The importance of tree cover and neighbourhood parks in determining urban property values

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Abstract

This paper presents a spatially explicit analysis of the contribution of urban trees and parks to residential property values. We estimated the effects of structural, neighbourhood, and environmental variables, including tree cover, on sale price of single-family homes in Perth using a generalized spatial two-stage least-squares model. The spatial model results indicate that, among other structural and neighbourhood variables, the proportion of tree cover on street verges (public space) and the extent and proximity of neighbourhood parks attract significant price premiums in the Perth housing market. However, we failed to find any evidence of impact of the tree cover on property (private space) on its sale price. Further, we find that the parameter estimate for street tree cover obtained from spatial hedonic model is half the size of estimate obtained from ordinary hedonic model, thus indicating importance of spatially explicit hedonic model on implicit price estimation. Based on the spatial hedonic model, it is estimated that 10% increase in tree cover on street verge above the median cover of 19.66% increases the median house price (AU$ 765,000) by about AU$ 3,250. Our findings have implications on managing and developing urban forest cover along the streets in Perth for both private and public benefits.

Introduction

Urban amenities are an integral part of urban living in major cities around the world. Trees are a particular type of urban amenities that provide direct and indirect benefits to urban residents. These benefits could vary from providing aesthetic beauty for residents (Sheets and Manzer 1991; Ellis *et al.* 2006) to improving their health (Perlman 1994; Powe and Willis 2004; Donovan *et al.* 2011), ameliorating micro-climate to reducing energy consumption (Dwyer *et al.* 1991; Simpson 1998; McPherson *et al.* 2005; Pandit and Laband 2010), and provisioning wildlife habitat (Dunster 1998) to sequestering carbon (Brack 2002; Nowak *et al.* 2006; Escobedo *et al.* 2011). Unlike conventional forest products such as timber, the benefits associated with urban trees can't conveniently be measured as they do not attract a market price (Powe *et al.* 1997). Therefore, much research in recent years has focused on estimating values of urban forests and trees using non-market valuation techniques, particularly the hedonic pricing method, to guide urban forest policies (Anderson and Cordell 1988; Tyrväinen 1997; Tyrväinen and Miettinen 2000; Payton *et al.* 2008; Bowman *et al.* 2009; Donovan and Butry 2010; Sander *et al.* 2010; Brander and Koetse 2011).

The hedonic pricing method (HPM) is a well established method based on consumer theory (Lancaster 1966), relying on the premise that the amount of money an individual is willing to pay for a particular good is dependent upon the individual attributes of that good (Rosen 1974; Freeman 1979). In the case of housing, the method explains the variations in house prices through differences in preferences for structural, neighbourhood, and environmental attributes of houses in question. In other words, on top of the structural attributes (i.e. bed rooms, bath rooms, land area etc.), house prices may reflect a premium for proximity to other neighbourhood (e.g., distance to city centre, distance to road ways etc.) and environmental (e.g., tree cover in and around the house, distance to urban parks, distance to forests etc.) attributes. Using HPM we can model the house price as a function of different attributes to derive marginal implicit price of the attribute, which reflects a value that homeowners place on the attribute.

In the hedonic literature, urban trees have been represented in the model mainly in two ways: sheer number of trees (Anderson and Cordell 1988; Dombrow *et al.* 2000) or proportional area covered by tree canopy (i.e., % tree cover) (Tyrväinen and Miettinen 2000; Kong *et al.* 2007; Donovan and Butry 2010; Netusil *et al.* 2010; Sander et al. 2010) on and around the immediate neighbourhood of urban properties. Furthermore, a distinction should be trees on a private space (i.e. within private property) and trees on a public space (i.e. area outside private property). The distinction is important from planning and management perspectives of urban trees as much as to examine externalities associated with tree cover on urban property values. This externality aspect of tree cover is receiving an increasing attention in recent literature (Donovan and Butry 2010; Sander et al. 2010).

Spatial dependence (i.e. spatial autocorrelation) has been a subject of growing interest in the hedonic literature, including literature on value of green space and urban tree cover (Cho *et al.* 2008; Conway *et al.* 2010; Sander et al. 2010). Hedonic models are based on spatial data, and it is therefore important to test for any spatial dependency and to control for such dependency in the hedonic. This can be done using spatial hedonic model (Anselin 1988). Recent studies have applied spatial hedonic models to control for spatial effects and to obtain unbiased and efficient parameter estimates. However, Mueller and Loomis (2008) argue that in the absence of substantial differences on parameter estimates between an ordinary hedonic model (i.e., based on ordinary least squares estimation; OLS) and an equivalent spatial hedonic model, the results obtained from the OLS model may be preferred for policy purposes. Nonetheless, spatial hedonic models are robust, are able to address bias in parameter estimates associated with 'omitted variables' (Anselin 1988; Piras 2010), and by explaining dependencies and correlations between neighbouring data can improve the precision of estimates of marginal implicit prices.

In Australia, where cities have followed a 'garden city' concept of development with an extensive network of neighbourhood parks and reserves (Powell 1976), hedonic studies focussing on valuing urban trees or tree-cover are relatively rare. To highlight the value of planted trees in Canberra, Brack (2002) estimated that the energy reduction, pollution mitigation and carbon sequestration value generated by 400,000 planted trees was between US$ 20 to 67 million during the Kyoto commitment period 2008-2012. A recent hedonic study by Pandit *et al.* (2012) used tree count data (broad-leaved and palms) from 23 suburbs of Perth to estimate the implicit price of urban trees located on private space (i.e., on a property) and on public space (e.g., on an adjacent street verge of the property). Controlling for spatial autocorrelation within 500 m threshold distance, they found that the sale price of a house is influenced by the sales prices of other houses in the neighbourhood. They report that among four combinations between tree locations (on property vs. street verge) and tree types (broad-leaved vs. palm), only broad-leaved trees on street verge have significant and positive impact on home sale price, with an estimated marginal implicit price of about $7,467 per broad-leaved tree on the street verge. Donovan and Butry (2010) pointed out the need to differentiate relative impact of different types, sizes, and species of trees on property value. The Pandit et al. (2012) study is thus a step forward in differentiating tree types into broad categories, but far from perfect. One limitation of studies based on tree count data is that it can't capture the tree size effects in the analysis. Using tree cover (i.e., proportionate area covered by trees), however, this limitation can be addressed with the assumption that large (small) trees have a larger (smaller) canopies and therefore large (small) tree cover area in general.

In this paper we examine how homeowners value urban tree cover (as measured by its proportion), using different forms of spatial hedonic model. In particular, we look at differences between how the owners value tree cover within property boundary (own private space), tree cover on neighbouring properties (neighbouring private space), tree cover on the street adjacent to the property (public space). This differentiation of tree cover is guided by the fact that the externalities and costs of tree cover are different for these different forms of private and public space, and therefore affect home sale prices differently.

Understanding location dependent (own private, neighbour's private, or public) value of tree cover will be useful to inform and guide future urban forestry policies and tree management strategies in the study region.

The remaining part of the paper is organized as follows: first, we present the study area, data and variables, and models employed in the study. Then we present and discuss the results. Finally, we conclude the paper with potential policy implications of our findings.

Materials and Method

Study area

The study area extends approximately 28 km north-south and 14.25 km east-west covering 398 sq. km of major residential areas around the city of Perth in Western Australia (Figure 1). This area extends from the northern boundary of the City of Stirling to the southern boundaries of the Cities of Fremantle and Melville in the south. The coastline defines the western border, whereas the eastern boundary is formed by a line joining the western edges of the city of Stirling and Melville (Figure 2). The various residential suburbs inside the study area represent various socio-economic and developmental settings in Perth, with the western suburbs of Claremont and Cottesloe generally older and more affluent than the rest.

Swan River, an important amenity in the study area, conveniently divides the study area into northern and southern parts (Figure 1). The entire study area is well-traversed by a network of roads, with the Mitchell and Kwinana freeways run north-south through the city centre, parallel to the West Coast Highway along the west coast and Wanneroo road inland to the east. Highways running east-west include the Leach, Great Eastern, and Canning to the south, with Morley drive Reid and Stirling highways in the north.

Other amenity or disamenity features of the study area include numerous parks, reserves, lakes, and industrial or commercial zones, which are well interspersed within the study area. Notable examples include Kings Park, Herdsman Lake and the Osborne-park industrial area in the north side of the river and Wireless Park, Booragoon Lake, and Canning Vale industrial area in the south. Industrial area/zone is considered as a disamenity from a residential housing perspective due to heavy traffic, aesthetics and noise.

To capture variations in property price and urban tree cover within the entire study area, we incorporated both north-south and east-west gradients represented by suburbs. These gradients, for example, capture the western suburbs (e.g. Fremantle, Cottesloe, City Beach, Nedlands, Subiaco) having older and more expensive houses with mature tree scapes on both street and private properties, compared to relatively new suburbs in the eastern border of the study area (i.e., Karawara, Dianella etc). Similarly, suburbs on the northern and southern borders of the study area are newer than suburbs closer to the city centre.

Our choice of study area was guided by an earlier hedonic study that examined the effect of wetlands on property value (Tapsuwan *et al.* 2009). They derived data from suburbs covering 86 sq km area within three city councils of Perth metropolitan area: Stirling; Vincent; and Cambridge. However, we have expanded the area considerably by adding new suburbs covering 14 city councils (Figure 2). In particular, we included suburbs south of the Swan River and east of the Perth city centre. Due to the broader coverage our findings will likely be more generalizable than those of Tapsuwan *et al.* (2009).

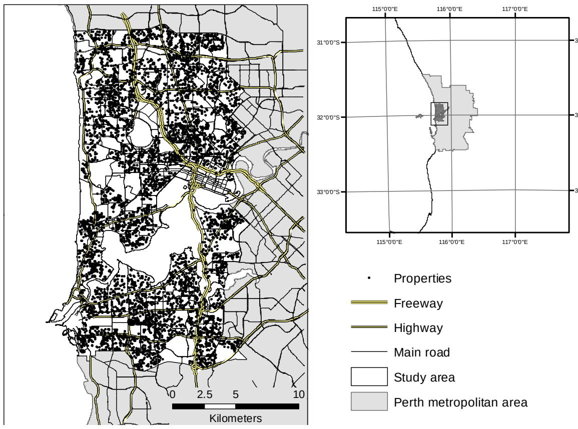

Figure 1 Study area with property locations

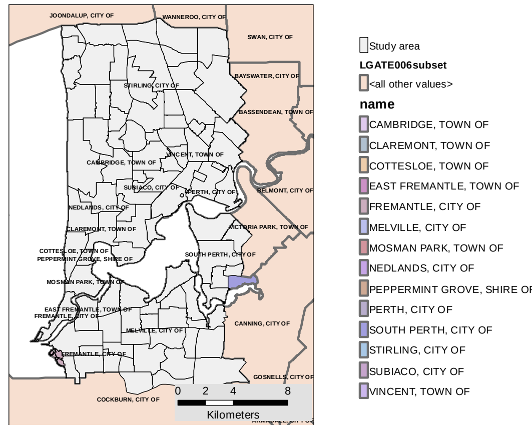

Figure 2 Study area showing different townships

Data and variables

We gathered property data, along with associated structural, neighbourhood, and environmental attributes from a variety of sources. First, we acquired property sales data for the year 2009 from Landgate, a state government agency that collects and distributes property data for Western Australia (http://www.landgate.wa.gov.au/corporate.nsf). The data contained sale price and structural characteristics of properties sold in 2009, such as: number of bedrooms; number of bathrooms; type of wall materials; type of roof; number of parking spaces etc. We selected single family homes, resulting in 5738 sale observations. A cadastral map retrieved from Landgate's Shared Land Information Platform (SLIP) allowed delineation of property boundaries and to spatially reference the sample properties.

Data on the extent and location of business, industrial and recreational areas (parks and reserves) were obtained from the GIS layer "Metropolitan Region Scheme - Zones and Reservations" (Department of Planning, Western Australia, available from SLIP). A gravity index of industrial and recreational areas within 3000 m for each property was constructed, following Polyakov *et al.* (2008) and Powe et al. (1997) to capture combined influence of their size and proximity on property value. The gravity index can be expressed as: $\mathrm{GI_i} = \sum_1^k \frac{A_k}{D_{ik}^2}$, where GI_i is the gravity index for i^{th} home in our sample, k is the number of 150 m x 150 m grid cells within 3000 m radius of the i^{th} home, A is the area of either of industrial or recreational zones within k^{th} grid, and D is the distance to the centre of the k^{th} grid from the i^{th} home. The square term for the distance suggest a distance-decay effect on index value. To further characterize each suburb data on burglaries for 2007 were acquired from the Western Australian State Police Service website http://www.police.wa.gov.au.

We used remotely-sensed image of the study area taken in January 2010 to extract urban tree cover layer with the Feature Analyst add-in for ArcGIS 10. The property boundary layer was superimposed on the urban tree cover layer to derive proportion of tree cover within each sample property (i.e. proportion of tree cover on the private space). Each property boundary was then buffered by 20 m to calculate proportional tree cover on the streets adjacent to the property (i.e., proportion of tree cover on the public space) and proportion of tree cover on the neighbouring properties (i.e., proportion of tree cover on the neighbouring private space).

Property value is influenced by various neighbourhood attributes. Major roads, city centre, ocean and river are significant features that could impact property value (Tapsuwan et al. 2009). To capture the influence of some neighbourhood attributes, we used shortest travel time to city, ocean, and river following the designated road speed on motor ways. We believe that using driving time instead of distance to key destinations may realistically reflect the influences of these destinations on property value, with urban residents using travel time to gauge proximity to nearby features that they often visit or use.

Table 1 presents the descriptive statistics (n=5738) of variables. Most of the structural variables are expressed in continuous form; a few structural variables are expressed in dichotomous form (i.e. dummy variable) that include swimming pool (presence '1' and absence '0'), wall material (brick '1' and else '0'), roof material (galvanised steel sheeting '1', else '0') and slope of house location (> 5 degree '1' and else '0'). The elevation of the house location was measured relative to the average elevation within 1000 m radius of a home to capture whether the home is in a valley or hill relative to surrounding area. A property buyer may have preferences for property shape, which may have a positive or negative premium attached to its value. Because it is likely that between two otherwise identical properties, a prospective buyer may prefer a property that has a rectangular or square shape than a property with a shape that has longer perimeter. Mathematically, circle gives the shortest perimeter for a given area, but houses are generally built on square or rectangular area that gives the alternative shortest perimeter. In order to capture the potential effect of property shape on its value we constructed a property shape index using perimeter (p) and area of properties (a) as: property shape index $= \frac{p}{\sqrt{a}}$.

The descriptive statistics presented in Table 1 are self-explanatory for many of the variables. In the sample of 5,738 houses sold in 2009, the average age was 42.2 years with each house occupying a 676 m^2 area on average. Swimming pools were observed for 22.5% of houses in the sample, with 85.6% of houses having solely brick walls, and 13.8% houses with galvanised steel roofing. In terms of a neighburhood attributes, only a small proportion of houses (8.2%) were located on the sloping faces of hills (> 5 degree slope), indicating that majority of the houses are located in relatively flat landscape. This coincides with a low 1.2 m average relative elevation for sample houses within a 1 km radius.

The average index for property shape, i.e. perimeter divided by the square root of property area, is 4.4. While the average gravity indices for industrial area and recreational area are 0.0106 and 0.0678, respectively indicating that a greater number or size parks and reserves are in close proximity of a house compared to industrial areas.

Relative to property area of a house (676 m^2), the area covered by tree cover on the property (private space) was 15.9%; within a 20 m buffer of the property on street verges (public space) the proportional tree cover is 28.7%;and, proportional tree cover within a 20 m buffer on neighbouring properties was about 18.9%. On average trees covered a larger proportional area outside the property boundary than within the property.

Table 1 Descriptive statistics

Variables	Median	Mean	SD	Min	Max
Dependent variable					
Sale price in 2009	765000	952465	7412456	104855	11910000
Explanatory variables					
a) Structural attributes of the property:					
House age (year)	43	42.185	25.209	1	141
Land area (m^2)	708	676	221.4	145	3032
Property shape index	4.323	4.403	0.386	3.810	8.312
Number of bathrooms	1	1.527	0.673	1	6
Number of bedrooms	3	3.183	0.883	1	6
Number of dining and meal-rooms	1	0.883	0.6701	0	3
Number of study-rooms	0	0.231	0.427	0	3
Number of garages	1	0.888	0.884	0	7
Number of carports	0	0.507	0.752	0	4
Dummy for swimming pool	0	0.225	0.417	0	1
Dummy for wall material	1	0.856	0.352	0	1
Dummy for roof material	0	0.138	0.345	0	1
b) Neighbourhood attributes:					
Relative elevation of house (m)	0.389	1.217	6.703	-20.316	37.195
Dummy for > 5 degree slope	0	0.082	0.274	0	1
Distance to bus stop (m)	266	304	207	0.1	1563
Distance to freeway (km)	2.876	3.378	2.373	0.032	9.498
Distance to highway (km)	0.678	0.857	0.709	0.001	3.699
Driving time to CBD (min)	9.2	9.0	3.2	1.8	17.8
Driving time to ocean (min)	7.0	7.0	3.8	0.1	14.8
Driving time to river (min)	4.3	5.0	3.4	0.1	13.7
Gravity index for industrial area	0.002	0.011	0.027	0	0.957
Number of burglaries per 1000 houses	36	38.929	21.077	10	190
Sale day (day of the year)	194	188.2	103.4	1	365
c) Environmental attributes:					
Proportion of tree cover on private space	0.129	0.1589	0.130	0	0.916
Proportion of tree cover on adjoining public space	0.197	0.287	0.306	0	0.999
Proportion of tree cover on neighbouring private space	0.170	0.189	0.251	0	0.883
Gravity index for recreational area	0.0478	0.068	0.066	0	0.558

Model

Non-market valuation methods have been used to value environmental goods and services for which direct market prices are not available (Hanley and Barbier 2009). One of the non-market valuation methods, based on revealed preference technique, is the Hedonic Pricing Method that can be used to investigate the effect that the attributes of a product have on its market price (Champ *et al.* 2003). This method has been applied to markets as varied as housing (Freeman 1979; Palmquist 1984), labour (Smith 1983), consumer durables (Nimon and Beghin 1999), agricultural commodities (Espinosa and Goodwin 1991; Bowman and Ethridge 1992), and cultural commodities (Chanel *et al.* 1996). Among these, the most common applications is in housing markets (Taylor 2003), where it is assumed that the market price of a house is made up of its structural, neighbourhood, and environmental attributes. The price varies between any two houses because of the differences in these attributes as house is considered to be a differentiated goods (Rosen 1974). Rosen's (1974) utility theoretic framework established the connection between consumer's preferences for characteristics of differentiated goods (i.e., attributes of a house) and its equilibrium price to estimate marginal implicit price of individual attribute using the hedonic price function (or hedonic model):

$$P_i = \alpha + \mathbf{X'}_i\boldsymbol{\beta} + \mathbf{Z'}_i\boldsymbol{\gamma} + \mathbf{N'}_i\boldsymbol{\theta} + \varepsilon_i \qquad \text{(Eq. 1)}$$

where

P_i is the sale price of i-th house;

$\mathbf{X}_i$ is a j×1 vector of j structural attributes of the house (Table 1, explanatory variables (a));

$\mathbf{Z}_i$ is a k×1 vector of k neighbourhood attributes of the house (Table 1, explanatory variables (b));

$\mathbf{N}_i$ is a m×1 vector of m environmental attributes in and around the property (Table 1, explanatory variables (c));

α is the model intercept;

$\boldsymbol{\beta}, \boldsymbol{\gamma}$, and $\boldsymbol{\theta}$ are parameter vectors to be estimated; and ε_i is the model error.

In equation 1, spatial relationships between a property and its associated neighbourhood and environmental attributes have been directly addressed by including them as explanatory variables or their construction. However, a more general intrinsic spatial relationship among properties, often referred to as spatial autocorrelation, has not been accounted for (Taylor 2003). Spatial autocorrelation refers to spatial dependence across observations mediated by spatial weight matrix W. A spatial weight matrix $\mathbf{W}$ defines the sense in which properties are believed to be neighbours (see Anselin 1988 for details; Taylor 2003; Conway et al. 2010). Generally two types of spatial dependence have been discussed in the literature: a spatial lag for neighbouring values of the dependent variable; and spatial error for unobserved variations (Anselin 1988). As housing data are inherently spatial in nature, spatial dependence needs to be tested for and, if present, should be accomodated in the eq. 1 to obtain robust and efficient parameter estimates. With defined weight matrix and inclusion of spatial lag and/or spatial error component(s) in the equation 1, it yields spatial hedonic model:

$$P_i = \alpha + \rho\mathbf{W'}_i\mathbf{P} + \mathbf{X'}_i\boldsymbol{\beta} + \mathbf{Z'}_i\boldsymbol{\gamma} + \mathbf{N'}_i\boldsymbol{\theta} + \varepsilon_i \qquad \text{(Eq. 2)}$$
$$\varepsilon_i = \lambda\mathbf{W'}_i\,\boldsymbol{\varepsilon} + v_i$$

where

$\mathbf{W'}_i$ is n×1 vector from the spatial weight matrix,

ρ is the spatial lag coefficient,

λ is the spatial error coefficient, and

v_i is uncorrelated error term, $v_i \sim \mathrm{N}(0, \sigma^2)$.

When ρ and λ are estimated to be zero then equation 2 reduces to equation 1; if ρ is non-zero then the dependent variable spatially correlated, and defines a spatial lag model; if λ is non-zero then a spatial error model is defined.

The weight matrix can be constructed in several ways depending on how observations can be influenced by each other. For our purpose, we constructed the weight matrix in two ways: using 8 nearest neighbours and 1000 m inverse-distance between observations in order to examine sensitivity of model results to the type of weight matrix. For computational simplicity of ρ and λ, the weight matrices were row-standardised (i.e. all the weights in a row add to 1). In the case of 8 nearest neighbours the weight is equally divided among neighbours, while for 1000 m inverse-distance the weight is proportionately divided among neighbours based on the distance to capture distance-decay effect. For example, the effect of a house's sale price on sale price of a neighbouring house declines as the linear distance between the two increases (Anselin 2005; Mueller and Loomis 2008).

We used series of the Box-Cox transformation of the sale price using SAS's TRANSREG procedure, which indicated a semi-log functional form as the most appropriate functional form. We also log-transformed all distance and time variables and added a square term for house age in the model to examine potential nonlinearities associated with house age (i.e. any cultural or heritage value of older houses). Further, to capture any trend in housing prices in 2009, we introduced a variable called 'date of sale' (day of year) in the model.

Model Estimation

We used R statistical software (sphet package) to estimate the spatial hedonic model (eq. 2) using generalized method of moment (GMM) and instrumental variable (IV) approaches following Piras (2010) and Kelejian and Prucha (2010). They argue that spatial patterns implied by models in eq. 2 are richer and more complex than those implied by separate spatial lag or spatial error models and suggest that GMM and IV estimation approaches (sphet package) might be better suited than the maximum likelihood (ML) approach when the errors are heteroskedastic and spatial dependence exits in both dependent variable and model errors.

Thus we used generalised spatial two stage least squares (GS2SLS) with GMM estimator for the coefficient of error term (λ) and IV estimators for the coefficients of other model variables. Then, following Greene (2011) a Wald test for the joint significance of spatial coefficients - ρ and λ was employed (for details on estimation process see Kelejian and Prucha 2010; Piras 2010).

Results and Discussion

Both ordinary least square (OLS) and generalized spatial two-stage least-square (GS2SLS) model results are consistent in their sign and significance across the models and spatial weight matrices used (Table 2). However, the results for four out of 28 variables (i.e. car ports, wall material, gravity index for industrial area, and number of burglaries) are sensitive to the types of spatial weight matrices chosen to characterize spatial dependence among observations.

Table 2 presents the estimation results for equations 1 and 2 for our model variables. Even though the fit of the OLS model was relatively high, adjusted R^2 value of 0.8222, we were concerned about the presence of spatial autocorrelation and heteroskedasticity in the data. We then checked for presence of spatial autocorrelation on model residuals using Moran's I and Geary's C tests (Moran 1948; Geary 1954) for both types of weight matrices: 8-nearest neighbours and 1000 m inverse-distance. These tests indicated that model residuals were spatially correlated in both types of specification for weight matrix (i.e. 8-nearest neighbours: I=0.2129, p=0.000; C=0.7734, p=0.0000; and 1000 m inverse-distance: I=0.2603, p=0.0000; C=0.7247, p=0.0000). We then tested the model residuals for the presence of heteroskedasticity in the data using Brusch-Pagan test (BP statistic=222.855, p=0.0000) and found that the estimated variance of residuals are dependent on values of explanatory variables (Breusch and Pagan 1979). Therefore in our results and discussion we mainly focus on results obtained from general spatial two-stage least squares (GS2SLS) model that account for both spatial autocorrelation and heteroskedasticity in the data (equation 3) and made relevant comparison with OLS model results for key variables.

Further, we find that controlling spatial dependence in the model is critical in these types of hedonic studies. For example, the coefficient estimate of street tree cover variable in spatial hedonic models is 41.56% (8-nearest neighbour weight) and 56.72% (1000 m inverse-distance weight) smaller than the estimate obtained from ordinary hedonic model (i.e. 0.0989, Table 2). The Wald test for joint hypothesis of no spatial dependence (both lag and error) is highly significant (p>0.001) for both types of spatial weight matrices (i.e. 8-nearest neighbours, Wald statistic = 1602.6 and 1000 m inverse-distance, Wald statistic = 919.11). Even though the dependence on spatial lag (i.e., ρ - lagged dependent variable) is sensitive to the specification of the weight matrix, we consistently find that the error dependence (i.e., λ – lagged error dependence) is highly significant in the GS2SLS model. Four of our explanatory variables (i.e. car ports, wall material, gravity index for industrial area, and number of burglaries) were also sensitive to the choice of weight matrix. For example, number of car ports and the wall material variable were significant only when the spatial weight matrix was defined on the basis of nearest neighbours.

Choosing a particular weight matrix for spatial models is a contentious issue in the literature (Taylor 2003; Sander *et al.* 2010) and it can influence not only the significance but also the magnitude of estimated coefficients. We find that the coefficient estimates are smaller for most of the distance and time related variables when inverse-distance weight matrix is used. The reasons behind this difference are not quite clear to us, but it is highly likely that inverse-distance based weight matrix may represent some aspects of distance variables more than that could be represented by nearest neighbours based weight and consequently, having impacts on coefficient estimates. As anticipated, all structural variables in the models have significant influences on property price. The house age is quadratic, with property price decreasing for properties up to 55 years of age before increasing again. Property shape index has a significant (p>0.001) and negative influence on property price, suggesting that for otherwise identical houses a property with a longer perimeter, and hence less compact in shape, has lower value.

Among neighbourhood variables, all distance based variables (i.e. distance to bus stop, distance to freeway and distance to highway) have positive signs indicating that proximity of freeway, highway or bus stop are disamenities and have a negative influence on property price. In the same time, the driving time to city or river or ocean have negative signs indicating that a property nearer to the city centre, Swan River, or Indian Ocean carries higher premium compared to otherwise similar properties. Similarly, a house at higher elevation with a slope > 5 degrees positively influence the property price while the gravity index for industrial area (proximity to industrial area based on its size and distance) and neighbourhood crimes (burglaries) negatively influence the value. All these results are consistent with our expectations.

The focus variables of the study – tree covers – have mixed impacts on property price. We expected that relative proportion of tree cover in private space (own property), within 20 m buffer of the property in neighbouring private space and on public space (road verge) have positive influence on property values. However, we find that only the tree cover on the public space have statistically significant (p>0.001) influence on property value. Despite no significant influence of proportion of tree covers on private properties (own property and neighbouring properties), we find that gravity index for recreational area positively influence property price. Having parks and recreational areas in proximity based on their size and distance from a property increase the property value in our sample.

Table 2 Ordinary Least-Squares and Generalised Spatial Hedonic Model results of factors affecting property values (dependent variable Log Property price in 2009, Australian $)

	Ordinary Least Squares Model		Generalised Spatial Two Stage Least Squares Model			
			8 nearest neighbours **W**		*1000 m inverse-distance* **W**	
Variables	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Intercept	14.65***	0.0664	14.626***	0.0963	7.4244***	0.4169
House age	-0.0075***	0.0006	-0.0084***	0.0007	-0.0082***	0.0007
House age^2	0.0001***	0.0001	0.0001***	0.0001	0.0001***	0.0001
Land area	0.0007***	0.0001	0.0007***	0.0001	0.0006***	0.0001
Property shape index	-0.0501***	0.0086	-0.0421***	0.0101	-0.0380***	0.0083
Number of bathrooms	0.1286***	0.0071	0.1039***	0.0075	0.1039***	0.0072
Number of bedrooms	0.0373***	0.0049	0.0344***	0.0051	0.0321***	0.0049
Number of dining/meal-rooms	0.0300***	0.0061	0.0110**	0.0056	0.0103*	0.0054
Number of study rooms	0.0834***	0.0082	0.0620***	0.0077	0.0551***	0.0076
Number of garages	0.0564***	0.0050	0.0416***	0.0048	0.0386***	0.0046
Number of car ports	0.0128**	0.0053	0.0103**	0.0047	0.0049	0.0047
Dummy for swimming pool	0.0911***	0.0079	0.0807***	0.0067	0.0761***	0.0067
Dummy for wall material	0.0433***	0.0105	0.0257***	0.0094	0.0137	0.0088
Dummy for roof material	0.0357***	0.0104	0.0391***	0.0104	0.0390***	0.0101
Relative elevation of the house	0.0033***	0.0005	0.0045***	0.0007	0.0030***	0.0005
Dummy for > 5 degree slope	0.0383***	0.0112	0.0316***	0.0115	0.0356***	0.0107
Log distance to bus stop (m)	0.0269***	0.0033	0.0335***	0.0035	0.0250***	0.0032
Log distance to freeway (km)	0.0512***	0.0039	0.0544***	0.0071	0.0274***	0.0060
Log distance to highway (km)	0.0516***	0.0032	0.0589***	0.0048	0.0387***	0.0039
Log driving time to central business district (min)	-0.555***	0.0121	-0.5198***	0.0217	-0.3138***	0.0223
Log driving time to ocean (min)	-0.2953***	0.0054	-0.2652***	0.0164	-0.1618***	0.0112
Log driving time to river (min)	-0.1562***	0.0038	-0.1549***	0.0090	-0.0872***	0.0081
Gravity index for industrial area	-0.2132*	0.1171	-0.2619*	0.1370	-0.0758	0.0780
Number of burglaries per 1000 houses	-0.0022***	0.0002	-0.0028***	0.0003	-0.0003	0.0002
Sale day (day of the year)	0.0003***	0.0001	0.0003***	0.0001	0.0003***	0.0001
Proportion of tree cover in private property	0.0111	0.0263	0.00285	0.0234	-0.0098	0.0227
Proportion of tree cover in public space within 20 m buffer	0.0989***	0.0115	0.0578***	0.0115	0.0425***	0.0109
Proportion of tree cover in neighbouring properties within 20 m buffer	0.0037	0.0123	0.0029	0.0049	-0.0042	0.0050
Gravity index for recreational area	0.6316***	0.0619	0.7129***	0.1042	0.4036***	0.0957
Spatial lag (ρ)			0.0021	0.0014	0.482***	0.0269
Spatial error (λ)			0.6072***	0.0152	0.6051***	0.0340
Adj R2	0.8222					
N	5738		5738		5738	

Marginal implicit price and elasticity for key variables

The marginal implicit price of a particular variable in the model is derived by taking the partial derivative of the hedonic price function (or model as represented by eq. 2) with respect to the variable of interest, and evaluated at the median (AU$ 765,000) sale price. This gives the value of changing one more unit or level of that variable while holding the level or unit of all other variables constant. In Table 3 we present the marginal implicit price and elasticities for key variables for the inverse-distance weight model at the median house price.

Table 3 Marginal implicit prices (MIP) and elasticities for key variables based on 1000 m inverse-distance weight matrix and median sales price

Key variable	MIP (AU $)	Elasticity
Land area (m^2)	490.33	
Bathroom	79,483.5	
Bedroom	24,586.34	
Dining and meal	7,900.92	
Study room	42,163.74	
Garage	29,509.88	
Swimming pool	60,462.50	
Roof materials	30,448.28	
Elevation (m)	2,330.88	
Slope > 5 degree	27,749.14	
Distance to bus stop (m)		0.025
Distance to freeway (km)		0.027
Distance to highway (km)		0.039
Driving time to CBD (minute)		-0.314
Driving time to ocean (minute)		-0.162
Driving time to river (minute)		-0.088
Increase in tree cover on public space by 10%	3,250.18	

The marginal implicit price reported in Table 3 generally follows earlier findings from parts of the same study area (Tapsuwan et al. 2009; Pandit et al. 2012), but varies on exact values. For instance, we find that the marginal implicit price associated with one additional bedroom is about AU$ 24,586, while the marginal price for additional bedroom was AU$ 40,152 (Tapsuwan et al. 2009) and AU$ 11,635 (Pandit et al. 2012). Similarly, we find the implicit price for an house located at 1 m higher elevation relative to surroundings is about AU$ 2,331, while the implicit price found by Tapsuwan et al. (2009) was about AU$ 3,362.45.

If a house has a swimming pool, galvanised sheet roofing, and located on slopes > 5 degree, its price increases by 8.4% (AU$ 60, 462), 3.99% (AU$ 30,448), and 3.21% (A$ 27,749) respectively, compared to a median house in our sample. All distance related variables have positive price elasticities suggesting that a 1% increase in distance to bus stop, freeway and highway increases the property price by about 0.025%, 0.027%, and 0.039%. Similarly, all of the driving time variables have negative price elasticities; thus 1% increase in driving time to city centre, ocean and river reduces the property price by about

0.314%, 0.162%, and 0.088%. Distances to highway and driving time to the city centre have relatively high impacts on house price compared to other distance and driving time variables.

With regard to tree cover variables, we find that only the tree cover on public space (i.e. street verges) within 20 m buffer has statistically significant ($p>0.001$) impacts property price. The coefficients for tree cover on property ($p=0.6656$) and on the neighbouring property within 20 m buffer ($p=0.4026$) were positive but not statistically significant. Evaluated at median property price of AU$ 765,000 and median tree cover on public space of 19.66%, the marginal implicit price of 10 % increase in tree cover (i.e., from 19.66% to 29.66%) was AU$ 3,250.18 (approx. 0.43% price increase). This percentage increase is similar to what Sander et al. (2010) reported in their Minnesota study for a 100 m buffer of the property boundary (0.48%),. Similarly, Donovan and Butry (2010) also found that 0.558 street trees in front of the house within 30.5 m buffer that have canopy cover of 84 m^2 add US$ 8,870 on sale price of an average house.

In an earlier study Pandit et al. (2012) examined the effect of tree types in Perth suburbs, it was reported that number of either broad-leaved or palm trees on the property has no significant impacts on its value but the broad-leaved trees on street verge have significant ($p>0.001$) effect on property value. The marginal implicit price associated with a single broad-leaved tree on street verge was AU$7467.

We find differences in the implicit price of variables, particularly structural variables, among studies from the same metropolitan city partly due to differences in coverage of study area, estimation techniques, and sample size. For instance, this study covers sufficiently larger area (398 sq. km) and thus sample sizes ($n=5738$, compared to $n=1741$ in Tapsuwan et al. (2009) and 2149 in Pandit et al. (2012)); and uses the GS2SLS estimation approach as opposed to OLS (Tapsuwan et al. 2009) and MLE (Pandit et al. 2012) approaches. In addition, the differences in the weight matrix applied to control for spatial dependence among the data also alters the bias in implicit price estimation.

Conclusions

This study examines the value of urban tree cover as reflected by property price in Perth metropolitan area. The GS2SLS approach was employed to estimate the value of urban tree cover, and controls for structural, neighbourhood, and environmental variables, and spatial dependence among property value observations. We find that an increase in tree cover on the public space next to the property from 20% (median value) to 30% adds AU$ 3,250 to the value of median home. This may justify actions by city councils or government agencies to expand canopy coverage along street verges and public areas in the metropolitan area.

The failure to find any significant evidence for the effects of private property tree cover may represent resident’s behavioural attitude in our study area. There might be several reasons why residents might value tree cover differently based on where it exists, i.e., on public space vs. on private spaces (own and neighbours). The tree cover on a resident’s property might have some disamenities attached to it, such as blocking views, dropping leaves, and damaging pavements (Donovan and Butry 2010). Despite its amenity benefits trees can damage pavements and other infrastructure (e.g., falling branches in storms), in addition to the opportunity cost of occupying valuable space that could be used for other purposes. Moreover, maintaining tree cover on private space incurs costs to residents, while tree cover on public space (i.e., street verges in our context) provides amenity benefits to residents without incurring significant private costs, i.e., space to grow and tree management costs. In public spaces tree management is generally undertaken by city councils while generating benefits for local residents. Thus from a societal perspective, developing or maintaining tree cover on immediate street verges (with in 20 m buffer of the property) allow resident to enjoy private benefits without much direct costs on themselves.

In addition to other structural and neighbourhood variables, our finding suggests that neighbourhood recreational areas, such as parks and reserves, have a positive effect on property value as evidenced by the gravity index for recreational areas, i.e., the size and proximity to recreational areas adds a premium to property value. Therefore, maintaining or developing parks and reserves around cities should be viewed as important public policy by local government to generate both private and public benefits to urban residents.

From modelling perspective, it is important to check and, if present, control for spatial dependency (i.e. spatial autocorrelation) in hedonic studies to obtain unbiased parameter estimates, and hence more precise marginal implicit prices. In addition, the estimation approach, and choice of a particular weight matrix to characterize the spatial relationship between observations, both influence estimates of model parameters and marginal implicit prices. Thus future spatial hedonic studies should shed light on advancing these estimation and modelling issues including non-stationary models of spatial dependency (i.e. does dependency vary between suburbs based on their economic status?).

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