Measuring the Contribution of Water and Green Space Amenities to Housing Values: An Application and Comparison of Spatially-weighted Hedonic Models

by

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This study estimates the influence of proximity to water bodies and park amenities on residential housing values in Knox County, Tennessee, using the hedonic price approach. Values for proximity to water bodies and parks are first estimated globally with a standard ordinary least square (OLS) model. A locally weighted regression model is then employed to investigate spatial non-stationarity and generate local estimates for individual sources of each amenity. The local model is able to capture the variability in the quality of water bodies and parks across the county, something a conventional hedonic model using OLS cannot do.

Key words: locally weighted regression, water bodies, park, hedonic model, spatial

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Introduction

Between 1998 and 2004, 935 out of 1,215 conservation ballot measures in the U.S. passed, raising close to $25 billion in funding for land conservation in 44 states (The Trust for Public and Land Trust Alliance). Voters have thus shown consistent support for open space protection across the United States. A key question, however, is the extent to which public open space is capitalized into nearby residential property values, and thus would increase property tax collections. In some communities open space protection is linked to water resources as well. For example, in Knox County, Tennessee, community leaders are seeking to protect open space along the French Broad River, an area threatened with development as the sprawling City of Knoxville continues to grow. This initiative is designed to create an open space corridor of river and land that would include a Blueway, equestrian trail, wildlife refuge, historic sites, natural areas, parks and agricultural land (Knoxville-Knox County Metropolitan Planning Commission). Estimates of the impact of water and parks on the value of nearby property would be of use in estimating the cost of such initiatives and prioritizing of land parcels to be conserved as open space.

There are two ways to measure these kinds of amenity values. One is to use a survey-based method such as travel cost or contingent valuation. The hedonic pricing approach is the other option. Hedonic methods have been gaining popularity in recent years with application of spatial analyses using geographical information system (GIS). The hedonic price approach has long been used to quantify the impact of open space on residential housing value, including urban parks (Barnett; Bolitzer and Netusil; Do and Grudnitski; Doss and Taff; Lutzenhiser and Netusil;

Vaughn) and golf courses (Bolitzer and Netusil; Lutzenhiser and Netusil). A common finding in these studies is that green spaces of these types have positive impacts on residential property values up to a distance of ¼ to ½ mile. Up to 3% of the value of properties could be attributed to park proximity, while proximity to golf courses increased surrounding property values as much as 21%. Recently, McConnell and Walls reviewed more than 60 published articles that have attempted to estimate the value of different types of open space.

The hedonic property price method also has been used to estimate the value of selected water resources, including lakes and reservoirs, on nearby property values (Brown and Pollakowski; D'Arge and Shogren; Darling; David; Feather, Pettit, and Ventikos; Knetsch; Lansford and Jones; Reynolds et al.; Young and Teti). A common finding across these studies is that both the size of lake frontage and lake proximity increase property values. Additionally, the demand for protecting freshwater lakes has been estimated using the hedonic approach (e.g., Boyle et al.). In another study, seven case studies were undertaken to investigate how much people value groundwater quality and why (Bergstrom et al.). Wilson and Carpenter provide a comprehensive synthesis of peer-reviewed economic data on surface freshwater ecosystems in the United States and examine major accomplishments and gaps in the literature from 1971 to 1997.

While the conceptual logic of the hedonic price approach for capturing the impacts of the green spaces, lakes and other environmental amenities appears sound, hedonic models are often criticized with regard to specification and calibration issues (Mason and Quigley; Orford). Claims of mis-specification resulting from missing house value determinants, collinearity among the determinants, and spatial dependency have been made. Furthermore, urban and regional economists have long challenged the assumption of the typical hedonic model that a stationary relationship exists between house prices and housing attributes within a housing market (Adair, Berry, and McGreal; Goodman and Thibodeau; Maclennan; Watkins; Whitehead). The critics suggest unitary housing markets might not exist, but rather are composed of interrelated submarkets.

Multilevel modeling techniques are often employed to deal with joint influence of different submarkets (Goodman and Thibodeau; Jones and Bullen; Orford). The multilevel modeling technique defines housing submarkets by structural attributes, geographical location, demander groups, and the joint influence of structural and spatial attributes. Two problems arise, however, with their application. One is the assumption that the exact pattern of non-stationarity in the relationships is known, which demands a priori knowledge and understanding of the local housing market which the researchers are unlikely to have. The second is that imposing a discrete set of boundaries on the housing market to identify sub-markets may not be realistic because the spatial processes in housing market dynamics are continuous (Fotheringham, Brunsdon, and Charlton 2002). In addition, necessary data for the multilevel modeling is limited.

The Box-Cox transformation is often applied to account for the well-known non-normality of disturbances in hedonic price functions. The Box-Cox model is estimated with correction for causes of heteroscedasticity in the literature (Goodman and Thibodeau; Fletcher, Gallimore, and Mangan). However, the Box-Cox model does not correct heteroscedasticity in the disturbances caused by spatial autocorrelation.

In this study, a locally weighted regression approach, as first proposed by Cleveland and Devlin, is adopted to deal with the non-stationarity and spatial autocorrelation issues and allow for estimates of the value of proximity to individual green spaces and water resources. The methodology allows regression coefficients to vary across space in terms of the first law of geography (Tobler, p.236).[1] No a priori assumption regarding a particular pattern of market non-stationarity is required. The approach has recently been applied intensively to test local heterogeneity (Brunsdon, Fotheringham, and Charlton 1996, 1999; Fotheringham and Brunsdon; Fotheringham, Brunsdon, and Charlton 1998, 2002; Huang and Leung; Leung, Mei, and Zhang 2000a, 2000b; Paez, Uchida, and Miyamoto, 2002a 2002b; Yu and Wu). To the best of our knowledge, there has been no prior attempt to measure values of multiple spatial attributes at the individual level using the approach in a hedonic property model framework.

The remainder of the paper is organized as follows. First, a brief discussion of the hedonic price model and application of the locally weighted regression methodology within the hedonic price model is presented. Second, the study area, Knox County, Tennessee, and the data are described. Third, the analytical results are presented and discussed. Finally, a summary and conclusions section is provided.

Methodology

Consider an hedonic model of housing sale prices expressed as

$$\ln y_i = \beta_0 + \sum_k \beta_k x_{ik} + \varepsilon_i , \tag{1}$$

where $\ln y_i$ is the natural log of the sale price of a house in a location *i*, x_{ik} are variables of structural, neighborhood, and location characteristics *k*, and ε_i is a residual capturing errors. The hedonic model establishes a functional relationship between the observed households' expenditure on housing and these characteristics. Eight key structural characteristics are available and included in this study: total finished square footage, lot size, building age, number of bedrooms, existence of a garage, existence of a fireplace, all sided brick exterior, and existence of swimming pool. In addition to the key characteristics, quality of construction and condition of the structure are included. These two variables are created by six scales, e.g., excellent, very good, good, average, fair, and poor that are rated by tax assessors' office. These structural characteristics and quality and condition variables serve as control variables and are typically found to play a large part in explaining housing price variation in the literature. Quadratic specifications for some of the structure variables such as total finished square footage, lot size, age, and number of bedrooms are used to capture non-linear effects (e.g., Bin and Polasky; Chan; Mahan, Polasky, and Adams).

Neighborhood characteristics were reflected primarily by data from the 2000 census on population density, average travel time to work, average per capita income, unemployment rate, vacancy rate, and urban versus rural areas at the level of census-block group. Population density is included as a measure of how its pressure on land and natural resources affects the housing market (Katz and Rosen). Average travel time to work is included as a spatial measure of the distance to the employment hub. The average per capita income and unemployment are included as measures of the relative economic status of a neighborhood (Downs; Phillips and Goodstein). Vacancy rate is included as an indicator to capture prevailing housing market conditions (Dowall and Landis). Another neighborhood variable employed was high school district, as a proxy for school quality. Previous literature has found a positive correlation between school quality with house prices (e.g., Bogart and Cromwell; Hayes and Taylor). In addition, dummy variables were included for the town municipalities within the county, the City of Knoxville and the Town of Farragut. The Knoxville Utilities Board confirmed that there are no community variations with the rates for gas, water, electricity. However, there are differences between the rural and urban areas with regard to public services such as roads and law enforcement. The differences are captured using a dummy variable reflecting urban and non-urban communities.

Location variables included distance to downtown, distance to nearest water body, distance to nearest greenway, distance to nearest railroad, distance to nearest park, and size of nearest park. These distance variables are intended to capture the effect on housing prices of the proximity to various amenities and disamenities. The size of nearest park is intended to capture the premium being closer to the bigger park. Park size has been found to be a significant factor on property value (Lutzenhiser and Netusil). By the same token, variables reflecting quality of water bodies and floodplain area might capture amenity or disamenity effects of being closer to water bodies. A dummy variable, indicating whether or not there is any impairment incident report by Environmental Protection Agency, is included. To separate any floodplain effect from the effect of proximity to water body, a dummy variable for location in a stream protection area (representing all of the flood fringe area of the 500 year flood plain) in the county is created and included in the model.

Previous studies have found that a log transformation of distance variables generally performs better than a simple linear functional form because the log transformation captures the declining effect of these distance variables (Bin and Polasky; Iwata, Murao, and Wang; Mahan, Polasky, and Adams). A log transformation of the quadratic specifications for some of the structure variables was attempted but the transformation was not found to improve the model. Thus, a natural log transformation for distance-related variables in X_{ik} is used in this study.

Previous studies have found that the mortgage interest rate is one of the significant drivers of housing price dynamics (e.g., Tsatsaronis and Zhu). Because the mortgage interest rate fluctuated a great deal during the years of the sales for our sample, monthly rate of the prime interest (Board of Governors of the Federal Reserve System) is used to capture this effect. House prices are also believed to be vary seasonally - that is, prices are higher in spring and summer irrespective of the overall trend. More buyers tend to be in the market during the spring and summer, pushing the demand curve to the right and increasing the equilibrium housing price. A seasonal dummy is included to capture the expected difference in housing prices between spring/summer and fall/winter.

Heteroscedasticity often occurs in cross-section data when there is a wide range to the X variables. A log transformation is one way in which heteroscedasticity can be removed, because this transformation reduces the variation in the variables. However, taking the logs may not prevent the problem. Thus, Breusch-Pagan Lagrange multiplier test was conducted for heteroscedasticity in the error distribution, conditional on a set of variables which are presumed to influence the error variance. The test statistic, a Lagrange multiplier measure, has a Chi-squared distribution under the null hypothesis of homoscedasticity. As the Lagrange multiplier measure rejects the hypothesis, the heteroscedasticity is corrected. Sometimes the form of the heteroscedasticity is clear and can be modeled. More commonly, though, heteroscedasticity is a nuisance that can not be modeled because its source is not well understood. Long and Ervin suggest that the approach using a heteroscedasticity consistent covariance matrix proposed by MacKinnon and White is the best. In Stata 9.1, the HC3 option is used in the REG command for the calculation of the consistent estimator in the presence of heteroscedasticity of an unknown form.

Another concern in regression models with many explanatory variables is multicollinearity. The multicollinearity can seriously inflate the standard errors of the estimates and render hypothesis testing inconclusive. If the correlation coefficient between two regressors is greater than 0.8 or 0.9, multicollinearity may be a serious problem (Judge et al., p.620). Multicollinearity can also be detected by variance inflation factors (Maddala). Variance inflation factors (vif) are a scaled version of the multiple correlation coefficients between variable k and the rest of the independent variables. Specifically, $\mathrm{vif_k} = 1/(1-\mathrm{R_k}^2)$, where $\mathrm{R_k}$ is the multiple correlation coefficient. Multicollinearity occurs when two (or more) variables are linearly related. There is no clear guideline for how big vif must be to reflect serious multicollinearity. The variables removed from the initial model because of a potential problem with multicollinearity were distance to nearest golf course and distance to the Great Smoky Mountains National Park. Both variables are highly correlated with distance to park with correlation coefficients greater than 0.6 and variance inflation factors greater than 10.0. Global Moran's Index (Moran) is used to measure spatial autocorrelation in sale price of a house variable. The index is a measure of the overall spatial relationship across geographical units and is defined as

(2) $$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (y_i - \bar{y})(y_j - \bar{y})}{(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}) \sum_{i=1}^{n} (y_i - \bar{y})^2}$$

where n is the sample size, y_i is the sale price of a house i with sample mean $\bar{y}$, and w_{ij} is the distance based weight that is the inverse distance between houses i and j. Like a correlation coefficient, a positive value of Moran's stands for positive spatial autocorrelation, e.g., similar, regionalized, or clustered observations, 0 (approximately in finite samples) for a random pattern, and negative value for negative spatial autocorrelation, for instance, a dissimilar, contrasting pattern (Goodchild, p.16-17). As spatial autocorrelation is detected in the sale price of a house variable, a neighborhood variable that can capture spatial autocorrelation is included. Median housing value of census-block group is used to capture direct interdependencies of housing prices in the neighborhoods at the level of census-block group.

Equation (1) can be considered as a global model, in contrast to the locally weighted regression. The partial derivatives of the hedonic price function with respect to each characteristic in the global model yield an overall marginal implicit price. For example, the first partial derivative for the characteristic distance to the nearest park represents the added value associated with being located one unit closer to the nearest park overall. It is important to note that this marginal implicit price for the nearest park overall is essentially an average across all parks in the study area. The willingness-to-pay (WTP) for increased proximity to any particular individual park is not revealed in the global model. This is especially troubling if the attributes of parks are not homogeneous in a given area.

We estimate the following hedonic price equation for the locally weighted regression using the software, GWR 3.0 developed by Fotheringham, Brunsdon, and Charlton (2002):

$$\ln y_i = \beta_0(u_i, v_i) + \sum_k [\beta_k(u_i, v_i) x_{ik}] + \varepsilon_i, \tag{3}$$

where, (u_i, v_i) denotes the coordinates of the *i*th point in space and $\beta_k(u_i, v_i)$ is a realization of the continuous function $\beta_k(u, v)$ at point *i*. That is, we allow a continuous surface of parameter values, and measurements of this surface are taken at certain points to denote the spatial variability of the surface (Fotheringham, Brunsdon, and Charlton 2002).

Calibration of the locally weighted regression model follows a local weighted least square approach. Different from OLS, the locally weighted regression assigns weights according to their spatial proximity to location *i* in order to account for the fact that an observation near location *i* has more of an influence in the estimation of the $\beta_k(u_i, v_i)$s than do observations located farther from *i*. That is,

$$\hat{\beta}(u_i, v_i) = (X^T W(u_i, v_i) X)^{-1} X^T W(u_i, v_i) Y \tag{4}$$

where, $\hat{\beta}$ represents an estimate of β, X is a vector of the variables of structural, neighborhood, and location characteristics $\ln x_{ik}$, Y is a vector of $\ln y_i$, $W(u_i, v_i)$ is an $n \times n$ diagonal matrix with diagonal elements w_{ii} denoting the geographical weighting of observed data point for location *i*.

To better understand how locally weighted regression operates, consider the locally weighted regression equivalent of the classical regression equation,

(5) $$Y = (\beta \otimes X)\mathbf{1} + \varepsilon$$

where $\otimes$ is a logical multiplication operator in which each element of β is multiplied by the corresponding element of X, and **1** is a conformable vector of 1's. If there are n data points and k explanatory variables including the constant term, both β and X will have dimensions $n \times k$. The matrix β now consists of n sets of local parameters and has the following structure:

(6) $$\beta = \begin{bmatrix} \beta_0(u_1, v_1) & \beta_1(u_1, v_1) & \ldots & \beta_k(u_1, v_1) \\ \beta_0(u_2, v_2) & \beta_1(u_2, v_2) & \ldots & \beta_k(u_2, v_2) \\ \ldots & \ldots & \ldots & \ldots \\ \beta_0(u_n, v_n) & \beta_1(u_n, v_n) & \ldots & \beta_k(u_n, v_n) \end{bmatrix}$$

$W(i)$ is an $n \times n$ spatial weighting matrix of the form

(7) $$W(i) = \begin{bmatrix} w_{i1} & 0 & \ldots & 0 \\ 0 & w_{i2} & \ldots & 0 \\ . & . & \ldots & . \\ 0 & 0 & \ldots & w_{in} \end{bmatrix}$$

where w_{ij} is the weight given to data point *j* in the calibration of the model for location *i*. The diagonal elements of the weight matrix, w_{ij}, are equal to:

(8) $$w_{ij} = [1 - (d_{ij} / b)^2]^2 \text{ if } d_{ij} < b$$

$$= 0 \text{ otherwise}$$

where d_{ij} is the Euclidean distance between point *i* and *j* and *b* is a chosen bandwidth.[2] At the regression point *i*, the weight of the data point is unity and falls to zero when the distance between *i* and *j* equals the bandwidth or higher.

As b tends to be infinity, w_{ij} approaches 1 regardless of d_{ij} in which case the parameter estimates become uniform and locally weighted regression is equivalent to OLS. Conversely, as *b* becomes smaller, the parameter estimates will increasingly depend on observations in close proximity to location *i* and hence have increased variance. A cross-validation (CV) approach is suggested for local regression for a selection of optimal bandwidth (Cleveland). CV takes the following form[3]:

(9) $$CV = \sum_{i=1}^{n}[y_i - \hat{y}_{\neq i}(b)]^2$$

where $\hat{y}_{\neq i}(b)$ is the fitted value of y_i with the observations for point *i* omitted from the fitting process. The bandwidth is chosen to minimize CV. Thus, in the local weighted regression model, only houses up to the optimal level of *b* are assigned non-zero weights for the nearest neighbors of census-block group i. The weight of these points will decrease with their distance from the regression point. Sensitivity analysis was conducted for bandwidths of plus and minus 50% of the b selected by the CV approach.

Because the local model allows regression coefficients to vary across space, the spatially varying partial derivative of the hedonic price function with respect to any characteristic is estimated locally. Measuring the spatially varying partial derivative of the hedonic price function with respect to any characteristic allows us to quantify the local value of that characteristic individually. For example, the first partial derivative of the nearest park in the local model can be used to calculate a marginal implicit price of proximity to that specific park individually. The local marginal implicit prices of individual parks are summarized to show the variation in values of different parks.

Study Area and Data

Knox County is located in East Tennessee, one of the state's three "Grand Divisions." Knoxville is the county seat of Knox County. The City of Knoxville comprises 101 square miles of the 526 total square miles in Knox County. Downtown Knoxville is 936 feet above sea level. The Great Smoky Mountains National Park, the most-visited national park in the country, is less than 15 miles away, and the county is surrounded by several Tennessee Valley Authority lakes.

The county has been growing rapidly in recent years. During the 1980s, the population of Knox County increased by 5%. During the following decade, the rate of population growth nearly tripled to 14%, rising from 335,749 to 382,032 residents. Most of the recent rapid growth in the county has occurred in portions of west and north Knox County, while other areas have seen slow growth or decline. Specifically, population in the Southwest and Northwest County Sectors, as defined by the Knoxville/Knox County Metropolitan Planning Commission (MPC), gained 36% and 29% respectively in the 1990s, accounting for about two-thirds of the countywide increase. The county has 40 local parks. There are 25 perennial streams and rivers, 49 perennial lakes and ponds, 2 perennial reservoirs, and 7 water bodies classified as an unknown water feature based on the U.S. Census Bureau's Census Feature Class Codes.

This study employs three data sets: (a) parcel records from Knoxville - Knox County - Knoxville Utilities Board (KUB) Geographic Information System (KGIS), (b) 2000 census-block group, and (c) geographical information from 2004 Environmental Systems Research Institute (ESRI) Maps and Data. The three data sets are all geographically digitalized. Property parcel records contain detailed information about the structural attributes of properties. The census-block group data describes neighborhood characteristics. The ESRI data describes distance characteristics.

The study uses sale price records for single-residential houses that were built and sold between January 1991 and December 2004. The reason for the use of only sale prices of houses that were built and sold over that time period, rather than all houses that were sold, was that some key variables such as age of houses were consistently missing in the records for homes built prior to 1990. Inclusion of the data might cause sample selection bias. House sales prices are adjusted to December 2004 using the consumer price index for urban areas in the South. There are 234 census-block groups in Knox County. After cleaning up the individual housing data, 15,894 housing sales transactions remained (see Figure 1). The block group information were assigned to the houses located within the boundary of block groups.[4] Distance calculations for various location variables were made using the shape files and ArcGIS 9.

Variable names, definitions, and descriptive statistics for the variables used in the estimations are presented in Table 1. The average selling price was \$145,523 in 2004 dollars with a maximum sales price of \$6,227,490. It should be noted that house prices below \$40,000 were eliminated from the sample data. County officials suggested that the sales prices below \$40,000 probably were associated with gifts, donations, and inheritances, and thus would not reflect true market value. Officials also suggested that the parcels records smaller than 1,000 square feet might be misinformation and those parcel smaller than 1,000 square feet were eliminated from the sample data. A typical sample home is about 9 years old and has 2,240 square feet of finished area, 20,100 square feet or 0.46 acres of lot area, and 3 bedrooms. About 73% of the sample homes have a fireplace, about 30% have all brick exterior walls, about 3% have a pool, and about 88% have a garage. Average travel time to work is 22 minutes, average per capita income is $27,000, and the average unemployment rate is 3%.

Estimation Results

The results of the global model and local model are presented in Table 2. The adjusted R^2 value for the global model is 0.46, while for the local model it is 0.48. The local model also reduces the residual sum of squares from 3,018 in the global model to 2,860. The adjusted R^2 with lower residual sum of squares suggests that the local model is more efficient than the global model. The positive and statistically significant variable for the housing value of the census-block group shows that the variable corrects for spatial autocorrelation of the housing price. The variable captures spatial spillover of housing value in the neighborhood at the level of census-block group. Specifically, evaluated at the average house value of $145,523, 21% of housing price or $30,560 is due to neighborhood effect. Since location characteristics are considered to be paramount in determining real estate value, a strong neighborhood effect seems to be reasonable.

The results from the global model show that all of the structural variables are statistically significant at the 1% level except for age variables. Coefficient signs of the structural variables are as intuitively expected. Evaluated at the average house value, the results indicate that house price increases by $41 per additional square foot of finished area. An additional 1,000 square feet of parcel size increases sale price by $199. The marginal implicit price of increasing the age of a house by one year, evaluated at the mean house value, yields an estimate of $1,892 in decreased house value. Similarly, having an additional bedroom increases estimated sale price by $6,403. A garage increases sale price by $41,193, a fireplace increases sale price by $16,590, and a brick exterior increases sale price by $6,257.[5] A 1% increase of prime interest decreases the estimated sale price by $3,929. The coefficient of the seasonal dummy variable shows that, in average, spring and summer sale prices are $2,037 higher than fall and winter sale prices. Everything else constant, a house in an area considered urban area can be sold for a $14,989 premium.

The coefficients of neighborhood variables from the census-block group, population density, vacancy rate, and unemployment rate are of the predicted sign with statistical significance at the 1% level. Evaluated at the average house value, house price decreases by $3,493 per additional 1,000 persons per square mile of population density. A 1% increase in the vacancy rate decreases the estimated sale price by $1,309. The coefficient for travel time to work is positive and statistically significant at the 1% level. The positive coefficient may reflect the geographically sprawled employment opportunities with people's desire to live in suburban areas further away from the employment center.

Six of the 11 coefficients of neighborhood variables for high school district dummy variables are statistically significant at the 10% level. Note that there are 12 high school districts in Knox County and the town of Farragut coincides with Farragut high school district. The reference area used for the high school dummy variables is the Austin-East high school district. Housing price is higher than the reference area of Austin-East high school district if the house is in Bearden, Central, Fulton, Halls, Karns, West, and Farragut high school districts,. The school districts with a positive effect have relatively higher average American College Testing (ACT) scores than the Austin-East high school district. This is consistent with previous research about school accountability ratings and house value (Kane, Staiger, and Samms). The negative coefficient for Knoxville indicates that house price is higher if the house is located outside the city boundary of

Knoxville. Though other factors may contribute, this relationship is likely due in large part to the perception that the value of additional public services provided to property owners within the city limits does not fully compensate for the higher city property taxes.

While the global model shows that the effect of per capita income is not significant, the local model shows that 50% of local marginal effects are within the range between -0.013 of lower quartile and 0.001 of upper quartile. The range of different signs of the local marginal effects shows the opposite effect of per capita income on house price in different parts of the study area. The different signs in different parts of the study area cancel each other out, suggesting lack of significance in the global model.

Coefficient signs for the distance variables are as expected. The coefficient for the distance to railroad variable is positive and statistically significant at the level of 1%, suggesting that house price increases with increasing distance from railroad. This may be explained by the fact that Knoxville does not have use of railroad for transportation and it is likely to be associated with a noise disamenity or other inconvenience. The coefficients for the distances to downtown, water body, and park are statistically significant at the 10% level or better in the global model. Moving 1,000 feet closer to water bodies increase the average house price by $331. Moving 1,000 feet closer to the nearest park increases the average house price by $303. The variable for park size is positive and statistically significant at the 1% level, suggesting that not just proximity to the parks but the size of parks affects housing price. The coefficient for the distance to greenway shows that proximity to greenway has a positive value but it is not statistically significant.

It appears that the variable included to reflect the quality of water bodies, the impairment dummy, is capturing the effect of water quality impairment caused by high priced cluster housing development such as more luxurious subdivision development. The positive coefficient value of 0.057 suggests that a house nearest to the water body with impairment report is $8,295 higher than the house nearest to the water body without impairment report. One explanation could be that homeowners in higher priced areas tend to report impairment incidents more than the homeowners in the lower priced area. In any case, the impairment dummy variable may not be a good indicator of water quality that captures the effect on house price. Unexpectedly, the coefficient for floodplain variable is found to be positive and statistically significant at the level of 10%. Although the floodplain should be a disamenity, homeowners may not fully recognize the flood hazard or are willing to take risks to be nearer water or bottomland settings.

Figure 2 shows the locations of the water bodies and spatial variation in the marginal effects of proximity to water bodies. Table 3 shows the summary results of the average local marginal implicit price of proximity to water bodies. The figure and the table show that the marginal effects of water bodies in the southwest of the county near Fort Loudon Lake and in the north and west of the county near Clinch River are the higher than the rest of the regions. Both marginal effect and marginal implicit price decrease as one moves away from the three regions of the county. In fact, some of the water bodies in the east and northeast regions show negative values for being closer to water bodies. The unexpected negative values of being closer to water bodies may be explained by the fact that there are areas where the relationships are significant and other areas where they are not. Alternately, this may be related with types of water bodies or qualities that make them possess disamenity features. It should be noted that the current model does not determine the exact cause of this negative value.

Figure 3 shows the location of the parks and spatial variation in the marginal effects of proximity to the parks. Table 4 shows the summary results of the average local marginal implicit prices of the parks. The table and figure show that the west region near Concord Park, the south region near Bell Road and Sequoya Hill Parks, and east region near Spring Place and Fountain City Parks have the higher marginal effects and marginal implicit prices. Concord Park The Cove was found to have the highest mean park value of $1,809. The positive effects decrease as one moves away from these three regions of the county. Only the Inkwood and Powell Levi Parks are found to have negative mean values. The negative value of being closer to some parks may be associated with poor quality due to low maintenance or other factors.

To examine the volatility of local regression estimates, the local model is estimated using a bandwidth that is 50% larger and 50% smaller than the bandwidth found using the CV approach in estimating equation (9).[6] The median value of the local marginal effects using both 39,384-feet and 9,846-feet bandwidths are fairly close to the median estimates using the CV approach that identified an optimal bandwidth of 19,692 feet. However, with a bandwidth of 39,384 feet, almost no variation across the area exists in the local marginal effects. As the bandwidth widens to 39,384 feet, the spatial heterogeneity captured by locally weighted regression using the CV approach is not captured and the local estimates are close to those estimated by OLS. This sensitivity analysis emphasizes the trade-off between a smaller bandwidth that retains the spatial heterogeneity inherent in the variables and the need to produce estimates that vary smoothly over the spatial regions of the study area (larger bandwidth).

Summary and Conclusions

Residential property value premiums resulting from proximity to amenities such as water bodies and parks are measured globally and locally at the individual level within the Knox County, Tennessee study area. Our results corroborate previous research establishing that natural and constructed amenities are valuable attributes in housing demand and positively impact sale prices. Moreover, our results suggest that hedonic models can be improved by including GIS information pertaining to natural amenities.

Our results also demonstrate the importance of going beyond the global modeling framework when including GIS information into hedonic models. Local values for individual amenity sources are estimated using locally weighted regression by allowing for non-stationarity in the relationships between proximity to water bodies and parks and sale prices in the hedonic housing price model. The marginal implicit price of proximity to water bodies (1,000 feet closer) was estimated to be \$331 in the global model, but ranged from \$12 to \$4,232 locally for individual water bodies. The marginal implicit price of proximity to local parks (1,000 feet closer) was estimated to be \$303 in the global model, but ranged from \$59 to \$1,809 locally at an individual park level.

Furthermore, the local model reveals some important local differences in the effects of proximity to water bodies and parks on housing price. The local parameter estimates of the both proximity to water bodies and parks have different signs in different parts of the map. These different relationships are obscured in the global model. Without the results from the locally weighted regression model, the different levels of effects by the individual water bodies and parks housing prices are not captured. However, the locally weighted regression results imply that there are areas where the relationships are significant and other areas where they are not. The unexpected negative values of being closer to water bodies and parks may be explained by the fact that there are areas where the relationships are significant and other areas where they are not. Alternatively, the negative values may be related with types of water bodies or qualities of parks that make them potential disamenities. It should be noted that the current model does not determine the exact cause of this negative value.

Estimates of the value of proximity to water body and park, such as those generated in this study, should prove useful as input to future debates about public initiatives to protect open space, whether through ballot measures or other means. The estimated values from locally weighted regression models for individual sources of these amenities can be used for budget decisions regarding resource management or in the prioritizing of specific water resources and parks to be protected. For example, assessing the added value of a given local park to proximal homes and the resulting level of tax revenues could prove useful to planners trying to justify maintenance expenditures in increasingly tight times. A future research effort could involve examination of values identified within the present modeling framework along with attribute bundles of specific parks or water bodies to identify potential management issues. Moreover, with a large enough set of parks, models could be developed wherein park values are regressed on park attributes to quantify attributes with the highest marginal benefits.

While the hedonic property price method can be used to estimate the value of some non-market goods and services, it is important to remember that the method provides only a limited measure of total economic benefits. For example, water bodies may provide many services in addition to positive amenities for residential property located in proximity to water bodies. These may include biodiversity, water recharge and discharge, and recreation. Parks also provide recreation to people from outside the immediate area. The value of these services may not be fully reflected in residential house prices. House prices also do not reflect benefits received by businesses, renters, and visitors. For these reasons, estimates from hedonic house price models will generally underrepresent the true value of these amenities. It also should be noted that because of the data restriction for the houses constructed prior to 1990, the values of non-market goods and services that are reflected in older houses are not captured in this study because of the potential sample selection bias.

Footnotes

1. Everything is related to everything else, but near things are more related than distant things.
2. In kernel estimation, a scalar argument to the kernel function that determines what range of the nearby data points will be heavily weighted in making an estimate. The choice of bandwidth represents a tradeoff between bias (which is intrinsic to a kernel estimator, and which increases with bandwidth), and variance of the estimates from the data (which decreases with bandwidth).
3. This process is almost identical as choosing b on a 'least squares' criterion except for the fact that the observation for point i is omitted.
4. Note that the timing cycle of the census and sales records do not match. However, given the periodic nature of census taking, census data should serve as proxies for real time data.
5. The marginal effects of a garage and fireplace seem to be high. Apparently the dummy variables for the existence of these two attributes pick up some of unspecified effects of more upscale housing which almost always has these features.
6. Estimates using these larger and smaller bandwidths can be obtained by request.

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Table 1. Variable Name, Definition, and Descriptive Statistics

Variable	Unit	Definition	Mean	Std Dev
		Dependent variables		
PRICE	$	Housing sales price adjusted to a December 2004	145,523.212	12,719.034
		Variable capturing spatial autocorrelation		
HVALUE	$	Median housing value for census-block group reported in 2000	106,670.000	54,190.000
		Structural variables		
SQFT	1,000 square feet	Total finished structure square footage	2.239	1.226
LOTSQFT	100,000 square feet	Lot square footage	0.201	0.459
AGE	year	Year house was built subtracted from 2005	8.901	3.039
BEDRM		Number of bedrooms	3.223	1.428
GARAGE		Dummy variable for garage (1 if garage 0 otherwise)	0.878	0.327
FIREPLC		Dummy variable for fireplace (1 if fireplace 0 otherwise)	0.726	0.446
BRICK		Dummy variable for all brick (1 if all brick 0 otherwise)	0.294	0.456
POOL		Dummy variable for pool (1 if pool 0 otherwise)	0.027	0.163
QCONST		Dummy variable for quality of construction (1 if excellent, very good, and good 0 otherwise)	0.376	0.484
CSTRUCT		Dummy variable for condition of structure (1 if excellent, very good, and good 0 otherwise)	0.944	0.229
		Neighborhood variables		
POPDNS	1,000 per square mile	Population density for census-block group in 2000	1.283	0.821
TRAVEL	minutes	Average travel time to work for census-block group in 2000	22.372	3.191
PCINC	$1,000 per resident	Per capita income for census-block group in 2000	26.659	9.341
UNEMP	ratio	Unemployment rate for census-block group in 2000	0.032	0.021
VACANT	ratio	Vacancy rate for census-block group in 2000, which is unoccupied housing units in 2000. Vacancy status was determined by census enumerators obtaining information from landlords, owners, neighbors, rental agents, and others.	0.058	0.025
BEARDEN		Dummy variable for Bearden High School District (1 if Bearden, 0 otherwise)	0.188	0.391

CARTER		Dummy variable for Carter High School District (1 if Carter, 0 otherwise)	0.017	0.127
CENTRL		Dummy variable for Central High School District (1 if Central, 0 otherwise)	0.062	0.241
DOYLE		Dummy variable for Doyle High School District (1 if Doyle, 0 otherwise)	0.033	0.178
FULTON		Dummy variable for Fulton High School District (1 if Fulton, 0 otherwise)	0.016	0.123
GIBBS		Dummy variable for Gibbs High School District (1 if Gibbs, 0 otherwise)	0.066	0.249
HALLS		Dummy variable for Halls High School District (1 if Halls, 0 otherwise)	0.064	0.248
KARNS		Dummy variable for Karns High School District (1 if Karns, 0 otherwise)	0.178	0.382
POWELL		Dummy variable for Powell High School District (1 if Powell, 0 otherwise)	0.099	0.299
WEST		Dummy variable for West High School District (1 if West, 0 otherwise)	0.081	0.273
FARRGT		Dummy variable for Town of Farragut & Farragut High School District (1 if Farragut, 0 otherwise)	0.188	0.391
KNOXVL		Dummy variable for City of Knoxville (1 if Knoxville, 0 otherwise)	0.180	0.382
		Distance variables		
DOWNTN	feet	Distance to downtown Knoxville	51,248.240	18,641.850
WATER	feet	Distance to nearest streams, lake, and river	10,090.360	6,816.050
GREEN	feet	Distance to nearest greenway	9,061.035	5,837.332
RAIL	feet	Distance to nearest railroad	7,703.711	5,865.993
PARK	feet	Distance to nearest local park	9,597.201	5,671.583
		Other variables		
PARKSZ	1,000 acres	Size of nearest local park	0.063	0.216
IMPAIR		Dummy variable for impairment incident by EPA on nearest stream, lake, and river	0.311	0.463
RATE	percentage	Prime interest rate	7.332	1.672

SEASON	Dummy variable for season of sale (1 if spring and summer, 0 otherwise)	0.402	0.490
URBAN	Dummy variable for urban/rural area (1 if a house is located in census block of 100% urban housing, 0 otherwise)	0.704	0.456
FLOOD	Dummy variables for flood area (1 if a house is located in stream protection area, 0 otherwise)	0.014	0.118

Table 2. Parameter Estimates of Global and Local Models (Dependent Variable = ln(PRICE))

	Global		Local				
	Coefficient	Std Error	Min	Lower Quartile	Median	Upper Quartile	Max
INTERCEPT	9.157***	0.333	6.503	8.313	9.849	10.864	14.295
			Variable capturing spatial autocorrelation				
ln(HVALUE)	0.210***	0.025	-0.285	0.170	0.212	0.240	0.447
			Structural variables				
SQFT/1,000	0.283***	0.010	0.063	0.235	0.294	0.349	0.495
$(SQFT/1,000)^2$	-0.017***	0.001	-0.057	-0.022	-0.018	-0.012	0.001
LOTSQFT/100,000	0.137***	0.014	-0.453	-0.021	0.043	0.118	0.385
$(LOTSQFT/100,000)^2$	-0.007***	0.002	-0.186	-0.022	-0.014	-0.003	0.058
AGE	-0.013*	0.007	-0.104	-0.028	-0.023	0.010	0.137
AGE^2	0.000	0.000	-0.009	-0.001	0.000	0.000	0.005
BEDRM	0.044***	0.008	-0.003	0.033	0.039	0.055	0.219
$BEDRM^2$	-0.001***	0.000	-0.006	-0.001	-0.001	-0.001	0.000
GARAGE	0.283***	0.010	0.063	0.235	0.294	0.349	0.495
FIREPLC	0.114***	0.009	-0.050	0.086	0.111	0.134	0.155
BRICK	0.043***	0.009	-0.037	-0.006	0.057	0.085	0.137
POOL	0.107***	0.022	-0.209	0.091	0.108	0.120	0.162
QCONST	0.146***	0.011	-0.063	0.104	0.131	0.174	0.350
CSTRUCT	0.067***	0.016	-0.048	0.052	0.063	0.071	0.221
			Neighborhood variables				
POPDNS/1,000	-0.024***	0.007	-0.138	-0.036	-0.026	-0.017	0.042
TRAVEL	0.009***	0.002	-0.016	0.004	0.010	0.014	0.026
PCINC/1,000	-0.001	0.001	-0.013	-0.002	-0.001	0.001	0.023
UNEMP	-0.419**	0.204	-2.471	-0.362	0.154	0.619	2.937
VACANT	-0.279*	0.165	-2.914	-0.371	0.130	0.462	1.829
BEARDEN	0.212***	0.042	-0.327	0.010	0.070	0.195	0.771
CARTER	0.036	0.049	-0.737	-0.463	-0.317	-0.048	0.668
CENTRL	0.095**	0.041	-0.455	-0.204	-0.086	0.061	0.398
DOYLE	0.054	0.048	-0.728	-0.216	-0.095	0.056	0.679

FULTON	0.084*	0.048	-0.929	-0.433	-0.197	0.097	0.293
GIBBS	0.048	0.043	-0.551	-0.206	-0.087	0.033	0.614
HALLS	0.090**	0.042	-0.457	-0.161	-0.057	0.065	0.340
KARNS	0.132***	0.042	-0.465	-0.022	0.042	0.116	0.389
POWELL	0.031	0.042	-0.717	-0.158	-0.073	0.020	0.291
WEST	0.076*	0.041	-0.762	-0.148	-0.072	0.037	0.368
FARRGT	0.112**	0.046	-0.624	-0.031	0.018	0.080	1.083
KNOXVL	-0.028*	0.016	-0.081	-0.052	-0.029	0.016	0.162
		Distance variables					
ln(DOWNTN)	-0.049*	0.026	-0.256	-0.180	-0.107	0.045	0.187
ln(WATER)	-0.012**	0.005	-0.068	-0.023	-0.017	-0.010	0.230
ln(GREEN)	-0.007	0.005	-0.190	-0.024	-0.011	-0.001	0.067
ln(RAIL)	0.012***	0.004	-0.061	0.004	0.017	0.026	0.057
ln(PARK)	-0.011*	0.006	-0.067	-0.023	-0.014	-0.006	0.030
		Other variables					
PARKSZ/1,000	0.031*	0.019	-0.221	-0.110	-0.001	0.032	0.546
IMPAIR	0.057***	0.009	-0.220	0.012	0.043	0.069	0.220
RATE	-0.027***	0.002	-0.055	-0.028	-0.025	-0.023	-0.021
SUMMER	0.014**	0.007	-0.005	0.004	0.010	0.017	0.072
URBAN	0.103***	0.012	-0.167	0.057	0.108	0.122	0.214
FLOOD	0.050*	0.030	-0.512	-0.064	0.027	0.078	0.185
Adjusted R^2	0.46		0.48				

***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively. Sample size is 15,894 and bandwidth is 19,692 feet.

Table 3. Mean Water Body Values using Estimates from the Local Model

Lake	Mean Marginal Effect	Mean House Price	Mean Water Body Values	N
Little River	-0.045	$492,500	$4,232	2
Tennessee River	-0.032	$185,751	$1,141	1020
Fleniken Branch	-0.038	$155,988	$1,130	17
Knob Creek	-0.028	$170,000	$1,108	3
Fort Loudoun Lake	-0.022	$226,750	$1,057	1230
Sinking Creek	-0.021	$241,673	$1,035	1680
Hickory Creek	-0.019	$253,421	$915	408
Sterchi Lake	-0.022	$187,151	$768	33
Clinch River	-0.026	$154,048	$758	640
Jolly Giant Lake	-0.025	$150,322	$702	184
Little Turkey Creek	-0.010	$263,662	$510	829
Turkey Creek	-0.012	$214,429	$508	480
Melton Hill Lake	-0.024	$118,077	$485	919
Stock Creek	-0.015	$147,140	$472	185
Lynnhurst Lake	-0.019	$109,416	$413	754
Presley Lake	-0.019	$113,479	$411	1803
Bradley Lake	-0.018	$113,429	$363	267
Bud Hodge Lake	-0.014	$133,574	$336	673
Dead Horse Lake	-0.011	$133,314	$286	1305
Holder Branch	-0.004	$220,745	$171	7
Susanne Lake	-0.001	$125,234	$12	1923
Lea Lake	0.013	$54,950	-$150	2
Beaman Lake	0.079	$55,423	-$822	11
Graveston Mill	0.045	$100,116	-$841	531
Chilhowee Park	0.059	$91,298	-$1,056	161
French Broad River	0.065	$97,897	-$1,283	251
Holston River	0.104	$101,096	-$1,992	520
Armstrong Pond	0.122	$126,603	-$2,910	48

Notes: The mean water body value is the marginal implicit price for reducing the distance to nearest lake by 1,000 feet, evaluated at the mean house value and an initial distance of one mile.

Table 4. Mean Park Values using Local Estimates from the Local Model

Park	Mean Marginal Effect	Mean House Price	Mean Park Value	N
Concord Park The Cove	-0.033	$297,396	$1,809	134
Bell Road Park	-0.050	$178,835	$1,673	133
Sequoyah Hills Park	-0.027	$272,347	$1,413	134
Admiral Farragut Park	-0.023	$267,335	$1,175	903
Cherokee Park	-0.029	$212,832	$1,168	131
Chester Doyle Memorial Park	-0.048	$114,279	$1,096	253
Carl Cowan Park	-0.025	$226,950	$1,074	631
Rocky Hill Park	-0.023	$210,699	$948	1588
Marbledale Park	-0.022	$220,333	$931	3
Halston Hills Community Park	-0.036	$124,116	$858	55
Farragut Anchor Park	-0.019	$230,375	$815	558
Spring Place Park	-0.042	$97,156	$771	362
Concord Park	-0.021	$179,307	$713	613
Mayor Bob Leonard Park	-0.014	$261,031	$704	877
White Springs Park	-0.030	$86,181	$508	129
Skaggstown County Park	-0.020	$125,492	$495	72
Fountain City Ballpark	-0.021	$124,025	$488	1711
Kimberlin Heights Park	-0.020	$113,546	$431	27
Mary Vestal Park	-0.035	$60,628	$401	7
Holston River Park	-0.035	$60,927	$398	13
Forks Of The River Park	-0.020	$92,185	$359	87
Solway Park	-0.012	$164,473	$354	257
Maynard Glenn Ballpark	-0.021	$86,590	$343	8
Ball Camp Community Park	-0.012	$134,025	$315	1363
Linden Park	-0.025	$55,119	$263	24
Fort Dickerson Park	-0.020	$61,750	$242	2
House Mountain State Par	-0.013	$103,483	$236	312
Riverdale Community Park	-0.012	$102,622	$226	144
Bull Run Park	-0.009	$135,766	$222	41
West Hills Park	-0.008	$125,509	$207	1647
Island Home Park	-0.023	$43,750	$189	2
Karns Community Park	-0.006	$147,829	$173	422
Woodbine Ave Ballpark	-0.015	$61,048	$167	24
Big Ridge State Park	-0.008	$105,841	$138	8
Worlds Fair Park	-0.010	$69,411	$132	19
Soloway Park	-0.011	$55,000	$115	1
Melton Hill Park	-0.003	$202,052	$113	103
John Tarlton Park	-0.003	$96,411	$77	188
Tyson Park	-0.008	$42,000	$59	2
Inkwood Park	0.000	$111,420	-$10	1202
Powell Levi Park	0.008	$106,140	-$150	1627
Carter Community Park	0.010	$116,118	-$218	46

Jaycee Park	0.020	$80,200	-$298	7
Norris Municipal Park	0.027	$91,300	-$460	3

Notes: The mean park value is the marginal implicit price for reducing the distance to the nearest park by 1,000 feet, evaluated at the mean house value and an initial distance of one mile.

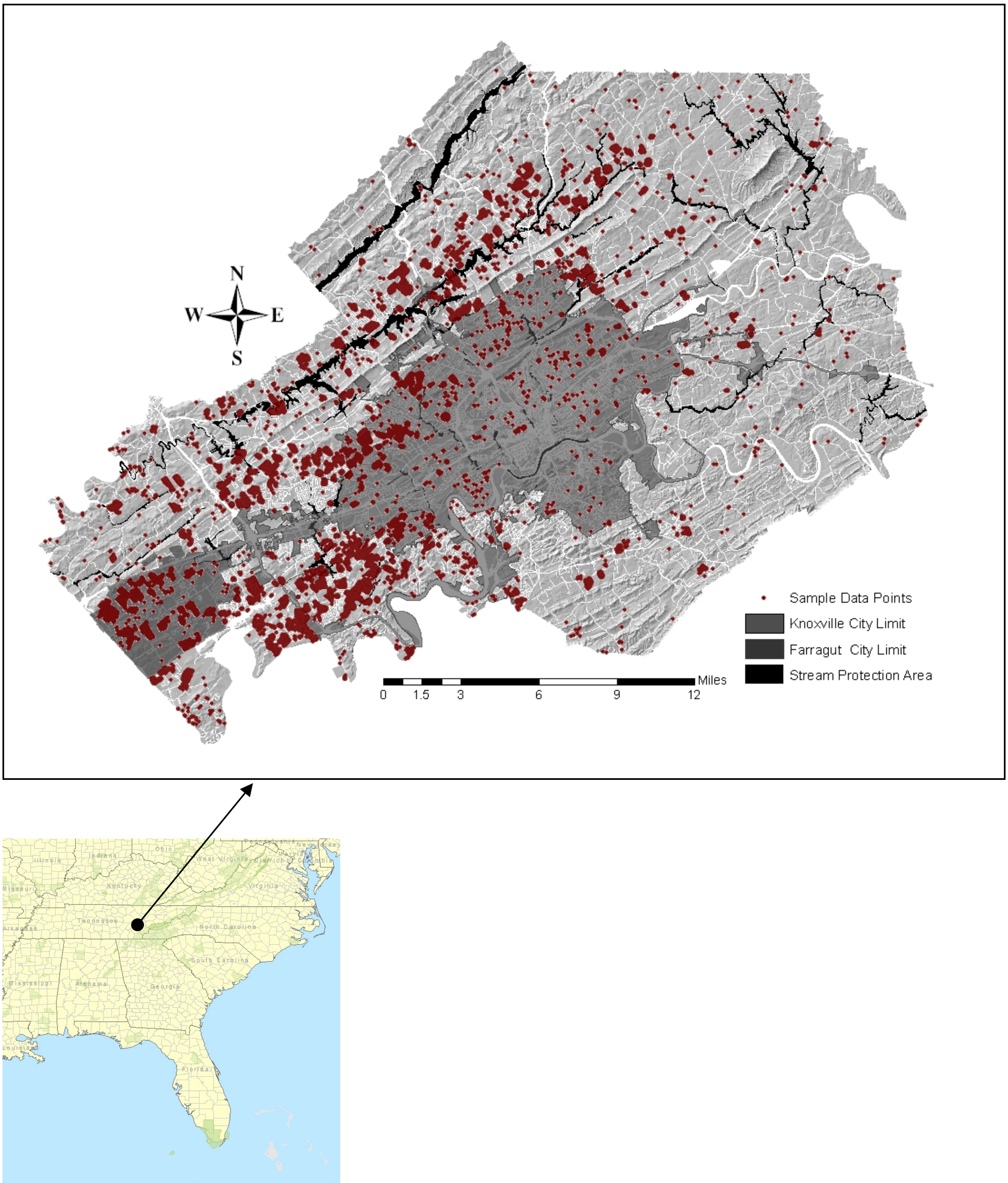

Figure 1. Study Area

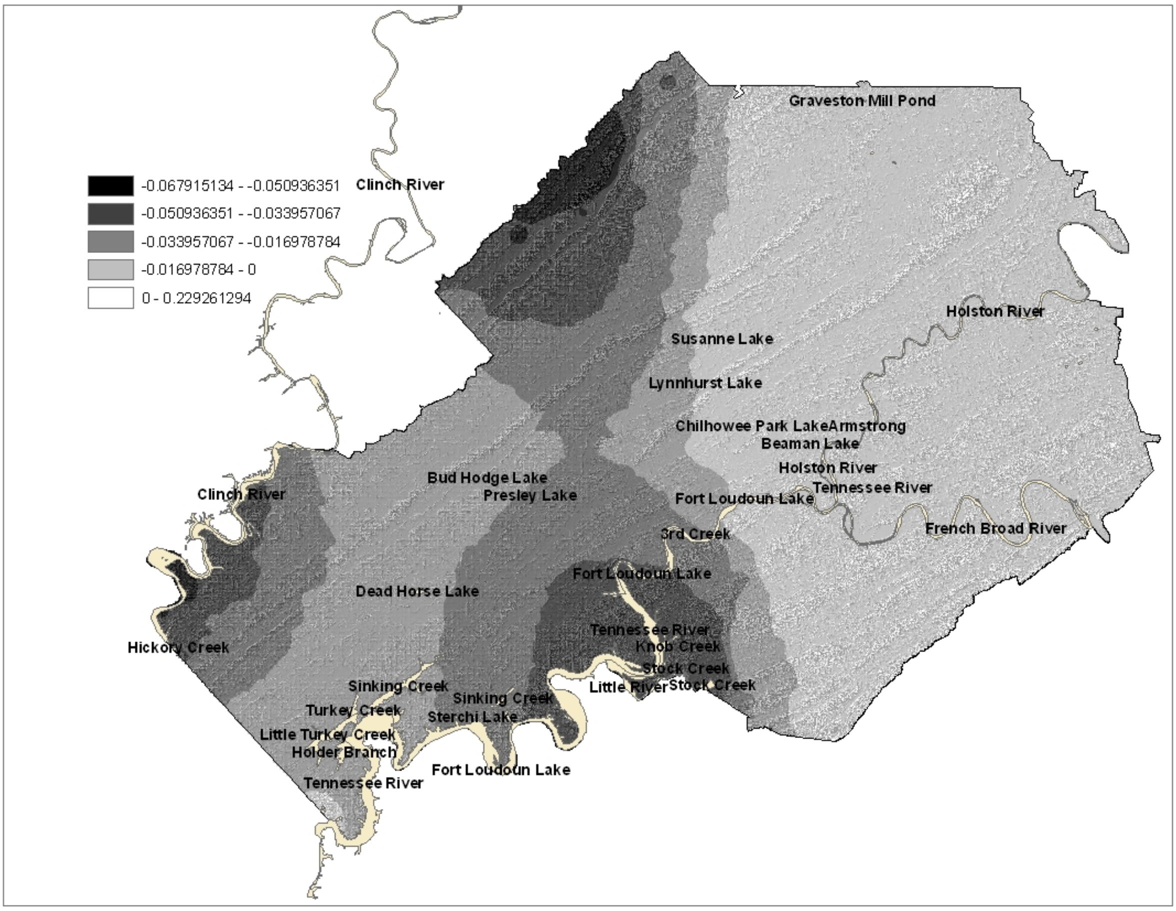

Figure 2. Spatial Distribution of Marginal Effect of Distance to Nearest Water Body on House price

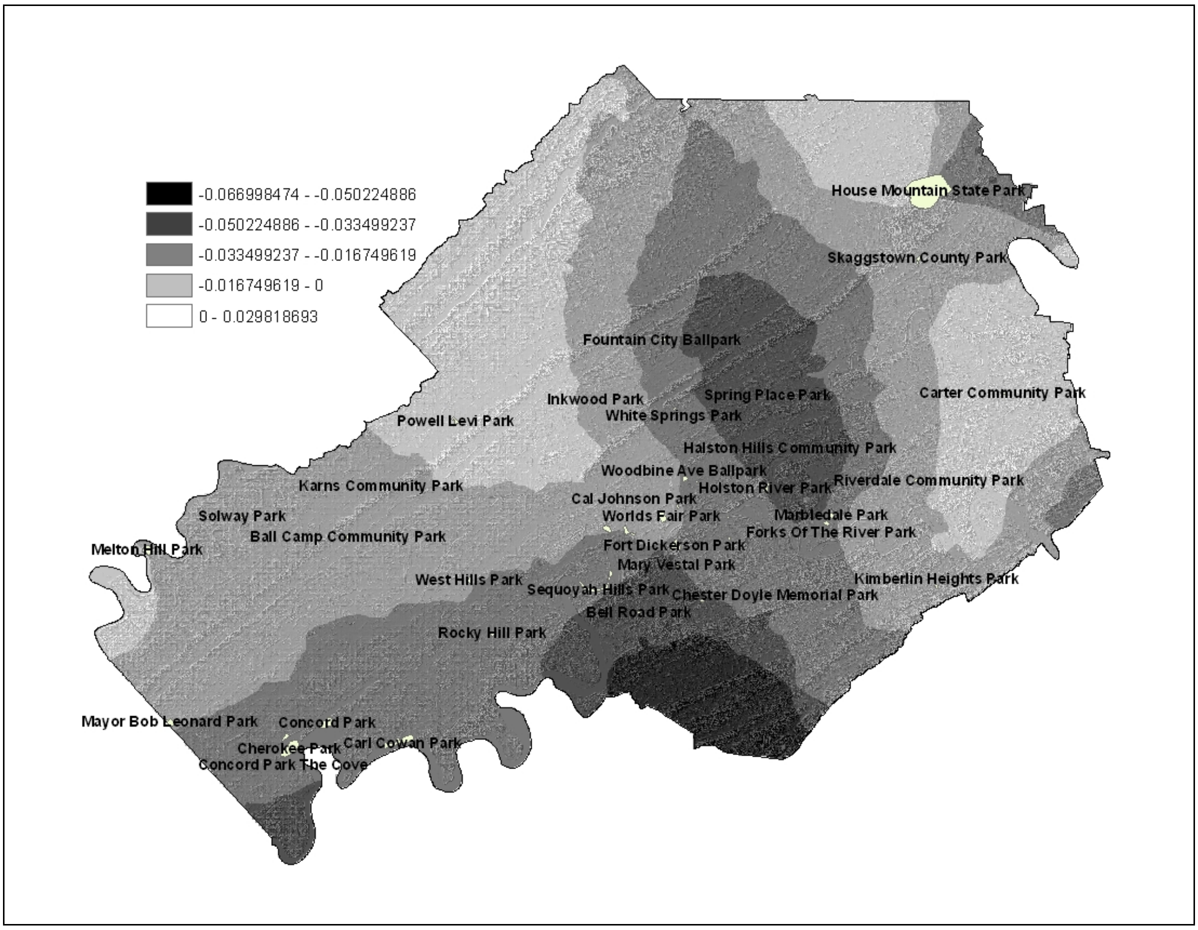

Figure 3. Spatial Distribution of Marginal Effect of Distance to Nearest Park on House Price