Journal of Environmental Management 396 (2025) 128051

Contents lists available at ScienceDirect

Journal of Environmental Management

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

Research article

Homeowners' willingness to pay for changes in urban tree canopy cover in the United States

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ARTICLE INFO

Keywords:
Benefit-cost analysis
Benefit transfers
Ecosystem services
Hedonic valuation
Meta-analysis
Revealed preference
Urban forestry

ABSTRACT

Homeowners' willingness to pay for urban forest benefits can be inferred from hedonic property value studies, which use real estate transactions to estimate the elasticity between home value and tree canopy cover (i.e., the % change in home value for a 1 % change in tree cover). We compiled a meta-dataset of 17 hedonic studies to predict this elasticity for 64,658 urban census tracts across the contiguous United States. Three benefit transfer methods were evaluated: matching value transfer using a nearest-neighbor technique, unit value transfer using weighted mean elasticities, and function transfer using a meta-regression model. The matching method produced the lowest out-of-sample transfer errors and best reproduced the observed distribution of elasticities. Using the matching method, we estimated that home values increase $9-$134 per home (2020 USD) for a 1 % increase in urban tree cover. Using projected changes in urban tree cover from 2020 to 2030, which are largely negative, we estimated regional home value losses ranging from $1.7 to $4.8 billion, with a total national loss of $11.8 billion. These results highlight the significant economic value of maintaining and expanding urban tree canopy cover in U.S. cities.

1. Introduction

Urban land comprised 3.6 % percent of the contiguous United States (U.S.) (27.4 million ha) in 2010 and was home to over 80 % of the U.S. population (Nowak and Greenfield, 2018a). Urban forests continue to provide substantial benefits to those residents (Nowak and Greenfield, 2018a; Pataki et al., 2021). Urban forests improve human thermal comfort through cooling and humidifying urban air and through shading (Wang et al., 2018; Ziter et al., 2019). Urban forests reduce stormwater runoff from impervious surfaces through canopy interception of rainfall and subsequent evaporation (Asadian and Weiler, 2009; Howard et al., 2022). Urban forests and green spaces are positively associated with measures of mental and physical health and negatively associated with mortality, short-term cardiovascular markers (heart rate), and violence (Kondo et al., 2018; Wolf et al., 2020).

Estimates of homeowners' willingness to pay for these benefits help decision makers estimate the economic benefits of proposals for protecting or expanding urban forests (Sander et al., 2010). A common way to estimate homeowners' willingness to pay for environmental benefits is the hedonic property value method (e.g., Sander et al., 2010). Hedonic models use real estate transactions to estimate elasticities between home value and environmental attributes (i.e., how much home value changes for a small change in an attribute) (Freeman, 2003). For neighborhood tree cover, the elasticity is the % change in the amount a buyer would be willing to pay for a home given a 1 % change in tree cover. All the homeowners' use values associated with urban tree cover are captured by the elasticity obtained with the hedonic model.

While hedonic studies of home value and tree cover have been conducted in over 20 U.S. cities (Siriwardena et al., 2016; Kovacs et al., 2022), most U.S. urban areas lack original studies. Rather than estimating a hedonic model for each urban area, which would be expensive and time consuming, elasticity predictions for areas where original studies are lacking can be made with benefit transfer tools. Benefit transfer is the use of pre-existing empirical estimates of economic value from one or more settings where research has been conducted to predict measures of economic value for other settings (Johnston et al., 2021). For example, Burlingame et al. (2024) provide step-by-step guidance on using benefit transfer methods to estimate how improvements in lake water clarity might affect home values in the surrounding community.

The primary goal of our study is to use benefit transfer tools to

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https://doi.org/10.1016/j.jenvman.2025.128051
Received 4 June 2025; Received in revised form 1 November 2025; Accepted 19 November 2025

predict the elasticity between home value and tree cover in each urban census tract in the contiguous U.S. Our study is the first to predict these elasticities nationally and to base those predictions on local housing market and forest conditions. A national prediction of elasticities is needed to support sound economic analysis of programs to address declining urban tree cover in the U.S. (Nowak and Greenfield, 2018b). Investment decisions for urban forestry are mostly made at the community level where planners weigh the net benefit of tree planting and care against the costs of no action, including the loss of property value as tree cover declines. These decisions are enhanced when estimates of benefits are based on local conditions. Our elasticity predictions would allow communities throughout the U.S. to quickly assess the added property value from incrementally increasing tree cover from current levels. At the national level, the USDA Forest Service Urban and Community Forestry Program (https://www.fs.usda.gov/managing-land/urban-forests/ucf) allocates millions of federal dollars annually to state and community forestry programs. A national prediction of elasticities informs decision makers about the relative benefits of protecting and expanding tree cover across regions and helps them prioritize investments.

A major contribution of our study is the use of a relatively new method for benefit transfer called statistical matching (D'Alberto et al., 2021). Matching methods were developed by economists to estimate the effect of a treatment, intervention, or policy (e.g., Caliendo and Kopeinig, 2008; Todd, 2010). The idea is to match each individual in a treated population with one or more similar individuals in an untreated population to estimate the treatment effect. In a forestry application, Moeltner et al. (2017) estimated the effect of forest pest damage on home values by comparing home values in the vicinity of pest damage with values of a matching set of homes far from the damage. In our application, we predict the elasticity between home value and tree cover in each urban census tract using elasticities that were estimated in hedonic studies in matching urban areas with similar housing market and forest attributes.

We also predict elasticities for urban census tracts using two commonly implemented methods of benefit transfer: unit value transfer and function transfer (Johnston et al., 2021). A unit value transfer uses a single study observation or a summary statistic (e.g., median or mean) of several study observations as the value estimate for transfer to a policy site. For example, McPherson et al. (2011) used a single observation of the increase in home value resulting from additional yard trees in Athens, Georgia, to estimate the increase in home value from a proposed urban tree planting program in Los Angeles, California. A weakness of this approach is that transferring a point estimate of a benefit value from one study site to an unrelated policy site ignores important differences in socioeconomic variables between the sites and may introduce error into valuation and decision making (Johnston et al., 2021). As a remedy, a function transfer uses study site information across sites with a range of attributes to develop a benefit function for predicting benefit values in policy sites (Loomis, 1992). Benefit functions can be derived from meta-regression analyses of the relationship between the benefit value and study site attributes from multiple prior valuation studies. For example, Siriwardena et al. (2016) and Kovacs et al. (2022) performed meta-analyses of hedonic property value studies in the U.S. and estimated benefit functions in which the value of a change in tree cover (the dependent variable) is related to tree cover and housing market characteristics (independent variables) of the study sites. Their models showed that the value of tree cover varies by region, largely increases with existing tree cover, and is positively related to population density. These results suggest that a unit value transfer of an observed elasticity from one region to another may not be accurate and emphasize the importance of accounting for the tree cover and housing market characteristics of the policy sites when making value transfers.

We compare the performance of the three benefit transfer methods—matching value transfer, unit value transfer, and function transfer—by analyzing out-of-sample transfer errors and comparing the predicted versus observed distributions of elasticities (e.g., D'Alberto et al., 2021; Guignet et al., 2022; Kovacs et al., 2022). We use the transfer method with the lowest median transfer error and the best reproduction of the observed distribution of elasticities to make predictions in the urban census tracts. Finally, our case studies use the predicted elasticities to estimate the economic benefits of local, regional, and national programs to protect urban tree cover from projected losses over the next decade. These case studies highlight the significant economic value of maintaining and expanding urban tree canopy cover in U.S. cities.

2. Methods

We use three different methods of benefit transfer to predict elasticities between home value and tree cover in urban census tracts of the U.S. Each of those methods uses observed elasticities from a set of study sites to make predictions of elasticities in the policy sites. First, we describe the meta-dataset of observed elasticities and study sites obtained from previously published hedonic studies, and we describe the policy sites. Next, we describe the three benefits transfer methods: a recently introduced matching value transfer method using the nearest-neighbor technique, a unit value transfer using mean elasticities, and a function transfer using a meta-regression model. Since our application of the matching method to ecosystem service valuation is relatively new, we describe the method in detail. The unit value and function transfer models were originally estimated by Kovacs et al. (2022). Next, we describe our procedure for evaluating the performance of the benefits transfer methods and selecting a method for making predictions. Finally, we describe the application of the selected benefits transfer method to predicting changes in home values as a function of tree cover changes in the policy sites.

2.1. Meta-dataset

Our applications of the three benefits transfer methods utilized the meta-dataset created by Kovacs et al. (2022), who assembled 157 observations of elasticities between home value and tree cover from 21 hedonic studies in U.S. cities and published between 2002 and 2019. We separated those observations into two distance bins based on proximity of the tree cover to homes: elasticities associated with on-property tree cover (59 observations from 12 studies) and elasticities associated with off-property tree cover within a mile from the home (98 observations from 17 studies). We used the 98 observations associated with off-property tree cover to implement the benefits transfer methods. Off-property tree cover includes trees growing in the vicinity of a home (i.e., trees growing along streets and on neighboring properties) as well as trees growing on the property and is a more comprehensive measure of tree cover in a community compared with tree cover only on the home's property. The majority (51 %) of the 98 observations were in western states, with 22 %, 15 % and 12 % in the Midwest, Northeast, and South, respectively (Fig. 1).

Because the hedonic models in the different studies used a range of functional forms (e.g. log-linear, double-log, linear, log-quadratic), Kovacs et al. (2022) transformed each model to obtain a formula for the elasticity, which is a consistent measure of the effect of tree cover on home value across studies. For example, many of the estimated hedonic models were loglinear, $\ln(p) = \mathbf{x}'\boldsymbol{\theta} + \beta TC$, where p is the real sale price, $\mathbf{x}$ is a vector of all variables other than tree cover, $\boldsymbol{\theta}$ is the vector of coefficients on $\mathbf{x}$. The key variable of interest is the tree cover (TC), and β is the coefficient on TC. The formula for the elasticity is $\partial p/\partial TC{*}TC/p =$

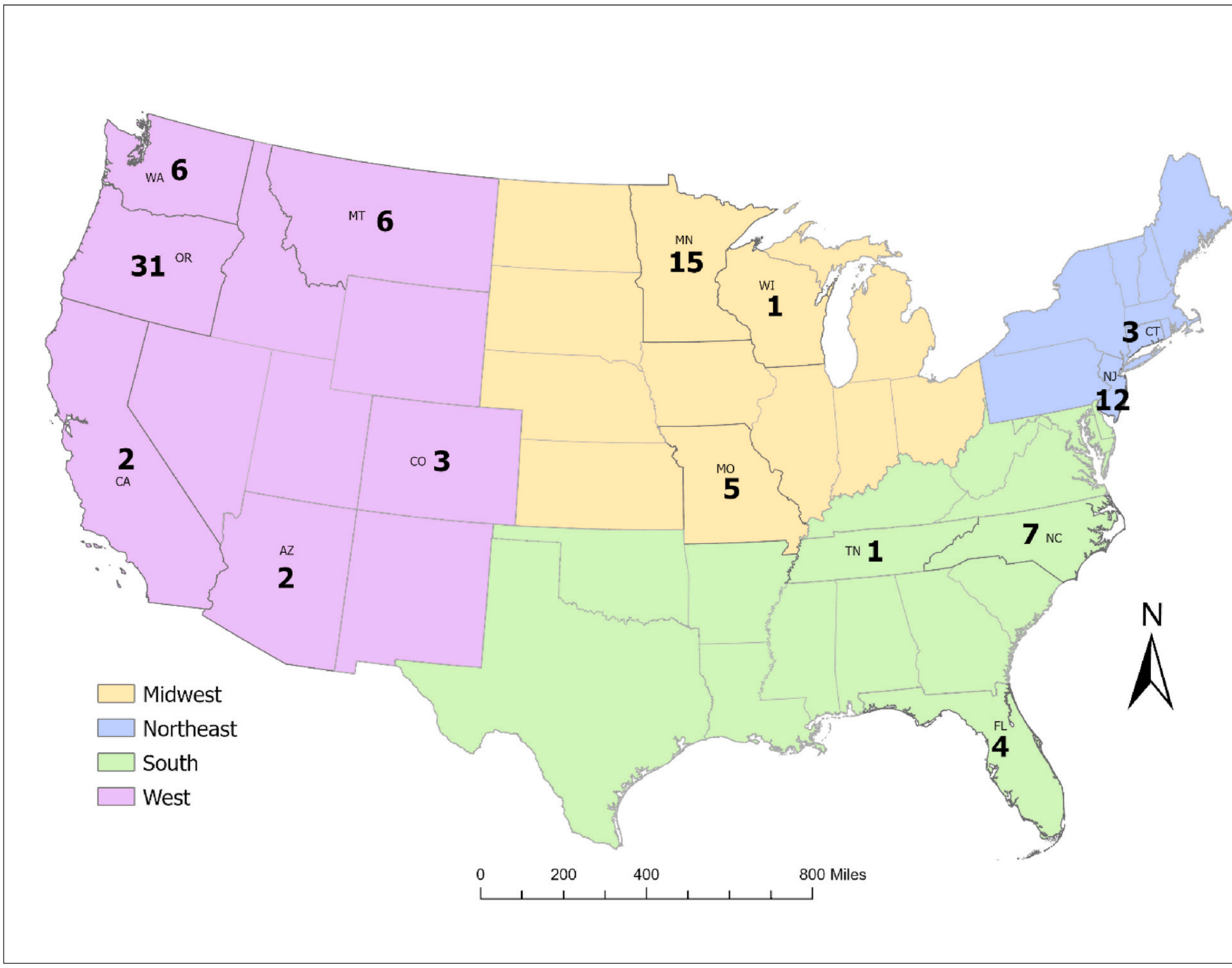

Fig. 1. Number of observations of elasticities between home value and tree cover by state and region in the U.S.

βTC.[1] As a result, the sample mean for TC is multiplied times its estimated coefficient β to generate the estimated elasticity. Similar derivations are used for other forms of the estimated hedonic equations (Kovacs et al., 2022).

The benefit transfer methods required measures of precision of the estimates of elasticities in the study sites to predict elasticities in the policy sites. Kovacs et al. (2022) used Monte Carlo simulation to estimate the standard errors of the elasticities in the study sites. The simulations used the coefficient estimates and their variances and sample means of relevant explanatory variables from the hedonic studies. The simulations take a hundred thousand random draws from the joint normal distribution of the relevant coefficients for each elasticity estimate. The mean and standard error of the elasticity is computed from the resulting empirical distribution. For example, suppose a hedonic study uses the loglinear form: $\ln(p) = \mathbf{x}'\boldsymbol{\theta} + \beta TC$, and the sample mean for TC is multiplied times its estimated coefficient β to generate the elasticity. Then, the coefficient estimate, β, its variance, and the sample mean of TC are used in the simulations to estimate the elasticity and its standard error.

We use boxplots to display the distributions of the 98 observed elasticities obtained from 17 primary hedonic studies across four regions (Fig. 2). Boxplots are nonparametric graphical devices that display the

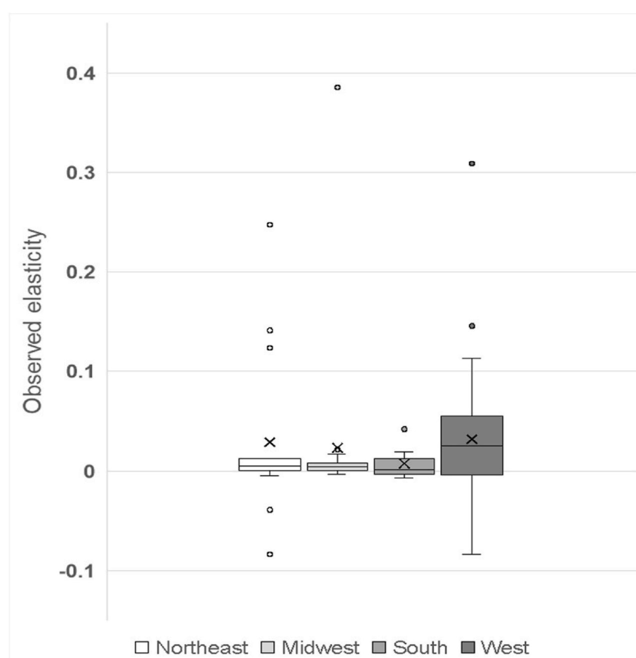

Fig. 2. Box plots of 98 observed elasticities across four regions of the U.S.

[1] The loglinear relationship between p and TC means $\partial\ln(p)/\partial TC = \beta$. We can also express $\partial\ln(p)/\partial TC$ as $[\partial\ln(p)/[\partial p]^*[\partial p/\partial TC]$. Using the fact $\partial\ln(p)/\partial p = 1/p$, we have the equality: $\partial\ln(p)/\partial TC = [1/p]^*[\partial p/\partial TC] = \beta$, which means $\partial p/\partial TC = p\beta$.

variation of a set of data without making assumptions of its underlying statistical distribution. Each boxplot depicts the median of the data (horizontal line within the box) as well as the first and third quartiles (lower and upper lines delimiting the box). The interquartile range (IQR) is the range of the middle half of the data (i.e., the difference between the first and third quartiles). The data above or below the first and third quartiles are further distinguished by their outlier status. Horizontal lines outside of the box represent values that are 1.5 times the IQR beyond the upper or lower quartiles, and data points above or below these lines are considered outliers. The boxplots have median elasticities that range from 0.001 to 0.025 across regions (Fig. 2). The observations are mostly positive and range from −0.083 to 0.386.

Each of the 98 observations of elasticities comes from a study site with a unique set of tree cover and housing market values. Statistics for the distributions of these tree cover and housing market variables across the 98 study sites are shown Table 1. The tree cover and housing market values of the study plots were used to estimate meta-regression models for elasticities in Kovacs et al. (2022), and they are used here in the matching methods for elasticity predictions.

Some of the primary hedonic studies found that the effect of tree cover on property value depended on the density of trees in the neighborhood (e.g., Netusil et al., 2010; Sander et al., 2010). To capture this density dependence, Kovacs et al. (2022) used three density classes to estimate elasticities of tree cover: low density (0–10 %), medium density (10–25 %), and high density (>25 %). Each of the 98 study sites was classified into one of those three density classes based on observed tree cover.

2.2. Policy sites

The policy sites in which we predict elasticities of home value and tree cover are urban census tracts. There are 70,923 census tracts in urban areas of the contiguous U.S. Census tracts are small, relatively permanent statistical subdivisions of a county with an average of about 4000 residents. An urban area is a densely settled core of census blocks (a smaller geography than a census tract) that meets minimum housing unit density and/or population density requirements. We obtained tree cover and housing market attributes of the urban census tracts from the 2021 National Land Cover Database and the 2017 to 2021 American Community Survey, respectively. Statistics for the distributions of these variables across the 70,923 census tracts are shown Table 1, for comparison with the statistics for the 98 study sites. Compared with the study sites, the census tracts have a slightly higher mean tree cover but significantly greater mean population density. Further, the distribution of population densities of the census tracts has a much longer right-hand tail, with a maximum of 819,000 people per square mile compared a maximum of 7880 people per square mile in the study sites. Since the hedonic property value studies in our meta-dataset took place in urban census tracts with less than 20,000 people per square mile, we removed 4416 census tracts with more than 20,000 people per square mile from the set of urban census tracts. Further, we removed an additional 1849 urban census tracts from the set because of missing tree cover and housing market values. We therefore predict elasticities between home value and tree cover in 64,658 of the 70,793 census tracts in urban areas of the U.S., and these 64,658 census tracts compose our set of policy sites.

2.3. Benefit transfer methods

Our descriptions of the three benefit transfer methods use some common notation. We use the letter S to denote the set of study sites, and ε_j^S represents the observed elasticity in study site j, where $j \in S$. We use P to denote the set of policy sites, and $\hat{\varepsilon}_i^P$ represents the predicted elasticity in policy site i, where $i \in P$. We describe three different methods that use

Table 1
Summary statistics for study and policy sites[a].

	Study sites[b]				Policy sites[c]			
	Mean	Median	Min	Max	Mean	Median	Min	Max
Tree cover variables								
Tree cover (%)	19.65	16.34	0.1	61.4	19.95	14.66	0	85.36
Low density (0–10 %)	0.286	0	0	1	0.388	0	0	1
Medium density (10–25 %)	0.398	0	0	1	0.285	0	0	1
High density (>25 %)	0.316	0	0	1	0.327	0	0	1
Coniferous tree type	0.122	0	0	1	0.073	0	0	1
Deciduous tree type	0.031	0	0	1	0.314	0	0	1
Mixed tree type	0.031	0	0	1	0.054	0	0	1
Housing market variables								
Median income (1000 2020$)	65.66	58.89	24.26	135.02	76.58	68.38	2.5	250
Population density (1000 people/mi^2)	1.99	1.27	0.008	7.88	6.60	2.98	0.0001	819.43
College degree (% population)	23.59	23.47	7.2	32.6	35.21	33.17	0	100
Hispanic (%)	8.70	6.87	1.8	33.9	19.03	9.75	0	100
Median population age (years)	36.05	35.77	27.1	42.5	39.22	38.51	18	89
Single family households (%)	53.22	52	25	68.9	70.57	78.57	0	100
Homes built prior to 1990 (%)	74.72	76.7	45.7	94.4	67.73	75.15	0	100
Rural-Urban Continuum Code (Very urban = 1 to Very rural = 9)[d]								
1	0.775	1	0	1	0.597	1	0	1
2	0.051	0	0	1	0.221	0	0	1
3	0.082	0	0	1	0.087	0	0	1
4	0.000	0	0	0	0.037	0	0	1
5	0.000	0	0	0	0.014	0	0	1
6	0.061	0	0	1	0.025	0	0	1
7	0.000	0	0	0	0.017	0	0	1
8	0.031	0	0	1	0.002	0	0	1
9	0.000	0	0	0	0.000	0	0	0
Number of observations	98				70,923			

[a] Variables shown in the table are the variables for the matching methods. Additional variables for the function transfer methods are in appendix Table A1.
[b] Study site data come from Kovacs et al. (2022).
[c] Policy sites are urban census tracts and the data for the sites come from the 2021 National Land Cover Database and the 2017 to 2021 American Community Survey.
[d] The Rural-Urban Continuum Codes (Economics Research Service, 2023) distinguish U.S. metropolitan counties by the population size of their metro areas, and nonmetropolitan counties by their degree of urbanization and adjacency to metro areas.

the values of ε_j^S from study sites to predict $\widehat{\varepsilon}_i^P$ in the policy sites. A conceptual flow chart (Fig. 3) displays the logic and data requirements of each method. The meta-dataset contains study sites in all four regions of the contiguous states (West, South, Northeast, and Midwest) (Fig. 1). Because housing markets likely differ by region, we applied each benefit transfer method within the confines of each region. To support this decision, we note that Siriwardena et al. (2016) and Kovacs et al. (2022) performed meta-analyses of hedonic property value studies in the U.S. and found that elasticities between home value and tree cover differed significantly across regions.

2.3.1. Matching value transfer

In our application of a matching method to benefit transfer, the idea is to match each policy site where we need an elasticity prediction with one or more study sites that have similar tree cover and housing market attributes. Then, a variance-adjusted, weighted average elasticity of the matched study sites is used as the predicted elasticity for the policy site. For each policy site, the study sites that are selected as matches are from the same region as the policy site and are closest to the policy site as measured by the distance between values of the tree cover and housing market attributes of the sites. The tree cover and housing market variables used to match study sites with policy sites are listed in Table 1. These variables were found to be significant predictors of elasticity and tree cover in the benefit functions estimated by Kovacs et al. (2022) in their meta-analysis of hedonic property value studies in the U.S.

First, we calculate the Mahalanobis distance between each policy and study site based on their tree cover and housing market characteristics. Suppose there are K variables describing the tree cover and housing market of each policy and study site. Let $\mathbf{x}_i^p = \left\{x_{i,1}^p, x_{i,2}^p, \ldots, x_{i,K}^p\right\}$ be the vector of variables for policy site i and $\mathbf{x}_j^s = \left\{x_{j,1}^s, x_{j,2}^s, \ldots, x_{j,K}^s\right\}$ be the same set of variables but for study site j. The Mahalanobis distance Δ_{ij} between $\mathbf{x}_i^p$ and $\mathbf{x}_j^s$ for policy site i and study site j is:

$$\Delta_{ij} = \left\{\left(\mathbf{x}_i^p - \mathbf{x}_j^S\right)' W^{-1} \left(\mathbf{x}_i^p - \mathbf{x}_j^S\right)\right\}^{1/2}. \tag{1}$$

Since $\mathbf{x}_i^p - \mathbf{x}_j^s$ contains a vector of distances between variables that are measured on different scales, a $K \times K$ scaling matrix W is used to transform the multiple distances into a single distance measure. We use the variance-covariance matrix for the tree cover and housing market variables in the study sites within a given region for the matrix W in Eq. 1

$$W = \frac{1}{N-1}\sum\nolimits_{n=1}^{N} (\mathbf{x}_n - \overline{\mathbf{x}})(\mathbf{x}_n - \overline{\mathbf{x}})' \tag{2}$$

where n is the index for each study site and N is the total number of study sites and $\overline{\mathbf{x}} = \frac{1}{N}\sum_{n=1}^{N}\mathbf{x}_n$. As a side note, there are several distance functions that can be used in non-parametric statistical matching (e.g., D'Alberto and Raggi, 2020; D'Alberto et al., 2021). For example, the Euclidean distance is an alternative metric that uses uniform weights on the covariates; however, this metric may have higher bias and produce a less precise match when some covariates are more important than others for outcomes (Rubin, 1973). We decided to use the Mahalanobis distance (Eq. (1)) because it utilizes the variation in each covariate, as well as covariance among different covariates, to weight the distances between covariate values of the study and policy sites.

The distances Δ_{ij}, $\forall j \in S$, relative to policy site i in Eq. (1) are used to rank the study sites from closest to furthest away. Then, the subset of closest study sites, $S_i^* \in S$, are selected to calculate the elasticity prediction for policy site i. Let J be the size of the subset of study sites (i.e., the number of study sites that are matched with each policy site). We explore the performance of matching transfers calculated with values of J ranging from one to 15 study sites.

The final step is to use the subset of closest study sites to calculate the

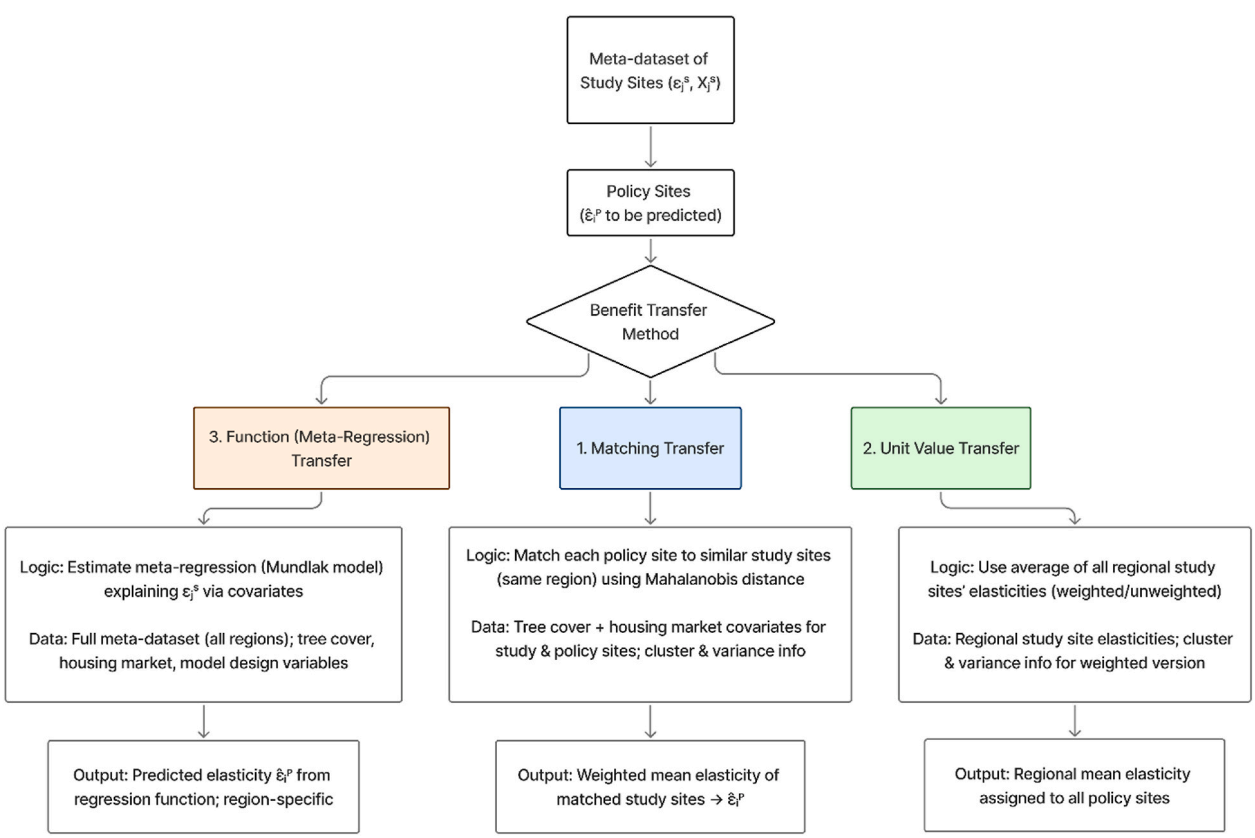

Fig. 3. Flow chart showing logic and data requirements of three benefit transfer methods, Matching Transfer, Unit Value Transfer, and Function Transfer.

predicted elasticity for policy site i. For a given value of J, we select the J closest study sites $j_i^* \in S_i^*$ for each policy site i. The predicted elasticity for policy site i, $\widehat{\varepsilon}_i^P$, could be the simple average of the elasticities for the nearest study sites $j_i^* \in S_i^*$:

$$\widehat{\varepsilon}_i^P = \frac{1}{J}\sum_{j_i^* \in S_i^*} \varepsilon_j^S \tag{3}$$

However, two considerations call for a weighted average rather than the simple average in Eq. (3). First, in the meta-dataset constructed by Kovacs et al. (2022), the 98 observed elasticities occur in 17 unique housing markets, defined as clusters. The clustered nature of the meta-dataset suggests that a cluster should be given the same overall weight regardless of the number of elasticity estimates in that cluster (Guignet et al., 2022). Second, because ε_j^S are estimated values, estimates with lower precision should be assigned lower weights. We follow the meta-analysis literature (e.g., Nelson and Kennedy, 2009; Borenstein et al., 2010) and weight each ε_j^S with the inverse of its variance, denoted as $1/v_j$. Suppose the J nearest neighbors matched with policy site i come from C clusters. Each cluster has G_c elasticity estimates where $\sum_{c=1}^{C} G_c = J$. We then re-index ε_j^S as ε_{cm}^S, the mth estimate in the cth cluster of the study sites. The predicted elasticity for policy site i, $\widehat{\varepsilon}_i^P$, is calculated as:

$$\widehat{\varepsilon}_i^P = \frac{\sum_{c=1}^{C} \sum_{m=1}^{G_c} \left\{ \frac{\frac{1}{v_j}}{\sum_{m=1}^{G_c}\left(\frac{1}{v_j}\right)} \varepsilon_{cm}^S \right\}}{J_i} \tag{4}$$

Similar to the use of variance-adjusted cluster weights in Guignet et al. (2022), the weighted average in Eq. (4) considers both the clustered nature of the meta-dataset and the estimation precision.

2.3.2. Unit value transfer

In the unit value transfer method, estimated elasticities from all study sites within a given region are used to calculate either an unweighted or a weighted average elasticity that is used as the prediction for the policy sites in that region. The predicted elasticity for policy site i, $\widehat{\varepsilon}_i^P$, using an unweighted average elasticity is the simple average of the elasticities for all of the study sites in the region:

$$\widehat{\varepsilon}_i^P = \frac{1}{J}\sum_{j \in S} \varepsilon_j^S \tag{5}$$

For the weighted average elasticity, we use the same weights as developed in matching value transfer method above (Eq. (4)). The predicted elasticity for policy site i is:

$$\widehat{\varepsilon}_i^P = \frac{\sum_{c=1}^{C} \sum_{m=1}^{G_c} \left\{ \frac{\frac{1}{v_j}}{\sum_{m=1}^{G_c}\left(\frac{1}{v_j}\right)} \varepsilon_{cm}^S \right\}}{J} \tag{6}$$

where J is the total number of elasticity estimates. Structurally, Eq. (3) and Eq. (5) are identical, and Eq. (4) and Eq. (6) are identical. In Eq. (3) and Eq. (4), only study sites that have been matched to policy site i are used. In Eq. (5) and Eq. (6) all study studies within the region of the policy site are used.

2.3.3. Function value transfer

Function transfer uses a meta-regression model to account for heterogeneity in the elasticity estimate. Here, we estimate two versions of a Mundlak regression model (Boyle and Wooldridge, 2018) as employed by Kovacs et al. (2022). Cluster specific effects are taken into account in the Mundlak models by subdividing the study sites into clusters. Further, we use all of 98 observations of off-property tree cover across the four regions in the estimation. We replicate the Mundlak regression model described by Eq. (8) in Kovacs et al. (2022):

$$\varepsilon_{mc}^S = \beta_0 + \mathbf{x}_{mc}^{S\,\prime}\boldsymbol{\beta}_1 + \mathbf{z}_{mc}^{S\,\prime}\boldsymbol{\beta}_2 + \overline{\mathbf{x}}_c^{S\prime}\boldsymbol{\delta}_1 + \epsilon_j \tag{7}$$

where ε_{mc}^S is the mth estimated elasticity in the cth cluster of study sites. The vector $\mathbf{x}_{mc}^S$ contains all tree canopy and housing market variables from study sites that are reported in Table 1. Three regional dummy variables (West, South, and Midwest) are included in $\mathbf{x}_{mc}^S$ to indicate locations of study sites. The vector $\mathbf{z}_{mc}^S$ also contains variables that describe the modeling choices of the primary study. In one specification, denoted Mundlak model 2, only the elasticity variance is included to control for publication bias. The second specification, denoted Mundlak model 3, uses a set of categorical time trend variables to control for study periods, a dummy variable that equals one if the functional form is log-linear and equals zero if it is linear or log-log, a dummy variable to indicate the use of spatial method, and two dummy variables to indicate the use of spatial fixed effects and spatial autocorrelation. Summary statistics for these variables are in Table A1. As in Boyle and Wooldridge (2018), the cluster averages of the explanatory variables, $\overline{\mathbf{x}}_c^S$, are used to control for cluster specific effects. A multilevel mixed-effects model is estimated for Eq. (7). Then the estimated coefficients ($\widehat{\beta}_0, \widehat{\boldsymbol{\beta}}_1, \widehat{\boldsymbol{\beta}}_2$, and $\widehat{\boldsymbol{\delta}}_1$) are combined with the covariates values from policy sites ($\mathbf{x}_{mc}^P$, $\overline{\mathbf{x}}_c^P$ and $\mathbf{z}_{mc}^P$) to predict elasticities:

$$\widehat{\varepsilon}_{mc}^P = \widehat{\beta}_0 + \mathbf{x}_{mc}^{P\,\prime}\widehat{\boldsymbol{\beta}}_1 + \mathbf{z}_{mc}^{P\,\prime}\widehat{\boldsymbol{\beta}}_2 + \overline{\mathbf{x}}_c^{P\prime}\widehat{\boldsymbol{\delta}}_1. \tag{8}$$

The values of $\mathbf{z}_{mc}^P$ are not available for policy sites, so the regional average values of $\mathbf{z}_{mc}^S$ from the study sites are used. Because the coefficients for the regional dummy variables are significantly different than zero, predicted elasticities using Eq. (8) are region specific.

2.4. Performance of benefits transfer methods

To assess the performance of each benefit transfer method, we apply the procedure of leave-one-out cross-validation within each region. For each observed elasticity ε_j^S in study site j in a given region, we use the observed elasticities in the remaining study sites in the region to predict the elasticity, $\widehat{\varepsilon}_j^S$, for comparison with ε_j^S. Then, we use the median absolute value of the % differences in predicted and observed elasticities as the measure of performance of each transfer method. The absolute value of the transfer error for a given study site j is TE $= \left|\widehat{\varepsilon}_j^S - \varepsilon_j^S\right|$. The size of the transfer error measured in % of ε_j^S is calculated as %TE $= \left|\frac{\widehat{\varepsilon}_j^S - \varepsilon_j^S}{\varepsilon_j^S}\right| \times 100$. With the matching value transfer method, we match study site j with a given number of nearest neighbor study sites in the same region. We calculate the weighted average of the observed elasticities in the nearest neighbor study sites using Eq. (4) and use that predicted elasticity, $\widehat{\varepsilon}_j^S$, for comparison with the observed elasticity, ε_j^S in study site j. With the unit value transfer method, we compute a weighted average elasticity for a region using Eq. (5) and all of the observed elasticities in the region except study site j. That weighted average is the predicted elasticity, $\widehat{\varepsilon}_j^S$, for comparison with the observed elasticity, ε_j^S, in study site j. With the function transfer method, we first estimate Eq. (6) for each study site j using the observed elasticities and information about the remaining study sites. Then, we use the estimated model to predict elasticity, $\widehat{\varepsilon}_j^S$, for comparison with the observed elasticity, ε_j^S, in study site j. In all three methods, leaving out the observed elasticity of study site j when making a prediction reduces the number of observations by one. Weights used in Eq. (4) to Eq. (6) are re-calculated accordingly. For Eq. (6), the cluster average $\overline{\mathbf{x}}_c^S$ is also re-calculated.

2.5. Predicting changes in home values for policy sites

To predict changes in home values in the policy sites, we used projected changes in tree cover in each urban census tract for the period 2020 to 2030 (Nowak et al., 2022). The projections come from a combination of county-level urban land use change (Nowak and Greenfield, 2018a), the National Land Cover Database tree cover for 2010 (Nowak and Greenfield, 2010), and state level estimates of urban tree cover change (Nowak and Greenfield, 2018b). The projected changes in tree cover for the urban census tracts are mostly negative with regional medians ranging from −8.0 % in the Midwest to −0.1 % in the West (Fig. 4). The South had the widest range of projected changes, which is consistent with Nowak and Greenfield's (2018b) finding that % decreases in tree cover between 2009 and 2014 were highest in Oklahoma (up to 92 %). The predicted change in home value in each urban census tract is the product of the predicted elasticity, average home value, and change in tree cover. Multiplying the predicted change in home value times the number of homes in the census tract is an estimate of the total change in home value associated with the predicted change in tree cover.

3. Results

3.1. Out-of-sample transfer errors

With one exception, the matching method had the lowest out-of-sample transfer error of the three transfer methods for predicting elasticities of home value and tree cover for each of the four regions of the U.S. (Table 2). The lowest median transfer errors for the matching method ranged from 27 % in the West, which had the most observations, to 95 % in the South, which had the fewest observations. For comparison, the unit value transfer method using weighted mean predictions had median transfer errors of 61 %–126 % across the four regions. These median transfer errors exceeded the lowest median transfer errors using the matching method in all regions except the Midwest, which had a slightly lower median transfer error (61 %) than the smallest obtained with the matching method (63 %). The median transfer errors using the function transfer method (Mundlak model 2) were 52 %–586 %, which exceeded the lowest median transfer errors obtained with the matching method for each of the four regions.

The median transfer errors obtained with the matching method varied with the number of nearest neighbors used (Table 2). For Midwest and West, the lowest median transfer errors (63 % and 27 %, respectively) were obtained with 15 and 3 nearest neighbors. For Northeast and South, the lowest median transfer errors (91 % and 95 %, respectively) were obtained with 4 and 8 nearest neighbors.

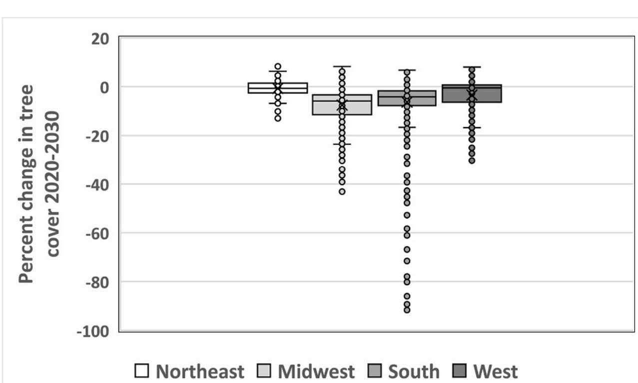

Fig. 4. Percent changes in tree cover from 2020 to 2030 in U.S. urban census tracts by region.

Table 2
Out-of-sample transfer errors: median absolute values of % differences in predicted and observed elasticities between home value and tree cover by region for three transfer methods.

	Region (number of observations)			
Transfer method	Northeast (n = 15)	Midwest (n = 21)	South (n = 12)	West (n = 50)
Matching[a]				
1	100	71	95	31
2	98	85	98	31
3	95	72	140	27
4	91	79	101	53
5	95	72	102	45
6	95	70	105	42
7	98	66	97	48
8	99	65	95	47
9	99	73	141	50
10	99	65	147	54
15	–	63	–	62
Unit Value				
Unweighted	266	515	508	66
Weighted	98	61	126	94
Function				
Mundlak model 2	586	92	178	52
Mundlak model 3	600	95	203	56

[a] Matching models are listed according to number of nearest neighbors used.

3.2. Elasticity predictions for policy sites

The boxplots in Fig. 4 show that the three benefit transfer methods produce very different predictions of elasticities for the 64,658 policy sites. For the matching method, elasticities were predicted with 4, 15, 8, and 3 nearest neighbors in census tracts in the Northeast, Midwest, South, and West, respectively. These are the numbers of nearest neighbors that produced the lowest transfer errors (Table 2). The matching predictions are not sensitive to the number of nearest neighbors if the median transfer errors are similar among the alternative models that use a different number of nearest neighbors. The predicted elasticities range between −0.05 and 0.10 and are mostly positive (i.e., the first quartile is greater than or equal to zero across the four regions). Median predictions range between 0.00 and 0.02. Predicted elasticities obtained with the function transfer have a much wider range (−50.0 to 35.0) than those of the matching method. Median predictions are positive and close to zero across regions. For the unit value transfer method, the predicted elasticity for each census tract in a region is the weighted mean of the observed elasticities in the study sites in the region. The boxplots show a single line for each region representing the regional mean (and median) prediction. These predictions are positive and range from 0.003 to 0.016 across regions.

Comparing the boxplots of predicted elasticities for the policy sites (Fig. 5) to the boxplots of observed elasticities in the study sites (Fig. 2), we find that the matching method better reproduces the observed distributions. For the matching method, the distribution of predictions for each region is skewed to the positive side and within the range of the corresponding observations (Fig. 2). Further, for each region except the Northeast, the middle 50 % of predictions using the matching method is within the first and third quartiles of the observed elasticities for the region. In contrast, the function transfer method produced regional distributions of predicted elasticities in which the interquartile ranges are far wider than the entire range of observations (Fig. 2). Finally, while the weighted mean elasticity predictions obtained with a unit value transfer are similar to the corresponding mean elasticities computed for the observations (Fig. 2), a unit value transfer to census blocks does not depict the distribution of elasticities.

The very high and very low predictions of elasticities obtained with function transfer are caused by large and opposite signs for the

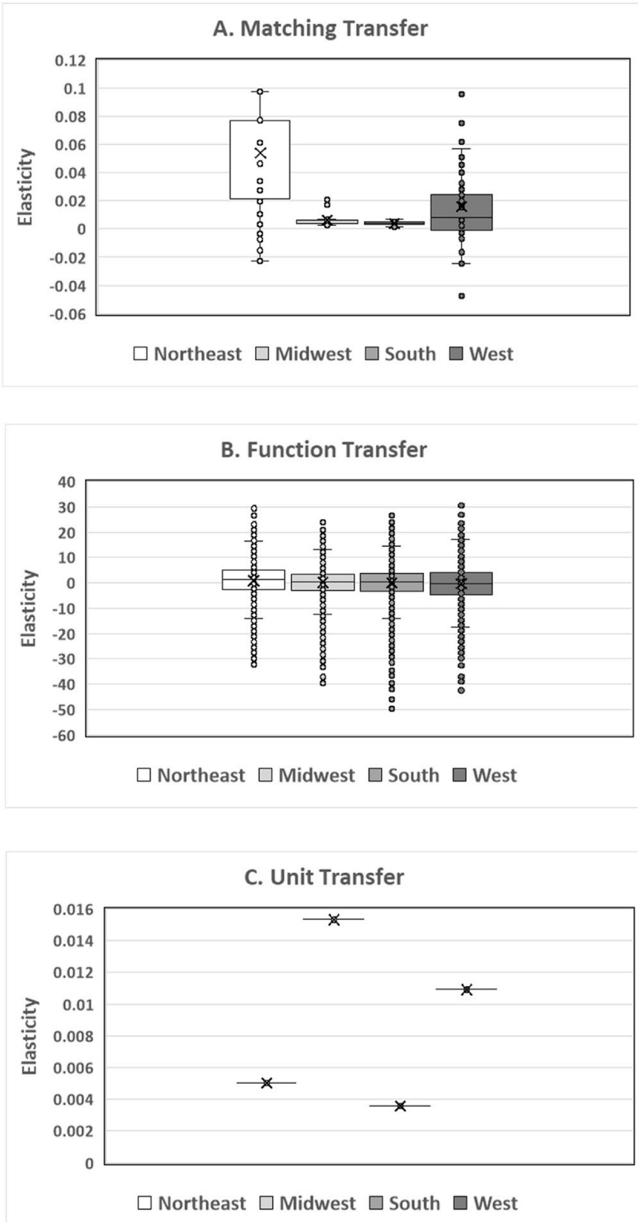

Fig. 5. Predicted elasticities between home value and tree cover in U.S. urban census tracts using three benefit transfer methods.

coefficients of the population density explanatory variables at the census tract and county levels. For example, the population density variable at the tract level has a coefficient of −1.9 and the group mean (county) population density variable has a coefficient of 2.0. Census tracts with predicted elasticities that are very large and negative have high population densities at the tract level and low county population densities. The tracts with very large and positive elasticities have low population densities at the tract level and high county population densities. Because the policy sites have higher population densities on average and a much wider range of population densities compared with the study sites, there are many census tracts that have elasticity predictions that are outside the range of observed elasticities.

3.3. Predicted changes in home value in regions of the U.S

To predict changes in home value, we use elasticity predictions from the matching method, which accounts for heterogeneity in tree cover and housing market conditions across study and policy sites and has the smallest out-of-sample transfer errors of the three methods that we tested. Here, we use the matching method to predict elasticities with 4, 15, 8, and 3 nearest neighbors in census tracts in the Northeast, Midwest, South, and West, respectively. These are the numbers of nearest neighbors that produced the lowest transfer errors. Multiplying the predicted elasticity in a census tract times the average home value (2020 USD) in the tract yields the change in home value for a 1 % change in tree cover. Multiplying this quantity times the predicted % change in tree cover yields a prediction of the change in home value for the predicted % change in tree cover. Multiplying this latter quantity times the number of homes in the tract yields the total change in home value for the predicted change in tree cover.

Changes in home value for a 1 % change in tree cover vary across regions (Table 3). Median changes range from $9 in the Midwest and South to $134 in the Northeast. The range of changes varies from narrow ($0.19 to $105 in the southern region) to wide ($-432 to $1950 in the northeastern region). The Northeast has the highest changes in home value because it has the highest predicted elasticities and average home values across census tracts.

Changes in home value for predicted changes in tree cover are mostly negative across regions (Table 3). Median changes range from $-53 in the Midwest to $2 in the South. Negative changes in home values result from the predictions of widespread reductions in tree cover over the next decade. Predictions of positive changes in home values occur in census tracts where predictions of elasticity and change in tree cover are either both positive or both negative.

Predictions of total changes in home value for the predicted changes in tree cover range from -$4.8 to -$1.7 billion across regions, and the total change in home value is -$11.8 billion for the 64,658 urban census tracts in the U.S. (Table 3).

3.4. Predicted changes in home value in a municipality

Community forestry programs are typically funded by county or municipal governments. For example, the Department of Parks and Recreation of the City of Saint Paul, MN, budgeted $4.5 million in 2024 to support its forestry unit, which manages boulevard and park tree planting, tree pruning, tree removal, stump removal, and tree diseases and pests (https://www.stpaul.gov/departments/parks-and-recreation/natural-resources/forestry). Here we show how our elasticity

Table 3
Changes in home value (2020 USD) with changes in tree cover in 64,658 urban census tracts using the matching value transfer method for elasticity prediction.

	Region				
	Northeast	Midwest	South	West	Entire U.S.
Number of census tracts	10,017	14,308	25,099	15,234	64,658
Number of households (millions)	17.0	23.4	41.4	24.4	106.2
	Change in home value ($) with a 1 % increase in tree cover				
Median	134	9	7	34	10
Mean	171	12	9	89	54
Min	−432	0.41	0.19	−377	−432
Max	1950	180	105	1510	1950
	Change in home value ($) with predicted changes in tree cover				
Median	−42	−53	−28	2	−29
Mean	−234	−82	−43	−177	−113
Min	−12,641	−1658	−1618	−11,771	−12,641
Max	6790	484	317	4307	6790
	Total change in home value ($ million) with predicted changes in tree cover				
Total	−3269	−2000	−1746	−4768	−11,783

predictions for census tracts in Saint Paul can be used to predict changes in home value associated with potential changes in tree cover. There are 85 census tracts in Saint Paul (Fig. 6). Multiplying the predicted elasticity times the median home value (2020 USD) in each census tract, we found that the change in median home value for a 1 % increase in tree cover ranges from $0-$64 across tracts with a mean of $9. Multiplying the change in median home value times the number of homes in each tract, we found that the total change in home value for a 1 % increase in tree cover ranges from $0-$120,000 across tracts (Fig. 6), with a total change of $1.9 million. These results suggest that a tree planting program that increases canopy cover by 10 % across the census tracts of the city would increase home values by $19 million, which is an estimate of homeowners' willingness to pay for the forestry program.

4. Discussion

The primary goal of our study is to use benefit transfer tools to predict the % change in home value for a 1 % change in tree cover (i.e., elasticity between home value and tree cover) in each urban census tract in the contiguous U.S. While there are many hedonic studies that show how tree cover changes affect home value at the local level (Siriwardena et al., 2016; Kovacs et al., 2022), our study is the first to use these results with benefit transfer methods to predict elasticities and changes in home value regionally and nationally. These elasticity predictions, which reflect homeowners' marginal willingness to pay for urban forest benefits, could help local, regional and national planners assess the economic benefits of increasing and protecting urban tree cover. We predicted elasticities using a meta-dataset of 98 observations of the effects of tree cover on home value obtained from 17 hedonic property value studies throughout the U.S. We compared the elasticity predictions and performance of three benefit transfer methods—a matching value transfer with the nearest-neighbor technique, a unit value transfer using a weighted mean elasticity, and a function transfer using a meta-regression model. The discussion below puts the results in context of previous literature and suggests extensions.

4.1. Out-of-sample transfer errors

The matching transfer method produced the smallest median transfer errors across the four regions (91 %, 63 %, 95 %, and 27 % for the Northeast, Midwest, South, and West, respectively). These errors are somewhat higher than the median transfer errors reported in summaries of previous benefits transfer studies. Kaul et al. (2013) reviewed 31 benefits transfer studies covering a wide range of environmental amenities and reported 1071 transfer errors ranging from 0 % to 7496 % with a median of 39 %. Rosenberger (2015) summarized the results for 38 studies and reported a median transfer error of 36 % for function transfers. Reviewing the accuracy of benefit function transfers in the area of water quality improvement, Moeltner et al. (2023) concluded that mean average percentage errors in leave-one-out exercises are in the range of 60 %–80 %, while median transfer errors were smaller. The median transfer error of our elasticity predictions was lowest in the western U.S. (27 %), which had the most observations of elasticities from primary studies and was consistent with median transfer errors in the literature. Median transfer errors in the other three regions were higher, and we encourage researchers to undertake new hedonic

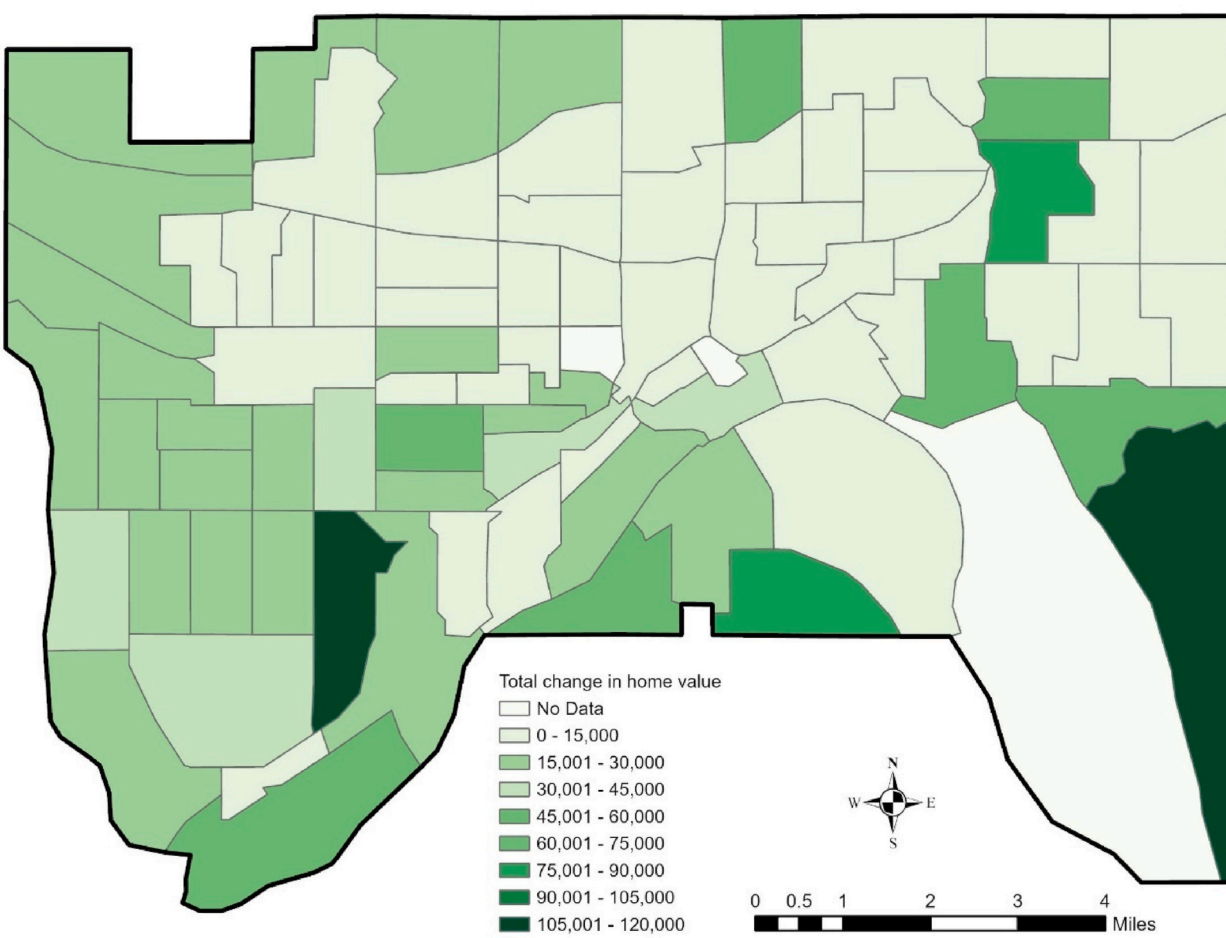

Fig. 6. Total change in home value (2020 USD) for a 1 % increase in tree cover in census tracts in the city of Saint Paul, MN, USA. Map lines represent census tract boundaries.

property value studies in these regions to bolster nationwide coverage and ultimately lead to more accurate benefit transfers.

It is not surprising that the matching method provides smaller transfer errors than unit value transfer. The matching method uses tree cover and housing market variables to select the set of study sites whose tree cover and housing market attributes are closest to the policy site attributes and then computes a mean elasticity across those study sites to transfer to the policy site. In contrast, unit value transfer is a weighted mean elasticity computed across all of the study sites and does not account for heterogeneity in tree cover and housing markets across the study sites. In general, value transfers using weighted means of observations are less accurate than transfer methods that adjust study-site value estimates according to observable differences in housing and environmental attributes between study and policy sites (Johnston et al., 2021).

Kovacs et al. (2022) report lower median transfer errors (54 % and 60 %) for their meta-regression models (Mundlak models 2 and 3) compared with the transfer errors for the estimated meta-regression models in our study. There are several differences between our modeling approaches that may cause these differences. We estimated the coefficients of the Mundlak model using 98 observations of elasticities from study sites with off-property measures of tree cover, whereas Kovacs et al. (2022) estimated their Mundlak models with 59 additional observations of on-property tree cover. Further, when calculating out-of-sample transfer errors, we removed one observation at a time and used the observed elasticities in the remaining study sites in the region to predict an elasticity for comparison with the observation. In contrast, Kovacs et al. (2022) iterate over clusters, removing all observed elasticities within that cluster, and estimating the meta-regression model with the observations of the remaining clusters to obtain the predicted elasticities for each observation in the excluded cluster. Finally, our sample sizes are smaller because we analyze out-of-sample transfer errors by region rather than for the entire U.S.

It is somewhat surprising that our function transfer models had the highest transfer errors of the three methods that we tested. In their meta-analysis of 31 empirical studies testing the convergent validity of benefit transfers, Kaul et al. (2013) conclude that function transfer methods outperform unit value transfers. Johnston et al. (2021) suggest that the superior performance of meta-functions arises from the estimation of models with variables that are fixed for individual studies or sites but vary across different studies or sites, and this variation may enhance the capacity of the resulting benefit function to calibrate value estimates to policy-site conditions.

4.2. Elasticity predictions for policy sites

While matching estimators for average treatment effects are widely used to evaluate the efficacy of social programs (Abadie and Imbens, 2006), the use of statistical matching for benefit transfer is relatively new. The method holds promise for challenging benefit transfer exercises that extrapolate from a limited number of study sites to many different policy sites (D'Alberto et al., 2021). The matching method is promising because it controls for the skewness in elasticity predictions through non-linear distance functions. The result is a bounded and perhaps more reasonable prediction of elasticities compared with function transfer. In our case, the function transfer method based on meta-regression model produced regional distributions of predicted elasticities (Fig. 5) in which the interquartile ranges are far wider than the entire range of observed elasticities (Fig. 2). The meta-regression model magnified elasticity predictions in policy sites that had socioeconomic characteristics that were outside the range of values for the study sites that were used to estimate the model.

A valuable extension of our study would be to evaluate the performance of new benefit transfer methods that address issues with current methods. For example, using a single meta-regression equation for function transfer may lack sufficient flexibility to maximize accuracy of value predictions (Boyle and Wooldridge, 2018; Moeltner et al., 2023). Estimating a single meta-regression model overlooks the possibility that value observations from study sites that are more similar to a given policy site might provide more relevant information to that policy site than study sites that are less similar. To address this challenge, Moeltner et al. (2023) developed a locally weighted regression algorithm that allows model coefficients to vary over data points rather than have fixed coefficients. Another promising approach to benefit transfer would be to develop statistical matching using propensity scores. In the treatment-effects literature, the propensity score is the probability that a unit in the combined sample of treated and untreated units receives the treatment, given the observed covariates of the units (Caliendo and Kopeinig, 2008). Then, one could choose the unit in the untreated comparison group as a matching partner for the treated unit that is closest in terms of propensity score (Caliendo and Kopeinig, 2008). The method could be applied to benefit transfer by computing propensity scores for a set of study and policy sites and then estimating the value transfer for a policy site based on the observed values obtained from study sites with closest propensity scores.

Like all benefit transfer exercises, our predictions of elasticities require appropriate caveats. The median out-of-sample transfer errors of our best-performing matching method are somewhat higher than median transfer errors found in the meta-analytic literature valuing environmental amenities (Kaul et al., 2013; Rosenberger, 2015; Moeltner et al., 2023). Given the range of the out-of-sample transfer errors, we recognize that elasticity predictions might be high or low especially in regions outside the western U.S. Therefore, caution should be exercised in using the predictions at face value. Examination of the differences between tree cover and housing market conditions of the policy site and those conditions of the study sites that were used to compute the value transfer is suggested. It is also important to note that elasticity estimates from the hedonic studies in our meta-dataset show marginal price effects based on regressions of Rosen's (1974) first-stage hedonic model. Consequently, elasticity predictions should only be used to evaluate marginal or small changes in tree cover. In our application, predicted changes in tree cover are largely plus or minus 10.0 % across census tracts; however, caution should be used when using the elasticity predictions to predict home value changes where tree cover changes are more than 10.0 %. Lastly, an implicit assumption of hedonic property value studies is that the housing market equilibrium where the study is conducted is not changing over time, and this assumption underlies our elasticity predictions.

4.3. Predicted changes in home value in regions of the U.S

In an important result, we showed that three benefit transfer methods produced very different distributions of predicted elasticities between home value and tree cover for 64,658 urban census tracts (Fig. 5). When applying these elasticities to predict changes in home value, we found the range of predictions using the unit value transfer method is somewhat less than the range produced using the matching value transfer (Table A2). However, the range of predicted changes in home value using the function transfer is three orders of magnitude greater than the range of predicted changes using the matching method (Table A2). This inflated range of predicted values resulted from the function transfer method magnifying elasticity predictions in policy sites that had socioeconomic characteristics that were well outside the range of values for the study sites that were used to estimate the transfer function, which casts doubt on the veracity of those predictions. In their study of the effects of improvements in lake water clarity on nearby home values, Burlingame et al. (2024) found very different predictions of benefits across different transfer methods.

4.4. Predicted changes in home value in a municipality

The results from the Saint Paul community forestry analysis offer valuable insights for federal urban forestry programs and equity-oriented policy design. The estimated $19 million increase in home values from a 10 percent rise in citywide canopy cover quantifies the economic benefits that local investments in tree planting can generate. When extrapolated, such localized valuation estimates can inform national cost-benefit assessments of federal urban greening initiatives, such as those under the U.S. Forest Service's Urban and Community Forestry Program. Moreover, the variation in predicted home-value gains across census tracts—ranging from negligible to substantial—highlights spatial disparities in how different neighborhoods capture the benefits of urban canopy expansion. This suggests that federal programs could more effectively promote environmental equity by prioritizing funding and technical assistance for lower-income or historically under-canopied neighborhoods, ensuring that the economic, health, and aesthetic benefits of urban trees are distributed more equitably across communities.

5. Conclusion

Benefit transfer tools combined with observations from local hedonic property value studies can be used to predict elasticities between home value and tree cover in urban census tracts in the U.S. With appropriate caution and in the absence of resources for more primary hedonic property value studies at the local level, we believe our predictions of elasticities give practitioners the information they need to assess how changes in tree cover from local, regional, and even national policies are capitalized into housing values, which is one way to assess homeowners' willingness to pay for the benefits of urban forests.

In future work, we plan to incorporate our elasticity estimates into i-Tree, a suite of software from the USDA Forest Service that includes tools to quantify the structure and benefits of urban and community forests (https://www.itreetools.org/). Combined with tree canopy and housing market characteristics available in i-Tree, the elasticity estimates will allow the prediction of changes in home value associated with potential changes in tree cover associated with proposed tree planting or forest protection programs. These predictions of changes in home value are estimates of homeowners' willingness to pay for tree planting and protection programs, and predictions of the monetary benefits can play an important role in quantifying the total benefits of those programs.

CRediT authorship contribution statement

Robert G. Haight: Writing – original draft, Investigation, Funding acquisition, Conceptualization. **Qiuqiong Huang:** Writing – original draft, Methodology, Data curation, Conceptualization. **Kent Kovacs:** Writing – original draft, Methodology, Funding acquisition, Data curation, Conceptualization. **Alexis Ellis:** Data curation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: This work is supported by the USDA Forest Service Northern Research Station, through cooperative agreement 20-JV-11242309-054. Any opinion, findings, conclusions, or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the USDA. The authors acknowledge Dennis Guignet, Thomas Holmes, and Phillip Rodbell for commenting on previous drafts, Gertrude Dotse Bampoe for composing Fig. 1, and the reviewers and associate editor for suggesting valuable changes. The authors are responsible for any remaining errors.

Appendix

Table A1Summary statistics for additional variables in the function transfer models for the study and policy sites

	Study sites [a]				Policy sites [b]			
	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
Tree cover variables								
Cluster mean tree cover (%)	19.32	11.45	7.53	61.4	19.95	14.36	0.003	79.73
Cluster mean coniferous tree type	0.122	0.278	0	1	0.073	0.163	0	1
On property	0	0	0	0	0	0	0	0
Cluster mean on property	0	0	0	0	0	0	0	0
Cluster mean medium density (10–25 %)	0.373	0.422	0	1	0.285	0.212	0	1
Cluster mean high density (>25 %)	0.335	0.390	0	1	0.327	0.343	0	1
On property*Medium density	0	0	0	0	0	0	0	0
On property*High density	0	0	0	0	0	0	0	0
Housing market variables								
Cluster mean population density (1000 people/mi^2)	1.99	1.93	0.007	7.88	6.60	11.56	0.003	119.37
Cluster mean median population age (years)	36.05	2.87	27.1	42.5	39.22	3.86	23	65.9
Midwest	0.214	0.412	0	1	0.211	0.408	0	1
South	0.122	0.329	0	1	0.371	0.483	0	1
West	0.510	0.502	0	1	0.233	0.423	0	1
Simulated elasticity variance	0.002	0.013	1.1E-7	0.12	0.0009	0.0008	7.8E-5	0.0023
Time trend	8.031	3.82	0	17	17	0	17	17
Spatial fixed effects [c]	0.76	0.42	0	1	0.76	0	0.76	0.76
Time fixed effects [c]	0.42	0.49	0	1	0.42	0	0.42	0.42
Spatial autocorrelation [c]	0.43	0.49	0	1	0.43	0	0.43	0.43
Rural-Urban Continuum Code (Very urban = 1 to Very rural = 9)[d]								
2	0.051	0.221	0	1	0.220	0.414	0	1
3	0.082	0.275	0	1	0.087	0.283	0	1
Number of observations	98				70,923			

[a]Study site data come from Kovacs et al. (2022).
[b]Policy sites are urban census tracts and the data for the sites come from the 2021 National Land Cover Database and the 2017 to 2021 American Community Survey.
[c]These are the additional variables that appear in the Mundlak model 3 function transfer model.
[d]The Rural-Urban Continuum Codes (ERS, 2023) distinguish U.S. metropolitan counties by the population size of their metro area, and nonmetropolitan counties by

their degree of urbanization and adjacency to a metro area. Among all nine Rural-Urban Continuum Codes, only codes 2 and 3 were significant variables in the meta-regression model for the study sites.

Table A2
Changes in home value (2020 USD) with changes in tree cover in 64,658 urban census tracts using three different methods of elasticity prediction

	Transfer method		
	Matching	Function	Unit Value
Change in home value ($) with a 1 % increase in tree cover			
Median	10	530	16
Mean	54	−504	25
Min	−432	−841,328	0
Max	1950	467,289	271
Change in home value ($) with predicted changes in tree cover			
Median	−29	−90	−37
Mean	−113	3185	−109
Min	−12,641	−3,903,082	−214,810
Max	6790	6,935,545	178,341
Total change in home value ($ million) with predicted changes in tree cover			
Total	−11,783	440,301	−10,644

Data availability

Data will be made available on request.

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