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Analysis

The value of urban tree cover: A hedonic property price model in Ramsey and Dakota Counties, Minnesota, USA

Heather Sander [a,*], Stephen Polasky [b], Robert G. Haight [c]

[a] Conservation Biology Program, University of Minnesota, St. Paul, MN, USA
[b] Department of Applied Economics, University of Minnesota, St. Paul, MN, USA
[c] Northern Forest Research Station, St. Paul, MN, USA

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ABSTRACT

Urban tree cover benefits communities. These benefits' economic values, however, are poorly recognized and often ignored by landowners and planners. We use hedonic property price modeling to estimate urban tree cover's value in Dakota and Ramsey Counties, MN, USA, predicting housing value as a function of structural, neighborhood, and environmental variables, including tree cover, using a spatial simultaneous autoregressive (SAR) error model. We measure tree cover as percent tree cover on parcels, and within 100, 250, 500, 750, and 1000 m. Results show that tree cover within 100 and 250 m is positive and statistically significant. A 10% increase in tree cover within 100 m increases average home sale price by $1371 (0.48%) and within 250 m increases sale price by $836 (0.29%). In a model including both linear and squared tree cover terms, tree cover within 100 and 250 m increases sale price to 40–60% tree cover. Beyond this point increased tree cover contributes to lower price. Tree cover beyond 250 m did not contribute significantly to sale price. These results suggest significant positive effects for neighborhood tree cover, for instance, for the shading and aesthetic quality of tree-lined streets, indicating that tree cover provides positive neighborhood externalities.

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1. Introduction

Trees in urban areas provide a wide range of benefits including protection against soil erosion, provision of habitat for wildlife, local air quality improvements, reductions in the urban heat island effect, energy savings through building shading and insulation, carbon sequestration, and reductions in stormwater runoff (Dwyer et al., 1992; Sailor, 1995; Laverne and Lewis, 1996; Scott et al., 1998; Simpson, 1998; Simpson and McPherson, 1996; McPherson et al., 1999, 2005; Beckett et al., 2000; Xiao et al., 1998; Brack, 2002; Nowak and Crane, 2002; Maco and McPherson, 2003; Nowak et al., 2006a). Urban tree cover also provides cultural benefits that lead to improved quality of urban life as trees may improve the scenic quality of a city neighborhood, provide privacy, reduce stress, shelter residents from the negative effects of undesirable land uses, and improve retail areas by creating environments that are more attractive to consumers (Dwyer et al., 1991; Sheets and Manzer, 1991; Hull, 1992; Laverne and Winson-Geideman, 2003; Westphal, 2003; Wolf, 2005; Ellis et al., 2006). These local benefits of urban tree cover, although generally recognized, are often poorly understood by local policy-makers and may be negatively impacted by local policies or the lack thereof.

Urban trees may also generate more widespread benefits. Cultural benefits arguably extend at least to neighborhoods and environmental benefits may accrue to the entire urban area (e.g., reduction of the urban heat island effect) or beyond (e.g., carbon sequestration). Tree planting, therefore, is likely to generate positive externalities and decision-making by private landowners will likely result in too few trees being planted.

Despite the range of benefits and the likelihood of positive externalities, most urban areas do little to maintain or expand tree cover. Several cities have programs to encourage tree planting. For example, the Los Angeles Department of Water and Power's Trees for a Green LA Program provides free shade trees to city residents (http://www.ladwp.com/ladwp/cms/ladwp000744.jsp). Other cities make use of zoning regulations to regulate urban tree cover. For example, St. Paul, MN requires a permit to remove or plant trees directly bordering public streets, Boston, MA requires public hearings to remove healthy shade trees in public areas, and Portland, OR requires permits to remove trees on both public and private properties. However, most cities do not have programs to encourage tree planting and restrictions on tree cutting, if they exist, generally only apply to trees in public areas and along roadways and not to trees on private property.

* Corresponding author. University of Minnesota, Dept of Geography, 414 Social Science Building, 267 19th Avenue S, 55455 Minneapolis, MN, United States. Tel.: +1 651 249 1514; fax: +1 612 624 1044.
E-mail address: evans324@umn.edu (H. Sander).

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Table 1
Summary of previous studies of the economic value of urban trees.

Study	Measurement used	Location	Method	Results
Anderson and Cordell (1988)	Number of large, small, pine, and hardwood trees in front yards of residential single family properties	Athens, Georgia, USA	Hedonic property price	Trees were found to be associated with a 3.5%–4.5% increase in homes sales price
Brack (2002)	Number, health, and size of trees planted in streets and parks	Canberra, Australia	Calculated dollar value of trees in terms of energy reduction, pollution mitigation, and carbon sequestration	Planted trees were estimated to have a combined value in terms of energy reduction, pollution mitigation, and carbon sequestration of US$20–67 million during the 2008–2012 time period
Dombrow et al. (2000)	Dummy variable to indicate single family residential properties that had mature trees	Baton Rouge, Louisiana, USA	Hedonic property price	The presence of mature trees on a parcel contributed about 2% to home sale prices
Garrod and Willis (1992)	Percentage of forested areas of broadleaved trees, larch, Scots pine, Corsican pine, and other conifers on Forestry Commission lands for homes located in 1 km squares	Great Britain	Hedonic property price	Broadleaved trees positively impacted home sales prices while coniferous trees negatively impacted home sale prices
Holmes et al. (2006)	Damages from exotic forest pest as indicated by hemlock health and percent deciduous, coniferous, and mixed forest types on parcels and within 0.1 km, 0.5 km, 1 km buffers of parcels	Sparta, New Jersey, USA	Hedonic property price	Deciduous cover within 0.5 km and 1 km of homes positively impacted property values, coniferous cover within 0.5 km enhanced property values, and mixed forests within 0.5 km and 1 km of homes negatively impacted property values; hemlock health significantly positively impacted property values
Jim (2006)	Detailed data on size, species, health, structure, appearance, rarity, and habitat of heritage trees	Hong Kong	Expert method (developed by author)	Values for individual heritage trees ranged from HK$3.0 million to HK$4.39 million depending on tree species and characteristics
Maco and McPherson (2003)	Tree survey data	Davis, California, USA	Calculated total annual expenditures for urban forest management (e.g., planting, tree maintenance, damage mitigation) and total benefits (through direct and implied valuation) of urban forests (energy savings, atmospheric carbon reduction, stormwater runoff reductions, air quality improvement, and aesthetic) for use in benefit–cost analysis	Benefits ($1.7 million) exceeded costs ($449,353) by $1,248,464 annually for an average benefit of $52.43 per publicly maintained tree. The benefit–cost ratio was 3.78:1.
Mansfield et al. (2005)	Percentage of residential single family parcel that was forested, acres of forest on a parcel, percentage of forested land within 400 m, 800 m, and 1600 m buffers around parcel, distances to private and institutional forests	Research Triangle, North Carolina, USA	Hedonic property price	Proximity to both forest types and proportion of parcel that was forested increased home sales prices, increasing forest cover on parcel by 10% adds less than $800 to home sales prices while adjacency to private forests add more than $8000
McPherson et al. (1999)	Survey data for street and park trees	Modesto, California, USA	Calculated total annual expenditures for urban forest management (e.g., planting, tree maintenance, damage mitigation) and total benefits (through direct and implied valuation) of urban forests (energy savings, atmospheric carbon reduction, stormwater runoff reductions, air quality improvement, aesthetic) for use in benefit–cost analysis	Benefits were valued as follows: aesthetic — $1,455,636, air quality improvement — $1,442,036 ($15.82/tree), energy savings — $1,000,560 ($10.97/tree), stormwater runoff reductions — $616,139 ($6.76/tree), carbon sequestration — $449,445 ($4.93/tree), total — $4,964,816 ($54.44/tree). Costs totaled $2,623,384. The benefit–cost ration was 1.89:1.
McPherson et al. (2005)	Tree survey data	Fort Collins, Colorado; Cheyenne, Wyoming; Bismark, North Dakota, Berkeley, California; and Glendale, Arizona, USA	Calculated total annual expenditures for urban forest management (e.g., planting, tree maintenance, damage mitigation) and total benefits (through direct and implied valuation) of urban forests (energy savings, atmospheric carbon reduction, stormwater runoff reductions, air quality improvement, and aesthetic) for use in benefit–cost analysis for each city	Benefits were valued as follows: aesthetic — $21–$67/tree, stormwater runoff reduc tion — up to $28/tree, energy savings — up to $15/tree, carbon reduction — $1–$2/tree, air quality improvement — $—0.57–$1.52/tree, total — $31–$89/tree. Benefits exceeded costs in all cities with benefit–cost ratios ranging from 1.37:1 to 3.09:1.
Morales et al. (1976)	Binary variable to indicate whether home had good or poor tree cover	Manchester, Connecticut, USA	Hedonic property price	Tree cover increased property values by 6% ($2686)
Morales (1980)	Binary variable to indicate whether a property has good tree cover or not	Manchester, Connecticut, USA	Hedonic property price	Tree cover increased property values by 6%
Morales et al. (1983)	Binary variable to indicate whether a property had mature tree cover or not	Greece, New York, USA	Hedonic property price	Trees on wooded lots added 10%–17% to home sale prices
Nowak et al. (2006b)	Number of trees, species, and canopy cover	Minneapolis, MN	Calculated dollar value of trees in terms of air pollution mitigation and carbon sequestration	Urban forest's carbon storage is valued at $46 million and annual carbon sequestration valued at $164,000. Tree and shrubs together remove $1.9 million worth of air pollution per year. Total structural value of the area's forests is estimated at $756 million.
Nowak et al. (2006c)	Number of trees, species, and canopy cover	Washington, D.C.	Calculated dollar value of trees in terms of air pollution mitigation and carbon sequestration	Urban forest's carbon storage is valued at $9.7 million and annual carbon sequestration valued at $299,000. Trees remove $2.5 million worth of air pollution per year. Total structural value of local forests is estimated at $3.6 billion.

(continued on next page)

Table 1 (*continued*)

Study	Measurement used	Location	Method	Results
Nowak et al. (2007)	Number of trees, species, and canopy cover	New York, NY	Calculated dollar value of trees in terms of air pollution mitigation and carbon sequestration	Urban forest's carbon storage is valued at $24.9 million and annual carbon sequestration valued at $779,000. Trees remove $10.6 million worth of air pollution per year. Total structural value of local forests is estimated at $5.2 billion.
Thompson et al. (1999)	Forest density and health	Lake Tahoe, California, USA	Hedonic property price	Forest density and health contribute 5–20% to values of properties location at urban–wildland interface
Thorsnes (2002)	Proximity of vacant building lots to forest preserves	Grand Rapids metropolitan area, Michigan, USA	Hedonic property price	Lots that directly bordered a forest preserve sold at 19%–35% higher prices than other lots
Treiman and Gartner (2006)	Willingness to pay a tax to establish a tree care fund for the local area	44 communities, Missouri, USA	Contingent valuation	Residents of communities with populations greater than 50,000 strongly supported establishment of a tree care fund with a tax of $14–$16 per household per year.
Tyrväinen (2001)	Willingness to pay to avoid construction on forested land and for wooded recreation areas	Joensuu and Salo, Finland	Contingent valuation	Half of respondents were willing-to-pay to avoid construction on forested land (average WTP of 74–206 FIM/year — $19.23–$53.56) and more than two-thirds were willing-to-pay for use of wooded recreation areas (average WTP of 42–53 FIM/month — $10.92–$13.78)
Tyrväinen and Miettinen (2000)	Distance to closest forest and existence of forest view for terraced homes	Salo, Finland	Hedonic property price	Property values decrease by 5.9% on average with a 1 km increase in distance to forest and properties with forest views are 4.9% more expensive than properties that are otherwise similar
Vesely (2007)	Willingness to pay to avoid 20% decrease in urban tree estate	Aotearoa, NZ	Contingent valuation	Household average annual WTP to avoid 20% reduction in urban tree estate was NZD 184 (2003) for a three year period ($143)

Some of the environmental and cultural benefits generated by trees in urban areas may be capitalized into the values of residential and commercial properties. Documenting the effect of increased tree cover on property values provides one way to provide evidence on the value of trees to urban communities. Examining the spatial pattern of the value of urban trees can also shed light on the degree to which urban trees generate positive externalities. A positive externality exists when trees on one property increase the property values of nearby properties. This study examines the impact of urban tree cover on residential home sale prices in the Minneapolis-St. Paul metropolitan area of Minnesota, USA. Our estimates contribute to the literature on the values of urban trees, improve understanding of how these values differ with location and context, and provide evidence of the degree to which urban trees provide positive externalities.

2. Previous studies of the value of urban trees

Several prior studies have estimated the monetary benefits provided to communities by urban forests (Table 1). These studies focus on different geographic locations and forest benefits and use different methods making direct comparison of results difficult. Nonetheless, these studies indicate that forests provide a positive economic benefit to local landowners and communities.

Several recent studies used contingent valuation (CV) to estimate the economic value of tree cover in urban areas (Tyrvainen, 2001; Treiman and Gartner, 2006; Veseley, 2007). In applying CV to the valuation of urban trees, researchers generate a scenario in which some aspect of an urban forest changes and ask individuals how much they would pay to avoid this change or to cause this change to occur. Results from all CV studies show that individuals in urban environments are willing-to-pay positive amounts to maintain urban forests. CV studies may be conducted with little or no data about local forests, which can be an advantage as tree cover data are limited or non-existent in many areas. CV studies may also capture benefits not captured by other methods, for instance, existence values or other non-use benefits. However, values estimated using CV are often questioned because they represent only what individuals claim they would pay in a hypothetical situation and may not correspond closely with what they would actually pay in a real situation (More et al., 1988).

Hedonic property price models can be used to calculate the value of urban trees based on property characteristics and sale prices or assessed values of properties. Some hedonic pricing studies have used very simple and somewhat subjective measures of urban forest character. Among these are several studies that used binary dummy variables to identify parcels with good or mature forest cover. These studies found that good tree cover increased home sale prices approximately 2% in Baton Rouge, Louisiana, USA (Dombrow et al., 2000) and 6% in Manchester, Connecticut, USA (Morales et al., 1976; Morales, 1980). Other hedonic pricing studies have used more well-defined metrics to quantify urban forest characteristics. Some of these studies used proximity to forested areas to identify the value of urban forests, finding that increased proximity to forested areas increases home sale prices. For example, a study conducted in the area near Grand Rapids, Michigan, USA found that housing lots that directly bordered a forest preserve were sold for 19%–35% higher prices than other lots (Thorsnes, 2002). A study conducted in Finland found that the values of homes decreased by an average of 5.9% with a 1 km increase in their distance from the closest forest, and homes with forest views were 4.9% more expensive than otherwise comparable properties (Tyrvainen and Miettinen, 2000). A similar study in North Carolina, USA found that proximity to both private and institutional forests increased home sale prices (Mansfield et al., 2005). These studies indicate that homeowners will pay more for homes that are closer to forests but they tell us little about the value of trees that are not part of contiguous urban forests, for instance trees along streets or in yards.

To address this problem, some hedonic pricing studies have examined the impact of tree cover on property values using counts of tree numbers or estimates of percent tree cover. These studies generally found that increasing tree cover increases home sale prices, although only within certain areas and for certain tree types. A North Carolina, USA study found that increasing forest cover on a parcel by 10% increased home sale prices by $800 (Mansfield et al., 2005).

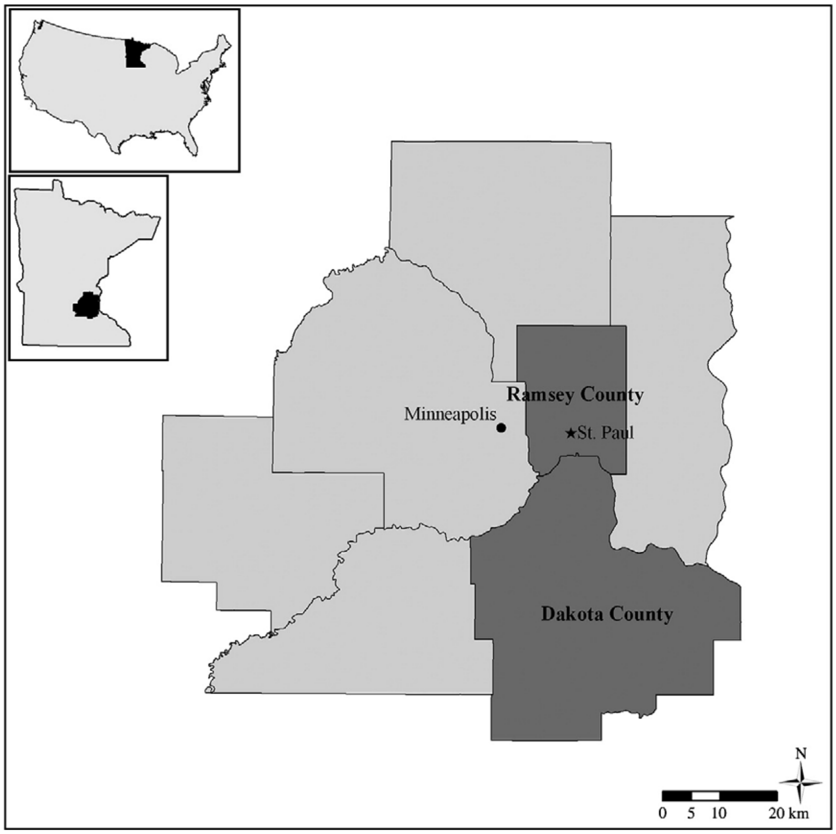

Fig. 1. Location of the study area.

Anderson and Cordell (1988) found that homes with more than five front yard trees sold for 3.5%–4.5% more than comparable homes with fewer trees, with a mean value of \$343 per tree, \$376 for each hardwood tree and \$319 for each pine. Other studies have also noted a similar difference in value with increases in broadleaved and deciduous cover in the area surrounding a home producing greater price increase than increases in conifer cover, and, in some cases, increases in conifer cover or in mixed cover types were actually found to reduce sale prices (Garrod and Willis, 1992; Holmes et al., 2006). For example, a study conducted in New Jersey, USA found that deciduous tree cover within 0.5 km and 1 km of homes positively impacted property values as did coniferous cover within 0.5 km, while mixed forests within 0.5 km and 1 km of homes negatively impacted property values (Holmes et al., 2006).

Some studies have used hedonic pricing to examine the impact of tree health on home values. In general, these studies found that healthier, better maintained forests increased home sale prices while less healthy forests could actually decrease home sale prices. A 1999 study conducted in the Lake Tahoe Basin of California, USA found that the degree of disease infection in trees near a home negatively impacted home sale prices and that thinning and removing infected trees increased home sale prices by between \$19,800 and \$109,300 (Thompson et al., 1999). Another study found that measures of hemlock health were positively related to property values in New Jersey, USA (Holmes et al., 2006).

Other studies have valued urban trees based on the values of the ecological services they provide (McPherson et al., 1999, 2005; Brack, 2002; Maco and McPherson, 2003; Nowak et al., 2006b,c, 2007). In such studies, the values of a series of benefits provided by urban tree cover are estimated for an area and are then summed to produce an overall estimate of value. Such studies are useful in quantifying the economic costs and benefits of urban tree cover and thus help in management and policy decision-making. However, they require detailed data on tree populations and community forestry expenditures that are currently unavailable in most urban areas making these studies impractical or impossible to conduct in many locations.

In sum, prior studies have shown that urban trees provide valuable benefits to urban communities, but do not fully address which aspects of urban tree cover are most valuable. Additional studies that assess value using similar methodologies and measures or that value similar benefits of tree cover will help to increase our understanding of the value of urban trees as well as studies that examine the patterns that exist in these values geographically and contextually. This study aims to improve our understanding of the values for urban trees by eliciting information about the spatial pattern of benefits to single family home property values as well as how values vary with different levels of tree cover. In so doing, we also aim to determine whether tree cover affects home prices beyond the local parcel and thereby uncover evidence of an externality.

3. Methods

3.1. Study area

Our study area included Ramsey and Dakota Counties, part of the Minneapolis-St. Paul metropolitan area, located in east central Minnesota, USA (Fig. 1). Ramsey County, which consists of eighteen cities and one township, is dominated by urban and suburban land uses while Dakota County, with 21 cities and 13 townships, is less urbanized and consists of a mix of urban, suburban, and agricultural land uses. Ramsey County is densely populated with a population of approximately 500,000 in an area of 441 km^2. Dakota County's population of approximately 360,000 occupies a land area of 1,475 km^2. Ramsey County has been largely urbanized for decades, while Dakota County's urbanization occurred more recently, with rapid urbanization occurring in the last 20 years and continuing today.

Table 2
Variable description and expected relationship to the dependent variable, home sales price.

Variable Name	Definition	Expected relationship to sale price
Structural variables		
PRICE	Home sales price (dependent variable)	
ACRES	Lot size in acres	Positive
FINSQFT	Finished square feet in home	Positive
HOME_AGE	Year home was built subtracted from 2005	Negative
TAX_RATE	Property tax rate	Negative
ELEV_FT	Elevation of lot on which the home sits in feet	Positive
Neighborhood variables		
BUSYRD	Distance to closest road with high traffic volume in meters	Positive[a]
CBD	Distance to closest central business district (Minneapolis or St. Paul) in meters	Negative[a]
SHOP	Distance to closest shopping center in meters	Positive[a]
COLLEGE	Distance to closest four-year college or university in meters	Negative[a]
MEAN_MCA	Average Minnesota Comprehensive Assessment score for local elementary and middle schools	Positive
IMPERVIOUS	Mean impervious surface in 500 m buffer around parcel	Negative
Environmental variables		
LAKE	Euclidean distance to closest lake in meters	Negative[a]
LGPKRD	Road distance to closest park in meters	Negative[a]
TRAIL	Euclidean distance to closest non-park trail in meters	Negative[a]
VIEW_AREA	Area of a home's viewshed in square meters	Positive
Tree cover variables		
TREE_PARCEL	Percent tree cover on parcel	Positive
TREE_100	Percent tree cover in 100 m buffer around parcel	Positive
TREE_250	Percent tree cover in area 100 m–250 m around parcel	Positive
TREE_500	Percent tree cover in area 250 m–500 m around parcel	Positive
TREE_750	Percent tree cover in area 500 m–750 m around parcel	Positive
TREE_1000	Percent tree cover in area 750 m–1000 m around parcel	Positive
Market segment variables (reference location is South St. Paul)		
APPLEVALLEY	Dummy variable equals 1 if home is located in Apple Valley school district, otherwise 0	Positive
BURNSVILLE	Dummy variable equals 1 if home is located in Burnsville school district, otherwise 0	Positive
CENTRAL	Dummy variable equals 1 if home is located in St. Paul Central school district, otherwise 0	Positive
COMO_ARL	Dummy variable equals 1 if home is located in St. Paul Como-Arlington school district, otherwise 0	Positive
EAGAN	Dummy variable equals 1 if home is located in Eagan school district, otherwise 0	Positive
EASTVIEW	Dummy variable equals 1 if home is located in Eastview school district, otherwise 0	Positive
FARMINGTON	Dummy variable equals 1 if home is located in Farmington school district, otherwise 0	Positive
HARDING	Dummy variable equals 1 if home is located in St. Paul Harding school district, otherwise 0	Positive
HASTINGS	Dummy variable equals 1 if home is located in Hastings school district, otherwise 0	Positive
HIGHLANDPK	Dummy variable equals 1 if home is located in St. Paul Highland Park school district, otherwise 0	Positive
HUMBOLDT	Dummy variable equals 1 if home is located in St. Paul Humboldt school district, otherwise 0	Positive
STANT_IRONDL	Dummy variable equals 1 if home is located in St. Anthony-Irondale school districts, otherwise 0	Positive
LAKEVILLE	Dummy variable equals 1 if home is located in Lakeville school district, otherwise 0	Positive
MOUNDSVIEW	Dummy variable equals 1 if home is located in Mounds View school district, otherwise 0	Positive
NSTPAUL	Dummy variable equals 1 if home is located in North St. Paul school district, otherwise 0	Positive
ROSEMOUNT	Dummy variable equals 1 if home is located in Rosemount school district, otherwise 0	Positive
ROSEVILLE	Dummy variable equals 1 if home is located in Roseville school district, otherwise 0	Positive
SIMLEY	Dummy variable equals 1 if home is located in Simley school district, otherwise 0	Positive
WSTPAUL	Dummy variable equals 1 if home is located in West St. Paul school district, otherwise 0	Positive
WHITE_BEAR	Dummy variable equals 1 if home is located in White Bear Lake school district, otherwise 0	Positive
Sale month variables (reference month is February)		
JAN	Sale month dummy variable (1 if January, otherwise 0)	Positive
MAR	Sale month dummy variable (1 if March, otherwise 0)	Positive
APR	Sale month dummy variable (1 if April, otherwise 0)	Positive
MAY	Sale month dummy variable (1 if May, otherwise 0)	Positive
JUNE	Sale month dummy variable (1 if June, otherwise 0)	Positive
JULY	Sale month dummy variable (1 if July, otherwise 0)	Positive
AUG	Sale month dummy variable (1 if August, otherwise 0)	Positive
SEPT	Sale month dummy variable (1 if September, otherwise 0)	Positive
OCT	Sale month dummy variable (1 if October, otherwise 0)	Positive
NOV	Sale month dummy variable (1 if November, otherwise 0)	Positive
DEC	Sale month dummy variable (1 if December, otherwise 0)	Positive

[a] For distance variables, a negative coefficient indicates that, as the distance between a home and a given feature decreases, home sale prices increase.

3.2. Hedonic property price model

Hedonic property price models are widely used to estimate the contribution of different attributes (structural, neighborhood, and environmental characteristics) to the value of a property as measured by its sale price or assessed value (Freeman, 2003). Hedonic property price models can be used to estimate the marginal implicit price of an attribute, the change in the amount an individual would be willing-to-pay for a small change in an attribute, holding all other attributes constant. In this paper, we use a hedonic property price model to estimate the marginal implicit prices of various structural, neighborhood, and environmental attributes, including tree cover. We use ordinary least squares (OLS) regression and spatial simultaneous autoregressive (SAR) error modeling. The OLS hedonic pricing model can be written as follows:

$$\ln P_i = \beta_0 + \beta_1 S_i + \beta_2 N_i + \beta_3 Q_i + \varepsilon_i \quad (1)$$

where the dependent variable, $\ln P_i$, represents natural log of the sale price of property i; S_i is a vector of parcel and structural characteristics for property i (e.g., finished square feet, home age, lot acreage); N_i is a vector of neighborhood characteristics for property i (e.g., distance to shopping centers, school quality); Q_i is a vector of environmental characteristics for property i (e.g., proximity to lakes, percent tree

Table 3
Descriptive statistics for variables.

	Mean	Std. deviation	Minimum	Maximum
PRICE (2005 US$)	287,636.65	137,852.92	65,000	2,870,250
ACRES	0.34	0.86	0.04	43.31
FINSQFT	1811.21	836.19	440	11,471
HOME_AGE	41.49	31.50	0	153
TAX_RATE (%)	0.95	0.23	0.03	4.32
ELEV_FT	925.55	60.89	686	1151
BUSYRD (m)	184.09	182.42	0	2678
CBD (m)	13,774.42	10,781.58	0	42,935
SHOP (m)	1847.30	1555.88	10	16,594
COLLEGE (m)	8974.76	7654.66	20	39,592
MEAN_MCA	1539.86	62.41	1372.67	1652.67
IMPERVIOUS (%)	32.75	19.51	0	100
LAKE (m)	917.19	771.14	0	9305
LGPKRD (m)	711.91	863.79	0	13,643.82
TRAILEUC (m)	442.50	805.405	0	14,095.82
VIEW_AREA (ha)	24.16	25.66	0	246.58
TREE_PARC (%)	15.44	22.10	0	93.00
TREE_100 (%)	14.55	15.70	0	90.00
TREE_250 (%)	14.67	15.84	0	88.57
TREE_500 (%)	14.81	16.18	0	90.00
TREE_750 (%)	15.02	16.17	0	89.29
TREE_1000 (%)	15.44	16.20	0	100.00

$n = 9992$.

cover); and ε_i is an error term for property i. We used natural logs for proximity variables, lot acreage, and home finished square footage as we expect the effect of these variables to decline as their values increase. For these variables, this specification assumes that elasticity is constant.

Estimation of the hedonic pricing model may be complicated by heteroskedasticity and spatial autocorrelation. We tested for heteroskedasticity using a Breusch–Pagan test. We used Moran's I to check for spatial autocorrelation in the OLS residuals. We found that the test statistic was statistically significant indicating the presence of spatial autocorrelation. In accordance with standard procedure, we then used Lagrange multiplier tests to assess the particular forms of spatial autocorrelation present (i.e., in the error term, lag term, or both) followed by robust Lagrange multiplier tests to identify which form or forms were significant sources of spatial autocorrelation. As our analysis showed that the error process, but not the lag process, was statistically significant, we then calculated an appropriate simultaneous autoregressive (SAR) model to address this spatial autocorrelation.

SAR models are used to address spatial autocorrelation in data by augmenting OLS regression models with additional terms to represent the spatial structure of autocorrelation. These models assume that the value of the dependent variable at each location is a function of both the explanatory variables at each location and the value of the dependent variable at nearby locations (Cressie, 1993; Haining, 2003; Kissling and Carl, 2008). Three types of SAR models exist: lag models where spatial autocorrelation occurs in the response variable (inherent spatial autocorrelation), error models where spatial autocorrelation occurs in the error term (induced spatial dependence), and mixed models where spatial autocorrelation impacts both the response and error terms (Cliff and Ord, 1981; Anselin, 1988; Haining, 2003; Kissling and Carl, 2008). As tests (see above) indicated that the spatial autocorrelation present in our residuals was better explained by assuming spatial autocorrelation in the error term, that is, spatial autocorrelation caused by a spatially correlated omitted variable, than by assuming a spatial lag in which a functional relationship exists among nearby properties, or by assuming autocorrelation in both the lag and error terms, we account for spatial autocorrelation using a SAR error model and estimate this model using maximum likelihood estimation (MLE; see Cressie, 1993 and Anselin and Bera, 1998 for a full description of this modeling approach). We then calculate White's standard errors (White, 1980) using a method designed for use with SAR error models to adjust for heteroskedasticity (R. Bivand, *personal communication*).

The SAR error model we estimate includes an additional term not present in Eq. (1) to represent the spatial structure of the spatially-dependent error term. This modified expression may be written:

$$P = X\beta + \lambda Wu + \varepsilon \tag{2}$$

where P is a vector of the natural logs of sale prices for $i = 1, 2, \ldots, n$ properties in the study, X is the matrix of structural, neighborhood and environmental variables for the n properties, β is a vector that represents the slopes of the explanatory variables in X, λ represents the spatial autoregression coefficient, W represents an $n \times n$ spatial weights matrix used in estimating the model (see Anselin and Bera, 1998; Fortin and Dale, 2005 for a discussion of methods for specifying weight matrices), u is the spatially-dependent error term, and ε is a vector of *iid* error terms.

3.3. Data

We assembled a dataset with a series of structural, neighborhood, and environmental variables for each property in the dataset using GIS techniques. These variables are summarized in Table 2 and descriptive statistics for them are given in Table 3. Data on sale price and most structural variables originated in the Metropolitan Twin Cities Parcel Dataset. This dataset is available from the Twin Cities Metropolitan Council and includes spatially-referenced information related to property ownership, taxation, and use for all parcels in the seven county Twin Cities metropolitan area. From this dataset, we identified 9992 single family, residential properties that sold in the year 2005 in Ramsey and Dakota Counties and that had valid, complete data for all fields of interest. We excluded parcels in the cities of Randolph and Cannon Falls in extreme southern Dakota County from this dataset as preliminary analyses indicated that these were more rural and part of a different housing market.

Using a geographic information system (GIS), we assembled information for each property related to its sale, structural, neighborhood, and environmental attributes (Tables 2 and 3). We chose to use sale prices rather than assessed values because sale prices are actual market values and are generally thought to be a more accurate data series to use in hedonic analysis (Freeman, 2003). Home sale prices in our sample ranged from $65,000 to $2,870,250, with a mean sale price of $287,637.

Structural variables in our study include lot size, finished square footage, age, elevation and tax rate for each home. Because we believed that the effect of age on home sale prices would change with age, we also include a squared term for home age. We also calculated a dummy variable to indicate the month in which the sale of each property occurred as sale month influences sale price in the Twin Cities area. Elevation of the home's lot in feet was calculated in a GIS using a digital elevation model (DEM) for the region obtained from the Twin Cities Metropolitan Council. All of these variables have been found to significantly impact home sale prices in previous studies (Doss and Taff, 1996; Anderson and West, 2006; Sander and Polasky, 2009). The parcels database did not contain other structural variables often used in hedonic studies, such as number of rooms, number of bathrooms, and features of the house (presence of fireplaces, hardwood floors, etc.), which prevented us from including such variables in the analysis.

We used GIS techniques to estimate neighborhood variables using data from several sources. Because neighborhood school quality may influence home sale prices, we calculated a mean Minnesota Comprehensive Assessment (MCA-II, a standardized test across multiple subjects) test score for each home's neighborhood schools using third, fifth, and seventh grade MCA-II scores for each school available from the Minnesota Department of Education (http://

education.state.mn.us/MDE/Data/index.html). Proximity to amenities and undesirable areas may also influence home sale prices, so we calculated four additional variables to identify the distance from each property to each amenity or disamenity. We calculated proximity to the closest four-year college or university and to the closest shopping center using a dataset produced by the Lawrence Group and available from the Twin Cities Metropolitan Council. We calculated distances to high traffic volume roads based on a functional class roads dataset from the Metropolitan Council and The Lawrence Group and distance to the central business districts of Minneapolis and St. Paul based on a Twin Cities Metro Transit downtown fare zones GIS dataset, also available from the Metropolitan Council. Based on the results of a previous study conducted in the region (Sander and Polasky, 2009), we believed that proximity to four-year universities and colleges would have a positive effect on home sale price (so that increasing distance would have a negative effect), while proximity to busy roads would have a negative relationship to home sale price (so that increased distance would have a positive effect). Distance to shopping centers and to central business districts of Minneapolis and St. Paul could have either sign. Being closer to work or shopping is more convenient and so might increase home prices while at the same time shopping centers and the downtown area are also associated with more crowded conditions, noise, pollution and other possible disamenities that might decrease home prices. We also calculated the mean percent impervious cover within 500 m of each sample parcel using a dataset available from the University of Minnesota's Remote Sensing and Geospatial Analysis Laboratory to identify neighborhood development intensity. We believed that this variable would be negatively related to sale price.

We divided the housing market in the two counties into a series of submarkets and assigned dummy variables to account for the impacts of different submarkets on home sale prices. We examined a number of methods for identifying housing submarkets, including using zip codes, city boundaries, and elementary, middle, and high school districts. We compared housing markets identified using each of these definitions on the basis of the weighted mean squared errors (MSEs) for hedonic price equations calculated using them. We found that housing submarkets defined using high school districts produced the lowest MSEs of all housing submarket classifications examined and thus use high school districts to define housing submarkets in the two counties. As a result, we identified a total of twenty-three market segments, twelve in Ramsey County and eleven in Dakota County.

Natural areas, trails, and lakes have previously been found to impact property values in the study area (Doss and Taff, 1996; Anderson and West, 2006; Krizek, 2006; Sander and Polasky, 2009). To account for these impacts, we calculated distances from sample properties to each of these features. We calculated Euclidean distances to lakes using datasets available from the Twin Cities Metropolitan Council and to trails using two GIS datasets, Metropolitan Council Regional and State Trails and a bikeways dataset from the Minnesota Department of Transportation. We screened these datasets to remove planned and proposed trails as these trails are tentative as well as trails that used city streets. We calculated proximity to large natural area parks, including recreational parks, wildlife refuges, nature reserves, and wildlife management areas with areas of 1 ha or greater as indicated by two datasets, the Lawrence Group Landmarks and Twin Cities Metropolitan Council Regional Recreation Open Space Features, both available from the Twin Cities Metropolitan Council. We calculated Euclidean distances to lakes and trails because these features generally have numerous access points and road distances to parks since these features typically have discrete access points that intersect roadways (Sander and Polasky, 2009).

The scenic quality of the landscape around a home may also impact property values (Sander and Polasky, 2009). To account for this, we included an additional variable, view area, to identify the areal extent of the view from each property. We calculated this variable using the viewshed function in ArcGIS 9.2 and a DEM that included natural topography and buildings, a GIS dataset containing Ramsey County building footprints available from the Ramsey County Surveyor's Office, and a GIS planimetric dataset for Dakota County available from the Dakota County Office of Geographic Information Systems. We calculated viewsheds for each property in the sample and calculated the area of the identified viewshed for each property. For a detailed description of the techniques used in calculating viewsheds, see Sander and Polasky (2009) and Sander and Manson (2007).

We used the National Land Cover Database (NLCD) 2001 to identify tree coverage for the study area. The NLCD 2001 includes three datasets generated using remotely-sensed imagery for the extent of the United States: land cover, impervious surface, and tree canopy (Homer et al., 2004). For our analysis, we used only the tree canopy dataset. This 30-m raster dataset depicts the percent canopy cover in each pixel in the study region estimated from Landsat Thematic Mapper imagery using regression tree techniques (for a detailed description of the creation of this dataset, see Huang et al., 2003). These data have been found to have a mean absolute error of 14.1% and a correlation coefficient between actual and predicted values of 0.78 for the study area's mapping zone (Homer et al., 2004). Although there is a temporal mismatch of four years between this dataset and our sale data, the NLCD tree canopy dataset is the only comprehensive tree canopy cover dataset for the study area and provides the most accurate assessment of the region's tree cover available. We considered using sale data from 2001 but found that the Metropolitan Twin Cities Parcel Dataset was largely incomplete for the study area until 2005. Additionally, tree cover in much of the study area is fairly stable and changes relatively little from year to year. The temporal mismatch between the sale price and tree cover data will introduce some additional measurement error into the analysis. We do not have reason to believe, however, that either the underlying measurement error or temporal mismatch will introduce systematic errors in the data. Using this dataset, we calculated mean tree cover for each parcel and, to identify the sphere of influence for neighborhood tree cover on parcels, for buffers around each parcel with radii of 0–100 m, 100–250 m, 250–500 m, 500–750 m and 750–1000 m. We expected tree cover to be positively related to home sale prices on the parcel and in each neighborhood radius.

Measurement error in the tree cover variables will tend to cause a downward bias in the estimated coefficient of tree cover variables in regression analysis. Measurement error, therefore, will make it harder to observe a statistically significant effect of tree cover on property values. The downward bias from measurement error should be strongest for the effect of tree cover on the parcel itself as most parcels are contained within a small number of pixels. The effect of measurement error should decline rapidly as the buffer expands as there are approximately 40 pixels in the 0–100 m buffer, over 200 pixels in the 100–250 m buffer, over 800 pixels in the 250–500 m buffer, and over 1000 pixels in the remaining buffers.

4. Results

We estimated two hedonic property price models. Model 1 included all variables described in the previous section. Model 2 also included squared terms for all tree cover variables. Inclusion of squared terms allows the relationship between tree cover and property value to vary with levels of tree cover.

We first ran each model using OLS regression. Even though the fit for these models was high, with adjusted R^2 values of 0.8073 and 0.8078, for Models 1 and 2 respectively, we were concerned about the presence of spatial autocorrelation and heteroskedasticity in the data. We calculated Moran's I statistic to quantify the degree of spatial autocorrelation in our data using distance-based 2500 m weights. The calculated Moran's I statistic for both models was significant at the 0.001 level providing evidence of spatial autocorrelation in the data. We calculated Lagrangian multiplier diagnostics for our residuals to identify the nature of this spatial autocorrelation. Our results

Table 4
SAR error model results with heteroskedasticity-consistent standard errors.

Variable	Model 1 (2500 m)				Model 2 (2500 m)			
	Coefficient	White's std. error	*t*-value		Coefficient	White's std. error	*t*-value	
Structural variables								
(Intercept)	7.960800	0.149000	53.428	***	7.968100	0.149010	53.47	***
LN_ACRES	0.132090	0.004376	30.187	***	0.131250	0.004378	29.98	***
LN_FINSQFT	0.522250	0.005926	88.126	***	0.522900	0.005926	88.24	***
HOME_AGE	−0.007209	0.000246	−29.337	***	−0.007183	0.000246	−29.21	***
HOME_AGE_SQ	0.000041	0.000002	20.664	***	0.000041	0.000002	20.60	***
TAX_RATE	−0.123310	0.008329	−14.804	***	−0.122600	0.008345	−14.69	***
ELEV_FT	0.000330	0.000055	6.0096	***	0.000324	0.000055	5.89	***
Neighborhood variables								
LN_BUSYRD	0.001558	0.000659	2.3638	*	0.001495	0.000659	2.27	*
LN_CBD	0.001831	0.000607	3.0177	**	0.001836	0.000606	3.03	**
LN_SHOP	0.006832	0.003635	1.8794		0.006738	0.003638	1.85	
LN_COLLEGE	−0.050212	0.006359	−7.8958	***	−0.050394	0.006354	−7.93	***
MEAN_MCA	0.000532	0.000061	8.6627	***	0.000525	0.000061	8.55	***
IMPERVIOUS	−0.000564	0.000113	−4.9732	***	−0.000569	0.000114	−5.00	***
Environmental variables								
LN_LAKE	−0.004674	0.000514	−9.0909	***	−0.004676	0.000515	−9.08	***
LN_LGPKRD	−0.000300	0.000227	−1.3232		−0.000311	0.000227	−1.37	
LN_TRAIL	−0.000765	0.000666	−1.1472		−0.000763	0.000666	−1.15	
VIEW_AREA	0.000742	0.000079	9.3873	***	0.000741	0.000079	9.38	***
Tree cover variables								
TREE _PARCEL	0.000165	0.000091	1.8056		−0.000731	0.000224	−3.26	**
TREE_100	0.000477	0.000150	3.1782	**	0.001056	0.000324	3.26	**
TREE_250	0.000291	0.000135	2.1484	*	0.000594	0.000306	1.99	*
TREE_500	−0.000038	0.000136	−0.2806		−0.000375	0.000300	−1.25	
TREE_750	0.000180	0.000129	1.3963		−0.000140	0.000290	−0.48	
TREE_1000	0.000006	0.000121	0.0464		0.000478	0.000280	1.71	
TREE_parcel2					0.000016	0.000004	4.37	***
TREE_100_2					−0.000012	0.000005	−2.32	*
TREE_250_2					−0.000005	0.000005	−1.14	
TREE_500_2					0.000006	0.000004	1.24	
TREE_750_2					0.000005	0.000004	1.19	
TREE_1k_2					−0.000008	0.000004	−1.84	
Submarkets (reference location is South St. Paul)								
APPLEVALLEY	0.122480	0.048479	2.5265	*	0.124970	0.048456	2.58	**
BURNSVILLE	0.068981	0.047131	1.4636		0.068646	0.047113	1.46	
CENTRAL	0.601000	0.048141	12.484	***	0.603600	0.048133	12.54	***
COMO_ARL	0.651700	0.052989	12.299	***	0.655380	0.052996	12.37	***
EAGAN	0.092995	0.046037	2.02	*	0.097503	0.046008	2.12	*
EASTVIEW	0.091950	0.046107	1.9943	*	0.093249	0.046080	2.02	*
FARMINGTON	0.121950	0.051978	2.3461	*	0.124450	0.051961	2.40	*
HARDING	0.527910	0.061668	8.5606	***	0.530890	0.061739	8.60	***
HASTINGS	0.181040	0.101880	1.777		0.183430	0.101860	1.80	
HIGHLANDPK	0.437890	0.048234	9.0785	***	0.440930	0.048205	9.15	***
HUMBOLDT	0.145210	0.041083	3.5345	***	0.146490	0.041059	3.57	***
JOHNSON	0.582760	0.058961	9.8839	***	0.585940	0.058997	9.93	***
LAKEVILLE	0.126120	0.050486	2.4982	*	0.128140	0.050464	2.54	*
MOUNDSVIEW	0.448130	0.063491	7.0582	***	0.453250	0.063540	7.13	***
NSTPAUL	0.491060	0.061092	8.038	***	0.496000	0.061149	8.11	***
WHITE_BEAR	0.409720	0.063960	6.4059	***	0.414560	0.063994	6.48	***
ROSEMOUNT	0.077320	0.047319	1.634		0.079598	0.047302	1.68	
ROSEVILLE	0.467510	0.056886	8.2184	***	0.470770	0.056935	8.27	***
SIMLEY	−0.131210	0.030025	−4.3702	***	−0.131710	0.030007	−4.39	***
STANT_IRONDL	0.379760	0.070625	7.3034	***	0.383230	0.070658	5.42	***
TARTAN	0.473240	0.064798	0.9571	***	0.477280	0.064898	7.35	***
WSTPAUL	0.035443	0.037030	5.3772		0.038680	0.037022	1.04	
Month of sale (reference month is February)								
JAN	0.028921	0.009420	3.0701	**	0.029185	0.009413	3.10	**
MAR	0.022638	0.009095	2.4889	*	0.022839	0.009088	2.51	*
APR	0.032279	0.008935	3.6126	***	0.033112	0.008931	3.71	***
MAY	0.041470	0.008670	4.783	***	0.042463	0.008665	4.90	***
JUNE	0.050296	0.008420	5.9735	***	0.050932	0.008413	6.05	***
JULY	0.056588	0.008605	6.5762	***	0.057695	0.008603	6.71	***
AUG	0.058387	0.008505	6.865	***	0.058919	0.008501	6.93	***
SEPT	0.062647	0.008759	7.1522	***	0.063125	0.008753	7.21	***
OCT	0.054718	0.009118	6.0015	***	0.055801	0.009114	6.12	***
NOV	0.043627	0.009292	4.6953	***	0.044273	0.009286	4.77	***
DEC	0.032482	0.009628	3.3738	***	0.033342	0.009622	3.47	***

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05

(continued on next page)

Table 4 (*continued*)

dep. var	LN_PRICE		LN_PRICE	
adj R2 (OLS)	0.807300		0.807800	
lambda	0.977950		0.978060	
LR test value	1028.000000	***	1024.800000	***
Log liklihood	4325.033000		4339.092000	
AIC (OLS)	−7508.100000		−7527.400000	
AIC (SAR)	−8534.100000		−8550.200000	
Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05				

indicated that both error and lag processes were present in each model, but robust tests indicated that only the error process was significant in these models ($p<0.001$) and that the lag process was not significant in either ($p>0.05$). As such, we corrected for the error process by calculating SAR error models using MLE. The SAR model fit was an improvement over the OLS fit for each model as evidenced by reduced AICs of −8534.1 versus −7508.1 in Model 1 and −8550.2 versus −7527.4 in Model 2. The estimated value of λ is high for both models, 0.97795 for Model 1 and 0.97806 for Model 2, and the *p*-values of the likelihood ratio tests, which compare the OLS model assuming no spatial autocorrelation to the fitted model with the estimated autocorrelation parameter, are significant ($p<0.001$), indicating that significant spatial autocorrelation, which was present in the OLS model, is sufficiently addressed in the SAR model. We then calculated a Breusch–Pagan test statistic for each model. These statistics were significant at the 0.001 level, indicating the presence of heteroskedasticity. To address this issue we calculated heteroskedasticity-corrected standard errors for the SAR model following White's method (R.Bivand, *personal communication*). The results of the estimation of the SAR error models with heteroskedasticity-corrected standard errors are presented in Table 4.

Coefficients for structural variables were significant and of the expected sign in both models. Increases in lot size, finished square feet, and elevation were associated with higher home sale price and increases in tax rates were associated with lower home sale price. Increases in home age were associated with lower sale prices to approximately 88 years of age and thereafter were associated with higher sale prices. Sale prices were lowest in February, the excluded category, as shown by positive dummy variables for all other months. Dummy variables for all school districts were positive, except for the Simley district, indicating higher sale prices in districts relative to South St. Paul (the excluded category), and most were statistically significant.

All coefficients for neighborhood variables in both models were of the expected sign and statistically significant. Higher neighborhood education testing scores, proximity to a four-year college or university, and greater distance from a busy road and central business districts of Minneapolis and St. Paul were all associated with higher home sale prices. Increasing distance to shopping centers was associated with higher home sale prices but this relationship was not statistically significant. The mean percent impervious surface in a 500 m neighborhood surrounding each home was negatively related to home sale prices.

In both models, all signs for the coefficients of environmental variables (exclusive of tree cover variables) were of the expected sign, but not all of these variables were statistically significant. Proximity to lakes significantly increases home sale prices in the study area, but proximity to trails and large parks does not. Additionally, properties with larger view areal extents have higher home sale prices than comparable properties with smaller view extents.

In Model 1, tree cover within a buffer of 250 m of a home increased home sale price, but tree cover further away did not. The coefficients for tree cover in the 100 m and 250 m buffers around parcels were positive and statistically significant. Evaluated at the mean home sale price of $287,637 and mean tree cover of 14.55%, the marginal implicit price of a 10 percentage point increase in tree cover within the 100 m buffer (e.g., increasing tree cover from 14.55% to 24.55%) was $1371 or a 0.477% price increase.[1] The marginal implicit price of a 10 percentage point increase in tree cover within the 250 m buffer was $836, or about 0.291% for the mean home. The coefficient for tree cover on the parcel level itself was positive, but was not statistically significant at the 5% level. However, the coefficient was statistically significant at the 10% level. It might be the case that the coefficient would be statistically significant at 5% without measurement error that causes a downward bias in the estimated coefficient. While the percentage of tree cover within the 500 m buffer was negatively related to sale price, the coefficient was quite small and not statistically significant ($p=0.7790$). The coefficients for tree cover in the 750 m and 1000 m neighborhood areas were both positive, but neither coefficient was statistically significant. These results indicate that the owners of single family residences will pay more for homes with higher levels of tree cover in the local neighborhood of their property (i.e., within 250 m). However, they provide much less evidence that owners of single family residences will pay more for homes with higher tree cover on their own lot or in neighborhoods with high tree cover beyond 250 m from their parcels.

In Model 2, which included squared terms for all tree cover variables in addition to all variables included in Model 1, the coefficient for parcel level tree cover on the property was negative and statistically significant while the coefficient for its squared term was positive and statistically significant. According to these estimates, increasing levels of parcel level tree cover were related to decreased home sale prices up to approximately to 23% tree cover and thereafter to increased home sale prices. The coefficient for tree cover in the 100 m neighborhood was positive while the coefficient for the squared term was negative, with both coefficients being statistically significant. Thus, increasing tree cover within a 100 m buffer increased home sale price up to 44% tree cover and thereafter led to decreasing sale price. The coefficient for the percentage of tree cover within the 250 m buffer was positive and statistically significant while the squared term was negative, but not statistically significant. Using the estimated coefficient values, increasing tree cover within the 250 buffer is related to increasing home sale price up to approximately 60% tree cover and decreasing price thereafter. As in Model 1, coefficients on tree cover beyond 250 m are not statistically significant.

5. Discussion and conclusions

The results of this study provide insights into how people value urban trees. Our results show that local tree cover is valued by the purchasers of residential single family properties in urban areas. Specifically, these results indicate that higher percentages of tree cover within 100 m and 250 m radii of a parcel increase home sale price. In Model 1, the marginal implicit price of a 10 percentage point

[1] The marginal implicit price for percent tree cover is ∂ sale price/∂ percent tree cover. Because the dependent variable in the regression is the natural log of sale price, the marginal implicit price is calculated as the sale price times the percent tree cover coefficient. For example, to calculate the marginal implicit price of tree cover within 100 m, we multiply its coefficient, 0.000477, by the mean home sale price, $287, 637, which generates a marginal implicit price of $137.08. To estimate the impact of a 10% change in tree cover, multiply the marginal implicit value by ten to get a value of $1370.84.

increase in tree cover within the 100 m buffer evaluated for the mean house value is $1371, and the equivalent figure for the 250 m buffer is $836. In Model 2, which included squared terms, increasing tree cover increases home sale value up to 44% tree cover in the 100 m buffer and 60% in the 250 m buffer. Tree cover on the parcel itself is positively related to home sale price in Model 1, but the effect is not statistically significant, though it is possible that without measurement error a statistically significant effect would be detected. In Model 2, increases in parcel level tree cover are initially negatively related to home sale price and only become positively related after tree cover reaches above 20%. Coefficients on tree cover beyond 250 m are generally small and not statistically significant. In sum, home owners value trees in their local neighborhoods, at distances that roughly correspond to the length of a city block. This value may reflect a preference for tree-lined streets and the shading and aesthetic environment they offer. Home owners appear to place less value on tree cover beyond their immediate local neighborhood and on tree cover over 40% in their immediate local neighborhood.

Our overall findings of a positive relationship between tree cover in local neighborhoods and home sale prices agree with the findings of previous studies (e.g., Garrod and Willis, 1992; Holmes et al., 2006). Our results, however, disagree with some of the specific results on the distance over which a positive relationship exists. For example, Holmes et al. (2006) found that, in Sparta, N.J., USA, tree cover within 100 m of properties did not significantly impact home sale prices, but that tree cover at greater distances (500 m and 1000 m) did. Our results also do not match with other previous studies which found that tree cover at the parcel level significantly positively impacted home sale prices (Morales et al., 1976; Morales, 1980; Anderson and Cordell, 1988; Dombrow et al., 2000; Mansfield et al., 2005). These studies, however, did not examine tree cover beyond the extent of the parcel. Since tree cover is spatially correlated (e.g., parcels with greater tree cover are likely to be in neighborhoods with greater tree cover), controlling for neighborhood tree cover more accurately may reduce the value of own parcel tree cover.

The present study dealt with both spatial autocorrelation and neighborhood effects, factors that have been ignored by most other prior analyses. Additionally, other environmental factors such as development intensity, access to natural areas, and view quality were included in this analysis and were not in many previous analyses. The inclusion of these additional relevant variables will likely increase the accuracy of estimates of the value of urban tree cover.

Due to limits in data availability, this study did not estimate the value of individual trees, trees of different sizes, or of different species of trees and thus cannot address the impact of canopy composition on home sale prices. As more detailed data related to urban forest stocks become available over the coming years, it would be well-worth repeating this type of study to investigate the value of specific tree species and forest conditions in more detail.

09It should be stressed that the values calculated using the hedonic property price model are only partial estimates of the value of urban tree cover because they capture only the portion of value that accrues to the owners of single family residential properties. As such, they are likely to include largely aesthetic and cultural values of trees and omit many of the other benefits provided by urban trees. Carbon sequestration, air pollution reduction, reductions in peak stormwater runoff, and wildlife habitat provision, benefits accrue to the wider public, are unlikely to be adequately measured using the hedonic property price approach. Thus, the total economic value of urban forests may be substantially larger than indicated by these results.

These results provide incentives for communities to preserve or augment their urban tree stocks. Urban tree cover provides positive externalities. In total, our results indicate that home owners would benefit if their neighbors planted more trees even though each individual property owner would not have an incentive to do so on their own. Thus, municipal governments may play a role in promoting tree planting as a way to overcome the externalities that prevent optimal tree cover. Zoning restrictions or incentives to plant trees on privately-owned single family parcels would help to overcome the inadequate incentive of individual home owners to plant trees. Consideration of even the partial value of tree cover measured here, with recognition that it serves as a minimum estimate of the value of urban tree cover, may provide an incentive for improved tree cover that would enhance social, economic, and environmental conditions in urban environments.

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