Landscape and Urban Planning 110 (2013) 134–142

Contents lists available at SciVerse ScienceDirect

Landscape and Urban Planning

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

Research paper

The effect of street trees on property value in Perth, Western Australia

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HIGHLIGHTS

- ► Effect of urban tree on property value differs depending on tree type and location.
- ► A broad-leaved tree on street verge increases property value by AU$16,889.
- ► Presence of trees on the property does not affect property value.
- ► Findings can be used for developing urban tree management policies.

ARTICLE INFO

Article history:
Received 7 April 2012
Received in revised form 31 October 2012
Accepted 3 November 2012
Available online 1 December 2012

Keywords:
Broad-leaved trees
Spatial hedonic model
Property value
Street trees

ABSTRACT

Trees provide a variety of benefits to urban residents that are implicitly captured in the value of residential properties. We apply a spatial hedonic model to estimate the value of urban trees in 23 suburbs of Perth Metropolitan Area in Western Australia. Results show that a broad-leaved tree on the street verge increases the median property price by about AU$16,889, suggesting a positive neighbourhood externality of broad-leaved trees. However, neither broad-leaved trees on the property or on neighbouring properties nor palm trees irrespective of the locations contributed significantly to sale price. Our result has potential implications on planting and maintaining broad-leaved trees on street verges for neighbourhood development and urban planning to generate public and private benefits of street trees.

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1. Introduction

Urban residents value a variety of amenities (e.g. wetlands, open spaces, parks and recreational facilities) that offer environmental, cultural, aesthetic, and health benefits. Urban trees are amenities that are found on residential properties, street verges, and parks and reserves in urban areas. The environmental benefits of urban trees include protection of the land from soil erosion, reductions in storm-water run-off, habitats for wildlife, filtration of air pollutants, improvements in local air quality, reductions in the urban "heat island" effect, and energy savings by providing shading and insulation (Brack, 2002; Dwyer, Schroeder, & Gobster, 1991; McPherson, Simpson, Peper, Maco, & Xiao, 2005; Nowak, Crane, & Stevens, 2006; Pandit & Laband, 2010b; Sander, Polasky, & Haight, 2010; Simpson, 1998). Urban trees also provide cultural and health benefits that improve the quality of urban life, as trees may make a city neighbourhood seem more scenic, provide privacy, shelter residents from negative effects of undesirable land uses, and improve retail areas by creating environments that are more attractive to consumers (Dwyer, Schroeder, & Gobster, 1991; Ellis, Lee, & Kweon, 2006; Sheets & Manzer, 1991; Wolf, 2005). These environmental, cultural, and health benefits of urban trees are often difficult to translate into monetary terms, (Anderson & Cordell, 1988) as the market for most of these benefits are absent due to their public good characteristics.

The hedonic pricing method (HPM) has been widely used to estimate the values of different environmental and recreational amenities (or disamenities), which are bundled in property values or sale prices (e.g. Dombrow, Rodriguez, & Sirmans, 2000; Geoghegan, Wainger, & Bockstael, 1997; Hatton MacDonald, Crossman, Mahmoudi, Taylor, Summers, & Boxall, 2010; Kim & Goldsmith, 2009; Loomis, Rameker, & Seidl, 2004; Mansfield, Pattanayak, McDow, McDonald, & Halpin, 2005; Payton, Lindsey, Wilson, Ottensmann, & Man, 2008; Samarasinghe & Sharp, 2010; Tapsuwan, Ingram, Burton, & Brennan, 2009; Zhang, Meng, & Polyakov, 2013). One of the several applications of HPM is to estimate the values of urban trees, open space, and forest cover (for example see, Anderson & Cordell, 1988; Cho, Poudyal, & Roberts, 2008; Dombrow, Rodriguez, & Sirmans, 2000; Donovan & Butry, 2010; Kong, Yin, & Nakagoshi, 2007; Netusil, Chattopadhyay,

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http://dx.doi.org/10.1016/j.landurbplan.2012.11.001

& Kovacs, 2010; Sander, Polasky, & Haight, 2010; Tyrväinen & Miettinen, 2000).

Recently, Donovan and Butry (2010) pointed out that the earlier studies that examined the effect of trees on property value have not differentiated the relative impact of different types, sizes, and species of trees on the property value. It is reasonable to expect that prospective home buyers may place different values on different types of trees as they provide different services. For instance, conifers provide year round greenery to urban residents, even though they might be less preferred than broad-leaved trees. Unlike conifers, broad-leaved trees provide different services at different times of the year, such as shade in the summer whilst allowing warmth and light to come through during the winter due to their deciduous nature (Pandit & Laband, 2010a). Similarly, prospective buyers may place different values on the same type of tree depending on its location – within one's property (private space) or on the next-door neighbours' property or on the street verge adjacent to the property (public space).

There have been a few studies that have examined location specific contribution of trees on property values, mostly in Europe and North America, using tree cover variables such as proportional area covered by trees within and adjacent to the property without differentiating the types of trees (Netusil, Chattopadhyay, & Kovacs, 2010; Sander, Polasky, & Haight, 2010; Tyrväinen & Miettinen, 2000). As Mansfield, Pattanayak, McDow, McDonald, & Halpin (2005) pointed out, "each type of forest cover provides different amenities to the homeowner and to society", it is thus important to differentiate tree cover by tree types to estimate their relative contributions on property values.

The missing link between the type and the location of trees in urban areas and their effect on property values is important to examine in an Australian context for multiple reasons. Firstly, the environmental and economic values of trees in residential settings have been widely recognised and strongly held among Australian residents and city planners (City of Perth, 2010; Powell, 1976). However, the effect of trees on the property price by their types and location had not been studied. Secondly, the property market is a major industry in Australian cities and understanding the link between tree location/types and sale price would be useful in property appraisal processes and/or developing new residential neighbourhoods to accommodate the growing population of the city. Thirdly, it could lend empirical support to the existing efforts of city councils to develop and maintain urban greenery in residential areas.

The choice between traditional, i.e. the non-spatial ordinary least squares model, and spatial hedonic models is of empirical interest partly because spatial hedonic models capture unobserved spatial effects among observations if such effects (or correlations) exist in the data. Non-spatial model results are biased if a spatial lag process is present, i.e. the neighbouring property price affects the price of a property; and they are inefficient if a spatial error process is present, i.e. the errors among observations are spatially correlated (Anselin, 1988). In addition, results are biased if omitted variables in the model are spatially correlated with the dependent variable (LeSage & Pace, 2009). In a wildfire risk study using both non-spatial and spatial models, Mueller and Loomis (2008) found that the model results were similar and suggested that traditional hedonic models might be preferable for policy purposes despite inefficient parameter estimates. However, their data exhibited only spatial error process and ignoring it did not cause substantial bias in the coefficients estimates. On the other hand, spatial hedonic models produce robust parameter estimates in the presence of spatial processes (Anselin, 1988). We therefore compare results of both types of models in our study.

The aim of this paper is to examine the effect of trees on property values using spatial hedonic models with the emphasis on the types of trees and their locations. We analyse two types of trees: broad-leaved and palm trees. Tree locations are differentiated according to whether they are situated within a property boundary (private space), on an adjacent street verge (public space), or on the neighbouring property (neighbouring private space). The paper is organised into four sections. Following the introduction, we lay out the methods of this study including a brief description of the study area, data and variables, and the modelling process. Then we present and discuss the results, and make some concluding remarks along with potential policy implications of the findings.

2. Materials and methods

2.1. Study area

This study covers 23 northern suburbs of the Perth metropolitan region in Western Australia within four city councils: City of Bayswater, Town of Vincent, City of Stirling, and City of Wanneroo. The study area extends approximately 22 km north–south and 2–4 km east–west, covering an area of approximately 92 km^2 with Wanneroo and Highgate as the northern and southern most suburbs, respectively. The socio-economic setting of the area ranges from the affluent and established suburbs close to the city centre to the middle-class newly developed suburbs farther away on the northern outskirts. Fig. 1 displays the extent of the study area, the physical locations of the single-family houses sold in 2006, and the main roads within the study area.

The land use of the study area is dominated by residential housing, although a mixture of industrial, recreational and commercial land uses is also present. Some significant environmental amenities within or surrounding the area include: the Swan River, parks (Bold, Hyde and Kings), bush reserves (Warwick and Koondoola), lakes (Monger, Joondalup and Goollelal) and several golf courses.

The study area is well connected by the road network with the Mitchell Freeway near its western border. The area runs parallel to the Indian Ocean in the north–south direction with a 2–3 km average distance from the western boundary of the area to the beach (Fig. 1).

2.2. Data and variables

Following a general practice of hedonic modelling and the insights from an earlier hedonic study in Perth (Tapsuwan, Ingram, Burton, & Brennan, 2009), we collected data on three groups of key variables: property, location and environmental. Using multiple sources, data on property sales, geographic locations and the extent of the property, neighbourhood characteristics including urban trees were collected. We used 2006 data on property sales that were acquired from Landgate, a government agency which is the custodian of property data in Western Australia. Property sales data contain the parcel number, sale price, date of sale, and structural characteristics for each of the properties sold. The sale price was deflated to the 1 January 2006 price using the Housing Price Index (HPI) obtained from the Australian Bureau of Statistics (www.abs.gov.au). HPI is available on a quarterly basis, so it was linearly interpolated for the dates between last days of the quarters. The housing price index had increased 42% between the last quarter of 2005 and the last quarter of 2006. For geospatial referencing and delineation of the boundaries of each property, we retrieved cadastral map data from the Shared Land Information Platform (SLIP) of Landgate. The cadastral map data were also used to identify small neighbourhood parks in the study area. These neighbourhood reserves are often small in size and covered with grass and individual trees, generally used as play grounds. The locations of large parks, which are mostly covered by natural vegetation

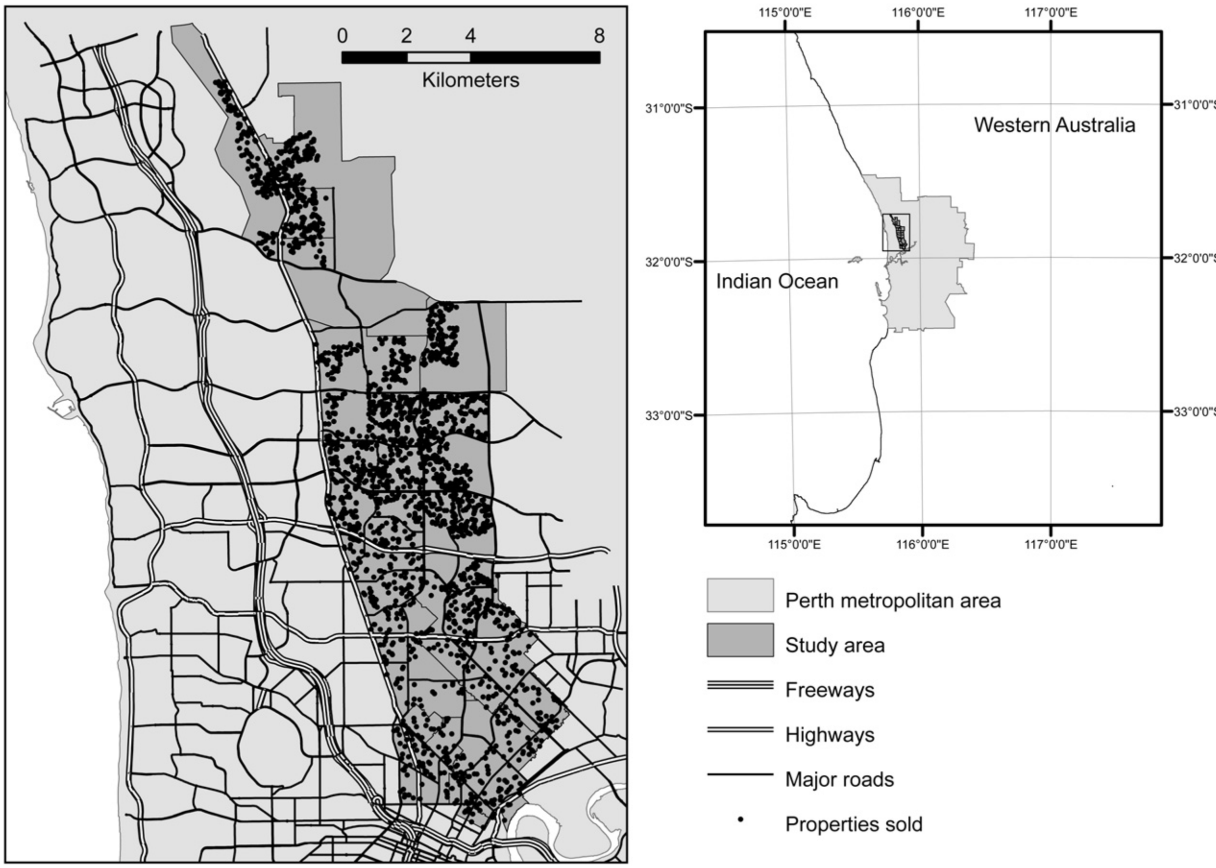

Fig. 1. Map of the study area and locations of the observations.

with hiking and bush-walking facilities, were identified using the 'parks and recreation' layer of the land-use and zoning map. The location of golf courses, sport reserves (i.e. parks with soccer/cricket pitches) and parks with lakes were identified using either a cadastral or land-use zoning map. A high resolution (30 cm) aerial image of the study area was accessed from SLIP using the Web Map Service (WMS) to identify and count trees on and around the sample properties. To characterise suburb specific criminal activities in the study area, we retrieved data on burglaries and assaults by suburb for 2005 from the website of the State Police Service, Western Australia (http://www.police.wa.gov.au).

From all sale records for 2006, we selected single (detached) family homes with a property area of less than 2 ha and a sale price of greater than \$100,000, which resulted in a total of 2149 observations for analysis. Spatial analysis to link the property location with other spatially explicit variables was conducted using ArcGIS 10. The property boundary layer extracted from the cadastral map was superimposed on the aerial image of the study area. Broad-leaved and palm trees within the boundaries of each property, on the neighbouring properties, and on the verges of the streets adjacent to each property were counted visually. Euclidian distances between each property and the Central Business District (CBD) of Perth city, the nearest main road, and different types of parks and reserves were computed in ArcGIS 10. The distance was measured from each property to the central location of Perth city, the nearest main road, and to the edges of the parks and reserves. A brief description of the variables and their descriptive statistics are presented in Table 1.

The number of trees on the properties ranged from 0 to 11 for broad-leaved and 0 to 10 for palms with a slightly higher mean for broad-leaved trees (i.e. 1.013 and 0.786 trees per property). Compared to the average number of trees on residential properties, fewer numbers of broad-leaved and palm trees were found on adjacent street verges (0.4 and 0.03) and on neighbouring properties (0.52 and 0.16). This reduction in the average number of trees on street verges is primarily due to the fact that for most of the properties in our sample, only one side was facing the street.

2.3. Model specification

The hedonic pricing model has been widely used to estimate the implicit price of different structural, neighbourhood and environmental attributes of a house or property from its sale price (Champ, Boyle, & Brown, 2003; Freeman, 1979). The model assumes that a house is a differentiated good and the differences in house prices are due to different attributes of the house including its neighbourhood and accessibility or location specific characteristics (Rosen, 1974). Following Rosen's seminal work we apply a traditional hedonic pricing model that represents the price of a differentiated good – a house in this case – which reflects the value of structural, neighbourhood, and location specific or accessibility characteristics associated with it. We consider the number of trees within the property boundary (private space), on the adjacent street verges (public space), and on the neighbouring properties as environmental characteristics of a house which are parts of both structural and neighbourhood characteristics in the model:

$$P_i = \alpha + \mathbf{X}_i'\boldsymbol{\beta} + \mathbf{Z}_i'\boldsymbol{\gamma} + \varepsilon_i \quad (1)$$

where P_i is the house sale price; $\mathbf{X}_i$ is a $j \times 1$ vector of structural characteristics of the house and the characteristics of the property (=j) that includes property area, house age, indicator for the presence of a swimming pool, the number of structural features of the house, including bathrooms, bedrooms, dining and meal rooms, study rooms, parking spaces, and the number of broad-leaved and

Table 1
Model variables and descriptive statistics.

Variable	Median	Mean	STD	Minimum	Maximum
Dependent variable					
Sale price (AU$)	$395,000	$448,000	$199,208	$102,500	$2,150,000
Explanatory variables					
Land area (m^2)	692	677	143.23	253	1657
House age (years)	23	26.32	19.47	1	102
Number of bathrooms	1	1.485	0.559	1	5
Number of bedrooms	3	3.344	0.772	1	6
Number of dining and meal rooms	1	0.954	0.649	0	2
Number of study rooms	0	0.17	0.386	0	3
Number of parking spaces in the garage	0	0.737	0.894	0	4
Presence of swimming pool	0	0.162	0.368	0	1
Number of broad-leaved trees on the property	0	1.013	1.381	0	11
Number of palm trees on the property	0	0.786	1.441	0	10
Number of broad-leaved trees on the neighbouring properties	0	0.518	0.761	0	5
Number of palm trees on the neighbouring properties	0	0.164	0.526	0	5
Number of broad-leaved trees on street verge adjacent to the property	0	0.403	0.756	0	9
Number of palm trees on street verge adjacent to the property	0	0.03	0.245	0	6
Distance to the CBD (km)	12.63	12.83	5.619	1.575	25.39
Distance to the nearest main road (m)	241	321	280	20	1541
Distance to the large park (hiking/bushwalking) (m)	1121	1499	1413	10	6881
Distance to the park with lake (m)	3436	3291	1880	11	7460
Distance to the small neighbourhood reserve (m)	152	180	121	8	674
Distance to the sport reserve (m)	409	540	456	9	2890
Number of burglaries in suburb per 1000 houses	30	36	18	11	70
Number of assaults in suburb per 1000 residents	6	11	8	0	29

palm trees on the property; $\mathbf{Z}_i$ is a $k \times 1$ vector of neighbourhood and location characteristics (=k) that includes the number of broad-leaved and palm trees on street verges adjacent to the property, the number of burglaries per 1000 houses and assaults per 1000 population by suburb, and distances to the CBD, the nearest main road, large parks (i.e. large parks with hiking and/or bush walking facilities), parks with lakes, sport reserves (i.e. large sporting fields for soccer/cricket/rugby games), small neighbourhood reserves (i.e. playgrounds), and golf courses; α is the intercept, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are parameter vectors to be estimated; and ε_i is the error term.

The hedonic model in Equation 1 does not account for any spatial relationships. However, spatial data such as house sale prices could exhibit spatial relationships in two-ways: spatial correlation among observations of the dependent variable (sale prices) and model errors (Anselin, 1988). Spatial relationships are rooted in the fundamental law of geography referred to as the "first law of geography" that captures the essence of spatial or geographical influence among observational units and states that "Everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). The relationship is referred to as spatial lag when the sale price of a house is affected by the sale prices of neighbouring houses. When omitted variable bias exists due to unobserved variables related to the location of a property, the errors of the model may be spatially correlated. The model that takes into account of both spatial lag and spatial error could be specified as

$$P_i = \alpha + \rho \mathbf{W}_i'\mathbf{P} + \mathbf{X}_i'\boldsymbol{\beta} + \mathbf{Z}_i'\boldsymbol{\gamma} + \varepsilon_i, \qquad (2)$$
$$\varepsilon_i = \lambda \mathbf{W}_i'\boldsymbol{\varepsilon} + \upsilon_i$$

where ρ is the spatial lag coefficient, $\mathbf{W}_i$ is a $n \times 1$ vector from the spatial weight matrix, λ is the spatial error coefficient and υ_i is an uncorrelated error term, i.e. $\upsilon_i \sim N(0, \sigma^2)$.The spatial weight matrix $\mathbf{W}$ defines the way in which observational units are believed to be neighbours and determines the influence of neighbouring observations (see Anselin, 1988; Conway, Li, Wolch, Kahle, & Jerrett, 2010; Taylor, 2003 for theory and applied examples). Most of the observations in the data set are not immediate neighbours. In such cases, common approaches to define the spatial weight matrix are the inclusion of the nearest neighbours or observations within a certain cut-off distance. It is common to assume that the strength of the spatial relationship declines as the distance between the two observations increases. Among assumptions of weakening spatial relationship with distance, the most common is that the spatial relationship decays proportionally to the inverse distance between the observations (Maddison, 2009). To determine the threshold of the inverse distance weight matrix, we examined the semivariogram of the residuals of Ordinary Least Square (OLS) model (Donovan & Butry, 2010). Row standardisation was used to normalise the total weight assigned to an observation to 1, which makes the interpretation of the spatial error or spatial lag coefficients more intuitive. In this study, we compare inverse distance weight matrix with the k-nearest neighbour (8-nearest neighbour in our case) weight matrix, which is also frequently used in the literature (Mueller & Loomis, 2008).

We applied the Box–Cox transformations of the dependent variable (adjusted sales price) using the SAS® v.9.2 TRANSREG procedure to identify the most appropriate functional form for the hedonic price function. Results indicate that the natural log transformed dependent variable is the most appropriate functional form. Among the explanatory variables, all of the distance related variables were also transformed to the natural log form. Given the structural differences and other variations on house attributes, it is possible that older houses may have some heritage premium attached which could be reflected in house price. To examine potential nonlinearities associated with cultural or heritage values of older houses, we included a squared term for house age in the model.

3. Results and discussion

First, we estimated a traditional hedonic model using OLS (Table 2) and explored a potential endogeneity concern in the model. To address a concern that the number of trees on the verge of the street could be endogenous in the model as trees on the street are more likely to be planted in rich communities, we performed a Hausman test of endogeneity by using property frontage as an instrument. Property frontage represents available space for planting trees on the street verge; thus the longer the property

Table 2
Ordinary least-squares (OLS) and spatial hedonic regression results of factors affecting property values (dependent variable Log Property price, AU$).

Variable	OLS model	Spatial model
Intercept	16.14000*** (0.17630)	7.35970*** (0.92201)
Land area	0.00059*** (0.00003)	0.00056*** (0.00004)
House age	−0.00743*** (0.00090)	−0.00779*** (0.00111)
House age^2	0.00008*** (0.00001)	0.00008*** (0.00001)
Number of bathrooms	0.11590*** (0.01098)	0.08156*** (0.01150)
Number of bedrooms	0.02448*** (0.00742)	0.02934*** (0.00736)
Number of dining and meal rooms	0.01813** (0.00757)	0.01667** (0.00665)
Number of study rooms	0.09611*** (0.01149)	0.07576*** (0.01067)
Number of garages spaces	0.06775*** (0.00514)	0.04205*** (0.00479)
Presence of swimming pool	0.04561*** (0.01112)	0.04754*** (0.01128)
Number of broad-leaved trees on the property	−0.00299 (0.00312)	−0.00243 (0.00314)
Number of palm trees on the property	−0.00525* (0.00279)	−0.00055 (0.00253)
Number of broad-leaved trees on the neighbouring properties	−0.00634 (0.00532)	−0.00418 (0.00483)
Number of palm trees on the neighbouring properties	−0.00768 (0.00733)	−0.00405 (0.00621)
Number of broad-leaved trees on street verge	0.02013*** (0.00556)	0.01943*** (0.00585)
Number of palm trees on street verge	0.00652 (0.01566)	0.01529 (0.01133)
Log distance to the CBD	−0.43600*** (0.01311)	−0.23289*** (0.02785)
Log distance to the main road	0.02236*** (0.00437)	0.02124*** (0.00482)
Log distance to the park (bushwalking)	0.03566*** (0.00525)	0.01238* (0.00717)
Log distance to the park with lake	−0.03308*** (0.00536)	−0.02094*** (0.00744)
Log distance to the small reserve	−0.01481*** (0.00497)	−0.00617 (0.00468)
Log distance to the sport reserve	0.02687*** (0.00474)	0.01393** (0.00691)
Burglaries per 1000 houses	−0.00008 (0.00057)	0.00044 (0.00095)
Assaults per 1000 residents	−0.00822*** (0.00117)	−0.00214 (0.00192)
Spatial lag		0.54557*** (0.05684)
Spatial error		0.66025*** (0.08313)
R^2	0.769	
Adjusted R^2	0.767	
Wald test that spatial lag and spatial error are both zero		167.31***

Note: Standard errors are in parentheses.
* Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

frontage, the higher the number of trees that could be on the street verge. The instrument is uncorrelated with the model error (0.005), but is correlated with the number of trees on the verge (r = 0.31). The Hausman test failed to reject the hypothesis of exogeneity (F-statistic = 0.0586, p-value = 0.8087), and therefore we conclude that the number of trees on the street verge is not endogenous in the model.

We then explored the presence of spatial dependence using a semivariogram of the OLS model residuals (Fig. 2). The semivariogram presents the semivariance as a function of distance between observations. If the residual semivariance of closely located observations is smaller than the residual semivariance of observations located further apart, spatial dependence is likely to be present (Donovan & Butry, 2010). Analysis of the semivariogram in Fig. 2 suggests the presence of spatial dependence, which disappears after approximately 2000 m distance. We use this distance as a threshold to create the inverse-distance row-normalised spatial weight matrix. This matrix was used to calculate Moran's I statistic, which confirms the presence of spatial dependence in the residuals (Table 3). For comparison, we also calculated Moran's I statistic using the 8-nearest neighbour spatial weight matrix (Table 3). It also confirms the presence of spatial dependence in the residuals, but the test using the inverse-distance spatial weight matrix provided slightly stronger evidence of spatial dependency.

In order to determine the type and magnitude of spatial dependence, we conducted a series of Lagrange multiplier (LM) and Robust LM (RLM) tests for the presence of spatial lag and spatial error dependencies (Anselin, Bera, Florax, & Yoon, 1996) using both types of spatial weight matrices (Table 3). The LM tests test the null hypothesis of no spatial lag or spatial error dependence, while the RLM tests test the null hypothesis of no spatial error (spatial lag)

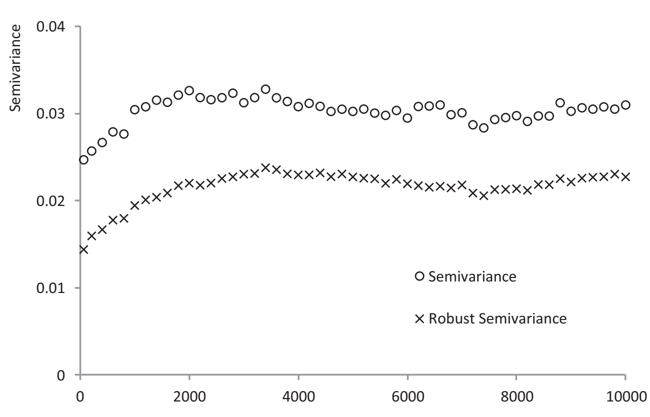

Fig. 2. Semivariogram of the residuals from the OLS hedonic price model.

Table 3
Tests of spatial dependencies in the OLS model.

Test	Spatial weight matrix	
	8-Nearest neighbours	2000 m inverse distance
Spatial error dependence		
Moran's I statistics standard deviate	15.30***	21.23***
Lagrange multiplier test	230.70***	434.49***
Robust Lagrange multiplier test	230.40***	215.14***
Spatial lag dependence		
Lagrange multiplier test	0.30	300.16***
Robust Lagrange multiplier test	0.01	80.82***
Spatial error and lag dependence (SARMA)		
Lagrange multiplier test	230.70***	515.31***

*** Significant at 1% level.

dependence in the presence of spatial lag (spatial error) dependence. The test statistics in Table 3 indicate the presence of strong spatial error dependence for both LM and robust LM tests based on both types of weight matrices, but the lag dependence was apparent only with the inverse-distance weight matrix. Finally, LM-SARMA test was applied to test the null hypothesis of both spatial lag and spatial error equal to zero. The test results for both types of spatial weight matrices are highly significant suggesting the presence of both lag and error dependence processes. However, the test based on the 2000 m inverse-distance spatial weight matrix suggests a stronger evidence of these processes. Based on these test results, we decided to estimate a model that accounts for both spatial lag and spatial error using the 2000 m inverse distance spatial weight matrix. We apply a general spatial two-stage least squares (GS2SLS) procedure that produces spatial heteroskedastic and autocorrelation consistent (HAC) estimators of the variance–covariance matrix of the model coefficients (Kelejian & Prucha, 2010) using the 'glsthet' package (Piras, 2010) for R statistical software (R Development Core Team, 2011). The model results are presented in Table 2.

The magnitude and significance of spatial control variables, as well as the result of the Wald test for joint significance of spatial lag and spatial error coefficients in Table 2, confirm the presence of both spatial error and spatial lag processes. The results are consistent across the OLS and spatial models in their direction of impact (i.e. sign) and significance for most of the structural variables and variables describing the number of trees on and around the property. The coefficient for the number of broadleaved trees on the street verge is slightly overestimated in the OLS model and the coefficient for palm trees on the property became insignificant in the spatial model. This indicates that there might be some spatially correlated unobserved factors impacting the OLS model estimates, which are unlikely to be correlated with tree variables. On the other hand, there is a substantial bias in the coefficients for most of the distance based and suburb based variables estimated using OLS (the magnitude is greater). For the distance based variables, the distance to a feature (such as CBD, park, or road) is only a proxy for the effect of the feature. Furthermore, the values of the variables are spatially correlated due to the way they were calculated. For the suburb based variables, such as crime, a measurement error is likely to be present due to the fact that the value of crime is assumed to be the same throughout the suburb. In reality, the crime might be concentrated in a certain part of a suburb and have an effect on the neighbouring suburb. These spatial effects are the likely causes of spatial autocorrelation. In the following sections we discuss the results of the spatial model that accommodates both spatial error and spatial lag parameters.

Regression coefficients of the structural characteristics of the house have the expected signs and significance (Table 2). The numbers of bathrooms, bedrooms, dining and meal rooms, study rooms, and parking spaces in the garage have positive and significant impacts on the sale price. Land area and the presence of swimming pools also have similar impacts on the sale price. House age and sale price have a non-linear relationship with 49.4 years as a threshold age. Up until this age house price decreases as age increases but after this, house price increases as age increases.

The significance of a spatial lag parameter (ρ) suggests the presence of spatial lag effect in the model and that there are direct (own) and induced (from the neighbours) effects on sale price as a result of marginal change in an attribute for each property within a threshold distance. When estimating marginal implicit prices these effects should be accounted for by the use of a spatial multiplier $[1/(1-\rho)]$ (Kim, Phipps, & Anselin, 2003). Table 4 presents the marginal implicit prices (MIP) of the statistically significant variables in the model at the median sale price and the medians of the explanatory variables. The marginal implicit prices are comparable to the findings of an earlier hedonic study by Tapsuwan, Ingram, Burton, & Brennan, (2009) in neighbouring Perth suburbs. But it is worth noting that there is a methodological difference between the two studies, particularly in relation to controlling spatial lag effect, which has an implication in determining marginal implicit prices. For example, we found that the median-based marginal implicit prices for land area and an additional bedroom are about AU\$489/m^2 and AU\$70,892 respectively, which are slightly higher than AU\$401/m^2 and AU\$61,152 found by Tapsuwan, Ingram, Burton, & Brennan, (2009).

Table 4
Marginal implicit price for significant variables based on median house price (AU\$395,000).

Variable	Marginal implicit price, AU\$
Land area, m^2	\$488.55
House age, year[a]	−\$3603.69
Number of bathrooms	\$70,891.91
Number of bedrooms	\$25,502.94
Number of dining and meal rooms	\$14,489.91
Number of study rooms	\$65,847.82
Number of garage spaces	\$36,551.60
Presence of swimming pool	\$41,321.02
Broad-leaved trees on street verge	\$16,888.96
Distance to the CBD (m)	−\$16.02
Distance to the main road (m)	\$76.68
Distance to the large park (m)	\$9.60
Distance to the park with lake (m)	−\$5.30
Distance to the sport reserve (m)	\$29.59

[a] The implicit price for house age was calculated at the median age (23 year), however the sale price is non-linearly related to the age with a threshold age of 49.4 years.

We found that both the distance to the CBD and the distance to the nearest main road have significant influences on sale price (Tables 2 and 4). While proximity to the Perth city centre has a positive effect of AU\$16 for each metre closer to the city, proximity to the main road constitutes a disamenity associated with traffic noise and decreases house prices by AU\$77 for each metre being closer to the main road. These results support earlier findings by Tapsuwan, Ingram, Burton, & Brennan, (2009) who found a premium of AU\$32 and AU\$26 for a house being closer to the city centre and it being away from main highways in Perth. In Adelaide, South Australia, Hatton MacDonald, Crossman, Mahmoudi, Taylor, Summers, & Boxall (2010) found slightly different premiums associated with distance to the Adelaide city centre (AU\$4/m) and distance to a main road (i.e. AU\$30/m).

Proximity to public open spaces such as parks and reserves can influence house sale prices depending on their types and sizes. Taking insights from the findings of Hatton MacDonald, Crossman, Mahmoudi, Taylor, Summers, & Boxall (2010) and Tapsuwan, Ingram, Burton, & Brennan, (2009), we differentiated parks and reserves into five categories – large parks, parks with lakes, sports reserves, small neighbourhood reserves, and golf courses – to accurately capture the amenity value associated with different types of parks and reserves. Our results suggest that the proximity to parks with lakes and small neighbourhood reserves have positive and statistically significant impacts on sale price (the coefficient for the distance is negative); while the proximity to large parks and sport reserves have negative impacts (Table 2). This latter result is contrary to the findings of earlier studies (Acharya & Bennett, 2001; Frech & Lafferty, 1984), but is consistent with findings of recent studies (Bark, Osgood, Colby, & Halper, 2011; Fierro, Fullerton, & Donjuan-Callejo, 2009; Hatton MacDonald, Crossman, Mahmoudi, Taylor, Summers, & Boxall (2010)). The reasons why the proximity to large parks negatively impacts house price depend on the study site and other contexts. For example, in northern Mexico, large parks were considered a disamenity because of crime and poor park maintenance (Fierro, Fullerton, & Donjuan-Callejo, 2009). In South Australia, the lack of aesthetic appeal and the fear of wild fires and poisonous snakes also led to parks becoming disamenities (Hatton MacDonald, Crossman, Mahmoudi, Taylor, Summers, & Boxall (2010)). Our finding of a positive proximity effect (AU$5/m) of parks with lakes (Tables 2 and 4) is in line with an earlier finding (Hatton MacDonald, Crossman, Mahmoudi, Taylor, Summers, & Boxall (2010)). The positive effect of small neighbourhood reserves on sale price is sensitive to model specification and becomes insignificant in the spatial model. Moreover, the positive premium associated with proximity to large sporting reserves (AU$30/m) in our context is at odds with the earlier finding in South Australia (Hatton MacDonald, Crossman, Mahmoudi, Taylor, Summers, & Boxall (2010)).

The focus of our study was on examining the effect of broad-leaved and palm trees on house sale prices depending on their location i.e. trees located on private space (within the property boundary and on neighbouring properties) versus trees located on public space (i.e. along the street verge next to the property). Contrary to our expectations, we found no statistically significant effect of palm trees on the house sale price regardless of their location – either on one's property, neighbouring properties or on street verges (Table 2). We found positive and sizable effects of broad-leaved trees on sale price only when such trees were located on street verges, while trees on the property and trees on neighbouring properties did not have statistically significant effects. The marginal implicit price of a broad-leaved tree on the street verge is about AU$16,889, which corresponds to approximately 4.27% increase in the median value of the property (AU$395,000) in our study area.

Our results are consistent with the findings of other studies that analysed the effects of trees both on and around the property on the sales price. In a recent study by Donovan and Butry (2010) in Oregon, they found that on average 0.558 street trees in front of the house combined with a canopy cover of 84 m^2 within 30.5 m adds US$ 8870 to the sales price of an average house. Similarly, Sander, Polasky, & Haight (2010) in Minnesota found that a 10% increase in the coverage of trees that are within 250 m of the house, including trees on street verges, increases sales price by about US$ 836 (0.29%). Similar to this study, they found no statistically significant effect of tree cover within the property on the sales price.

We believe that both trees on the property and trees on the street verge benefit homeowners. However, trees on the property are associated with the cost of establishment and maintenance as well as opportunity cost (e.g. trees compete for valuable space with other land uses such as lawns, garden beds, swimming pools), which might outweigh the benefit. At the same time, the homeowners do not bear costs associated with planting or maintaining trees on the street verges because they are maintained by the public agencies (such as city councils). Therefore, the private net benefit of street trees could be higher to residents while the opportunity costs associated with these trees are lower compared to the trees on the property. Furthermore, since tree cover is spatially correlated, models that do not control for neighbourhood tree cover and spatial error might yield an inflated value of the coefficient of trees on the property (Sander, Polasky, & Haight, 2010).

We found that controlling for spatial autocorrelation has an impact on the estimated regression coefficients and the marginal implicit price of the variables. Among two sets of model results (Table 2), we found that the coefficient estimates for some of the highly significant variables are substantially different between the models but the estimates for the number of broad-leaved trees are not. For example, the 95% confidence interval of the OLS estimates of distance to the CBD (−0.4617 to −0.4103), distance to bush-walking parks (0.0252–0.0462) and distance to sport reserves (0.0176–0.0362) indicate statistical differences between the OLS and the spatial model estimates. Consequently, the implicit prices in Table 4 associated with these variables would also be substantially different; for example, the implicit price associated with proximity to the CBD is AU$14/m and AU$16/m (Table 4) based on OLS and spatial model estimates, respectively. The differences in the implicit prices of the variables between the models indicate an omitted variable bias in the OLS model estimates, which signifies the importance and relevance of controlling for spatial lag effects in hedonic modelling.

4. Conclusion

It has been shown by a number of hedonic studies that urban trees are valued by the home owners (Abbott & Klaiber, 2010; Anderson & Cordell, 1988; Dombrow, Rodriguez, & Sirmans, 2000; Tyrväinen & Miettinen, 2000). Our study is consistent with these findings while improving our understanding of how people value urban trees in two ways. Firstly, we found that different types of trees have different effects on sale prices: broadleaved trees increase the sale prices while palms have no effect. Secondly, broad-leaved trees are valued differently depending on whether they are located within the property boundary (private space), on the neighbouring property, or on the street verge adjacent to the property (public space). A broad-leaved tree on the street verge, but not on the property, increases the median property price of a house by about AU$16,889 (4.27%).

There might be several reasons why home-buyers value trees on the public space more than trees on the private space. Trees on the property might have some disamenities such as blocking views, dropping leaves, and damaging pavements (Donovan & Butry, 2010), despite their amenity benefits. Broad-leaved trees found in our study area are mostly eucalyptus; they are fast growing and often damage pavements and other infrastructure (i.e. drainage) due to their root system, in addition to occupying valuable space that could be used for other purposes. Moreover, maintaining these trees imposes costs on the homeowners. In contrast, broad-leaved trees on the public space are highly valued by residents as they provide amenity services without incurring significant private costs. The management costs associated with pruning, thinning, and removals of street trees (public space) are borne by the city councils while the benefits are shared among local residents at a modest involvement at their will primarily for watering trees in the early stages of plantings. Growing trees on the street verges allows residents to enjoy benefits from the street trees without substantial involvement in their management.

One implication of our findings is that it is economical from the residents' point of view to promote broad-leaved trees along the street verges compared to palm trees, because broad-leaved trees have other benefits to residents, including ameliorating micro-climate. For example, shade cast by broad-leaved trees during hot summer months would help to reduce the temperature underneath the tree thereby ameliorating the micro-climate. This view may particularly be relevant given the intense dry heat in Perth that could be in the low to mid 40 °C during summer months. Secondly, the residents have some stake in managing urban trees on the street as it adds value to their property. Urban forestry programmes targeted to develop greenery along the streets would be positively viewed by the local residents and therefore city councils can use a public–private partnership approach in managing street trees, particularly for watering trees in the early stages of establishment.

Methodologically, our study highlights the importance of incorporating spatial effects into hedonic models. Spatial hedonic models accommodate the influence of neighbouring observations and unobserved spatial correlation, thus the estimates are, arguably, robust, consistent, and efficient. Ignoring spatial dependencies yields inflated regression coefficients (Table 2) and thus imprecise implicit prices. For example, the implicit price of an additional bedroom increased from AU$9670 to AU$25,503 based on

OLS and spatial model estimates, respectively. Such differences could be attributed to omitted variables in the OLS model, such as size or type of bedrooms and bathrooms, age of suburbs, and different designs between old and new houses. Similarly, the difference in the estimated implicit price of proximity to sports reserves (AU$27/m without spatial control versus AU$30/m with spatial controls) also revealed the importance of controlling for spatial effects in hedonic studies.

We differentiated tree types into two broad categories by appearance but not by their sizes or origins (such as exotic versus native). As Donovan and Butry (2011) suggested, it is important to differentiate between the sizes of the trees as residents could have size based preferences. In differentiating trees by size, canopy cover can be used as a proxy, i.e. bigger trees have bigger canopies. This is an avenue for further research which can be accomplished using remote sensing data to delineate tree cover in private and public spaces to find amenity values associated with different types and sizes of green spaces in Perth. In addition, valuing trees based on their origin would provide useful information to city planners to make choices regarding tree species, such as whether to opt for native species that are more suitable for the dry Perth climate or non-native species that could be more aesthetically pleasing.

Acknowledgments

The authors wish to acknowledge the valuable comments and suggestions provided by internal reviewers of CSIRO and anonymous reviewers of the journal to improve the earlier version of the manuscript. This research was conducted with funding support from University of Western Australia (Research Development Award) and the Australian Research Council Centre of Excellence for Environmental Decisions. We acknowledge the support received from both of these institutions. All omissions and errors are authors' responsibility.

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