Landscape and Urban Planning 215 (2021) 104234

Contents lists available at ScienceDirect

Landscape and Urban Planning

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

Research Paper

Heterogeneous preferences and economic values for urban forest structural and functional attributes☆

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HIGHLIGHTS

- This study examines preferences for multiple urban forest structure-function attributes.
- We quantify the differences in willingness-to-pay for these attributes across the population.
- Findings can inform policy initiatives and provide evidence of preference heterogeneity.

ARTICLE INFO

JEL codes:
Q23
Q51
C25

Keywords:
Latent class
Discrete choice
Heterogeneous preferences
Ecosystem services
Ecosystem disservices
Willingness to pay

ABSTRACT

The structural and functional attributes of urban and peri-urban forests are the basis for the provision of a suite of ecosystem services that directly and indirectly benefit residents across scales, tenures and land uses. As such, many local governments promote municipal urban forest initiatives such as maintenance and management plans, ordinances, and tree-giveaway programs (e.g. Orlando, USA and Sydney, Australia). However, the effectiveness and distributional fairness of these activities often overlooks residents' values and preferences for certain tree functional traits, sizes, densities and associated costs. This study implements an online survey of 724 Florida, USA residents, to: 1) examine preferences/tradeoffs for multiple urban forest structure-function attributes; 2) quantify and assess the differences in willingness-to-pay (WTP) for these forest structure attributes in public areas; and 3) examine the implications of value heterogeneity for tree function-structure attributes for purposes of crafting policies or designing public programs dealing with urban forests. Only 19% of respondents indicated a serious concern about living close to trees and flowering plants that produce pollen that can result in allergies. Similarly, only 12% were concerned about hurricane wind impacts to and from their treescapes. Using latent class modeling and a stated preferences panel data, our results reveal important differences in WTP along multiple value groups, each with different WTP values for: tree nativity (native vs. exotic); number of species (many vs. few) and size of trees (fully grown vs. mix of ages); as well as maintenance costs. The novel approach of this study indicates the importance of using tree functional traits versus species taxa and accounting for diverse values among the public for more effective decisions. Findings can be used to inform timely policy initiatives, while providing additional evidence of the ubiquity of the public's heterogeneous values and providing guidance to avoid potentially misleading policy interpretations.

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https://doi.org/10.1016/j.landurbplan.2021.104234
Received 14 May 2020; Received in revised form 18 August 2021; Accepted 23 August 2021
Available online 31 August 2021

1. Introduction

The increasing pace of urbanization worldwide makes urban forests key in providing a wide range of ecosystem services that contribute to human well-being in multiple ways. The United Nations estimates that 55 percent of the world's population already lives in urban areas, and by 2050, 68% of the globe's people will be living in urban areas. North America is the world's most heavily urbanized region, with an estimated 82 percent of people currently living in urban areas (United Nations, 2019). Forests in the urban and peri-urban landscape provide many ecosystem services that directly and indirectly benefit human beings, such as carbon sequestration, temperature regulation, noise reduction, air quality improvements through particulate deposition, wildlife habitat, recreational opportunities, water cycling, reduced storm water runoff, and aesthetic benefits that improve land and home values as well as human health outcomes, among many others (Donovan, Michael, Butry, Sullivan, & Chase, 2011; Kondo, Han, Donovan, & MacDonald, 2017; Oldfield, Warren, Felson, & Bradford, 2013; Escobedo, Adams, & Timilsina, 2015; Nowak, Noble, Sisinni, & Dwyer, 2001).

However, humans in general cannot directly manage for complex ecological processes and ecosystem services *per se*, rather the role of urban forests as providers of ecosystem services is largely driven by structural and functional attributes such as: composition, species diversity, size class distribution, nativity, tree cover, leaf area as well as their social, environmental and financial costs (i.e., ecosystem disservices Cariñanos & Casares-Porcel, 2011; Giergiczny, Czajkowski, Żylicz, & Angelstam, 2015; Soto, Escobedo, Khachatryan, & Adams, 2018). For example, composition, diversity, and nativity can drive ecosystem resilience and biodiversity habitat, while tree size and density determine climate regulation and property values, and leaf area and tree cover determine air quality and energy use reduction (Adams et al., 2020; Escobedo et al., 2015; Horn, Escobedo, Hinkle, Hostetler, & Timilsina, 2015). Indeed, it is this link between urban forest structural-functional attributes and the ecosystem service-benefits provided that is the basis for managing, planning, and valuing the ecosystem services provided to different beneficiaries (Cariñanos & Casares-Porcel, 2011; Donovan et al., 2011; Fan, Johnston, Darling, Scott, & Liao, 2019). In addition, it is also these same structural-functional attributes that are often used as indicators and monitoring metrics for assessing and evaluating the provision of highly valued ecosystem services or minimizing ecosystem disservices (Dawes, Adams, Escobedo, & Soto, 2018; Soto et al., 2018; Gwedla & Shackleton, 2019).

Urban forests are present across different land uses and tenure, and include natural, forested stands in peri-urban and rural areas as well as treescapes growing along urban streets, private residential lots, public parks, and other open spaces. Urban forests are also habitat for plant, bird, mammal, reptile, and amphibian diversity, and in many cases, urban forests contain higher species richness than rural or unpopulated areas, including endemic and threatened species (Alvey, 2006). The spatial distribution of urban forests and the biodiversity they hold, have also been found to be dependent on humans' socioeconomic and cultural characteristics—including their preferences and values (Blood, Starr, Escobedo, Chappelka, & Staudhammer, 2016; Kinzig, Warren, Martin, Hope, & Katti, 2005). In general, these forests are managed by private property owners or municipal governments to achieve certain structural objectives such as increased urban tree cover, a diversity of species, patch distribution, composition, nativity and certain planting configurations and densities (Fan et al., 2019; Nowak et al., 2001).

Even though exotic species represent a substantial component of urban forests throughout the world (Sjöman, Morgenroth, Sjöman, Sæbø, & Kowarik, 2016), urban forestry programs have tended to focus on planting and maintaining native rather than exotic tree species (Dawes et al., 2018). In large part, this focus on native species relies on the assumption that species adapted to local conditions use available resources more efficiently and provide superior habitat to support other native plants and animals (Oldfield et al., 2013). This narrative has gained a foothold in many practice-oriented publications, government websites, environmental groups, and the media, and in some cases exotic trees are depicted as incapable of providing ecosystem services. It is likely that some of this narrative is rooted in a common misconception that equates exotic or non-native species to invasive species, even though one of the basic insights of invasion science and regulatory listings is that not all introduced (exotic, non-native) species are invasive (Horn et al., 2015; Sjöman et al., 2016). Other common misconceptions that have impacted urban forest structure, composition and configurations include the belief that most people prefer shade trees (Dawes et al., 2018); that urban tree cover is at odds with crime prevention and effective policing (Kondo et al., 2017); that stringent restrictions on private tree canopy leads to urban canopy loss (Carmichael & McDonough, 2019); and that non-experts and homeowners cannot identify the trade-offs between tree-based risks (ecosystem disservices) and ecosystem service benefits (Soto et al., 2018).

From a normative perspective one could also posit that managing urban forests so as to optimize the provision of ecosystem services would be an acceptable and pragmatic policy objective (e.g., Piponiot, 2019; Alvarez, Larkin, & Ropicki, 2017; Pribadi & Xu, 2017; Tsiafouli, Drakou, Orgiazzi, Hedlund, & Ritz, 2017). However, in practice, maximizing ecosystem services and minimizing ecosystem disservices from urban forests would entail weighing benefits and costs of different forest structural and functional attributes, which correspond to different potential urban forest structural configurations (Giergiczny et al., 2015). Accordingly, research to better understand people's (i.e., voters, stakeholders, land managers, individuals from different socio-demographic groups, etc.) preferences and values for attributes of goods, services, and policies can inform the management of ecosystems, their structure, function, and subsequent provision of ecosystem services in cities across the globe (Tyrväinen & Väänänen, 1998; Vandermeulen, Verspecht, Vermeire, Van Hyulenbroeck, & Gellynck, 2011; Gwedla & Shackleton, 2019).

Furthermore, monetary estimates of the economic value of urban forests across different urban forest attribute configurations can be developed using non-market valuation methods that rely on the identification of people's preferences toward urban forest structural and functional attributes. In the realm of natural resources and the environment, preferences for policies and policy attributes have been explored using discrete choice models, where the stated or revealed choices of individuals are analyzed using logit models in a random utility framework. This type of research can inform public policies dealing with fish consumption advisories (Morey, Thacher, & Breffle, 2006), compensation to outdoor recreationists impacted by oil spills (Alvarez, Larkin, Whitehead, & Haab, 2014), drinking water supply (Thiene, Scarpa, & Louviere, 2015; Kreye, Adams, Escobedo, & Soto, 2016), wetland management (Birol, Karousakis, & Koundouri, 2006; Milon & Scrogin, 2006), as well as forest ecosystem services and disservices (Soto et al., 2018).

Discrete choice models can also be used to forecast demand for environmental assets and policies impacting them, as well as to estimate individuals' willingness to pay for these assets and their attributes. However, early methods used to analyze discrete choice data had several shortcomings, key among them the assumption that the coefficients that describe preferences are the same for all individuals (Train, 1998). Hence, policies informed by these models would be designed to serve a hypothetical 'average' respondent whose characteristics match the mean of the estimated parameter distributions, but would ignore the diversity of preferences in the population, thereby unintentionally creating winners and losers. Given that policymakers' decisions involve welfare weightings based on distributional impacts and other factors (Just, Hueth, & Schmitz, 2005), they are likely to be sensitive to distributional impacts, and thus information that illuminates distributional impacts can be of high value in policymaking.

Advances in computing power and statistical methods now allow researchers to account for diversity or heterogeneity in consumer preferences inherent in people's choices that are captured in discrete choice data. With the random parameters logit (RPL), researchers can assume a distribution for the preference parameter and recover estimates for mean and standard deviation (Train, 1998). With the latent class logit (LCL), researchers can determine the number of available latent classes and recover preference parameters for each latent class (Boxall & Adamowicz, 2002). While both methods account for heterogeneity in preferences expressed through individual's choices, they are not equally useful for policy decision making, as their practicality can be expected to hinge on the specificity of their results.

In this study we incorporate context-specific urban forest structure, composition, and functional attributes (Escobedo et al., 2015: Soto et al., 2018) along with survey methods (i.e., choice experiments) to examine residents' preferences and values for urban forest structure-function attributes and costs in Florida, USA. Our objectives were to 1) to examine public preferences and willingness to pay for management-relevant urban forest attributes such as native and exotic trees, forest diversity, and overall quantity of trees in urban forested landscapes; and 2) examine if values for these attributes are heterogeneous in the population.

The rest of this study is structured as follows. First, we summarize the survey instrument and its stated preference approach, and describe the data and econometric methods used to analyze the data. Second, we present the results of the analysis, and third we provide a discussion of the management and policy relevance of our findings. The study concludes with presenting our study limitations and recommendations for future research.

2. Methods

2.1. Survey effort and data

Urban forest structure and functional data and information were obtained from relevant Florida, USA specific studies including Soto et al. (2018), Dawes et al. (2018), Escobedo et al. (2015), and Horn et al. (2015). We specifically used the following four urban forest structure-function attributes in subsequent analyses: tree nativity, number of tree species, tree size and age, and the monthly costs associated with treescape maintenance. The stated preference data used in this study were obtained through an online survey of Florida residents who were recruited using Qualtrics, a third-party marketing firm.

The objective of the survey was to investigate the preferences of Florida residents towards forested landscapes, or streetscapes in their homes and neighborhoods as well as individuals' willingness to pay for prevention of forest pests. The survey was developed in 2016, using the Dillman Method (Dillman, Smyth, & Christian, 2009). For pre-testing, we sought input from 15 individuals ranging from experts in the field of forestry to lay members of the public. Following pre-testing, the survey was soft-launched in late July 2016 through a pre-recruited Qualtrics online panel. After two days of data collection, the survey was taken offline for a preliminary results review. After deeming that the online platform was performing appropriately, the survey was fully launched in early August 2016 targeting a representative sample of Florida adults by fulfilling respondent quotas for statewide demographics obtained through the US Census bureau. The survey was closed in late August after 724 respondents submitted completed surveys, exceeding our target of 500 completed surveys.

During pre-test and full launch, Qualtrics sent a total of 14,386 email invitations to members of their online panel. A total of 3,210 individuals started the survey, but 2,413 individuals were screened out due to ineligibility. In addition, 73 individuals dropped out after beginning the survey. Therefore, the 724 completed surveys resulted in a completion rate of 24.82%, considered good when compared to similar studies (e.g. DiSogra & Callegaro, 2016; Callegaro & DiSogra, 2008).

The survey was composed of four major sections. The first section introduced the subject matter of the survey and contained a series of demographic and socioeconomic questions. Respondents were told that the survey had to do with the importance of urban forests and included two major components: preferences and values for urban forests including different forest settings and costs, and invasive pest prevention options for protecting urban forests. The demographic section consisted of multiple-choice questions about household income, gender, age, education, employment status, race and ethnicity, relationship status, and number of children. The section finalized with an attention check question prompting respondents to select a particular number from a list. The invasive forest pest prevention component of the survey was analyzed in a separate study (Adams et al., 2020).

The second section contained the discrete choice experiment, which was modeled after the scenario used by Garrod (2002). Respondents were asked to consider a scenario where they will be moving into a new home in Florida, and a series of questions followed this visioning exercise. First, they were asked about the factors that are important to them when selecting a new home, such as proximity to work, low crimes rates, and quality of public schools, among others. They were then asked if they prefer living in urban areas, suburban areas, or rural areas. Given that Florida experiences hurricane force winds on a regular basis (Soto et al., 2018; Brown, Alvarez, Eluru, & Huang, 2021), respondents were also asked about their main concerns associated with potential storm damage involving trees. Since tree pollen, particularly from certain types of trees, is known to trigger allergic reactions (i.e. ecosystem disservice) across different demographics (Cariñanos & Casares-Porcel, 2011), respondents were also asked about their level of concern due to pollen from trees or other sources, as well as the region of the state that they would prefer to live in.

These above questions led respondents into the discrete choice experiment task, in which they were told to imagine that after searching for their prospective new home they had found their top three options. Respondents are also told to imagine that the main difference between the three options is related to the type of shrubs, trees, and landscaping in the home and the surrounding neighborhood. They were also told that landscaping differs in terms of four urban forest structure-function attributes: the types or species of trees (native vs. exotic), the ages and sizes of trees (only tall, large, and fully grown trees vs. trees of different ages, sizes, and heights), the number of tree and shrub species (few species vs. many species), and the monthly costs to maintain the landscape (US$1, US$4, US$7, or US$10).

At this point, the sample was split in two, with half being asked to answer questions about their preferred streetscape in their favorite home's yard, and the other half being asked about their preferred streetscape in the public areas around their favorite home. Given that our objective is to provide information that can be used in public policy making, the rest of this study focuses on responses from the 362 individuals who were asked about preferences for streetscapes in public areas. Choice experiment design and variables used in the analysis are summarized in Table 1; an example of the choice experiment question is shown in Fig. 1. Note that we use a dummy-variable coding scheme rather than an effects-coding scheme for the attribute coding. The choice experiment was designed using the ADX Interface of the SAS statistical software (D-optimal criterion), with four factors which resulted in eight scenarios (D-efficiency of 100), consisting of three options plus a status quo or opt-out option, labeled as alternative specific constant (ASC). In addition, each choice task was followed by a question asking respondents how certain they were of their response in the preceding task. The third section contained the double-bounded contingent valuation experiment dealing with invasive forest pests on urban forests, which is the subject of a different study (Adams et al., 2020). The fourth and final section contained a series of attitudinal and psychometric questions.

2.2. Econometric methods

Discrete choice experiments are repeated choice occasions by the same individuals, in which each individual chooses one profile from

Table 1
Choice experiment design and variables used in the study based on information from: Soto et al. (2018), Dawes et al. (2018), Escobedo et al. (2015) and Horn et al. (2015).

Attribute (Structural characteristic)	Levels	Variable Name, Coding Scheme, Source
Type of trees (Tree Nativity)	Native	Native = 1
	Exotic	Native = 0 Dawes et al., 2018
Number of tree species (Tree Density)	Few species	Fewspp = 1
	Many species	Fewspp = 0 Escobedo et al., 2015
Size and age of trees (Size class distribution)	Only tall, large, and fully grown trees	Fullgrown = 1
	Trees of different ages, sizes, and heights	Fullgrown = 0 Soto et al., 2018
Monthly cost to maintain landscape (Financial costs)	$1	Monthly cost = 1
	$4	Monthly cost = 4
	$7	Monthly cost = 7
	$10	Monthly cost = 10 Horn et al., 2015; Soto et al., 2018
Alternative Specific Constant (ASC)	Status-quo or opt-out choice	ASC = 1
	Other choice	ASC = 0

among a set of available options (Hensher et al., 2015). We analyze this choice data using random utility theory, where individual n gets utility U_{nit} from selecting alternative i on choice occasion t:

$$U_{nit} = V_{nit} + \varepsilon_{nit}, \tag{1}$$

where V_{nit} is a deterministic component of utility and ε_{nit} is a stochastic component. If choice occasion t includes a set of J alternatives, individual n will choose alternative i if $U_{nit} > U_{njt}$; for all $j \neq i$. Hence, the probability that individual n chooses alternative i is given by:

$$P_{nit} = \Pr\,(V_{nit} + \varepsilon_{nit} > V_{njt} + \varepsilon_{njt};\ \text{for all } j \neq i). \tag{2}$$

The deterministic component of utility takes the form $V_{nit} = \beta' X_{nit}$, where β' is a vector of random parameters that represent individual preferences, and X_{nit} is the vector of attributes found in alternative i. Assuming that the stochastic terms (ε_{nit}) are i.i.d. extreme value yields McFadden (1974) conditional logit, where the probability of choice is given by:

$$P_{nit} = \frac{\exp(\beta^{'} X_{nit})}{\sum_j \exp(\beta^{'} X_{njt})}. \tag{3}$$

The conditional logit yields point estimates for the preference parameters (β'), implicitly assuming that preferences are homogeneous.

Heterogeneous preferences can be accommodated using a latent class logit [LCL] (Boxall & Adamowicz, 2002). The LCL model assumes that parameter vectors, β', are distributed among individuals with a discrete distribution. Thus, it is assumed that the population consists of a finite number, S, of groups of individuals, where the groups are heterogeneous, with common parameters, β_s, for the members of the group, but the groups themselves are assumed to be different from one another (Hensher et al., 2015). In that case, the choice probability is given by:

$$P_{nit} = \sum_{s=1}^{S} \frac{\exp(\beta_s^{'} X_{nit})}{\sum_j \exp(\beta_s^{'} X_{njt})} R_{ns}, \tag{5}$$

where β_s' is the specific parameter vector for class s, and R_{ns} is the probability that individual n belongs to class s. In turn, the class membership probability (R_{ns}) can be modeled as:

$$R_{ns} = \frac{exp(\theta_n^{'} Z_n)}{\sum_r exp(\theta_r^{'} Z_n)}, \tag{6}$$

where Z_n is a set of observable individual characteristics that affect class membership, and θ_s is the parameter vector for individuals in class s. It is important to recognize that class membership is only known up to a probability and each respondent has a finite probability of belonging to each class. Mean probability of belonging to each class is not the same as a share of respondents belonging to each class (Mariel et al., 2020; Hess, 2014). In reality, the population is far more heterogeneous than what the latent class representation suggests, as the model mixes data points into a discrete number of classes to represent the underlying heterogeneity.

In this framework, willingness to pay for a given attribute level q, by a member of class s, is given by the marginal rate of substitution arising from the ratio of the utility parameter estimates associated with q, and the utility parameter associated with the maintenance cost (*Monthly cost*), for each class s (Louviere, Hensher, & Swait, 2000):

$$WTP_{qs} = -\left(\frac{\widehat{\beta_{qs}}}{\widehat{\beta_{price,s}}}\right) \tag{7}$$

We note that as seen in Table 1, all non-monetary attributes have two levels and are dummy coded. As such, the utility (or WTP) that respondents derived from the levels which were explicitly included in the model should be interpreted as relative to their respective base levels. Namely, since "native" was set as the base level for attribute "Type of trees" (see Table 1), the coefficients of "exotic" should be considered as the utility that respondents derived from such tree types, relative to native. Similarly, "many species" was set as the base level for Number of tree species, and "trees of different ages, sizes, and heights" was set as

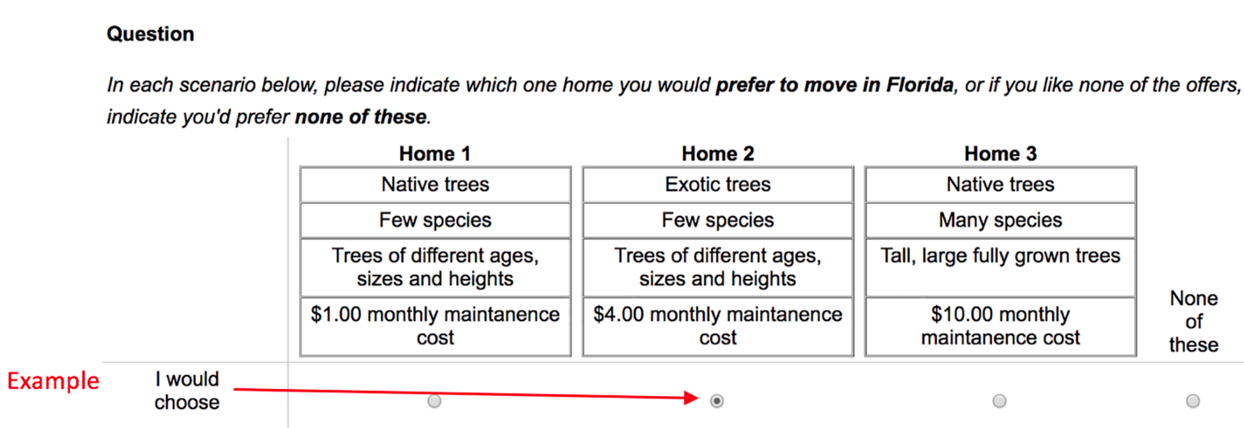

Fig. 1. Sample question from the choice experiment portion of the survey. This image was used to train respondents on how to answer the choice experiment.

the base level for Size and age of trees (e.g., Pienaar, Soto, Lai, & Adams, 2019).

In this study, we estimated a series of latent class logits using one half of the sample data from the online choice experiments, or 362 responses. Only 362 survey responses are used, as the other 362 responses experienced a different version of the questionnaire that focused on urban trees in private yards. We estimate latent class logit models by increasing the number of allowed classes from two to four. This allows us to explore the existence of preference and value heterogeneity in the data, as well as to find the best fitting latent class logit model that exposes the number of latent preference classes that best represents existing preference heterogeneity in the sample.

3. Results

3.1. Overview

Descriptive statistics are presented in Table 2. There is variability in the sample across all demographic characteristics, but women and respondents under 25 years of age appear to be somewhat over-represented. Nearly two-thirds of respondents reported having no children. When it comes to attitudes towards the environment, 59% expressed being concerned about water quality, and 73% of respondents reported that they recycle most or all of the time. Sixty percent of respondents reported they are willing to make lifestyle changes to reduce the impact they have on the environment, while 40% reported that outdoor recreation is important to them. Similarly, 48% reported being concerned about invasive species. In a double-hurdle question where respondents were first asked if they believe climate change is happening, and those that answered 'yes' were then asked if they think it is mostly caused by humans (as opposed to mostly naturally occurring, or both naturally occurring and caused by humans equally), only 35% of respondents indicated that they believe it is happening and is mostly caused by humans.

When asked about the costs or ecosystem disservices of urban forests, only 19% of respondents indicated they are extremely or very concerned with living close to trees, flowering plants, or sources of pollen that may result in seasonal allergies, while 59% are only slightly or not at all concerned about tree pollen. When asked about potential storm and wind damage, a majority of respondents expressed concern about home damage due to falling trees, and half of respondents expressed concern about power outages due to trees damaging electric power lines. Only a small proportion of respondents (12%) expressed no concern about the negative impacts of storms and hurricane winds on trees.

Table 2
Descriptive statistics and coding strategy of the respondent sample.

Income 1 if over $100 k	Less than $25,000	31%
	$25,000 to $49,999	27%
	$50,000 to $99,999	26%
	$100,000 to $199,999	11%
	$200,000 or more	5%
Gender 1 if male	Female	64%
	Male	36%
Age 1 if under 35 years old	Under 25 years	26%
	25–34 years	16%
	35–44 years	15%
	45–54 years	13%
	55–64 years	14%
	65–74 years	10%
	75 years or over	6%
Children 1 if they have children	None	66%
	1	17%
	2	12%
	3	3%
	4	1%
	More than 4	1%
Water Pollution 1 if very/extremely concerned	Not concerned	41%
	Concerned	59%
Invasive Species 1 if very/extremely concerned	Not concerned	52%
	Concerned	48%
Recycling 1 if always/most of the time	No recycle	27%
	Recycle	73%
Outdoor Recreation 1 if very/somewhat important	Not Important	60%
	Important	40%
Climate Change 1 if believe climate change occurring and caused by humans	No	65%
	Yes, caused by humans	35%
Lifestyle Change 1 if extremely/very willing	Not Willing	40%
	Willing	60%
Concern with Pollen	Extremely concerned	7%
	Very concerned	12%
	Moderately concerned	22%
	Slightly concerned	19%
	Not at all concerned	40%
Concern with storm and wind damage	Not concerned about any of these	12%
	Home damage due to falling trees	56%
	Power outages due to trees on utility lines	50%
	Home damage due to wind	45%
	Power outages due to wind	44%
	Vehicle damage	46%
	Damage to trees	28%
	Flooding	48%
	Other	1%

3.2. Identification of preferred model

To test for preference consistency, or the assumption that that individuals consistently know their preference ordering, we performed a procedure following Brouwer, Dekker, Rolfe, and Windle (2010). More precisely, we compared results from RPLs with no calibration against a calibration where we re-code all choices where the certainty falls below the average certainty, as 'opt-out' choices. The comparison showed that the coefficients of interest remain stable, and no subsequent calibration for consistency was necessary. Thus, we proceeded with estimating CL, RPL (assuming a normal distribution for random parameters and using 1000 Halton draws to simulate the random parameters model log-likelihood) and LCL models that include individual characteristics with up to four latent classes.

While all these models present relevant valuation information, the models differ in terms of goodness of fit and explanatory power. Accordingly, we compared model fit using the Akaike Information Criteria (AIC) and the Bayesian Information Criteria (BIC; Fig. S1) to aid in the selection of a superior model, and to better inform policy formulation and decision making. In our case, the models improved in terms of goodness of fit as they provide more flexibility in regards to accommodating preference heterogeneity. That is, the conditional logit, which assumes that all individuals have the same preferences, is the model with the poorest fit, whereas the random parameters logit, which provides the most flexible framework to accommodate preference heterogeneity, is the model with the best fit. Our discussion of results in Section 3.3 will focus on the 4-class LCL model which provides more actionable policy and management-relevant recommendations (see results for CL, RPL and LCL models with 2 and 3 classes in Supplementary material Tables S1–S4). A sensitivity analysis of the RPL model with different distribution assumptions is available in Supplementary materials (Table S5). The policy-relevance and actionability of results from different models is further discussed in Section 4.

3.3. Preferences and willingness to pay for structural attributes of urban forests

Table 3 provides results for the 4 class LCL, the best fitting model describing the public's preferences for urban forest attributes, while Table 4 summarizes the willingness to pay (WTP) differences across levels of dummy-coded attributes – for all four latent classes. In both of these tables, a positive coefficient or WTP indicates that the class exhibits a preference toward the indicated variable, while a negative coefficient or willingness to pay indicates that the class exhibits a preference toward the converse of the indicated variable. For example, a positive coefficient for 'exotic' indicates that as a whole the class prefers exotic trees, while a negative coefficient indicates that the class as a whole prefers native trees. The WTP estimates for the 3 urban forest attributes across the four latent classes is shown in Fig. 2.

Respondents in the sample had a mean probability of belonging to *Class 1* equal to 0.265 (Table 3). The *Class 1* preference profile favors native trees, and is willing to pay a hefty $32.07 per month to avoid exotic trees (or conversely, to have native trees). This preference profile also prefers to have many tree species (WTP -$3.48 per month for few species) of various stand-structural features such as age class, height, diameter, and density (i.e., negative WTP of $4.08 for full grown trees only), for urban forests in parks and medians of their neighborhoods (Table 4). This class is sensitive to treescape maintenance cost, tree nativity, number of species, and tree stand-structure, as the variables are statistically significant. Men are less likely to belong to *Class 1* (relative to *Class 4*), as indicated by the negative coefficient for gender (Table 3). Similarly, individuals aged under 35 are more likely to belong to *Class 1*, as indicated by the coefficient for age. Individuals who indicated they are willing to make lifestyle changes to protect the environment are also less likely to belong to *Class 1* (Table 3).

The mean probability of belonging to *Class 2* was equal to 0.112 (Table 3). The *Class 2* profile also prefers native trees (WTP -$4.06 per month for exotic) of various stand-structural features (WTP -$4.95 per month for full grown trees) around their neighborhood (Table 4). *Class 2* appear to be indifferent about the number of species, as the coefficient for few species is not statistically significant. This class is less likely to be composed of individuals with incomes higher than $100,000 (relative to *Class 4*), as well as by individuals who expressed being concerned about invasive species, and those who indicated they would be willing to make lifestyle changes to protect the environment. Conversely, *Class 2* membership is more likely to be composed of individuals who are younger than 35 years of age (Table 3). Class 2 preferences appear to be in line with the *Class 1* in terms of sign, but seem to exhibit weaker preferences or lower WTP for native trees, also suggesting that the *Class 2* preference profile is more accepting of exotic trees. However, in contrast to *Class 1*, the *Class 2* profile appears to be indifferent regarding the number of tree species.

Class 3, whose mean probability of membership is equal to 0.298, appears to have the weakest preferences for the urban forest functional and structural attributes examined, or the lowest WTP. Namely, while this class seems to exhibit a preference toward urban forests composed of few native tree species of various stand-structural features (e.g. age class, height, diameter, density), their WTP values are the smallest of all groups. This class membership has a low (but negative) WTP value for exotic trees, implying that while they prefer native trees, they are more accepting of exotic trees than *Class 1* and *Class 2*. The most important difference of this preference profile centers on the positive valuation of few species of trees (WTP $1.64). Individuals who are younger than 35 years of age are more likely to belong to *Class 3*, relative to *Class 4* (Table 3).

Class 4, the largest class, has a mean class membership probability of 0.326 (Table 3), and appears to have strong preferences towards urban forests with many species of exotic trees, and weaker preferences towards urban forests containing various stand-structural features (Table 4). However, the latent class coefficient for monthly maintenance

Table 3
Preferences for Forests in Public Areas – Four Latent Class Logit. Average class probability is indicated in parenthesis next to each class number label.

	Coef.	Std. Err.	z	p-val	95% CI	
Class 1 (0.265)						
Monthly cost	−0.108***	0.031	−3.460	0.001	−0.169	−0.047
ASC	−3.740***	0.298	−12.560	0.000	−4.323	−3.156
Exotic	−3.467***	0.540	−6.420	0.000	−4.525	−2.408
Few Species	−0.376***	0.131	−2.880	0.004	−0.633	−0.120
Full Grown Trees	−0.441**	0.181	−2.430	0.015	−0.796	−0.086
Class 2 (0.112)						
Monthly cost	−0.182***	0.043	−4.210	0.000	−0.267	−0.097
ASC	0.466	0.311	1.500	0.134	−0.143	1.076
Exotic	−0.838***	0.282	−2.970	0.003	−1.392	−0.285
Few Species	−0.179	0.269	−0.670	0.505	−0.707	0.348
Full Grown Trees	−0.903***	0.284	−3.180	0.001	−1.459	−0.347
Class 3 (0.298)						
Monthly cost	−0.449***	0.044	−10.310	0.000	−0.534	−0.364
ASC	−4.226***	0.275	−15.350	0.000	−4.766	−3.687
Exotic	−0.287*	0.165	−1.740	0.081	−0.611	0.036
Few Species	0.737***	0.178	4.140	0.000	0.389	1.086
Full Grown Trees	−1.152***	0.166	−6.920	0.000	−1.478	−0.826
Class 4 (0.326)						
Monthly cost	−0.016	0.013	−1.210	0.225	−0.042	0.010
ASC	−3.346***	0.454	−7.370	0.000	−4.236	−2.457
Exotic	0.345***	0.096	3.580	0.000	0.156	0.534
Few Species	−0.358***	0.088	−4.050	0.000	−0.531	−0.185
Full Grown Trees	−0.048	0.083	−0.570	0.566	−0.210	0.115
Individual Characteristics: Class 1						
Constant	-0.962*	0.562	−1.710	0.087	−2.065	0.140
Income	0.117	0.438	0.270	0.789	−0.742	0.976
Gender	-0.745*	0.401	−1.860	0.063	−1.532	0.041
Age	2.030***	0.412	4.930	0.000	1.223	2.837
Child(ren)	−0.349	0.401	−0.870	0.384	−1.135	0.436
Water Pollution	0.407	0.380	1.070	0.285	−0.338	1.151
Invasive Species	−0.097	0.383	−0.250	0.799	−0.847	0.653
Recycle	0.688	0.442	1.560	0.120	−0.178	1.553
Outdoor Recreation	−0.333	0.367	−0.910	0.364	−1.052	0.386
Climate	0.525	0.403	1.300	0.193	−0.266	1.316
Lifestyle Change	-0.732*	0.392	−1.870	0.062	−1.500	0.036
Individual Characteristics: Class 2						
Constant	−0.643	0.605	−1.060	0.288	−1.828	0.542
Income	−1.680*	1.014	−1.660	0.097	−3.667	0.306
Gender	0.571	0.484	1.180	0.238	−0.377	1.519
Age	1.782***	0.535	3.330	0.001	0.734	2.831
Child(ren)	−0.478	0.596	−0.800	0.423	−1.647	0.690
Water Pollution	0.124	0.584	0.210	0.832	−1.020	1.268
Invasive Species	−1.228**	0.592	−2.080	0.038	−2.388	−0.069
Recycle	0.315	0.594	0.530	0.595	−0.848	1.479
Outdoor Recreation	−0.451	0.540	−0.840	0.403	−1.510	0.607
Climate	0.020	0.592	0.030	0.973	−1.141	1.181
Lifestyle Change	−1.197**	0.603	−1.990	0.047	−2.379	−0.015
Individual Characteristics: Class 3						
Constant	0.419	0.438	0.960	0.339	−0.440	1.278
Income	−0.668	0.472	−1.420	0.157	−1.593	0.256
Gender	−0.227	0.358	−0.640	0.525	−0.929	0.474
Age	1.520***	0.394	3.860	0.000	0.748	2.293
Child(ren)	−0.222	0.360	−0.620	0.537	−0.928	0.483
Water Pollution	0.092	0.382	0.240	0.809	−0.656	0.840
	−0.539	0.373	−1.450	0.148	−1.271	0.192

(continued on next page)

Table 3 (*continued*)

	Coef.	Std. Err.	z	p-val	95% CI	
Invasive Species						
Recycle	−0.320	0.370	−0.860	0.388	−1.045	0.406
Outdoor Recreation	−0.302	0.372	−0.810	0.416	−1.031	0.426
Climate	0.195	0.396	0.490	0.622	−0.581	0.972
Lifestyle Change	−0.353	0.391	−0.900	0.367	−1.119	0.413

LL = -2814.47487; AIC = 5734.949; BIC = 5812.425.
Statistical Significance: *0.10; **0.05; ***0.01.

Table 4
Willingness to pay for structural and functional urban forest attributes across all four latent classes (USD).

	Class 1	Class 2	Class 3	Class 4
Exotic[1]	−$32.07	−$4.60	−$0.64	$21.54
Few Species[2]	−$3.48	−$0.98	$1.64	−$22.34
Full Grown Trees Only[3]	−$4.08	−$4.95	−$2.57	−$2.97

[1] WTP relative to Exotic; [2]WTP relative to Many species; [3]WTP relative to Trees of different ages, sizes, and heights.

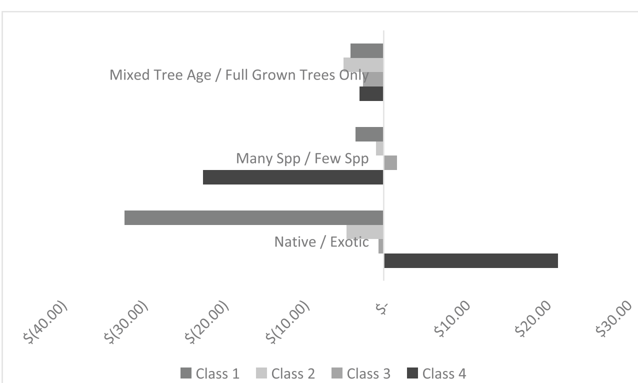

Fig. 2. Willingness to pay for urban forest attributes across four latent classes.

cost is not statistically significant, making estimation of WTP problematic (Table 3). Bearing this in mind, the estimated WTP for exotic trees is $21.54 per month, while for few species of trees the WTP is negatively valued (-$22.34 per month, implying a preference for many species of trees). The estimated coefficient for full grown trees is also not statistically significant, which makes the interpretation of WTP for this attribute even more problematic. Given the above, it is perhaps clear that *Class 4* has relatively strong preferences compared to other classes, but they seem unwilling to pay for the exotic forest stand (Table 4). While the model does not estimate class membership coefficients for class four, we can use results for other classes to understand how individual characteristics affect membership in *Class 4*. For instance, individuals older than 35 are more likely to belong to *Class 4* than the other three classes. Similarly, individuals who expressed a willingness to change their lifestyle to protect the environment are also more likely to belong to *Class 4*, relative to classes 1 and 2. Finally, individuals who are concerned about invasive species are more likely to belong to *Class 4*, relative to *Class 2* (Table 4).

4. Discussion

This study valued the WTP and heterogeneity in the public's preferences for different types and configurations of urban forests, and illustrated a methodology that could serve as an information bridge between the public—represented by respondent classes in the sample—and urban forest managers and policymakers. Historically, decisions regarding urban forest management and planning have been driven by the technical training of experts as well as the availability of, and preference for, certain tree species, and achieving certain ecosystem service outcomes; often without considering tree functional traits or structural attributes (Fan et al., 2019; Horn et al., 2015). Often, there are few available tree species lists based on the preferences of the public, and instead most lists are based on local availability or to maximize urban tree cover (Dawes et al., 2018).

Studies in the US and elsewhere have documented the role of urban forests on human health outcomes (Cariñanos & Casares-Porcel, 2011; Donovan et al., 2011), crime perception (Kondo et al., 2017) and even in providing habitat for biodiversity (Fan et al., 2019). But our approach and findings contribute to the existing literature by identifying the preferences of different segments of the public for specific urban forest attributes that can be mapped, monitored, and managed across functional traits and land tenures rather than on a species-by-species or taxonomic basis. In other words, it is more practical and actionable to ask the public to express their preferences in terms of forest functional and structural attributes, than it is to ask them to express preferences for complex socio-ecological processes. Therefore, the methodology presented in this study can be replicated in other contexts to address the mismatch between forest management decisions and public preferences (Kinzig et al., 2005). However, it is important to recognize that addressing this mismatch will require cooperation between the public, urban forest managers, and local nurseries, as it may require shifts in availability of certain tree species that provide the desired functional and structural attributes, but that are not currently grown or sold by the local nursery industry.

Previous studies such as Dawes et al. (2018) identified the preferences of different demographic groups in Florida USA for specific tree functional traits and their relationship to urban tree cover policies. Other studies have also documented the relationship between subtropical urban forest structure and composition to property values and carbon offsets (Escobedo et al., 2015; Horn et al., 2015) as well as assessing the tradeoffs between urban forest ecosystem services-disservices (Soto et al., 2018). However, our findings provide insights into the public's preferences for specific urban forest structural-functional attributes that could be used to account for associated costs. For example, in terms of ecosystem disservices, only 19% of respondents indicated a serious concern about living close to trees and flowering plants that produce pollen that can result in allergies. Similarly, only 12% were concerned about hurricane wind impacts to and from their treescapes.

Our approach and findings can also provide research-based information to develop more effective management programs, planning scenarios and policy goals. Assume that a local government is revamping its urban forest management programs and is contemplating the role of specific forest attributes considered by this study, namely, use native or exotic trees, a small number of species or a large number of species, and whether to use only large and fully-grown trees or a combination of small and large trees. Assume further, for the sake of argument, that for the local government officials in charge, cost differences of providing different types of trees are less important than the preferences of the public. In such a situation, local government decision-makers could be inclined to keep things simple and develop a specific Urban Tree Cover (UTC) metric and goal that appeals to the 'average' resident, and thereby ignore heterogeneous values for urban forest attributes. In that case, local decision-makers could rely on the conditional logit model of preferences for urban forests in public areas (Table S1), and conclude that the UTC program should rely entirely on native trees with high tree diversity (many species of trees) and of a mixed forest structure (trees of different ages, sizes, and heights). However, some decision-makers may see the importance of value heterogeneity across the population, and would be hesitant to approve the implementation of a program that does not consider variation in the values and preferences of their voting constituency. For example, Dawes et al. (2018) found that high income, white participants in a tree giveaway program in Florida preferred native trees while Latinx and African Americans preferred fruit trees. Accordingly, decision-makers could use results from either the random parameters logit (Table S2) or the four latent class logit (Table 3), as both models account for value heterogeneity.

Relying on the random parameters logit model (Table S2), local decision-makers could also glean that preferences for the three urban forest attributes under consideration are indeed heterogeneous, suggesting that a one-size-fits-all tree planting program that plants only native trees, and preserves stands with high tree species diversity and mixed age, size, and height in all available parcels will not satisfy all stakeholders in the community (Carmichael & McDonough, 2019). In addition, while the random parameters logit provides some information on the magnitude of the variability in preferences for each attribute, it would be challenging to tailor a program to fit the values revealed in the study using only the results from this model.

If the intent of local decision-makers were to design a context-specific UTC program, the four-latent class logit model (Table 3; Fig. 2) provides the most useful information. For example, this model reveals that surveyed respondents had a 32.6% probability of being in *Class 4* (indeed the largest of the four classes), fitting a preference profile that strongly prefers exotic trees over native trees, and so it would be equitable to plant exotic trees in at least some of the parcels. Similarly, given that three of the four classes were found to prefer urban forest stands with many species of trees, and that the class that expressed a preference for having stands with few species of trees exhibits only a weak preference in terms of a WTP of small magnitude, it could be argued that a community-specific tree giveaway or UTC program should target most parcels for tree plantings with a high diversity of tree species. Notably, there seems to be agreement among all latent classes in preferring a mix of tree ages and sizes over fully grown trees only. In practice, however, large trees are more expensive to purchase, transport, and plant, which makes this particular attribute more convenient than the other attributes explored in this study.

Overall, our study presents an approach for examining public values and estimating the WTP for management and policy-relevant urban forest attributes that are key to supplying ecosystem service benefits. As such, it is another example of how non-market valuation information can be used for policy decision making by providing a suite of commensurate metrics to compare different ecosystem services and tradeoffs between these benefits and other economic activities that may impact the ecosystems that produce them (Milon & Alvarez, 2019; Börger et al., 2014). For example, research identifying residents' WTP for urban tree planting programs could be used to justify the need for, or evaluate, such programs or to identify the magnitude of the investments that would be warranted from a cost-benefit perspective (Vandermeulen et al., 2011; Arrow et al., 1996). Such findings are in line with other studies of heterogeneous preferences for forested landscapes in rural areas (Giergiczny et al., 2015). Indeed, further research should continue to explore how the non-market values of forested landscapes in urban areas are not heterogeneous across the population; and hence analyses such as this one that rely on identification of different respondent classes (i.e. stakeholder groups, segments of the public) that could guide adaptive management, planning, governance alternatives and even modelling scenarios (Bateman et al., 2013; Liebelt, Bartke, & Schwarz, 2018).

5. Conclusion

Econometrically, a comparison across all models developed in this study reveals that the four latent class model outperforms all other models. However, we do note some limitations. For example, to identify the best fitting latent class model, it is necessary to run a large number of models and compare them using different information criteria. These resulting models, however, are not equally useful from a policy-making perspective. Research identifying preferences for specific attributes of urban forests—as done in this study—could be used to design effective monitoring metrics and different adaptive management alternatives to best satisfy the wants of citizens. In such cases, the way that findings regarding people's preferences are reported determine how useful these findings can be for the development of policies or programs supporting urban forest management and tree planting efforts.

Although our study demonstrates the importance of accounting for preference heterogeneity when using non-market valuation to inform public policy decision-making, we acknowledge that our manuscript falls well short of a much-needed discussion that brings together researchers, practitioners, and policy-makers to define what should be the role of preference heterogeneity information in decision-making. Given the enormous potential for valuation of ecosystem services in guiding land use decision-making at all scales, we hope our contribution may spark a wider and more equitable discussion on how to use tree functional traits, rather than specific tree taxa, for management and planning purposes as well as better designing non-market valuation studies to better inform the actionable levers of relevant decision-makers.

Conventional urban forest management approaches have mostly depended on traditional forestry, horticulture, landscape architecture and natural resource and expert-based technical metrics and goals such as percent tree cover, locally defined vegetation pallets, and regional native tree lists. However, this and other recent studies indicate that both the public and policy makers have a much more nuanced and diverse set of values and preferences for urban forest structural metrics and functional traits, or attributes. Indeed, this and other studies indicate that stakeholders more readily identify tree types based on functional traits, as opposed to specific taxa. Also, as mentioned by one of this paper's reviewers, this and other studies show that there really is no such thing as an "average" stakeholder, but a continuous distribution of stakeholders with diverse preferences. As such, more effective policy formulation and relevant research is warranted that incorporates co-production of knowledge and transdisciplinary approaches, as well as developing program goals based on adaptive management and public participation processes.

CRediT authorship contribution statement

Sergio Alvarez: Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Visualization. **José R. Soto:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - review & editing, Visualization, Supervision, Project administration. **Francisco J. Escobedo:** Conceptualization, Methodology, Investigation, Resources, Writing - review & editing. **John Lai:** Software, Formal analysis, Investigation, Writing - review & editing, Visualization. **Abu S. M.G. Kibria:** Software, Validation, Formal analysis, Investigation, Data curation, Writing - review & editing, Visualization. **Damian Adams:** Conceptualization, Investigation, Resources, Writing - review & editing, Supervision.

Declaration of Competing Interest

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

Acknowledgements

We thank the United States Department of Agriculture's McIntire-Stennis program and Florida Agricultural research project for funding this project (FLA-FOR-005278).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2021.104234.

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