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Valuing Environmental Amenities across Space: A Geographically Weighted Regression of Housing Preferences in Greenville County, SC

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Abstract: As global consumption and development rates continue to grow, there will be persistent stress placed on public goods, namely environmental amenities. Urban sprawl and development places pressure on forested areas, as they are often displaced or degraded in the name of economic development. This is problematic because environmental amenities are valued by the public, but traditional market analysis typically obscures the value of these goods and services that are not explicitly traded in a market setting. This research examines the non-market value of environmental amenities in Greenville County, SC, by utilizing a hedonic price model of home sale data in 2011. We overlaid home sale data with 2011 National Land Cover Data to estimate the value of a forest view, proximity to a forest, and proximity to agriculture on the value of homes. We then ran two regression models, an ordinary least squares (OLS) and a geographically weighted regression to compare the impact of space on the hedonic model variables. Results show that citizens in Greenville County are willing to pay for environmental amenities, particularly views of a forest and proximity to forested and agricultural areas. However, the impact and directionality of these variables differ greatly across space. These findings suggest the need for an integration of spatial dynamics into environmental valuation estimates to inform conservation policy and intentional city planning.

Keywords: geographically weighted regression; land use change; spatial analysis; green space; land use planning

1. Introduction

By 2030, global urban land cover is likely to increase by 1,527,000 km^2 leading to habitat loss, forest fragmentation, and reduced ecosystem services [1,2]. As developmental pressures continue to rise at regional levels, the environmental quality will become more strained, eventually resulting in inequitable access to green spaces [3]. This pattern is further complicated by ex-urbanization and amenity migration, whereby the increased ease of travel and use of telecommuting has pushed development beyond the typical suburban sprawl, as urbanites seek residence in greener, more rural areas [4,5]. Local governments are then challenged to preserve place-based resources, such as protected public land and open space, while satisfying new residents and their desire for the infrastructure that allows them to live near such resources [6]. Understanding these urban to exurban development trends is critical to effective land use planning, as they weaken the efficiencies of urban development and potentially threaten biodiversity conservation [7–9].

An analysis of the housing market reveals the values consumers place on environmental amenities, and the challenges of incorporating those values into more robust planning [10–12]. Open ("green") spaces significantly influence housing prices, and this effect is contingent upon the amenities provided by the space [13]. For example, the presence of trees alone has been found to positively affect the selling price of housing units by anywhere from 1.9% [10] to 7% [14]. Perhaps ironically, green space draws in the very development that then leads to environmental degradation [15]. This is further complicated by the fact that there is a high public demand for conservation, and the benefits of green spaces extend beyond the housing market and accrue to the general public [16]. Landscape planning at the city and county level is critical to ensure that development does not degrade these spaces that are valued by the public [17,18].

Hedonic pricing methods can be an effective tool for understanding the value of environmental amenities for subsequent incorporation into conservation policy and land use planning decisions [19]. Hedonic price models use statistical regression to understand the impact of variables on the price of a good [20]. Commonly, these models are used to explain the effects of neighborhood characteristics (crime rates, school zoning, etc.), structural characteristics (number of bedrooms, bathrooms, square footage, etc.), and environmental/spatial characteristics (proximity to landfills, air quality, etc.) on the selling price of a home [20].

One aspect of environmental characteristics that has drawn some attention from researchers using hedonic price models is the value of green space, including proximity to forested and agricultural areas and visibility of forested areas. Kong et al. (2007) used a hedonic model to estimate the value of green space in urban mainland China and found that it contributed positively to housing prices [21]. Chamblee et al. (2009, 2011) examined the impact of conservation easements, including proximity to forested areas and forested views, on housing prices and found that they had a positive effect [22,23]. Likewise, Morancho (2003) assessed the impact of distance from green spaces on housing prices in Spain, finding an inverse relationship (proximity had a positive impact on the price) [24]. A similar relationship was found for proximity to green spaces in Finland, where proximity to forest and view of a forest were found to increase property values [25]. These examples used global regression models to estimate the value of green space, and generally found a positive association between green spaces and housing prices. However, green space, by definition, is a spatially contingent variable—we should assume that not all green spaces are of equal value [26]. This assumption holds true for the housing market [13], as it does for conservation [27].

Numerous complementary studies have identified that green spaces can have a mixed impact on consumer utility. A contingent valuation study in New Zealand found that respondents had a wide range of values for urban green spaces—most identified a positive value for trees and green spaces, but some had an associated disutility, including negative associations with tree pollen, drainage issues, and leaf litter [28]. Similarly, a broad survey in the USA found that the general public tends to have a positive perception of trees in cities, but that the ways in which the public values trees are shaped by local culture [29]. A study in Oregon, USA, found that the type of green space is also important to consider—with natural area parks having the largest positive impact on housing price, followed by public parks and golf courses [30]. Sander et al. (2010) employed a spatial simultaneous autogregressive (SAR) model in the USA to demonstrate that the density of tree cover also matters—up to 60% tree cover had a positive impact on sales price, but after that density was surpassed, the relationship flipped, and it had a negative impact on housing value [31].

Geographically Weighted Regression (GWR) models have been developed to account for the heterogeneity in the relationship between the dependent and independent variables across a given region [32]. In the hedonic modeling literature, GWR has been shown to improve global estimates by accounting for local spatial variation [33,34]. Hedonic models employing GWR have found spatially contingent relationships between housing values and proximity to transportation systems [35,36], and between air quality and housing prices in the USA [37]. A study in Austria used spatial regression to demonstrate that locally weighted models are the most appropriate for informing local planning and policy [38].

In this paper, we explore the differing values of forested areas across Greenville County, SC, through the use of two models: A global ordinary least squares (OLS) hedonic model, and a spatially weighted (GWR) hedonic price model of homes. In doing so, we seek to contribute to the above literature by demonstrating an application of GWR that explores spatial heterogeneity in the value of green space across a rapidly developing county. Further, we show that an understanding of this heterogeneity has direct implications for policy as land use planners attempt to preserve the multiple values of green spaces, while mitigating the impacts of urban sprawl across a region.

2. Materials and Methods

2.1. Study Area

Greenville County is located in the northwestern region of South Carolina, known locally as the Upstate (Figure 1). We selected this region because of its close proximity to the Mountain Bridge Wilderness Area, a threatened tract of land that possesses a majority of the biodiversity in the area. Southern Appalachia is a priority conservation area, due to the abundance of endemic species and its consideration as a biodiversity hotspot [39,40]. This critical biodiversity is at risk, due to anthropogenic activities, including rapid housing development [41,42]. Past and current development patterns have led to the rapid depletion of many of the region's ecosystem services and environmental amenities, and population growth is predicted to continue [43].

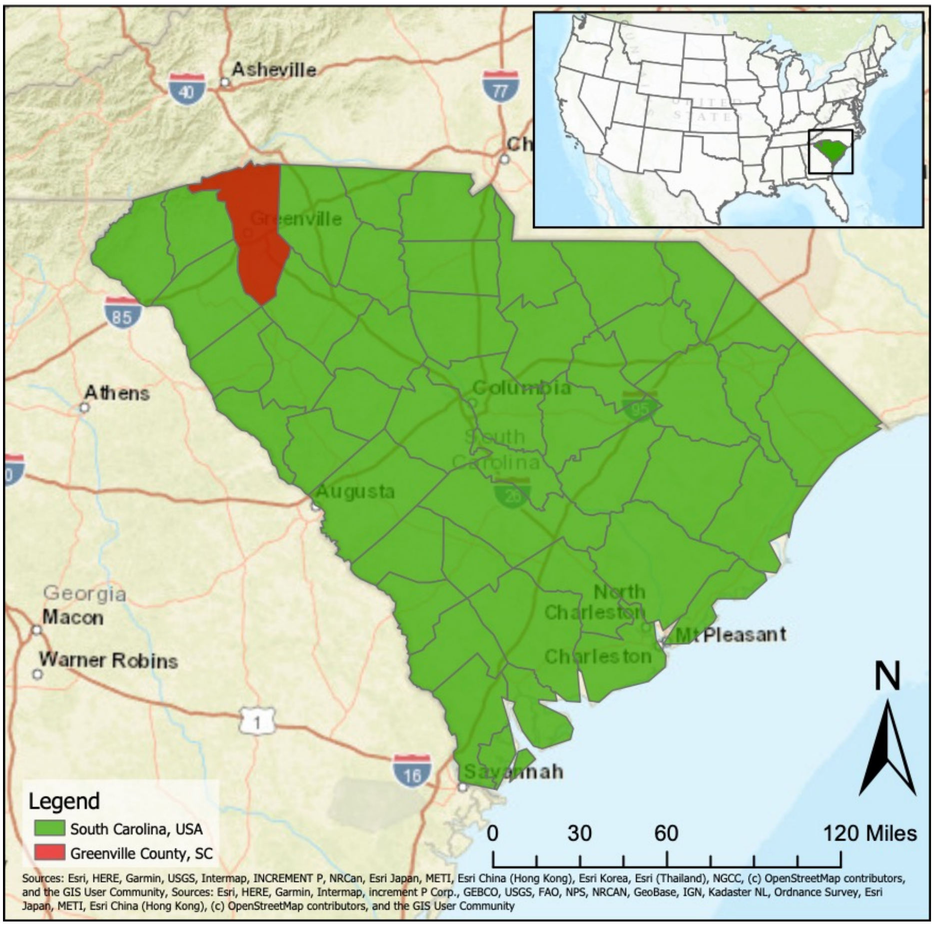

Figure 1. Greenville County, SC, USA.

Economic development throughout Greenville County has attracted new residents that continue to seek housing in and around the Greenville City center. The Carolina Piedmont and Georgia Piedmont megapolitan areas are expected to grow by 44.6% and 54.9% respectively from 2000–2030 [44]. Much of the current and projected expansion in the region follows the post-1950's trend of sprawl style development caused by consumers in search of more living space, with less of a need to be in walking distance of the urban center [45]. This has put tremendous stress on local biodiversity hotspots and is causing a reduction in environmental services in the region [43]. Additionally, some of the most popular tourist destination areas in the region are green spaces with visible and interactive environmental amenities [45].

2.2. Data

Our original MLS (Multiple Listing Service) dataset included all the home sales that occurred in the year 2011, sales prices, and structural features of those homes. We used ArcMap 10.4.1 to create a geographic information system (GIS) in which we overlaid the home locations with county-level data sets to extract environmental variables and neighborhood demographics. We collected data on crime in the area from the local sheriff offices and converted to a kernel raster utilizing a Jenks distribution. School attendance schedule data was found on Sabin.com, and we overlaid the school zones with our housing vector data. We included in the final regression models only schools that had positive, significant coefficients. Greenville county has a "school choice" system that allows students to apply to attend schools across the county, with only a default allocation of space for official school zones. Therefore, the importance of school zoning mostly applies in the cases of the most popular schools and is reflected in this methodology. We derived forest and agriculture polygon shapefiles from the 2011 National Land Cover Database (NLCD) files (Figure 2). Proximity was calculated to each polygon utilizing the nearest neighbor tool from the home site location to the boundary of the nearest polygon. For proximity to downtown, we selected the City of Greenville offices (206 S Main St, Greenville, SC 29601) as the central point of downtown, and used the nearest neighbor tool to calculate proximity in feet.

Next, we used "visibility analysis" to extract data on the viewshed for each home in the dataset. We added an additional 40 ft. in elevation to forested areas in the DEM to address the issues of fixed land screen cover coming from trees [46]. We built a model in ArcGIS that was programmed to iterate through each home observation using the iterate feature selection tool. Parameters for the visibility tool in ArcMap 10.4.1 included an observer height of 6 ft. and observer radius of 3 mi (maximum length a human can see) [46,47]. Finally, we ran a zonal histogram on visible areas using 2011 NLCD data to show which land cover types were visible from each home location. Descriptive statistics for the final regression are shown in Table 1.

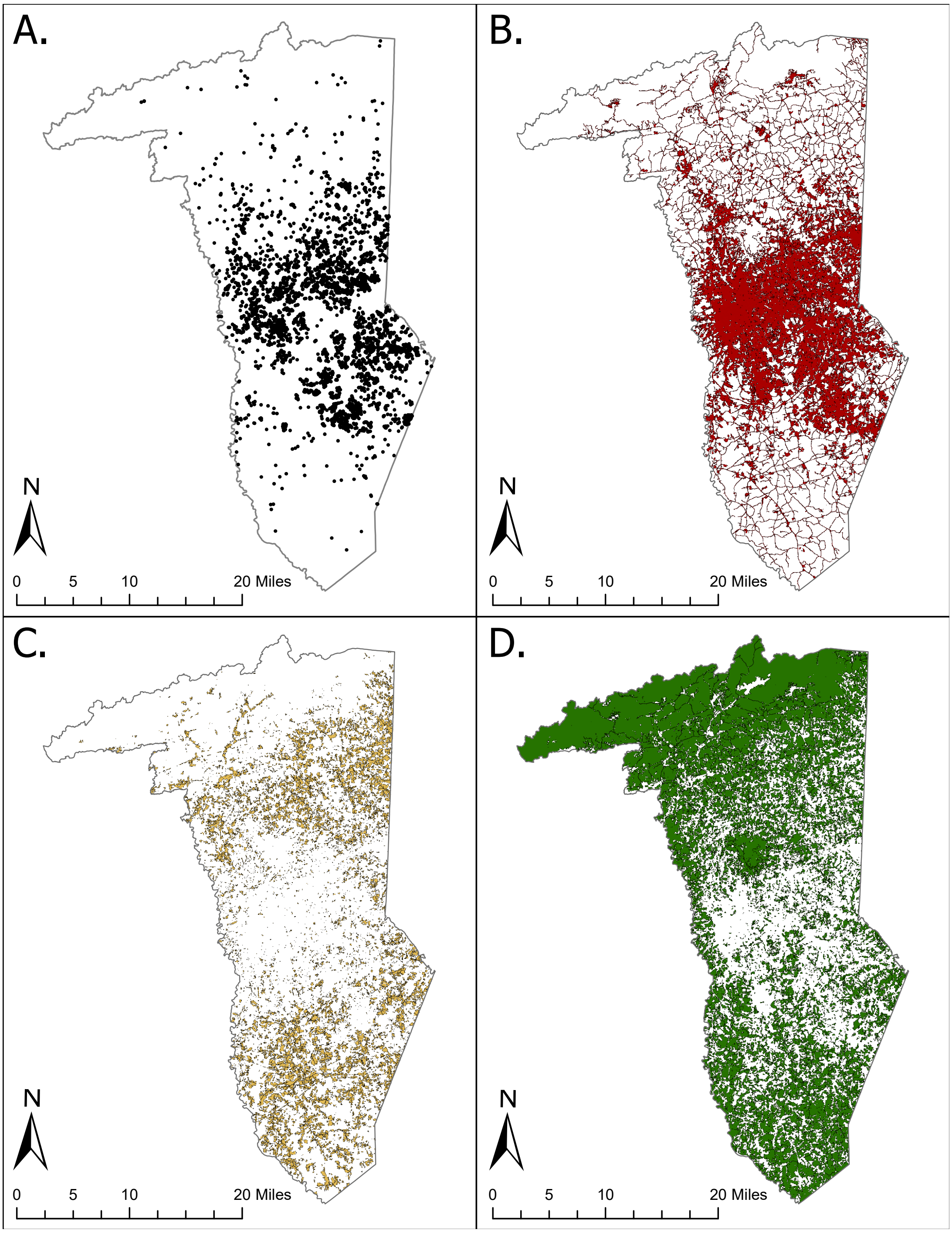

Figure 2. Greenville County, SC 2011 Homes Sales (**A**), Urban/Developed Land Cover (**B**), Pasture Land Cover (**C**), and Forest Land Cover (**D**).

Table 1. Descriptive statistics for variables used in global ordinary least squares (OLS) hedonic model (N = 4034).

Variable	Description	Transformation	Mean	Std. Dev.	Min	Max
Sold Price	Sale price of home (in 2011 USD), continuous	Logarithmic	182,998.40	128,937.30	5000	1,075,000
Total Finished Sqft.	Square footage of home, continuous	None	2168.95	937.62	600	7575
Baths	Number of bathrooms, continuous	Logarithmic	2.16	0.74	1	7
Garage Capacity	Number of cars garage can hold, continuous	None	1.57	0.86	0	3
Pct. African American	Racial composition of area near home, continuous	None	14.60	15.40	0	91.33
Lot Size	Size of lot (in acres), continuous	None	0.51	1.27	0	25.40
Crime	Density of crimes per square mile, per year, continuous	Logarithmic	43.47	68.98	0	531.32
School	Elementary school zoning, binomial	None	N/A	N/A	N/A	N/A
Nearest Forest	Distance to the nearest forest (in feet), continuous	None	369.35	369.67	0	3539.60
Nearest Agriculture	Distance to nearest agriculture (in feet), continuous	None	1358.35	1296.02	0	8418.92
GVL City Limits	Inside Greenville City limits, binomial	None	0.10	0.30	0	1
Pct. Of View Forest	Percentage of home view that is forested, continuous	Logarithmic	0.44	0.16	0.10	1

2.3. Hedonic Model

Hedonic methods are based on the consumer behavior theory that assumes all individuals are utility-maximizing in their decision making [48]. This implies that price is a function of all the attributes of a home (structural, lot, neighborhood, and spatial/environmental) such that:

$$P = f(X_1, X_2, X_3, \ldots X_N), \tag{1}$$

where P, the market price of the home, is a function of the characteristics of the property. Additionally, an individuals' utility is expressed such that:

$$U = U(Q, X_S, X_L, X_N, X_E), \tag{2}$$

where Q is a composite commodity comprising all other goods consumed, X_S is a vector of structural characteristics, X_L is a vector of lot characteristics, X_N is a vector of neighborhood characteristics, and X_E is a vector of spatial/environmental characteristics [47–50]. In other words, an individual is assumed to maximize the characteristics of the home at a given price point, in relation to all other goods and services (for a given income).

For any specific attribute, in this case, an environmental attribute, e, it is assumed that the consumer will choose a property that equates marginal willingness to pay a price for that characteristic. However, given that consumers are not able to treat individual housing characteristics as discrete items that are able to be picked and combined at will, non-linearity is to be expected, and thus a semi-log functional form was used to estimate the price better [21]. Thus, the semi-log function is such that:

$$lnP = \alpha + S\beta + L\gamma + N\eta + E\varepsilon + \mu, \tag{3}$$

where P represents price; S, L, N, and E, represent their respective characteristic vectors; α, β, γ, η, and ε represent associated parameter vectors; and μ represents the stochastic error term.

Despite the hedonic method being a popular form of valuing environmental amenities, as well as other goods, it has its limitations. The underlying assumption that consumers have perfect knowledge of the environmental benefit or detriment may not always hold true [51]. There is an additional underlying assumption of equilibrium in the willingness to pay for housing and housing stock. For this to be achieved, houses must have perfect information on all housing prices and attributes and prices must adjust instantaneously to changes in supply or demand, which is not always the case [51]. There are also statistical issues related to variable selection and bias in hedonic models. Batabyal (2011) explains whether other amenities are positively correlated with the environmental measure, and those other amenities are omitted from the equation, the value of the environment will be overstated [52]. Conversely, if buyers do not perceive all the damages from say, pollution or degradation of water quality, the benefits from increased environmental quality will be understated [52]. Knowing these limitations, we crafted our model to mitigate as many of these issues as possible, yet we accept limitations to the method at large.

We used Stata 14.0 to perform a simple OLS multivariate regression. We attempted several combinations of variables and functional forms in order to identify a robust and theoretically sound model. After exploring a linear price function, we moved to a semi-log form because we theorized that explanatory variables had a differential impact on the price at different price points in the model, and the semi-log form is well tested in the hedonic literature [53,54]. We explored the structural, neighborhood, and environmental variables commonly found to be significant in hedonic price functions and that were available for this dataset, including the age of home, income characteristics or neighborhoods, crime rates, and demographic characteristics [55]. We also consulted with local experts in real estate and housing markets to determine which characteristics were most likely to impact housing sales in Greenville County [20]. We then determined a series of stable models in terms of the relationship between explanatory variables and price and chose the final model that had the best fit relative to R^2 and AIC. We included significant variables at the 5% level, and removed variables from the model that caused problems with multicollinearity, as demonstrated by Variance Inflation Factor (VIF) estimates. The final model did not demonstrate the multicollinearity of variables. We transformed variables to eliminate heteroscedasticity, as shown in Table 1. We tested transformed variables for heteroscedasticity using the Breusch-Pagan test and found none. We identified outliers by calculating leverage, Cook's distance, and standard residuals. If an observation violated all three of the outlier measurements, based on accepted thresholds for each measurement, then we dropped the observation from the dataset. Seventy-one observations were dropped based on the outlier methodology, leaving a sample size of 4034 home sales. The final model had an R^2 squared value of 0.773.

2.4. Geographically Weighted Regression

We modeled the global hedonic price model using a Geographically Weighted Regression (GWR) to test for spatial variation in the explanatory variables using ArcPro 2.4.0. A GWR estimates the global model for every point in the dataset, based on the location and neighborhood characteristics [32,49,56]. Thus, following Charleton and Fotheringham (2009), the GWR takes on the following form:

$$lnP_i(\omega) = \alpha_i(\omega) + S\beta_i(\omega) + L\gamma_i(\omega) + N\eta_i(\omega) + E\epsilon_i(\omega) + \mu_i(\omega), \tag{4}$$

where ω represents an index vector of Cartesian coordinates [32].

GWR has been shown to improve estimates and allows us to understand intraregional variation in environmental preference [57]. Binary location variables (inside vs. outside Greenville City limits and school zoning) were omitted when running geographically weighted regression to avoid local multicollinearity [58,59]. We used an adaptive kernel determined by the Akaike Information Criterion (AIC) method, which ensured a bandwidth that could account for spatial clustering with an appropriate number of neighbors [32]. We then summarized the range of coefficients for each variable and examined the spatial distribution of the predictive strength of explanatory variables.

2.5. WTP Estimates

Marginal willingness to pay estimates can be derived from hedonic models by estimating the marginal change in a given variable representing a characteristic of a house, compared to a marginal change in price. Variable transformations prior to regression, due to the nonlinear relationship between house characteristics and price, require the computation of WTP estimates at a relative price. Given the varying transformations of explanatory variables in our model, implicit prices were derived based on the transformation of the explanatory variable in question, following Champ et al. [20]. In Table 2, the WTP estimate for the double-logged view of forest variable was derived using the following equation:

$$\frac{\partial P}{\partial E_{view}} = \beta_{view} \times \frac{P}{E_{view}}. \tag{5}$$

Table 2. Global OLS hedonic model results. All coefficient values are significant at the 5% significance level. Only the most significant school is shown in the table, but all positively valued schools were controlled for in the regression.

VARIABLES	Coefficients	Robust Standard Errors	p-Values	Standardized Beta Coefficients
Focus Variables				
Log Pct. of View Forest	0.112	0.0202	<0.01	0.0542
Nearest Forest	−0.0000872	(−0.0000228)	<0.01	−0.0424
Nearest Agriculture	−0.0000157	(−0.00000673)	<0.05	−0.0265
Control Variables				
Lot Size	0.0168	(0.00490)	<0.01	0.0278
Log Bathrooms	0.511	(0.0313)	<0.01	0.231
Garage Capacity	0.203	(0.0102)	<0.01	0.228
Total Finished Sqft	0.000302	(−0.0000111)	<0.01	0.372
Pct. African American	−0.00872	(0.000601)	<0.01	−0.176
Log Crime Density	−0.0315	(0.00490)	<0.01	−0.0609
Stone Academy Elem	0.644	(0.0628)	<0.01	0.103
GVL City Limits (1 = if in city limits, 0 = otherwise)	0.312	(0.0410)	<0.01	0.123
Constant	10.76	(0.0356)	<0.01	
Observations	4034			
R-squared	0.773			

The other variables in Table 2 were in the semi-log form and therefore were derived using the following equation:

$$\frac{\partial P}{\partial E_i} = \beta_i \times P, \tag{6}$$

where β_i is the coefficient estimate for a given variable, evaluated at price P.

3. Results

3.1. Global OLS Hedonic Model Results

Environmental amenities correlate significantly with housing prices in Greenville County, SC (Table 2). Structural characteristics had the strongest overall relationship with home price, while environmental factors possessed a relationship with price about as strong as neighborhood crime or the size of the lot. All environmental amenity values are statistically significant, albeit with low coefficient values. Results show that if the percentage of one's view of a forest in their viewshed increases by 1 percent, predicted home sale price will increase by about 0.112%, holding all else equal (Table 3).

So, given the mean home price of $182,998.40 and the mean 44% forested viewshed, a 10% increase of forested area in a home's viewshed would lead to an additional $4,658.14 increase in the estimated sale price. Control variables show the effects of structural and neighborhood characteristics on predicted home price. These results are in line with theoretical predictions. Structural characteristics appeared to have the strongest positive relationship with predicted price, with total finished square footage, number of bathrooms, and garage capacity having the greatest respective beta coefficient values. Schools coefficients are relative to schools that had a negative relationship with price. Due to lack of space, only Stone Academy Elementary, the school with the largest coefficient value, was included in the regression results (Table 2). The environmental variables of focus were about as important at predicting price as school quality and preference. It should also be noted that higher levels of crime density in an area led to a negative relationship with price, implying citizens prefer to live in safer areas. Increased racial diversity (as measured by the percentage African American of people in a census tract in which a home is located) was negatively correlated to price. Though not the focus of this study, this finding possibly implies a degree of inequity in housing options and reveals underlying structural racism in the area.

Table 3. Global OLS hedonic willingness to pay estimates of the environmental "focus" variables compared to total finished square footage. Measured via impact on 25th percentile ($104,200), mean ($182,998.40), and 75th percentile prices ($229,000).

Variable	Amount of Change in Variable	25th Percentile	Mean	75th Percentile
Pct. of View Forest	10% increase forested area in one's viewshed	+$2652.36	+$4658.14	+$5829.09
Nearest Forest	Home located 528 feet further away from forested area (1/10 mile)	−$4797.53	−$8425.54	−$10,543.53
Nearest Agriculture	Home located 528 feet further away from agricultural area (1/10 mile)	−$863.78	−$1516.98	−$1898.32
Total Finished Sqft.	100 square foot increase in home size	+$3146.84	+$5526.55	+$6915.80

3.2. Geographically Weighted Regression Model Results

GWR results show that environmental factors have a greater influence on home prices in specific regions of Greenville County (Table 4). In areas where the supply of green space is minimal, such as downtown, or in corridors leading to abundant natural amenities, such as trails and state parks, citizens reveal a preference for greenspace. The negative values for the "near forest" variable indicate that every foot further away from green spaces has a negative relationship with price. Homes stretching from downtown north through the Mountain Bridge Wilderness Area show a decrease in predicted housing price the further a property is located from a forested area (Figure 3). In rural areas to the northeast and southeast of downtown, preference for being near pasture lands is much greater than in other locations and has a positive relationship with price. Conversely, proximity to forested areas seems less important in these regions.

Table 4. Geographically weighted regression (GWR) results. The estimates from the global OLS regression are listed for comparison with GWR mean and median results.

VARIABLES	MIN	MAX	MEAN	MEDIAN	GLOBAL ESTIMATES	MEAN STD ERROR
LOT SIZE	−0.190	0.0816	−0.00227	0.00829	0.0168	0.0260
LOG OF PERCENT VIEW FOREST	−0.157	0.353	0.0238	0.00194	0.112	0.0518
PERCENT AFRICAN AMERICAN	−0.0145	0.00804	−0.00611	−0.00665	−0.00872	0.00182
LOG OF CRIME DENSITY	−0.260	0.090	−0.0299	−0.0152	−0.0315	0.0157
NEAREST AGRICULTURE	-6.34×10^{-5}	9.74×10^{-5}	2.23×10^{-5}	1.14×10^{-5}	−0.0000157	1.87×10^{-5}
TOTAL FINISHED SQFT	0.000274	0.000606	0.000380	0.000355	0.000302	3.03×10^{-5}
GARAGE CAPACITY	0.0622	0.339	0.167	0.163	0.203	0.0255
LOG BATHROOMS	−0.000744	0.407	0.128	0.127	−0.0315	0.0356
NEAREST FOREST	−0.000448	6.84×10^{-5}	-6.79×10^{-5}	-5.18×10^{-5}	−0.0000872	5.59×10^{-5}
OBSERVATIONS	4034					
AICC	3211.2					
MORAN'S I	0.0378					
R-SQUARED	0.791					

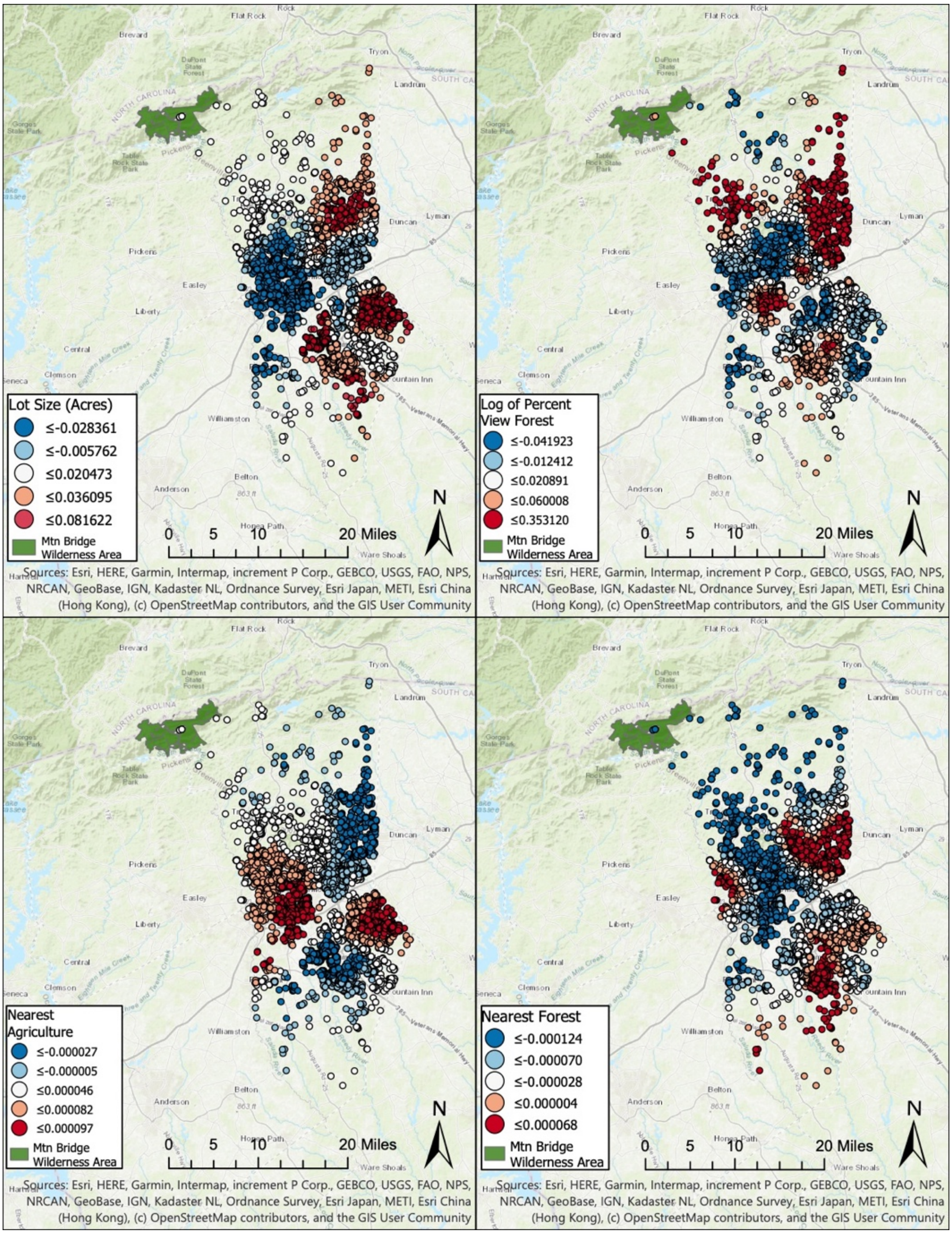

Figure 3. GWR coefficient estimates for lot size, log of percent view of forest, nearest agriculture, and nearest forest variables.

Environmental preferences translate to differing impacts on home sale values (Table 5). For example, in areas where homeowners showed the greatest preference for being a near forest, an increase in a tenth of a mile away from any forested area resulted in a 23.65% decrease in predicted housing sale price. In other words, the Greenville County homebuyer that values being near forested areas the most, would pay an additional $43,248.52 for a home that is located a tenth of a mile closer to forested areas. Furthermore, these buyers are tending to congregate in areas north of the city, along the corridor running toward the Mountain Bridge Wilderness Area and Asheville, NC (Figure 3). This trend is a prime example of forest amenities disproportionately driving land development in a particular region.

Table 5. GWR willingness to pay estimates of the environmental "focus" variables compared to total finished square footage. Measured via impact on the mean sale price ($182,998.40) at minimum, mean, and maximum GWR coefficient values.

Variable	Amount of Change in Variable	Minimum Coefficient Value	Mean Coefficient Value	Maximum Coefficient Value
Pct. of View Forest	10% increase forested area in one's viewshed	−$6532.21	+$998.61	+$14,686.45
Nearest Forest	Each additional 0.1 miles in distance from forested area	−$43,248.52	−$656.36	+$6608.44
Nearest Agriculture	Each additional 0.1 miles in distance from agricultural area	−$6121.08	+$2153.73	+$9408.49
Total Finished Sqft.	100 square foot increase in home size	+$5018.36	+$6945.70	+$11,090.80

4. Discussion

4.1. The Value of Environmental Amenities in Greenville County

The global OLS model reveals that citizens in Greenville County have a strong demand for environmental amenities, as expressed through their home purchasing decisions; however, the GWR demonstrates that this relationship varies across space. Coefficient values in the global model indicate a desire to be close to both forested and agricultural areas (as the distance from these areas increases, predicted home price falls). This is consistent with other studies in the region—much of the recent growth in Southern Appalachia has followed that of typical ex-urbanization or amenity migration patterns, whereby the rolling mountains and rural character is a draw to people moving out from suburban areas [4,60,61]. Residents also reveal a high WTP for a view of forested areas (Table 5), and this is reflected in development patterns in the region that have begun to encroach on mountain slopes [62]. However, these preferences are not constant through space, and coefficient values vary significantly based on differences in land cover and access to amenities.

The GWR reveals amenity migration pushing north of Greenville toward the Mountain Bridge Wilderness Area (Figure 3). Within the bounds of Greenville, it appears that structural and neighborhood characteristics are the main factors driving home purchases. East of downtown, in a traditionally rural area, view of a forest and proximity to agricultural spaces appear to be particularly strong variables driving home sales. The opposite is true for citizens living north of Greenville, where proximity to forest and price exhibit a strong positive relationship. There is an inherent contradiction in this pattern of exurban development—the growth in home sales outside of the urban limits is spurred by amenities that the very process of sprawl threatens to deteriorate. This is true for both forested and agricultural areas. Our global OLS model explains a potential reason for this by showing that structural characteristics, such as square footage, are the most consistently valued attributes of a home, independent of location. So, while it may be true that citizens in Greenville County value the environment, and that these characteristics drive *where* people are moving, other characteristics of homes are dominating the market as a whole, and are therefore shaping housing and infrastructure development.

The GWR also highlights that there is not a consistent relationship among housing prices and environmental variables across space. In some regions, proximity to forested areas has a positive relationship to price, while in others it appears to have a negative relationship. The same is true for proximity to agricultural areas, and percent view of the forest. The fluctuations in the perceived values of environmental variables across space are consistent with the literature. Bulteau et al. 2018 found a similar result in their study of the impacts of sustainable transportation on housing markets in France. In some regions there was a surprising disutility associated with transportation, despite the general positive relationship, and the authors surmised that it might relate to noise pollution and other negative externalities of transportation systems [36]. Likewise, the value of green space might be expected to fluctuate based on localized perceptions.

Our findings regarding the spatial variation in values of green space are corroborated by other studies. Though overall green space is found to generally contribute positively to public utility [29,63,64], there can be perceived disutility associated with these spaces, including increased pollen, and perceived danger [28,65]. WTP for green amenities may be particularly strong near urban centers, where these resources are scarce [66]. For example, a study in the Netherlands revealed a significant positive amenity affect for views of water and parks, particularly when near value-added land, such as developed areas [67]. Our GWR model results illustrate this trend in downtown Greenville, where the distance from a forest is most negatively correlated with housing price. Hence, the GWR leads to a more complete understanding of the variation in demand for environmental amenities across space.

There are some limitations to our model that could be improved upon in future studies. School zoning data does not take quality into account and could be supplemented with test scores or school quality grades to further improve estimates. Likewise, indicators of forest quality, such as density or recreational value [31], would have likely improved the model and should be explored in future research. Additionally, a time-series model would reveal the change in preference for environmental amenities overtime, which we hypothesize would increase over time as the supply of forests has decreased, due to rapid development in the region [15]. Furthermore, it would have been interesting to perform factor analysis to detect latent data structures prior to running regression models. A factor analysis could serve to increase the accuracy of WTP estimates, but we do not feel that it would change the overall nature of the relationships identified here.

4.2. Implications for Land Use and Development Policy

The failure of markets to endogenize the costs of environmental degradation in the face of positive values for environmental amenities, a phenomenon known as "market failure," reveals a central challenge of effective planning for city officials and citizens alike. This frequently leads to inequitable outcomes for consumers of public amenities. Solutions to this dilemma differ along political and economic lines [68]. Given our current economic paradigm, urban planners typically place economic growth and development as top priorities, with less consideration given to the environment [69,70]. However, policy objectives could have adverse effects on consumer utility if environmental amenities are destroyed at the expense of development. As the built environment continues to expand, and environmental amenities continue to be degraded, it is likely that the value of environmental amenities will increase [66]. However, ecosystem services that are undervalued in the present might suffer irreversible damage that cannot be repaired on demand, despite a future value associated with them [71]. Thus, more stringent conservation and responsible development policies should be enacted to ensure the long-term utility maximization of citizens.

Effective conservation policy can tangibly benefit from a spatial consideration of environmental values. For example, the use of conservation easements in the area has had success in ensuring forest cover and water quality, particularly along with the northern areas of the county [43]. However, when conservation easements are implemented, there is little consideration given to the effect of increased biodiversity and forested land cover on surrounding property values [22]. Similarly, Armsworth et al. demonstrated that protected area establishment can trigger market feedbacks, causing land values to rise in response to regional conservation, thus inhibiting future conservation efforts [15]. This is particularly true when conservation investment in an area attracts additional development through demand for higher quality environmental amenities. To further complicate matters, zoning, a critical tool for regional development planning, often ignores the spatial values of ecosystem services and is therefore a less effective conservation tool [43].

Increasingly, policy analysts argue for case-based, nuanced policy that considers the local context [72]. The spatially weighted method proposed here is one technique that provides policymakers with a quantitative estimate of the preferences of their constituents. These estimates, though imperfect, offer a means for policymakers to compare the potential values of various development scenarios within their districts, potentially optimizing ecosystem services across space [73]. Spatially weighted hedonic models offer the potential to estimate the demand for these amenities in a region, and shape policy to prevent development from counteracting the conservation gains from easements and protected area establishment.

5. Conclusions

Citizens in Greenville County, SC, revealed a demand for environmental amenities, including proximity to forested and agricultural areas, as well as views of forested areas, as reflected in home sales data. A spatial analysis of home sale patterns through a geographically weighted hedonic regression model demonstrates that the demand for these environmental amenities is not consistent across the county. The protected areas to the north of Greenville, including the Mountain Bridge Wilderness Area, seem to be driving up house prices in that region, while those moving east of the city seem to seek a rural agricultural landscape. As development continues to expand at the expense of forested and agricultural areas, demand for these environmental amenities may paradoxically increase. With this potential outcome in mind, a shift in long-term development should consider the different environmental amenities offered in Greenville County, and maximize both ecosystem services and consumer utility across space.

To improve long term city planning, future research in the area should consider time-series regressions to understand changes in non-market values through time better. Additionally, mixed methodologies could seek to integrate the non-economic values for environmental amenities, such as non-use values and cultural ecosystem services, with valuation estimates. Interviews with city planners and comparison to official planning documents could better relate the estimates of the values of green spaces to broader urban planning challenges. Furthermore, these results could be placed in the context of broader stakeholder analyses and ecological studies that help to target the protection of lands that are not only valued by citizens in the area, but that are biologically important as well.

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