Paper Title:

Valuing Visual Accessibility of Scenic Landscapes 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 effect of visual accessibility of scenic lands on housing price. It estimates households' implicit willingness to pay for the visual accessibility of privately owned voluntarily protected scenic lands in a single family housing market. These lands are protected in perpetuity for natural, historic, and scenic characteristics. The premium price effect was captured using the visual accessibility variable, a combined weighted measure of visibility and proximity. This is named as Gravity Inspired Visibility Index (GIVI). A comprehensive review of eight environmental amenity from multidisciplinary sources provides basis on significance of 'proximity' and 'view.' A detailed methodology on developing spatial interaction variable using 3D GIS and viewshed[1] technology is provided. This variable was used to estimate the capitalized premium from the preserved lands. Both global (*adjusted* R^2= 0.52, *AICc*= 29828) and geographically weighted regression (GWR) models (*adjusted* R^2= 0.59, *AICc*= 29729) estimated the marginal price effect. The results indicate an average 3.4% price premium on mean home value from the GWR model. The article offers a useful framework for evaluating effects of land protection for planning and real estate scholars. It also offers useful insight to conservation agencies, local governments, professional planners, and real estate professionals for prioritizing land sites with scenic views and for property development.

1. Introduction

The study was conducted in Worcester, Massachusetts -- the second largest city in the state. A cluster of 26 privately owned Conservation Easement (CE) properties with historically important

[1] The viewshed identifies cells in an input raster that are visible from one or more observation points. Binary values are added to the output raster with 1 meaning visible and 0means not visible.

sites and land parcels with scenic amenities were the focus of this article. This study estimates the externality effect of these voluntarily protected lands, on prices of surrounding 1,243 single family detached homes. The protected lands serve as public amenities, offer several indirect and direct environmental, and health benefits to the local community. In past, several parks, trails, waterways, and wildlife areas have been protected this way using CE in the United States. CE involve legal agreements between private landowners and a non-profit or a government agency in the United States to perpetually restrict any future development rights on preservation worthy lands. Under the agreement, the private landowners are allowed to retain their land titles, continue to retain their right to own and use lands. They also have the option to donate or sell the restricted development rights, and claim equivalent federal tax credits (Mittal 2014; Wright, 1994; Gustanski and Squires, 2000). Billions of dollars' worth of public money is involved as tax credits to incentivize private landowners; therefore, to motivate conservation organizations and local governments to promote land preservation activities, this article estimates direct monetary benefits to the local property tax base due to value enhancement of surrounding homes.

Using ArcMap, 3D GIS and Spatial Analyst value capturing explanatory variable was developed, and was used in the hedonic framework to capture the marginal price effect of preserved lands. Both OLS and geographically weighted regression (GWR) models were used. The two datasets used were a cluster of 26 CE parcels (***j***) as amenity generators and 1,243 single-family detached (SFD) homes (***i***) as amenity absorbers. These homes were transacted between 2005 and 2008 and were located within a ½ mile distance from the CE parcels. A Gravity Inspired Visibility Index (GIVI) was used as a distance weighted measure of visibility of protected lands. A distance decay function was used to incorporate the role of proximity. The methodology of the distance

weighted view variable, application of GIS and viewshed, and use of gravity based measurement offers a new conceptual foundation to real estate and planning scholars and professionals. The application of methodology is not only limited to scenic CE parcels but can also be applied in evaluating effect of other amenities. Further, this article is useful not only to the American audience, but can also be applied in other places and context. Both the global and geographically weighted regression (GWR) models (Nakaya et al. 2014; Fotheringham et al. 2002, Brundson et al. 1996) were calibrated to estimate the marginal price effect of the CE parcels, and the GWR model provided an average premium of 3.4% on mean home price. A review of over 75 hedonic studies provided the theoretical basis for this article and are presented in the next section.

2. Literature review and theoretical foundation

A substantial body of scholarly literature exists that has established an economic relationship between environmental amenities and surrounding home prices. The literature in this area is quite extensive and several reviews and meta-analysis were published in the past. For example, Mittal and Byahut (2016); Brander and Koetse (2011); Simons and Saginor (2006); McConnell and Walls (2005); Crompton (2005); (2001); Bourassa et al. (2004); Boyle and Kiel (2001); Fausold and Lilieholm (1999); and Freeman III (1979) are noteworthy studies. Using these reviews and their bibliographic references as a base and including several recently published articles, this literature review was synthesized. The three key variables that were found common in the reviewed studies include proximity to amenity (Crompton 2006; 2005; 2001), view of amenity (Bourassa et al. 2005; 2004), and accessibility to locational externality (Xiao 2016; Orford 2002). A palette of variants of Proximity defining variables and View defining variables

used in past studies are summarized in Table 2. A more detailed and systematic review of nine different environment amenities including their impacts on home values is available from (Mittal and Byahut 2016). A summary findings of the reviewed studies is presented below.

2.1. Proximity to environmental amenities and price premium

When the demand for scenic locations from amenity seeking homeowners is greater than the supply of such locations, owners cluster around amenities. Owners clsuetr to take advantages that proximity and scenic view those amenities offer and pay a higher amenity premium for those locations (Brewer 2003; Mitchell and Johnson, 2005). As presented in this article, this premium price varieswith amenity types. The amenity premium is higher for discreet amenities and lower for non-discreet ones. The discreet amenities included ones that are clearly recognizable such as, ocean fronts, lakefronts, river streams, parks, golf courses, or trails/greenways. The capitalized premium are higher for surrounding homes as shown in Figure 1. On the other hand, the non-discreet amenities included small parks and array of open spaces or green patches available throughout the urban landscape. These include farms, forests patches, low impact developments, vegetation, tree canopies, tree covers and other urban greenspaces. Houses near such amenities accrue a relatively lower premium. This section of the article presents the review findings for different amenity types as summarized in Table 1. Various measurement variables are also presented in Table 2 that were used to define *proximity*.

2.1.1 Proximity to Discrete Amenities

The price effect of water fronts on homes near waterfronts was found to be the highest among all amenity types in the reviewed studies. Among different types of waterfronts, homes in proximity of oceans with well-developed beaches had the highest price premium and ranged over 101.9%

(Conroy and Milosch 2011). This premium was found to be even higher of 147% when both proximity and view of ocean were available from homes (Benson et al. 1997). The second highest proximity premium for waterfronts was for the lakefront homes. It ranged from 31.8% for homes near Lake Austin (Lansford and Jones 1995) to 89.9% for larger lakes such as Lake Erie (Bond et al. 2002). It was found that lakefront homes accrued even higher premium value of 127% when both proximity and lake views were available to homeowners. This was found in a study in Bellingham, Washington (Benson et al. 1998). The proximity premium for homes near rivers and streams was relatively lower than lake front or ocean front homes. A premium of 7% was recorded for homes fronting small stream in a study in Oregon (Mooney and Eisgruber 2001). The premium was found to be 12.9% for homes within 200 feet of stream when both streams and trees were present (Netusil 2005). This premium was found to be even much larger of 54.4% for homes within 200 feet from a larger river in Portland, Oregon.

The marginal price effect on home values due to *"proximity of"* golf courses were also studied. The premium ranged from 1.1% for homes that were within one mile from the course (Cho et al 2009) to a high of 28% for homes facing privately managed golf courses with high maintenance and clear views of golf greens (Shultz and Schmitz 2009). Price premium for homes near trails and greenways was found to have a range of 2.4% to 14% in a study in Marion County, IN (Lindsey et al. 2004). In another study, premium ranged from 12.2% to 20.2% for homes near greenways in Austin, TX when both proximity and view to greenways was available to homeowners (Nicholls and Crompton 2005). The price premium for homes near parks averaged 20% (Crompton 2005) and the premium declined with increasing distance. However, location rent for vacant land near the 1,294-acre Pennypack Park in Philadelphia accrued 33 % premium

at 40 feet from the park (Hammer et al. 1974). This premium decayed with increasing distance -- to 9% at 1,000 feet, and to 4.2 % at 2,500 feet from the Park. Size of the park is important too. Each acre of the park land generated a value of $2,600 in the location rent. Also notable from the past studies is that proximity to dis-amenities have negative effects on home values. Several pasts studies supported this notion for example, study noted effect of crime (Troy and Grove 2008), effects of flood hazard zones (Bin et al. 2008), and effects of hotspots of noisy highways or rail lines (Lake et al. 1998). Other disamenities are proximity of a noisy bar, liquor store and fast -food joint. Such activities have a negative price contributory effects on home values.

----- Insert Figure 1 here -----

2.1.2 Proximity to Non-Discrete Amenities

At a metropolitan scale, an array of amenity generating natural landscape features that exist as diverse land uses. Such land use features are found in multiple patches throughout the metropolitan geography and have a lower amenity premium. These features are diverse land uses and are non-discrete amanities with no defined or clear entity, no edge or a boundary. Array of such amenity generating landscape features were studied in the past. Such non-discrete amenities included various land cover types in the proximity of a house (Walls et al. 2015; Li and Saphores 2012), undeveloped lands by their development potentials near homes (Borchers and Duke 2012; Irwin and Bocksteal 2001), and acreage of diverse lands by their uses and ownership types (Ham et al. 2015; Irwin 2002). Studies also included urban greenspaces (Saphores and Li 2012; Conway et al. 2010), vegetation (Kadish and Netusil 2012; Kestens et al. 2004), and diversity of land use/covers surrounding homes (Sander and Polasky 2009), rural, semi-rural and urban land

covers, open spaces, forests cover, water, fields and agriculture landscapes (Acharya and Bennett 2001). Other studies included urban tree coverage (Sander and Haight 2012; Sander et al. 2010), tree canopy cover (Conway et al. 2010), and presence of street side trees and their effects on homes (Donovan and Butry (2010).

Those homeowners in proximity of such landscapes prefer such nicer surroundings, and pay a premium to enjoy it. The direct capitalized amenity premiums of such landscapes are relatively lower as compared to the discrete amenities, but greater number of homeowners benefit because of their more uniform presence in a city. As a comparison, the amenity premiums for both discreet and non-discreet amenities is presented in Figure 2. Notice that the premium values are lower for the non-discreet amenities listed on the right side of the Figure 2.

In past studies that focused on such non-discrete amenities, typically, a predefined distance buffer was used as a proximity measure. Various landscapes characteristics within this buffer were studied to capture the characteristics of surrounding landscapes near homes. The studied measures were proportional mix of land uses, percentages of land uses, land use areas in acres and diversity of these land covers and land uses.

Conway et al (2010) studied the effect of urban greenspaces such as tree canopies, parkways, landscaped areas, sports fields, lawns, and cemeteries using aerial images for fixed distance buffers near downtown Los Angeles. Their study concluded that with every 1% increase in greenspaces, median house price increased by 0.07%. Another study by Li and Saphores (2012) in Los Angeles focused on the price effect of Tree Canopy Cover (TCC) on multi-family homes (MFH). Their study found a $790 (0.12%) premium for every 1% increase in the TCC around the MFHs. Ham et al. (2015) studied effect of proximity to Pike national forest in El Paso County,

CO. Their study used distance buffers and found that the forest premium ranged from 2% to 10% within a 1 to 3 mile distance from the forest. As a comparison home premium was found to be 6% for county and state owned open spaces for the same distance. Kadish and Netusil (2012) studied effect of land cover types around homes. Their study focused on proportions of high-structure vegetation (trees and woodlands), low vegetation (shrubs and grassy lands), and water & impervious surfaces surrounding homes in Portland, OR. The study concluded that by increasing the amount of high structured vegetation from its initial average of (26%) to the amount that is estimated to have the maximum effect on a property's sale price (32%), it increased sale prices by 0.05%, or approximately $155. This study also found that increasing vegetation beyond that has a negative effect on home prices. It may be notable here that while presence of trees contribute to home values, planting and maintenance costs may sometimes outweigh the benefits. The Saphores and Li (2012) study in Portland concluded that 97% homeowners liked trees in their neighborhoods, but not so much on their own land parcel. Sander et al. (2010) studied the effects of urban tree cover in Dakota and Ramsey Counties, MN. Their study used percent tree cover as the variable of interest. This study examined tree covers within 100, 250, and 500m-buffers from each homes including trees on the individual home lots. This study concluded that a 10% increase in tree cover yielded a 0.48% ($1,371) premium within 100m, and a 0.29% ($836) premium within 250m. Borchers and Duke (2012) studied the price effects of 'developable' and 'protected' agricultural and natural lands within a 200 meter radius from homes in Delaware, and found that with every 1% increase in protected lands, home value increased by $667. Irwin and Bockstael (2001) studied the effect of open spaces by their ownership types in the D.C. area, and concluded that a 10% increase in publicly owned lands

increases home values by 0.3%, while a 10% increase in privately owned lands reduces home values by 0.08% to 0.6%. Geoghegan et al. (2003) studied the value capitalization effects of agricultural easements on home prices and therefore effect on the property tax base in Calvert and Howard County, MD. Using the percent of permanent open spaces, agriculture, and forest lands within a 100 m and a 1600 m buffers from homes, their study concluded that by increasing preserved agricultural land by 1% (144 acres), sufficient incremental tax revenues can be generated from properties within a one-mile radius of the preserved parcel to purchase additional 88 and 110 acres respectively. This study clearly shows how land protection could be an effective tool for increasing the local property values and tax base, and how land protection could be self-financed via this land value and tax increments.

Walls et al. (2015) studied effects of three land cover types around homes: farmlands, grassy recreational and forest areas. Their study measured percentage of each land cover types within a 200 m buffer of homes, and found that for every 10% increase in farmland, recreational grasslands, and forest covers home prices increase by 2%, 1.4%, and 0.6%, within the buffer. It is noteworthy from the above review that surrounding landscapes are amenity generators and have a widespread effect. The amenity premium range attributed to proximity of both discreet and non-discreet amenities is presented in Figure 2. Also notable from the past studies is, that proximity to amenities is important; however, with proximity if view of amenity exists, the premium value is even higher and is presented in the next section.

----- Insert Figure 2 here -----

2.2 View of environmental amenities and premium price

Good quality view is a significant price contributor for any real estate property. The reviewed studies show that having *"View"* of scenic amenities fetched a significantly higher premium than *"proximity"* alone of similar amenities. Uninterrupted urban views of cities skyline, high quality scenic views of natural landscapes -- view of mountains and valleys, and views of oceans and lakes, command high premium for homes that are in proximity of such amenities and have a view. Views of discretely identifiable scenic amenities were found to be higher than the non-discrete ones as shown in Table 1.

2.2.1 View of Discrete Amenities

Home value premiums for oceanfront views were the highest amongst all discrete amenities. It ranged from 47% (Bin et al 2008) to a high of 147.2% (Benson et al. 1997) depending on the quality of view. Lakefronts views were the second highest with 126% premium (Benson et al 1998). The riverfront homes accrued 54% premium for homes with views. Studies also found price contributing premiums for views to waterfalls and forested areas. Views of downtowns, urban skyline views, and views of preserved open spaces also contributed positively to home prices. Views of quieter, scenic, and well-maintained urban parks averaged 20% premium (Crompton 2005; 2001). Golf course views accrued a premium of 7% (Asabere & Huffman 1996) to a high of 28% for homes abutting high quality privately managed golf courses (Shulz & Schmitz 2009). This 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). Studies focusing on trails and greenways found a view premium of 20.2% (Nicholls & Crompton 2005), while a

lower premium of 3% to 8% for wooded areas, landscaped areas, and forest views. Premium for undeveloped lots abutting forest preserve, ranged from 19% to 35% (Thorsnes 2002).

2.2.2 View of Non-Discrete Amenities

Various landscape patterns with mosaics of diverse land covers or spatial ecological features were also found to be amenity generating characteristics surrounding homes (Acharya and Bennett 2001). Such mosaics and patches of green landscapes and land uses surrounding homes were used as a proxy of desirable surroundings or desirable views. These landscapes were defined by land use types, and their varying degree of development intensities as a proxy of view richness (Sander and Polasky 2009). To capture a measurable variable for such landscape features, remotely sensed land use characteristics data were used. For example, the Normalized Difference Vegetation Index (NDVI[2]) data was used to differentiate effects of different types of green spaces around homes on their values (Bark et al 2011; Payton et al. 2008). Most studies that included miscellaneous landscape patterns surrounding homes used distance to, view of, and percentage visible areas of such landscapes around homes in estimating the amenity effect. A few studies used surrounding land use characteristics within a predefined viewable distance of (200', a 1/4 mile or 1/2 mile or more from homes). This distance serves as a proxy to both "proximity to" and "view of" pleasant surroundings (Conway et al. 2010; Sander and Haight 2012). These easily accessible (within walking distance) and aesthetic landscapes (scenic) surrounding homes were usually measured using remotely sensed land use / land cover aerial data and GIS viewshed analysis. Poudyal et al. (2010) used viewshed for forest areas within a viewable radius of ¼ mile to ½ mile from each home. Bark et al (2011) studied effects of

[2] NDVI value ranges from -1 to 1, value close to +1 signifies dense vegetation, values close to -1 signify water,

spectral characteristics of vegetation in arid Tucson, AZ, and concluded that greenness around homes created a premium of 21.4% ($45,729) if this greenness is at the neighborhood scale. The greenness premium was found to be 8.4% ($17,860) if the greenness was at home lot-level. Bowman et al. (2009) studied housing market in Cedar Rapids, IA and concluded a conservation premium of 3.9% ($8,688) if subdivision had more conservation features. Cho et al (2011) found 4.3% to 6.2% premium (~$14.000) for every 10% increase in the developed open space. Few studies have also used 3D Light Detection and Ranging (LiDAR) data technology and introduced view automation using viewshed technique to calculate true angular view of scenic amenity from homes (Bin et al. 2008; Hamilton and Morgan 2010).

Table 1 below is a summary of range of minimum and maximum marginal price effect as found from the reviewed studies for eight amenity types for both proximity and view category.

----- Insert Table 1 here -----

The above review of proximity and view for both discrete and non-discrete amenities corroborates the fact that scenic views are significant price contributor, and the accrued premium value varies for quality of the views of amenities, their distance from homes, and the characteristics of the amenity itself. It also further supports the notion that homeowners have greater willingness to pay amenity premium if they are in close proximity of scenic amenity -- easy access to scenic view.

2.3 Accessibility to environmental amenities

The concept of accessibility is defined by the level of opportunities available for spatial interaction between two point pairs. Such interaction measure is used in transportation studies (Lin et al. 2016) and in retail market analysis extensively (De Beule et al. 2014; Huff and Jenks 1968). A similar, accessibility measure was also used to capture proximity effect when more than one amenity types were present. For example, (Orford 2002) used accessibility to environmental amenity as a weighted index in a Cardiff, UK study. The weighted index is a measure of spatial interaction between homeowners and their relative attraction to the amenities. Numerically, accessibility as a measurement variable is defined as the weighted sum of inverse distance. It is the influence of a land use externality (or amenity) on home owners as it depends upon distance of the amenity (proximity) from a home and depends on the size (attraction factor) of the amenity itself (Orford 2002). Similar weighted index was also employed in Powe et al. (1997) for approximating price effects of access to woodlands, where the index measured the ratio of forest acreage to its squared distance from home to woodland areas in the Southampton and New Forest in Great Britain. In such a weighted index, those homes located closer to larger forest experienced a greater influence of forest. More details on similar gravity inspired accessibility indices and their uses are available from Xiao et al. (2016); Wang (2015); Geogheghan (1997); Pooler (1987).

One way to tie the proximity variable and view variable together is a single measurement variable of visual proximity or, visual accessibility. This variable would assign higher weight to the quantity and quality of scenic views, and lower weight to their increasing distance from homes. A single variable with distance declining inverse function is used to define proximity and

visible area of the scenic amenity was used as presented in the next section. This variable simply means that larger the scenic view more important it is, and farther the scenic view is, less important it is for homeowners, thus lowering its amenity value and thus premium. This single variable of visual accessibility was used in this article and its methodology is presented in the next section.

----- Insert Table 2 here -----

From the above review it is clear that both "proximity to" amenity and "view of" amenity matter. However, both effects were captured using a single variable as presented in the next section.

3. Data and Methodology of Creating Explanatory Test Variable

3.1 Data

This article employed two GIS-based parcel datasets. The first dataset included a set of 26 Conservation Easement (CE) protected parcels – CE(***j***) – the Environmental Amenity Generators. These CE parcels varied in size (1 acre to 400 acres) and clustered around 7/8 location. They contained various natural and scenic amenities such as waterfalls, streams, ponds, large boulders, marsh, wetlands or vernal pools, golf course, trails, parks, woods and vegetated lands including hardwood forests, mountain laurels, and silver beech trees. The second dataset included 1,243 home parcels – the Environmental Amenity Absorbers – Homes (***i***). This set included all single family detached (SFD) homes sold between 2005 and 2008, and located within ½ mile of the CE(***j***) clusters. This Homes (***i***) dataset had a mean Price *M* = $174,313; *SD* = $56,361.

Descriptive statistics of these homes is provided in Table 3. Figure 3 shows spatial distribution of Home (***i***) in red dots relative to the location of CE Parcels (***j***) shown in green polygons.

----- Insert Figure 3 here -----

3.2 Viewshed and Methodology of Creating Visual Accessibility Variable

The price contributory effect of 26 CE(***j***) parcels was to be observed on the sale price of 1,243 Homes (***i***). Multi step GIS methodology was employed to develop the GIVI variable as detailed below:

3.2.1 Step 1 : Development of 3D Merged Raster for view shed

In the absence of high precision LiDAR data for Worcester, an alternative strategy that was a close substitute to LiDAR data was employed. A merged raster surface was created using the topographic spot elevation data and all potentially view impending buildings and structures in the city. Both spot elevations and building footprint features with their z values were embedded to create a single merged raster for the entire city. To prepare this raster, first, using ArcGIS Spatial Analyst, a digital topographic surface raster was created using spot elevations. A second raster with all building footprints and building heights was created (Sander and Manson 2007). Finally, the two rasters were added using the map algebra function and a single merged digital surface was created for the entire city. This surface had a raster cell size of 10'x10,' and was used as input raster for viewshed analysis as discussed in step 2.

Past environmental-benefit studies by Mittal (2014); Sander and Polasky (2009); Shultz and Schmitz (2008); Lake et al. (2000; 1998) have presented quantifiable view capturing

methodology using viewshed analysis in GIS. Mittal (2014) used a dichotomous variable for view (as visible and nonvisible) in its view estimation. Using the same dataset as (ibid), a true viewable areas of visible CE parcels were computed from each home location using viewshed for this article.

3.2.2 Step 2: Development of Gravity Inspired Visibility Index (GIVI) variable

The computation of the GIVI variable involved three additional steps after the input raster surface was created. Using MS Visual Basic, an algorithm was developed inside ArcMap to create two different matrices: a visible area matrix (V_{ij}) and a distance matrix (d_{ij}). Each row of these matrices was $Home(_i)$ with MAP-ID as unique identifier for homes, and each column of these matrices was CE($_j$) parcel with MAP-ID as the unique identifier for CE. Both matrices were *[1243x26]* dimensional matrix (Figure 4 and 5).

1. ***Development of <u>Visible Area Matrix:</u>*** 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 and invisible areas from a set of observer locations. The output viewshed rasters had two values: 1 for visible cells of the raster and 0 for invisibility. This was a computer-intensive process where the processing time is dependent on the raster resolution.[3] Viewsheds were run from each *Home(i)* as an observer location, assuming human height of 5.5 feet. The process was looped to repeat for every observer $Home(_i)$. The final outputs were a set of viewshed$_{ij}$ rasters

[3] ESRI, "Viewshed (3D Analyst)," ESRI Developers Network, Documentation Library, ESRI. Accessed from http://edndoc.esri.com/arcobjects/9.2/CPP_VB6_VBA_VCPP_Doc/shared/geoprocessing/3d_analyst_tools/viewshed_3d_analyst_.htm on Mar 10, 2016.

for 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 sq ft, the number of visible cells were multiplied by its 10'x10' pixel size. Only the values of 1 inside the *CE*($_j$) parcel were accounted in for the calculation. This square feet visible area value was then filled for each *Home (i)* against each *CE(j)* in the *Visible Area Matrix* $V_{ij.,}$ resulting in many cells with values=0 in the matrix. The cell value of 0 in the matrix meant that the particular *CE(j)* was not visible from the particular *Home (i)*. The *[1243x26]* dimension visible area matrix is shown in Figure 4.

----- Insert Figure 4 here -----

Note: In Figure 4, 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*($_i$).

2. ***Development of distance matrix:*** The Euclidean function in ArcMap was used to calculate the shortest distance from each *Home*($_i$) to the visible portion of each *CE*($_j$) parcel, and the returned values were filled in 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 the interdependency, if a cell in the *Visible Area Matrix* V_{ij} had value=0, the corresponding cell in the distance matrix also received the value=0. Later, 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} was the denominator term of the *GIVI*, and 0 value would give erroneous results. This generated a *[1243 x 26]* dimensional output matrix of shortest distances of the visible area, as shown in Figure 5.

----- Insert Figure 5 here -----

3. ***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 squared-inverse-distance based on the visible size of protected properties and their inverse distances from SFH. This sum of distance weighted visible area was calculated as follows:

Distance weighted some of visible area for each *Home(i)* = $V_i = \sum_{j=1}^{26} CE_{ij} / d_{ij}^{\lambda}$ .....(1)

CE_{ij} is the attraction factor[4] of the scenic CE parcel (*j*) defined by its total visible area from Home(*i*). Its value was taken from the visible area matrix for each Home *i*, and where *i* = 1243 and *j*=26; denominator $d_{ij} > 0$, represented the distance between Homes (*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 value of this parameter λ specific to environmental amenities is not known a priori, one option attempted in this article was to calibrate various models for three λ values as conducted in Orford (2002) study. While estimation of appropriate λ value could be a topic of research itself, but for this article, three parameter values for λ = 1, 1.5 and 2 were applied in computing the $GIVI_i$. After initial OLS model calibration, the model with the $GIVI_i$ value of

[4] Attraction factor could be any characteristics of CE such as 'Size,' or any environmental feature that could cause attraction. For this research, Visible area of scenic CE parcel is used as attraction factor

λ = 2, was chosen for two reasons: for intuitive simplicity[5] and for not excluding homes that are relatively father from CE clusters in the effect estimation. From the equation 1 shows that λ being a power function in the denominator term, a greater λ value would mean that higher weightage would be given to homes that are really close to the CE clusters. Higher value of λ would have resulted in reducing the significant home samples in the effect estimation. providing very high weights to homes near the visible CEs and ignoring all others. Therefore, values of $\lambda > 2$ were not attempted. The $GIVI_i$ variable was computed using the following formula:

$$HGIVI_i = V_i / (\sum_i \sum_j V_{ij}) \cdots\cdots\cdots\cdots\cdots (2)$$

$$HGIVI_i = \sum_{j=1}^{26} CE_{ij} d_{ij}^{-\lambda} / (\sum_{i=1}^{1243} \sum_{j=1}^{26} V_{ij}) \cdots\cdots\cdots (3)$$

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 visible CE area is from a given $Home(_i)$. $GIVI_i$ is a single variable that was used to measure both proximity and visibility simultaneously. In other words, it is 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*).

4. Model

[5] Models for three λ values of 1, 1.5 and 2 were calibrated and it was found that all models were significant; however, the model improved when λ =2.

SPSS and GWR4.0 were used for modeling purposes and the descriptive of the home data used was as follows:

----- Insert Table 3 here -----

4.1 Global Model

A hedonic equation in its simplest form is a regression of expenditures (rents or values) on various characteristics of home samples (Malpezzi 2003). Following Sirmans et al. (2006), the key value-contributing variables were used to control for the structural and neighborhood characteristics of homes. These were used as independent variables in the regression equation. The descriptive statistics of the dependent and independent variables are presented in Table 3. . The regression coefficients were computed to estimate the implicit prices of homes' individual characteristics. The generic form of the initial OLS based global hedonic model was specified as

$$\boldsymbol{Y} = f\,(\boldsymbol{X}_{structural}, \boldsymbol{X}_{neigborhood}, \boldsymbol{X}_{Externality})$$

$$\begin{aligned}
\text{Or Sales_HPI9} = {} & LotSqft + TULA + Bath + H_Bath + Qual + Age + Deck && (Structure)\\
& + Hous_Dens + MedHsg_Val + Perc_Black && (Neighborhood)\\
& + GIVI_\lambda && (Externality)\\
& + \varepsilon_i && (Error)
\end{aligned}$$

The dependent variable Y_i = Sales_HPI9 is home sale price. The sale prices were adjusted using the 2009 house price index of the Worcester metro area.[6] The control independent variables X_i

[6] The adjustment for the house price index, Worcester metro area data available from the Office of Federal Housing Enterprise was used. "The House Prices Indexes Quarterly Data OFHE - 2009 was available here: http://www.ofheo.gov/hpi_download.aspx. Accessed on January 3, 2009. Now available through http://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx#qexe accessed on February 19, 2016.

included 7 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), age of the house (Age), binary dummy for deck (Deck), and 3 neighborhood variables at census block group level: housing density per acre (Hous_Dens), median housing value (MedHsg_Val), percentage black population (Perc_Black). The single externality capturing variable used was gravity inspired visibility index -- *GIVI with* $\lambda=2$.

As part of model building, several OLS-based global models were calibrated using the step-wise process in SPSS. The candidate model that minimized the Akaike Information Criterion (AIC) value was chosen. The explanatory variables chosen were consistent with Sirmans et al. (2006), and their descriptive statistics are in Table 3. The candidate variables were found free of multi-collinearity with VIF<3 for all 11 predictors, and the OLS model was found as robust. Using the residual values from this model, the test of heteroscedasticity was conducted as a visual analysis. On plotting residuals, errors were found to be randomly scattered without any systematic pattern, which signifies homoscedasticity. In SPSS, any linear form of heteroscedasticity can also be detected using the *Breusch-Pagan* test for heteroscedasticity. After running the test, the small chi-squared value indicated that heteroscedasticity was absent.

4.2 Local GWR Model

In conjunction with OLS based global model as above, a semiparametric local GWR model was employed in the form as shown in equation 5 below:

$$Y_i = \beta_{0i} + \sum_k \beta_k(u_i, v_i) x_{k,i} + \sum_l \sigma_i z_{l,i} + \varepsilon_i \text{ .....(5)}$$

Y_i = house price at location i;

β_{0i} = intercept parameter at location i;

β_k = kth locally varying coefficient of $x_{k,i}$ variables at location i (with u,v coordinates).

σ_i = fixed coefficient of z_{li} variables

z_{li} = lth independent variable

Equation 5 had two parts: the first half is the local model and the second half is the global model. The last term is the error term.

The semiparametric GWR model was chosen because predictor variables had spatially varying characteristics at the local level and fixed characteristics at the neighborhood level. Nakaya et al. (2014) recommended that such a mixed model may reduce complexities and enhance the model's predictable performance. Crespo and Gret Regamey 2013) also provides details on the use of similar mixed-GWR method for a study conducted in Zurich.

After calibrating the OLS model, the Geographically Weighted Regression (GWR4.0) software was utilized to model the geographically varying relationships between the home prices (Sales_HPI9) as the dependent variable and home characteristics as independent (Fotheringham et al. 2002). The GWR4 software 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 – individual regression models for each *Home(i)* location. This weighting was achieved through a kernel function with a given bandwidth. The GWR model was applied with the following settings:

- Model type: Gaussian

- Geographic kernel: adaptive bi-square
- Method for optimal bandwidth search: Golden section search
- Criterion for optimal bandwidth: AIC
- Number of varying coefficients: 9
- Number of fixed coefficients: 3
- Number of sample points : 1243

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 et al. (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 9 varying coefficients (the dependent variable house price and 8 independent variables of structural attributes) and 3 fixed coefficients (neighborhood level variables fixed at census block group geography) at *n*=1243 data points. GWR4.0 after iteration selected the optimal bandwidth size of 186.0 with a minimum AIC value of 29702.56.

4.3 Model Discussion

GWR4.0 also provides a comparison of the global model with the local GWR model. Comparatively, the results of the GWR model were more pronounced. The global model had an *adjusted R-square*=0.518, and the local GWR model had an average *adjusted R-square* =0.589 (Nakaya et al. 2014). All coefficients and their signs in both models were as expected (See Table

4), and all the estimated coefficients were found significant at $p<0.05$ in the global model. The local estimates of varying coefficients were saved in a separate file along with predicted value and values of residuals. The mean value of estimated coefficient from the two models are presented below:

----- Insert Table 4 here -----

The GWR ANOVA Table 5 shows that the model improved with lower residual values. The classic AIC from the global model was 29828, which reduced to 29702.5 in the GWR model, and is thus a superior model.

----- Insert Table 5 here -----

Following the framework of Crompton's "proximate principle" (Crompton 2006; 2005), and Bourassa et al. (2005; 2004) significance of view, and following the spatial interaction approach of (Orford 2002), GIVI was developed using viewshed. This variable was a single measure developed to capture the joint effect of proximity and view.

The GWR model provided locally varying estimated coefficients of predictors and adjusted *R-squared* values at every data point. The spatially varying characteristics of $GIVI_i$, spatially varying values of adjusted R-squared, residuals and Cooks'D are displayed in Figure 6. The greater values of $GIVI_i$ were represented with larger size circles in Figure 6. Consistent with the literature that proximity of amenity is important, higher values of GIVI and adjusted *R-squared*

values were found to cluster around the edges of CE parcels. Note the first and second figures showing cluster of higher GIVI values and adjusted *R-squared* values in the Figure 6. This is due to the Proximity effect. Similarly, consistent with the literature that view of scenic amenity is important, higher values of adjusted *R-squared* were found to cluster around the larger size CE parcels. This is the View effect or more scenic area effect. The adjusted *R-squared* values for *Homes (i)* were also found to be relatively higher near and around the larger size CE parcels. The Moran's *I* statistic was computed to test for any spatial auto-correlation in residuals. The positive but very low values of Moran's I= 0.039, $p<0.26$, and $z=2.224$ signified extremely low positive autocorrelation in the GWR results. The Cook's D values were also analyzed and had low variation, meaning there weren't any specific observation points (home samples) that were more important than the others in the model.

The only externality value capturing explanatory variable of interest was GIVI (*Mean* = 0.07, *SD* = 0.48), and the estimated coefficient for GIVI from the global model was β =2,843.08. This β value was statistically significant but practically insignificant when converted in dollar terms. The value in dollar term means a $199 premium for average homes in the sample. It is relatively insignificant $ premium for n = 1,243 homes with sale price M =$174,313, SD= $56,361 in the global model. A little more investigation reveals that the home with the maximum value of GIVI, has the value premium of 1.45% or $ 25,274. This was estimated as cross product of *Max GIVI*=8.89 and β=2,843.08.

The GWR model provided much finer spatially varying characteristic of the GIVI test variable and its price contributing role in home values. As comparison, the mean value of the estimated coefficient for GIVI from the local GWR model was β_{Mean}= 83,855.97, SD = 864,582. The

average premium for n = 1,243 homes with sale price M =$174,313, SD= $56,361 in the GWR model was 3.4% or $5,870 of the mean home prices. It was estimated as cross product of (*Mean GIVI value*=0.07) x (β=83,855.97) in the GWR model.

5. Conclusion

The perpetually preserved scenic landscapes increase desirability of the neighborhood and the local real estate and housing markets respond to the 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 home values (Crompton 2005; 2001).

The value of $ premium on home price was estimated as a cross product of a home's $GIVI_i$ estimate and its corresponding β_i value for location i. Figure 7 shows spatially varying characteristics of home premiums. The higher home value premium is found to be clustering near the CE parcels (due to proximity effect) and was highest near the larger scenic CE parcels (View effect). On average homes in the sample accrued 3.4% incremental price premium as estimated in the GWR model The highest premium for select homes was estimated as high as 34% of the average home price. This is a significant value enhancement. These estimated higher percentage of premium values were shown in larger size circles in Figure 7 and were found to cluster around larger size clusters of CE parcels. No premium was observed on homes that were farther away from CE parcels and shown in white dots in Figure 7.

Notably, among the home samples, there are a few clusters of homes which experienced negative $GIVI_i$ coefficients. As empirical evidences and literature supports the fact that safer, quieter,

cleaner, and well preserved attractive neighborhoods contribute to the home values due to amenity effects. However, proximity to 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 home values. The negative effect as observed in few clusters is potentially attributed to the localized negative effect of crime spots, noise and threat of infestations near wooded areas.

It can be concluded from the above model that the size of the scenic view and the distance of the view both matter. The amenity seeking homeowners prefer to locate where they could maximize view while minimize distance from the amenity, as evident from the clustered nature of GIVI and the value contributing effect of GIVI.

The local municipal agencies could recapture the value enhancement effect due to conservation efforts (incremental value premium of 3.4%) of homes as incremental taxes. These incremental taxes could be used to promote more local land conservation efforts and improve the quality of life in the local communities further enhancing the values of homes.

Conservation Easements are officially sponsored by both private and public efforts and benefits mutually. To attract businesses and homeowners, private landowners, municipal policy makers, and elected officials could advocate the neighborhood greening efforts using conservation easement as it helps them fulfill their sustainability agenda and bring nature back into the city (Anguelovski 2015). Using the approach and findings from this article, 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 as presented in this article.

For scholars, this article provides a useful methodological contribution in estimating the value of visual accessibility; it provides useful insight 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 objectively without physically visiting every individual site. The methodology can also be applied in evaluating the effect of any other environmental externalities and in any other location.

----- Insert Figure 6 here -----

----- Insert Figure 7 here -----

Appendix 1 here (Optional)

----- Insert Table 6 here -----

----- Insert Table 7 here -----

----- Insert Table 8 here -----

----- Insert Table 9 here -----

----- Insert Table 10 here -----

References:

Acharya, Gayatri and L. L. Bennett (2001). Valuing open space and land-use patterns in urban watersheds. *The Journal of Real Estate Finance and Economics* 22(2): 221-237.

Anguelovski, Isabelle (2015). From toxic sites to parks as (green) LULUs? New challenges of inequity, privilege, gentrification, and exclusion for urban environmental justice. *Journal of Planning Literature*: 1-14, 0885412215610491

Asabere, Paul K., and Forrest E. Huffman (1996). Negative and positive impacts of golf course proximity on home prices. *Appraisal Journal* 64(4): 351-355.

Asabere, Paul K., and Forrest E. Huffman (2009). The relative impacts of trails and greenbelts on home price. *The Journal of Real Estate Finance and Economics* 38(4): 408-419.

Bark, Rosalind H., Daniel E. Osgood, Bonnie G. Colby, and Eve B. Halper (2011). How do homebuyers value different types of green space? *Journal of Agricultural and Resource Economics* 36 (2): 395-415.

Benson, Earl D., Julia L. Hansen, Arthur L. Schwartz Jr, and Greg T. Smersh (1998). Pricing residential amenities: the value of a view. *The Journal of Real Estate Finance and Economics* 16 (1): 55-73.

Benson, Earl D., Julia L. Hansen, Arthur L. Schwartz, and Gregory T. Smersh (1997). The influence of Canadian investment on US residential property values. *Journal of Real Estate Research* 13 (3): 231-249.

Bin, Okmyung, Thomas W. Crawford, Jamie B. Kruse, and Craig E. Landry (2008). Viewscapes and flood hazard: Coastal housing market response to amenities and risk. *Land Economics* 84 (3): 434-448.

Bond, Michael T., Vicky L. Seiler, and Michael J. Seiler (2002). Residential real estate prices: a room with a view. *Journal of Real Estate Research* 23 (1/2): 129-138.

Borchers, Allison M., and Joshua M. Duke (2012). Capitalization and proximity to agricultural and natural lands: Evidence from Delaware. *Journal of Environmental Management* 99: 110-117.

Bourassa, Steven C., Martin Hoesli, and Jian Sun (2005). The price of aesthetic externalities. *Journal of Real Estate Literature* 13 (2): 165-188.

Bourassa, Steven C., Martin Hoesli, and Jian Sun (2004). What's in a view? *Environment and Planning A* 36: 1427-1450.

Bowman, T., J. Thompson, and J. Colletti (2009). Valuation of open space and conservation features in residential subdivisions. *Journal of Environmental Management* 90(1): 321-330.

Boyle, Melissa and Katherine Kiel (2001). A survey of house price hedonic studies of the impact of environmental externalities. *Journal of Real Estate Literature* 9(2): 117-144.

Brander, Luke M., and Mark J. Koetse (2011). The value of urban open space: Meta-analyses of contingent valuation and hedonic pricing results. *Journal of Environmental Management* 92 (10): 2763-2773.

Brewer, Richard (2003). *Conservancy: The Land Trust Movement in America*. Lebanon, NH: University Press of New London.

Brunsdon, C., Fotheringham, A.S., and Charlton, M.E. (1996). Geographically weighted regression: A method for exploring spatial nonstationarity. *Geographical Analysis*, 28(4): 281-298.

Cho, Seong-Hoon, Christopher D. Clark, William M. Park, and Seung G. Kim (2009). Spatial and temporal variation in the housing market values of lot size and open space. *Land Economics* 85(1): 51-73.

Cho, Seong-Hoon, Seung G. Kim, and Roland K. Roberts (2011). Values of environmental landscape amenities during the 2000-2006 real estate boom and subsequent 2008 recession. *Journal of Environmental Planning and Management* 54(1): 71-91.

Conroy, Stephen J., and Jennifer L. Milosch (2011). An estimation of the coastal premium for residential housing prices in San Diego County. *Journal of Real Estate Finance and Economics* 42: 211-28.

Conway, Delores, Christina Q. Li, Jennifer Wolch, Christopher Kahle, and Michael Jerrett (2010). A spatial autocorrelation approach for examining the effects of urban greenspace on residential property values. *Journal of Real Estate Finance and Economics* 41: 150-69.

Crespo, R and A. Gret Regamey (2013). Local hedonic house-price modelling for urban planners: Advantages of using local regression techniques. *Environment and Planning B: Planning and Design* 40: 664 – 682.

Crompton, J (2001). The impact of parks on property values: A review of the empirical evidence. *Journal of Leisure Research* 33(1): 1-31.

Crompton, J., and Sarah Nicholls (2006). An assessment of tax revenues generated by homes proximate to a greenway. *Journal of Park and Recreation Administration* 24(3): 103-108.

Crompton, John L (2005). The impact of parks on property values: Empirical evidence from the past two decades in the United States. *Managing Leisure* 10(4): 203-218.

De Beule, M., Van den Poel, D., & Van de Weghe, N. (2014). An extended Huff-model for robustly benchmarking and predicting retail network performance. *Applied Geography*, 46: 80-89.

Donovan, Geoffrey H., and David T. Butry (2010). Trees in the city: Valuing street trees in Portland, Oregon. *Landscape and Urban Planning* 94(2): 77-83.

Fausold, Charles J., and Robert J. Lilieholm (1999). The economic value of open space: A review and synthesis. *Environmental Management* 23(3): 307-320.

Fotheringham, A. S., C. Brunsdon, and M. Charlton (2002). *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. West Sussex, UK: Wiley.

Freeman III, A. Myrick (1979). Hedonic prices, property values and measuring environmental benefits: A survey of the issues. *The Scandinavian Journal of Economics*: 154-173.

Geoghegan, Jacqueline, Lori Lynch, and Shawn Bucholtz (2003). Capitalization of open spaces into housing values and the residential property tax revenue impacts of agricultural easement programs. *Agricultural and Resource Economics Review* 32(1): 33-45.

Geoghegan, Jacqueline, Lisa Wainger, and Nancy E. Bockstael (1997). Spatial landscape indices in a hedonic framework: an ecological economics analysis using GIS. *Ecological Economics* 23(3): 251-264.

Gustanski, Julie Ann, and Roderick H Squires (2000). Conservation easements, voluntary actions and private lands. In *Protecting the Land: Conservation Easements Past, Present and Future.* California: Island Press, Chapter 1.

Ham, Charlotte, John B. Loomis, and Patricia A. Champ (2015). Relative economic values of open space provided by national forest and military lands to surrounding communities. *Growth and Change* 46(1): 81-96.

Hammer, Thomas R., Robert E. Coughlin, and Edward T. Horn IV (1974). The effect of a large urban park on real estate value. *Journal of the American Institute of Planners* 40(4): 274-277.

Hamilton, Stuart E., and Ash Morgan (2010). Integrating Lidar, GIS and hedonic price modeling to measure amenity values in urban beach residential property markets. *Computers, Environment and Urban Systems* 34(2): 133-141.

Hidano, Noboru (2002). *The Environmental Valuation of the Environmental and Public Policy.* North Hampton, MA: Edward Elgar Publishing Inc.

Huff, David L. and George F. Jenks (1968). A graphic interpretation of the friction of distance in gravity models. *Annals of the Association of American Geographers*. Vol. 58(4): 814-824.

Irwin, Elena G (2002). The effects of open space on residential property values. *Land Economics* 78(4): 465-480.

Irwin, Elena G. and Nancy E. Bockstael (2001). The problem of identifying land use spillovers: measuring the effects of open space on residential property values. *American Journal of Agricultural Economics*: 698-704.

Kadish, Jonathan, and Noelwah R. Netusil (2012). Valuing vegetation in an urban watershed. *Landscape and Urban Planning* 104(1): 59-65.

Kestens, Yan; Marius Thériault, and François Des Rosiers (2004). The impact of surrounding land use and vegetation on single-family house prices. *Environment and Planning B: Planning and Design* 31(4): 539-567.

Lake, Iain R., Andrew A. Lovett, Ian J. Bateman, and Ian H. Langford (1998). Modeling environmental influences on property prices in an urban environment. *Computers Environment and Urban Systems* 22(2): 121-136.

Lake, Iain. R., AA Lovett, Ian J Bateman, and B Day (2000). Using GIS and large-scale digital data to implement hedonic pricing studies. *International Journal of Geographical Information Science* 14(6): 521-541.

Lansford, Notie H., and Lonnie L. Jones (1995). Marginal price of lake recreation and aesthetics: An hedonic approach. *Journal of Agricultural and Applied Economics* 27: 212-223.

Li, Wei, and Jean-Daniel Saphores (2012). A spatial hedonic analysis of the value of urban land cover in the multifamily housing market in Los Angeles. *Urban Studies* 49(12): 2597-2615.

Lin, T. G., Xia, J. C., Robinson, T. P., Olaru, D., Smith, B., Taplin, J., & Cao, B. (2016). Enhanced Huff model for estimating Park and Ride (PnR) catchment areas in Perth, WA. *Journal of Transport Geography*, 54: 336-348.

Lindsey, Greg, Joyce Man, Seth Payton, and Kelly Dickson (2004). Property values, recreation values, and urban greenways. *Journal of Park and Recreation Administration* 22(3): 69-90.

Malpezzi, Stephen (2003). Hedonic pricing models: a selective and applied review. *Section in Housing Economics and Public Policy: Essays in Honor of Duncan Maclennan*.

McConnell, Virginia D., Margaret A. Walls, and Elizabeth A. Kopits (2005). Zoning, TDRs, and the density of development. *Resources for the Future*, Discussion Paper 05-32 (July) accessed on February 2, 2009 from http://www.rff.org/RFF/Documents/RFF-DP-05-32-rev.pdf.

McConnell, Virginia, and Margaret A. Walls (2005). *The value of open space: Evidence from studies of nonmarket benefits*. Washington, DC: Resources for the Future.

Mitchell, Steven B., and Bruce B. Johnson (2005). Valuing farmland conservation easements. *Institute of agriculture and natural resources, University of Nebraska - Lincoln Extension*. Accessed from http://www.ianrpubs.unl.edu/epublic/live/g1428/build/g1428.pdf on July 24, 2007.

Mittal, Jay and Sweta Byahut (2016 in Press). Value capitalization effect of golf course, waterfront, parks and open spaces – A cross disciplinary review. *Journal of Sustainable Real Estate* 8 (1), p. 27.

Mittal, Jay. (2014). Value capitalization effect of protected properties – A comparison of conservation easement with mixed-bag open spaces. *Journal of Sustainable Real Estate* 6(1): 23-46.

Mooney, Sian, and Ludwig M. Eisgruber (2001). The influence of riparian protection measures on residential property values: the case of the Oregon plan for salmon and watersheds. *The Journal of Real Estate Finance and Economics* 22(2-3): 273-286.

Nakaya, Tomoki (2014). GWR4 user manual: Windows application for Geographically Weighted Regression modelling. accessed on February 2, 2016 from https://geodacenter.asu.edu/drupal_files/gwr/GWR4manual.pdf.

Netusil, Noelwah R (2005). The effect of environmental zoning and amenities on property values: Portland, Oregon. *Land Economics* 81(2): 227-246.

Nicholls, Sarah, and John L. Crompton (2005). The impact of greenways on property values: Evidence from Austin, Texas. *Journal of Leisure Research* 37(3): 321.

Orford, Scott (2002). Valuing locational externalities: a GIS and multilevel modelling approach. *Environment and Planning B: Planning and Design* 29: 105–127.

Payton, Seth, Greg Lindsey, Jeff Wilson, John R. Ottensmann, and Joyce Man (2008). Valuing the benefits of the urban forest: A spatial hedonic approach. *Journal of Environmental Planning and Management* 51(6): 717-736.

Pooler, James (1987). Measuring geographical accessibility: A review of current approaches and problems in the use of population potentials. *Geoforum* 18(3): 269-289.

Poudyal, Neelam C., Donald G. Hodges, John Fenderson, and Ward Tarkington (2010). Realizing the economic value of a forested landscape in a viewshed. *Southern Journal of Applied Forestry* 34(2): 72-78.

Powe, Neil A., Guy Garrod, Chris Brunsdon, and Ken Willis (1997). Using a geographic information system to estimate a hedonic price model of the benefits of woodland access. *Forestry* 70(2): 139-49.

Sander, Heather A., and Robert G. Haight (2012). Estimating the economic value of cultural ecosystem services in an urbanizing area using hedonic pricing. *Journal of Environmental Management* 113: 194-205.

Sander, Heather, Stephen Polasky, and Robert G. Haight (2010). The value of urban tree cover: A hedonic property price model in Ramsey and Dakota Counties, Minnesota, USA. *Ecological Economics* 69(8): 1646-1656.

Sander, Heather A., and Stephan Polasky (2009). The value of views and open space: estimates from a hedonic pricing model for Ramsey County, Minnesota, USA. *Land Use Policy* 26: 837–845.

Sander, Heather A., and Steven M. Manson (2007). Heights and locations of artificial structures in viewshed calculation: How close is close enough? *Landscape and Urban Planning* 82: 257–270.

Saphores, Jean-Daniel, and Wei Li (2012). Estimating the value of urban green areas: A hedonic pricing analysis of the single family housing market in Los Angeles, CA. *Landscape and Urban Planning* 104(3): 373-387.

Shultz, Steven D., and Nicholas J. Schmitz (2009). Augmenting housing sales data to improve hedonic estimates of golf course frontage. *Journal of Real Estate Research* 31(1): 63-79.

Shultz, Steven and Nick Schmitz (2008). View shed analyses to measure the impact of lake views on urban residential properties. *The Appraisal Journal* 76(3): 224-232.

Sirmans, G. Stacy, Lynn MacDonald, David A. Macpherson, Emily Norman Zietz (2006). The value of housing characteristics: A meta-analysis. *The Journal of Real Estate Finance and Economics* 33(3): 215-240.

Simons, Robert, and Jesse Saginor (2006). A meta-analysis of the effect of environmental contamination and positive amenities on residential real estate values. *Journal of Real Estate Research* 28(1): 71-104.

Thorsnes, Paul (2002). The value of a suburban forest preserve: Estimates from sales of vacant residential building lots. *Land Economics* 78(3): 426-441.

Troy, Austin and Morgan Grove (2008). Property values, parks, and crime: A hedonic analysis in Baltimore, MD. *Landscape and Urban Planning* 87: 233–245.

Walls, Margaret, Carolyn Kousky, and Ziyan Chu (2015). Is what you see what you get? The value of natural landscape views. *Land Economics* 91(1): 1-19.

Walsh, Patrick J., J. Walter Milon, and David O. Scrogin (2011). The spatial extent of water quality benefits in urban housing markets. *Land Economics* 87(4): 628-44.

Wang, Fahui (2015). GIS-based measures of spatial accessibility and application in examining health care access. Chapter 5 in *Quantitative Methods and Socio-Economic Applications in GIS* 2nd Ed. Boca Raton, Fl: CRC Press Taylor & Francis Group.

Wright, John B (1994). Designing and applying conservation easements. *Journal of the American Planning Association* 60(3): 380-388.

Wyman, David, Norman Hutchison, and Piyush Tiwari (2014). Testing the waters: A spatial econometric pricing model of different waterfront views. *Journal of Real Estate Research* 36(3): 363-382.

Xiao, Yang, Scott Orford, Chris J Webster (2016). Urban configuration, accessibility, and property prices: A case study of Cardiff, Wales. *Environment and Planning B: Planning and Design* 43: 108–129.

Table 1: Summary of all environmental amenities by type, and their effects on surrounding home values due to 'proximity to' and aesthetic 'view of' from reviewed studies

Sl No.	Environmental Amenity by Land Use Type	% Price effect on home values due to 'Proximity to' amenity		% Price effect on home values due to Aesthetic 'View of' amenity	
		Min	Max	Min	Max
1	Golf Course	1.1% Cho et al (2009)	28.0% Shulz & Schmitz (2009)	7.0% Asabere & Huffman (1996)	28.0 % Shulz & Schmitz (2009) 85% -- empty lots Wyman et al (2014)
	Water Fronts	1.2%	101.9.	0.03	147% (223 -- lots)
2	Oceanfront and Ocean nearing	1.7% Hamilton & Morgan (2010)	101.9% Conroy and Milosch (2011)	47% Bin et al. (2008)	147.2% Benson et al. (1997)
3	Lakefront and Lake nearing	1.24% Walsh et al. (2011)	31.8% Lansford and Jones (1995)	7.5% Shulz and Schmitz (2008)	126.7% Benson et al. (1998) 223% -- empty lots Wyman et al (2014)
4	Rivers/ Streams	1% Cho et al (2009)	54.4% Netusil (2005)	-	9.6% Bowman et al. (2009)
5	Trails and Greenways	2.4 Lindsey et al. (2004)	14.0% Lindsey et al. (2004)	2-5% Asabere & Huffman (2009)	20.2% Nicholls & Crompton (2005)
	Miscellaneous Open Spaces				
6	Large Urban Parks	-	20% Crompton (2005)	-	20% Crompton (2005)
7	Misc. Surrounding Open Spaces	Difficult to report in percentage terms but price contributory in general			
8	Farms and Forests				19-35.0% Thorsnes (2002)
	All				

Source: Authors compiled.

Table 2: Palette of variables used to define Proximity and View of home to environmental amenity

Variants of "Proximity of" Amenity	Variants of "View Of" Amenity
Discreet Amenities	
House to amenity direct (crow flying, Euclidean) distance in feet/miles *defined as* d_{ij}	Whether amenity is visible or not visible from home samples (binary dummy as yes/no)
House to amenity road network distance in feet/miles	The extent of view as angular view from home to amenity (site inspection +view shed)
House is adjacent, or abutting, or fronting the amenity (same as view)	House is adjacent, or abutting, or fronting the amenity (same as proximity)
Buffer distance circles (from amenity to home)	View extent, angle and quality of view (Inspection based)
Gravity based accessibility indices as a weighted average of inverse distances for multiple amenities: $A_i = \sum_j Size_{ij} / d_{ij}^{\lambda}$	
Non-Discrete Amenities	
Buffer distance circles (from home to amenity) Houses at a fixed buffer distance from amenity (200', ¼, mile ½, mile, 1 mile) buffer or location dummies). Buffer is drawn around amenity, if it is a recognizable amenity, otherwise buffers are drawn around each homes to capture amenity surrounding homes that is not distinctly identifiable as amenity.	Home to amenity, GIS based view sheds within a predefined buffer distance to measure (View scores; total viewable surface areas, percentage visible open spaces with types; percentage of visible desirable land uses or land covers; measuring land use diversity index)
	Extent and visible area covered using GIS view sheds[7] (locations visible / not visible as binary); total visible acreage of amenity such as ocean area, lake area, green areas, tree canopy cover)

Source: Authors complied

[7] Viewshed is a term used to indicate the entire area an individual can see from a given point.

Table 3: Descriptive statistics of home samples (n=1,243) 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	$56,361
LotSqft	Lot area (Sqft)	1,227	231,198	10,186.9	9391.40
TULA	Total Utilizable Built Area (Sqft)	?	?	?	?
Bath	No. of Bathrooms	1	6	1.30	0.54
H_Bath	No. of Half Bathrooms	1	2	0.45	0.52
Qual	Assessor assigned home quality index (20 to 60)	0	60	40.1	4.20
Age	Age of Home (Year)	0	166	57.8	32.9
Deck	Deck Binary (Y/N)	0	1	0.30	0.46
Hous_Dens	Housing Density in the neighborhood-(No. of Houses/ Acre in census block group)	0.11	13.24	3.10	2.50
MedHsg_Val	Median Housing Value ($) of owner occupied houses in census block group	71,700	$261,500	$121,797.70	25,059.20
Perc_Black	Percentage of Blacks in census block group	0.00	34.84	4.64	5.12
GIVI_1	Gravity Inspired Visibility Index (B=1)	0.00	3.623	0.0801	0.277
GIVI_1.5	Gravity Inspired Visibility Index (B=1.6)	0.00	7.37	0.0723	0.417
GIVI_2	Gravity Inspired Visibility Index (B=2)	0.00	8.89	0.0676	0.480

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

Table 4 Global Model Vs. Geographically weighted regression (GWR) Model Outcomes

Variables	Expected Sign	Global Model		GWR Local Model
		Estimates	t Values	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_1~~	~~+ ve~~	-	-	-
~~GIVI_1.5~~	~~+ ve~~	-	-	-
GIVI_2	+ ve	2843.08	1.22	83855.97
Diagnostics				
Adjusted Rsq		**0.518**		**0.589**
AIC		29828		**29702.56**
Bandwidth		Global		

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

Table 5: GWR ANOVA Table

Source	SS	DF	MS	F
Global Residuals	1882199518757.44	1231.00		
GWR Improvement	456090993427.64	137.40	3319480301.33	
GWR Residuals	1426108525329.80	1093.60	1304047481.16	2.55

Table 6 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 7 GWR bandwidth selection

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

Table 8 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

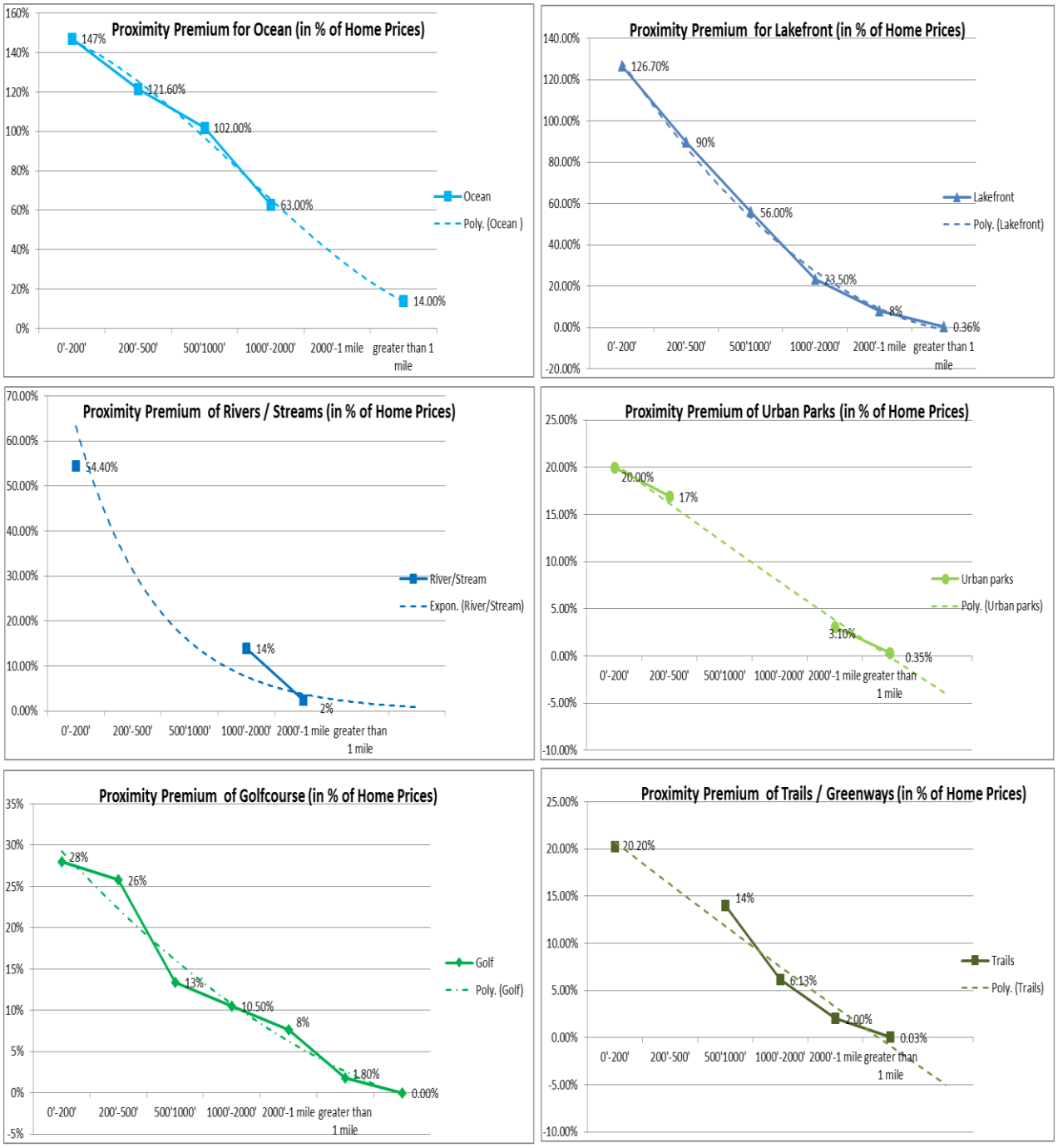
Table 9 Fixed (Global) coefficients

Variable	Estimate	Standard Error	t(Estimate/SE)
HOUS_DEN	Chk??	748.41	-2.88
MD_HSgVal	-0.31	0.14	-2.29
PRC_BLAC	-756.90	285.33	-2.65

Table 10 Summary statistics for varying (Local) coefficients from GWR

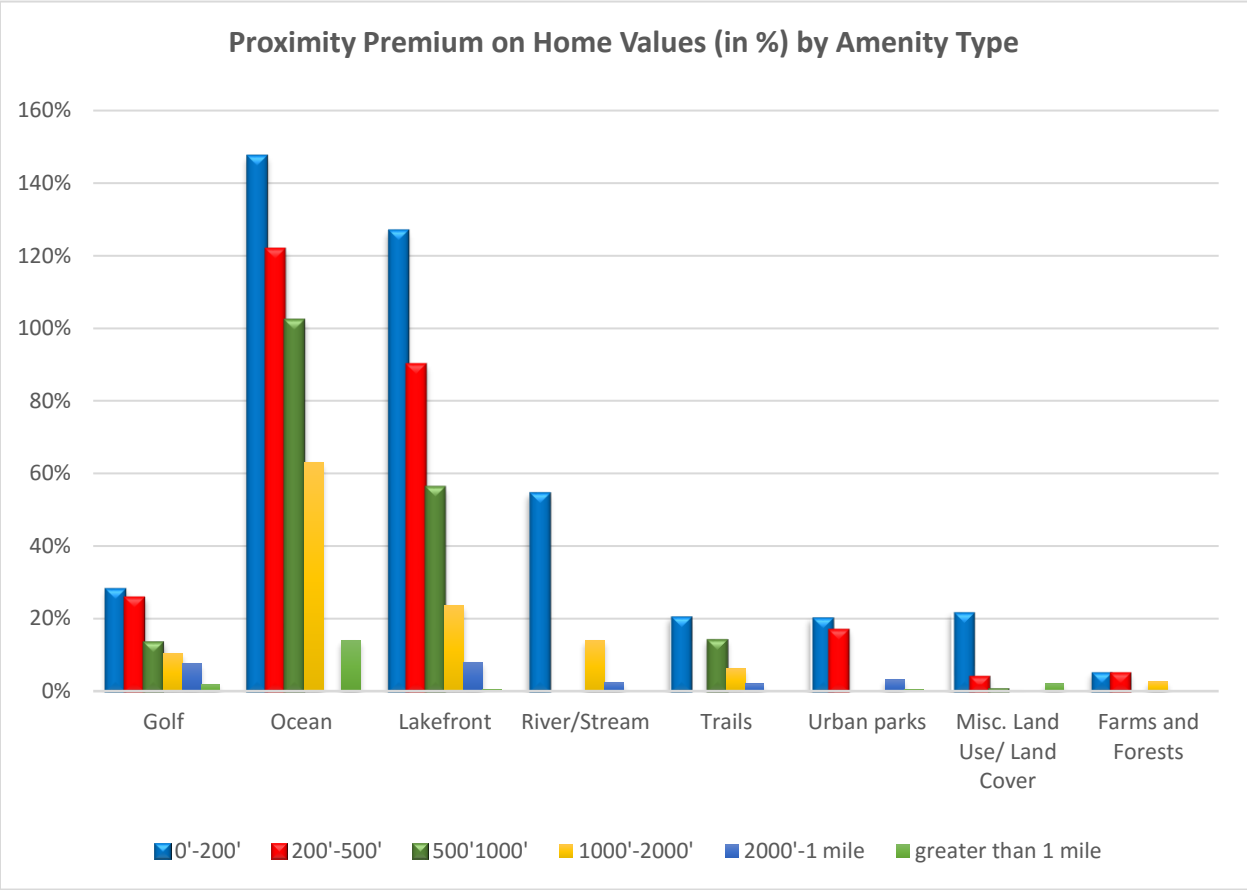
Variable	Mean	STD	Min	Max	Range	Lwr Quartile	Median	Upr Quartile
Intercept	58268.86	118567.95	-202988.56	227138.07	430126.64	-45616.46	90343.80	163479.49
LOTSFt	1.73	1.15	-0.077	5.87	5.95	1.02	1.34	2.25
BATH	10575.07	8722.39	-13722.46	26032.27	39754.73	3894.76	14403.61	17406.47
HBATH	1405.16	8600.31	-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 1: Proximity Premium by Amenity Types



Source: Author Compiled

Figure 2 Proximity Premium on Home Values by Amenity Type



Source: Extracted from reviewed studies

Figure 3: Map of Home samples *(i)* and the CE Parcels *(j)* in Worcester, MA

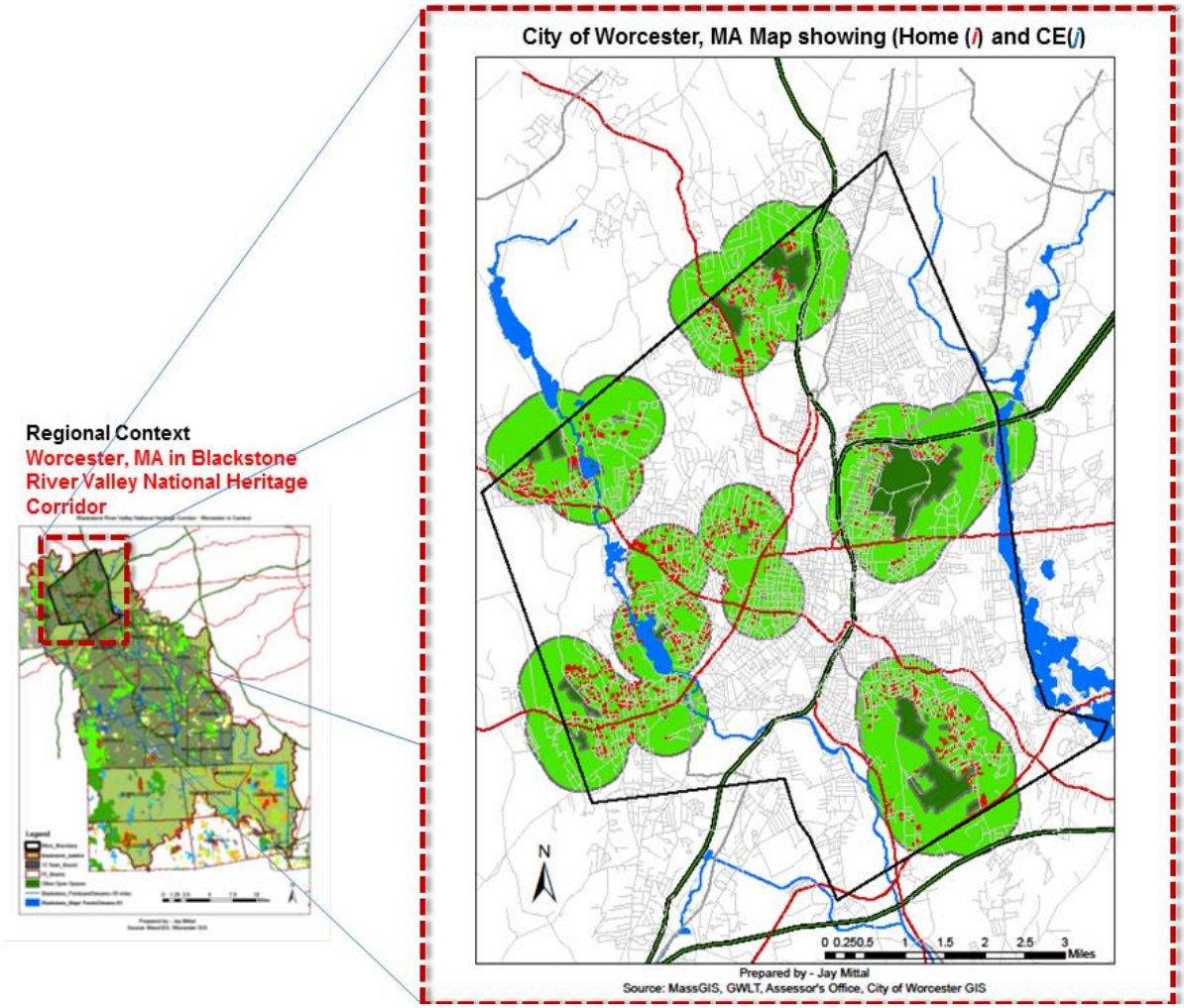


Figure 4: Visible Area Matrix V_{ij}

$$\textit{Visible Area Matrix } V_{ij} = \begin{vmatrix} & CE1 & - & CE26 \\ Home1 & V1,1 - & - & - \\ Home2 & - & - & - \\ - & - & - & - \\ - & - & - & - \\ - & - & - & - \\ Home\ 1243 & V1243,1 & - & V1243,26 \end{vmatrix}$$

Figure 5: *Distance Matrix* d_{ij}

$$\textit{Distance Matrix } d_{ij}..= \begin{vmatrix} & CE1 & - & CE26 \\ Home1 & d1,1 - & - & - \\ Home2 & - & - & - \\ - & - & - & - \\ - & - & - & - \\ - & - & - & - \\ Home\ 1243 & d1243,1 & - & d1243,26 \end{vmatrix}$$

Figure 6 : Spatially varying characteristics of GIVI values, R-squared values, and Cooks'D

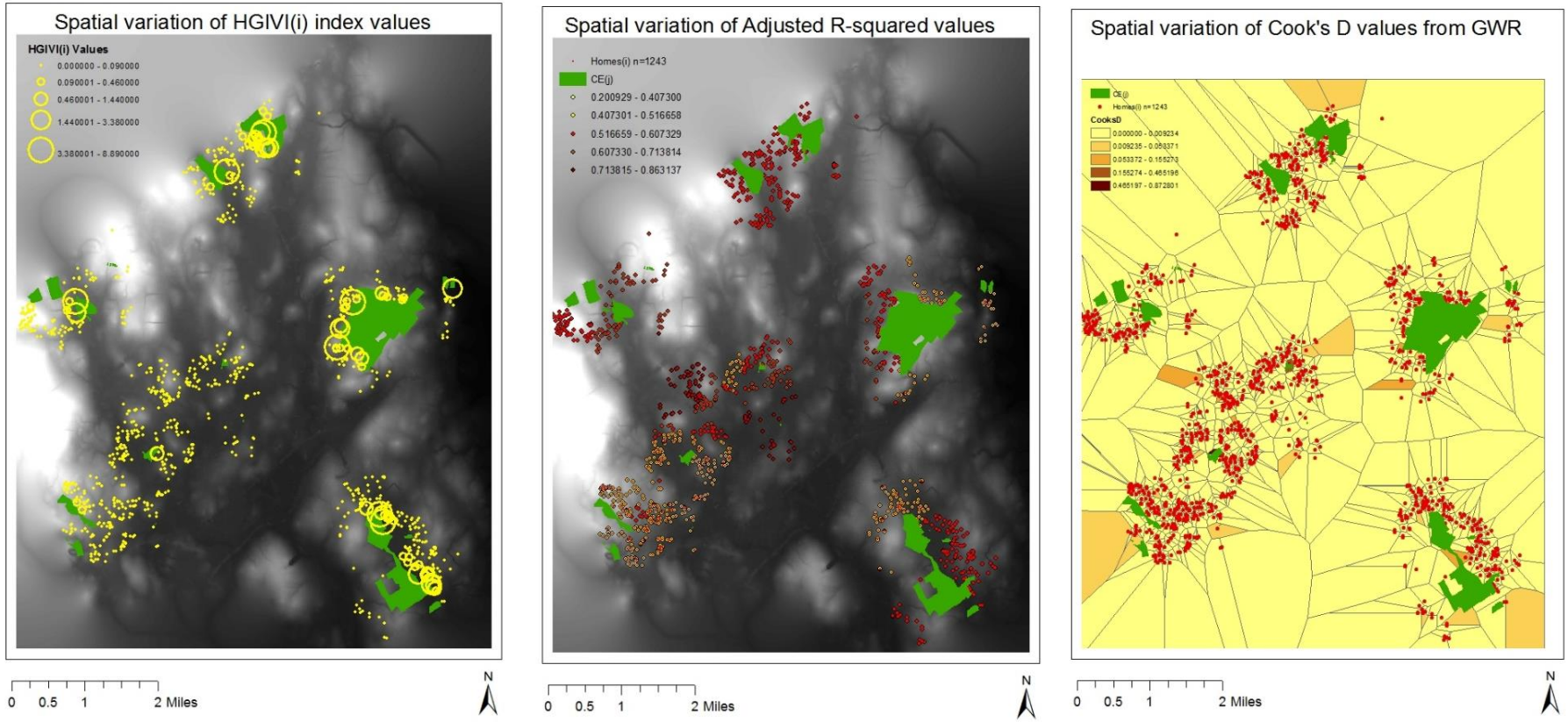


Figure 7: Spatially varying characteristics of Home premiums (Percentage values)