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# The Influence of Urban Landscape Spatial Patterns on Single-Family Property Values

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## Introduction

Urban natural environments containing trees and/or forested areas provide a wide range of ecological benefits including air and water pollution mitigation, protected habitat for wildlife, and storm water runoff reduction (Alberti, 2005; Nowak and Dwyer, 2007; Nowak et al., 2006; Newman et al., 2014; Berke et al., 2015), as well as social benefits to neighborhoods by decreasing crime rates and promoting community involvement (Kuo and Sullivan, 2001; Troy et al., 2012). Various health benefits of urban green space include the prevention of obesity, asthma relief, shorter recovery times for patients, and increases in mental health and quality of life (Hartig et al., 1991; Kaplan, 1995; Kim et al., 2014; Kim et al., 2016; Lovasi et al., 2008; Matsuoka, 2010; Sugiyama et al., 2008; Ulrich, 1984).

In addition to the ecological, health and social benefits, much empirical economic based research suggests that urban green space can increase the value of nearby residential properties (Conway et al., 2010; Li and Saphores, 2012; Morancho, 2003; Payton et al., 2008; Sander et al., 2010; Sander and Polasky, 2009; Saphores and Li, 2012). Positive correlations between urban green space and housing price have been consistently documented. Prior studies, however, have primarily relied only on the total amount of aggregated green areas using land use data and/or proximity to green space near a single property. This approach has not fully captured the quality of urban green space regarding broader landscape and ecological patterns. Simultaneously, most research on landscape patterns has not fully controlled for spatial autocorrelation effects. This research assesses the relationships between residential property sale prices and landscape spatial patterns. It seeks to identify the strongest predictors for housing sale prices, positing that ecologically healthier landscape patterns can contribute to increases in property sale prices.

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## Literature Review

### Urban Green Space and Housing Sales Prices

Housing proximity to urban green space has been continuously found to contribute to increased home sale prices; larger proportions of total green space have also been shown to have a positive influence on sales prices (Bolitzer and Netusil, 2000; Geoghegan, 2002; Irwin, 2002; Luttik, 2000; Lutzenhiser and Netusil, 2001; Tyrväinen, 1997; Tyrväinen, 2001; Tyrväinen and Väänänen, 1998; Morancho, 2003; Mansfield et al., 2005; Sander and Polasky, 2009). Mansfield et al. (2005) further clarified these findings, showing that proximity to forests and percentage of forested areas surrounding parcels, with the exception of institutional forests, increased home sale prices. Size and amount, however, are not the only factors related to green space influencing sales price; variety of open space can also have an effect. Lutzenhiser and Netusil (2001) reported that natural parks and other types of open spaces (including urban parks and golf courses) had a positive influence on housing sale prices.

Recent studies have paid more attention to relationships between different land cover types and housing property values rather than using aggregated size and/or distance to urban green space (Conway et al., 2010; Saphores and Li, 2012). Different land cover measurements such as percentage of distinct types of land cover (Saphores and Li, 2012) or number of street trees fronting a house (Donovan and Butry, 2010) have been used to estimate the value of urban green space surrounding a property, at different scales. Sander et al. (2010) assessed the relationship between urban tree cover and 9,992 homes in Dakota and Ramsey Counties, Minnesota, USA, finding that a 10% increase in tree cover in the 100 meters radii of a house increased home sale price by $1,371, on average. Kadish and Netusil (2012) assessed the associations between single-family residential sale price and four different land cover types including high structure vegetation (trees), low structure vegetation (shrubs and lawns), water and impervious surfaces, finding that trees showed a statistically positive contribution to increasing housing sale prices.

Some recent studies have attempted to analyze green space with more objective measures, incorporating remote sensing techniques with aerial photographs or satellite imagery (Li and Saphores, 2012; Sander et al., 2010; Saphores and Li, 2012; Payton et al., 2008; Li et al., 2015b). Saphores and Li (2012) analyzed 20,660 single family detached homes in Los Angeles, California, USA, and found that additional tree canopy cover slightly increased sales prices in tangential properties, at the neighborhood level. Payton et al. (2008) used the Normalized Difference Vegetation Index (NDVI) to assess the influence of green space on housing prices. Similarly, the results showed that greener vegetation around a property had a positive effect on housing price at the neighborhood level.

Previous studies, however, have concentrated primarily on individual green spaces and have not adequately addressed these findings in regards to landscape spatial patterns. The effects of the ecological quality of urban trees and forests on surrounding properties nor how to measure spatial heterogeneity in the entire urban green structure ecosystem are not yet fully understood. Only a few studies have examined the role of urban landscape patterns on housing prices. A study by Geoghegan et al. (1997) was one of the first attempts to show that landscape patterns economically effected nearby parcels. They used landscape ecology indices in a hedonic pricing model and reported that the proportion of open space within a 0.1km radius of a parcel positively impacted its sale price. They also found that an increase in heterogeneity in land uses (diversity) and more subdivided land uses (fragmentation) in the immediate neighborhood of the house did not have a positive impact on land values (Geoghegan et al., 1997). Geoghegan (2002) also documented that open spaces within a 1,600km radius from a parcel had positive correlations on housing price. In addition, Kong et al. (2007) assessed the value of urban green space on housing prices in Jinan City, China. They analyzed urban landscape patterns using six landscape metrics, and found that both the proximity to green spaces and the percentage of green space were positively associated with housing prices. Those studies, however, did not fully control for spatial autocorrelation effects. Considering spatial variables measuring landscape configuration using the hedonic pricing model helps capture the detailed quality of landscape patterns of urban natural environments surrounding properties and offers the potential for producing richer estimation models (Geoghegan et al., 1997; Kong et al., 2007).

## Quantifying Landscape Spatial Patterns

Research in the field of landscape ecology has improved the understanding of the interactions between the causes and effects of spatial patterns in natural and human-dominated landscapes (Turner, 2005; McGarigal and Marks, 1995; Turner et al., 2001). The goals of landscape ecology include reducing habitat fragmentation and connecting fractured landscapes to build more functional patterns which have greater ecological resilience and sustainability (Marsh, 2005). There are numerous physical, biological and social forces which contribute to spatial patterns in landscapes. Almost all landscapes have been affected by human activities. As such, the resultant landscape patterns occur through a complicated mixture of natural and human-dominated patches characterized by various sizes, shapes, and arrangements (Turner, 1989).

Since landscape ecology has focused on the reciprocal interrelationships between spatial patterns and processes (Gustafson, 1998; Turner, 1989; Forman and Godron, 1986), quantification of landscape patterns and their effects is one of the most significant issues in research on the topic (Haines-Young and Chopping, 1996; Li and Reynolds, 1995; Li and Wu, 2004; McGarigal and Marks, 1995; O'Neill et al., 1988; Riitters et al., 1995; Schumaker, 1996; Turner et al., 1989; Gustafson, 1998). Interests in measuring landscape patterns have been linked to the premise that ecological processes are connected to, and can be estimated by, various broad-scale spatial patterns (Gustafson, 1998).

One method of examining ecological quality is through assessing and interpolating landscape patterns. Landscape patterns, or arrangements, are determined by the functional flow and movements of nutrition, energy, animals, and materials through the landscape elements, over time. In addition, the pattern and process of the landscape is generated by simultaneous factors such as patch size and shape, the characteristics of corridors, connectivity and edges (Forman, 1995a; Forman, 1995b; Turner, 1990). There have been notable efforts made to develop principles to assess and indicate ecologically healthy landscapes. The theory of island biogeography (McArthur and Wilson, 1967) emphasized that patterns of immigration and extinction of species are strongly associated with the size of a given island. This principle has been repeatedly applied to the design/planning of projects. Diamond (1975), Shafer (1994), and Forman (1995b; 1995a) all developed slightly different suggested guidelines for spatial patterns in order to compare and explore the relationships between higher and lower quality landscapes based on this theory. From these guidelines, several criteria have been proposed for creating sustainable and ecologically sound landscape conditions: 1) larger patches (a relatively discrete area having homogeneous environmental conditions with a nonlinear shape) than smaller patches, 2) less-fragmented landscape patterns, 3) irregularly shaped boundaries of patches, 4) closer distance between single patches avoiding isolated patches, and 5) well-connected patches and corridors (a linear and narrow landscape element connected to a patch) (Shafer, 1994; Diamond, 1975; Dramstad et al., 1996; Forman, 1995a; Forman, 1995b; Haines-Young and Chopping, 1996).

The Patch-Corridor-Matrix model (P-M model) analyzes landscape patterns by characterizing landscape in three spatial components: patches (green spaces), corridors (connections of green spaces) and the matrix (the built environment that the corridors must traverse through), is a useful theoretical framework to evaluate and indicate ecologically viable landscape spatial patterns (Forman, 1995a). The P-M model highlights the heterogeneity of landscape elements, and each component provides a specific ecological function. In the P-M model, a pattern (structure) is identified by the landscape process (function) (Forman, 1995a).

The study of landscape patterns, processes and changes is a common concentration in landscape ecology research. The application of landscape indices to landscape ecology allows researchers to evaluate the quality of landscape patterns through quantitative approaches (Gustafson, 1998; Turner, 1989; Turner, 2005). Landscape indices are algorithms quantifying the spatial attributes of landscapes recognized by proportion, size, density, richness, proximity, shape and complexity. They are useful in estimating the interrelationships between human activities and ecosystems; more accurate quantitative values can also be derived by applying objectively measured analytical approaches reflecting and interpolating landscape patterns (Gustafson, 1998; Haines-Young and Chopping, 1996; Li and Wu, 2004; O’Neill et al., 1988; Riitters et al., 1995; Turner, 1989; McGarigal and Marks, 1995). There are, however, inherent limitations of using landscape indices such as uniqueness, sensitivity, redundancy and scale issues (Gustafson, 1998; Haines-Young and Chopping, 1996; Li and Wu, 2004; O’Neill et al., 1988; Riitters et al., 1995) because the basic formula for most landscape indices is based on the number, area and perimeter of each patch. Thus, to be useful for quantifying landscape patterns, a set of landscape indices should meet several criteria. For example, the selected indices should have a particular purpose to their analysis and the indices should be independent of each other. In addition, the behavior of the indices should be discrete and the measured values should cover the full range of potential values (Haines-Young and Chopping, 1996; Turner et al., 2001).

### Research Objectives

To address the aforementioned literature gaps, this study assesses the relationships between residential property sale price and landscape spatial patterns shaped by urban trees and forests, through objective measurements. The research seeks to identify which characteristics of landscape patterns are the strongest predictors of capturing housing sale price. To quantify the quality of landscape spatial patterns, this research used landscape indices after classifying land cover types surrounding a property. Based on current literature findings and theoretical backgrounds, it was hypothesized that housing sale price would be positively associated with landscape spatial patterns having larger size, less-fragmented, less-isolated, and/or less clumped conditions. For developing appropriate models by controlling the spatial autocorrelation effects, this research employed the spatial Cliff-Ord model and compared its results with an ordinary least squares (OLS) model (Cliff and Ord, 1981; Li et al., 2015b; Saphores and Li, 2012).

## Methods

### Study Location and Data Collection

As the capital of Texas, the city of Austin is one of the fastest growing U.S. metropolitan areas and is the 11$^{th}$ largest city in the U.S. (it was only the 42$^{nd}$ largest in 1980) (U.S. Census Bureau, 2010). The total population of Austin was estimated to be over 912,000 in 2014, a 20% increase since 2000 (U.S. Census Bureau, 2016). In addition to the population growth, Austin shows one of the highest growths in economy of all U.S. geographic areas, increasing nearly 6% in 2013 (Carlyle, 2014). The city has a relatively diverse physical environment setting with a wide range of natural and built environments from newly developed or historic communities.

Data to analyze the study site included housing transaction variables from January 2010 to December 2012 which was based on the Multiple Listing Service (MLA) data provided by the Austin Board of REALTORS®. The study collected 12,158 single-family home sale transactions in Austin. The original MLS data included detailed information about housing characteristics with variables such as living area, built year, lot size and numbers of bedrooms, full/half bathrooms, stories, fireplaces and garage spaces. The MLS data also contained binary variables including the existence of a pool and water frontage. Among the full data set, this research ultimately selected 11,326 home sale transaction samples after excluding any missing or mistyped records. To remove outliers in the sample selection, single-family houses with a lower sale price than $63,000 (the 1 percentile of the sample) or higher than $1,485,000 (the 99 percentile of the sample) were also excluded.

In order to control for the numerous factors which might influence property sale prices, we collected various variables of the neighborhood data to represent the social and environmental attributes. Based on Geographic Information Systems (GIS) data from the City of Austin, we calculated the distances to major infrastructure and/or amenities using both Euclidian distance (lakes and ponds, highways, and railroads) and street network distance (rail stations). We also analyzed locations of traffic accidents involved with pedestrians or cyclists and crime rates. To capture the school performance in the study area, we collected Texas Assessment of Knowledge and Skills test scores from the Texas Department of Education.

### Measuring Landscape Spatial Patterns

This research used landscape indices as environmental variables to examine the relationship between landscape spatial patterns and sale price of single family homes. Utilizing landscape indices enables to generate sets of quantitative data examining landscape patterns by comparing the differentiation and various groups of forms (McGarigal and Marks, 1995; Antrop, 2000). To assess the quality of landscape spatial patterns, we acquired Digital Orthophoto Quarter Quadrangles (DOQQ) aerial photograph images (1-meter color infrared high resolution imagery taken in 2010) from the Texas Natural Resource Information System (TNRIS). The collected DOQQ imageries were classified into 40 different land cover classes using the ISODATA unsupervised classification method based on the spectrum of the light band similarity using a remote sensing program, EVNI 4.3 (ITT Visual Information Solutions, White Plains, New York). The 40 classes were then grouped into three main land cover types: tree, grass and impervious areas. To improve accuracy in the classifying outcome, post classification processes including sieving, clumping, and filtering were conducted (Gong et al., 2003; Mas et al., 2010). Using ArcGIS 10.2 (ESRI, Redlands, California) software, the final classified imagery with three land cover types was converted into GRID files with the 1 by 1-meter pixel size. To determine the neighborhood of this study, we used 800 meters radius Euclidian buffers from the centroid of each property to capture the quality of landscape spatial patterns in the neighborhoods (Figure 1). The 800m distance has been widely used in many previous studies; it is the distance that neighborhood residents, including both adults and children population groups, would likely be willing to walk (Ewing, 1995; Lee and Moudon, 2006; Lee et al., 2006; Timperio et al., 2004; Kim et al., 2014). Then, to compute values of landscape indices, each GRID file was analyzed using FRAGSTATS 4.1, a spatial pattern analysis program applying the four-cell rule, which uses only orthogonal neighbors of a cell considering only the four adjacent cells sharing each side (McGarigal and Marks, 1995).

To quantify the quality of landscape spatial patterns, this research selected a series of diverse landscape indices. Based on previous studies and guidelines from the landscape ecology literature, this research selected five main criteria representing the quality of landscape spatial patterns: size, fragmentation, shape, isolation, and connectivity (Dramstad et al., 1996; Forman, 1995b; Forman, 1995a; Shafer, 1994; Haines-Young and Chopping, 1996). Then, the eight most appropriate landscape indices including total area (TA), percentage of tree cover (PLAND), number of tree patches (NP), mean patch size (MPS), mean shape index (MSI), mean nearest neighborhood distance (MNN), patch cohesion index (COHESION) and area-weighted mean radius of gyration (GYRATE, a measure of patch context examining how far a patch traverses across a landscape) were selected for representing each criterion (Table 1).

### Data Analysis

This research used the hedonic pricing framework to investigate the relationship between the quality of landscape spatial patterns and housing prices. Hedonic pricing models have been most widely applied to analyze the effects of various environmental attributes on housing price (Cropper et al., 1988; Rosen, 1974; Tse, 2002). They rely on regression analysis and are based on the fact that heterogeneous housing goods are affected by a number of factors, such as housing, neighborhood and locational characteristics (Conway et al. 2010; Payton et al. 2008; Geoghegan, 1997). The coefficients which a hedonic model generates for a certain characteristic can be interpreted as the implicit price that residents are willing to pay for such a characteristic (Morancho, 2003). The following equation describes our hedonic modeling framework:

$$\mathbf{P} = \mathbf{S}\boldsymbol{\beta}_{\mathbf{S}} + \mathbf{L}\boldsymbol{\beta}_{\mathbf{L}} + \mathbf{N}\boldsymbol{\beta}_{\mathbf{N}} + \mathbf{Q}\boldsymbol{\beta}_{\mathbf{Q}} + \mathbf{M}\boldsymbol{\beta}_{\mathbf{M}} + \boldsymbol{\varepsilon} \quad (1)$$

where **P** is a vector of sale transaction prices; **S**, **L**, **N**, and **Q** are matrices representing the variables of housing structural characteristics (e.g. square footage, number of bedrooms), locational characteristics (e.g. proximity to neighborhood facilities/amenities), neighborhood characteristics (safety and school quality), and landscape spatial patterns (landscape indices in Table 1) respectively; **M** is a matrix of the monthly binary variables to control for the housing market situations between 2010 and 2012. $\boldsymbol{\beta}_{\mathbf{S}}$, $\boldsymbol{\beta}_{\mathbf{L}}$, $\boldsymbol{\beta}_{\mathbf{N}}$, $\boldsymbol{\beta}_{\mathbf{Q}}$ and $\boldsymbol{\beta}_{\mathbf{M}}$ are vectors of their corresponding coefficients to be estimated; and $\boldsymbol{\varepsilon}$ is a vector of error terms.

When estimating hedonic pricing models, it is important to account for spatial autocorrelation, which refers to the correlation of variable with itself throughout the sample space. When a house is listed for sale, the offer price could largely depend on the sale prices of neighboring properties. Contemporarily, a buyer could utilize a realtor and/or various professional real estate websites to easily obtain the sales and some structural information of neighboring properties. The sale prices of neighboring properties can also influence appraisal/assessment values of a home; for example, the commonly used “sales comparison” method in real estate appraisal calculates the appraisal value of a home based on the sales information of similar houses in the neighborhood.

Spatial autocorrelation effects can exist in the dependent variable and cause biased estimates; they can also lead to inconsistent estimates when they occur in the error term. In order to examine whether such effects exist in our housing sample, we performed the Moran’ I test and obtained a highly significant Moran’ I statistic (11.39 at the 0.01 level). In order to control for spatial autocorrelation effects, we estimated the Cliff-Ord spatial model, also known as the general spatial model or SAC (Anselin, 1988; Arraiz et al., 2010; Saphores and Li, 2012; Li et al., 2015a; Li et al., 2014; Cliff and Ord, 1981). Our spatial hedonic model is as follows:

$$\begin{cases} \mathbf{P} = \lambda\mathbf{W}\mathbf{P} + \mathbf{S}\boldsymbol{\beta}_{\mathbf{S}} + \mathbf{L}\boldsymbol{\beta}_{\mathbf{L}} + \mathbf{N}\boldsymbol{\beta}_{\mathbf{N}} + \mathbf{Q}\boldsymbol{\beta}_{\mathbf{Q}} + \mathbf{M}\boldsymbol{\beta}_{\mathbf{M}} + \boldsymbol{\varepsilon}, \\ \boldsymbol{\varepsilon} = \boldsymbol{\rho}\mathbf{W}\boldsymbol{\varepsilon} + \mathbf{e}, \end{cases} \quad (2)$$

where W is a spatial weight matrix; $\lambda$ and $\rho$ are spatial lag coefficients; e ~ N (0, σ2In) is a vector of error terms in which the spatial autocorrelation effects are mitigated. Following Saphores and Li’s (2012) approach, we developed our spatial weight matrix so that all neighboring properties located in the same census block group had an equal weight of influence on one’s property price. There are two reasons to choose such a spatial weight matrix for this research. First, the census block group, which includes one or more contiguous city blocks, fits well with the neighborhood definition by the commonly used real estate appraisal approach – the comparable sales method. When real estate professionals use the method to appraise the value of a non-complex residential property such as the single family homes, they generally select comparable properties which are located within a few blocks of the subject. Second, various test results (e.g. Moran's I, Lagrange Multiplier Tests, etc…) confirm that our selection of the weight matrix can well reflect spatial autocorrelation in the data. We used the STATA package SPPACK by Drukker et al. (2011) to estimate our spatial model, with maximum likelihood as the estimator.

To assess the risk of multicollinearity issues in our model, we conducted preliminary correlation analyses between the selected landscape indices. Since all landscape indices were calculated based on size, perimeter, and numbers of patches, some of them showed a high correlation each other. Thus, this research tested several different combinations of eight selected landscape indices to determine the most appropriate set to be added in the final model. We also calculated the Variance Inflation Factor (VIF) for each independent variable to mitigate the risk of multicollinearity in the final model.

# Results

## Characteristics of the Housing Sample

Table 2 shows the descriptive statistics for sale prices and the four categories of variables in Equation 1. For the housing structural characteristics, the average home sale prices ranged from $63,000 to $1,480,000 with a mean sale price of about $300,000. The average size of living area was about 180 $m^2$ (1,950 sf) with about three bedrooms and two full bathrooms. The mean lot size of houses was about 960 $m^2$ (0.24 acres) and they were, on average, 33 years old at the time of sale. Only a few houses had a pool or were located at the waterfront. Among the variables measuring locational characteristics, the selected houses were, on average, about 10 km (network distance) away from Metro rail stations, while located in 767 meters (direct distance) away from the nearest lake or pond. Regarding neighborhood characteristics, the average school quality score was 70.38 ranging from 28 to 95. There were, about 260 property crimes (e.g., burglary, larceny-theft, and motor-vehicle theft) and 20 violent crimes (e.g., robbery, murder, and aggravated assault) around sample properties. In terms of landscape spatial patterns, over 39 percent of area within an 800 meter-radius buffer was covered by trees or urban forests, on average. There were about 4,000 tree patches, on average, and the mean distance between the two closest patches of the same type within each spatial setting was 2.59 meters.

## Influence of Landscape Spatial Patterns on Single-family Housing Sale Prices

In Table 3, we presented the primary results estimated with the Ordinary Least Square (OLS) model and the spatial Cliff-Ord model. The spatial Cliff-Ord model achieved a higher performance over the OLS based on the measures of Akaike Information Criterion (AIC: 5,837.172 lower than the OLS model) and Bayesian Information Criterion (BIC: 5,822.503 lower than the OLS model), and was considered the optimal modeling form for this study. Our study showed that the OLS model generated biased estimations on several variables. For example, the age of house at year of sale was positively associated with housing price in the

OLS model; such an estimate is counter-intuitive and the bias might be because homes within the same census block group would probably have been built around the same time, resulting in a clustering effect. Another counter-intuitive finding from the OLS model is that having more garage spaces would significantly reduce property values. However, both of the above variables showed expected signs in the spatial regression model. In addition, the OLS model has considerably overestimated the magnitude on the living area, numbers of full/half bathrooms, school quality, traffic safety, violent crime rate, as well as some landscape spatial characteristics (MSI and MNN); on the other hand, the OLS model has underestimated the magnitudes on the proximity to railroad, property crime and the total area of landscape (TA).

The above inconsistency occurs because the term $\lambda \mathbf{WP}$ is omitted in OLS; this term influences the sale price and is correlated with several independent variables as listed above, resulting in the omitted variable bias (Wooldridge, 2009). The OLS model also generated misleading significance levels on variables such as the proximity to railroad, total landscape area (TA), and patch cohesion index (COHESION). This typically occurs because spatial autocorrelation exists in the error terms and inflates the standard errors on these variables.

In the final spatial regression model, the effects of housing structural characteristics on transaction values were highly significant and showed expected signs. A single-family house would be sold at a significantly higher price with larger living area and lot size, younger age and a larger number of full and half bathrooms, while the number of bedrooms would be negatively associated with sale price. With keeping other factors constant, the property sale price significantly benefited from having more garage space, a pool and a waterfront location, whereas having two or more stories negatively affected sale prices.

Among variables assessing the correlations between locational and neighborhood characteristics, and housing transaction value, the closer network distance to Metro rail stations contributed to higher transaction values, while houses located within 400 meters of railroad showed significantly less valuable in the spatial regression model. This is a consistent finding from previous research (Armstrong and Rodríguez, 2006). The direct distance to the nearest lake or pond was negatively associated with property sale price at the .01 level, which means that a closer distance to a water body was more desirable by Austin residents. In addition, higher school quality based on the Texas Assessment of Knowledge and Skills test scores significantly benefited transaction values.

Interestingly, positive relationships were found between property sale price and two variables: the number of traffic accidents involved with cyclists and the number of total property crime in neighborhoods. These results were shown to be related to neighborhood characteristics. Many previous researchers found that pedestrian/cyclist friendly and transit-oriented development positively influenced property price (Bartholomew and Ewing, 2011; Litman, 2003), and a higher volume of pedestrians/cyclists was associated with more crashes (Dumbaugh et al., 2013). Thus, we assume that a wealthier community may have more cycling supportive facilities, which may cause induced demand for cycling and accordingly increase the chance of crash incidents. In addition, a wealthier sub-division could be a more attractive target for certain types of property crime (burglary, larceny-theft, and motor-vehicle theft), while less violent crime (robbery, murder, and aggravated assault) occurred in the neighborhood. However, either or both of the above two variables may serve as a proxy for other unobserved neighborhood characteristics which are positively associated with property values.

The effects of landscape spatial patterns on property sale price were highly significant and generally consistent with findings from previous studies. The spatial regression model showed the size of urban forests and tree patches (TA) was positively associated with the property transaction value. This suggests that larger tree areas within an 800 meter-radius buffer would be likely to increase the single-family housing transaction price. The final spatial regression model also represented that the number of tree patches (NP) was negatively associated with housing price at the 0.01 level, indicating that fragmented landscape spatial patterns in a neighborhood could decrease property sale price. MSI showed a negative relationship, which indicated that irregularly shaped landscape patterns were harmful to property sale price. MNN measuring the status of isolation was negatively associated with housing price. This finding suggests that less isolated patterns with closer distances between the nearest tree patches positively contributed to property sale price. There was a statistically negative association between COHESION and transaction value. The COHESION assesses the physical connectivity of the corresponding patch. The value of COHESION increases as the corresponding patch type have more clumped or aggregated in the given spatial distribution as the same patch type is more physically connected (McGarigal and Marks, 1995; Schumaker, 1996; McGarigal et al., 2012). This finding could be interpreted in that that more clumped tree areas would be less valuable to increase housing transaction value. This result may be associated with safety concerns about landscape structure in neighborhoods. Previous studies found that more open space with landscape structure having less dense understories and cleaner edge conditions would improve a sense of safety than closed landscape patterns in neighborhoods (Jorgensen et al., 2002; Ulrich, 1986). Thus, the landscape patterns by more clumped urban forests nearby properties may not be desirable to increase transaction values.

## Discussion and Conclusions

This research used spatial regression models to estimate the value of landscape spatial patterns on housing transaction prices using objective and quantitative measurements. Most previous hedonic studies about urban green space only measured the proximity to and/or the total size of green space (Irwin, 2002; Lutzenhiser and Netusil, 2001; Tyrväinen, 1997; Tyrväinen and Väänänen, 1998; Morancho, 2003; Mansfield et al., 2005; Sander and Polasky, 2009). Some studies have relied on NDVI measures as a proxy of the health and quantity of green space (Payton et al., 2008); however, there are some limitations when applying the NDVI measures into planning policy development, as NDVI cannot reflect spatial configurations of green space. Only few studies have examined the relationship between landscape ecological patterns and property values (Geoghegan et al., 1997; Kong et al., 2007); however, in these studies, the potential spatial autocorrelation issue was not fully addressed.

The results from our spatial regression model indicated that larger urban green space (TA) surrounding a single-family house was positively correlated with the transaction prices, while more fragmented- (NP), isolated- (MNN), or irregularly shaped (MSI) landscape spatial patterns were negatively associated with property sale price. In addition, there was a positive impact of less clumped (COHESION) tree areas on housing prices. According to previous landscape ecology research, larger patch sizes, less fragmented and less isolated conditions indicate healthier status of landscape and better environmental quality (Dramstad et al., 1996; Forman, 1995b; Forman, 1995a; Riitters et al., 2002). Our study suggested that ecologically healthier landscape patterns in neighborhoods were actually desirable among residents and could positively contribute to property sale price.

This research used several landscape indices using FRAGSTATS software. Landscape indices are useful variables generating more accurate statistical evidence with quantitative forms to estimate the ecological quality by measuring landscape spatial characteristics (Bogaert et al., 2000; Gustafson, 1998; Haines-Young and Chopping, 1996; Li and Wu, 2004; O'Neill et al., 1988; Riitters et al., 1995; Turner, 2005). A number of landscape indices have been developed and tested for monitoring natural resources and estimating the interrelationship between human activity and the ecosystem. However, there is no ideal single index that performs better than the others, and landscape patterns cannot be captured by any singe index. Understanding the nature and limitations of using landscape indices is necessary to select an appropriate set of landscape indices regarding the main purpose of research analysis. To quantify the quality of landscape patterns, spatial guidelines and theories from previous studies should be extensively reviewed. In addition, the easiness of applying landscape indices using spatial statistic software and the simplicity of interpolating outcomes should be considered to select an appropriate set of landscape indices. FRAGSTATS is a widely used software program to compute a series of values of landscape indices. From the results of this research, we agreed the program can offer analytical benefits of comparing diverse spatial aspects of landscapes. Utilizing FRAGSTATS allowed us to interpolate and describe a certain landscape pattern intuitively with quantitative approaches evaluating spatial patterns based on the existing landscape ecology principles and theories. The methods of this research confirmed the potential of using FRAGSTATS. The program provides opportunities to design more comprehensive methods to analyze multiple aspects of ecological conditions in the built environment by offering quantitatively analytical approaches to urban landscape pattern analyses with values from diverse landscape indices.

In this study, we compared results from the conventional OLS model and the spatial regression model to obtain robust estimates. The two modeling forms generated different estimates on several variables, including house age, garage space, the total area of trees and urban forests (TA) and the patch cohesion index (COHESION). Real estate market property values were determined through a complex mechanism; the sale prices and characteristics of neighboring properties may have spatial autocorrelation effects on one's property sale price. These effects could not be controlled in the OLS modeling form and therefore introduced omitted variable biases to OLS estimation results. Our study, however, did demonstrate that the spatial regression model mitigated the risk of spatial autocorrelation and achieved higher modeling performance than OLS.

This research has several limitations. First, the study area was limited to the City of Austin and the results focused on only single-family houses. Thus, our findings may not be able to be fully generalizable to other housing forms and geographic areas. Second, although we tried to collect the most appropriate variables to represent the neighborhood characteristics associated with determining housing prices, the final model may not fully include some of the key control variables potentially representing neighborhood characteristics. Third, this research utilized DOQQ imagery to measure the quality of landscape spatial patterns. DOQQ images only allow classifying land cover types with two-dimensional information which does not show the full layers of landscape structure under the tree canopy. Future research should consider more advanced media such as the Light Detection and Ranging (LIDAR) imagery to fully capture the full layers of landscape structure. Fourth, this study is a cross-sectional study. The future research needs to continue monitoring and measuring the effect of landscape spatial changes on housing transaction value through time. Finally, this study focused only on Austin's city-wide single family market. We expect that residents' preference on landscape spatial patterns may differentiate depending on heterogeneous socio-economic, demographic and geographic characteristics; these characteristics will change based on locations such as the inner city downtown areas and suburban neighborhoods. Thus, future research should explore such disparities in more depth.

Despite these limitations, however, this research is one of the first empirical studies in which the spatial regression modeling approach was applied to assess the impact of landscape spatial patterns on property sale price. The findings of this research call for future investigation to shed insights on whether and to what extent landscape ecological patterns are valued by residents based on property sale price analysis.

Rapid urban expansion has become one of the major issues in the U.S. Cities increasingly recognize the benefits of urban green spaces to enhance overall environmental quality and public health. To respond to this challenge, planners and policy makers should reconsider their decision-making processes for land use planning by including the arrangement and connectivity of urban natural environments. The application of the principles of landscape ecology has influenced diverse planning areas such as natural resource management and land use planning. In addition, since the primary focus of landscape ecology research is associated with large areas, large scales and long-term changes, it can provide a foundation for designing and planning, with a more sustainable future in mind (Forman, 1995a). Our results suggested that residents in urban areas would likely pay a premium for houses located in larger tree areas with less fragmented-, less isolated-, less clumped, and more regularly shaped landscape spatial patterns. These results suggested that preserving natural environment systems in neighborhoods could not only enhance ecological quality, but also generate economic benefits by potentially increasing property tax revenues; assessment of property value regarding the impact of neighborhood green spaces can therefore assist policy makers in understanding the fiscal sustainability of urban greening policies. These findings could be used to produce community landscape design and/or development guidelines to address the challenge of rapid urbanization.

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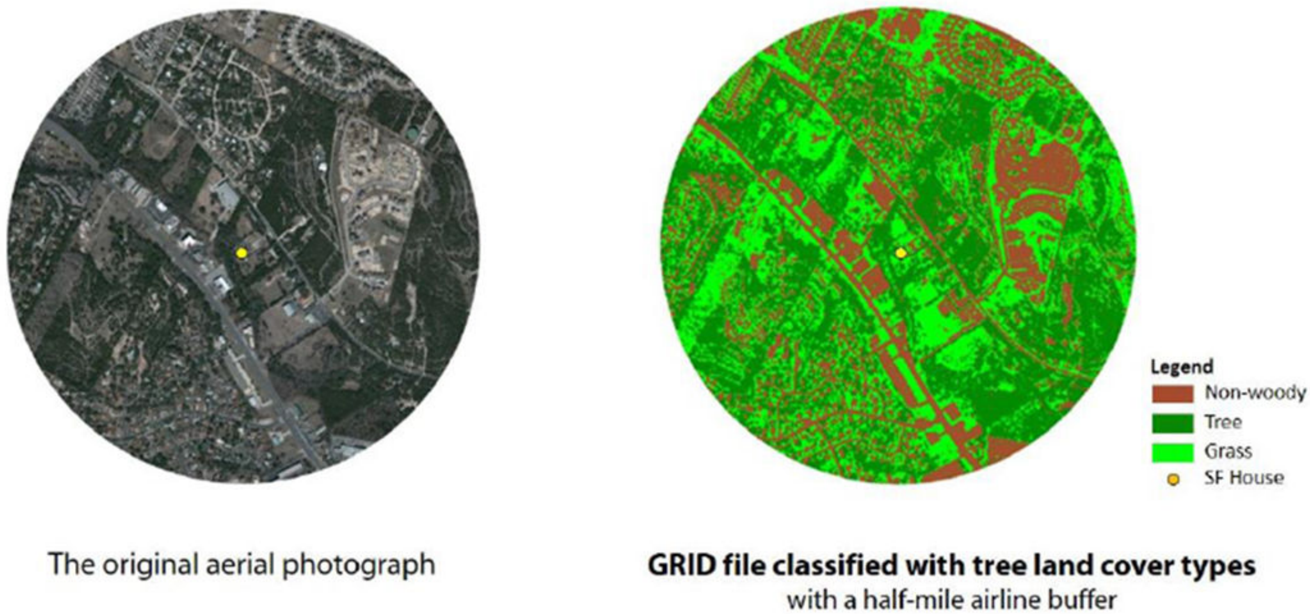


**Figure 1.**
Euclidian buffer to measure landscape spatial patterns

**Table 1.**

Selecting criteria, landscape indices, and formulas

| Criteria | Landscape Indices (Acronym) | Formula[a] | Description | Unit (Range) |
|---|---|---|---|---|
| *Size* | Total area (TA) | $\sum_{j=1}^{a} a_{ij} \times \left(\frac{1}{10,000}\right)$ | Higher TA and PLAND values indicate larger patch sizes. | Hectares |
| | Percentage of tree cover (PLAND) | $\sum_{j=1}^{a} a_{ij} \ / \ A \times 100$ | | % |
| *Fragmentation* | Number of patches (NP) | $n_i$ | Higher NP values and lower MPS values indicate more fragmented conditions. | Count |
| | Mean Patch size (MPS) | $\sum_{j=1}^{n} a_{ij} \ / \ n_i$ | | Square-meter (MPS≥0, without limit) |
| *Shape* | Mean shape index (MSI) | $\left\lfloor \sum_{j=1}^{n} \left(0.25p_{ij} \ / \ \sqrt{a_{ij}}\right) \right\rfloor \ / \ n_i$ | Higher MSI values indicate more irregular shapes. | None (MSI≥1, without limit) |
| *Isolation* | Mean nearest neighbor distance (MNN) | $\sum_{j=1}^{a} h_{ij} \ / \ n_i$ | Higher MNN values indicate more isolated patterns. | Meter |
| *Connectivity* | Patch cohesion index (COHESION) | $\left(1 - \sum_{j=1}^{n} p_{ij} \ / \ \sum_{j=1}^{n} \left(p_{ij}\sqrt{a_{ij}}\right)\right) \times \left(1 - 1 \ / \ \sqrt{A}\right)^{-1} \times 100$ | Higher COHESION values indicate more connected patterns. | % |
| | Area-weighted mean radius of gyration (GYRATE) | $\sum_{i=1}^{m} R_i P_i$ | Higher GYRATE values indicate longer expected distance of a particular patch. | Meters (GYTARE≥0, without limit) |

$n_I$= number of patches in the landscape of patch type *I*; $a_{ij}$ = area ($m^2$) of patch *ij*; $A$ = total landscape area; $p_{ij}$ = perimeter of patch *ij*; $h_{ij}$ = distance (m) from patch *ij* to nearest neighboring patch of the same type, based on edge-to-edge distance; $R$ = patch radius of gyration; $P$ = proportion of landscape; $C_{ijk}$ = joining between parch *j* and *k* of the corresponding patch type *i*

[*]Adopted and revised from Kim et al. (2014)

[a]See McGarigal and Marks (1995) for more details.

**Table 2.**

Summary Statistics (N = 11,326)

| Variables (units) | Mean | SD | Min. | Max. |
|---|---|---|---|---|
| Home sale price ($) | 301,008.73 | 200,795.17 | 63,000.00 | 1,480,000.00 |
| Structural characteristics | | | | |
| Living area ($m^2$) | 181.19 | 77.58 | 33.17 | 666.56 |
| Lot size ($m^2$) | 964.32 | 1077.01 | 141.64 | 37,761.22 |
| House age at year of sale | 33.48 | 23.21 | 0.00 | 123.00 |
| # of bedrooms | 3.27 | 0.74 | 1 | 11 |
| # of full bathrooms | 2.01 | 0.68 | 1 | 7 |
| # of half bathrooms | 0.33 | 0.49 | 0 | 9 |
| Binary: 1 = having 2 or more stories | 0.38 | 0.48 | 0 | 1 |
| Binary: 1 = having one or more garage space | 0.66 | 0.48 | 0 | 1 |
| Binary: 1 = having one or more fireplace | 0.60 | 0.49 | 0 | 1 |
| Binary: 1 = having pool | 0.07 | 0.25 | 0 | 1 |
| Binary: 1 = located at the waterfront | 0.01 | 0.11 | 0 | 1 |
| Locational characteristics | | | | |
| Network distance to rail stations (m) | 9,840.01 | 6,249.10 | 251.64 | 24,452.02 |
| Direct distance to nearest lake or pond (m) | 767.81 | 500.00 | 0 | 2,734.56 |
| Binary: 1 = highway within 400m | 0.61 | 0.49 | 0 | 1 |
| Binary: 1 = railroad within 400m | 0.15 | 0.35 | 0 | 1 |
| Neighborhood characteristics | | | | |
| School quality score in the past year (0-100) | 70.38 | 13.66 | 28.00 | 95.00 |
| # of traffic accidents involving pedestrians within 800m | 1.23 | 1.66 | 0 | 17 |
| # of traffic accidents involving cyclists within 800m | 1.21 | 1.67 | 0 | 16 |
| # of total property crime within 800m | 263.49 | 235.39 | 0 | 1,961 |
| # of total violent crime within 800m | 20.88 | 30.85 | 0 | 319.67 |
| Landscape spatial characteristics (acronym, unit) | | | | |
| Total area (TA, ha) | 80.89 | 20.61 | 11.09 | 157.69 |
| Percent of tree cover (PLAND, %) | 39.77 | 10.13 | 5.45 | 77.53 |
| # of tree patches (NP) | 3,991.79 | 1,465.58 | 1,109 | 9,028 |
| Mean patch size (MPS, $m^2$) | 251.30 | 167.71 | 41.00 | 1,331.00 |
| Mean shape index (MSI) | 1.24 | 0.03 | 1.15 | 1.35 |
| Mean nearest neighborhood distance (MNN, m) | 2.59 | 0.40 | 1.96 | 5.85 |
| Patch cohesion index (COHESION, %) | 99.21 | 0.56 | 95.72 | 99.98 |
| Area-weighted mean radius of gyration (GYRATE, m) | 143.88 | 90.60 | 18.98 | 521.00 |

Note: SD = standard deviation; min. = minimum; max. = maximum. The monthly binary variables are not listed in this table for brevity

**Table 3.**

Housing sale price estimation results

| Variables (units) | OLS | | Spatial Regression | |
|---|---|---|---|---|
| | Coefficients | Robust SE | Coefficients | Robust SE |
| Structural characteristics | | | | |
| Living area ($m^2$) | 1.729 *** | 0.038 | 1.305 *** | 0.022 |
| Lot size ($m^2$) | 0.005 ** | 0.002 | 0.006 *** | 0.001 |
| House age at year of sale | 0.211 ** | 0.085 | −0.751 *** | 0.053 |
| # of bedrooms | −40.966 *** | 2.275 | −17.208 *** | 1.414 |
| # of full bathrooms | 54.685 *** | 3.323 | 35.254 *** | 1.829 |
| # of half bathrooms | 15.083 *** | 3.346 | 9.526 *** | 1.993 |
| Binary: 1 = having 2 or more stories | −20.937 *** | 3.368 | −26.688 *** | 2.173 |
| Binary: 1 = having one or more garage space | −6.335** | 2.910 | 10.013 *** | 2.143 |
| Binary: 1 = having pool | 34.946 *** | 5.534 | 28.540 *** | 3.036 |
| Binary: 1 = located at the waterfront | 51.901 *** | 18.530 | 50.398 *** | 6.547 |
| Locational characteristics | | | | |
| Network distance to rail stations (m) | −0.011 *** | 0.001 | −0.009 *** | 0.001 |
| Direct distance to nearest lake or pond (m) | −0.017 *** | 0.002 | −0.012 *** | 0.003 |
| Binary: 1 = railroad within 400m | −0.556 | 2.951 | −14.693 *** | 3.113 |
| Neighborhood characteristics | | | | |
| School quality score in the past year (0-100) | 2.034 *** | 0.101 | 0.464 *** | 0.144 |
| # of traffic accidents involved in cyclists within 800m | 10.535 *** | 1.014 | 4.460 *** | 1.168 |
| # of total property crime within 800m | 0.030 *** | 0.066 | 0.066 *** | 0.013 |
| # of total violent crime within 800m | −1.352 *** | 0.066 | −0.506 *** | 0.094 |
| Landscape spatial characteristics (acronym, unit) | | | | |
| Total area (TA, ha) | −0.020 | 0.112 | 0.231 * | 0.127 |
| # of tree patches (NP) | −0.020 *** | 0.002 | −0.011 *** | 0.002 |
| Mean shape index (MSI) | −311.235 *** | 48.323 | −202.982*** | 56.230 |
| Mean nearest neighborhood distance (MNN, m) | −74.928 *** | 5.390 | −27.839 *** | 5.934 |
| Patch cohesion index (COHESION, %) | 1.208 | 3.047 | −11.752 *** | 0.760 |
| Constant | 544.532 | 336.041 | 1511.751 | - |
| Akaike information criterion (AIC; value) | 135,863.472 | | 130,026.300 | |
| Bayesian information criterion (BIC; value) | 136,310.894 | | 130,488.391 | |

Note: SE = standard error. The dependent variable is the housing sale price ($1,000) with 11,326 single-family transactions during 2010-2012. The adjusted $R^2$ for the OLS model was 0.77. The monthly binary variables and statistically insignificant variables were not reported for brevity.

* p < .10;

** p < .05;

$^{***}$p < .01