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Scenic landscapes, visual accessibility and premium values in a single family housing market: A spatial hedonic approach

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Abstract

This article uses a hedonic modelling approach to assess the implicit willingness to pay for the visual accessibility of voluntarily protected, privately owned, scenic lands based on single family houses. These lands are perpetually protected to preserve natural, historic, and scenic characteristics. The capitalized house premium was captured using a visual accessibility variable, which was a combined weighted measure of 'view' and 'proximity,' referred to here as the Gravity Inspired Visibility Index. Both global (*adjusted* $R^2 = 0.52$, $AICc = 29{,}828$) and geographically weighted regression models (*adjusted* $R^2 = 0.59$, $AICc = 29{,}729$) estimated the price effect but the geographically weighted regression model outperformed the global model. The results from the geographically weighted regression model indicated an average 3.4% price premium on the mean value of homes in the study area. The paper offers a useful framework for evaluating the effect of land protection for planning and real estate purposes. It also offers useful insights for conservation agencies, local governments, professional planners, and real estate professionals for prioritizing land sites with scenic views.

Keywords

Real estate valuation, environmental amenities, hedonic model, geographical information systems, spatial analysis

Introduction

The theoretical foundation of the hedonic price modelling (HPM) technique was laid down by Lancaster (1966). According to this theory, consumers derive their utility for any good from a large bundle of its characteristics. For example, housing is a composite good, which consists of structural characteristics, such as the size and number of bedrooms and

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bathrooms, as well as neighborhood features, such as local sub-market characteristics. These individual characteristics do not have an explicit market price but are sold as bundles, which in this case are houses that are valued for their utility bearing characteristics with marginal prices that represent the specific price of each individual characteristic that a buyer is willing to pay for. The HPM framework helps to disassociate these individual prices from the total price, e.g. by capturing urban externalities. It has been used because of its superiority over other methods, such as survey-based, stated-preference methods or willingness to pay. The HPM has also proved to be very useful for estimating the value of non-market environmental amenities, such as value contributing parks, open spaces, and waterfronts as well as dis-amenities, such as air pollution, noise, and proximity to noxious facilities, and has been used extensively in housing market studies and real estate valuation (Bjorkund et al., 2002). In fact, many studies have already shown that there is an economic relationship between various environmental amenities and house prices (see, e.g. Brander and Koetse, 2011; Mittal and Byahut, 2016; Simons and Saginor, 2006) where there three key variables have been identified. The first is proximity to an amenity (Crompton, 2006, 2005). Theoretically, greater demand for scenic locations by amenity-seekers will push up the price, which will also vary with the type of amenity. Discreet amenities are clearly recognizable such as ocean fronts, lakefronts, river/streams, parks, golf courses or trails/greenways. Numerous studies have attempted to quantify the price premiums of discreet amenities. For example, the premium price effect of waterfronts was found to be the highest of all amenity types; among different waterfronts, the proximity of oceans with well-developed beaches accrued the highest premium of over 101.9% (Conroy and Milosch, 2011). Other studies have demonstrated premiums for lakefront homes (Bond et al., 2002; Lansford and Jones, 1995), proximity to rivers and streams (Mooney and Eisgruber, 2001; Netusil, 2005), golf courses (Cho et al., 2009; Shultz and Schmitz, 2009; Asabere and Huffman, 1996), trails and greenways (Lindsey et al., 2004; Nicholls and Crompton, 2005) and parks (Crompton, 2005; Hammer et al., 1974). Golf course premium in terms of percentage values of undeveloped lots was found to be 85%, if the lots were facing well maintained golf course (Wyman et al., 2014).

Non-discreet amenities, on the other hand, include an array of open spaces or green patches that are available throughout the urban landscape. Mosaics and patches of green landscapes surrounding homes were used as a proxy of desirable low impact, quieter surroundings, with desirable views. To capture a measurable variable for such landscapes, remotely sensed land use characteristics data – the Normalized Difference Vegetation Index (NDVI) data was used to differentiate effects of different types of green spaces on home values (Bark et al., 2011; Payton et al., 2008). Houses near such amenities accrue a relatively lower premium. An array of amenity generating landscape features have been studied in the past including land cover types in the proximity of a house (Walls et al., 2015; Kadish and Netusil, 2012), undeveloped lands by development potentials (Irwin and Bocksteal, 2001), lands by use and ownership (Ham et al., 2015), urban green spaces (Saphores and Li, 2012), urban tree coverage (Sander et al., 2010), tree canopy cover (Conway et al., 2010), and vegetation (Kestens et al., 2004). For example, Conway et al (2010) studied the effect of urban greenspace on house prices and found that with every 1% increase in greenspace, the median house price increased by 0.07%. Other studies have shown increases with tree cover canopy (Li and Saphores, 2012) and proximity to forests (Ham et al., 2015).

The second variable affecting house prices is the view of the amenity (Bourassa et al., 2005, 2004) where discrete scenic amenities fetch higher premiums than non-discrete ones. For example, premiums for oceanfront views were found to be the highest among all discrete amenities, ranging from 47% (Bin et al., 2008) to 147.2% (Benson et al., 1997). Lakefronts views (Benson et al., 1998), riverfront homes (Netusil, 2005), views to waterfalls (Yin and Hastings, 2007) and forested areas (Ham et al., 2015), and views of city or urban skyline views (Wolverton, 1997), and views of farmlands and preserved open spaces (Geoghegan et al., 2003) have also been shown to contribute positively to house prices, among other types of views. When both proximity to amenities and the view of the amenity are considered together, then the premium value is even higher. For example, when homes were found to have both proximity to and a view of the ocean, premiums were found to be as high as 147% (Benson et al., 1997). Similar additive effects were found by Benson et al. (1998) in a study in Bellingham, Washington, when considering both views and proximity to lake fronts.

Accessibility to locational externalities is the third variable that has been found to affect house prices (Orford, 2002; Xiao et al., 2016). The concept of accessibility is defined by the level of opportunities available for spatial interaction between two point pairs. Such interaction measure is commonly used in transportation studies (Lin et al., 2016) and in retail market analysis, extensively (Huff and Jenks, 1968). Accessibility is defined as the weighted sum of the inverse distance between a home and an amenity, which further depends upon the size or attractiveness of the amenity (Orford, 2002). Orford (2002) used accessibility to amenities as a weighted index in a study in Cardiff, UK. Similar weighted indexes have also been employed in Powe et al. (1997) for estimating the price effects of access to woodlands. The index measured the ratio of woodland forest to the squared distance from homes in the Southampton and the New Forest regions in Great Britain. Homes located closer to larger forests experienced a greater influence by the forests in such a weighted index. Other similar gravity-inspired indices are discussed in Xiao et al. (2016).

An HPM approach applied to a conservation context is not unique and has been used extensively in the past to estimate the view, proximity and accessibility to different features such as golf courses, water fronts, open spaces, farm lands, etc. However, HPM has not been used in the context of privately owned conservation lands. Billions of dollars' worth of public money are put into tax credits to incentivize private landowners in land conservation in the form of Conservation Easements (CEs), which serve as public amenities, and offer direct and indirect environmental and health benefits to the local community. In the past, several parks, trails, waterways, and wildlife areas have been protected in the USA via this mechanism. CEs are legal agreements signed between private landowners and non-profit organizations or a government agency, to perpetually conserve preservation-worthy lands. Through the agreement, private landowners restrict future development rights and retain their land titles, and their right to own and use the preserved land. Owners have the option to donate or sell their restricted development rights, and claim federal tax credits equivalent to the restricted development value (Wright, 1994). As none of the studies in the literature have used the HPM framework with CEs, the aim of this paper is to apply this framework to capturing the marginal price effect of preserved lands using both ordinary least squares (OLS) and geographically weighted regression (GWR). A second innovation is to link the proximity and view variables together into a single measurement variable of visual accessibility called visual proximity. Referred to here as a Gravity Inspired Visibility Index (GIVI), it is used as a distance weighted measure to capture the visibility of protected lands while a distance decay function incorporates the role of proximity. This variable assigns higher weights to the quantity and quality of scenic views, and lower weights with increasing distance from homes. This approach is demonstrated for CE properties located in Worcester, Massachusetts, as outlined in the next section. This is followed by a description of the development of the GIVI index and the OLS and GWR models. The results of the models are then presented including reflections on the utility of applying these approaches to preserved lands more generally.

Study area and data

This study was conducted in Worcester, which is the second largest city in Massachusetts in the USA. The externality effect of voluntarily protected lands in Worcester on the prices of the surrounding 1243 single family detached (SFD) homes is estimated. Two datasets were used: a cluster of 26 CE_j parcels as amenity generators and 1243 SFD $Home_i$ as amenity absorbers.

These CE parcels varied in size from 1 acre to 400 acres and were clustered around 7 or 8 locations. They contained various natural and scenic amenities such as waterfalls, streams, ponds, large boulders, marshes, wetlands or vernal pools, golf course, trails, parks, woods and vegetated lands including hardwood forests, mountain laurels, and silver beech trees. The 1243 $Home_i$ included all SFD homes sold between 2005 and 2008 that were located within 0.5 miles of the CE_j clusters. The $Home_i$ dataset had a mean price of $174,313 and a standard deviation of $56,361. Descriptive statistics of these homes is provided in Table 1. Figure 1 shows the spatial distribution of the $Home_i$ in black dots relative to the location of the CE_j parcels shown as grey polygons.

Table 1. Descriptive statistics of home samples (n = 1243) within 0.5 mile from CE-protected parcels (n = 26).

Variables	Units and explanation of variables	Min	Max	Mean	SD
Sales_HPI9	Home Sale Price in ($) – Adjusted to House Price Index for year 2009	$13,939	$675,000	$174,313	$56,361
LotSqft	Lot area (Sqft)	1227	231,198	10186.9	9391.40
TULA	Total Utilizable Built Area (Sqft)	–	–	1401	580.41?
Bath	No. of Bathrooms	1	6	1.30	0.54
H_Bath	No. of Half Bathrooms	1	2	0.45	0.52
Qual	Assessor assigned home quality index (20 to 60)	10	60	40.14	4.20
Age	Age of Home (Year)	0	166	57.8	32.9
Deck	Deck Binary (Y/N)	0	1	0.30	0.46
Hous_Dens	Housing Density in the neighborhood-(No. of Houses/Acre in census block group)	0.11	13.24	3.10	2.50
MedHsg_Val	Median Housing Value ($) of owner occupied houses in census block group	71,700	$261,500	$121797.70	25059.20
Perc_Black	Percentage of Blacks in census block group	–	34.84	4.64	5.12
GIVI_2	Gravity Inspired Visibility Index (B = 2)	–	8.89	0.0676	0.480

Valid n = 1243 Source: City of Worcester and Assessor's office and author estimated

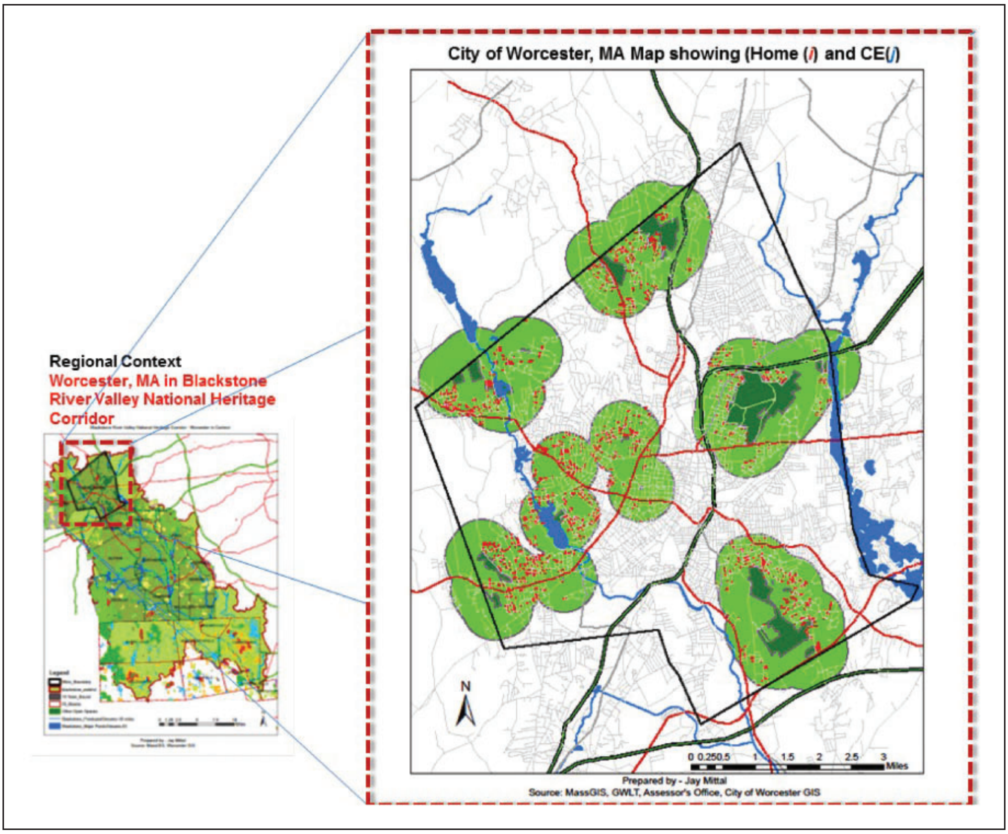

Figure 1. Map of Home samples *(i)* and the CE Parcels *(j)* in Worcester, MA.

Methodology

Viewshed analysis and the development of the GIVI index

A multi-step GIS methodology was employed to develop the GIVI variable as detailed below. The Step 1 involves development of 3 D raster. This methodology is presented in more detail in Mittal (2014).

Step 1: Development of 3D merged raster for the viewshed analysis. The first step in the methodology involved creating an input raster for viewshed analysis, where similar approaches have been used in past environmental-benefit studies (Lake et al., 1998, 2000; Shultz and Schmitz, 2008). The viewshed identifies cells in an input raster that are visible from one or more observation points. In the absence of high precision LiDAR data for Worcester, an alternative approach was used as described here. A single raster surface was created by merging an initial raster created from digital topographic spot elevation data with a second raster containing the building heights and footprints (Sander and Manson, 2007) using Spatial Analyst in ArcGIS. The cell size of the merged raster was $10' \times 10'$ and served as the input to the viewshed analysis outlined in step 2.

Step 2: Development of a Gravity Inspired Visibility Index (GIVI) variable. The computation of the GIVI variable involved three additional steps after the input raster

$$\text{Visible Area Matrix } V_{ij} = \begin{array}{l|lll|} & CE1 & - & CE26 \\ Home1 & V1,1 - & - & - \\ Home2 & - & - & - \\ - & - & - & - \\ - & - & - & - \\ - & - & - & - \\ Home\ 1243 & V1243, 1 & - & V1243, 26 \end{array}$$

Figure 2. Visible Area Matrix V_{ij}.

Note: In Figure 2, V_{ij} in each cell of the visible area matrix is visible areas (in sqft) of CE_j parcel as captured via the viewshed from each Home$_i$.

$$\text{Distance Matrix } d_{ij}..= \begin{array}{l|lll|} & CE1 & - & CE26 \\ Home1 & d1,1 - & - & - \\ Home2 & - & - & - \\ - & - & - & - \\ - & - & - & - \\ - & - & - & - \\ Home\ 1243 & d1243, 1 & - & d1243, 26 \end{array}$$

Figure 3. Distance matrix d_{ij}.

Note: In Figure 3, d_{ij} in each cell of the distance matrix is the shortest distance (in linear ft) from each Home$_i$ to the visible portion of each CE_j parcel. Cell value in d_{ij} has interdependency on the V_{ij}.

surface was created. An algorithm was developed to create two different matrices: a visible area matrix (V_{ij}) and a distance matrix (d_{ij}). The rows of these matrices contained the $Home_i$ while the columns contained the CE_j parcels. Both matrices had dimensions of 1243×26 (Figures 2 and 3).

Step A: Development of the Visible Area Matrix. The first objective was to quantify the visible area of each CE_j parcel from each $Home_i$ and fill the returned values in the V_{ij} matrix. The viewshed analysis uses the input raster and returns an output raster showing visible (with a value of 1) and non-visible areas (with a value of 0) from a set of observer locations. Viewsheds were run iteratively from each $Home_i$ as an observer location, assuming a human height of 5.5 feet. The final outputs were a set of viewshed$_{ij}$ rasters containing the view from every $Home_i$. Each output Viewshed$_{ij}$ raster was then clipped with the CE_j parcel boundaries. To calculate the visible area of the raster in square feet, the number of visible cells were multiplied by the $10' \times 10'$ pixel size. Only the values of 1 inside the CE_j parcel were accounted for in the calculation. The visible area in square feet was then transferred to the *Visible Area Matrix* V_{ij} *for each* $Home_i$ and CE_j, resulting in many cells with values of 0 in the matrix, which means that a given CE_j is not visible from $Home_i$. The dimension of the visible area matrix is 1243×26 as shown in Figure 2.

Step B: Development of the Distance Matrix. The shortest distance from each $Home_i$ to the visible portion of each CE_j parcel was calculated, returning values to the *distance* d_{ij} matrix in linear feet. Each cell value in the *distance* d_{ij} matrix was dependent on the output cell values of the *Visible Area Matrix* V_{ij}. Notably, because of this interdependency, if a cell in the *Visible Area Matrix* V_{ij} had a value of 0, then the corresponding cell in the distance matrix also received a value of 0. For the calculation of V_{ij} and $GIVI_i$, all 0 values from the *distance* d_{ij} matrix were replaced with a value of 1 to avoid computation errors, as d_{ij} is in the denominator of the *GIVI*, and 0 value would give erroneous results. The result was a 1243×26 dimensional output matrix containing the shortest distances to the visible area, as shown in Figure 3.

Step C: Computation of Index values for the GIVI matrix. The cell values generated in the two steps above were used in computing the weighted summation of the inverse-distance-squared based on the visible size of the protected properties and their inverse distances from SFH. The sum of the distance weighted visible area was calculated as follows:

$$\text{Distance weighted sum of visible area for each } Home_i = V_i = \sum_{j=1}^{26} CE_{ij}/d_{ij}^{\lambda} \tag{1}$$

where CE_{ij} is the attraction factor of the scenic CE_j parcel defined by its total visible area from $Home_i$. An attraction factor can be any characteristic of the CE such as the size or any attractive environmental feature. For this research, the visible area of the scenic CE parcel is used as the attraction factor. This value was taken from the visible area matrix for each $Home_i$, where $i = 1243$ and $j = 26$; denominator $d_{ij} > 0$, represented the distance between $Home_i$ and CE_j and the value of d_{ij} was used from the distance matrix for corresponding cell values of the visibility matrix. The parameter λ is a distance-decay exponent in estimating the value of $GIVI_i$. Past literature does not offer much guidance on the appropriate value of the exponent λ. As the value of parameter λ is specific to environmental amenities and is not known a priori, we calibrated various models for three $\lambda = 1$, 1.5 and 2 values as undertaken by Orford (2002). In equation (1), the decay term λ is a power function in the denominator so the greater the λ value, the higher the value of homes that are really close to the CE clusters. A higher value of λ would result in reducing a significant number of home samples in the effect estimation, providing very high weights to homes near the visible CE_j and ignoring all others. Therefore, values of $\lambda > 2$ were not attempted and as mentioned above, three parameter values $\lambda = 1$, 1.5 and 2 were applied in computing the $GIVI_i$. After the initial OLS model calibration, the model with the $GIVI_i$ value for $\lambda = 2$ was chosen for two reasons: (a) the model with $\lambda = 2$ provided the best performance and (b) to avoid exclusion of homes that are farther from the CE clusters. The $GIVI_i$ variable was then computed using the following formula:

$$GIVI_i = V_i \Big/ \left(\sum_i \sum_j V_{ij} \right) \tag{2}$$

Or,

$$GIVI_i = \sum_{j=1}^{26} CE_{ij} d_{ij}^{-\lambda} \left(\sum_{i=1}^{1243} \sum_{j=1}^{26} V_{ij} \right) \tag{3}$$

The $GIVI_i$ captured the distance weighted effect of how visible a protected site CE_j is from $Home_i$ in the presence of other competitive CE locations, and how far the visible CE area is from a given $Home_i$. The $GIVI_i$ is a single variable that was used to measure both proximity and visibility simultaneously and is thus a measure of visual accessibility. Therefore, with the data samples used in this research, visual accessibility of a $Home_i$ to the CE-protected property parcels CE_j is a weighted summation of squared-inverse-distance based on the visible size of the scenic protected properties and their inverse distances from a $Home_i$.

Description of the models

The global OLS model. A hedonic equation in its simplest form is a regression of expenditures (rents or values) on various characteristics of a sample of homes. Following Sirmans et al. (2006), only selected variables were used to control for the structural and neighborhood characteristics of homes. As part of the model building, several OLS-based global models were first calibrated using a step-wise process. The candidate model that minimized the Akaike Information Criterion (AIC) was chosen. In the final model, the control independent variables X_i included seven structural characteristics: size of the lot (LotSqft); total utilizable built area (TULA); number of full baths (Bath); number of half baths (H_Bath); the assessor's defined house quality (Qual); the age of the house (Age); a binary dummy for deck (Deck), and three neighborhood variables at the census block group level: housing density per acre (Hous_Dens); median housing value (MedHsg_Val); and the percentage of the black population (Perc_Black). The variable that captures the externality was the *GIVI with* λ*=2*. The dependent variable Y_i = Sales_HPI9 is the sale price of the homes. The sale prices were adjusted using the 2009 house price index for the Worcester metropolitan area obtained from the Office of Federal Housing Enterprise (2009). The descriptive statistics of the variables are listed in Table 1.

The regression coefficients were computed to estimate the implicit prices of the individual characteristics of the homes. The generic form of the initial OLS based global hedonic model was specified as:

$$Y(Sale\ price) = f\left(\mathbf{X}_{structural}, \mathbf{X}_{neigborhood}, \mathbf{X}_{Externality}\right) \tag{4}$$

$$\begin{aligned} \text{Or Sales\_HPI9} = {} & LotSqft + TULA + Bath + H\_Bath + Qual + Age + Deck && (Structure) \\ & + Hous\_Dens + MedHsg\_Val + Perc\_Black && (Neighborhood) \\ & + GIVI\_\lambda && (Externality) \\ & + \varepsilon_i && (Error) \end{aligned}$$

The candidate variables were found free of multi-collinearity with VIF<3 for all 11 predictors and the OLS model was found to be robust. Using the residual values from this model, the test of heteroscedasticity was conducted as a visual analysis. Furthermore, on plotting the residuals, the errors were found to be randomly scattered with no systematic patterns, which signifies homoscedasticity. In SPSS, the *Breusch–Pagan* test for heteroscedasticity was run and the small chi-squared value indicated that heteroscedasticity was absent.

The local GWR model. The GWR methodology was used to estimate the premium price effect. GWR explores spatial non-stationarity and provides mappable statistics to visualize the spatial patterns of the relationships between dependent and independent variables (Brunsdon et al., 1996). In conjunction with the OLS-based global model outlined above, a semi-parametric local GWR model was employed in the form shown below:

$$Y_i = \beta_{0i} + \sum\nolimits_k \beta_k(u_i, v_i)x_{k,i} + \sum\nolimits_l \sigma_i z_{l,i} + \varepsilon_i \tag{5}$$

where Y_i is the house price at location i; β_{0i} is the intercept parameter at location i; β_k is the kth locally varying coefficient of $x_{k,i}$ variables at location i (with u,v coordinates); σ_i is a fixed coefficient of z_{li} variables where z_{li} is the lth independent variable. Equation (5) has two parts; the first half is the local model, the second half is the global model and the last element is the error term.

A semi-parametric GWR model was chosen because the predictor variables had spatially varying characteristics at the local level and fixed characteristics at the neighborhood level. Nakaya (2014) recommended that such a mixed model may reduce complexities and enhance the model's prediction performance. Crespo and Regamey (2013) provide details on the use of a similar mixed-GWR method for a study conducted in Zurich.

After calibrating the OLS model, the Geographically Weighted Regression software (GWR4.0) was utilized to model the geographically varying relationships between the house prices (Sales_HPI9) as the dependent variable and the house characteristics as independent variables (Fotheringham et al., 2002). This model was employed to extract the locally varying nature of price contributory variables. In GWR, a series of local point regressions were calibrated at each target regression location resulting in individual regression models for each $Home_i$ location. This weighting was achieved through a kernel function with a given bandwidth.

The observed values to calibrate the local models were geographically weighted based on their proximity to the regression point so that data from near observations were weighted higher than the ones farther away. A Gaussian model with adaptive spatial kernels using a bi-square function as defined in Nakaya (2014) was used. For the selection of bandwidth, an automated golden section search method was employed to determine the optimal size for the bandwidth. The minimum AIC bandwidth selection criteria were chosen for estimating nine varying coefficients (the dependent variable house price and eight independent variables of structural attributes) and three fixed coefficients (neighborhood level variables fixed at census block group geography) for $n = 1243$ data points. An optimal bandwidth of 186.0 with a minimum AIC value of 29702.56 was determined by the GWR4.0 software. Furthermore,

Table 2. Global model vs. geographically weighted regression (GWR) model outcomes.

Variables	Expected sign	Global model Estimates	Global model t Values	GWR local model Mean coefficients
Intercept		27443.32	2.16	58268.86
LotSqft	+ ve	1.29	10.33	1.73
TULA	+ ve	44.33	15.37	42.48
Bath	+ ve	12182.59	4.33	10575.07
H_Bath	+ ve	2216.28	0.91	1405.16
Qual	+ ve	956.73	2.93	2134.23
Age	− ve	−278.08	−7.00	−235.9
Deck	+ ve	303.93	0.12	1219.33
Hous_Dens	− ve	−961.3	−1.92	−2153.45
MedHsg_Val	+ ve	0.31	6.02	−0.31
Perc_Black	− ve	−531.17	−2.21	−756.90
GIVI_2	+ ve	2843.08	1.22	83855.97
Diagnostics				
Adjusted Rsq		**0.518**		**0.589**
AIC		29,828		**29702.56**
Bandwidth		Global		

$N = 1243$ all significant at $p < 0.05$ in global model

Table 3. GWR ANOVA table.

Source	SS	DF	MS	F
Global Residuals	1882199518757.4	1231.0		
GWR Improvement	456090993427.6	137.4	3319480301.3	
GWR Residuals	1426108525329.8	1093.6	1304047481.2	2.55

Table 4. Global regression results.

Residual sum of squares	1882199518757.44
ML based global sigma estimate	38913.23
Unbiased global sigma estimate	39102.44
−2 log-likelihood	29802.24
Classic AIC	29828.24
AICc	29828.53
BIC/MDL	29894.87
CV	1585325516.31
R square	0.522
Adjusted R square	0.518

Table 5. GWR bandwidth selection.

Bandwidth search	Golden section search
Best bandwidth size	186
Minimum AIC	29702.56

Table 6. GWR diagnostic information.

Residual sum of squares	1426108525329.80
Effective number of parameters (model: trace(S))	121.62
Effective number of parameters (variance: trace(S'S))	93.84
Degree of freedom (model: n - trace(S))	1121.38
Degree of freedom (residual: n - 2trace(S) + trace(S'S))	1093.60
ML based sigma estimate	33871.99
Unbiased sigma estimate	36111.60
−2 log-likelihood	29457.32
Classic AIC	29702.56
AICc	29729.64
BIC/MDL	30331.03
CV	1766921577.89
R square	0.64
Adjusted R square	0.59

Table 7. Fixed (Global) coefficients.

Variables	Estimate	Standard Error	t(Estimate/SE)
HOUS_DEN	−2153.45	748.41	−2.88
MD_HSgVal	−0.31	0.14	−2.29
PRC_BLAC	−756.90	285.33	−2.65

Table 8. Summary statistics for varying (Local) coefficients from GWR.

Variables	Mean	STD	Min	Max	Range	Lower Quartile	Median	Upper Quartile
Intercept	58268.86	118567.95	−202988.56	227138.07	430126.64	−45616.46	90343.80	163479.49
LOTSFt	1.73	1.15	−0.077	5.87	5.95	1.02	1.34	2.25
BATH	10575.07	8722.39	−13722.46	26032.27	39754.73	3894.76	14403.61	17406.47
HBATH	1405.16	8600.31	−20104.55	22643.65	42748.21	−4286.32	750.26	9160.18
QUAL	2134.23	3196.64	−2602.87	8940.02	11542.89	−928.87	1572.36	4900.97
DECK	1219.33	7742.62	−17292.99	22486.52	39779.51	−3993.04	2275.12	5707.25
TULA	42.48	12.84	10.70	80.61	69.91	33.49	40.72	52.96
AGE	−235.958	161.61	−723.07	147.32	870.39	−306.86	−201.80	−146.11
GIVI_2	83855.98	864582.05	−2990132.05	3856094.09	6846226.14	−26579.53	−1677.87	4122.60

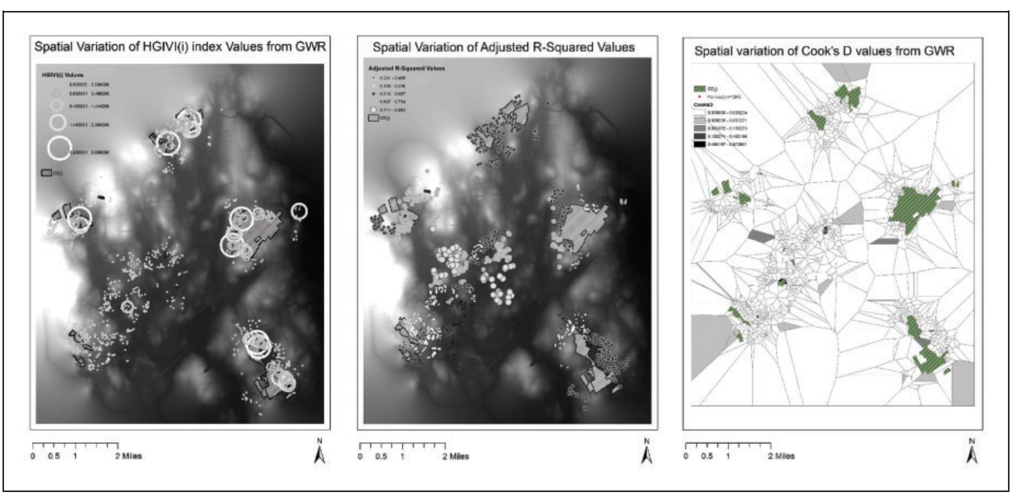

Figure 4. Spatially varying characteristics of GIVI values, R-squared values, and Cooks' D.

since the GIVI (λ,i) was a function of location (i) for a chosen distance-decay λ, the output of the GWR β coefficients varied for each $Home_i$ and for the chosen λ.

Results

A comparison was made between the global model and the local GWR model. Comparatively, the results of the GWR model were more pronounced. The global model

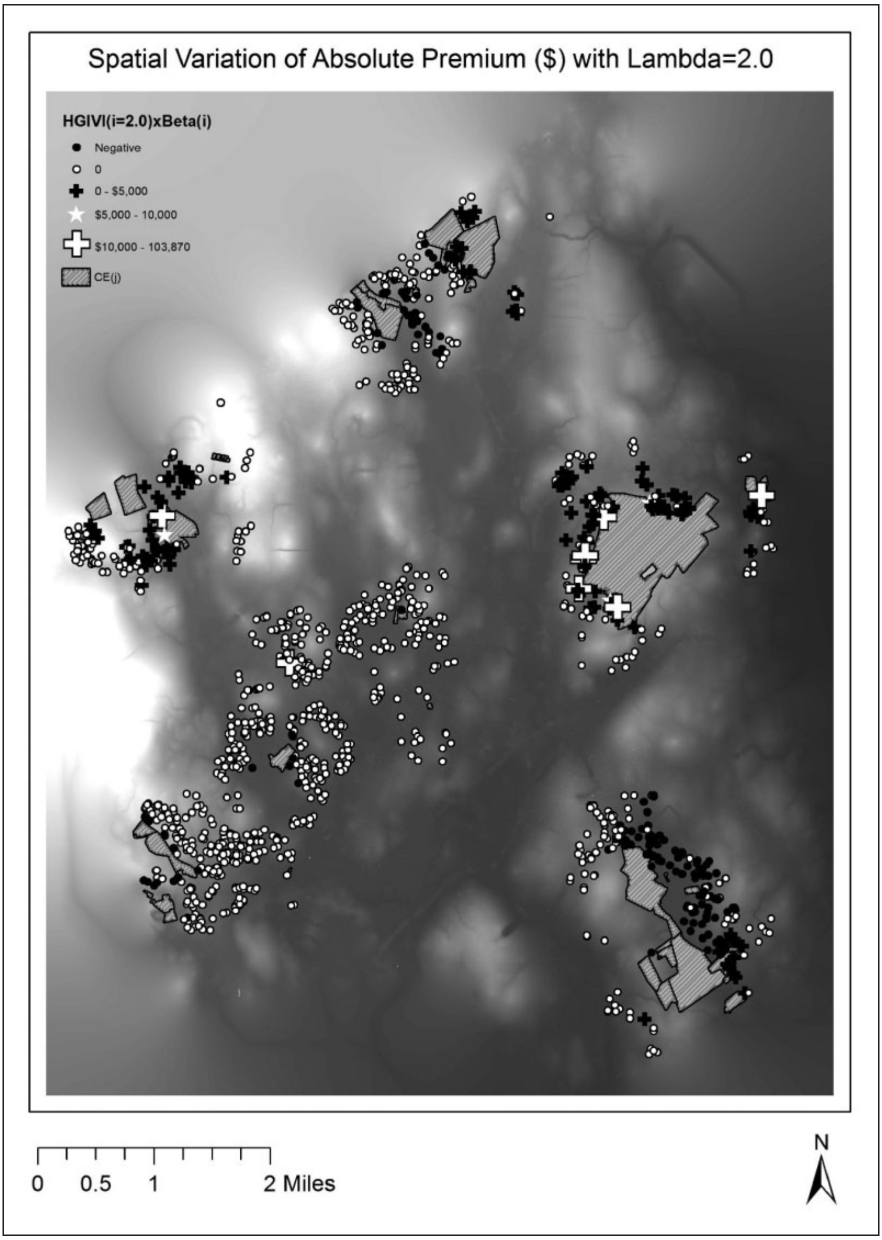

Figure 5. Spatially variation of absolute premium (in $) for GIVI with $\lambda = 2$.

had an *adjusted R-squared* value of 0.518, while the local GWR model had an average *adjusted R-squared* of 0.589 (Nakaya, 2014). All coefficients and their signs in both models were as expected (see Table 2), and all the estimated coefficients were found to be significant at $p < 0.05$ in the global model. The local estimates of the varying coefficients were saved in a separate file along with the predicted values and the residuals. The mean value of the estimated coefficients from the two models is presented in Table 2. In Table 3, the GWR ANOVA shows that the model improved with lower residual values. The classic AIC from

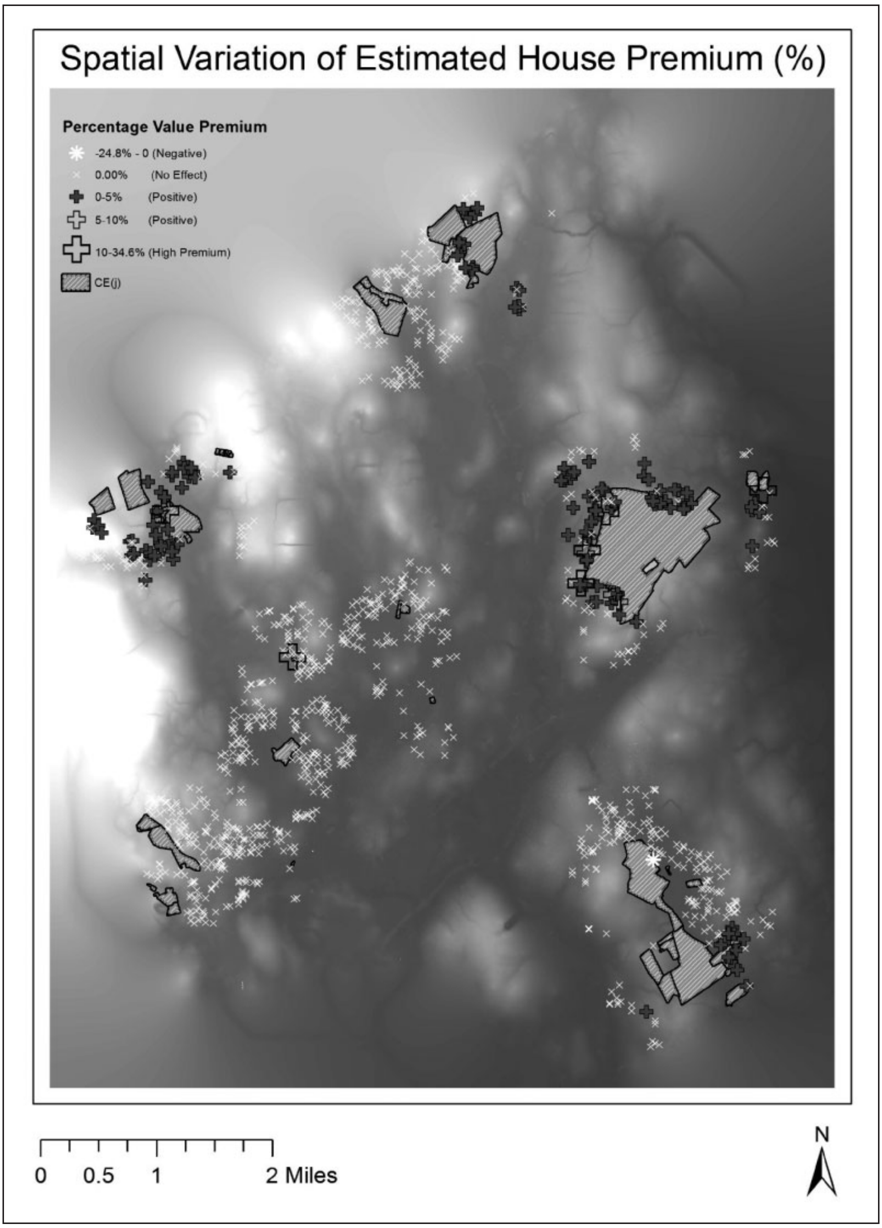

Figure 6. Spatially varying characteristics of home premiums (percentage values).

the global model was 29,828, which reduced to 29702.5 in the GWR model and thus performed better. Table 4 provides global regression results with adjusted R squared value of 0.512. Table 5 and 6 presents bandwidth selection and the diagnostic information for the GWR model. Estimates of fixed neighborhood level coefficients are in Table 7 and summary statistics of varying coefficients from GWR aree provided in Table 8.

The GWR model provided locally varying estimated coefficients of predictors and adjusted *R-squared* values at every data point. The spatially varying characteristics of $GIVI_i$, the spatially varying values of the adjusted R-squared, and the residuals and the Cook's D are displayed in Figure 4. Larger values of $GIVI_i$ are represented with larger size circles in Figure 4 (see the first figure). Consistent with the literature, the proximity of the CE amenity was found to be important. Higher values of GIVI and the adjusted *R-squared* values were found to cluster around the edges of the CE parcels. Note that in Figure 4, the first and second figures show clusters of higher GIVI values and adjusted *R-squared* values. This is due to the proximity effect. Similarly, consistent with the literature that the view of the scenic amenity is important, higher values of adjusted *R-squared* were found to cluster around the larger sized CE parcels. This is the view effect or more scenic area effect. The adjusted *R-squared* values for $Home_i$ were also found to be relatively higher near and around the larger sized CE parcels.

Moran's *I* statistic was computed to test for any spatial auto-correlation in the residuals. The positive but very low values of Moran's *I* of 0.039, $p < 0.26$, and $z = 2.224$ signified extremely low positive autocorrelation in the GWR results. Cook's D values were also analyzed and exhibited low variation, meaning there were no specific observation points (i.e. home samples) that were more important than others in the model.

The only explanatory variable of interest that captures the value of the externality was GIVI ($Mean = 0.07$, $SD = 0.48$), where the estimated coefficient for GIVI from the global model was a β of 2843.08. This β value was statistically significant but practically insignificant when converted to dollar terms. The value in dollar terms means a \$199 premium on average homes in the sample. This is a relatively insignificant \$ premium for $n = 1243$ homes with a sale price of $M = \$174{,}313$ and $SD = \$56{,}361$ in the global model. Further investigation revealed that the home with the maximum value of GIVI has a value premium of \$25,274. The value of \$ premiums on house prices was estimated as the cross product of a home's $GIVI_i$ estimate and its corresponding β_i value for a given location *i*, i.e. the cross product of $Max\ GIVI = 8.89$ and $\beta = 2843.08$.

In contrast, the GWR model provided a much finer spatially varying characteristic of the GIVI test variable and its price contributing role in house prices. As a comparison, the mean value of the estimated coefficient for GIVI from the local GWR model was $\beta_{Mean} = 83{,}855.97$ and $SD = 864{,}582$. The average premium for $n = 1243$ homes with a sale price of $M = \$174{,}313$ and $SD = \$56{,}361$ in the GWR model was 3.4% or \$5870 of the mean house prices. This was estimated as the cross product of $(Mean\ GIVI\ value = 0.07) \times (\beta = 83{,}855.97)$ in the GWR model.

Both $GIVI_i$ and β_i values vary spatially, which is shown in Figure 5. Note that the higher home value premium was found to be clustered near the CE parcels due to the proximity effect, but these premium values were also the highest near the larger sized scenic CE parcels due to the scenic view effect. From the model, it can be concluded that, on average, homes in the sample in Worcester city accrued a 3.4% incremental price premium as estimated by the GWR model. Figure 6 presents spatial variation in home premiums (as percentage values). The highest premium for select homes was estimated to be as high as 34.6% of the average home price. This percentage value is a significant value enhancement. These estimated higher percentages in the premiums are shown as larger sized circles in Figure 4 (first figure) and in

Figures 5 and 6 with large size plus signs. Note that spatially these high premium values clustered around larger sized clusters of CE parcels. Moreover, it can be noted that no premium was observed on homes that were farther away from the CE parcels, shown as white dots in Figure 5.

Conclusions

Consistent with the literature, the findings in this paper support the notion that perpetually preserved scenic landscapes increase the desirability of a neighborhood and that the local real estate and housing markets respond to these neighborhood greening efforts positively. The findings in this article support the established notion that proximity to environmental amenities in a pleasant neighborhood is a significant price contributor to the value of homes (Crompton, 2005). It can also be concluded from this article that the size of the scenic views and the distance of the view are both significant contributors to home premiums. Amenity seeking homeowners in the study area preferred to locate where they could maximize their view while minimizing the distance from the amenity, as evident from the clustered nature of the GIVI and the value contributing effect of the GIVI near larger CE clusters.

Notably, among the sample of homes used, there were a few clusters of homes that experienced negative $GIVI_i$ coefficients. Empirical evidence and the literature support the fact that safer, quieter, cleaner, and well preserved attractive neighborhoods contribute to the value of homes due to amenity effects. However, the proximity of disamenities such as crime (Troy and Grove, 2008), flood hazards (Bin et al., 2008), and hotspots of noisy highways, rail lines, heavy traffic areas (Lake et al., 1998), bars, liquor stores and fast-food joints have negative effects on the value of homes. These negative $GIVI_i$ coefficients were most likely the effects of localized negative features. These observed negative value clusters could potentially be due to the localized negative effects of crime hotspots, noise and more importantly the threat of infestations near the wooded areas.

We also showed that GWR is a useful spatial exploratory tool, but like other analytic methods, it has limitations. A few issues include kernel bandwidth selection criteria, multicollinearity, and the challenge that presentation and synthesis of a large number of mappable results generated by local GWR models pose (Matthews and Yang, 2012). Another criticism of GWR is that when the GWR algorithm is applied to spatially random data points, it is still possible to see some form of spatial pattern in the estimated parameters (Fotheringham et al., 2002: 83).

Despite these limitations, it is clear from this study that CEs have positive effects on property values. Local municipal agencies can create scenarios of enhanced local property taxes due to the value enhancement of homes near conserved lands, i.e. an incremental value premium of 3.4%. These incremental taxes could be used to promote more local level land conservation efforts and improve the quality of life in the local communities, further enhancing the value of these homes.

CEs are officially sponsored by both private and public efforts and benefit both parties. To attract businesses and homeowners, private landowners, municipal policy makers, and elected officials could advocate for neighborhood greening efforts using CEs as this can help them achieve their sustainability agendas and bring nature back into the city. Using the approach and findings from this paper, local land conservation agencies, urban planners and cities could strategically identify lands and spatially target land parcels in their conservation efforts using the view and distance based interaction approach presented here.

For researchers, this paper provides a useful methodological contribution in estimating the value of visual accessibility; it provides useful insights for real estate appraisers on integrating GIS-based viewshed techniques in real estate valuation. The methodology is useful as it can be directly employed as an automated-computation tool in an objective way without physically visiting every individual site. The methodology can also be applied to evaluating the effect of other environmental externalities in any other location.

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