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The price of a view: estimating the impact of view on house prices

Ajith S. Jayasekare[a], Shanaka Herath[b], Rohan Wickramasuriya[a] and Pascal Perez[a]

[a]SMART Infrastructure Facility, University of Wollongong, Wollongong, Australia; [b]School of Built Environment, University of Technology Sydney, Sydney, Australia

ABSTRACT

Houses with desired aesthetic views have a price premium over similar houses without such views. This article raises the following questions in relation to view as a location-specific amenity: How can we calculate a reliable indicator for view using available information? Are dwellings with a view sold for a premium compared to otherwise similar properties? Using more than 5,000 house transactions in the Illawarra region in Australia, and applying hedonic price method, the study analyses the price effects of key aesthetic views. Due to unavailability of view as a housing characteristic within historical records, spatial analysis tools were used to estimate views for housing locations. The results confirm the significance of aesthetic views in explaining house prices. Beach view is the most important aesthetic view. An increase of 1% of beach view drives house prices up by nearly 2–3%. Significant positive contributions to prices are also evident from sea, conservation area and inland water views. In addition to the views, other location-specific attributes also influence house prices. Methods developed in this study to quantify the value of aesthetic views and location-specific characteristics associated with residential locations form an important contribution to urban planning and policy development.

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1. Introduction

In their purchasing decisions, home-buyers consider a range of housing characteristics such as size of the house and accessibility of the location. As an aesthetic amenity, a scenic view further increases the attractiveness of a house (Benson, Hansen, Schwartz, & Smersh, 1998) and buyers are willing to pay a premium for the presence of this amenity (Baranzini & Schaerer, 2011; Bourassa, Hoesli, & Sun, 2004; Jim & Chen, 2009; Luttik, 2000). Water, sea, beach and forest (or green space) views are thus important house price determinants. Since buyers aim to optimise associated amenities including structural and location-related amenities, a strong relationship between housing-associated amenities and the values is expected.

CONTACT Ajith S. Jayasekare asj968@uowmail.edu.au

The relationship between price and associated amenities can be assessed using computational models. These models are based on different principles. Hedonic price model, estimated via least squares estimation, is widely used as a technique for house price modelling. Multilevel structured additive regression (Brunauer, Lang, & Umlauf, 2013), decision tree regression (nonparametric) (Fan, Ong, & Koh, 2006) and machine learning algorithms (Park & Bae, 2015) are among other models. All these models depend on historical records that provide house prices and their determinants (structural, locational and neighbourhood variables). Some of these characteristics associated with properties are often recorded and can be fed into house price models. However, other characteristics are not recorded and need to be generated from alternative sources (e.g. remote sensing data).

To address this gap we examine the following research questions:

- How can we calculate a reliable indicator for "view" using available information?
- Are dwellings with a "view" sold for a premium compared to otherwise similar properties?

To address the first question, we compute a range of variables related to view not available elsewhere. The innovative methodology involves spatially extracting properties via a "digital surface model" (see Section 2 for details) to generate a reliable indicator of view. Based on this model, view can be extracted for different distance thresholds (e.g. 1 km, 2 km and 3 km) from the centre position within a land parcel. Five key variables were included reporting the percentage of view from different distance thresholds. To address the second question, we incorporate those five variables into a predictive house price model.

Illawarra, New South Wales (NSW) is chosen as the study area due to its unique geography in that views are obtainable from all angles of a house, including the views of ocean and escarpment. This makes the region considerably unique when compared to other major Australian population centres. As a result, this region has become one of the most expensive housing markets in Australia, highlighted by many top end properties with glamorous views. Thus, this paper represents an important addition to the understanding of how localised amenities impact upon prices of individual houses.

This research emphasises that, based on the spatial amenities available in some areas, new indicators of housing value may be warranted. By incorporating the view indicators, the study also addresses the "omitted variable problem". The new methodology of calculating the view indicators adds to the analytical knowledge within house price modelling.

The article is structured as follows: Section 2 presents the theoretical background of the study and provides an introduction to the hedonic price method. Section 3 presents the dataset and the methodology used both to extract the associated variables for houses and estimate the monetary values of housing characteristics. Section 4 discusses the results of the analysis, focusing on the influence of view on house prices, particularly comparing different view thresholds. The article closes by summarising the key points and briefly deliberating on the planning implications in Section 5.

2. Theoretical background and the hedonic price method

Urban amenities theory provides a theoretical basis for the analysis. This theory predicts residents are attracted to locations with abundant amenities and that prices of houses reflect the values the residents assign to nearby amenities. These may include a range of amenities that facilitates economic and social interactions of residents including job centres (Cervero & Duncan, 2004), schools (Chiodo, Hernández-Murillo, & Owyang, 2010; François, Marius, & Paul-Y, 2000) health facilities and shopping centres (Addae-Dapaah & Lan, 2010), and recreational spaces (Park et al., 2017).

As hedonic price method estimates the desirability of a house generated by its surrounding environment and the structure, it could be used to test the urban amenities theory. For instance, the surrounding environment and the ecosystem influence house prices: a desirable ecosystem and an environment increase prices while unattractive atmosphere will decrease them. For example, the view of a lake and the availability of a park nearby increase housing values (Panduro & Veie, 2013). As a dis-amenity, a road with higher traffic generates noise and reduces housing values (Lake, Lovett, Bateman, & Langford, 1998). These impacts are not limited to locational variables but are also triggered by structural attributes of the dwelling and the building. Hence, the price of a house is the aggregate effect of several positive and/or negative influencing factors.

The principal theoretical foundations of the hedonic pricing model are Lancaster's consumer theory (1966) and Rosen's model (1974) (Herath & Maier, 2010). Those studies made early but significant contributions to the development of the model. Lancaster built upon microeconomic foundations to analyse utility properties of houses and applied that to different study areas including housing markets, financial assets and the labour-leisure trade-off. In his model, goods and quantities of characteristics were linked by the household production function. Lancaster focused on the demand side of the market through his model. In Rosen's integration of the hedonic price model with standard economic theory, he derived two kinds of functions, "bid function" of utility maximising consumers and the "offer function" of profit-maximising producers. His study extended to analyse buyer and seller choices in a hedonic price model through market equilibrium.

The hedonic price method concerns the characteristics associated with the dwelling. In the literature, those characteristics are grouped into different categories. Most of the studies consider three major categories: structural, locational and neighbourhood.

Dwelling structure may vary from one dwelling to another, and hence structural characteristics are commonly used as unit-level variables (Adair, McGreal, Smyth, Cooper, & Ryley, 2000; Kauko, Hooimeijer, & Hakfoort, 2002; Wilhelmsson, 2002) – i.e. number of bedrooms, bathrooms, car spaces, floor area, etc. Alternatively, some studies use average values of structural characteristics for geographical areas (e.g. average number of bedrooms) (Abelson, Joyeux, & Mahuteau, 2013). Structural characteristics generally show a positive relationship with house prices and, this relationship may be linear or non-linear (Wolverton, 1997). Age of a dwelling is also considered as a structural characteristic and shows a negative relationship with house prices (Stevenson, 2004; Tyrväinen & Miettinen, 2000; Wilhelmsson, 2002), unless the house is of heritage status.

Apart from the structural variables, locational variables also play a major role in the formation of house prices. The latter also includes neighbourhood characteristics. As discussed in the literature, locational variables can be represented in two ways: as fixed (also known as fixed-effects variables) or relative variables (Chau & Chin, 2003). The fixed location attributes have common values based on the location within a given geographic area – e.g. suburb or district. Most of the neighbourhood variables are fixed-effects variables, and the census is a major data source for such variables. Examples include ethnicity (Jud & Watts, 1981), per capita income, unemployment rate (Limsombunchao, 2004), and population density (Visser & van Dam, 2006). On the other hand, relative locational attributes are specific to the precise dwelling location. Common variables in this category are nearby amenities/dis-amenities such as percentage of views (Baranzini & Schaerer, 2011; Michael, Vicky, & Michael, 2002; Song & Knaap, 2003), distances to shopping malls (Addae-Dapaah & Lan, 2010; Tatt, Yi, & Lin, 2015) and distances to public transport (So, Tse, & Ganesan, 1997).

3. Estimation strategy

The relationship between house prices and explanatory variables is typically estimated using multiple regression analysis. It either uses ordinary least squares regression (LSE) or maximum likelihood estimation of the log-likelihood function derived from the hedonic function (Herath & Maier, 2010). Hedonic models are often estimated as single stage equations, i.e. the hedonic model estimates the effects of characteristics on price and does not assess the structural parameters of the individual characteristics (Brunauer et al., 2013).

The method analyses the effects of several independent variables on the dependent variable, that is, price (Malpezzi, Ozanne, & Thibodeau, 1980):

$$P = f(S, L, N, t)$$

where P is price of the houses; S is structural characteristics of houses; L is locational attributes; N is neighbourhood characteristics; and t is an indicator of time.

The hedonic regression function can be linear, log-linear or log-log form (Herath & Maier, 2010). In the log-linear model, continuous variables among the explanatory variables are converted into log values. There is no specific theoretical method to choose the correct functional form of the hedonic regression. However, according to Green and Malpezzi (2003), the log-linear form has a number of advantages over the linear form. The coefficients of log-transformed variables in a log-linear model have a simple and appealing interpretation. They represent the approximate percentage change in the rent or price given a change in an independent variable by 1%. In addition, log-linear models are computationally simple and they often mitigate the common statistical problem known as heteroscedasticity, or changing variance of the error term (Green & Malpezzi, 2003).

The widely used log-linear model is implemented in this study where price is incorporated in natural log form and the independent variables in linear form (except for continuous variables) (Sirmans, Macpherson, & Zietz, 2005). It takes the following form:

$$\ln \mathrm{P} = \beta_0 + S\beta_1 + N\beta_2 + L\beta_3$$

where *ln P* is the natural log of house prices, *S*, *N* and *L* are structural, neighbourhood and locational characteristics of houses, respectively. β_i represents the hedonic regression coefficients and ε is the error term.

A number of independent variables can be included in the hedonic model; however, the high correlation between some of these variables can create estimation problems. Therefore, correlated independent variables should be excluded from the model.

2.1. Data description

The LSE method relies on data representing independent variables (characteristics related to dwellings) and a dependent variable (dwelling price). For this study, the NSW Valuer General's sales records were obtained from the Australian Urban Research Infrastructure Network (AURIN). The study uses sales records from 2010 to 2012, as a three-year period increases the number of records whilst keeping the temporal fluctuations low compared to longer time series studies. This time period also facilitates using 2011 census data (as midpoint) for computing neighbourhood variables. The data set contains addresses of houses that were used as input for the geocoder. The geocoded houses (i.e. housing locations attached) were used for the extraction of spatial attributes.

Table 1 lists the details of spatial data used and the extracted spatial variables for dwellings. Figure 1 presents the study area of Illawarra region and the surrounding natural environment.

2.2. Incorporating the aesthetics of a view

View is a function of location's attributes in the 3D space such as surrounding land use and terrain. Therefore, from an analytical perspective, view is an extractable amenity. Majority of studies use view as a dummy variable, identifying whether the amenity is visible or not (Michael et al., 2002; Song & Knaap, 2003). However, some researchers consider view as a continuous variable. As an example, Paterson and Boyle (2002) use visible percentage of each amenity within a given distance.

Table 1. Data used to generate the spatial variables.

Source	Extracted spatial data component	Variable generated
LiDAR	DEM (Digital Elevation Model)[a]	View (as percentage)
LiDAR	DSM (Digital Surface Model)[b]	
Land use	Land use	
NSW Open Data Portal	Land parcels	Distance to facilities and services
NSW Spatial Data	Road network	
Google maps and OpenStreet maps (2014), NSW transport open data and Open Data NSW Planning Portal	Service and facilities	

Source: Author calculations.
[a]This is called a model as these data can be modelled in a visualised form. It represents bare-ground without objects.
[b]This is also the same in visualisation, but it includes ground objects on bare-ground

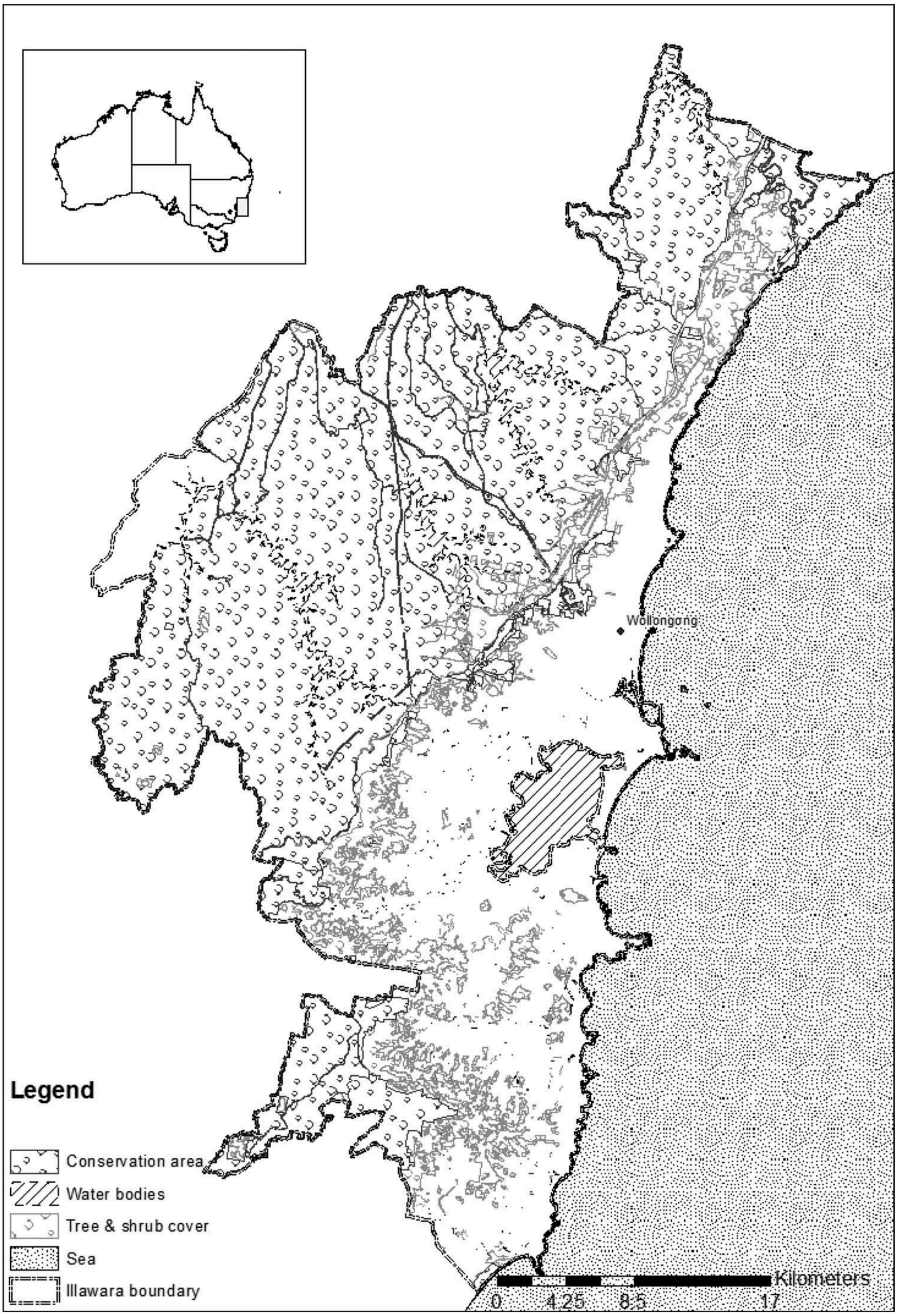

Figure 1. Study area and the surrounding natural environment.

In the present study, 17 land use categories were calculated, generating 17 potential view variables, but five views were selected based on the literature: water, beach, conservation area, recreational area and sea view. Provided our study area has attractive coastal views as well as inland waterbodies, sea and water views were separately included within the chosen five view variables. The views were extracted using DEM, DSM and the land use map (see Table 1). The specific land parcel that a dwelling is built on was selected as the location for that dwelling. Additionally, units in upper flows or houses with several stories can have better views than those at ground level. However, the view with respect to the land parcel (i.e. ground level) was considered, rather than from the relevant floor of a dwelling, due to data limitations. View was initially analysed for a 1-km radius by considering an offset of 1.4 m above the DEM height as base height for the land parcel. However, beyond the land parcel, DSM height was used as the land use height for the analysis. The latter reflects the actual obstacles, which may affect the view (e.g. buildings, vegetation, etc.). In addition to the 1 km radius, views were extracted for 2 km and 3 km radii for comparison purposes. Figure 2 shows an example of how the views were measured considering different distance thresholds from a land parcel.

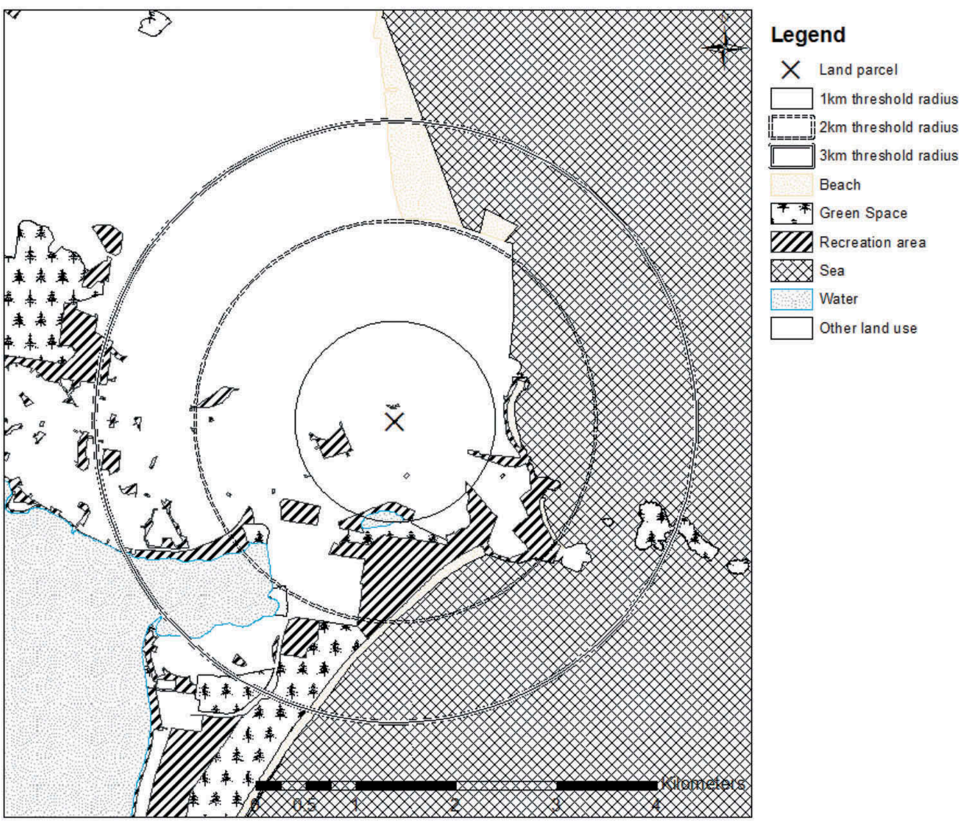

Figure 2. View extraction for different threshold radii.

2.3. Incorporating the other locational variables

Based on the evidence from the literature, fixed and relative locational variables were used in the study. Locations of schools, shopping malls, supermarkets, public transport, public parks, major roads, rail roads and beaches were used for the analysis. Influences of these amenities change with the distance and they are measurable as direct distance (Euclidean distance) or road network distance (travel distance). We initially considered both these distances from dwellings to the above-mentioned amenities. In addition, neighbourhood variables were incorporated as fixed-effects variables at the SA1 level – i.e. the smallest geographical area in the Australian census. The neighbourhood variables population density, unemployment, income (over $2,000), population over 60 and Australia-born population were used as proportions of the total SA1 population. Summary statistics for the variables are shown in Tables 2 and 3.

Table 2 summarises the descriptive statistics of variables reflecting the dwelling-related characteristics. The descriptive statistics show estimated view variables: green area views are more common as indicated by mean values of parks (9.40%) and conservation (8.75%) views. Additionally, distances calculated for different amenities demonstrate how the services and infrastructure are distributed in the study area in relation to dwellings. Maximum distance (network distance) to any amenity is

Table 2. Descriptive statistics (continuous variables).

Variable	Description	Minimum	Maximum	Mean	Std. Deviation
e_price	Price ($)	81,000	4,000,000	413,731	180,715
bedrooms	Number of bedrooms	0.00	9.00	2.95	0.92
bathrooms	Number of bathrooms	1.00	7.00	1.45	0.65
parking	Number of parking spaces	0.00	8.00	1.43	0.87
prcategory	House: 75.7%, units: 24.3%				
Area	Land area	121	34,882	1,259	1,684
RailS_E	Euclidean distance to closest rail station (m)	43.48	6,551.19	1,597.71	1,233.55
Schol_E	Euclidean distance to closest school (m)	43.07	3,576.61	653.16	428.02
Parks_E	Euclidean distance to closest park (m)	9.72	2,687.73	420.62	342.09
Malls_E	Euclidean distance to closest shopping mall (m)	112.96	5,792.68	2,016.94	1,272.26
MjrRd_E	Euclidean distance to closest major road (m)	16.41	6,716.77	1,162.38	1,403.79
BusSt_E	Euclidean distance to closest bus stop (m)	3.27	1,139.86	178.26	137.43
Beach_E	Euclidean distance to closest beach (m)	41.40	1,0419.72	2,348.56	1,924.48
RailRD_E	Euclidean distance to closest rail road (m)	22.88	6,291.49	1,251.67	1,171.44
MjRods_E	Euclidean distance major road (m)	16.41	6,716.77	1,162.38	1,403.79
RailS_N	Network distance to closest rail station (m)	32.27	7,642.22	2,143.60	1,462.89
Schol_N	Network distance to closest school (m)	0.00	4,410.35	977.71	591.93
Parks_N	Network distance to closest park (m)	0.00	3,507.67	607.86	493.25
Malls_N	Network distance to closest shopping mall (m)	119.23	6,998.85	2,581.58	1,507.56
MjRods_N	Network distance to closest major road (m)	2.28	8,964.36	1,673.78	1,868.03
BusSt_N	Network distance to closest bus stop (m)	0.03	1494.99	267.22	215.52
Beach_N	Network distance to closest beach (m)	0.00	14,735.31	3,075.94	2,398.15
AgeOver60	Fraction of age over 60 year	0.03	0.69	0.22	0.08
Income	Household over $2000/week	0.00	0.67	0.20	0.11
Aus_percen	Fraction of Australian born people	0.33	0.99	0.86	0.09
UnEmp	Unemployment rate	0.00	0.09	0.03	0.01
Density	Population density (SA1)	40.63	11,149.60	2,828.62	1,710.39
Beach1V	Beach view (%)	0.00	12.23	0.03	0.37
Sea1V	Sea view (%)	0.00	97.65	1.28	9.83
Cons1V	View of conservation (green) area (%)	0.00	92.40	8.75	18.16
Recr1V	View of recreation area (%)	0.00	79.08	9.40	12.22
Water1V	Water view (%) from total visibility area within 1km	0.00	98.84	2.08	12.32

Table 3. Descriptive statistics (categorical variable).

Suburb name	Percentage of records in the sample	Suburb name	Percentage of records in the sample
Albion Park Rail	4.1%	Mount Keira	1%
Balgownie	3.1%	Mount Kembla	0.1%
Barrack Heights	3%	Mount Pleasant (NSW)	0.7%
Bellambi	1.6%	Mount Ousley	1%
Berkeley	2.9%	Mount Saint Thomas	0.9%
Blackbutt (NSW)	0.3%	Mount Warrigal	2.3%
Bulli	3.9%	North Wollongong	1.5%
Coniston:	1.3%	Oak Flats	0.4%
Cordeaux	2%	Port Kembla	1.7%
Heights	3.2%	Primbee	0.6%
Corrimal	0.8%	Russell Vale:, Shellharbour City	0.9%
Cringila	2.5%	Centre	0.1%
East Corrimal	3.6%	Tarrawanna	0.9%
Fairy Meadow:	2.3%	Towradgi	1.2%
Farmborough	0.4%	Unanderra	3.1%
Heights	5.2%	Warilla	2.9%
Fernhill	1.1%	Warrawong	1.4%
Figtree	<0.1%	West Wollongong	3%
Gwynneville	1.6%	Windang	1.3%
Horsley	1.7%	Wollongong	17.1%
Keiraville	2.5%	Woonona	9%
Lake Heights	1.9%	**Total**	**100%**
Lake Illawarra			
Mangerton			

The description column for categorical variables (e.g. suburbs) includes the proportions of each category within the variable. Views were taken as percentages.

14,735 m, and it indicates that all amenities considered can be accessed by travelling less than 14,735 m. As the study area is located in a coastal zone, sea view is prominent in the area. Because of that, some dwellings are completely exposed to sea and a major portion of the total view is represented by the sea view (e.g. 97%). House price as the dependent variable varies from $ 81,000 to $ 4,000,000.

4. Results and discussion

Sales records included a structural characteristic called "area". This term is ambiguous as to whether this refers to floor area, in which case the coefficient is expected to be positive, or to land area of the parcel, which could result in a negative coefficient for larger buildings. As a result, models were estimated without the area variable. Furthermore, number of parking spaces, bedrooms and bathrooms were used without converting to log values due to the limited range of values. Additionally, variables measured in percentages (views) and fractions (neighbourhood variables) were used in their original form.

Due to our interest in controlling for the possible negative effects from noise and pollution, and since individuals are exposed to noise and pollution regardless of actual road distances from a dis-amenity, we included direct (Euclidean) distance in relation to proximity to a rail road. The other two location variables – proximity to major roads and train stations – do impact upon accessibility and as such network distances from houses to those nodes were considered. This is consistent with the travel behaviour of most workers in the Illawarra region where they drive to and from train stations.

The correlation matrix was populated to evaluate the bivariate correlations between independent variables. According to the matrix, few variables are highly correlated and majority of these correlations are present between network and Euclidean distances from the same amenity. To keep consistency, the models with the network distances are evaluated (except for rail road due to the above-mentioned reason). The correlation matrix suggests Euclidean distance from rail road, network distance from major roads and network distance from train stations are correlated. Therefore, influences of these variables were estimated in separate models. This strategy also helps in addressing multicollinearity. Figure 3 shows the correlation matrix and a sub plot highlighting the correlations between Euclidean distance to rail road, network distance to major roads and network distance to train stations.

Suburbs have their own reputations depending on socio-economic characteristics of residents. As an example, suburbs with high crime rates can have a bad reputation, decreasing dwelling prices in those suburbs. To take into account these factors, models

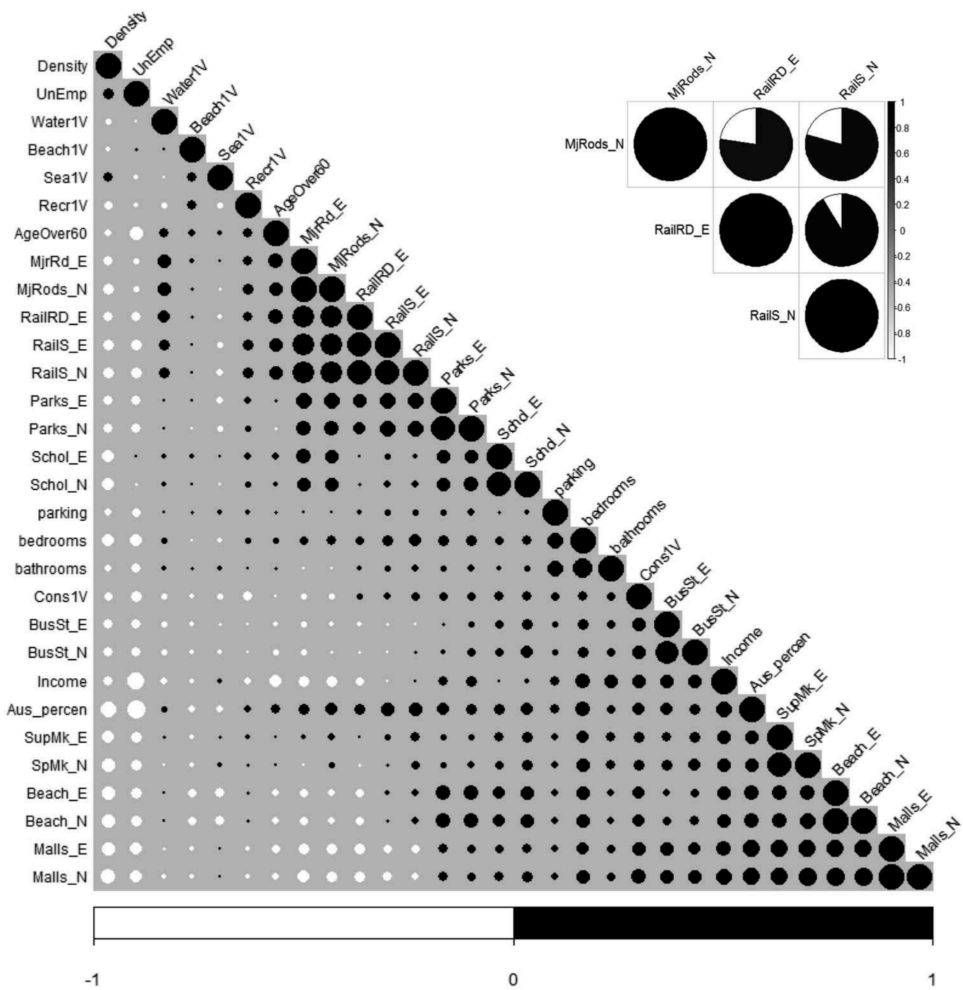

Figure 3. Correlation matrix.

were estimated with and without suburbs. For each version, linear and log-linear models were estimated. These four versions were estimated with each correlated variable (Euclidean distance from rail road, network distance from train station and network distance from major roads), resulting in 12 versions of models (see Table 4). The influence of the explanatory variables shows low R^2 values in linear models (with and without suburbs) compared to the log-linear models. Therefore, log-linear models were selected for the final analysis as they explain more variation of the dependent variable compared to the linear models. In suburb, variables are not shown due to space reasons.[1]

4.1. View as an amenity for house price variation

A key finding from the analysis is that the "view" variables show similar effects in all the six models – the "view" has a positive impact on house prices. The results further demonstrate that the dwellings with beach and sea views in particular have higher values compared to similar dwellings without such views. As an example, a 1% increase in sea view induces an increase in dwelling price by 0.33% to ~0.36% across the six models. Among the view variables, the influence of the beach view is considerable, and significantly affects the house price variation. Here, a 1% increase in beach view increases the price of a dwelling by 2.1% to 3.1% across the six models. Except the recreational areas (e.g. parks), other views show positive and significant impact on house prices. Despite the positive impact of majority inland water views in six models, levels of significance are low for models without suburbs. Generally, the effect of view is positive and significant for view variables considered.

Our findings further confirm closer views have higher impact on house prices. This was clear from the results with respect to different threshold radii for the calculation of views (1 km to 3 km radius). For most views considered, similar patterns of change were evident when increasing the threshold radius – i.e. decreases in the effect. According to the estimated coefficients (see Figure 4), views related to water, sea and conservation areas show a clear negative relationship between increases in radius and price. The effect of the beach view shows a slightly different pattern: the effect slightly decreases when radius increases from 1 km to 2 km (by 0% to 0.25%), but drastically decreases when threshold radius increases from 2 km to 3 km (by 0.99% to 1.81%). Beach areas are smaller compared to other land uses and an increase of threshold radius reduces the percentage of beach view drastically. Overall, findings suggest closer views have a higher impact on house prices.

4.2. Other explanatory variables

The estimated models explain positive effects of included structural variables on house prices. For instance, consistent with the literature, number of bedrooms and bathrooms have a positive influence on house prices (Adair et al., 2000; Kauko et al., 2002; Wilhelmsson, 2002). The results show an increase of bedrooms by 1 induces an increase of dwelling price by ~13–14% (Table 5). Similarly, increment of bathrooms by 1 increases the dwelling price by ~11–13%. The same pattern can be observed in relation to car spaces: the relationship is positive and an additional car space generates a price

Table 4. Model statistics.

	Linear			Log-linear		
Models without suburbs						
	Network distance to major road	Euclidean distance to rail road	Network distance to train stations	Network distance to major road	Euclidean distance to rail road	Network distance to train stations
Residual standard error	114,500	116,000	115,400	0.2145	0.2180	0.2154
DF	5,156	5,156	5,156	5,156	5,156	5,156
Multiple R-squared	0.5999	0.5899	0.5935	0.6596	0.6483	0.6569
Adjusted R-squared	0.5983	0.5883	0.5919	0.6583	0.6469	0.6556
F-statistic	386.5	370.8	376.3	599.5	475.2	493.5
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Models with suburbs						
Residual standard error	109,300	109,300	109,300	0.1939	0.1945	0.1943
DF	5,114	5,114	5,114	5,114	5,114	5,114
Multiple R-squared	0.6389	0.6385	0.6386	0.7240	0.7223	0.7229
Adjusted R-squared	0.6345	0.6342	0.6342	0.7207	0.7190	0.7195
F-statistic	145.9	145.7	145.8	216.4	214.6	215.2
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Source: Author calculations.

premium of ~6–7%. Furthermore, property category as a structural variable shows the expected negative impact associated with the units compared to detached houses.

As a locational variable, distance to nearest beach has an inverse relationship with house prices. Comparing all the six models, a 1% reduction in network distance to beach increases house price by ~0.06% to 0.12%, and the influence is greater for models without suburbs: ~0.10% to 0.12%. The models with suburbs thus indicate that suburbs duplicate the effects that are already captured by the included locational variables.

The variable measuring proximity to shopping malls is not significant in the five models, and it may be due to the mixed effects associated with shopping malls in close proximity. As an example, Tatt et al. (2015) reported that, when residents tend to drive instead of walk to a mall, prices near shopping malls may not be that high. That influence can also come from other factors associated with shopping malls, such as traffic congestion and noise. Addae-Dapaah and Lan (2010) published contrasting findings on shopping malls near residential locations. According to that study, a higher premium for a house occurs when it is located within a 100 m circle from a shopping mall. The study assumed a monotonic relationship between price and distance to shopping malls.

As a variable associated with leisure, network distance to recreational areas shows a negative influence, and it is significant for models without suburbs. In models with suburbs, the effect may have been captured by suburbs. In addition, schools and bus stops are dispersed over the study area, and the influence of accessibility variable for schools is significant at the 10% level. The variable measuring proximity to bus stops is not significant for house prices.

The proportion of those aged over 60 and those with higher incomes (more than \$2000/week) as neighbourhood variables have significant positive impact on house prices. As expected, unemployment rate in the neighbourhood results in a significant negative impact on house prices.

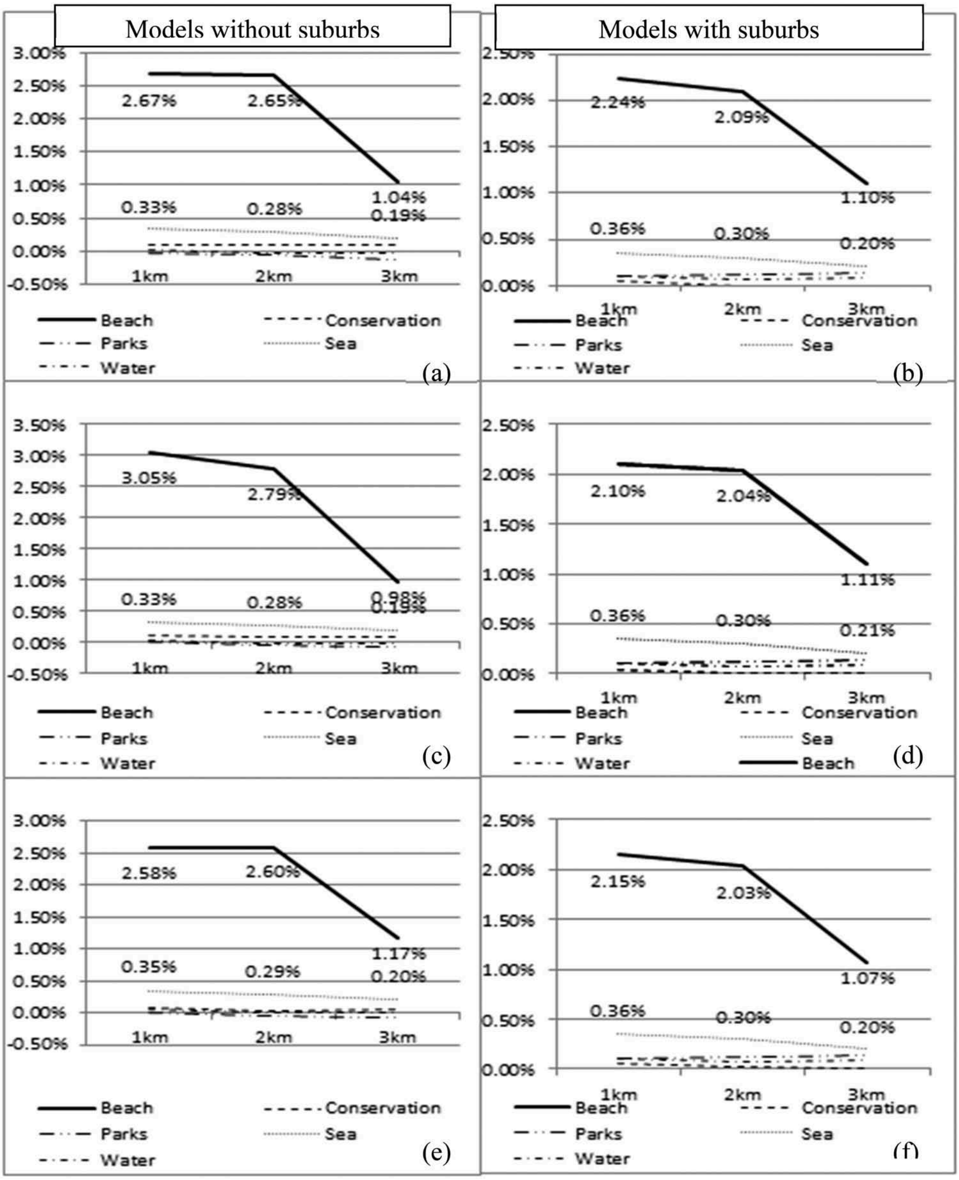

Figure 4. Influence of view on dwelling prices with the view thresholds considered (a) and (b) – models with Euclidean distance to rail road, (c) and (d) – models with network distance to train station, (e) and (f) models with network distance to Major roads).

5. Conclusions

Price of a house is affected by many factors. This paper uses hedonic price method to estimate the effect of aesthetic view on house prices. A number of structural characteristics such as number of bedrooms and bathrooms, and locational attributes such as distances to available services are incorporated into the models as control variables. Consistent with previous literature, structural attributes have a significant impact on prices.

Table 5. Estimates of models.

	Models with suburbs			Models without suburbs		
Variable	Network distance to major road	Euclidean distance to rail road	Network distance to train stations	Network distance to major road	Euclidean distance to rail road	Network distance to train stations
(Intercept)	12.5747***	12.5609***	12.4092**	13.4600***	13.5387***	13.8400***
	(0.1141)	(0.1154)	(0.1232)	(0.0877)	(0.0931)	(0.0957)
bedrooms	0.1374***	0.1390***	0.1396***	0.1352***	0.1285***	0.1299***
	(0.0044)	(0.0044)	(0.0044)	(0.0048)	(0.0049)	(0.0048)
bathrooms	0.1130***	0.1124***	0.1112***	0.1217***	0.1259***	0.1272***
	(0.0056)	(0.0056)	(0.0056)	(0.0061)	(0.0062)	(0.0061)
parking	0.0642***	0.0636***	0.0637***	0.0645***	0.0675***	0.0665***
	(0.0035)	(0.0035)	(0.0035)	(0.0038)	(0.0039)	(0.0038)
prcategoryUnit	−0.2301***	−0.2326***	−0.2329***	−0.1970***	−0.1864***	−0.1953***
	(0.0096)	(0.0096)	(0.0096)	(0.0101)	(0.0102)	(0.0101)
Parks_N_log	−0.0002	−0.0005	−0.0006	−0.0137***	−0.0189***	−0.0146***
	(0.0028)	(0.0028)	(0.0028)	(0.0027)	(0.0027)	(0.0027)
RailS_N_log			0.0318***			−0.0741***
			(0.0078)			(0.0049)
RailRD_E_log		0.0115*			−0.0335***	
		(0.0046)			(0.0034)	
MjRods_N_log	0.0295***			−0.0494***		
	(0.0048)***			(0.003)		
Schol_N_log	0.0035	0.0067	0.0065	0.0071	−0.007	−0.0065
	(0.0043)	(0.0043)	(0.0043)	(0.0042).	(0.0042).	(0.0042)
Malls_N_log	−0.0275**	−0.0166	−0.0178	0.0131*	0.0127*	0.0065
	(0.0103)	(0.0102)	(0.0102).	(0.0059)	(0.0061)	(0.006)
BusSt_N_log	0.0012	0.0034	0.0024	0.0030	0.0026	0.0028
	(0.0027)	(0.0027)	(0.0027)	(0.0028)	(0.0029)	(0.0028)
Beach_N_log	−0.0645***	−0.0705***	−0.0705***	−0.1156***	−0.1085***	−0.1003***
	(0.0056)	(0.0055)***	(0.0055)***	(0.0039)***	(0.0039)***	(0.0039)***
AgeOver60	0.1406***	0.1499***	0.1511***	0.2062***	0.2096***	0.2040***
	(0.0445)	(0.0452)	(0.0445)	(0.0447)	(0.0462)	(0.0449)
Income	0.5619***	0.6090***	0.5972***	1.1990***	1.2064***	1.2060***
	(0.0495)	(0.0492)	(0.049)	(0.0393)	(0.04)	(0.0395)
Aus_percen	−0.0426	0.0091	0.0109	−0.5402***	−0.6553***	−0.6387***
	(0.063)	(0.0625)	(0.0624)	(0.0467)	(0.0467)	(0.0461)
UnEmp	−0.9690***	−1.0065***	−0.9748**	−0.7297**	−1.0300***	−1.1520***
	(0.2553)	(0.2562)	(0.2561)	(0.2658)	(0.2701)	(0.267)

(*Continued*)

Table 5. (Continued).

	Models with suburbs			Models without suburbs		
Variable	Network distance to major road	Euclidean distance to rail road	Network distance to train stations	Network distance to major road	Euclidean distance to rail road	Network distance to train stations
Density_log	−0.0068	−0.0067	−0.0057	0.0153	0.0149	0.01
	(0.0063)	(0.0064)	(0.0063)	(0.0059)	(0.006)	(0.006)·
Beach1V	0.0215**	0.0224**	0.0210**	0.0258**	0.0267**	0.0305***
	(0.0079)	(0.0079)	(0.0079)	(0.0086)	(0.0087)	(0.0086)
Cons1V	0.0005**	0.0005*	0.0004*	0.0007***	0.0010***	0.0011***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Recr1V	0.0011***	0.0011***	0.0011***	0.0001	−0.0002	
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Sea1V	0.00360***	0.0036***	0.0036***	0.0035***	0.0033***	0.0033***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Water1V	0.0011***	0.0011***	0.0011***	0.0006*	0.0002	0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)·
Res. standard error	0.1939	0.1945	0.1943	0.2145	0.218	0.2154
Degrees of freedom	5114	5114	5114	5156	5156	5156
Multiple R-squared	0.724	0.7223	0.7229	0.6596	0.6483	0.6569
Adjusted R-squared	0.7207	0.719	0.7195	0.6583	0.6469	0.6556
Model DF	62	62	62	20	20	20
F-statistic	216.4	214.6	215.2	499.5	475.2	493.5
p-value	0.0000	0.0000	0.0000	0.0000	0.00006	0.0000

Source: Author calculation Note: Standard errors are in brackets.

As an amenity, aesthetic views provide a relaxing sensation to the owners and increases the value of a house. Therefore, houses with desired sea, beach, park, water and conservation area (forest) views attract some of the highest market prices compared to houses without such views. Results of the study indicate that the beach view has the highest influence on house prices compared to other views considered (sea, conservation area, park and water views). Specifically, we found that a 1% increase in beach view from the visible area within 1-km radius increased dwelling prices by 2–3%. Based on the calculated views for different threshold radii (1–3 km), views that are close to the housing locations are more relevant for house prices. A beach view within 1 km explains more of the price variation in houses than beach view within 3 km.

This article puts forward evidence that nearby aesthetic views are important for explaining house price variations. This finding is useful for urban planning as specific sites can be identified with significant aesthetic values. Such sites may provide ideal locations for residential developments. This would be of benefit to local governments when considering which locations to rezone for further development. A further outcome from this research could include that town planners consider whether views are obtainable and if so what will be the impact upon rating and taxing revenue from this improved amenity.

Note

1. These are available on request.

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ORCID

Ajith S. Jayasekare http://orcid.org/0000-0002-4237-4153
Shanaka Herath http://orcid.org/0000-0002-7958-3274
Rohan Wickramasuriya http://orcid.org/0000-0003-2745-0207
Pascal Perez http://orcid.org/0000-0001-6151-6228

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