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Urban forest structure effects on property value

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ABSTRACT

Studies have quantified urban forests using well established field sampling methods. Other studies have used hedonic regression with real estate prices and remotely sensed vegetation cover data in valuation models. However, remote sensing introduces unfamiliar perspectives since it changes the scale and resolution perceived by humans. Real estate prices also fluctuate and are not regularly used in urban decision-making processes. This study values an urban forest cultural ecosystem service by integrating an explanatory hedonic regression model with randomly field-measured tree, shrub, and turf data from four cities across Florida, USA, during 2006–2009, and congruent parcel tract-level home attributes and appraised property values from single and multi-family units for 2008–2009. Results, on average, indicate trade-offs in that more trees with greater Leaf Area Indices (LAIs) add to property value, while biomass and tree–shrub cover have a neutral effect, and replacing tree with grass cover has lower value. On average, property value increased by $1586 per tree and $9348 per one-unit increase in LAI, while increasing maintained grass from 25% to 75% decreased home value by $271. Our ecological approach is an alternative, applied method that can be used by decision-makers for policy and cost–benefit analyses that calculate the stream of net benefits associated with urban forests.

1. Introduction

The urban forest structure–ecosystem services nexus has been the basis for many studies that value the benefits obtained from urban ecosystems (Conway et al., 2010; McPhearson et al., 2013; Nowak et al., 2008; Stigarll and Elam, 2009; Donovan and Butry, 2010). Urban forest attributes (e.g. tree–shrub–grass cover, tree type, beneficiaries proximity to vegetation, tree size) have been associated with increased benefits and are commonly used as metrics to link the amount of urban forests and green spaces with the provision and value of mostly regulation ecosystem services (Escobedo et al., 2008, 2011; Dobbs et al., 2011; Wyman et al., 2012). Hedonic valuation analyses have also been used by other studies to estimate the effect of remotely sensed vegetation cover on real estate prices (Anderson and Cordell, 1988; Dombrow et al., 2000; Donovan and Butry, 2010; Mansfield et al., 2005; Sander and Haight, 2012; Saphores and Li, 2012). However, information on the effect of specific field measured, multistory urban forest structure attributes on the economic value of these cultural ecosystem services is largely lacking in the subtropics and is mostly based on city-specific information from temperate areas, remotely sensed land cover data, and real estate clearing prices.

In the study below, we will briefly review the relevant urban forest ecology and ecosystem service literature. Second, we review the economic valuation literature that primarily uses available remote sensing land cover data to link large amounts of vegetation cover and housing component data with real estate values to increase the number of observations and the power of valuation models. Third, we review how this literature uses hedonic valuation models and the value placed on these remotely sensed amenities and disamenities as an implicit price for components of the urban vegetation–housing bundle. The implicit price of each component is determined by real estate clearing price and the multiple attributes of the housing bundle that are related to property value.

We then build from this literature and present an alternative and complementary approach that posits that remote sensing introduces an unfamiliar perspective since it changes the scale and resolution perceived by humans since they are better at pattern recognition than computers especially when the world is viewed or illuminated in various ways (e.g. shading and shadows; Adams and Gillespie, 2006). That is, remotely sensed, aerial, two-dimensional vegetation cover in a pixel is necessary but not sufficient to characterize the vertical and horizontal components of urban forest structure (Adams and Gillespie, 2006; Escobedo et al., 2011; Nowak et al., 2008). This differentiation between remotely sensed land cover components and field measured urban forest structure is important since field measurements identify

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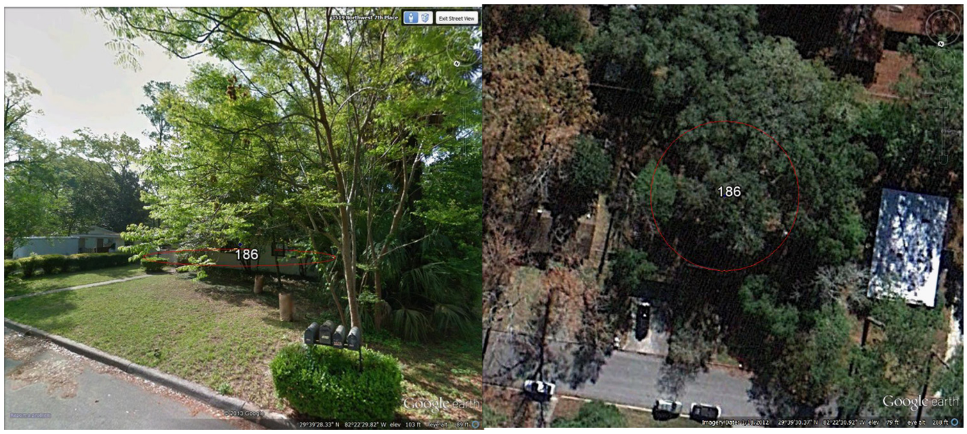

Fig. 1. Visual differences between a representative field (left) and aerial view (right) of the same urban forest site (Plot 186) in a residential urban forest in north central Florida, US using Google Earth®. Note in the field view, maintained grass and shrub cover below tree canopy, discernible tree crown and form, visible tree stem sizes and numbers relative to buildings, and the presence of tree crowns on the site from adjacent properties (left). Additionally, specific property boundary lines are not easily discernible in either view.

attributes that are not spectrally specific (Adams and Gillespie, 2006), yet are key for these types of studies and human perception such as distance of trees to homes, multi-story canopy cover, overlapping crowns, vegetation density and composition (Fig. 1). Additionally, clearing prices in many cities have recently – and in the past – been substantially affected by real estate market and foreclosures (Hess and Almeida, 2007). Thus, an alternative approach is needed that takes disparate methods that quantify urban forest structure–services as well as vegetation effects on property value and integrates them using site-specific field measurements of urban forest structure as an improved measure of the homeowner's, bidder's, and manager's three dimensional perspective of the urban forest ecosystem–housing bundle.

The ecological approach we lay out below posits that urban forest cultural ecosystem service value is better captured by site-specific field measurements at fixed area sites and that assessed value is an alternative to market value since the latter is an unobserved value that is not regularly used in urban forest management decision-making processes. We define regulation ecosystem services as urban forest ecosystem functions that are most relevant in mitigating urban pollution (i.e. air quality improvement and climate mitigation via carbon dioxide reduction), whereas cultural ecosystem services are an urban forests' function of contributing to esthetic values such as increased property value premiums as well as the direct and positive human physiological and psychological responses to urban forests (Escobedo et al., 2011).

1.1. Urban forest structure and ecosystem services

Several studies have quantified urban forest ecosystem structure using well established geospatial methods and field data from random plots or street segments that effectively and efficiently characterize the structure of urban tree populations (McPherson et al., 2005; Nowak et al., 2002, 2008). This data has been used in models to primarily assess regulation ecosystem services such as air and water quality improvement, climate regulation via carbon sequestration, and building energy use among others (Escobedo et al., 2010a; Flock et al., 2011; McPhearson et al., 2013, 1998). Other studies have also used urban forest structure in urban forest function-services and economic valuation models to assign use and non-use values to urban forest regulation and cultural ecosystem services (Donovan and Butry, 2010; Nowak et al., 2008). McPherson et al. (1998) and Escobedo et al. (2008) have used cost-effective analyses to value the air quality improvement by urban trees based on field data using plot level measurements. Pandit and Laband (2010) used parcel level tree measurements, energy usage, and building characteristics in an econometric model to value the energy savings benefits from the amount and type of tree shade adjacent to homes.

The value of urban forest cultural ecosystem services has also been estimated using plot-level data and can be calculated in several available urban forest structure-functional models (Anderson and Cordell, 1988; McPherson et al., 2005; Nowak et al., 2008). Anderson and Cordell (1988) used econometric hedonic analyses of 844 sales of single family properties from a board of realtors' Multiple Listing Service and tree count data from the listings' photo. The authors found that the average house had 5 trees in the front yard and landscaping with trees was associated with 3.5–4.5% increase in sale price over a 3-year period and thus, increased city property tax revenues. They also found that home sales price increases (1985 USD) were largely due to "medium" and "large" sized trees, regardless of whether they were evergreen or deciduous.

1.2. Hedonic analyses of urban vegetation and cover

The hedonic analysis approach has been used by other studies to estimate the increased property value provided by urban trees (Dombrow et al., 2000; Donovan and Butry, 2010). Dombrow et al. (2000) found that mature trees – as indicated by a notation of "presences of mature tree" – on a property increased value by 1.9%. Morales et al. (1983) also found that mature trees on wooded lots increased home sale prices by 10–17%. Donovan and Butry (2010) found that public street trees add 3% to a home's median sales price, and crown area and number of street trees within 30.5 m of a home were the only statistically significant field measured tree structural variables in the hedonic model. Garrod and Willis (1992) found that broadleaved trees increased, and conifer trees decreased, home sale prices in Great Britain. Also, Holmes et al. (2006) documented the effect of *Tsuga spp.* tree condition on property values as being positive. Similarly, Thompson et al. (1999) observed that diseased trees near peri-urban homes decreased home sale prices but thinning and removal of diseased trees increased it.

Other literature has integrated remotely sensed data with hedonic models to analyze the effects of urban vegetation cover on property value (Sander and Haight, 2012). Kadish and Netusil (2012) used 2005–2007 sale price and property characteristic data as well as high resolution, color infrared-derived land cover classes (i.e. "high" and "low" levels of structure vegetation) in a hedonic price model to examine the effect of tree, shrub, and impervious land cover types on the sale price of single family residential properties. Properties with 32% tree cover (i.e. "high" structure vegetation class) contributed positively (6%) to an average property's sale price. Mansfield et al. (2005) used Landsat data and a normalized difference vegetation index and found that a 10% increase in a parcel's tree cover added $800 to home sale prices while adjacency to private forests added $8000. Sander et al. (2010) used similar Landsat data and analyzed over 20 covariates and determined that neighborhood-level (i.e. less than 250 m from a home) tree cover significantly and positively contributed to a home's sale price. Saphores and Li (2012) estimated the value of urban trees and grass using high resolution remote sensing data and aerial photos with a hedonic model that used over 30 covariates that accounted for spatial autocorrelation and parcel and neighborhood scale characteristics. The study found that 88% of analyzed properties increased in value with additional amounts of lawn in the parcel, but additional trees in the parcel would decrease the value of 40% of the analyzed properties.

Spatial analyses and real estate data in hedonic models have also been used to determine the effects of green space and urban forests on home sale prices. Conway et al. (2010) found that there was a positive effect on home values and green space within 200–300 ft of a home increased prices by 7%. Similarly, Poudyal et al. (2009) found that both distance and the size of an urban recreation park, relative to a property, had a significant and positive effect on property values. In Finland, Tyrväinen and Miettinen (2000) found that a home's proximity to, and view of, forested areas had a significant and positive effect on housing prices resulting in these homes being, on average, more expensive than other houses with similar attributes. However, Des Rosiers et al. (2002) found that dense vegetation within visible distance of a single family home lowered its sale price.

1.3. Objectives

Overall, these previous studies from mostly temperate cities are generally based on real estate clearing price data from single cities and include few non-tree cover, urban forest structure variables. Therefore, the aim of our research is to present an ecological approach that can be used by managers and policy makers to analyze the influence of key, yet little studied, urban forest structure attributes on residential property values in four subtropical cities spanning the different geographical regions of Florida, United States (US). Our specific study objective is to value a portion of the cultural ecosystem services provided by subtropical urban forests. We do this by applying an explanatory hedonic valuation model using measured urban forest structure data based on random plots and congruent parcel tract-level appraised property values from single and individual multi-family residential units. A novel contribution to this literature is that rather than solely using remotely sensed land cover data, our study used site-specific field measured, multistory tree, shrub and grass structural attributes from random, fixed area plots.

Information from this type of analysis can be used for making more informed decisions regarding the influence of managing subtropical urban forest ecosystem structural attributes on cultural ecosystem services. Moreover, results of this and similar studies can inform owners and leasers of residential and commercial property of the perceived worth of urban forest structure indicators. The information can also inform public policy makers particularly at the local level, of the potential benefits of conservation efforts, managing for particular management goals, and designing optimal urban forest structure arrangements; either directly through maintenance activities or indirectly through ordinances.

2. Methods

2.1. Conceptual hedonic model

Hedonic models of property prices assume that the prevailing market price of a given piece of property is defined by the sum of the marginal values of its individual attributes (Rosen, 1974). Accordingly, the marginal values are derived from econometrically-estimated parameter weights of the individual explanatory variables, where property value is the dependent variable (Kennedy, 2003). Here, we define the property value, Y, of single or individual, multi-family homes as a function of n explanatory variables, including house attributes (e.g., size in square feet), urban forest attributes (e.g., number of trees), and location (e.g., specific city):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \quad (1)$$

Previous studies show that house prices are driven by important real estate property characteristics, including age of home, area, number of bathrooms, and location (Sander and Haight, 2012; Stigarll and Elam, 2009). Prices are also driven by urban forest structure, including number, size, and age of trees (Anderson and Cordell, 1988; Dombrow et al., 2000; Donovan and Butry, 2010; McPherson et al., 2005; Morales et al., 1983); percent of vegetation cover (e.g., tree, shrub) and impervious landcover (Kadish and Netusil, 2012; Mansfield et al., 2005; Sander et al., 2010; Stigarll and Elam, 2009; Saphores and Li, 2012); and even tree characteristics such as leaf size (Garrod and Willis, 1992; Holmes et al., 2006) and tree crown type and size (Pandit and Laband, 2010).

While prior studies using hedonic models have typically included up to 20 or more variables (Sander et al., 2010; Saphores and Li, 2012), in this study we developed an alternative explanatory model involving a small set of influential urban forest structure and residential property variables we identified during our literature review. Each of the variables included in our model is based on established and repeatable urban forest measurement protocols and publically available assessed property value data from local governments. The use of these variables for our model (Eq. (1)) is explained and justified in Section 1 and later in Sections 2.3 and 2.4. All urban forest structure, housing, and appraised property value data were collected during 2006–2009. Data used to parameterize the conceptual hedonic model are described below.

2.2. Study areas

The study sites include four moderately- to highly-urbanized areas across the state of Florida, US: the greater Pensacola area of southern Escambia County, the City of Gainesville, eastern portions of the Orlando Metropolitan Area, and incorporated and unincorporated municipalities in Miami-Dade County (Fig. 2). Housing density for these areas ranged from 228–1600 housing units/km^2, including Oviedo (228 units/km^2) and adjacent Orlando (364 units/km^2) in the Orlando Metropolitan Area; Gainesville (320 units/km^2); Pensacola (457 units/km^2); and Homestead (300) and adjacent Miami (1600 units/km^2) in the Miami Metropolitan Area (USCB, 2009). Florida has been subject to recent – and historic – real estate "booms and busts" that have been affected by changes in the economy, speculation, migrations and even hurricanes (Schiller, 2008). Average tree cover in residential plots in the different study areas varied from 11.6% in Pensacola (Standard Error; SE of 2.2), 15.4% in Orlando (S.E. 3.2), and 17.4% in Miami-Dade (S.E 1.9) to 44.9% in Gainesville (S.E. 5.3) according to Escobedo et al. (2010b), and Escobedo et al. (2010a), respectively.

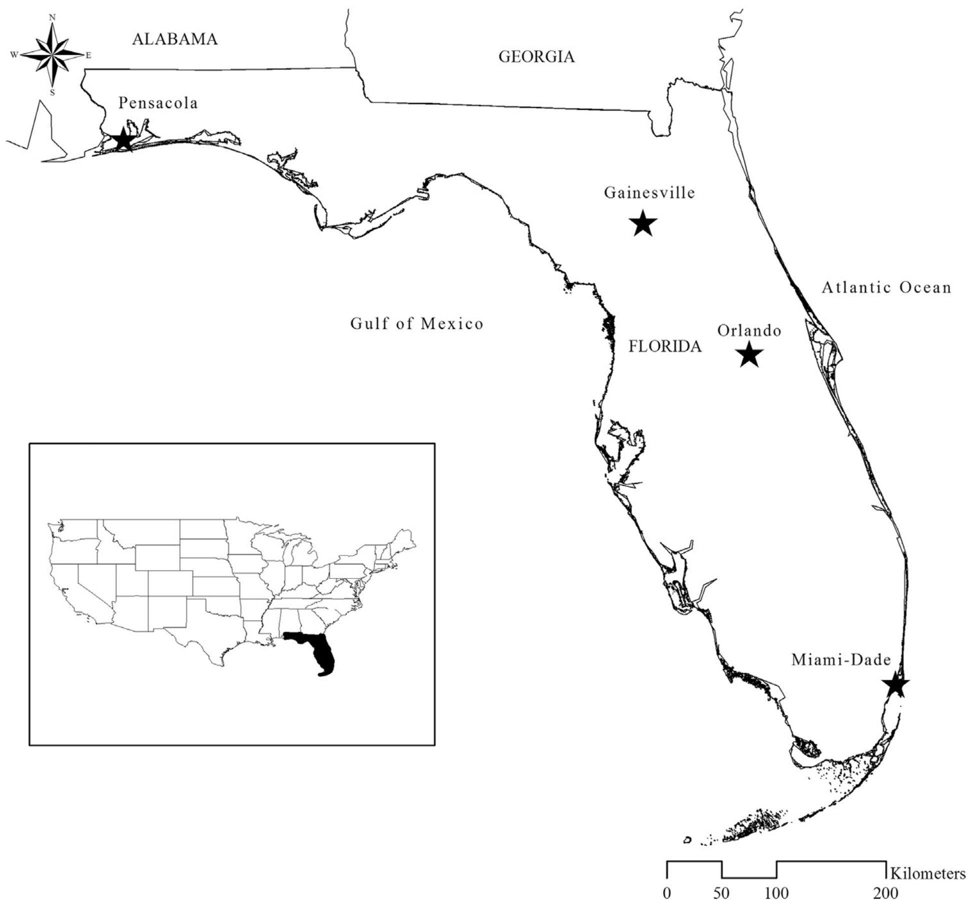

Fig. 2. Study areas in four cities in the state of Florida in the United States.

2.3. Urban forest structure data

Random plot centroids were allocated across the four respective study areas and then located, accessed, and field data measured using 0.04 ha plots situated across different land uses (Table 1). On each plot, data were collected for each tree and palm with a minimum diameter at breast height (DBH at 1.37 m above ground surface) of 2.5 cm, regardless of growth form. The percentage of overstory tree and palm cover, midstory shrub cover, and understory maintained grass cover was estimated visually on each 0.04 ha plot; shrubs are defined as woody, or palm-like plants with a DBH of less than 2.5 cm but greater than 30 cm in height. Specific plot and plot centroid establishment and field measurement methods are outlined in Nowak et al. (2008) and Escobedo et al. (2010a). Miami-Dade had a total of 229 plots that were measured in January–May 2008 and Gainesville consisted of 93 plots measured during July 2005–May 2006 (Escobedo et al., 2010a). Pensacola had 75 plots measured in the summer of 2008 and Orlando 100 plots measured in the summer of 2009 (Escobedo et al., 2010b). Please refer to Escobedo et al. (2010a, 2010b) for specific sampling characteristics such as plot distribution and the extent of residential land uses in each study area.

Average plot level total tree carbon storage was a proxy for site biomass and Leaf Area Index (LAI) – the projected area of the tree crown on the ground – a proxy for tree crown density and condition. Both were calculated using tree measurements and the Urban Forest Effects (UFORE ACE 6.5) model (Nowak et al., 2008). Carbon storage was estimated by the UFORE model using allometric equations and tree measurements assuming that 50% of tree dry weight is biomass (Escobedo et al., 2010a and Nowak et al., 2008). The LAI was estimated by the UFORE model using regression equations and shading coefficients for urban deciduous trees while conifer LAI was estimated using average shading coefficients and tree height-to-width ratios from the literature (Nowak et al., 2002). Individual LAI is the amount of one-sided leaf surface area (m^2) over ground unit area (m^2) and is often used as a proxy for the amount of tree crown density and overall tree health, and is a key indicator for ecosystem service provision (Escobedo et al., 2008; Nowak et al., 2002, 2008). All analyzed single or individual multi-family home parcels had to have congruent measured, plot-level structure data.

2.4. Assessed property values

The effect of urban forest structure on residential property value was measured using county property tax assessed value data from 2008 to 2009 (Table 1). We used assessed value data rather than real estate clearing price data because of its applicability for municipal urban forest management decisions and possible biases in the real estate price data given Florida's recent housing market crisis and the disproportionate occurrence of sales involving foreclosed and distressed properties (Hess and Almeida, 2007; Rosen, 1974). Further, because knowledge of the property's attributes and amenities is considered in the valuation assessment, assessed property values should also reflect the positive externalities of properties located on or immediately adjacent to each plot, other recreation opportunities (e.g. parks) and quality of schools nearby, as well as other characteristics in the vicinity (e.g. vacancy rates, crime rates, traffic, noise). Thus, we assume that assessed property values are a partial measure of the cultural ecosystem service perceived by the population for residential properties across the four subtropical study sites.

Table 1
Description of property and urban forest structure model variables from four cities in Florida (US).

Variable (label)	Units	Definition	Data source
Dependent variable			
Difference from median price (Diff_price)	Pensacola and Orlando Year 2008 USD; Miami-Dade and Gainesville Year 2009 USD	Assessed value difference from local median home sales. Assessed properties located in Miami-Dade County, incorporated and non-incorporated areas; Gainesville, City limits; Pensacola, southern Escambia County; East Orlando, Orange and Seminole Counties	Assessed value for Miami-Dade, Alachua, Escambia, Orange and Seminole County Assessors (Alachua County, 2011; Escambia County, 2011; Miami-Dade County, 2011; Orange County, 2011; Seminole County, 2011) Median home sale price is from the Florida Housing Data Clearinghouse, Housing Profiles for each county (FHDC, 2011).
House attributes			
House size (Square feet)	Square feet	Area of residential unit on parcel	County Assessor data
Number of bathrooms (No. Bathrooms)	Number of bathrooms	Number of bathrooms in residential unit on parcel	County Assessor data
Number of bedrooms (No. Bedrooms)	Number of bedrooms	Number of bedrooms in residential unit on parcel	County Assessor data
House Type	Single family Multifamily	Type Dummy Variable (Dum 1single, Dum 2=multi)	County Assessor data
Age (Age)	Years	Age of the unit	County Assessor data
Urban forest attributes			
Percent tree cover (%Tree)	Percent of 0.04 ha plot	Percent of plot covered by tree crown; trees were woody plants >2.5 cm in DBH	Sample plot
Percent maintained grass (% Grass)	Percent of 0.04 ha plot	Percent of plot that is maintained grass/turf	Sample plot
Number of trees (No. Trees)	Number of tree stems	Number of trees or palms with a DBH $>$ 2.5 cm in 0.04 ha plot	Sample plot
Percent shrub (% Shrub)	Percent of 0.04 ha plot	Percent of plot that is woody plants >30 cm in height and <2.5 cm in DBH	Sample plot
Plot Tree Leaf Area Index (LAI)	m^2/m^2	Total sum of 1-sided leaf area of an individual tree crown/ surface ground area	Sample plot and Urban Forest Effects model
Plot tree biomass	kg	Individual tree total carbon storage	Sample plot and Urban Forest Effects model
Location attributes			
City (Dum 2 and Dum 3)	Gainesville, Pensacola, Orlando, Miami-Dade	City Dummy Variables (Dum 2=Miami, Dum 3=Orlando)	County Assessor data

No., Number of; ha, hectare; LAI, Average Individual Leaf Area Index; DBH, Diameter at Breast Height is tree stem diameter at 1.37 m above ground surface; Dum, Dummy Variable.
Note: plot sample sizes were 21 in Gainesville, 99 in Miami-Dade, 32 in Orlando and 38 in Pensacola.

Property value for each plot was obtained from the County Assessor's databases using the assessed value for each unique parcel with a home located at each plot centroid. In Florida, the assessed value of real property for tax purposes is 100% of "the present cash value of the property" and is the amount a "bidder would pay a willing seller" (Fla. Stat. 193.011(1)). The assessed value in our data cannot exceed market value and is the base year market value adjusted for annual percentage factor or consumer Price Index, whichever is less (Miami-Dade County, 2012).

The dependent variable "property value" in our model was the difference between this previously described assessed value and local median home sale price. This adjusted property value was used to better standardize for the relative housing market pressures in the state of Florida during the analysis period (Hess and Almeida, 2007). A negative value for the standardized assessed value implied that the property was below the median house price for that city. A negative sign on an explanatory variable parameter estimate indicated that a 1-unit increase in the variable should decrease the expected standardized assessed value. If the assessed value was below the median price, it implied that this will drive it further below the median price, whereas a positive sign should increase it. Lack of spatial autocorrelation in our property value data and the use of adjusted property values should also account for extreme ranges of assessed value and both positive and negative externalities in and adjacent to the parcels on our plots.

2.5. Empirical hedonic model

We developed an empirical hedonic model of urban forest structure and single and individual multi-family home property values for our four study sites:

$$\begin{aligned}\hat{Y} = {} & b_0 + b_1\%Grass + b_2\%Shrub + b_3No.Trees \\ & + b_4TreeLAI + b_5Treebiomass \\ & + b_6Treecover + b_7SquareFeet + b_8No.Bathrooms + b_9\mathrm{Age} \\ & + b_9HouseType + b_{10}Miami + b_{11}Orlando + \varepsilon \qquad (2)\end{aligned}$$

where $\hat{Y}$ is the estimated assessed property value standardized to the community-specific median home price; %Grass is the percent of plot with maintained grass or turf, %Shrub is the percent of plot with woody plants of a minimum height and DBH, No.Trees is the number of trees per 0.04 ha plot, TreeLAI is Leaf Area Index measuring the ratio of tree crown to surface ground area, Tree-biomass is plot level total tree carbon storage in kg, Treecover is plot tree cover, SquareFeet is the house size in square feet, No. Bathrooms is the number of bathrooms, Age is house age in years, HouseType a dummy variable indicating single or multifamily unit, and Miami and Orlando are dummy variables indicating plot location, and ε is an error term. We assume a normal distribution on the error term, and parameterize the empirical hedonic model (Eq. (2)) using ordinary least squares (OLS) linear regression (Greene, 2008) with the PROCREG procedure in the Statistical

Application Software (SAS version 9.2). Model variables were selected using a stepwise approach where variables that were not statistically significant at or near the 95% level of confidence were removed (Kennedy, 2003). We compared nested models using adjusted R^2 values (Greene, 2008).

The dummy variables for our Gainesville and Pensacola locations and tree biomass were not statistically significant and were dropped from the model. The number of bedrooms variable was also dropped due to its collinearity with the number of bathrooms variable (Kennedy, 2003). Data used in our final model included 190 observations from four Florida cities (Fig. 1): Gainesville ($n=21$), Miami-Dade ($n=99$), Orlando ($n=32$), and Pensacola ($n=38$). Although 229 plots in Miami-Dade, 93 plots in Gainesville, 75 plots in Pensacola, and 100 plots in Orlando were located and measured originally; the attrition of the data can be attributed to the use of plot data exclusively from residential land uses and/or missing values in any variable for the analysis period. Descriptive statistics were estimated for each variable and spatial autocorrelation for standardized property values was tested with Moran's I and a hypothesis of 0 autocorrelation. Residual plots and LOESS curves as well as variance inflation factor were used to assess issues of heteroskedasticity and collinearity in our data, respectively (Kennedy, 2003). Finally, using an analysis of variance (ANOVA) with the PROC GLM procedure in SAS 9.2, we further assessed variance in adjusted property values between and within the four study cities.

3. Results

3.1. Urban forest structure

Findings indicate that urban forest structure in residential land uses varied across the four cities in Florida (Table 2). Overall, cities other than Gainesville had fewer trees and tree cover on each plot, but LAI was higher in south Florida cities but in general very low across all cities. Orlando and Pensacola had the greatest grass cover but shrub cover was greatest in north Florida. In all other cities, except Gainesville, plots had higher grass cover than tree cover. Orlando had the lowest differential property values but Miami-Dade the greatest range of values in all parcel-level variables (Table 2). On average, properties with an adjusted value greater than USD$100,000 had 24% grass cover while properties with an adjusted property values less than USD $100,000 had 37% grass cover.

3.2. Hedonic model Results

Our final regression model (Eq. (3)) after eliminating non-significant variables (Eq. (2)) was statistically significant at the 99.9% level of confidence ($F=53.11$, $p<0.0001$). The model had an R^2 of 0.70 (and adjusted R^2 of 0.6881), indicating that the explanatory variables included in the model explain almost 70% of the variation in property value. Post-estimation diagnostic tests indicated no serious problems with OLS model assumptions. We tested for multicollinearity and found variance inflation factors under 2, ranging from 1.09–1.88, further indicating no serious issues. Also, residuals and statistical tests indicated no issues with heteroskedasticity or spatial autocorrelation between our observations (Moran's $I=0.043$ and $p=0.09$).

$$\hat{Y} = b_0 + b_1\%Grass + b_2No.Trees + b_3TreeLAI + b_4SquareFeet + b_5No.Bathroom + b_6HouseType + b_7Miami + b_8Orlando \quad (3)$$

The second model (Eq. (2)) included several explanatory variables that were statistically significant at or above the 95% level of confidence, and the parameter estimates had the theoretically-expected signs (Table 3). Five house attribute and location variables (SquareFeet, No.Bathrooms, Hous. Type and the two location dummy variables for Miami-Dade and Orlando Metropolitan Areas) were significant at the 99% level of confidence, while three of the landscape variables (No. Trees, LAI, and %Grass) were significant at the 95% level of confidence. Age of house (Age), tree biomass (Treebiomass), shrub cover (%Shrub), and tree cover (%Tree) were not significant at the 95% level of confidence. As expected, based on our third model (Eq. (3)) we found that increases in house size and type and number of bathrooms increased the value. On average, each additional square foot of house size and each additional bathroom increased expected home value by $31 and $42,707, respectively.

Overall, tree-related structure variables (i.e. number of trees and LAI) increased property values, while percent grass cover decreased values on average in the four study sites (Eq. (3)). On average, expected home value increased by $1586 per tree and $9348 per one-unit increase in LAI. For example, increasing from 0.25 to 0.75 Leaf Area Index – a +0.50 change – is expected to increase the house value by $4674 (or 0.5 times $9348), on average. A one-unit increase in the percent of maintained grass cover decreased expected home values by $541. For example, increasing the percent of maintained grass from 25% to 75% – a +0.50% change – decreased expected home value by $271. We also found statistically-significant differences in expected home values in Miami-Dade and Orlando as compared to Gainesville and Pensacola; as captured by the model intercept. In addition, the ANOVA determined that variance within cities was 48% and variance between cities was 52%. Although between cities variation was higher than within cities variation, the overall model was not statistically significant at typical levels of confidence ($F=1.09$ and $P>0.33$). Comparison of the means also did not exhibit significant difference in adjusted property values between the cities; thus supporting the use of our aggregate model (Eq. (3)) for the four study cities.

4. Discussion

Our final hedonic model results indicate an interesting relationship between property value and location, home attributes, and urban forest structure that has implications for ecosystem service tradeoffs between tree and non-tree urban forest structure indicators. Although we did not find statistically significant relationships between field measured tree cover and biomass, shrub cover and the value of property in the four cities, we found that number of trees and LAI have a positive impact on value, while percent grass cover has a small, negative impact on property values. Overall, our results, on average, indicate that individual trees with larger LAIs add value to homes, while biomass, tree and shrub cover have a neutral effect on property values, and replacing trees with grass is expected to lower home value. For example, assume two parcels that are otherwise identical except for grass cover, number of trees, and Leaf Area Index. One having 10% less grass cover, 1 more tree, and 1 more unit of LAI, on average, is worth $10,988 more (e.g. [0.1 * $541]+[1.0 * $1586]+[1.0 * $9348]).

Our findings are consistent with other studies that show that increased amounts of urban trees in residential areas increases property value at the plot, parcel (Anderson and Cordell, 1988; Dombrow et al., 2000; Mansfield et al., 2005), and neighborhood scales (Holmes et al., 2006; Sander et al., 2010), and that urban forest structure in the immediate vicinity of a property (i.e. plot and parcel-level) positively increases value (Mansfield et al.,2005; Conway et al., 2010; Poudyal et al., 2009; Sander et al., 2010). Earlier studies have reported that increase tree cover increases property values (Mansfield et al., 2005; Sander et al., 2010; Kadish

Table 2
Summary statistics for residential urban forest structure variables in four cities in Florida (US).

City (Area)	Variable	N	Mean	Maximum	Minimum	S.D.
Gainesville (12,200 ha)	Diff_price	21	−31,250.00	266,350.00	−116,710.00	91,520.9
	SquareFeet	21	1,835.0	3,591.0	925.0	672.2
	No. Bathrooms	21	2.3	6.0	1	1.3
	Age	21	14.9	34.0	0	11.8
	% Grass	21	31.1	80.0	0	24.4
	No. Trees	21	9.8	21.0	0	7.2
	% Shrub	21	19.9	50.0	1	12.5
	% Tree	21	51.8	100.0	3	29.1
	LAI	21	1.0	2.0	0	0.6
Miami-Dade (127,300 ha)	Diff_price	99	−32,175.90	1,105,845.00	−224,020.00	178,592.0
	SquareFeet	99	2,550.2	36,714.0	900.00	3703.4
	No. Bathrooms	99	2.1	6.0	0	0.9
	Age	99	29.5	85.0	0	20.4
	% Grass	99	33.7	100.0	0	27.0
	No. Trees	99	3.9	59.0	0	7.4
	% Shrub	99	4.3	70.0	0	8.3
	% Tree	99	10.7	80.0	0	15.1
	LAI	99	2.3	6.3	0	1.7
Orlando (20,000 ha)	Diff_price	32	−71,946.30	65,331.00	−165,908.00	54,192.3
	SquareFeet	32	1,957.3	3,600.0	988.0	557.9
	No. Bathrooms	32	2.3	3.5	1	0.6
	Age	32	7.9	27	0	7.8
	% Grass	32	37.1	99.0	0	23.1
	No. Trees	32	4.9	96.0	0	4.8
	% Shrub	32	6.9	65.0	0	17.0
	% Tree	32	22.3	65.0	0	19.1
	LAI	32	2.5	4.3	0	1.0
Pensacola (2290 ha)	Diff_price	38	−34,463.70	212,786.00	−109,038.00	61,984.7
	SquareFeet	38	1,581.3	3,035.0	820	582.2
	No. Bathrooms	38	1.9	4.5	1	0.8
	Age	38	23.4	85.0	0	18.4
	% Grass	38	42.9	100.0	0	26.7
	No. Trees	38	5.2	39.0	0	8.8
	% Shrub	38	11.5	82.0	0	17.9
	% Tree	38	26.9	85.0	0	28.8
	LAI	38	0.6	2.3	0	0.6
Total	Diff_price	190	−39,229	1,105,845	−224,020	137,395
	SquareFeet	190	2,177.5	36,714.0	820.0	2,728.1
	No. Bathrooms	190	2.1	6.0	0	0.9
	Age	190	23.1	85.00	0	19.4
	% Grass	190	35.8	100.0	0	26.2
	No. Trees	190	5.0	59.0	0	7.8
	% Shrub	190	7.9	82.0	0	13.7
	% Tree	190	20.4	100.0	0	24.4
	LAI	190	1.9	6.3	0	1.6

S.D., Standard Deviation; N., Number of plots analyzed; LAI, Leaf Area Index.

Table 3
Hedonic regression model estimates for the effects of urban forest structure on adjusted property values in Florida (US).

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	−208,273	26,517	−7.85	< 0.0001
SquareFeet	31.2	2.4	13.07	< 0.0001
No.Bathrooms	42,707	7,348	5.81	< 0.0001
Hous.Type	40,824	16,671	2.45	0.0153
% Grass	−541.06	221.26	−2.45	0.0154
No.Trees	1585.87	811.93	1.95	0.0523
LAI	9,347.99	4,337.76	2.16	0.0325
Citydum2 (Miami-Dade)	−36,821	15,274	−2.41	0.0169
Citydum3 (Orlando)	−72,053	18,830	−3.83	0.0002

No., Number; Hous., Housing; LAI, Leaf Area Index; Citydum, City Dummy Variable.

and Netusil, 2012), but tree cover from our plot level data was not a significant predictor of property values.

Our finding that greater LAI and increased number of trees increased property values implies that type, distribution, and possibly condition of trees are more important than tree and shrub cover alone. Although tree size, maturity, and condition were not directly analyzed in our analysis, LAI can be used as a proxy for the amount of tree crown density and condition (Escobedo et al., 2008; Nowak et al., 2008), thus it is tenable that results also mirror the finding of Dombrow et al. (2000) and Morales et al. (1983) who found that “mature and large” trees increased property values. In fact, our literature review found only two studies that imply a negative relationship between tree cover and home value. Des Rosiers et al. (2002) found that dense vegetation within visible distance of homes lowered their sale price. However, few of our plots were characterized as having “dense” vegetation (Table 2). Saphores and Li (2012) found that additional trees on a parcel would decrease property values, perhaps suggesting unique site conditions or presence of additional tree-related costs (e.g. irrigation).

Variation in our results could be attributed to other omitted variables, particularly housing variables such as those reported by Saphores and Li (2012). Field measurements are more expensive and time consuming when mapping land covers across the landscape, thus sample size is low (Adams and Gillespie, 2006). But, the increasing number of previously mentioned studies using site-specific field measurements should facilitate the availability – and use- of this type of data for this type of research (Nowak et al., 2008). As such, we also acknowledge the limitations in our hedonic model in that it indicates a positive, linear relationship between tree numbers, LAI and property values. But biophysical and socioeconomic realities will lead to diminishing returns as the positive externalities associated with tree numbers (e.g. property values, shade, pollution mitigation), might eventually become negative externalities (i.e. ecosystem disservices) due to increased maintenance needs, presence of pests and nuisance wildlife, increased litter and storm debris generation, and overall diminished esthetics (Lyytimäki and Sipilä., 2009; Escobedo et al., 2011).

In addition, we did not test for the specific effect of palms, species diversity, and tree condition on property value. On the other hand, our model reported a positive relationship between home values and tree numbers and LAI despite urban trees in Florida being associated with higher maintenance cost, due to past experiences with hurricane related damage (Wyman et al., 2012). Low income neighborhoods in particular are disproportionately affected by these maintenance costs (Flock et al., 2011). Therefore, houses with low prices might tend not to have trees and so grass might be a more inexpensive means of increasing the esthetic value of homes. These same homeowners might also prefer not having trees in the immediate proximity to their homes thereby minimizing the risk of future maintenance needs or damage during hurricanes (Wyman et al., 2012).

The findings also have implications for the importance of design, form, and the arrangement of urban forest structure attributes around a home. Since number of trees and LAI were statistically significant, but tree cover and biomass was not, it may be that type and distribution of trees, or palms, present on the property are important considerations. This might indicate that plot level information that can be used to distinguish between differing tree types (e.g., palms versus broad leaf deciduous), with different esthetic appeal, is just as important as remotely sensed tree cover estimates. Further, despite having good model performance, our final sample was reduced to 190 plots from over 500 plots in four different cities. Thus, property value and urban forest structure data will always be limited because of the random nature of this sampling design and costs associated with site access and sampling in these complex, urban environments.

The negative effect of grass cover on property values, although small, was particularly interesting since grass is considered a key component in the beautification of urban landscapes in Florida (Stigarll and Elam, 2009). This relationship was particularly evident in coastal Pensacola ($r=-0.33$) and Miami-Dade ($r=-0.21$). But given Florida's climate, vegetation growth is rapid and water scarcities and saltwater exposure are common, thus it can be difficult and costly to grow and maintain grass particularly in areas with high tree densities, and therefore the resulting negative correlation. Furthermore, unless a homeowner has a large parcel of land (i.e. higher property value), it is difficult to maintain grasses due to the shading effects from trees. According to our findings, on average, higher valued properties had less grass cover than did lower values properties. Conversely, the opposite relationship was found in more arid, coastal Los Angeles US, where property values were greater in areas with increased amounts lawns. However, while Saphores and Li (2012) used a larger sample in their hedonic analyses and measures of green space, their data were obtained using remote sensing alone, while our tree, shrub and grass variables were based on field-based measurements.

Overall, urban forest structure attributes, or indicators used in our hedonic model were conservative compared to other studies such as those by Flock et al. (2011) and Dobbs et al. (2011) who found that low tree cover in coastal cities might be a result of soil condition and past hurricanes as well as the presence of rental properties, which in Miami-Dade have lower tree LAI and tree-shrub cover than do owner-occupied homes. However, the model and findings can be used to better understand and estimate the interactions among urban forest structure indicators and their effect on cultural ecosystem services and co-benefits and resulting tradeoffs – and synergies- with other ecosystem services.

As mentioned earlier, our dependent variable is the difference between actual assessed and median assessed value for each community. Thus, for each parameter estimate, a positive (negative) coefficient value indicates that, on average, the variable leads to an increase (decrease) in the expected assessed property value relative to the median home price when holding all other variables constant. We emphasize that our approach does not argue that assessed value is a better measure of real estate clearing price. Rather field measured, multi-storied structural components and assessed property values are more similar at capturing and determining the perceived value of these housing and urban forest amenities by owners and managers (i.e. homeowners, policy makers, and municipalities) of a property.

5. Conclusion

Although a number of studies have used hedonic analyses to determine the effects of specific urban forest structure variables on real estate values and rental prices, most of these, particularly those from temperate areas of the United States, are based on remotely sensed tree- grass cover data, number of public trees near the residential parcels, and real estate sales data from mostly single family homes. Indeed the commonly accepted test for the validity of classified images is whether they agree with field observations. We know of few urban forest valuation studies that account for site-specific biophysical and socioeconomic contexts in the subtropics such as: multistoried structure, rapid growth rates, regional real estate markets, and unique demographics. Thus, it is important that the influence of context on regulating and cultural services be addressed for sub-tropical areas such as Florida that face unique conditions. For example, although community leaders in Florida perceive many of the same benefits towards urban forests as in the rest of the US, many associated specific costs unique to the subtropics are different from these other temperate areas such as increased litter generation and maintenance costs that are particular to this region's vegetation growth rates and post-hurricane tree debris and damage (Wyman et al., 2012).

We found higher property values for single-family and individual multi-family homes with more trees and higher Leaf Area Index. But interestingly, we found tradeoffs in the influence of urban forest structure attributes on property value in that biomass, tree and shrub cover had no effect, yet an increase in grass cover has a small negative impact on home value. As expected, we also found that other property characteristics, including number of bathrooms, home size-type, and location (e.g., Orlando) were important factors in expected home value.

Our findings point to the importance of urban forest structure – in addition to vegetation cover - on ecosystem services and the implied value to homeowners and local governments. These relationships and results can be used to inform local and state policies regarding urban forests and conservation of green spaces in cities. Many cities have tree protection and green space preservation ordinances that encourage the replacement of removed trees to maintain long-term tree canopy cover goals. But, financial limitations of local governments, often results in decreased investments in urban forestry programs. Also, many residents in Florida US, for example, fear trees damaging homes during windstorms and see enforcement of tree protection ordinances as excessive government intrusion into private property rights. Thus, our results provide a justification and indicators for promoting and advocating the benefits of properly managing and maintaining urban forest ecosystems.

In conclusion, this approach can be used by local and regional urban planners, landscape architects, urban foresters, policy makers and researchers to assess the relative value of establishing and maintaining specific urban forest structure goals. Results can also be used to evaluate and justify urban forestry programs and ordinances that promote or enforce desired levels of key urban forest structure parameters, both directly (i.e., increased home values) and indirectly (i.e., tax revenues increase as a result of higher assessed value), which may be important considerations for decision makers. When coupled with information about expected costs of maintaining trees (e.g., pruning and removal) over time, our results could be used in cost-benefit analyses of urban forest programs and management plans to better calculate the stream of net benefits associated with managing and preserving urban forests.

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