Public and Private Preferences for Urban Forest Ecosystem Services

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Public and Private Preferences for Urban Forest Ecosystem Services

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Abstract

Ecosystem services are important for Floridians as they are directly related to water quality, clean air, property values and overall quality of life. A few studies have valued the economic benefits of these services from forests and Floridian's willingness to pay for ornamental attributes and control of invasives. This study collected survey data from 1,052 Florida homeowners to elicit consumer preferences for key urban forest attributes and their ecosystem services and disservices. We use existing plot field data, conjoint analysis, best-worst scaling surveys, and econometric modeling to identify attributes and tradeoffs between urban forest structure and ecosystem service/disservice. The integration of these approaches is novel and can better assess the value of ecosystem services of Florida's urban forests. This method can also be used to identify the preferences of public policy-makers and private homeowners. From the attributes considered in this study, our findings indicate that Property Value has the highest impact on urban forest preferences, followed by Tree Condition and Tree Shade. To increase participation in efforts that generate urban forest ecosystem services, at the public or private level, policymakers may need to design programs that cost less than $7.00 per month, while maintaining good condition trees that provide high shade.

Keywords: Urban Forest; Ecosystem Services; Best-Worst Choice; Best-Worst Scaling; Discrete-Choice Experimentation; Willingness-to-Pay

1. Introduction

Forest ecosystem services are important for Floridians as they are directly related to water quality, clean air, and overall quality of life (Stein et al. 2014). Studies have valued the economic benefits of these services from forests (e.g., Kreye et al. 2014). Other studies in urban landscapes have assessed consumers' environmental concerns and willingness to pay (WTP) for ornamental attributes in urban landscapes (Khachatryan et al., 2014). However, little is known about preferences for - and the economic value of - ecosystem services from Florida's urban forests. To address this, we use existing plot field data, conjoint survey analysis, and econometric modeling to identify attributes and tradeoffs between urban forest structure and ecosystem service/disservice. The integration of these approaches is novel and can better assess the value of ecosystem services

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of Florida's urban forests. It can also be used to identify the preferences of homeowners towards urban forests in their community and private properties. Findings can be used to develop best management practices and lead to a better understanding of what specific landscape design and forest structures homeowners prefer, and policy-makers can manage, for the sustainability and provision of ecosystem services.

As of 2008, 94% of Florida's population lived in urban areas, and approximately 7 million acres of rural land will be converted to urban uses by 2060[1]. These increasing urban forest landscapes are often composed of non-natives that require high maintenance, and have low tree cover (Horn et al., 2015). While local or state governments manage larger populations of trees along rights-of-way, in parks, or in natural areas, most urban trees grow on private lands and are managed by a diverse assemblage of managers and homeowners (Koeser et al., 2015). Studies from the north and west coast areas of the US have also made a link between urban tree cover and improved air quality, temperatures, and property values (Escobedo et al., 2015). A few ecological and geospatial analyses in Florida have begun to make the link between urban forest structure and: improved air quality, carbon offsets, hurricane debris, wood waste and property values (Dobbs et al., 2011; Escobedo et al. 2009, 2015).

In urban areas, choice modeling has been used to gauge consumer interest in a range of environmentally sustainable ornamental production and landscape management practices (Khachatryan et al. 2014), and factors that drive perceptions of tree risk (Koeser et al. 2015). We have three specific research objectives: 1. Determine the urban forest structure and diversity attributes that consumers prefer, 2. Identify the ecosystem service/disservice attributes, and 3. Analyze the tradeoffs in preferences among homeowners and renters. In addition, this research applies a relatively new innovation in best-worst scaling (BWS), called best-worst choice (BWC). This innovation was introduced by Flynn et al. (2007) and successfully implemented in multiple disciplines (e.g., Coast et al., 2006; Soto et al., 2016). The limitation of BWS with regard to the estimation of willingness to pay (see Louviere and Islam, 2008) is circumvented, in BWC, by providing two survey tasks: 1) select a best and a worst attribute from a profile, and 2) to accept or reject the scenario as a whole (see Figure 1). This method yields estimations of scaling, while enabling measurements of traditional discrete-choice experimentation (Soto et al., 2016).

Preliminary results indicate that homeowners in our study are more influenced (based on attribute impact) by property value, than good condition trees and tree shade. Programs that cost less than $7.00 per month are positively impacting the production of urban forest ecosystem services, while poor condition trees with low tree shade are less favored. As expected, BWC was able to approximate most of the WTA values of DCE, but with a slight over estimation.

2. Background

Traditionally used in marketing research, conjoint analysis (Hall et al.,d 2010) and choice modelling (Khachatryan et al., 2014; Soto et al., 2016) can identify product attributes or combinations that influence a consumer's choice decision. This allows product developers and manufacturers to focus their efforts when refining and marketing their products. A payment vehicle can be added to the choice approach to model consumer behavioral "statements" within constructed or hypothetical markets for goods or services. For example, choice modeling has been used to assess Florida State Park visitors' WTP to control invasive plants (Adams et al., 2011). In

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[1]Florida 2060: http://www.1000friendsofflorida.org/connecting-people/florida2060/

urban areas, choice modeling has been used to gauge consumer interest in ornamental plant attributes and a range of environmentally sustainable ornamental production and landscape management practices (Khachatryan et al. 2014), and factors that drive perceptions of tree risk (Koeser et al. 2015).

To our knowledge, there are no choice modeling studies of Floridians' preferences for particular urban forest attributes (tree cover-densities, diversity), ecosystem services (socioeconomic benefits), and ecosystem disservices (socioeconomic costs). Further, the tradeoffs that occur when selecting one set of urban forest attributes over others has not been studied (e.g., park-like urban forests with exotic species increase property values but play a minor role in improving environmental quality and are high maintenance).

The empirical work in this study was conducted within the context of a previous research, Escobedo et al. (2015), which valued urban forest ecosystem services as they relate to property value appraisals from single and multi-family units in four cities (Pensacola, Gainesville, Orlando, and Miami-Dade) across the state of Florida. Our stated preference study was guided by the results of said research, alongside existing literature (e.g., Kreye et al., 2014; Khachatryan et al., 2014; Koeser et al. 2015) that was used to identify attributes and levels – guaranteeing that all attributes included were relevant and grounded in empirical observations and preferences.

Escobedo et al. (2015) modeled and quantified urban forest ecosystem services such as air pollution, carbon sequestration, wood-debris generation, and property value for several, random 400 m2 field plots in Pensacola (n=70), Gainesville (n=90), Orlando (n=100), and Miami-Dade (n=229 plots) across different land uses, neighborhoods, and forest types. Their results indicate that, on average, more trees with greater Leaf Area Indices (LAI) add to property value, while biomass and tree–shrub cover have a neutral effect, and replacing tree with grass cover lowers property values. The average increase in property value, given their estimates, amounts to roughly $1,586 per tree and $9,348 per one-unit increase in LAI, while increasing maintained grass from 25% to 75% decreases property value by approximately $271. Other studies have also developed plot-level ecosystem service indicators for Gainesville and the role of hurricanes and invasives on urban forests in Miami-Dade and Pensacola has also been the subject of research (Dobbs et al. 2011; Escobedo et al. 2009; Timilsina et al. 2014). Urban forest maintenance surveys and carbon emissions-offsets have been determined at the plot-level as well (Horn et al. 2015).

3. Methodology

To estimate consumer preferences for key urban forest attributes and their ecosystem services and disservices, we used a panel (balanced with the most recent Florida Census data) of 1,052 Florida homeowners who answered one of two hypothetical urban forest landscape surveys– one regarding trees in their private property (PP) and the other in their neighborhood (NH). Both surveys used similar attribute levels and survey background information, but differed in terms of the hypothetical question, the vehicle for payment (utility tax increase vs home improvement program), and the location of trees that produce ecosystem services (ES). The hypothetical question for NH prompted participants with a ballot initiative referendum question regarding a "Florida Neighborhood Urban Forest Program" (NH; see Figure 1), while the PP presented a "Home Improvement Project."

Participants in PP survey were told to "assume that you will invest in a home improvement project using trees. The cost of this project will be presented as a 'monthly maintenance cost'." NH survey participants were instructed to "assume that you are asked to vote on an election referendum that will increase your 'monthly utility tax' to cover related tree maintenance costs associated with a neighborhood urban forest program. This program will be administered by the city government. The city will plant trees in proximity to your house that will raise your property's value and provide shade."

Figure 1. Example best-worst choice question.

Referendum 1: Florida Neighborhood Urban Forest Program
(Check one option as the most important and one option as the least important)

Most Important		Least Important
☐	High tree shade	☐
☐	Above $4,800 increase in property value (more than 3 trees)	☐
☐	Good condition (no poor condition trees)	☐
☐	$10.00 monthly utility tax	☐

Would you vote for this neighborhood urban forest program? Yes ☐ No ☐

The questionnaires were electronically administered using the marketing firm Qualtrics. There were two 2-level attributes (tree-shade and tree condition) and two 4-level attributes (property value improvements and monthly maintenance cost). Property value improvements were based on Escobedo et al. (2015), which found evidence for an increase in property value of $1,586 per tree (Woody tree/palm greater than 2.5 cm in DBH; Escobedo at al. 2015) for a typical single family home 0.3 has (0.75 acres). Maintenance costs were based on the number of times per year shrubs are hedged and trees received pruning in an average single family home 0.3 has (0.75 acres) - based on lawn maintenance survey in Orlando (Escobedo et al., 2015). Each hedging and pruning activity takes on average 1 hour (Horn et al. 2015), this estimate was multiplied by the minimum wage in Florida ($8.05 per hour; Section 24, Article X of the State Constitution and Section 448.110, Florida Statutes) to produce the values found in Table 1.

Table 1. Attributes and levels used to create choice experiment questions.

Attribute	Definition	Levels
Tree Shade	Higher tree shade near property will reduce temperature and energy use while lower tree shade near homes will have minimal effects on temperature and energy use.	High tree shade Low tree shade

Tree Condition	Trees in poor condition decrease the visual quality of your home and increase the risk of damage to homes and infrastructure.	Good condition tree Poor condition tree
Property Value	More trees on properties in your neighborhood can increase overall property values (approximately $1,600 per tree).	$1,600 $1,601 to $3,200 $3,201 to $4,800 >$4,800
Maintenance Cost	Monthly cost of maintaining trees in each neighborhood urban forest program (or home improvement program); only includes hours of labor and estimated monetary cost for pruning and care to maintain trees in good condition. This does not include or account for removal of poor condition trees.	$1.00 $4.00 $7.00 $10.00

Plot-level photos characterizing the structure-services from model sites were developed and displayed to participants for background - along with Florida findings from Wyman et al. (2012). A pre-survey questionnaire was used to further refine a set of critical attributes and feasible attribute levels needed to populate the choice and scaling questions, with a goal of limiting survey length and reducing respondent fatigue and choice task complexity (Dillman et al., 2009; Louviere et al., 2000). Following the methodologies prescribed by Flynn et al. (2007), an orthogonal main effects plan with 100% D-efficiency was used to construct the survey. The blocks were created using the MktEx macro from SAS statistical software package. This resulted in 16 questions, presented in two blocks of eight.

The best worst scaling (BWC) choice task was selected to produce more information - as compared to traditional discrete choice experimentation methods (DCE; Flynn et al., 2007). As seen in Figure 1, by asking respondents to perform two tasks: 1) choose a "most important" (best) and "least important" (worst) attribute level from a given profile or choice set; and 2) choose to reject/accept the entire profile, BWC can produce data that can estimated using best worst scaling (BWS) methodologies, along with binary data for DCE (conditional demand and willingness to pay; Flynn et al., 2007; Soto et al., 2016).

The BWS data can be estimated in four principle ways using a marginal or paired model, which in turn can be estimated at the sample or individual level (Flynn et al., 2007). We analyze both surveys (PP and NH) at the individual level using paired estimation (e.g., Lusk and Briggeman, 2009; Soto et al., 2016). This model selection and specification was due to the fact that marginal BWS models are an approximation of paired estimations (which may also lead to larger standard errors in estimated utility parameters due to fewer observations), but also to account for individual differences requires an analysis at the respondent level analysis (Flynn et al., 2007).

Paired estimations, at the respondent level, can be assessed using a conditional multinomial logit (clogit; Louviere et al., 2015) or a random parameters logit (RPL; Lusk and Briggeman, 2009). Following Flynn et al. (2007) and Lusk and Briggeman (2009), we manipulated the BWS data to accommodate the built-in clogit or RPL models of the statistical software STATA. This was done by expanding each outcome to account for all possible best-worst pairs in a given choice set. There were $J(J-1) = 12$ best-worst pairs available per choice set, where J is the number of attribute levels per choice set or profile.

The dependent variable was binary coded, it took 1 for the chosen best-worst pair and 0 for the all other (non-chosen) pairs available in each choice set. Following Louviere et al. (2015), all independent variables were coded using effects coding (see Appendix 1). Unlike DCE, BWS has the advantage of separating attribute impact (mean utility across all attribute levels) and level scale values (LSV; deviations from mean utility - attribute impact). Effects coding is mean centered, which allows for the separation of these estimates (Flynn et al., 2008).

The relationship between the utility difference of best-worst pairs and the attributes in this study can be illustrated by the following equation:

Equation 1.

$$U_{diff}^{i} = \beta_{Att1}^{i} D_{Att1}^{i} + \cdots + \beta_{Att3}^{i} D_{Att1}^{i} + \cdots + \beta_{Att1level1}^{i} D_{Att1level1}^{i} + \beta_{Att1level2}^{i} D_{Att1level2}^{i} + \cdots$$

$$+ \beta_{Att4level1}^{i} D_{Att4level1}^{i} + \cdots + \varepsilon^{i}$$

Where i is an observation of an individual who selects a best-worst pair, "Att#" and "Att#levels#" indicate attribute impact and LSV variables, respectively, β^{i} are the variable coefficients and D^{i} are the effects coding "dummies." For attribute impact variables, using effects coding, $D_{Att\#}^{i}$ takes one for the attribute (corresponding to the chosen attribute level) chosen as best, negative one for the attribute chosen worst, and zero otherwise. Similarly, the effects coded dummy of LSV variables, $D_{Att\#level\#}^{i}$, reverses its sign when chosen as worst (see Appendix 1 for LSV effects coding table). The standard conditional logistical function (and RPL) links the dependent variable (zero and one) with the estimated latent utility. Equation 1 includes 3 attribute impact variables (one per attribute minus one that is omitted) and 8 LSV (one for each attribute level minus one per attribute that is effects coded in the remaining attribute levels – the latter is later recovered using the estimations of the others; see Table 1). A key limitation of clogit models stems from the required assumption that all individuals in the sample place the same level of preference on each value. We relax this assumption using RPL (also referred to as mixed logit model). Please see Lusk and Briggeman (2009) for a formal description of the RPL for BWS.

The binary data produced by BWC (reject/accept; Binary hereafter) can also be estimated using logistical models (Louviere et al., 2000). We estimated both surveys using a random effects logit model (REL) to adjust for potentially unobserved individual-specific heterogeneity (e.g., socioeconomic characteristics and contextual effects such as survey fatigue; e.g., Coast et al., 2006; e.g., Soto et al., 2016). The dependent variable was also binary coded (0 and 1) – took one if the profile was "accepted" and zero if "rejected." Similar to BWS, all independent variables were effects coded. Note that in the case of BWS these switch sign – not in Binary. From the conditional demand estimations of Binary, we can calculate the willingness to pay (WTP) for urban forest ecosystem services of if the WTP sign is negative, the compensation requested for ecosystem disservices. WTP equals the ratio of the attribute's marginal effects coefficient with the price coefficient in the denominator – yielding monetary units (Louviere et al., 2000).

4. Results

The survey implementation yielded 1,052 completed (and verified) surveys (526 for each survey type). The third party marketing firm, Qualtrics, implemented the survey from March to

April of 2016. They contacted 4,659 survey participants and 1,716 completed the entire survey, resulting in a 40% response rate. Qualtrics provides a modest compensation to participants, which is not disclosed to scientists purchasing survey panels. The marketing firm filtered 664 participants (from the 1,716 completed surveys) who did not pass a "quality control test," namely, participants were asked to type the word "Florida," to filter participants who did not take the time to read and follow survey instructions. As seen in Table 2, several quotas (age and education) were not balanced with the most recent Florida Census data. To correct for this sampling imbalance, we created sampling weights using iterative proportional fitting techniques based on all variables displayed in Table 2 (e.g., Lusk and Parker, 2009).

Table 2. Characteristics of Private Property and Neighborhood survey participants vs US Census respondents from the State of Florida.

Category	Qualtrics Panel Private Property (n=526)	Qualtrics Panel Neighborhood (n=526)	US Census
Under 25 years	56.65[a]%	14.83%	29.96%
25 to 34 years	15.21%	29.66%	12.44%
35 to 44 years	23.19%	24.14%	12.50%
45 to 54 years	3.61%	14.26%	14.18%
55 to 64 years	0.76%	11.41%	12.75%
65 to 74 years	0.38%	4.56%	9.80%
75+ years	0.19%	1.14%	8.38%
Less than 12th grade	6.27%	3.23%	13.50%
High school graduated or GED	21.1%	17.68%	29.70%
Some College	27.76%	23.76%	20.90%
Associate or technical degree	12.93%	16.92%	9.20%
Bachelor's degree	20.91%	22.05%	17.10%
Graduate degree	11.03%	16.35%	9.60%
Female	50.95%	51.14%	51.10%
White/Caucasian	56.65%	56.84%	55.80%
African American	15.21%	15.02%	16.80%
Hispanic	23.19%	23.19%	24.10%
Asian	3.61%	1.52%	2.80%
Native American	0.76%	0.76%	0.50%
Pacific Islander	0.38%	0.38%	0.10%
Other	0.19%	2.28%	-
Annual HH income less than $25,000	22.05%	14.83%	25.60%
Annual HH income $25,000 to $49,999	26.62%	35.74%	26.80%
Annual HH income $50,000 to $99,999	29.28%	29.28%	29.20%
Annual HH income $100,000 to $199,999	17.11%	16.35%	14.40%
Annual HH income $200,000 or more	4.94%	3.8%	3.90%

[a] Percent of respondents falling in the respective category

Table 3 presents the BWS results for both private property survey (PP) and neighborhood improvement (NH). Following BWS convention, the attribute with least impact (Maintenance Cost) was omitted to avoid the "dummy variable trap" and to serve as reference point for the underlying latent scale of importance (e.g., Soto et al., 2016; Lusk and Briggeman, 2009). For the PP survey, all variables were significant at 1% level of statistical significance, except for increase in property value ranges of $1,601 to $3,200 and over $4,800, as well as monthly maintenance cost of $4.00. The level scale variable of maintenance cost, $7.00, was also significant at the 10% level. Similarly, for the NH survey, all were significant (p-value < 0.01) except for property value ranges of $1,601 to $3,200 and $3,200 to $4,800, as well as monthly maintenance costs of $4.00 and $7.00.

Table 3. Results from best-worst scaling for Private Property and Neighborhood survey participants: random parameters logit model estimations.

Attribute Impacts	Private Property Coefficient	Neighborhood Coefficient
Maintenance Cost	0 {1}	0 {1}
Tree Shade	0.78* (0.06)[b] [1.40][c] {2}	0.78[a]* (0.06)[b] [1.75][c] {2}
Tree Condition	1.02* (0.06) [1.30] {3}	0.85* (0.07) [1.55] {3}
Property Value	1.46* (0.07) [1.80] {4}	1.16* (0.07) [-1.83] {4}
Level Scale Values	**Coefficient**	**Coefficient**
High Shade	0.43* (0.04) [-0.55] {11}	0.37* (0.03) [0.40] {12}
Low Shade	-0.43[e] {6}	-0.37[e] {5}
Good Condition	0.5* (0.04) [-0.58] {12}	0.30* (0.03) [0.26] {11}
Poor Condition	-0.50[e] {7}	-0.30[e] {3}
$1,601 in Property Value	-0.28[e] {5}	-0.31[e] {4}
$1,601 to $3,200 in Property Value	-0.06 (0.05) [-0.07] {3}	0.04 (0.05) [0.20] {8}
$3,200 to $4,800 in Property Value	0.32* (0.05) [0.05] {10}	0.04 (0.05) [-0.09] {7}
Over $4,800 in Property Value	0.02 (0.05) [0.42] {8}	0.23* (0.05) [0.13] {9}
$1.00 Maintenance Cost	-0.01[e] {1}	-0.23[e] {2}
$4.00 Maintenance Cost	-0.05 (0.05) [0.09] {2}	0.02 (0.05) [0.01] {6}
$7.00 Maintenance Cost	-0.09*** (0.05) [0.01] {4}	-0.05 (0.05) [0.20] {1}
$10.00 Maintenance Cost	0.15 * (0.05) [0.18] {9}	0.25* (0.05) [0.30] {10}
Number of Respondents	526	526
Number of Choices	50496	50496
Log Likelihood	-8416.79	-8495.35
Chi-Square Statistic	0.00[d]	0.00[d]

[a] One (*), two (**), and (***) asterisk represent 0.01, 0.05, 0.10 level of statistical significance, respectively.
[b] Number in parentheses () are standard errors.
[c] Number in brackets [] are standard deviations.
[d] Chi-square statistic associated with a test of the hypothesis that all model parameters are zero.
[e] Effects coding: negative sum of the above level scale values corresponding to this attribute.
[f] Number in swirly brackets {} are Rank Order designations.

Both surveys showed the same rank order (ordered by sign and magnitude) of importance for attribute impact variables (mean utility of an attribute across all levels). Overall, Maintenance Cost had the lowest impact, Property Value the highest, followed by Tree Condition. However, both surveys differed slightly in terms of LSV (deviations from mean utility - attribute impact) estimates. Namely, for PP survey, the Good Condition attribute level had the highest level of importance (this LSV placed second, in terms of importance for NH survey), while High Shade ranked highest for NH (this ranked second, in terms of importance for PP survey). Their reverse order may signal higher importance for good condition trees inside their private property (given potential structural damage), than those outside (albeit near) their property. Conversely, homeowners, when considering a NH program, place the highest degree of importance on Shade. Note that both differences (Good Condition vs High Shade), in both surveys, are relatively small and are equal in magnitude (7 units), under the latent scale of importance. This implies a high degree of importance for both.

The last two important attribute levels, for both surveys, were the bottom categories of monthly maintenance cost. The top category ($10.00) of this attribute resulted in some of the highest levels of importance (9 in rank order for private property survey and 10 in rank order for neighborhood), but the lower categories (all bottom three for neighborhood and the bottom two for private property) lacked significance (p>0.10). This result may signal a threshold effect for cost, in both surveys, given said prices. The attribute levels appear to become relevant (or significant) above $7.00 per month.

Only one attribute level, per survey, was significant for Property Value ($3,200 to $4,800 in PP survey and >$4,800 in in NH). Nevertheless, each placed high in rank order (10 for private property and 9 for neighborhood) and, as previously noted, the attribute as a whole ranked highest in attribute impact.

Table 4 features the results for Binary (dichotomous choice random effects logit) estimations of both PP and NH surveys. The second and third columns (left to right) were coded using effects coding for all independent variables, but the last two feature WTP, which uses a quantitatively coded "Maintenance Cost" attribute needed for said calculations (Louviere et al., 2000). The attribute level "$1,601 to $3,200 in Property Value" was the only insignificant (p>0.10) variable in both surveys. Similar to BWS, the Maintenance Cost attribute seems to be exhibiting a threshold effect, namely, for both surveys, the attribute level estimates become negative at $7.00. The top two categories of property value, are positive and the bottom two negative for the PP survey, whereas the only top category for NH is positive and significant (p<0.01). As expected, high shade and good condition are positive. Most WTP estimates also have the expected signs, but it is interesting to note that all NH WTP estimates are larger (in magnitude) than PP WTP. The highest WTP, for both, was Good Condition trees. For PP survey, participants are willing to invest $3.12 in a home improvement that includes good condition trees. Conversely, a compensation requirement of the same amount would be needed for the ecosystem disservice afforded by poor condition trees. The analogous analysis applies to good condition trees in NH, but the WTP is slightly larger ($3.88). Similarly, participants in NH expressed a WTP of $1.54 for a neighborhood urban forest program with high tree shade.

Table 4. Results from BINARY (dichotomous choice random effects logit) model estimations for Private Property (PP) and Neighborhood (NH) surveys.

Attribute Level	Private Property Estimate	Neighborhood Estimate	WTP PP	WTP NH
High Shade	0.11a** (0.05)[b]	0.23[a]** (0.05)[b]	$0.68	$1.54
Low Shade	-0.11[c]	-0.23[c]	-$0.68	-$1.54
Good Condition	0.53* (0.05)	0.59* (0.05)	$3.12	$3.88
Poor Condition	-0.53[c]	-0.59[c]	-$3.12	-$3.88
$1,601 in Property Value	-0.32[c]	-0.44[c]	-$1.90	-$2.85

$1,601 to $3,200 in Property Value	-0.24* (0.08)	0.12 (0.09)	-$1.41	$0.81
$3,200 to $4,800 in Property Value	0.23** (0.09)	-0.26* (0.09)	$1.33	-$1.69
Over $4,800 in Property Value	0.34* (0.08)	0.57* (0.09)	$1.99	$3.73
$1.00 Maintenance Cost	0.75[c]	0.64[c]		
$4.00 Maintenance Cost	0.28* (0.08)	0.32* (0.09)		
$7.00 Maintenance Cost	-0.27* (0.08)	-0.28* (0.09)		
$10.00 Maintenance Cost	-0.76* (0.08)	-0.69* (0.09)		
Constant	1.05* (0.16)	1.53* (0.18)		
Number of Respondents	526	526		
Number of Choices	4208	4208		
Log Likelihood	-1904.38	-1760.07		
Chi-Square Statistic	0.00[d]	0.00		

[a] One (*) and two (**) asterisk represent 0.01 and 0.05, level of statistical significance, respectively.
[b] Number in parentheses () are standard errors.
[d] Chi-square statistic associated with a test of the hypothesis that all model parameters are zero.
[c] Effects coding: negative sum of the above level scale values corresponding to this attribute.

5. Discussion and Conclusion

This study uses Best-Worst Choice modeling to estimate willingness to pay for urban forest ecosystem services in Florida, and identify the urban forest structure and diversity attributes consumers prefer. Two surveys were administered, via Qualtrics online survey software, to elicit responses for a hypothetical private property home improvement investment and neighborhood urban forest referendum. The combined response rate was completed with a 40%. The results show a higher preference for hypothetical urban forest programs that primarily increase property value, followed by good condition trees and high tree shade. The willingness to pay estimates, for both surveys, had the expected signs and significance, but potential "scale effect" was observed where NH WTP estimates are larger (in magnitude) than PP WTP. This effect, albeit small, may be due to the manner in which we defined "neighborhood," namely, we instructed participants to consider it as an area proximate their home such that trees will raise property values and provide shade. Survey participants of NH may have had higher WTP estimates given that poor condition trees, for example, if planted in proximity to their home, may amplify the odds of property damage and bodily harm – higher than perhaps a personal investment on their own property. Overall, the attribute "Maintenance Cost" had the lowest impact, Property Value the highest, followed by Tree Condition and Tree Shade. Determining Floridians' preferences toward specific forest-landscape attributes and their ecosystem services can enable homeowners and policy makers to make more sustainable land use decisions. To increase participation in efforts that generate urban forest ecosystem services, at the public or private level, policymakers may need to design programs that cost less than $7.00 per month, while maintaining good condition trees that provide high shade.

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Appendix 1. Description of Effects Coding for Econometric Analysis of Best-Worst Choice Data

Attribute	Effects coding	Effects coding	Effects coding
Property Value	\$1,601 to \$3,200	\$3,201 to \$4,800	>\$4,800
\$1,600	-1	-1	-1
\$1,601 to \$3,200	1	0	0
\$3,201 to \$4,800	0	1	0
>\$4,800	0	0	1
Maintenance Cost	\$4.00	\$7.00	\$10.00
\$1.00	-1	-1	-1
\$4.00	1	0	0

$7.00	0	1	0
$10.00	0	0	1
Tree Condition			
Good condition tree	1	-	-
Poor condition tree	-1	-	-
Tree Shade			
High tree shade	1	-	-
Low tree shade	-1	-	-