.1 and 0.1–0.5 buffers).

We see that property-value capitalization of tree cover generally increases from the 0.0–0.1 buffer to the 0.1–0.5 buffer with one exception, Milwaukee (Table 5). The pattern of increasing property-value capitalization, again, generally occurs for the 0.5–1.0 buffer relative to the 0.1–0.5 buffer with three exceptions. In Milwaukee, capitalization in the 0.5–1.0 buffer is greater than for the 0.1–0.5 buffer but less for the 0.0–0.1 buffer: households value tree cover nearest their homes the most. In New Bedford and Portland, tree cover in the 0.5–1.0 buffer has the lowest capitalization: again, indicating that households value tree cover near their homes but at a slightly broader spatial scale.

Variation across study areas may be due to factors such as climate and landscape composition. For example, in cities where watering may be required (Phoenix) and wildfire risks are high (Fresno), tree cover near on or near properties may not be as highly valued. The mean marginal values for the 0.0–0.1 buffer vary from about $9 in Fresno to $3520 in Milwaukee. Across buffers, taking Durham as an example, marginal values for a 1 % change in tree cover range from $655 to $9341 for the 0.0–0.1 and 0.5–1.0 buffers, respectively. Households here value tree cover near their homes, but value tree cover more distant from their homes much more.

6.2. Internal meta-analysis estimation

The variability in the hedonic results highlights the role an internal meta-analysis can play in understanding variation in empirical outcomes. Here we estimate three equations. The first is the meta-equation as specified in Eq. (5) using all marginal value estimates. The second and third are robustness investigations given the overwhelming prevalence of positive marginal values noted in the preceding section. The second considers only positive marginal values, again following Eq. (5). This was done because the inclusion of all marginal values contains the implicit assumption that the effects of the meta-regressors are symmetrical for positive and negative value estimates, which is a strong assumption. The third is a probit where the regressors are the same as Eq. (5) but the dependent variable is an indicator of whether the marginal values are positive or negative (1/0, respectively).

Tree-cover capitalization increases significantly, by about $500, in the 0.1–0.5 buffer relative to the 0.0–0.1 buffer in both meta-equations, and by about $1100 dollars for the 0.5–1.0 buffer relative to the 0.0–0.1 buffer (Table 6). The probit estimation indicates the proportion of positive values significantly increases relative to the 0.0–0.1 buffer and the effect is approximately the same for the two larger buffers.

Increasing precipitation significantly increases marginal values while higher temperatures significantly reduce values (Table 6). Our interpretation of these results is that lower precipitation and higher temperatures can be associated with tree stress that compromise the health of trees and may indicate areas where trees may be susceptible to pests and disease and where fire may be a greater risk. These effects are consistent and approximately the same in both meta-equations.

Robustness checks were performed for the “all observations” meta-equation reported in Table 6:

- Removing New Bedford marginal values from the estimation of the meta-equations due to the broad range of computed values in all three buffers (see Table 5).
- Removing New Bedford and Paterson marginal values from the estimation of the meta-equations due to the small sizes for these cities relative to the other cities included in the analyses (see Table 4).
- Removing each of the cities one at a time (see Boyle et al., 2013)

Here we summarize the outcomes of these robustness analyses that are reported in Appendix Table C. Removing New Bedford observations from the data did not change the signs nor the significance of the coefficients for the buffer variables in the meta equation, and the absolute percentage changes in the magnitudes of these coefficients is much less than 10 % (see Table 7). Similar outcomes arise when both Patterson and New Bedford observations were removed from the estimation of the meta-equation. Removing each of the cities one at a time also did not

Table 4
Hedonic Coefficient Estimates for Tree Cover Variables.

Variables	Cities (Study Areas)								
	Durham	Fresno	Milwaukee	New Bedford	Patterson	Phoenix	Pittsburgh	Portland	Tampa
	(NC)	(CA)	(WI)	(MA)	(NJ)	(AZ)	(PA)	(OR)	(FL)
					0.0–0.1 km Buffer				
treecover	−0.0001[a]	−0.0018**	0.0506***	0.0216***	0.0174	0.0020***	0.0023	0.0418***	−0.0024***
	(0.0005) [b]	(0.0008)	(0.007)	(0.004)	(0.0113)	(0.0006)	(0.0021)	(0.0037)	(0.0004)
treecoversq	4.6E-05***	0.0001**	2.05E-05***	2.8E-05***	0.0002***	0.0001***	1.9E-05***	3.9E-06	4.0E-05***
	(5.2E-06)	(2.3E-05)	(5.6E-06)	(1.4E-05)	(0.0001)	(1.8E-05)	(5.7E-06)	(3.2E-06)	(3.1E-06)
					0.1–0.5 km Buffer				
treecover	0.0329***	−0.0105***	0.026***	0.085***	0.0241**	0.0204***	0.0181***	0.0518***	0.0210***
	(0.0019)	(0.0015)	(0.004)	(0.004)	(0.0119)	(0.0013)	(0.0084)	(0.0041)	(0.0012)
treecoversq	−0.0001***	0.0004***	−5.3E-05	−8.9E-05***	0.0002	−0.0005***	0.0001***	9.2E-06**	−5.5E-06
	(1.5E-05)	(4.7E-05)	(1.2E-05)	(2.8E-05)	(0.0002)	(4.2E-05)	(1.3E-05)	(4.8E-06)	(5.9E-06)
					0.5–1.0 km Buffer				
treecover	0.1519***	0.0210***	0.029***	0.014***	0.005	0.1045***	0.0281*	0.0255***	0.0546**
	(0.0025)	(0.0061)	(0.004)	(0.004)	(0.0232)	(0.0031)	(0.0156)	(0.0019)	(0.0023)
treecoversq	−0.0007***	0.0006***	2.3E-05	−1.2E-05	0.0005	−0.0033***	−7.8E-06	−9.4E-06**	0.0001**
	(2.2E-05)	(0.0002)	(1.9E-05)	(3.9E-05)	(0.0004)	(0.0001)	(3.2E-05)	(3.8E-06)	(8.6E-06)
n	30,592	50,659	40,466	6343	5396	250,726	75,894	152,362	145,420

[a] Single asterisk indicates significance at 10 % level; double asterisks indicate significance at 5 % level; triple asterisks indicate significance at 1% level.
[b] Robust standard errors are in parenthesis.

Table 5
Mean Property-level Marginal Values for a 1 % Increase in Tree Cover.

Summary Statistics	Cities (Study Areas)								
	Durham	Fresno	Milwaukee	New Bedford	Patterson	Phoenix	Pittsburgh	Portland	Tampa
	(NC)	(CA)	(WI)	(MA)	(NJ)	(AZ)	(PA)	(OR)	(FL)
					0.0–0.1 km Buffer				
mean	$655	$9	$3520	$1867	$974	$115	$279	$3416	$103
min	-$0.15	-$88	-$0.004	-$108,473	$21	-$0.05	-$0.02	-$0.02	-$322
max	$10,179	$12,823	$30,637	$192,553	$14,934	$4577	$5958	$68,760	$4344
% positive[a]	99	36	100	61	100	100	100	100	72
					0.1–0.5 km Buffer				
Mean	$2306	$95	$1532	$6140	$1201	$133	$925	$4614	$1347
Min	$377	-$280	$90	-$95,379	$183	-$2425	$0.20	$196	43
Max	$14,546	$8981	$11,397	$203,713	$8182	$3208	$8776	$74,915	$16,617
% positive[a]	100	50	100	82	100	96	100	100	100
					0.5–1.0 km Buffer				
Mean	$9341	$673	$1724	$1020	$1226	$443	$2099	$2146	$4319
Min	$1674	$0.07	$126	-$111,469	$108	-$16,409	$0.34	-$0.04	$149
Max	$54,015	$9086	$13,156	$188,809	$8069	$13,396	$25,536	$30,610	$43,540
% positive[a]	100	100	100	55	100	90	100	100	100

[a] A negative minimum and 100 % positive occurs when there is a small number of negative values and the percents positive round to 100.

affect the sign nor significance of the buffer coefficients but the changes in the magnitudes of the coefficients were greater than 10 %; 16 % and 20 %, respectively for the 0.1–0.5 and 0.5–1.0 buffers. This latter outcome emphasizes the importance of the city fixed effects in the meta-equation.

7. Discussion and conclusions

Overall, the hedonic results indicate that homeowners value tree cover on or adjacent to their properties and at greater distances up to the 1.0 km boundary. The novel contribution is the internal meta-analysis that confirmed that the capitalization of tree cover increases with distance from properties without the confounds across independent hedonic studies of different data sources and investigator analysis decisions.

Further, the capitalization of tree cover increases with buffer distance from properties. Why might this be? While trees on or adjacent to properties are positively valued, they come with maintenance such as falling leaves and other tree debris and the risks falling limbs and trees pose to people and structures. Trees on or near properties provide localized benefits like shade and privacy and they may also obstruct views.

Trees that are not on or near a person's property, beyond 0.1 km here, might be viewed as community trees, even if on private property, and provide public amenity benefits such as views from a property, shade when walking, and the esthetics of driving to and from properties for daily activities without the on-property maintenance and risks. This public good aspect presents a significant community challenge. Since most urban land is privately owned, and it appears that property owners value tree cover on land owned by others more than on their own properties, there is likely under investment in urban trees, and subsequently tree cover. The fact that people value trees on others' property more is likely a key motivator for community policies and programs related to removing trees and planting trees. But are these policies and programs enough? The results of this study can be used to educate community leaders about the financial (capitalized property value) benefits of community tree cover, and to educate community members that your actions can benefit me, and my actions can benefit you – help me help you help us.

The hedonic coefficient estimates and the marginal values for 1 % increases in tree cover, while being useful for considering the significance and variability in the capitalization of tree cover into property values, may not convey the full economic significance of tree cover in the urban environment. Consider Fresno and Milwaukee, the cities with the highest

Table 6
Internal Meta-analysis Coefficient Estimates.

Variables	Meta-equations		Probit
	All Observations	Positive Observations	All Observations[c]
0.1–0.5 km Buffer	553.9***[a]	472.8***	0.52***
	(3.50)[b]	(3.60)	(0.003)
0.5–1.0 km Buffer	1138.3***	1129.9***	0.55***
	(3.93)	(3.93)	(0.004)
precip	5.4***	5.7***	−0.0023***
	(0.37)	(0.38)	(0.0003)
temp	−11.7***	−12.3***	−0.0089***
	(1.63)	(1.62)	(0.002)
Phoenix (AZ)	−3487.2***	−3415.5***	−1.23***
	(31.73)	(31.89)	(0.039)
Fresno (CA)	−3578.4***	−3598.2***	−2.67***
	(22.05)	(22.47)	(0.028)
Patterson (NJ)[d]	−3099.2***	−3113.6***	.
	(20.35)	(20.35)	.
Portland (OR)	−797.1***	−807.6***	0.49***
	(23.35)	(23.24)	(0.040)
New Beford (MA)	−1248.5***	3048.7***	−2.59***
	(84.50)	(96.11)	(0.031)
Milwaukee (WI)	−1891.8***	−1901.3***	1.39***
	(21.77)	(21.68)	(0.229)
Tampa (FL)	−2185.0***	−2046.6***	−1.55***
	(15.04)	(15.13)	(0.023)
Pittsburg (PA)	−3067.1***	−3077.6***	0.86***
	(20.13)	(20.06)	(0.067)
Constant	4350.2***	4423.1***	3.50***
	(148.7)	(147.63)	(0.192)
n	2,273,574	2,132,448	2,273,574

[a] Riple asterisk indicates significance at 1% level.
[b] Robust standard errors are in parenthesis.
[c] Omitted category is Durham (NC).
[d] Omitted city so matrix is not singular and coefficients for other cities are interpreted relative to Paterson where all observations were positive.

and lowest marginal values. The effect of tree cover varies across these two cities. For Fresno, tree cover first decreases property values and then increases values with a minimum at 17 %. In Milwaukee tree cover increases property values at an increasing rate. A 1 % change in tree cover, while a mathematical calculation from our study outcomes, may not be noticeable to homeowners. So, we consider 10 % increases in tree cover for Fresno and Milwaukee within the 0.0–0.1 and 0.5–1.0 buffers. Fresno has a mean tree cover of 12 % (Table 2), and a 10 % increase in tree cover within the 0.0–0.1 buffer reduces the value of an average-priced property by $114 (0.1 %). If the tree-cover increase occurs in the 0.5–1.0 buffer, an average-priced property increases in value by $6751 (3.2 %). For Milwaukee with 41 % mean tree cover (Table 2), the comparable figures are $39,701 (24 %) and 27,194 (16 %) for the 0.0–0.1 and 0,5–1.0 buffers, respectively. Thus, tree cover has a small economic effect on property values in Fresno and considerable impact in Milwaukee. For Fresno, with the much larger economic impact of tree cover in the 0.5–1.0 buffer, this is a case where community leaders would likely need to incentivize landowners to reach a socially desirable level of tree cover in the community. It is just the opposite in Milwaukee as people value tree cover on or near their homes more than community tree cover.

With tree cover being capitalized into property values, community leaders may also ask if this greening creates gentrification that may squeeze out lower income households. Wolch et al. (2014) argued that greening displaces the residents that programs are designed to benefit. While Donovan et al. (2021) found a greening effect, they concluded it was modest with about a $900 increase in property values associated with a 1 % increase in tree cover. This number falls withing the range of marginal values we report for the capitalization of tree cover, but $900 may not be insignificant to a first-time home buyer and limited income households. For example, the National Association of Realtors (2024) reported that the median income of first-time buyers was $97,000 in 2022 with a median downpayment on a property of 9 %. This compares to all home buyers who had a median income of almost $109,000 and a median downpayment of 18 %. In 2020 the median sale price for a starter home was $169,000 and it increased to $240,000 in 2024 (Moneywatch, 2024). Following our economic example in the preceding paragraph, changes in tree cover are unlikely to have a substantial impact on purchases by first-time or limited-income home buyers but this is not the case for Milwaukee where the impact could be quite substantial on down payments and mortgage payments.

The health benefits of tree cover identified by Donovan et al. (2013) also play an important role and may be an important consideration for limited income households who have a lower community health status (World health organization, 2018). Thus, the importance of tree cover in communities comes face-to-face with the burgeoning need for affordable housing globally (Coupe, 2021). Perhaps the gentrification effect can be offset through programs that increase the supply of housing and the availability of affordable housing.

Climate change, particularly severe storm events that fell trees and foster wildfires, can affect how people view trees and therefore tree cover. Given the increased incidence of these events globally, and that our property-sale data covers the period 2005–2014, one could also ask if our results reflect these increasing global concerns that might affect the relationships between property values and tree cover. Our results indicate that climate variables are important and that areas with more rainfall and higher temperatures are less likely to have positive tree-cover capitalization, and areas with higher temperatures have lower capitalization of tree cover. This is an important consideration as climate change brings higher temperatures and more severe storms and wildfires that pose great risks to individual properties and communities. In addition, as climate change evolves, the risks to forests from pests and diseases that damage or kill trees (e.g., Simler-Williamson et al., 2019; Sturrock et al., 2011) increases and numerous hedonic studies have shown that these conditions reduce property values (e.g., Cohen et al., 2016; Holmes et al., 2010; Kovacs et al., 2011; Li et al., 2019). Yet, treed areas can reduce urban heat islands, absorb storm runoff, and stabilize soil. This highlights the importance of strategically maintaining tree cover in the face of climate change while recognizing the concerns of homeowners.

The open question is if and how changes through time might affect preferences for tree cover. Consider, a recent study by Phillips et al. (2025) who found that owners of riparian buffers value tree cover that provides important ecosystem services to riverine ecosystems. They used sales from 2005 through 2020 to estimate a hedonic model for Ashe and

Table 7
Internal Meta-equation (All Observations) City Exclusion Robustness Results.

Variable	Without New Bedford, MA			Without Patterson, NJ and New Bedford, MA			Excluding all cities one at a time		
	Sign changed	Significance changed (10 % level)	Average absolute percent change in coefficients	Sign changed	Significance changed (10 % level)	Average absolute percent change in coefficients	Sign changed	Significance changed (10 % level)	Average absolute percent change in coefficients
0.1–0.5 km Buffer	No	No	5.7	No	No	5.3	No	No	16
0.5–1.0 km Buffer	No	No	1.5	No	No	2.0	No	No	20

Watauga Counties in North Carolina, USA. The study area was one of the locations hit the hardest by Hurricane Helene in September 2024 and did catastrophic damage to riparian areas along streams in the study area (Hagen et al., 2025). Will this extreme storm event change preferences in that study area, only time will tell. The effects of climate change on our study results are potentially more subtle with indirect knowledge of the potentially dramatic effects of climate changes and subtle changes that evolve through time. The mitigating effects that trees can have on climate warming and storm water runoff may lead to people placing a higher value on tree cover, whereas the damaging effects of storm events on trees might lead people to place lower value on tree cover, or these could be offsetting effects with no net effect on tree cover valuation.

While it is not possible to directly address the stability of preferences for tree cover through time, insight can be provided by the General Social Survey that "is the only full-probability, personal-interview survey designed to monitor changes in both social characteristics and attitudes currently being conducted in the United States" and it has been conducted since 1972 (NORC, 2025a). When asked about "improving and protecting the environment" the majority of respondents indicated that too little is being done in 33 of the 34 years the survey has been conducted, 65 % answered too little in 1973 and the comparable result in 2022 was 69 % (NORC, 2025b).[12] This is evidence that public preferences for the environment, which tree cover is one element, have been very stable over the past 50 years.

Our results align with the findings of Siriwardena et al. (2016) and Kovacs et al. (2022), which were based on different sets of hedonic studies conducted in various locations, that people value tree cover. Our results also align with the Kovacs result that capitalization of tree cover is greater for property that the owner does not own (maintain). In contrast, in a case study, Sander et al. (2010) found significant capitalization only for 0.1 and 0.25 km buffers around a property while we find an effect out to 1.0 km. There is room for more research to understand the gradient of tree cover capitalization, where the capitalization can be maximized and at what distance there is no effect.

The potential underinvestment in tree cover from social and environmental perspectives, and the tensions between enhancing tree cover and gentrification and climate change presents a challenging policy question for communities that is perhaps not fully addressed in policy discussions and analyses at the local level (Hill et al., 2010; Mincey et al., 2013; Schwarz et al., 2015; Timilsina et al., 2020). In addition, there is not coordinated action across communities with decentralized individual household decision making and individual community policies. Expansion of community forest programs, such as those implemented by the European Union (European Environment Agency, 2018) and the U.S. Forest Service's (Forest Service, nd) Urban and Community Forestry Program and Community Forestry Program, can be important stimuli for coordinating and motivating efforts to address the challenges of maintaining and enhancing urban tree cover at landscape scales.

CRediT authorship contribution statement

Shyamani D. Siriwardena: Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kevin J. Boyle:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Thomas P. Holmes:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors received financial support for this research through a grant from the U.S. Forest Service to Virginia Tech. At the start of the research Holmes was employed by the U.S. Forest Service and is now retired. The time of Siriwardena and Boyle was also supported by Virginia Tech. The authors have no financial interest in the research nor the outcomes of the research.

Appendix A. Appendix

Table A1
Hedonic coefficient estimates for property characteristics.

Variables[a]	Cities (Study Areas)								
	Durham	Fresno	Milwaukee	New Bedford	Patterson	Phoenix	Pittsburgh	Portland	Tampa
	(NC)	(CA)	(WI)	(MA)	(NJ)	(AZ)	(PA)	(OR)	(FL)
living_sqft	7.29E-04***[b]	6.73E-04***	5.29E-04***	4.62E-04***	5.82E-04***	5.78E-04***	5.63E-04***	4.33E-04***	5.82E-04***
	(1.19E-05)[c]	(2.82E-05)	(1.93E-05)	(2.55E-05)	(2.97E-05)	(7.99E-06)	(9.53E-06)	(3.35E-06)	(6.24E-06)
living_sqftsq	−5.48E-08***	−6.51E-08***	−4.40E-08***	−3.27E-08***	−7.19E-08***	−3.92E-08***	−4.66E-08***	−2.63E-08***	−3.85E-08***
	(2.30E-09)	(5.55E-09)	(4.69E-09)	(6.04E-09)	(6.07E-09)	(1.54E-09)	(1.76E-09)	(6.77E-10)	(1.24E-09)
lot_acres	0.0767***	0.2558***	0.0546***	0.1477***	1.2262***	0.0720***	0.6851***	0.2627***	0.1903***
	(0.0098)	(0.0332)	(0.0117)	(0.0170)	(0.2287)	(0.0075)	(0.0365)	(0.0169)	(0.0078)
lot_acressq	−0.0049***	−0.0142***	−0.0038***	−0.0096***	−2.0994***	−0.0050***	−0.0747***	−0.0206***	−0.0127***
	(0.0013)[c]	(0.0025)	(0.0012)	(0.0019)	(0.4636)	(0.0010)	(0.0125)	(0.0033)	(0.0012)
age	−0.0050***	.	−0.0036***	−0.0049***	.	−0.0086***	−0.0101***	−0.0047***	−0.0085***
	(0.0004)	.	(0.0003)	(0.0003)	.	(0.0002)	(0.0003)	(0.0001)	(0.0002)
agesq	3.79E-05***	.	3.9E-06	1.79E-05***	.	1.99E-05***	5.33E-05***	3.69E-05***	5.94E-05***
	(5.12E-06)	.	(2.41E-06)	(1.56E-06)	.	(1.69E-06)	(3.67E-06)	(9.18E-07)	(2.27E-06)

[a] Variable definitions: *living_sqft* = square feet of living area, *living_sqftsq* = squared living area, *lot_acres* = lot size (acres), *lot_acressq* = squared lot size, *age* = age of residence (years), and *agesq* = squared age.
[b] Triple asterisk indicates significance at 1 % level.
[c] Robust standard errors are in parenthesis.

[12] The specific question wording is: "We are faced with many problems in this country, none of which can be solved easily or inexpensively. I'm going to name some of these problems, and for each one I'd like you to name some of these problems, and for each one I'd like you to tell me whether you think we're spending too much money on it, too little money, or about the right amount. First (READ ITEM A) … are we spending too much, too little, or about the right amount on improving and protecting the environment?"

Table B1
Hedonic coefficient estimates for landcover variables, 0.0–0.1 km buffer.

Variables[a]	Cities (Study Areas)								
	Durham	Fresno	Milwaukee	New Bedford	Patterson	Phoenix	Pittsburgh	Portland	Tampa
	(NC)	(CA)	(WI)	(MA)	(NJ)	(AZ)	(PA)	(OR)	(FL)
water	0.0081***[b]	−0.0005	0.0555***	0.0353***	0.0434***	0.0102***	−0.0091**	0.0475***	0.0063***
	(0.0012)[c]	(0.0012)	(0.0082)	(0.0060)	(0.0134)	(0.0006)	(0.0049)	(0.0039)	(0.0004)
watersq	−3.14E-05	3.74E-05	1.44E-04	−2.10E-04*	−6.72E-04*	6.00E-05***	4.25E-04***	1.25E-04**	−2.41E-05***
	(3.07E-05)	(4.36E-05)	(1.31E-04)	(1.18E-04)	(3.51E-04)	(1.63E-05)	(1.41E-04)	(5.32E-05)	(6.84E-06)
impervious	0.0087***	0.0075***	0.0554***	0.0258***	0.0327***	0.0185***	0.0064***	0.0463***	0.0043***
	(0.0008)	(0.0014)	(0.0074)	(0.0039)	(0.0127)	(0.0008)	(0.0017)	(0.0037)	(0.0005)
imperviousssq	−6.34E-05***	−7.87E-05***	−4.84E-05***	−3.13E-05**	−5.16E-05	−1.67E-04***	−4.82E-05***	−6.36E-05***	−4.58E-05***
	(7.34E-06)	(1.30E-05)	(8.76E-06)	(1.45E-05)	(5.65E-05)	(8.36E-06)	(8.81E-06)	(4.69E-06)	(3.38E-06)
shrubs	.	.	.	.	.	0.0521***	.	.	.
	.	.	.	.	.	(0.0017)	.	.	.
shrubssq	.	.	.	.	.	−3.39E-04***	.	.	.
	.	.	.	.	.	(1.29E-05)	.	.	.
grass	−0.0023***	−0.0038***	0.0540***	0.0273***	0.0236**	0.0031***	0.0093***	0.0464***	0.0016***
	(0.0009)	(0.0009)	(0.0074)	(0.0042)	(0.0120)	(0.0004)	(0.0018)	(0.0037)	(0.0005)
grasssq	1.48E-04***	6.18E-05***	−2.32E-05**	−3.29E-05	1.94E-04	1.33E-04***	−6.61E-05***	−5.48E-05***	2.18E-06
	(1.95E-05)	(2.14E-05)	(1.15E-05)	2.45E-05	1.66E-04	(1.16E-05)	(1.15E-05)	(5.77E-06)	(4.19E-06)
agriculture	.	−1.86E-04	0.0539***	.	.	0.0022***	.	0.0388***	0.0056***
	.	(8.79E-04)	(0.0078)	.	.	(0.0006)	.	(0.0039)	(0.0017)
agriculturesq	.	8.65E-06	−5.89E-05	.	.	6.97E-05***	.	7.91E-05***	−1.42E-04***
	.	(2.16E-05)	(1.02E-04)	.	.	(1.42E-05)	.	(2.94E-05)	(5.28E-05)
orchard	.	0.0005***	.	.	.	.	.	.	.
	.	(0.0041)	.	.	.	.	.	.	.
orchardsq	.	−6.08E-05***	.	.	.	.	.	.	.
	.	(1.52E-04)	.	.	.	.	.	.	.
woodywet	.	.	0.0523***	0.0211***	.	.	.	0.0439***	0.0014***
	.	.	(0.0074)	(0.0040)	.	.	.	(0.0039)	(0.0005)
woodywetsq	.	.	4.31E-05**	4.44E-05	.	.	.	3.06E-05	−3.71E-06***
	.	.	(2.15E-05)	(3.90E-05)	.	.	.	(4.09E-05)	(9.03E-06)
emergentwet	.	.	0.0547***	0.0330***	.	.	.	0.0347***	0.0025***
	.	.	(0.0076)	(0.0057)	.	.	.	(0.0039)	(0.0007)
emergentwetsq	.	.	−3.63E-05	−1.22E-04	.	.	.	2.56E-04***	−1.97E-05
	.	.	(5.99E-05)	(1.41E-04)	.	.	.	(4.65E-05)	(1.81E-05)

[a] Variable definitions: % surface area within buffer covered by each land cover. Barren land is the excluded land cover in the analyses.
[b] Single asterisks indicate significance at 10 % level; double asterisks indicate significance at 5 % level; triple asterisks indicate significance at 1% level.
[c] Robust standard errors are in parenthesis.

Table B2
Hedonic coefficient estimates for landcover variables, 0.1–0.5 km buffer.

Variables[a]	Cities (Study Areas)								
	Durham	Fresno	Milwaukee	New Bedford	Patterson	Phoenix	Pittsburgh	Portland	Tampa
	(NC)	(CA)	(WI)	(MA)	(NJ)	(AZ)	(PA)	(OR)	(FL)
water	0.0100***[b]	0.0027***	0.0255***	0.0828***	0.0201***	0.0121***	0.0125	0.0535***	0.0223***
	(0.0025)[c]	(0.0010)	(0.0050)	(0.0046)	(0.0121)	(0.0010)	(0.0084)	0.0043	0.0011)
watersq	−1.80E-04	−2.80E-05	9.51E-05**	−2.47E-05	9.24E-04	−2.45E-04***	−4.36E-05	2.57E-05	4.29E-05***
	(2.38E-04)	(6.44E-05)	(4.84E-05)	(2.90E-05)	(9.15E-04)	(5.22E-05)	4.81E-05)	2.25E-05	9.87E-06)
impervious	0.0041***	0.0191***	0.0247***	0.0727***	0.0467***	0.0256***	0.0064	0.0513	0.0218***
	(0.0016)	(0.0035)	(0.0047)	(0.0045)	(0.0171)	(0.0010)	0.0074)	0.0043	0.0012)
imperviousssq	2.45E-04***	−1.67E-04***	−7.27E-06	5.30E-05**	−1.15E-04	−2.62E-04***	8.27E-05***	−1.51E-05	−2.57E-05***
	(2.10E-05)	(3.21E-05)	(1.30E-05)	(2.41E-05)	(1.18E-04)	(1.06E-05)	1.54E-05)	6.43E-06	6.15E-06
shrubs	.	.	.	.	.	−0.0058***	.	.	.
	.	.	.	.	.	(0.0004)	.	.	.
shrubssq	.	.	.	.	.	1.18E-04***	.	.	.
	.	.	.	.	.	(5.46E-06)	.	.	.
grass	0.0062***	0.0196***	0.0230***	0.0956***	0.0395***	0.0122***	0.0114	0.0540***	0.0273***
	(0.0020)	(0.0030)	(0.0048)	(0.0050)	(0.0157)	(0.0009)	(0.0075)	(0.0041)	(0.0013)
grasssq	3.70E-04***	−2.96E-04***	4.30E-05**	−2.35E-04***	2.09E-04	−1.10E-04***	4.40E-05**	−1.66E-05*	−1.27E-04***
	(4.85E-05)	(6.07E-05)	(2.14E-05)	(4.71E-05)	(3.28E-04)	(2.30E-05)	(2.12E-05)	(9.27E-06)	(9.93E-06)
agriculture	.	0.0012**	0.0279***	.	.	0.0054***	.	0.0480***	0.0251***
	.	(0.0006)	(0.0049)	.	.	(0.0004)	.	(0.0043)	(0.0016)
agriculturesq	.	7.93E-05***	−5.84E-05	.	.	1.81E-05**	.	3.58E-05***	−1.67E-04***
	.	(2.11E-05)	(5.74E-05)	.	.	(7.85E-06)	.	(1.30E-05)	(6.02E-05)
orchard	.	0.0183***	.	.	.	.	.	.	.
	.	(0.0028)	.	.	.	.	.	.	.
orchardsq	.	−4.14E-04***	.	.	.	.	.	.	.
	.	(7.78E-05)	.	.	.	.	.	.	.

(*continued on next page*)

Table B2 (*continued*)

Variables[a]	Cities (Study Areas)								
	Durham	Fresno	Milwaukee	New Bedford	Patterson	Phoenix	Pittsburgh	Portland	Tampa
	(NC)	(CA)	(WI)	(MA)	(NJ)	(AZ)	(PA)	(OR)	(FL)
woodywet	.	.	0.0261***	0.0787***	.	.	.	0.0450***	0.0194***
	.	.	(0.0045)	(0.0045)	.	.	.	(0.0046)	(0.0011)
woodywetsq	.	.	−2.57E-05	−2.60E-05	.	.	.	1.17E-03***	3.26E-05***
	.	.	(2.82E-05)	(6.97E-05)	.	.	.	(2.31E-04)	(1.01E-05)
emergentwet	.	.	0.0256***	0.0826***	.	.	.	0.0429***	0.0301***
	.	.	(0.0050)	(0.0049)	.	.	.	(0.0046)	(0.0015)
emergentwetsq	.	.	−8.48E-05	−5.07E-04*	.	.	.	1.59E-03***	−2.11E-04***
	.	.	(8.45E-05)	(2.97E-04)	.	.	.	(3.30E-04)	(4.45E-05)

[a] Variable definitions: % surface area within buffer covered by each land cover. Barren land is the excluded land cover in the analyses.
[b] Single asterisks indicate significance at 10 % level; double asterisks indicate significance at 5 % level; triple asterisks indicate significance at 1 % level.
[c] Robust standard errors are in parenthesis.

Table B3
Hedonic coefficient estimates for landcover variables, 0.5–1.0 km buffer.

Variables[a]	Cities (Study Areas)								
	Durham	Fresno	Milwaukee	New Bedford	Patterson	Phoenix	Pittsburgh	Portland	Tampa
	(NC)	(CA)	(WI)	(MA)	(NJ)	(AZ)	(PA)	(OR)	(FL)
water	0.0590***[b]	−0.0002	0.0324***	0.0113***	0.0176	0.0341***	0.0244*	0.0259***	0.0640***
	(0.0028)[c]	(0.0019)	(0.0045)	(0.0031)	(0.0182)	(0.0016)	(0.0138)	(0.0020)	(0.0024)
watersq	2.14E-03***	4.05E-04***	1.55E-04***	4.58E-05**	1.50E-03***	−1.30E-04***	7.57E-05	−8.15E-06	3.72E-05***
	(4.36E-04)	(7.89E-05)	(5.04E-05)	(2.34E-05)	(1.92E-03)	(7.63E-05)	(8.37E-05)	(1.24E-05)	(8.57E-06)
impervious	0.0336***	0.0353***	0.0349***	0.0100***	0.0988***	0.0446***	0.0249**	0.0241***	0.0754***
	(0.0019)	(0.0053)	(0.0045)	(0.0030)	(0.0263)	(0.0015)	(0.0106)	(0.0019)	(0.0027)
imperviousssq	7.07E-04***	−2.92E-04***	−5.38E-05***	2.27E-05	−5.27E-04***	−3.54E-04***	8.15E-06	4.82E-06	−1.63E-04***
	(2.94E-05)	(4.43E-05)	(2.13E-05)	(2.90E-05)	(2.15E-04)	(1.38E-05)	(4.98E-05)	(4.62E-06)	(9.43E-06)
shrubs	0.0292***	.	.	.	.	0.0292***	.	.	.
	(0.0009)	.	.	.	.	(0.0009)	.	.	.
shrubssq	0.0000***	.	.	.	.	4.34E-05***	.	.	.
	(0.0000)	.	.	.	.	(5.52E-06)	.	.	.
grass	0.0393***	0.1021***	0.0392***	0.0181***	0.0395	0.0735***	0.0332**	0.0268***	0.0761***
	(0.0028)	(0.0149)	(0.0051)	(0.0042)	(0.0312)	(0.0023)	(0.0142)	(0.0020)	(0.0028)
grasssq	7.57E-04***	−2.91E-03***	−1.26E-04***	−1.62E-04**	5.73E-04	−1.75E-03***	−3.70E-05	−2.81E-05***	−1.36E-04***
	(7.55E-05)	(4.38E-04)	(4.09E-05)	(6.81E-05)	(1.05E-03)	(6.40E-05)	(4.18E-05)	(7.27E-06)	(1.49E-05)
agriculture	.	0.0157***	0.0362***	0.0218***	.	0.0223***	.	0.0258***	0.0847***
	.	(0.0020)	(0.0046)	(0.0037)	.	(0.0007)	.	(0.0019)	(0.0035)
agriculturesq	.	−6.36E-06	−2.03E-04*	−2.14E-04***	.	7.57E-06	.	4.39E-06	−5.34E-04***
	.	(1.90E-05)	(1.11E-04)	(7.70E-05)	.	(6.73E-06)	.	(1.06E-05)	(7.17E-05)
orchard	.	0.0259***	.	.	.	.	.	.	.
	.	(0.0048)	.	.	.	.	.	.	.
orchardsq	.	−6.15E-04***	.	.	.	.	.	.	.
	.	(1.44E-04)	.	.	.	.	.	.	.
woodywet	.	.	2.74E-02***	.	.	.	.	1.76E-02***	6.91E-02***
	.	.	(4.24E-03)	.	.	.	.	(2.63E-03)	(2.51E-03)
woodywetsq	.	.	1.45E-04***	.	.	.	.	6.06E-04	−6.41E-05***
	.	.	(4.69E-05)	.	.	.	.	(3.92E-04)	(1.33E-05)
emergentwet	.	.	0.0301***		.	.	.	0.0352***	0.0687***
	.	.	(0.0048)		.	.	.	(0.0034)	(0.0027)
emergentwetsq	.	.	2.01E-05		.	.	.	−0.0006	−0.0002**
			(0.0001)		.	.	.	(0.0004)	(0.0001)

[a] Variable definitions: % surface area within buffer covered by each land cover. Barren land is the excluded land cover in the analyses.
[b] Single asterisks indicate significance at 10 % level; double asterisks indicate significance at 5 % level; triple asterisks indicate significance at 1% level.
[c] Robust standard errors are in parenthesis.

Data availability

Data will be made available on request.

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