Using Geographic Information Systems to Improve Real Estate Analysis

*Mauricio Rodriguez**
*C. F. Sirmans***
*Allen P. Marks****

Abstract. **Geographic information systems (GIS) technology provides users with the ability to improve real estate analysis. First, we describe GIS in general and then discuss some GIS real estate applications. Next, we illustrate how GIS can be used to calculate a shortest-path algorithm that produces a location variable superior to the traditionally used straight-line distance variable. Our sample provides empirical evidence of a statistically significant relationship between residential sales prices and the additional information provided by the GIS-created variable.**

Introduction

Geographic Information Systems (GIS) technology provides users with the ability to enhance real estate analysis. The application of GIS technology may improve the analysis of many research questions and their related insights. This paper illustrates how GIS can improve commonly used regression models for residential real estate. Specifically, we show how GIS can provide a superior location variable relative to the traditionally used straight-line distance assumption. Our sample provides evidence of a statistically significant relationship between residential sales prices and the additional information provided by the GIS-created variable.

In the next section we introduce the concept of spatial analysis and its applicability to real estate research and then discuss some of the GIS-related real estate research. In the third section, we use GIS to calculate the shortest-path algorithm and thus produce an alternative hedonic variable relative to the traditionally used straight-line distance variable. The fourth section describes the data and develops the model; the fifth section reports the results and the final section offers some concluding remarks and directions for future research.

GIS Introduction and Real Estate Applications

Real estate research has long recognized the importance of location. In fact, the spatial dimension of real estate is a principal distinguishing characteristic that has contributed to the creation of a separate field of study. However, before the development of geographic information systems software, it was difficult to accurately measure the impact of location in real estate models. GIS is one of many techniques developed by scientific geographers to facilitate their analytic spatial reasoning (see Arbia, 1989; Tomlin, 1990; Huxhold, 1991; Star and Estes, 1990).

*M. J. Neeley School of Business, Texas Christian University, P.O. Box 32868, Fort Worth, Texas 76129.
**Department of Finance, University of Connecticut, 368 Fairfield Road, Storrs, Connecticut 06269-2041.
***Spatial Decisions & Analysis, 444 N. Frederick Ave., Suite L, Box 323, Gaithersburg, Maryland 20877.
Date Revised—September 1994; Accepted—September 1994.

GIS software automates many of the spatial processes performed by quantitative geographers. It is designed to work with data referenced by spatial or geographic coordinates. GIS software contains both a database manager and a set of spatial functionalities that allow the analysis of data across a desired geographic landscape. Thrall and Marks (1993) provide a detailed discussion of the application of GIS to real estate research.

While GIS can take the form of a manual system, most users prefer today's computerized systems. Unlike the case with some other software applications, an understanding of both programming and spatial reasoning is required before a user can create GIS software. Similar to word processing and spreadsheet software, a wide variety of GIS software products are available. The type of analysis that can be performed is controlled by the level of functionality embodied in any particular GIS software package.[1]

Just as maps are developed for specific tasks and users (road maps, weather maps, vegetation maps, and so forth), GIS can be created for specific applications. GIS technology, data structures, and analytic techniques are gradually being incorporated into a wide range of management and decisionmaking operations. General areas of GIS application include cartography, surveying and engineering, remote sensing, and science and research. GIS facilitates a variety of specific analyses within each of these areas.[2]

GIS can potentially play an important role in real estate research.[3] Particularly in the areas of spatial interaction models (Haynes and Fotheringham, 1984) and spatial diffusion models (Morrill, Gaile and Thrall, 1988). Spatial interaction models, which are often referred to as gravity models, forecast traffic flow, store patronage, and shopping center revenue and may be used to identify optimal site locations. Clapp and Rodriguez (1995) illustrate how real estate market analysis can be improved using GIS. Spatial diffusion models study the spread of a phenomenon over space and time. They can be used to forecast the timing and characteristics of new development, the growth or decay of neighborhoods, population movement and absorption rates. GIS technology permits the study of location to be easily factored into the explanation of various phenomena.

In particular, GIS software is ideal for examining the spatial component of real estate. Within GIS, real estate data can easily be disaggregated according to existing spatial market segments. Readily available boundary files (such as line segments that inscribe census tracts, census block groups, towns, counties, states, and other areas) can be joined together to define a market area. Market segments can also be described within a GIS according to any desired shape. Such spatial segmentation is difficult to accomplish without a spatial database. GIS technology can be used to produce an unlimited number of variables that can be applied to a variety of real estate analyses. GIS supports spatial analysis in the same way that statistical packages support statistical analysis.

The Scientific Geography Series (Thrall, 1984–1988) contains many relevant works that bridge the gap between the geography, real estate and urban economic disciplines. Other literature covers such topics as central place theory (King, 1984), point pattern analysis (Boots and Getas, 1988), and spatial autocorrelation (Odland, 1988). Point pattern analysis is of interest in that most real estate research does not require the specification of precise boundaries surrounding a parcel. As such, the precise location of a parcel is represented by only a single point contained somewhere within the boundaries of that parcel of land. Nonetheless, given that each location on the surface of the earth is influenced by other locations, econometric analysis must be concerned not only with the possible errors introduced by the problem of time autocorrelation but must also address the errors that can be introduced by the problem of spatial autocorrelation. The real estate literature has not yet dealt adequately with these issues.[4]

The Distance Variable in Multivariable Regression Models

Regression models have long been used to study the effects of various attributes on housing prices. Traditionally, models of residential real estate include variables that control for physical and locational characteristics, market conditions, and conditions of sale such as nonmarket financing.

One common variable used to examine locational characteristics is the distance from a house to the central business district (CBD). The use of a distance variable (from house to the CBD) was a by-product of the standard monocentric model of urban spatial structure (Alonso, 1964; Muth, 1969; Mills, 1972).

While the monocentric model does not address such issues as multiple workplaces and the substantial transaction costs of relocation, it does embody the often useful premise that transportation to the downtown workplace (CBD) is costly (Bechman, 1973; Richardson, 1977). For households to be indifferent among locations, property prices must fall with decreased accessibility to the CBD to offset increased transportation costs, thereby establishing a negative relationship between house prices and distance (or travel time) to the CBD.

Previous studies have used the straight-line distance from each house to the CBD as a proxy for travel costs. Calculation of the straight-line distance was formerly a painstaking affair that required the measurement of distances on a paper map. By contrast, GIS software products can easily calculate the straight-line distance between two points.[5]

We, however, propose the use of a shortest-path algorithm to calculate the shortest travel distance along the road network (Dial et al., 1977).[6] The shortest-path distance (*SPDIST*) is a more appropriate proxy for travel costs than straight-line distance (*SLDIST*) in that it more accurately reflects the absolute or true travel distance faced by commuters.[7]

Does the use of a *SPDIST* travel distance make any difference in model estimation? We predict that the difference will be significant in most cases and insignificant in only a few cases. At one extreme, if all homes were located along a straight road leading to the CBD, the use of either the *SPDIST* or *SLDIST* variable would produce identical results.

In almost all cases, the *SPDIST* is greater than the straight-line travel distance and the difference between these two measurements can be expressed as:

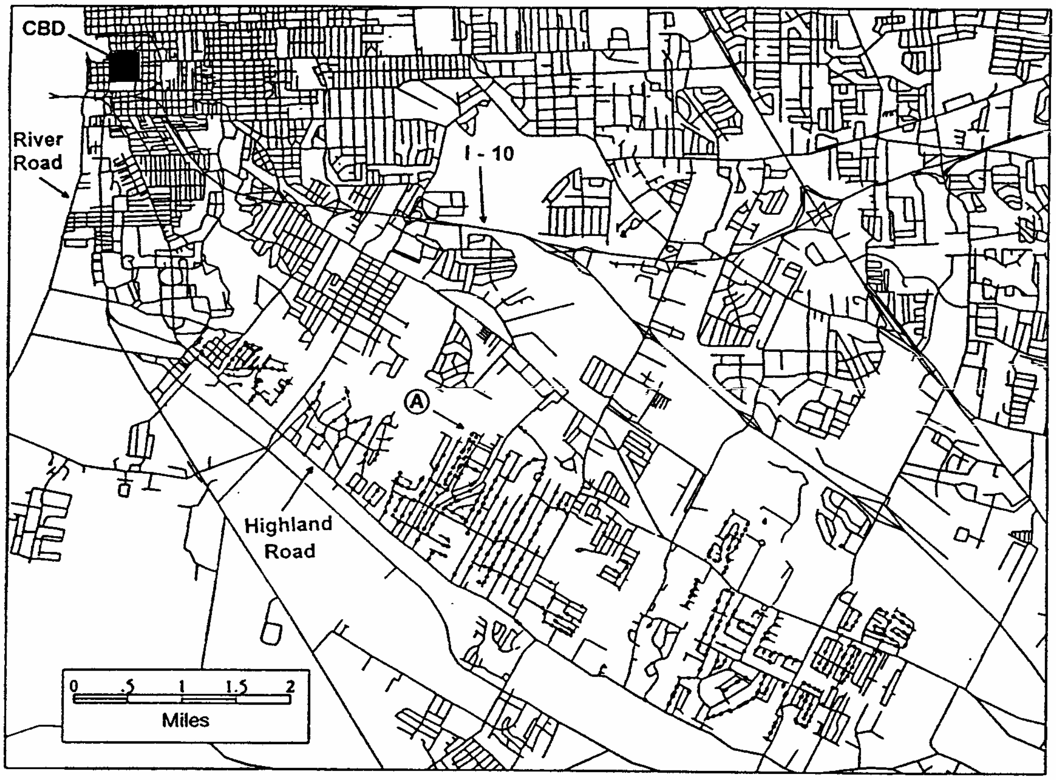
$$DIFF = SPDIST - SLDIST, \quad (1)$$

where:

SPDIST = shortest-path distance along the road network,
SLDIST = the straight-line distance (as the crow flies), and
DIFF = the difference between the two distance measurements.

These variables can be created within GIS. Exhibit 1 illustrates how *SPDIST* and *SLDIST* can differ. The shortest path distance along the road network between the CBD and sample point A is about 6.8 miles while the straight-line distance is 4.75 miles. Therefore, the difference between the two distance measurements is slightly over two miles.[8]

Exhibit 1
Spatial Distribution of Sample



Data and Model Description

Sales price, date of sale, property address, and property characteristics data are collected from the local multiple listing service (MLS) for a subarea within the Baton Rouge, Louisiana metropolitan area. Transcad directly imports geographic information contained in TIGER files and uses the information as a base map for the area under study.[9] Transcad is used to create other variables factored into the model.

The dependent variable in our model is the natural log of sales price ($\mathrm{LN}SP_{it}$). Exhibit 2 defines the independent variables. The model to be estimated is

$$\mathrm{LN}SP_{it}=f(SQFTLA_i,\ SQFTOA_i,\ DOM_i,\ FP_i,\ MONTH_i,\ VAC_i,\ VDOM_i,\ AGE_i,\ NHT_i,\ SLDIST_i,\ DIFF_i,\ SLAGE_i)\,. \qquad (2)$$

Sales involving nonmarket financing are not included in the sample. All transactions are located within a few adjoining subdivisions, thereby ensuring the comparison of similar properties. Exhibit 1 displays the location of the CBD relative to the properties in our sample. The total sample contains 563 observations.

Exhibit 3 presents descriptive statistics for the variables used in the models. The average selling price for homes in our sample is about $92,000. The mean living area is 1,946 square feet while the mean other area is 676 square feet. The latter includes porches

Exhibit 2
Variable Definition List

Symbol	Definition
SQFTLA	square feet of living area
$SQFTLA^2$	square feet of living area squared
SQFTOA	square feet of other area
$SQFTOA^2$	square feet of other area squared
DOM	number of days the property was on the market
FP	1 if the house has a fireplace
MONTH	number of months from 1985 that the house was sold
$MONTH^2$	number of months from 1985 that the house was sold squared
VAC	1 if the house was vacant when it was sold
VDOM	interaction variable between *VAC* and *DOM*
AGE	age of the house
AGE^2	age of the house aquared
NHT	1 if the house was not on a high-traffic street
SLDIST	straight-line distance (miles) between the house and the CBD
DIFF	difference between *SPDIST* and *SLDIST*
SPDIST	shortest-path distance along the road network (miles) between the house and the CBD
SLAGE	interaction variable betrween *SLDIST* and *AGE*
SPAGE	interaction variable between *SPDIST* and *AGE*

Exhibit 3
Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
SPRICE	91, 889	34,162	40,900	199,000
SQFTLA	1,946.4	552.7	988	3,933
$SQFTLA^2$	4,093,600	2,383,500	976,140	15,468,000
SQFTOA	675.96	318.06	0	2,044
$SQFTOA^2$	557,900	521,370	0	4,177,900
DOM	91.54	69.25	1	269
FP	.6732	—	0	1
MONTH	44.377	25.577	1	84
$MONTH^2$	2,622.3	2,228	1	7,056
VAC	.03144	—	0	
VDOM	33.229	—	0	269
AGE	12.163	8.856	1	39
AGE^2	226.24	294.47	1	1,521
NHT	.5684	—	0	
SLDIST	6.4508	1.7998	2.7565	9.0885
DIFF	.95623	.3319	.2852	2.085
SPDIST	7.4071	1.7006	3.1324	9.9452
SLAGE	73.514	50.610	4.1236	256.9
SPAGE	85.488	58.659	5.3646	288.41

or patios, garages or carports, and storage areas. The average property age is approximately twelve years and the average time a house was on the market was about ninety-two days. More than half the homes (67%) have a fireplace and about one-third (31%) were vacant when sold.

The shortest-path distance along the road network from each house to the CBD varies from slightly over three miles to slightly under ten miles. The average straight-line distance and average shortest-path distance between each sample house and the CBD is 6.45 miles and 7.4 miles, respectively. The average difference in these two distance measurements is, therefore, only about .95 miles.

Given that we expect buyers to pay more for more living area space, we predict that *SQFTLA* and *SQFTOA* will be positively related to the dependent variable. However, due to the diminishing marginal utility of acquiring larger and larger space, we expect $SQTLA^2$ and $SQFTNA^2$ to be negatively related to house prices. The relationship between the number of days a house is on the market (*DOM*) and its sales price is not easy to predict a priori. If a house is on the market for a long time, it may have time to appreciate in value. Yet, it is common for a seller to lower the asking price on a house when it has not sold after a given period of time.[10] Fireplace (*FP*) is expected to be positively related to sales prices. The time trend variable is *MONTH*, which is the number of months from the start of 1985 after which the property sold. It accounts for overall market conditions in the subject area during the sample period which includes transactions from 1985 through 1992.

The vacancy variable is expected to be negatively related to sales prices. Following Sirmans, Turnbull and Dombrow (1994), we include an interaction variable between *DOM* and the vacant dummy variable to control for any combined effect on house prices. *AGE* and AGE^2 are included to control for depreciation. We expect the age of the house to be negatively related to house prices since, ceteris paribus, older homes have depreciated more than newer homes.[11] Hughes and Sirmans (1993) find negative externalities may be associated with location on a high-traffic street. Specifically, they report a significant negative relationship between location on a high-traffic street and home sale prices. We include a variable (*NHT*) to control for any positive effects of not being on a high-traffic street. Land availability for new construction often tends to grow as the distance to the CBD increases. We include an interaction term (*SLAGE*) to control for any combined effects of *AGE* and *SLDIST*.

Three distance variables are used in different models to reflect any negative relationship between housing prices and distance to the CBD. The first variable is the traditionally used straight-line distance (*SLDIST*). The second measure (*DIFF*) reflects the additional distance a commuter must travel to the CBD. If this second GIS-generated variable yields any significant information relative to the traditionally used *SLDIST* variable, the coefficient for *DIFF* should be significantly negative. Finally, we provide a variable that indicates the shortest-path distance along the road network (*SPDIST*). Given the available technology, this variable most accurately reflects the actual travel distance homeowners must traverse to reach the CBD.

Results

Exhibit 4 presents the results for four models.[12] Model 1 is the typical hedonic model that uses *SLDIST*. Model 2 includes the *DIFF* variable to test for any significant

Exhibit 4
Regression Results
(t-statistics in parentheses)

Variable	Model 1	Model 2	Model 3	Model 4
CONSTANT	10.4320	10.4850	10.4770	10.4840
	(120.04)	(112.46)	(114.15)	(112.28)
SQFTLA	.7347E-3	.7375E-3	.7363E-3	.7358E-3
	(10.77)	(10.86)	(10.85)	(10.85)
SQFTLA^2	−.6312E-7	−.6445E-7	−.6403E-7	−.6389E-7
	(−4.12)	(−4.23)	(−4.22)	(−4.21)
SQFTOA	.2794E-3	.2900E-3	.2871E-3	.2850E-3
	(4.88)	(5.06)	(5.04)	(4.99)
SQFTOA^2	−.6100E-7	−.6528E-7	−.6411E-7	−.6331E-7
	(−1.84)	(−1.97)	(−1.95)	(−1.92)
	−.2092E-3	−.2276E-3	−.2227E-3	−.2199E-3
	(−2.05)	(−2.23)	(−2.19)	(−2.17)
FP	.1451E-1	.1642E-1	.1608E-1	.1622E-1
	(.98)	(1.10)	(1.09)	(1.10)
MONTH	−.3134E-2	−.3151E-2	−.3147E-2	−.3136E-2
	(−3.51)	(−3.53)	(−3.53)	(−3.51)
MONTH^2	.3003E-4	.2995E-4	.2998E-4	.2994E-4
	(2.84)	(2.83)	(2.84)	(2.83)
VAC	−.6934E-1	−.7221E-1	−.7134E-1	−.7092E-1
	(−3.47)	(−3.60)	(−3.59)	(−3.57)
VDOM	.1462E-3	.1581E-3	.1540E-3	.1512E-3
	(.87)	(.95)	(.92)	(.91)
	−.2462E-1	−.2586E-1	−.2587E-1	−.2664E-1
	(−5.64)	(−5.83)	(−5.83)	(−5.59)
	.5962E-3	.6051E-3	.6055E-3	.6074E-3
	(8.05)	(8.20)	(8.20)	(8.38)
	.5461E-1	.7551E-1	.6958E-1	.6727E-1
	(4.32)	(4.23)	(5.86)	(5.58)
SLDIST	−.2962E-1	−.3316E-1	—	—
	(−4.43)	(−4.58)		
		−.4511E-1		
		(−1.86)		
SPDIST		—	−.3296E-1	−.3359E-1
			(−4.58)	(−4.69)
	.2299E-3	.3808E-3	.3835E-3	—
	(.47)	(.76)	(.77)	
SPAGE	—	—	—	.4327E-3
				(.88)
F-Statistic	229.565	215.995	230.719	230.826
Adjusted R^2	.8592	.8596	.8598	.8598
Sample Size	563	563	563	563

relationship between house prices and the additional information provided by this GIS-generated variable. Models 3 and 4 use the shortest travel distance along the road network as an explanatory variable.[13]

Each of the four models is significant at the 1% level. In each model, the variation in the independent variables explain about 86% of the variation in selling prices. As expected, the square feet of living area (*SQFTLA*) and the square feet of other areas (*SQFTOA*) are positive and significantly related to the dependent variable. Also as expected, $SQFTLA^2$ and $SQFTOA^2$ are negatively related to house prices due to the diminishing marginal utility of acquiring larger and larger space.

Few of the explanatory variables are not significant. In all the models, the coefficient for the fireplace (*FP*) variable is positive but insignificant. Similarly, the interaction term between vacancy status and days on the market (*VDOM*) is positive but insignificant. Likewise, the interaction between age and distance to the CBD is positive but insignificant.

The remaining explanatory variables were significant with the predicted signs. The negative results for the (*DOM*) coefficient indicate that, for our sample, homes that remain on the market longer sell for relatively less than other homes. The time trend variables (*MONTH* and $MONTH^2$) point to lower housing values in later years relative to 1985. The results suggest a declining real estate market in the years following 1985, though the rate of decline decreased over time. Vacant homes tend to sell for less than occupied homes as indicated by the negative coefficient on the vacant dummy variable (*VAC*). The age proxies for depreciation provide results consistent with our expectations that properties depreciate over time at a decreasing rate. For example, the typical depreciation in the first two years of a new home is usually greater than that between the unit's twentieth and twenty-second years. Also as expected the variable that controls for not living on a high-traffic street (*NHT*) is positively related to home values.

The results for Models 1 and 2 show that the traditionally used straight-line distance variable (*SLDIST*) is significant and negatively related to house prices. The negative and significant coefficient for *DIFF* ($t=-1.86$) in Model 2 indicates that the additional travel distance, not accounted for if using only *SLDIST*, has a significant effect on house prices. Models 3 and 4 provide results in the case where the shortest path along the road network (*SPDIST*) is used as an explanatory variable. The coefficient for *SPDIST* is slightly more negative than that found for *SLDIST*. It should be noted again that the area under study is relatively small, and that the average difference between *SPDIST* and *SLDIST* is slightly under one mile. Analysis of a larger area (perhaps with a great divergence between the shortest-path distance and the straight-line distance) could demonstrate a more economically meaningful difference in the coefficients.

Conclusion

Location is an important factor when conducting real estate research. GIS facilitates the creation of many types of variables that can be useful in real estate analysis. GIS-created variables can be neighborhood or regional characteristics that would be otherwise difficult or time-consuming to create. Future research could employ other GIS-created variables. For example, GIS can easily generate a variable that identifies all properties adjacent to a property meeting a particular set of criteria. This type of identification would be difficult without a spatial database.

Distance variables are also easily produced with GIS. How distance is measured is important. These variables can be useful in implementing previously discussed real estate models (such as gravity models) or as illustrated (in real estate hedonic models.) The GIS-created variables expedite analysis within or outside the GIS environment.

We show how GIS can be used to calculate a shortest-path algorithm that produces a superior distance variable relative to the traditionally used straight-line distance variable. Our sample provides empirical evidence of a statistically significant relationship between residential sales prices and the additional information provided by the GIS-created variable.

The magnitude of any differences generated from the employment of various distance variables will, of course, be sample-specific. Nonetheless, given the declining costs of obtaining GIS technology, the potential advantages of using a shortest-path or shortest-travel-time variable should not be overlooked.

Notes

[1]See Marks, Stanley and Thrall (1994). A good source of information on new GIS products is *Geo Info Systems*, published by Advanstar Communications. We used a GIS software product called Transcad to facilitate the analysis in this paper. Transcad is available from Caliper Corporation, Newton, Massachusetts.

[2]Many GIS have been installed by state and federal governments and by companies in the resource industries, especially the forestry, and oil and gas industries. Some successful applications include watershed management, development of infrastructure (roads), forest regeneration, and studies that focus on agriculture.

[3]For a review of the literature and the spatial aspect of retail location analysis, see Berry and Parr (1988) and Ghosh and McLafferty (1987); examples of retail site selection applications are Marks, Thrall and Arno (1992) and Kerfoot (1993); industrial site location, Warden (1993) and Webber (1984); tax assessment, Thrall (1979, 1993); economic development, Pittman and Thrall (1991); decisions related to real estate acquisition, McCartney and Thrall (1991); mortgage foreclosure, Alberts and Bible (1992); appraisal applications, Weber (1990); and forecasting housing demand and residential development patterns, Thrall et al. (1993).

[4]Dubin (1988) explains that the use of appropriate spatial explanatory variables reduces the amount of spatial dependence in data, but it is likely that some spatial autocorrelation remains.

[5]To calculate a straight-line distance, most GIS software products simply require the user to point (with a mouse) to two different locations in a map on the screen. Some GIS products allow similar calculations for several points at one time. Spatially referenced data can also be exported from most GIS products to calculate straight-line distances in other products. If data is exported to non-GIS products, the user should be aware of the projection that was used by the GIS product utilized. GIS can be used to calculate Manhattan Distance (Thrall and Elshaw-Thrall, 1990). If the straight-line distance is considered to be the hypothenuse of a right triangle, then Manhattan Distance is the sum of the length of the other two sides. This distance more closely approximates the absolute distance along the road network in a typical grid city.

[6]The step-by-step instructions for using a variety of shortest-path algorithms in Transcad (Version 2.0) can be found on page 12 in section 7 of the reference manual provided with the software.

[7]If there are differences in speed limits and traffic patterns in the area under study, travel time could be incorporated into the analysis. The impact on travel time with the use of a multinodal transportation system is discussed in Thrall (1987).

[8]At the very least, GIS products can facilitate the calculation of the *SLDIST* variable. All distance measurements were calculated within Transcad.

[9]The TIGER (Topologically Integrated Geographic Encoding and Referencing) system is a computer-readable (digital) map database that contains data for many geographic features.

Information in TIGER files (such as roads, railroads, rivers, boundaries for census tracts, counties, address ranges) can be directly or indirectly brought into GIS software products.

[10]Sirmans, Turnbull and Benjamin (1991) find *DOM* to be negatively but insignificantly related to house prices.

[11]Shilling, Sirmans and Dombrow (1991) find a significant positive relationship between AGE^2 and home prices, providing evidence that homes depreciate over time at a decreasing rate.

[12]Tests for heteroskedasticity rejected the hypothesis of a constant variance. Because the form of heteroskedasticity is unknown, we used White's (1980) heteroskedasticity-consistent covariance matrix estimation procedure to correct for the unknown form of heteroskedasticity.

[13]The only difference between these last two models is the interaction term that is used to account for any combined effects of age and distance from the CBD. Model 3 employs the same interaction term used in the first two models. Model 4 employs an interaction term between *AGE* and the shortest travel distance (instead of straight-line distance).

References

Alberts, R. J. and D. S. Bible, Geographic Information Systems: Applications for the Study of Real Estate, *Appraisal Journal*, 1992, 60:4, 483–92.

Alonso, W., *Location and Land Use: Toward a General Theory of Land Rent*, Cambridge, Mass.: Harvard University Press, 1964.

Arbia, G., *Spatial Data Configuration in Statistical Analysis of Regional Economic and Related Problems*, Boston: Kluwer Academic Publishers, 1989.

Bechman, M. J., Equilibrium Models of Residential Location, *Regional and Urban Economics*, 1973, 3:4, 361–68.

Berry, B. J. L. and J. Parr, *Market Centers and Retail Location: Theory and Application*, Englewood Cliffs, N.J.: Prentice-Hall, 1988.

Boots, B. and A. Getas, *Point Pattern Analysis*, Vol. 10 in G. I. Thrall, editor, *Scientific Geography Series*, Newbury Park, Calif.: Sage Publications, 1988.

Clapp J. and M. Rodriguez, Using a GIS for Real Estate Market Analysis: The Problem of "Grainy" Data, working paper, University of Connecticut, 1995.

Dial, R. B., F. Glover, D. Karney and D. Klingman, *A Computerized Analysis of Alternative Algorithms and Labeling Techniques for Finding Shortest Path Trees*, Research Report CCS 291, Austin, Tex.: University of Texas Center for Cybernetics Studies, 1977.

Dubin, R. A., Estimation of Regression Coefficients in the Presence of Spatially Autocorrelated Error Terms, *Review of Economics and Statistics*, August 1988, 70:3, 466–74.

Ghosh, A. and S. L. McLafferty, *Location Strategies for Retail and Service Firms*, Lexington, Mass.: Lexington Books, 1987.

Haynes, K. E. and A. S. Fotheringham, *Gravity and Spatial Interaction Models*, Vol. 2 in G. I. Thrall, editor, *Scientific Geography Series*, Newbury Park, Calif.: Sage Publications, 1984.

Hughes, W. T. and C. F. Sirmans, Adjusting House Prices For Intra-Neighborhood Traffic Differences, *Appraisal Journal*, 1993, 61:4, 533–38.

Huxhold, W. E., *An Introduction to Urban Geographic Information Systems*, Oxford and New York: Oxford University Press, 1991.

Kerfoot, G. L., Regional Mall Site Selection and GIS, *Geo Info Systems*, 1993, 3:8, 51–54.

King, L. J., *Central Place Theory*, Vol. 1 in G. I. Thrall, editor, *Scientific Geography Series*, Newbury Park, Calif.: Sage Publications, 1984.

Marks, A. P., C. Stanley and G. I. Thrall, Evaluation of GIS Software for Real Estate Analysis, *Journal of Real Estate Literature*, 1994, 2:2, 227–41.

Marks, A. P., G. I. Thrall and M. Arno, Siting Hospitals to Provide Cost-Effective Health Care, *Geo Info Systems*, 1992, 2:8, 58–66.

McCartney, J. W. and G. I. Thrall, *Real Estate Acquisition Decisions with GIS, Proceedings of the Annual GIS/LIS Conference,* Atlanta, Georgia, November 1991, 90–99.

Mills, E. S., *Studies in the Structure of the Urban Economy*, Baltimore, Md.: Johns Hopkins, 1972.

Morrill, R., G. Gaile and G. I. Thrall, *Spatial Diffusion*, Vol. 10 in G. I. Thrall, editor, *Scientific Geography Series*, Newbury Park, Calif.: Sage Publications, 1988.

Muth, R., *Cities and Housing*, Chicago: University of Chicago Press, 1969.

Odland, J., *Spatial Autocorrelation*, Vol. 9 in G. I. Thrall, editor, *Scientific Geography Series,* Newbury Park, Calif.: Sage Publications, 1988.

Pittman, R. and G. I. Thrall, Using Geographic Information Systems in Economic Development: An Introduction, *Economic Development Review,* 1991, 9:4, 14–21.

Richardson, H. W., *The New Urban Economics: An Alternative,* London: Pion Limited, 1977.

Shilling, J., C. F. Sirmans and J. Dombrow, Measuring Depreciation in Single-Family Rental and Owner-Occupied Housing, *Journal of Housing Economics,* 1991, 1:4, 368–83.

Sirmans, C. F., G. K. Turnbull and J. D. Benjamin, The Markets for Housing and Real Estate Broker Services, *Journal of Housing Economics,* 1991, 1:3, 207–17.

Sirmans, C. F., G. K. Turnbull and J. Dombrow, Quick House Sales: Seller Mistake or Luck?, working paper, University of Connecticut, 1994.

Star, J. and J. Estes, *Geographic Information Systems: An Introduction,* Englewood Cliffs, N.J.: Prentice-Hall, 1990.

Thrall, G. I., A Geographic Criterion for Identifying Property Tax Assessment Inequity, *Professional Geographer,* 1979, 31:3, 278–83.

———, *Land Use and Urban Form: The Consumption Theory of Land Rent,* London and New York: Routledge/Methuen, 1987.

———, editor, *Scientific Geography Series*, Newbury Park, Calif.: Sage Publications, 1985–1988.

———, Using GIS to Rate the Quality of Property Tax Appraisal, *Geo Info Systems,* 1993, 3:3, 56–62.

——— and S. Elshaw-Thrall, A Computer Assisted Decision Strategy for Evaluating New Satellite Hub Sites for a Local Utility Provider, *Computers, Environment, and Urban Systems,* 1990, 14:1, 37–48.

Thrall, G. I. and A. P. Marks, Functional Requirements of a Geographic Information System for Performing Real Estate Research and Analysis, *Journal of Real Estate Literature,* 1993, 1:1, 49–61.

Thrall, G. I., C. F. Sidman, S. Elshaw-Thrall and T. J. Fik, The Cascade GIS Diffusion Model for Measuring Housing Absorption by Small Area with a Case Study of St. Lucie County, Florida, *Journal of Real Estate Research*, 1993, 8:3, 401–20.

Tomlin, C. D., *Geographic Information Systems and Cartographic Modeling,* Englewood Cliffs, N.J.: Prentice-Hall, 1990.

Warden, J. T., Industrial Site Selection: A GIS Case Study, *Geo Info Systems,* 1993, 3:8, 36–45.

Webber, M. J., *Industrial Location*, Vol. 3 in G. I. Thrall, editor, *Scientific Geography Series,* Newbury Park, Calif.: Sage Publications, 1984.

Weber, B. R., Applications of Geographic Information Systems to Real Estate Market Analysis and Appraisal, *Appraisal Journal,* 1990, 58:1, 127–32.

White, H., A Heteroskedasticity-Consistent Covariance Matrix Estimator and Direct Test for Heteroskedasticity, *Econometrica*, 1980, 48:4, 817–38.

We gratefully acknowledge valuable comments from Joe Lipscomb, two anonymous referees, and participants at the 1994 American Real Estate Society meetings.