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Shades of Green: Measuring the value of urban forests in the housing market

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Abstract

Urban areas can contain public parks, protected forests, unprotected (or undeveloped) forest areas, and trees growing around a house or in the neighborhood surrounding the house. Each type of forest cover provides different amenities to the homeowner and to society at large. In particular, while trees on a parcel of land or in a neighborhood may add value for homeowners, the ecological value of these trees as habitat is far less than large, unbroken parcels of forest. We explore different definitions of forest cover and greenness and assess the relative value of these various types of forest cover to homeowners. Using data from the Research Triangle region of North Carolina, we test the hypothesis that trees on a parcel or in the neighborhood around that parcel are substitutes for living near large blocks of forest. The findings have implications for land-use planning efforts and habitat conservation in particular.
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Introduction

Forest cover in an urban setting takes many shapes and comes in many shades. Urban areas can contain public parks, protected forests, unprotected (or undeveloped) forest areas, and trees growing around a house or in the neighborhood surrounding the house. Each type of forest cover provides different amenities (or a probability of disamenities as undeveloped parcels are developed) to the homeowner and to society at large. In particular, while trees on a parcel or in a neighborhood may add value for homeowners, the ecological value of these trees as habitat is far less than large, unbroken parcels of forest.

In this paper, we explore various definitions of forest cover and greenness and assess the relative value of these different types of forest cover to homeowners. Using data from the Research Triangle region of North Carolina, we test the hypothesis that the contribution of trees to an individual property or in the neighborhood around that property is conditional on whether the property is adjacent to or near large parcels of forest to explore substitution and complementarity of private, neighborhood, and public forests. Our findings have implications for land-use planning efforts and habitat conservation in particular.

Many studies over the past three decades have suggested that people should be willing to pay more to live near forests. For example, studies have shown that the scenic quality of a town is increased by tree cover, but that houses in that town are not necessarily more valuable (Schroeder and Cannon Jr., 1983; Schroeder and Cannon, 1987; Civco, 1979). Many of the studies that quantify the impact of open space on housing focus on public open space. Some research has focused primarily on distance to public forests (see Tyrvainen and Miettinen, 2000; More et al., 1988; Luttik, 2000). A few studies have looked at distance to a variety of land uses and open space definitions (for example, Mahan et al., 2000; Lutzenhiser and Netusil, 2001; Smith et al., 2002) or the proportion of open space or other land uses in the neighborhood around a house (Irwin and Bockstael, 2000a,b; Acharya and Bennett, 2001).

In the Research Triangle, forests are the dominant landscape (i.e., environmental) feature. Analyzing only public forests in the region would ignore the largest area of forests – those in private hands. Although these forests are not protected, they can provide important public value such as watershed and habitat, in addition to potentially providing "private" value to neighboring homeowners.

Our study extends the work in this area with a focus on specific measures of forest cover. We explicitly explore the interactions between varieties of forest variables that capture different services offered by forest cover. Using geographic information systems (GIS) technology and Thematic Mapper imagery, we can measure the "greenness" of 30-m square pixels with the Normalized Difference Vegetation Index (NDVI), a common index that is monotonically related to canopy leaf area (Rouse et al., 1974; Tucker, 1979).[1] These small-scale measurements allow us to construct

[1]In general, NDVI takes on high values (approaching 1) on sites with more forest cover, and low values (near 0) on sites with little or no forest cover.

measures of greenness and forest cover at the property level. The continuous measure of "greenness" complements data on aggregate land use classes and provides a more complete picture of how a property contributes to the quality of life in a neighborhood. The data also provide the researcher with increased flexibility in identifying blocks of forest with particular characteristics. In this analysis, we identify 40-acre and greater blocks of privately held forests, which are believed to offer valuable habitat for wildlife.

Thus, our reference to "greenness" is both specific and figurative. It is specific in the sense that we use satellite imagery and thematic mapping to characterize forest cover more accurately, and combine this pixel-specific measure with ownership categories in a GIS-generated image to comprehensively characterize the different configurations of private, neighborhood, and public forests in an urban setting. We then apply the hedonic property valuation logic to these specific measures to understand and explain how different interpretations of forest greenness are valued by people, as reflected in their choices of where to buy and build houses.

We present a brief review of the literature examining the value of forests and greenness to homeowners. We explore the forest cover and greenness variables used in this research and present evidence of correlations among these variables. Then we present a hedonic price model that uses the greenness and forest cover variables described earlier, and finally we offer some conclusions.

Background

Several recent articles explored the connection between open space and property values. Many real estate professionals agree that houses with mature trees are preferred to comparable houses without mature trees (Dombrow et al., 2000). Due in part to the broad array of data collection methods, various studies on the impact of increasing tree cover or proximity to forest parks on housing prices show mixed results. Two studies have suggested that housing values decrease rapidly as the distance from urban parks increases, with the positive price effect declining to near zero in less than a half mile (More et al., 1988; Tyrvainen and Miettinen, 2000). Thornes (2002) found that houses adjacent to a protected forest sold for a premium of about 7%, but that the effect did not seem to carry over even to houses across the street. Yet a similar study reported difficulty in finding a significant correlation with park proximity and housing values (Luttik, 2000). The presence of trees has been found to increase the selling price of a residential unit by 1.9% (Dombrow et al., 2000) to 4.5% (Anderson and Cordell, 1988) to 7% (Payne, 1973). However, the variable measuring forest cover can lack robustness, decreasing the reliability of the coefficients (Powe et al., 1995). More recently, Kim and Johnson (2002) found that proximity to a research forest in Oregon increased the value of houses, and that homeowners appear to have preferences for the type of forest near their houses. Irwin (2002) examined the proportion of different land uses and ownership around houses and found a premium associated with permanently protected open space compared to developable land. She found that increasing the proportion of forest around a neighborhood decreases the value of the houses.

Another method of valuing forests is to analyze the improvement in visual quality of trees or forest cover. Separating the effect of visual improvements from forest proximity can be quite difficult. Aesthetic qualities largely comprise the value of a forest view. These aesthetic values have been documented on a limited scale, with residential housing prices varying from 4.9% with a forest view (Tyrvainen and Miettinen, 2000) to 8% with a park view (Luttik, 2000). Paterson and Boyle (2002) found that the amount of a particular type of land use or land cover located near a home and what was visible from the home can have different impacts on property values. Their data suggest that living near forests adds value to a house, but forest visibility decreases the value of the house.

More broadly, the aesthetic value of old, large trees has been shown to increase the attractiveness of town streets (Schroeder and Cannon Jr., 1983; Schroeder and Cannon, 1987; Civco, 1979) and may positively affect the psychology of residents (Sheets and Manzer, 1991). In a town setting, trees at intermediate and far visual distances has a positive impact on a town's scenic quality, while trees at intermediate distances provides the largest increase in scenic quality[2] (Brush and Palmer, 1979). Increased development intensity has the strongest negative impact on scenic quality with vegetation providing a positive influence (Anderson and Schroeder, 1983; Civco, 1979). Similarly, the natural vegetation of urban parks enhances scenic value while manmade objects decrease visual quality (Schroeder, 1982).

Urban forests provide a wide range of benefits beyond just the aesthetic, including reducing solar radiation, limiting runoff, absorbing urban noise, modifying air quality, improving human health, and providing wildlife habitat (see Dwyer et al., 1992, for a more complete discussion). Bird diversity was found to vary between urban and suburban landscapes due to differences in forests structure and tree density (DeGraaf, 1985). In urban settings, wooded parks provide the best habitat for bird species with some evidence that tree-lined streets provide flight corridors (Fernandez-Juricic, 2000). Urban forests protect water quality by reducing the amount of runoff and thus reducing the sediment running into streams (Xiao et al., 1998; Sanders, 1984).

The forest-derived human health benefits include improved air quality, decreased urban noise levels, and reduced psychological stresses. Urban trees reduce regional air pollutants (Ozone, PM_{10}, NO_2, SO_2, CO) by 1–3% of anthropogenic sources (Scott et al., 1998; Nowak, 1994). Yet, natural emissions of hydrocarbons, mainly from forests, have been found to be as large as anthropogenic sources, possibly masking improvements in other air quality indicators (Chameides et al., 1988). Forest belts may reduce and/or mask urban noise by as much as 50% (Huang et al., 1992). Increasing the forest cover in a city reduces summertime heat more than it increases wintertime cold (Sailor, 1997). Planting trees around residential structures

[2]Distances were defined as "a near zone within which individual leaves of trees could be discerned; a middle zone in which the forms of trees could be discerned; and a far zone in which the shapes of trees could not be discerned." (Brush and Palmer, 1979).

may reduce cooling and heating costs due to reduced summer heating and a wind-shielding effect (Huang et al., 1990).

Forests have a mixed and unresolved impact on the development of adjoining communities. A recent debate highlighted the uncertainty of the impact of parks and green spaces to either foster neighborhood social ties or to create barriers to community interactions (Solecki and Welch, 1995; Gobster, 1998). Stronger neighborhood social ties have been documented around common spaces with higher levels of vegetation than similar common spaces lacking such trees or other green vegetation (Kuo et al., 1998). Yet not everyone living near parks or urban forests uses such spaces (Bixler and Floyd, 1997), and crime is often cited as a reason to avoid densely wooded areas (Talbot and Kaplan, 1984).

Although it is difficult to synthesize this range of empirical analyses, four general themes emerge. First, forests in urban settings take many different shapes and forms, generating potentially many different uses. Second, the main empirical modeling strategy relies on evaluating the uses and contributions of forests in urban housing markets, with or without an explicit hedonic model. Third, hedonic models typically use distance to a generic forest area or percent of adjoining land in generic forests as the primary "forest quality" variables. Fourth, hedonic models generate a wide range of estimated premiums for forest quality, presumably because "distance to forests" or "percent of neighborhood in forests" do not adequately capture the range of contributions provided by different types of urban forests. While we address several of these issues in this paper, we focus on the idea that different kinds of forests impact housing values differently by exploiting a rich data set that combines remote sensing, satellite imagery, and real estate transaction data within a GIS. Additionally, our use of parcel greenness introduces a new type of data that researchers can employ to better understand the economic value of urban forests.

Using remote sensing and satellite imagery

Data collection has remained a primary obstacle to conducting hedonic price studies with forest variables. Hedonic studies often rely on data collected by private or governmental organizations such as the Multiple Listing Service, which rarely contain information on tree cover (Dombrow et al., 2000). Photographs of houses have been used to actually count the number of trees per lot (Anderson and Cordell, 1988). Other researchers have used small data sets (60 to 300 observations) to conduct on-site tree inventories, measure accessibility to green spaces, and quantify the view of adjoining properties (Thompson et al., 1999; Luttik, 2000; Morales, 1980). A large body of literature is being developed using maps and GIS to analyze environmental amenities (More et al., 1988; Powe et al., 1995; Geoghegan et al., 1997; Irwin and Bockstael, 2000a,b; Tyrvainen and Miettinen, 2000; Acharya and Bennett, 2001).

Using aerial photographs to delineate vegetation types has a long history and is well-documented (Kadmon and Harari-Kremer, 1999). A decade ago, aerial photography was used to accurately measure the visual impacts of development on hillsides (Schroeder, 1988). Today, using satellite remote sensing, land cover and vegetation indices can be constructed over large multicounty areas (Owen et al., 1998; Geoghegan et al., 1997; Leggett and Bockstael, 2000; Acharya and Bennett, 2001; Mahan et al., 2000). The use of remote sensing data has allowed economists to join with landscape ecologists to include spatial and vegetation indices in hedonic models. GISs provide a means of organizing very large data sets spatially and have been used to assess urban forests and green spaces (Pauleit and Duhme, 2000; Dwyer and Miller, 1999).

Seeing the forest for the green: understanding greenness

In this study, we explore the impact of a variety of forest cover and greenness measures on housing prices in the Research Triangle region of North Carolina. Research Triangle is a rapidly urbanizing conglomeration of 3 to 15 counties, depending on the definition. This study focuses on Durham and Orange counties, two representative counties at the core of the Triangle. From the technology and employment centers of southeast Durham County to the rural northwest corner of Orange County, a spectrum of residential housing choices exists within the integrated housing market. The city of Durham (pop. 170,000) dominates the urban housing market while Chapel Hill (pop. 45,000) and to a lesser extent Carrboro (15,000) and Hillsborough (pop. 5000) provide small-town atmosphere.

Measuring greenness and forest cover

We begin by exploring the forest cover and greenness variables employed in this study. Most studies in environmental economics employ some measure of distance to public parks and open space or, more recently, the percentage of open space near a parcel. In addition to several different variables based on distance to forests or parks, we also use greenness of the parcels themselves as measured by satellite images.

"Greenness"

We measured the "greenness" of the parcels and surrounding area using 1997 Landsat TM coverage of the two-county region. The minimum spatial resolution of Landsat TM (excluding band 6) is $30\,\text{m} \times 30\,\text{m}$ cells (or pixels). From these data, the NDVI was calculated for each pixel (Rouse et al., 1974; Tucker, 1979). The NDVI is a commonly used index of vegetation state (Gallo et al., 2002), and is a ratio of the reflectance in two spectral bands measured by Landsat TM, normalized to range from –1 to 1. This ratio has been shown in numerous studies to be monotonically related to the amount of leaf area within each pixel (for example, Gobron et al., 1997). High values of NDVI (approaching 1) indicate pixels with more leaf area and low values (approaching 0) indicate pixels with little or no leaf area.

In addition, we used a quadratic discriminant analysis to classify each pixel to one of four land cover categories: water; forest; sparse vegetation (for example, lawns and golf courses); and developed (for example, built surfaces, roofs, or pavement).

Training data for the quadratic discriminant analysis was obtained from high-resolution aerial photos of the region. Each pixel was classified into the land cover class that it was statistically most likely to have come from (i.e., the class it was spectrally most similar to). We conducted a modest error assessment using known cover types from the region.

In a GIS database, the housing parcel map was overlaid on the pixel map. For each parcel, we calculated the mean greenness or mean NDVI index for the pixels in that parcel (*mean greenness*). In addition, we generated the proportion of the parcel that is forested, covered with sparse vegetation, water, or developed based on the proportion of the total pixels in the parcel in which the category was the dominant land cover (*prop_for*, *prop_dev*).[3] We then used these variables to create a rough estimate of the number of acres in each pixel devoted to forest and sparse vegetation (*acres_for*, *acres_veg*).

Finally, we constructed three buffer areas around each parcel (0–400 m, 400–800, and 800–1600 m) and calculated the proportion of forested land in the buffer. These variables (*buffer400*, *buffer800*, *buffer1600*) provide a measure of the greenness of the neighborhood in which the parcel is located.

Institutional forests

The Triangle area, and Durham and Orange counties in particular, contains a number of institutional forests located close to or within the residential and commercial areas of the counties. In addition to state parks and federal lands (including Army Crop of Engineering land near two local reservoirs), Duke University and North Carolina State University own several large tracts of forest in the two counties. These forests, which offer opportunities for recreation in addition to aesthetic value, are mapped in a GIS mapping system along with the housing parcels.

Using a GIS cover of publicly owned land, we measured the minimum Euclidean distance in meters from the edge of each parcel to the nearest institutional forest (*inst_dist*). An adjacency dummy variable (*inst_adj*) was coded 1 if a parcel was within 20 m of the institutional forest. A buffer of 20 m was included to account for GIS error in either the parcel coverage or the forest boundary map. Fourteen parcels in the data set used for our analysis were adjacent to the institutional forests, all of which were located in Durham County. We also created an interaction term between the distance from a parcel to the nearest institutional forest and the *mean greenness* of the parcel (*inst* $\times$ *green*). This variable is a proxy for the interaction between parcel greenness and proximity to institutional forests, and it will be used to test hypotheses about the relationship between trees on a parcel and proximity to institutional forests.

[3] Water and sparse vegetation form the excluded category in the regression analysis presented in Section 4 of the paper.

Private, undeveloped forest blocks

In addition to institutional forests, privately owned forest covers a significant proportion of the Triangle area, especially outside the urban areas of Durham and Chapel Hill. According to a report prepared for the Triangle Land Conservancy, "forests important to wildlife are hardwood and mixed forests at least 40 acres in size with no or only slight disturbance by human activities (Ludington et al., 1997)." We identified blocks of privately held forest 40 acres or larger containing no developed pixels, water, or sparse vegetation using the pixel-level data on land cover.[4] These blocks were created without reference to ownership and may contain multiple parcels with different owners.

Using the map of forest blocks, we measured the distance in meters from each parcel to the nearest private forest block (*priv_dist*) and created a dummy variable for adjacency to a private forest (*priv_adj*) if the parcel was within 20 m of the forest block. Two hundred and thirteen parcels were adjacent to a private forest block in the data used for the analysis, of which 78 were located in Durham County. Finally, we created an interaction term between the distance from the parcel to the nearest private forest block and the *mean greenness* of the parcel ($priv \times green$) similar to the institutional forest interaction term.

Blocks of development

Finally, we used the land cover map to identify developed or built areas of 10 or more acres. For each parcel, we calculated the distance from the parcel to the closest block of developed land (*dev_dist*). This variable should capture the proximity of the parcel to smaller shopping centers outside the major employment centers in addition to areas of dense development. The variable may also provide an indirect measure of the greenness of the neighborhood in which the parcel is located. The developed blocks are mostly clustered around the cities of Durham and Chapel Hill in our study area.

Structural and parcel variables

Data for housing sales in Orange and Durham counties, North Carolina, was purchased from TransAmerican Intellitech, a commercially available database of real estate transactions drawn from county records. The database contained nearly 150,000 transactions for residential and commercial properties. For our study, we looked only at residential sales for parcels sold between 1996 and 1998. The final data set contains just over 11,200 observations after trimming the top and bottom 5% of sales prices and parcel acreage and deleting observations with missing data. Of these, slightly over 8300 are located in Durham County and 2900 are located in Orange County. The data set did not contain a full set of structural variables for most observations, so the structural variables include the number of bedrooms (*bedrooms*), number of stories (*stories*), and the year the house was built (*yr_blt*). In

[4]The forest land cover category contains deciduous, mixed, and conifer forests; however, the classification is most robust at the aggregate category of "forest."

addition, we calculated the size of the parcel in acres (*acres*) and acres squared (*acres_sq*). The median lot size of the parcels in our data set is 0.35 acres. The average size of a parcel in Durham County was 0.31 acres, smaller than the average parcel in Orange County, which was just over 0.50 acres. The *acres_sq* variable was included to capture the potential for diminishing marginal return of increasing parcel size. We estimated the size of the "footprint" of the house on the parcel by multiplying the proportion of the pixels in the parcel that were classified as "developed" by the size of the parcel in acres (*acres_dev*). Because the dominant land cover in the 30-m^2 pixels determines its classification, this should approximate the footprint of the house.

Using the parcel map, we created variables measuring the travel time to employment centers. Traffic analysis zones, provided by the Triangle J Council of Governments, allowed us to determine the three largest employment centers in the two counties: Duke University (located in the City of Durham), Research Triangle Park (located southeast of Durham), and the University of North Carolina (located in the City of Chapel Hill). Using ArcInfo, we calculated the distance along the road network from each employment center to each parcel using major and secondary highways (Halpin et al., 2000). Anticipated average speeds were varied among the road types with an additional impedance factor added to each route to more accurately represent actual travel time. For locations away from the major road network, the linear distance from the nearest road was determined and added to the travel time. We merged the parcel map and the travel time grid to derive an expected travel time from each parcel to each of the three major employment centers. These values created three continuous distance variables: distance to Duke University (*duke_dist*), distance to the University of North Carolina (*unc_dist*), and distance to Research Triangle Park (*dist_rtp*). A histogram of the distance from the parcels in our data set to Duke University Hospital in minutes shows that the variable initially spikes at just less than 10 min with a larger maximum at approximately 20 min and a rapid decrease thereafter. Very few parcels are more than 50 min from Durham.

Finally, we created dummy variables for the municipal boundaries in the area. The municipalities include Durham County (*dur_co*) and the City of Durham (*durcity*), which is located in Durham County. In Orange County, we identified properties in the cities of Chapel Hill (*chaphill*) and Carrboro (*carrboro*). These boundaries are especially important in Orange County where the Chapel Hill-Carrboro school system is considered to be the highest quality system in the two counties. The other municipalities in Durham and Orange are much smaller and contain only a few parcels.

How green is green?

Correlation of greenness variables

One would suspect that several of the variables described above play a similar role in people's utility and housing choices with respect to environmental variables.

Table 1 presents the correlation matrix for the variables described above. Almost all of the correlation coefficients are significant at the 1% level. As expected, the mean greenness of the parcel is highly correlated with the proportion of the parcel that is forested. Mean parcel greenness and the proportion of the parcel that is forested are positively correlated with adjacency to private forest blocks and distance from developed blocks. Parcels located adjacent to private forest blocks are both greener on average than other parcels, while parcels located away from developed blocks are also greener, all else equal. Finally, the number of acres of forest within a parcel is positively correlated with adjacency to a private forest block and the acres of sparse

Table 1. Correlation coefficients

	Mean greenness	prop_for	prop_veg	acre for	acre veg	priv_dist	inst_dist
mean greenness	1.0000						
prop_for	0.6843	1.0000					
	0.0000						
prop_veg	−0.0155	−0.3867	1.0000				
	0.0382	0.0000					
acre for	0.1603	0.1786	−0.0502	1.0000			
	0.0000	0.0000	0.0000				
acre veg	0.0472	−0.0037	0.1504	0.4940	1.0000		
	0.0000	0.6284	0.0000	0.0000			
priv_dist	−0.1015	−0.1213	−0.0827	−0.1335	−0.1235	1.0000	
	0.0000	0.0000	0.0000	0.0000	0.0000		
inst_dist	0.0856	0.0601	0.0966	0.1420	0.1880	−0.0616	1.0000
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	
dev_dist	0.2835	0.2263	0.1358	0.1487	0.1633	−0.3082	0.3351
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
inst_adj	0.0482	0.0571	−0.0212	0.1303	0.0945	−0.0488	−0.0613
	0.0000	0.0000	0.0045	0.0000	0.0000	0.0000	0.0000
priv_adj	0.2346	0.2730	−0.0933	0.3545	0.1592	−0.2532	0.1565
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
yr_blt	−0.1753	−0.0705	0.0172	−0.0683	−0.0557	−0.4122	−0.0387
	0.0000	0.0000	0.0454	0.0000	0.0000	0.0000	0.0000

	dev_dist	inst_adj	priv_adj	yr_blt
dev_dist	1.0000			
inst_adj	0.0017	1.0000		
	0.8166			
priv_adj	0.2568	0.0921	1.0000	
	0.0000	0.0000		
yr_blt	0.1783	−0.0034	0.0064	1.0000
	0.0000	0.6891	0.4546	

Note: Significance level of correlation listed underneath correlation coefficient. See Table 2 for definitions of variable names.

vegetation within the parcel.

The variable measuring distance to developed blocks is positively correlated with distance to institutional forests and negatively correlated with distance to private forest blocks. This finding suggests that in Orange and Durham counties, parcels located closer to institutional forests are also located closer to developed areas, while parcels located closer to private forest blocks are farther from developed areas.

Finally, the year in which the house was built is negatively correlated with distance to private forests. This may imply that newer houses are being located away from developed areas and closer to private, developed forest blocks. As the Research Triangle area expands, most of the building is going to occur on privately owned forest tracts, so this association makes intuitive sense.

Regression results

To estimate the hedonic equation, we combined data on land use and greenness with housing sales information in a GIS framework. The tax parcel maps for the two counties form the first layer of data. To this we added parcel-specific information about housing sales and structural characteristics. The third layer contains maps of federal, state, and local or institutional parklands. Finally, the top layer contains data from remote sensing images of the area that are used to identify greenness and categorize the parcels into different categories of land use. Table 2 lists all the variables with summary statistics. Below we describe our basic hedonic price function model and the structural and other parcel variables used in the regressions.

A hedonic price function usually takes a form such as

$$P = f(Q, N, S) + e,$$

where P is the sales price of the house, Q is a vector of environmental attributes of the house, N is other neighborhood variables, and S is the structural characteristics of the house. The error term, e, reflects uncertainty in the measurement of the variables and in the preferences of the individual homebuyers. The hedonic price function refers to market equilibrium, which includes the joint decisions of buyers and sellers of houses. Demand for housing, including its various attributes, stem from the contribution of housing and its elements to a buyer's utility function. Values for particular attributes – such as greenness – are reflected in the extra premium a buyer is willing to pay for the particular attribute. These decisions are the outcome of a constrained utility maximization choice for the buyer (Freeman, 1993). With our data, we provide a richer characterization of Q (forest and greenness variables) with which to explore interactions between the elements of Q, as well as the impact of Q on property values.

As summarized earlier, most studies conclude that trees and forested parks provide value to homeowners. This leaves open the empirical question about how homeowners value different measures of forest cover and greenness. Our data set allows exploration of the extent to which trees on a homeowner's parcel substitute for or complement distance to institutional and privately held forest tracts.

Table 2. Summary statistics

Variable	Description	Mean	Standard deviation	Min	Max
sales price	Sales price	135,127.10	68,912.03	18,500.00	360,000.00
sales price $1998	Sales price converted to 1998 dollars using the Consumer Price Index	137,630.30	70,126.88	18,500	373,996.10
inst_dist	Minimum linear distance to nearest institutional forest boundary in meters	2865.97	2075.43	0.00	18,540.80
inst_adj	Dummy variable = 1 if within 20 m of an institutional forest	0.00	0.04	0.00	1.00
inst × green	*inst_dist * mean greenness*	1762.93	1441.01	0.00	12,000.14
priv_dist	Minimum linear distance to boundary of nearest private forest block of 40 acres or more in meters	771.98	620.51	0.00	2962.67
priv_adj	Dummy variable = 1 if within 20 m of a private forest block	0.02	0.14	0.00	1.00
priv × green	*priv_dist * mean greenness*	475.06	414.70	0.00	2524.07
mean greenness	Mean NDVI of 30 × 30 m pixels in parcel	0.61	0.16	0.00	0.95
prop_for	Proportion of pixels in the parcel that are categorized "forest"	0.30	0.39	0.00	1.00
prop_for_0 to 400	Proportion of pixels in a buffer of 0–400 m buffer around parcel categorized "forest"	0.35	0.18	0	0.96

prop_for_400 to 800	Proportion of pixels in a buffer of greater than 400–800 m around parcel categorized "forest"	0.38	0.16	0	0.89
prop_for_800 to 1600	Proportion of pixels in a buffer of greater than 800–1600 m around parcel categorized "forest"	0.40	0.14	0	0.82
acres dev	*prop_dev * acres*	0.10	0.14	0.00	3.19
bedrooms	Number of bedrooms	3.12	0.73	1.00	11.00
stories	Number of stories	1.12	0.35	1.00	12.00
acres	Acreage of parcel	0.55	0.65	0.06	5.28
acres_sq	Acres squared	0.73	2.50	0.00	27.85
yr_blt	Year house was built	1974.12	22.47	1822.00	1997.00
dur_co	Dummy = 1 if house in Durham County	0.74	0.44	0.00	1.00
carrboro	Dummy = 1 if house in Carrboro	0.03	0.18	0.00	1.00
chaphill	Dummy = 1 if house in Chapel Hill	0.09	0.28	0.00	1.00
durcity	Dummy = 1 if house in the city of Durham	0.51	0.50	0.00	1.00
duke_dist	Driving time to Duke University Medical Center in Durham	16.68	7.82	1.84	56.28
unc_dist	Driving time to University of North Carolina in Chapel Hill	21.56	9.33	1.18	60.24
rtp_dist	Driving time to Research Triangle Park	18.84	9.30	2.97	66.63
dev_dist	Minimum linear distance to boundary of nearest 10 acre or greater developed block	548.76	991.00	0.00	8293.90
N	Number of observations	11,206			

Model 1 in Table 3 is the base model. Model 1 includes only one measure of forest amenities, the distance to an institutional forest (*inst_dist*), in a regression with sales price in 1998 dollars as the dependant variable. As discussed above, this regression is typical of much of the prior work in this area in that it includes only distance to defined parks. As expected and consistent with other studies, the coefficient on distance to the nearest institutional forest is negative, indicating that parcels located closer to institutional forests have higher value.

However, this simple distance measure masks more complex relationships between parcel greenness, institutional forests, private forest blocks, and distance to developed blocks. Model 2 contains additional measures of forest amenities: proportion of the parcel that is forested (*prop_for*) and the distance to the nearest private forest block (*priv_dist*). In addition, we added the variable measuring distance to the nearest block of developed land (*dev_dist*). The TM imagery allows identification of blocks of forest and developed land that may cut across several parcels, which provides more information about the area than simple distance to institutional forests or parks. Based on previous work, we expect a negative coefficient on *priv_dist* and a positive coefficient on *dev_dist*. Comparing Model 1 with Model 2, adding these three variables reduces slightly the size of the coefficient on distance to the nearest institutional forest. Again, a location closer to either a private or institutional forest increases the sales price of the house, but the coefficient on distance to an institutional forest is larger. Properties with a higher proportion of forest are also more highly valued. As expected, *Dev_dist* has a positive coefficient.

As described earlier, we used the mean greenness values (the NDVI values) to create several additional greenness and forest cover variables. Models 3 and 4 contain the results from regressions that include several greenness and forest cover variables. Additional variables include two dummy variables that equal 1 if the parcel is adjacent to an institutional forest or a private forest to allow for additional benefit or loss from direct adjacency as suggested by the previous literature. In addition, we included the two interaction terms defined earlier: $inst \times green$ and $priv \times green$. In Model 2, decreasing distance to private and institutional forests increased the sales price of a property. If the coefficient on the interaction term between distance and parcel greenness is positive, then the value of being closer to an institutional or private forest is smaller for parcels that are greener. This finding would suggest that parcel greenness is a substitute for locating close to a forest block.

The results in Models 3 and 4 reveal a more diverse pattern of the influence of trees on housing prices. The models are the same except that Model 4 includes a measure of the mean greenness of the parcel based on the NDVI values. In both models, distance to both institutional and private forest blocks remains negative and significant. Proximity to either type of forest increases the sales price of the house; however, the size of the coefficient on distance to private forest blocks has increased dramatically while the coefficient on distance to institutional forests has declined compared to Model 2. Distance to developed blocks has a positive coefficient of similar magnitude to Model 2. The coefficient on *prop_forest* remains positive and significant. Controlling for acres, parcels with a greater proportion of forest cover (*prop_for*) have greater value. However, in Model 4 *mean greenness* has a negative

Table 3. Hedonic price functions with forest proximity and greenness variables, coefficient and (robust standard error[a]) Dependent variable: Sales Price \$1998

Variable	Model 1	Model 2	Model 3	Model 4
inst_dist	−6.13***	−5.91***	−2.46***	−4.22***
	(0.33)	(0.33)	(0.97)	(1.20)
inst_adj			−22,161.82	−20,050.90
			(21,881.77)	(21,852.90)
inst × green			−5.45***	−2.71
			(1.45)	(1.82)
priv_dist		−1.87**	−23.61***	−27.74***
		(0.96)	(3.08)	(3.53)
priv_adj			7620.97	8347.25*
			(4726.99)	(4746.80)
priv × green			35.52***	42.24***
			(4.83)	(5.59)
mean greenness				−20,027.00***
				(7992.27)
prop_for		9434.83***	6600.78***	7878.86***
		(1422.35)	(1561.77)	(1617.94)
acres dev	8301.14*	23,512.19***	26,088.17***	24,031.12***
	(4519.34)	(4928.06)	(5021.67)	(5095.61)
bedrooms	25,033.44***	24,661.77***	24,540.19***	24,596.86***
	(1119.27)	(1108.48)	(1093.67)	(1093.23)
stories	32,012.14***	32,222.55***	32,457.95***	32,396.58***
	(6339.65)	(6315.68)	(6158.32)	(6139.31)
acres	43,325.85***	31,061.51***	30,274.79***	31,766.31***
	(3011.93)	(3263.89)	(3302.75)	(3365.79)
acres_sq	−7994.05***	−5920.55***	−5708.39***	−5995.58***
	(728.13)	(748.06)	(755.46)	(767.92)
yr_blt	630.65***	617.35***	621.12***	609.05***
	(31.53)	(32.32)	(32.26)	(32.61)
dur_co	30,130.89***	31,951.63***	32,425.07***	31,959.79***
	(4096.28)	(4063.60)	(4020.44)	(4028.98)
carrboro	19,457.67***	22,174.23***	21,193.23***	21,571.94***
	(3881.01)	(3947.30)	(3910.85)	(3921.94)
chaphill	34,654.67***	34,966.82***	34,137.64***	34,401.10***
	(3035.29)	(3051.55)	(3035.21)	(3037.45)
durcity	6173.21***	6755.79***	6187.72***	6322.58***
	(1153.28)	(1158.17)	(1161.33)	(1159.75)
duke_dist	704.05***	615.08***	688.01***	661.65***
	(114.26)	(118.14)	(118.74)	(119.13)
unc_dist	−2644.97***	−2829.35***	−2865.53***	−2848.46***
	(117.40)	(115.05)	(116.72)	(116.81)
rtp_dist	1661.12***	1456.32***	1443.60***	1427.54***
	(116.30)	(116.97)	(117.83)	(118.26)
dev_dist		8.04***	8.18***	8.24***
		(0.97)	(0.97)	(0.97)

Table 3. (*continued*)

Variable	Model 1	Model 2	Model 3	Model 4
sold 1996	−10,416.18***	−9851.79***	−9864.30***	−10,079.53***
	(1148.89)	(1140.55)	(1138.30)	(1138.38)
sold 1997	−3663.95***	−3291.06***	−3379.15***	−3441.73***
	(1138.27)	(1128.44)	(1124.55)	(1124.15)
cons	−1,232,929.00***	−1,201,213.00***	−1,208,339.00***	−1,172,270.00***
	(57,651.89)	(59,930.62)	(59,941.38)	(61,765.43)
R^2	0.48	0.49	0.49	0.49
N	11,206	11,206	11,206	11,206

***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.
[a]White-correct Standard errors (White, 1980).

and significant coefficient. Interpreting the *mean greenness* variable is not as easy as *prop_forest* because the measure captures overall greenness of the parcel based on an index accounting for all types of vegetation, water, and developed areas. As the size of the house increases relative to the parcel size, all else equal, the value of the *mean greenness* variable will decline. So the negative coefficient on mean greenness could reflect a smaller percentage of housing stock, all else being equal.

Being adjacent to a private forest further increases the value of the house (the coefficient is significant at the 10% level in Model 4 and just over 10% in Model 3). Houses located in and around private forest blocks outside urbanized areas may be more desirable, similar to the "leap-frog" pattern of development observed by Irwin and Bockstael (2000a,b) in the rural area between Washington, DC, and Baltimore, Maryland. On the other hand, adjacency to an institutional forest block is not significant in either model. This may also reflect the diversity of institutional forest land within the study area. Some of the institutional forests are owned by the local universities and contain walking trails and other recreational opportunities, while some of the institutional forest is owned by the Army Corp of Engineers around the local reservoirs. Unfortunately, we have very few properties adjacent to institutional forests in our data set, and so we cannot investigate if any of these factors result in the lack of significance of this variable.

The two interaction terms, *inst* × *green* and *priv* × *green*, represent a first attempt to capture substitution effects between the various types of greenness a homebuyer may value. *Priv* × *green* is positive and significant in both models. The positive coefficient on the interaction term is consistent with the interpretation that greater parcel greenness can compensate for living a greater distance from a private forest block. The negative coefficient, which is significant in Model 3, on *inst* × *green*, is less intuitive. The addition of the variable mean greenness in Model 4 reduces the significance of *inst* × *green*. Institutional forests may complement parcel greenness in some manner, whereby people who like trees choose parcels that have lots of trees and are located close to well-recognized institutional forests. Holding mean greenness constant, properties that are closer to institutional forests are more valuable. While it would be premature to come to strong conclusions, the statistical results offer some evidence of how people may be substituting or complementing parcel level, neighborhood, and institutional forests in choosing their homes.

In all the regressions, the structural variables, *bedrooms*, *stories*, and *yr_blt*, are positive and significant as expected. The size of the parcel, *acres*, is positive and significant, while *acres_sq* is negative and significant, indicating that parcel value increases at a decreasing rate as the size of the parcel increases. Our approximate measure of the footprint of the house (*acres_dev*) is also positive and significant. The dummy variables for living in Chapel Hill and Carrboro, both in Orange County, are positive and significant and consistent with the local expectations regarding the desirability of living in these cities. Having accounted for the positive impact of living in Chapel Hill or Carrboro, living in Durham County and, within Durham County, living in the city of Durham has a positive impact on property values.

The commuting distance from the parcel to Duke University Hospital and Research Triangle Park (*duke_dist* and *rtp_dist*) are positive and significant indicating that parcels located farther from these employment centers are more valuable. While this may seem counterintuitive, Research Triangle Park contains almost exclusively business development. Duke University Hospital is located near the center of downtown Durham, a less desirable area of the city. Furthermore, commuting distance to downtown Durham from Chapel Hill is short by the standards of larger cities. Distance from the University of North Carolina (*dist_unc*, which is located in Chapel Hill) has the expected negative sign.

Model 5 in Table 4 contains a final regression in which distance to institutional and privately held forests are measured in discrete blocks, rather than as a continuous variable. We also included variables measuring the mean greenness of the immediate neighborhood around the parcel in expanding circles. Table 5 presents the distribution of parcels within different distances from institutional forests, private forests, and developed blocks. All the parcels in the data set are within 3200 m of a private forest and the majority of the parcels are within 800 m. In contrast, 38% of parcels are more than 3200 m from an institutional forest and only 15% are within 800 m. Over 80% of the parcels are located within 800 m of a 10-acre or larger block of developed land.

In general, the results in Table 4 are similar to the regressions presented in Table 3. The coefficients on the distance categories from private forests (*distpriv 800*, *1600*, *3200*) suggest a nonlinear relationship between distance to private forests and parcel value. Looking at institutional forests, the only significant coefficient is for parcels located more than 3200 m from an institutional forest (*distint* > *3200*). Properties that are more than 800 m from developed blocks (*disdev 800*) are more highly valued. The measures of neighborhood greenness in buffers around the parcels (*buffer 400*, *800*, *1600*) are all positive, but not individually significant. The joint significance of the three buffer variables cannot be rejected at a 1% confidence level. Also, in Table 4, *mean greenness* is positive and significant.

Using the models in Tables 3 and 4, we can compare the marginal effect of different variables on sales price. In general, traditional structural variables such as

Table 4. (a) Hedonic price function with discrete forest proximity variables, coefficient and (robust standard error[a]). Dependent variable: Sales Price $1998

	Model 5
distpriv 800	−3641.12***
	(1473.06)
distpriv 1600	−7465.54***
	(2327.45)
distpriv 3200	−17,441.23***
	(4094.08)
distinst 800	−1017.13
	(2480.73)
distins 1600	625.61
	(2479.36)
distinst 3200	2340.03
	(2679.09)
distinst >3200	−8085.17**
	(3365.14)
disdev 800	−13,657.04***
	(2093.23)
buffer400	5806.06
	(4024.11)
buffer800	4543.78
	(6020.95)
buffer1600	9106.20
	(5994.42)
inst_adj	−23,061.55
	(22,518.93)
priv_adj	8025.73*
	(4776.06)
inst × green	−5.95***
	(0.86)
priv × green	12.59***
	(3.40)
prop_for	8988.49***
	(1634.89)
mean_greenness	9498.80*
	(5816.80)
acredev	21,504.82
	(5043.61)

(b) Hedonic price function with discrete forest proximity variables, coefficient and (standard error) (continued)

Variable	Coeff (std err)
bedrooms	24,569.57***
	(1104.26)
stories	31,910.51***

Table 4. (*continued*)

	Model 5
	(6346.09)
acres	32,541.85***
	(3353.73)
acres_sq	−6086.65***
	(772.59)
yr_blt	627.83***
	(32.58)
dur_co	30,052.96***
	(4017.90)
carrboro	24,736.82***
	(4072.84)
chaphill	33,418.41***
	(3158.07)
durcity	6385.72***
	(1175.20)
duke_dist	574.52***
	(127.09)
unc_dist	−2691.48***
	(123.21)
rtp_dist	1358.78***
	(126.32)
sold 1996	−9841.20***
	(1143.03)
sold 1997	−3249.54***
	(1130.56)
cons	−1224,718.00***
	(61,071.02)
R^2	0.49
N	11,206

***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.
[a]White-correct Standard errors (White, 1980).

bedrooms, stories, and the acres of land in the parcel add more to the value of the house than the greenness variables. From Model 4, an additional bedroom adds about \$24,000 to the sales price of a house, while increasing forest cover on the parcel by 10% adds less than \$800. Among the greenness variables, adjacency to a private forest block has the most substantial impact on housing price, increasing price by more than \$8000.

Table 5. Distance to Institutional Forests, Private Forest Blocks and Developed Blocks

Distance	Institutional Forests: Number of parcels (percent of parcels)	Private Forest Blocks: Number of Parcels (percent of parcels)	Developed Blocks: Number of parcels (percent of parcels)
0–400 m	730 (7%)	4025 (36%)	
400–800 m	928 (8%)	2796 (25%)	
800–1600 m	1786 (16%)	3009 (27%)	
1600–3200 m	3495 (31%)	1376 (12%)	
Greater than 3200 m	4267 (38%)	0	
0–800 m			9119 (81%)
Greater than 800 m			2087 (19%)

Conclusion

Unlike other environmental variables often included in hedonic price functions, such as local air quality, there is no ambiguity about whether potential homebuyers are aware of trees and forests in the neighborhood. It is well documented that trees on parcels and in neighborhoods provide aesthetic and environmental value. Anecdotally, everyone has observed that the first thing people do in new, clear-cut subdivisions is to plant trees.

In this paper, we use several new methods for measuring greenness and local forest cover to explore the interrelationships between similar, but not identical, environmental variables related to forest cover and greenness. Consider three potential extensions of this line of research. First, it may be possible to more formally investigate "cross-green" substitution and complementarities between institutional, neighborhood, and personal forests that extends beyond interaction terms. Second, one could consider different definitions of neighborhood by looking at greenness and forest cover in areas of different sizes around the parcels, as well as the greenness of the institutional forests. Finally, the regression model could be extended to account for potential for spatial autocorrelation and spatial lag.[5]

Overall, we find that greenness and forest cover add value to parcels, as does proximity to institutional and private forests. However, while adjacency to private forests seems to add value to houses, adjacency to institutional forests was not significant. The results of the regressions suggest that parcel greenness can substitute

[5]Spatial dependence in the error terms could result from omitted variables that are spatially correlated. Whether this possible correlation would affect the significance of the forest cover and greenness variables is an open question. Acharya and Bennett (2001) did not find evidence of spatial autocorrelation in their hedonic property analysis of the value of open space and diversity of land-use patterns.

for proximity to private forest blocks and possibly complement proximity to institutional forests.

Previous analyses have tended to focus on public open space or public forests, in part because of the difficulty of obtaining data on private forest blocks. In this paper, we probe beyond open-space questions by examining the Research Triangle area, where most of the forest is privately held, using satellite data with GIS maps of land ownership. We find that private forests provide an important source of value to houses in the area. In addition, we see that the influence of the institutional forests variable decreased significantly as the other measures of private forest and parcel greenness were added to the specification. Reflecting on the different measures used to capture the natural environment around the parcel, the variable mean greenness, based directly on the NDVI, proved less intuitive than variables such as the percentage of forest on the property, which were calculated using the NDVI.

From a policy perspective, the results have implications for land use and conservation efforts. Parcel greenness may provide a substitute for nearness to private forest blocks in the minds of homebuyers, but it does not provide an ecological substitute for large, unbroken tracts of forest. Undeveloped tracts of forest provide public goods to society, but their market value in an undeveloped state is undermined by the willingness and ability of homebuyers to purchase the private, aesthetic benefits of forest cover through greener parcels.

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