LOCATIONAL DETERMINANTS OF REAL ESTATE VALUATION:
AN ANALYSIS OF SPATIAL AUTOCORRELATION IN
THE HEDONIC PRICING OF REAL ESTATE

DISSERTATION

Presented to the Graduate Council of the
University of North Texas in Partial
Fulfillment of the Requirements

For the Degree of

DOCTOR OF PHILOSOPHY

By

John F. Shampton, B.A., J.D.
Denton, Texas
May, 1992
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Recent studies of the valuation of real estate have concentrated on the use of hedonic pricing techniques in which the implicit prices of the component characteristics of an asset are inferred from the observed sale price using regression analysis. All of these studies include as explanatory variables one or more locational factors, such as distance to the central business district, as proxies for the effect that location has on the utility of land. In this research, the explicit consideration of the location of real estate in terms of the geographic or Cartesian coordinates (spatial attributes) of observed sales is shown to be a potential substitute for such proxies, either wholly or in part. Such use of spatial attributes could improve the usefulness of the hedonic methodology while at the same time significantly reducing cost and eliminating sources of error.

A statistical test of spatial models, developed for use in the regional sciences, is adapted for use in evaluating spatially sensitive hedonic pricing functions. Statistically significant improvement in both descriptive and forecasting applications of the hedonic technique are
achieved, supporting the conclusion that spatial attributes should be considered for such models. In addition, the use of the Moran Coefficient, a statistical measure of spatial autocorrelation, is introduced as an indicator of the ability of a model to capture spatial trend. High calculated values of the Moran Coefficient raise the question of whether hedonic pricing studies of land may require correction for spatial autocorrelation.

The data examined in this research consist of observations of actual prices and certain physical and land use characteristics of 2,788 sales of vacant land in Dallas County, Texas, obtained from a commercial data base. Pricing and forecasting models are developed using spatial attributes of these observations and a set of representative locational factors. Typical statistical tests as well as the measurement of spatial autocorrelation in the residuals were performed and the results are presented and analyzed.
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John F. Shampton, Denton, Texas
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CHAPTER I

INTRODUCTION

Economists admit to little theoretical understanding of land pricing, in spite of its unquestioned economic importance. Both theoretical and practical problems in achieving such knowledge abound. In particular, the familiar financial models do not appear to work well for land (Lusht 1988).

Studies of land pricing have suffered from both the lack of a useable index of real estate valuation (Hoag 1980, Quan and Quigley 1989, Lusht 1988, Gau 1987, Capozza and Schwann 1989) and a characteristic shortage of reliable information on sale prices, financing terms and other typical pricing information (Jarrow 1980, Figlewski 1981, Quan and Quigley 1989). Generally, little can be done about the paucity and unreliability of land pricing data.

Development of theoretical models or analytical tools which improve, even slightly, the understanding of the pricing process is therefore significant. This need is the primary motivation for this research. Creation of new, and untested, tools, however, may not be necessary to achieve such improvement. It may, instead, be possible to adapt methods or concepts already recognized in other disciplines which deal specifically with land, although in different contexts.

Among the essential economic qualities of land,
immobility stands out as the most characteristic. Any parcel of land, being fixed in location, can be described by its spatial attributes (defined for these purposes as Cartesian coordinates on a fixed geographic grid system). These attributes describe the location of the land, and thus are unique to each parcel. Spatial attributes can be readily measured, or quantified, and are easily compared among several parcels. It is reasonable to inquire, then, whether they may be useable in establishing the value, as well as the location, of the land.

The field of urban economics deals specifically and broadly with the location and economic effects of land and land use, among other things. The spatial attributes of land (and the interrelationship based on location known as spatial autocorrelation) are explicitly analyzed, but not in the same context as in economics. Pricing models, for example, are not derived. It should be possible to make use of concepts such as spatial attributes in the analysis of land values.

Implicit recognition of the importance of spatial considerations in the study of land abounds in the existing literature on real estate and urban economics; virtually all of the valuation studies rely, at least in part, on the measurement of distances (i.e.: spatial attributes), and postulate the existence of some sort of effect on value resulting from spatial relationships (i.e.: spatial
autocorrelation).

The effects of the location of land are variously described as measures of access (Jackson 1979), externalities (e.g., Johnson and Ragas 1987) or merely influences (Peiser 1987). Almost all of the land pricing studies refer explicitly or implicitly to location, and thus rely to a greater or lesser extent on spatial attributes, but rarely do they actually refer to them.

The first purpose of this research is to explore the explicit consideration of a form of spatial attributes as explanatory variables in the pricing of land. The use of spatial attributes in this way represents a potentially important advance in the analysis of land valuation for two reasons. First, the identification of some form of the spatial attributes as appropriate variables may lead to improvement in the explanatory and forecasting power of existing models for land valuation. Second, the inclusion of such variables in the models being tested will permit the use of accepted techniques for dealing statistically with spatially-based processes.

For that reason, the second part of this research lays a foundation for the introduction into land pricing studies of techniques for the analysis of spatially based processes. This is done by taking an accepted procedure from economic geography for the measurement of one such characteristic, spatial autocorrelation, and examining how it might be
applied to land pricing models. Borrowing such statistical tools from the regional sciences is justified by the fact that the pricing of land uses much the same data, shares the same problems and is amenable to the same treatments as the geographic studies in which the techniques were developed (see, e.g.: Berry and Marble 1968, Haggett, Cliff and Frey 1977).

As an introduction to the review of the currently accepted techniques for pricing land, it would be appropriate to briefly consider the basic economic characteristics of real estate.

The Economic Characteristics of Land

Theoretically, a parcel of real estate may be treated like any other asset. The financial measurements of land—its returns and the variance of those returns—may be used in risk-based analyses (Friedman 1971, Hoag 1980) to determine the efficient allocation of investments. That is, the characteristic covariance of returns on a parcel with those of other assets or the market in general, if such can be measured, may be used to establish its place in a portfolio (Fogler 1984). Also, undeveloped land may be analyzed in the context of asset pricing approaches (e.g.: Capozza and Schwann 1989) and financial option price models (Geltner 1989).

Anomalies appear, however, when financial models are
used to analyze land. Thus, there is evidence that real estate investments may produce average returns with lower risk when compared with common stocks (Lusht 1988, Roulac 1976, Webb and Rubens 1986) and even have some inflation-hedging capability (Lusht 1988, Fogler et al. 1986, Hartzell et al. 1987). Investment portfolios should be dominated by real estate if this is true, however, and such is not the case.

Similarly, real estate market indices should, in such a case, play a significant role in portfolio studies. Again, this is not the case. The probable reason for this, however, is that there are no useable market indices of real estate performance (Hoag 1980, Quan and Quigley 1989, Lusht 1988, Gau 1987, Capozza and Schwann 1989). This results from certain characteristics of real estate markets which are not generally shared by markets for financial assets.

Such irregularities as extremely infrequent trading, virtually unknown holding periods (Hoag 1980) and high amounts of undisclosed leverage (Lusht 1988) make observations on land prices rare and unreliable. In addition, the lack of any reporting facility or clearinghouse for land prices makes the collection of such data highly problematical. The actual value of a parcel of real estate is not observable at any particular time in the absence of an organized market, i.e., there are no obtainable spot prices (Quan and Quigley 1989). The
characteristically thin trading of real assets further hinders discovery of true prices because the few individual sales prices which become available are not statistically valid indicators of market prices (Hoag 1980). Valuation estimates of real assets must therefore rely almost exclusively on the opinion of appraisers rather than the market (Quan and Quigley 1989).

In the absence of short sales, as is the case in real estate, risk levels are unknown and asset prices will be biased because there is no mechanism for taking advantage of expected price decreases (Jarrow 1980, Figlewski 1981, Quan and Quigley 1989). Problems also arise in the absence of reliable measures of expectations. This is revealed in two recent studies where attempts were made to apply "pure" financial models to vacant land. Geltner (1989) observed that the lack of an underlying asset in the analysis of land as an option makes the measurement of risk preferences and expectations difficult, and thus the use of option models problematical. Capozza and Schwann (1989) were severely criticized (Case 1989) for their selection of a proxy for expectations in the empirical test of their asset-based model, with the same result.

In both of these cases, the source of the difficulty was the lack of information which is readily available for financial assets. As a result of this lack, accepted models such as the Capital Asset Pricing Model are almost
impossible to apply to valuing real estate (Hoag 1980). Calculation of returns and the other performance measures for real assets, given no useable market proxy, is extremely difficult and unreliable (Hoag 1980, Geltner 1989, Giliberto 1988).

An obvious response, of course, would be to construct a market index for real estate. Such an index would serve the same functions as the recognized financial market proxies (such as the S&P 500) in the measurement of risk and returns. This was, in fact, attempted by Hoag (1980). However, Hoag's proposed index, which included a wide range of macro- and microeconomic measures as well as variables specific to the parcel, has not been widely adopted in financial research. The reasons for this lack of acceptance are undoubtedly the absence of theoretical specification and the general unavailability of data upon which to construct such an index (Lusht 1988, Quan and Quigley 1989, Capozza and Schwann 1989).

---

It has been argued that the returns on Real Estate Investment Trusts (REITs) might be used as a proxy for the performance of direct investments in land (Smith and Shulman 1976, Burns and Epley 1982, Kuhle et al. 1986, Kuhle 1988). Due to legislated conditions on their favorable tax status, REITs are constrained to almost exclusive investment in real estate or mortgages, and thus may logically be expected to be useable in financial models as a substitute for real estate equity investments. This expectation has not, however, been authoritatively or consistently proved or disproved in the literature, probably because of the thin trading of the very few issues which might qualify as such proxies (see Haight and Ford 1987).
Since the collection and reporting of information on land pricing is not developed to the extent it is for financial assets, and the measurement of market returns on real estate is so difficult, it would be appropriate to look for additional indicators of valuation. That is, one might examine whether some specific aspect of land, not considered in financial asset pricing models, might be used to assist in revealing the rules governing its pricing.

There is one such characteristic of land which, arguably, distinguishes it from any other type of asset: its unique and invariable physical location. Conventional wisdom holds, only somewhat facetiously, that "location, location and location" are the three primary determinants of the value of real estate. Among all assets, only real estate can be classified according to its spatial relationship to other assets of the same sort.

In the context of valuation studies, "location" actually refers to the place utility of land as it is affected by well-accepted factors such as proximity to markets, the existence of externalities, and the like. Distance to markets, for example, was identified as a cost factor by Von Thünen as long ago as 1826, and has been used recently in the same sense by Capozza and Schwann (1989). Location, as the term applies to land, has been defined as "the time-distance relationship, or linkage, between a property . . . and all possible origins or destinations" of
persons relative to the parcel (AIREA 1987, p. 41, emphasis added). If accessibility as proxied by location, then, is accepted as an important value factor for land, attention naturally turns to whether it has been considered adequately in the models typically proposed for pricing land.

The costs (such as transportation) and risks (such as variance in the expected demand for a "mislocated" development) associated with accessibility form part of the basis for traditional analysis of real estate investments. In fact, virtually all of the hedonic pricing models discussed in Chapter II make reference to the distance of a parcel from the central business district. Such models clearly measure pricing variability based on access.

Nearly all factors related to the costs or risks of access to land are relatively fixed in their influence on a particular parcel since the parcel itself can never be moved. The locational influences such as distance to the central business district thus remain static unless the influence, itself, moves. But, even over fairly long periods, these access-based factors remain unchanged. It takes many years, for example, to plan, construct and open a new freeway. Thus, the effects of such value influencing factors, whether direct, indirect or resulting from interactions among two or more such factors, remain relatively fixed and fairly stable over time. These locational factors are analogous to the general market
factors that affect the value of financial assets.

Land valuation studies have taken these factors into account by including various proxies for location as variables in pricing models. The heterogeneous nature of land lends itself to such an approach (Griliches 1967). Thus, during the past fifteen years, studies of the valuation of real estate have turned almost exclusively to the use of a multi-factor pricing technique suggested by Griliches and refined by Rosen (1974). This approach, known as hedonic pricing, relies on the identification and measurement of many of these factors.

The hedonic studies of real estate pricing purport to decompose observed sale prices into implicit component prices based on the assumption that the total price is not less than the sum of such component prices. The components, also referred to as attributes or characteristics, vary among the studies but fall generally into three categories: attributes of the particular observed sale (such as number of bedrooms or zoning classification), macroeconomic conditions which constitute supply and demand shift variables, and measures of accessibility to amenities such as the central business district or transportation nodes.

The last category includes the locational characteristics of the parcel. All of the hedonic pricing studies as well as Capozza and Schwann's asset-based analysis (1989) have considered some such measure of
distance to one or more amenities. Implicitly, at least, all of these studies have relied upon the importance of location. None, however, have explicitly treated the spatial attributes or any other form of explicit geographic coordinates of the subjects, nor, generally, have the interactive effects of two or more influences been considered.

It is clearly unrealistic to attempt to identify, measure and calculate the effect of every potential influence on a single parcel. Of necessity, some relevant factors as well as all unsuspected influences or unmeasured interactions must be omitted from hedonic studies. The hedonic methodology could be greatly improved, then, if a method could be developed for including or summarizing the effects of all such influences.

Most locational influences on land pricing are relatively (but not absolutely) immobile. Such influences are generally tied to particular uses of land and thus tend to be fixed, but some things, such as highway ramps can be moved. Therefore the effect over distance of a particular influence should be fixed and measurable. If this is so, the cumulative effect of all actual influences should also be measurable at any given point. It follows, then, that this overall effect could be expressed as some mathematical function of the location of the observation.

Parcels of land which are adjoining should show nearly
identical influences, since the effects of location over short distances are likely to be slight. Such effects should be continuous, varying smoothly over the relevant range as distances increase. If so, one process—the overall trend related to location—might be identified and quantified to satisfy at least some of the effect of these spatially dependent amenities. This concept, known in the geographic sciences as spatial autocorrelation, appears to be adaptable to the study of land pricing.

Explicit consideration of spatial attributes, defined as locational or spatial coordinates on a uniform grid system, may lead to improvements in the models currently in use. When the distances to named amenities measure the access of a parcel to those amenities, the spatial attributes of a parcel may be found to incorporate these and many other known, unknown, suspected or even unsuspected locational influences besides those explicitly measured. Statistical tests currently used in hedonic pricing, however, do not effectively deal with this explicit treatment of location.

In this study, the effect of introducing an explicit measure of location in the form of spatial attributes into the hedonic model was measured and the results examined for statistical evidence of improved explanatory or predictive power over that of the conventional hedonic pricing function. A statistically significant improvement over the
A traditional hedonic model was found, and further exploration of the explicit consideration of location appears to be justified. Also, the measurement of spatial autocorrelation, at least in one form, appears to serve as an indicator of improved explanatory power. Thus, it may be that the spatial attributes of real estate are among the missing pieces of what Lusht (1988) has called the "real estate pricing puzzle."

In Chapter II, the literature on the use of hedonic pricing in real estate valuation is reviewed, with attention to the problem of selection of the variables and to an alternative approach which resolves some of these questions. Chapter III reviews the sparse literature which relates the analysis of spatial attributes to the economic issue of land valuation. Chapter IV outlines the research methodology and describes the model used and the data set. Results are presented in Chapter V, and analysis and conclusions follow. The mathematical notation used throughout is specified in Appendix A. Appendix B gives the calculation of the Moran Coefficient and significance tests, with Appendix C including the computer code used to make the calculations. The regression results are shown in Appendix D.
CHAPTER II

THE HEDONIC VALUATION OF REAL ESTATE

The Hedonic Pricing Function (HPF) is an economic technique for decomposing observed prices into their implicit component prices. Where some method (such as regression analysis) exists to permit the separation of those components, the resulting information may be used to explain or predict the pricing process. Hedonic pricing is uniquely adapted to the valuation of real estate, given the extreme heterogeneity of this class of assets (Chicoine 1981). That is, every parcel of real estate may be described in terms of a bundle of physical attributes (including location), legal rights and financial characteristics, all of which might in theory be priced separately.

Sherwin Rosen's approach (Rosen 1974) appears to be the de facto standard for hedonic pricing of real estate. In fact, Rosen's paper has become the single most frequently cited work in the academic real estate literature (Alvayay and Chandy 1991). Rosen proposed a two-stage analysis which may require the use of variables which are not needed in some studies, however. Therefore, an equivalent single-step procedure based on Lancaster's "new approach" was used in this study.
The Rosen Hedonic Pricing Model.

Rosen's hedonic model describes the implied conditions of supply and demand necessary to produce the observed prices of the studied goods. Milon et al. (1984), Diamond and Smith (1985) and Epple (1987), among others, have provided treatment of the basic technique. Rosen's contribution, the two-stage estimation of the system, first regresses observed price of the goods (such as real estate) on quantities of characteristics (such as size, amenities, access and the like) to obtain marginal implicit prices, then using these as endogenous variables, estimates the supply and demand equations implicit in the data.

The use of supply and demand shift variables is required in the Rosen approach to assure that the estimated functions are adequately identified. That is, unless there are sufficient shift variables with adequate variation, the supply and demand functions will be underidentified (Diamond and Smith 1985, Epple 1987), a problem rarely mentioned in the many studies using the Rosen model. Unless the purpose of a particular study is to estimate demand, however, there would appear to be no particular reason to use this model. That is, the need for inclusion of supply and demand shift variables such as macroeconomic conditions can be eliminated by using Lancaster's "new approach" of interpreting the observed prices as expenditures on the attributes rather than prices of the goods (Lancaster 1974, Lucas 1976,
Edmonds 1984).

The "New Approach" to Hedonic Pricing.

The "New Approach" to consumer theory presented by Lancaster (1966) involves the assumption that the consumer selects quantities of commodities (or, more correctly, the characteristics associated with or produced by one or more commodities) based on a linear consumption technology and a budget constraint. Lancaster proposes that the consumer will obtain utility from the characteristics, rather than the commodities, may obtain proportionate satisfaction of a single need from more than one commodity, and may obtain different characteristics from combinations of commodities than from the individual commodities (Lancaster 1966, page 134). Lancaster's "new approach" is useful in the context of hedonic valuation of land because it provides a theoretical basis for the selection of the variables to be included in the hedonic model.

As stated above, the hedonic pricing technique is based on the concept that observed prices may be decomposed into components representing the implicit price paid for acquisition of a particular attribute of the bundle being valued. In the Lancaster-Lucas approach proposed by Edmonds (1987), the implicit prices of the characteristics are obtained by ordinary least squares regression of the observed characteristics on the observed sales price.
We may assume a pricing function for land, \( V \), such that:

\[
V = v(a_z) \quad (z=1, \ldots, k) \tag{1}
\]

where \( (a_z) \) represents the set of \( (k) \) characteristics of the land such as access or zoning classification. The implicit marginal prices of each of the attributes are the partial derivatives:

\[
dV = \frac{\partial V}{\partial a_z} \quad (z=1, \ldots, k) \tag{2}
\]

\[
V = \int \frac{\partial V}{\partial a_z} \, da_z \quad (z=1, \ldots, k) \tag{3}
\]

Defining the price of a particular attribute as

\[
\beta_z = \frac{\partial V}{\partial a_z} \tag{4}
\]

we find

\[
V = \int \beta_z \, da_z \quad (z=1, \ldots, k) \tag{5}
\]

Rosen substitutes these partial derivatives, as marginal prices, into the system of supply and demand equations in order to determine implicit demand for the characteristic under study. In the literature on hedonic pricing of land, observed prices are generally presumed to
be the simple sum of the constituent attribute prices.²

If, however, as assumed under Lancaster's requirement of a fixed consumption technology, the partial derivatives in (4) are constant, or nearly so, for all (k) attributes, then the observed sale price of parcel (i), interpreted by Lancaster as the expenditure on its individual attributes, may be approximated as:

\[ V_i = \sum_{s=1}^{k} \beta_s \int d a_{s,i} \]  \hspace{1cm} (6)

\[ V_i = \sum_{s=1}^{k} \beta_s a_{s,i} \]  \hspace{1cm} (7)

The prices, as estimated by ordinary least squares regression coefficients \((b_n)\), including the intercept \((b_0)\), as well as an error term, make up a regression model in the form:

\[ \hat{y}_i = b_0 + \sum_{s=1}^{k} b_s a_{s,i} + e \]  \hspace{1cm} (8)

Edmonds (1984) applied Lancaster's analysis to hedonic pricing of housing, suggesting that the observed price becomes the consumer's budget, and hence, expenditure, on attributes (such being acquired as a bundle in the "model"

²This sum of constituent prices may actually be a lower limit, since there is support for some synergistic effects such as the value increase (known as "plottage") which results from combining small parcels into a larger one (AIREA 1987).
or particular home purchased) rather than the prices of the attributes. The implicit marginal prices estimated in the first step of the Rosen model thus may be interpreted as the expenditures on the characteristics (price times quantity consumed) and, quantities being directly observable, there is no need to continue, as does Rosen, to estimation of the supply and demand equations and calculation of equilibrium prices. Importantly, then, there is no need to include supply and demand shift variables in the model.

Edmonds also discusses the important contribution of the Lancaster model to the choice of variables and interpretation of the coefficients of hedonic models. Edmonds notes that given the interpretation of the left hand side of the hedonic equation as "expenditure on characteristics," rather than "price of models" (which he observes are, by definition, equal in housing markets), the budget constraint is "...merely an accounting identity linking expenditure to what is purchased via prices" (p.80). His conclusion is that

"[a] consumer's (own) income, age, or any other taste-affecting, demand-shifting variable has no place in the budget constraint. Nor is there any justification for including the characteristics of suppliers or cost conditions as extra dimensions of a budget constraint. Only those utility-affecting characteristics that are components of the purchased consumption--and of these, only those with quantity variation across models in the market--should be included as dimensions (independent variables) of the HPF." (p. 80).
This interpretation of Lancaster's "new approach" provides a useful theoretical basis for selection of variables: only those characteristics which are, or theoretically may be, sought by consumers should be considered for inclusion in a hedonic pricing model.

In addition, Edmonds provides an interesting interpretation of the troublesome intercept term. Noting some researchers' difficulty in reconciling the existence of a positive intercept with the expectation that the price should equal the total of the characteristics' prices, Edmonds argues that the intercept represents the value of those characteristics which are "unpriced" because no variation is available in the market. As an example, he suggested that brick construction, in a market where all available models are brick, would not (indeed, should not) appear as a priced characteristic, but rather should be included in the intercept. This interpretation is highly satisfying, does not appear to rely on Lancastrian analysis, and should be given serious consideration regardless of the choice of Rosen or Lancaster as the underlying hedonic model.

Variables in Hedonic Studies of Real Estate.

Property-specific characteristics such as the size and nature of improvements and the size of the property in question are universally accepted as determinants of value
in the reported hedonic studies of real estate. In addition, the permitted use of the land is explicitly recognized in most studies of nonresidential land and implicitly in all studies of housing (which are by definition limited to the examination of land put to a specific use—residence).

Virtually all of the studies of residential properties include variables for lot size and, where improvements are considered, for the nature, size, quality and functionality of the houses. Dale-Johnson (1982) included a large number of such housing characteristics in a study using residential appraisal data, for example. More unusual, and specific, amenities have also been considered. Brown and Pollakowski (1977) and Milon et al. (1984) valued the access to recreational shoreline, while Shilling et al. (1985) and MacDonald et al. (1987) focused on less desirable properties of water—flood hazards. In a study of development costs, White (1988) measured the value of large lot zoning restrictions.

Land use has also been examined in housing valuation studies. Thus, Grether and Mieskowski (1980) concentrated on the use of neighboring parcels while Jud (1980) studied the external effects of zoning. In a similar vein, Mark and Goldberg (1986) looked at zoning, but from a time-series perspective. Although many of the studies consider locational variables implicitly in the form of measures of
distance to central business district or other facilities, none explicitly examine spatial attributes (Cartesian or geographic coordinates).

In all of the commercial land studies reviewed, land use and distance to amenities were included as explanatory variables. In addition to these, Chicoine (1981) included a measure of fertility in a study of farmland, Downing (1973) considered race and income levels, and Johnson and Ragas (1987) the availability of downtown tourist and entertainment facilities in New Orleans. McMillen and McDonald (1979), Kowalski and Paraskevopolous (1990), and Peiser (1987) considered land use, macroeconomic measures and linear distances to specified amenities.

The approaches to land use as a factor in valuation have been varied. Studies conceding the importance of use restrictions without explicitly treating them include Kau and Sirmans (1979), Mills (1969) and Yeates (1965). Those measuring the effect of land use as a commercial/non-commercial dummy variable include Chicoine (1981), Hushak (1975), Hushak and Sadr (1979), Jud (1980), Mark and Goldberg (1986) and Kowalski and Paraskevopolous (1990). On the other hand, Downing (1973) and McDonald and Bowman (1979), as well as all those considering housing without express reference to zoning or land use, examined only a single classification thus implicitly conceding the importance of this factor. Finally, Adams et al. (1968),
Clonts (1970) and Peiser (1987) estimated separate functions for each of multiple zoning classifications.

In general, then, location and permitted use appear to be the significant categories of exogenous variables recognized in the hedonic pricing studies. Such site specific characteristics as lot size, improvements and the like make up the endogenous influences. In addition, macroeconomic and demographic variables appear in the studies based on the Rosen model. For this study, consistent with Lancaster as interpreted by Edmonds, variables in the three categories of site characteristics, locational proxies and permitted use were selected for the hedonic pricing model discussed below.
CHAPTER III

SPATIAL ANALYSIS IN THE STUDY OF LAND ECONOMICS

Geography is concerned with the study of spatial patterns and processes at the Earth's surface. In particular, the distribution of factors affecting the value of land is important in the present context, thus bringing this work into the purview of geography (specifically, urban economics). In the present context, the distribution of economic factors is of interest since the immobility of land prevents moving it to a "more favorable" market. The market for, and therefore value of, any parcel of land is thus a spatial characteristic to some extent. For this reason, the study of the interactions of immobile market factors, i.e. the analysis of spatial autocorrelation, may be expected to provide clues to the valuation of land.

Historical background

As early as 1826, in his pioneering model of the "isolated state," Von Thünen observed that rents decline with distance. As an explanation, he proposed that land use patterns reflect both production costs and access to the market. The result, on a theoretical "featureless plain" around the population center, is the organization of land use into a series of concentric rings. Each ring represents the use which most nearly balances marginal costs and revenues, given the cost of obtaining access to the market.
for the products. This simple design relies on assumptions of absence of natural barriers or transportation routes, homogeneous soil conditions and isolation of the population center (Berry, et al. 1987). The identical model has been used in the analysis of land values as recently as 1989 (Capozza and Schwann 1989).

Thus, land closest to the city would be used for intensive production of perishables and dairy products, a bit farther out building materials and fuel would be obtained from a ring of forests, and so on. This concentric-circle model was adapted, a century later, to the description of urban centers by Burgess in 1923, and Park and Burgess in 1925, who observed "filtering" patterns in housing, in which the more affluent tended to build on the urban periphery while occupancy of older properties "filtered" down to lower income users who were thus concentrated closer to the central business district. Again, the cost of access was observed to be a major factor.

By 1939, transportation technology improvements underscored the importance of this measure of access, and Homer Hoyt introduced a theory of axial growth along transportation corridors. In 1943, Harris and Ullman proposed a model combining all the previous into a complex structure of multiple nuclei and districts including the central business district (CBD) and various manufacturing, commercial and residential nuclei. All of these models
reject the oversimplification inherent in Von Thünen's "featureless plain" and rely on various models of decline of rents over distance from the activity centers (Berry et al. 1987). This gradient concept has been the subject of several economic, as well as geographic studies.

Following the basic concept of the gradient, Muth (1969) proposed a negative exponential function as a sufficient explanation for the distribution of population around an urban center. Knos (1977) used a reciprocal to map land values, again around a single center. In general, the gradient concept has either explicitly or implicitly been adopted in, for example, studies of population (Muth 1969, Harrison and Kain 1974 and Yeates 1965), rents (Grieson and Murray 1981 and Schmerner 1981) and land values (Knos 1977, Johnson and Ragas 1987). In each, a peak of value falls off at varying rates over distance illustrating an inverse relationship of the dependent variable to distance.

Other studies, however, have explicitly recognized that more than one center may exist or that a more complex function may better describe the relationship. Thus, Schroeder and Sjoquist (1976) postulated a three-dimensional

---

3 As did Von Thünen, in the extension of his basic model to allow consideration of "villages" (alternate population or consumption centers) and rivers as transportation routes or barriers. This progression from overly simplified to more complex, and thus realistic, models, represents an important early contribution by Von Thünen to social science methodology.
surface capable of describing a high order polynomial relationship of population to map coordinates. The technique they used was a form of response surface methodology called trend surface analysis (TSA). Parker (1981) applied the same methodology to rent gradients and Jackson (1979) applied a form of analysis similar to TSA to hedonically derived values for the accessibility of housing. All found a relationship between the dependent variable and spatial coordinates consistent with the concepts of the response surface approach (see, generally, Box and Draper 1986).

A recent use of TSA in the context of real estate research is found in Sharkawy (1990) who used the clear visual differences in trend surfaces estimated for the Atlanta area from data obtained from three different sources to show that the data sources appeared to be inconsistent. In that study, the use of TSA allowed Sharkawy to avoid problems in matching submarket boundaries which otherwise make the three data sets noncomparable. Although not strictly a valuation study, Sharkawy's work provides a further foundation in real estate valuation analysis for the application of response surface methodology and the explicit consideration of location.

The Analysis of Response Surfaces

The application of response surface methodology to the
direct consideration of real estate valuation models is a natural extension of the TSA studies, particularly Jackson (1979). By applying a form of hedonic pricing to the left hand side of the response surface equation, the explicit consideration of spatial characteristics could be facilitated.

More importantly, statistical tests developed expressly for response surface methodology, such as the test for spatial autocorrelation discussed below, the Moran Coefficient, become applicable to the combined methodology. It thus becomes possible to determine whether or not the results improve the explanatory power of the previous uncombined models.

In a study of the value influences present in the New Orleans central business district, Johnson and Ragas (1987) applied two techniques explicitly treating spatial attributes in the form of geographic coordinates measuring both distances and directions. The first, which they referred to as a "behavioral" model, included both the familiar location proxies (for such amenities as the Superdome and tourist attractions) as well as interaction terms (cross products) relating pairs of amenities. With the increasing mathematical complexity of their model, they found serious potential problems with multicollinearity, of which they warned.

As an alternative to their preferred model, Johnson
and Ragas tested a sixth-degree Trend Surface Analysis (TSA) model (discussed below), which they found more predictive than their behavioral model. They criticized this approach, however, on econometric grounds, and because the TSA model "totally ignores behavioral factors" (Johnson and Ragas 1987, at p. 344).

In spite of their rejection of the response surface methodology for their purposes, Johnson and Ragas do not discount the importance of spatial attributes in land valuation studies. Thus, by way of conclusion, they note "virtually all topics in urban economics have spatial effects. It seems proper that analysts should use spatial tools." (Id. at 347).

Given that the pricing of land is a function of financial (as well as other) factors, the effect of the hedonic pricing technique is the removal of only the financial trend, or systematic variation in the residuals due to financial factors. It follows, then, that the spatial factors may be treated similarly, to remove spatial trend as well. The TSA form of analysis adopted for this proposal is only one of several approaches to the quantification of spatial factors. These techniques fall into the classification known as response surface methodologies.

The response surface methodologies are mathematical models used to describe geometric surfaces relating the
value of a dependent variable (the response) to the actions
and interactions of two or more independent variables. If,
as appears to be fairly well accepted, the distance
variables in standard hedonic pricing studies of land are
all proxies for the same valuation process, it may be that
the observed sales prices at the points located by the
spatial attributes of each sale collectively define a
surface representing the total effect of the spatially-based
process. Mathematically describing that surface should
produce a function which captures the spatially-based
process.

The "trend surface" resulting from such a statistical
smoothing of land pricing data is a mathematical
representation of the expected value of a parcel of land
given a specific set of spatial attributes, and no other
information. By thus describing the trend or process
associated only with location, this approach will have the
effect of removing such spatial trend from the regression
residuals, and will therefore permit testing residuals for
evidence of uncaptured trend.

It is important to note that the Trend Surface
Analysis (TSA) form of response surface methodology is not
proposed as a required, or even a satisfactory, methodology
for the explanation of the real estate valuation process.
Rather, the purpose of this research is limited to exploring
whether the capture of spatial trend in land valuation
models by use of some form of spatial attributes is potentially useful. That is, whether spatial attributes are suitable explanatory variables at all, and whether spatial autocorrelation might be useful as a measure of added explanatory power for a land pricing model including such variables. The task of examining the many possible approaches for the most effective means of including spatial attributes in hedonic pricing functions is left to future research.

The Combined HPF/TSA Model

In general, the concept of the response surface involves the fitting of a regression surface to data consisting of responses (here, sales prices) and explanatory variables, which for the TSA form of response surface methodology are the spatial attributes (the coordinates at which the responses are measured). The relationship presumed by TSA is of the general form:

\[ H = f(x, y) \]  

(9)

where the function \( f \) is a polynomial of degree \( m \), and \( x \) and \( y \) are the Cartesian coordinates of the response, \( h_i \), which represents a value measured as a distance above or below the \((x,y)\) plane. To permit identification of any underlying processes, a mathematical smoothing of the entire surface may be performed (Box and Draper 1986, Jackson 1979). This smoothing consists of the fitting of a surface,
called a response surface, to the observed values by means of ordinary least squares regression.

In order to identify the surface with the best fit to the data, polynomial functions of increasing degree in the cartesian coordinate terms may be fitted until termination criteria are met (Schroeder and Sjoquist 1976). Higher orders of polynomial with varying coefficients produce extraordinarily complex surfaces. In general, however, orders above the fifth \( m=5 \) are rarely needed or used (Cliff and Ord 1981, but see, Johnson and Ragas 1987, who use a sixth-order TSA). The technique is extremely robust, and even highly clustered data will not unduly distort the estimated surface (Haggett et al. 1977).

When a Taylor Series expansion of the \( m \)th-order expression of this regression model is simplified, it takes the form:

\[
f(x, y) = \sum_{q=0}^{m} \sum_{s=0}^{m-q} \beta_{q,s} x^q y^s + \epsilon_i
\]  

(10)

The relationship described in (1), representing as it does the effect of locational factors among others, may be augmented by the inclusion of the above as a proxy for any omitted locational variables (the \( L_i \) variables in the working model). Alternatively, the TSA variables may be seen as a full substitute for all locational proxies and thus supplant the \( L_i \) variables entirely. If the value
influences of the various amenities are assumed to be constant, their effect should be measurable in the form of residuals (the observed sale prices less the financial trend caused by nonlocational variables), which of course may be tested by the statistical tests described below.

Merely adding additional regressor variables will almost always increase such common measures of explanatory power as Adj. \((R^2)\). Thus, some less common measure of effectiveness is needed. A logical measure of optimality would be a combination of the method used by Schroeder and Sjoquist (1976), Jackson (1979) and Parker (1981) (comparison of increase in explanatory power Adj. \((R^2)\) with loss in degrees of freedom, see Haggett et al. 1977) and a method relying on a measure of reduction in spatial autocorrelation found in the residuals.

The model for this combined analysis may readily be developed from (8) and (10). Given (1) as the underlying process, by the additivity assumption the \((a)\) values may be divided into locational and financial factors:

\[
V_i = v(a_d)
\]

\[
= v(a_f, f(x_i, y_i))
\]

where \((r)\) is the number of terms included in the TSA function. Combining (8) and (10), produces the Hedonic Pricing Function (HPF) regression model augmented by the
Trend Surface Analysis (TSA) form of the response surface function:

\[ \hat{y}_i = b_0 + \sum_{s=1}^{k-1} b_s a_{i,s} + \sum_{q=0}^{m-q} \sum_{s=0}^{q} b_{q,s} x_i^a y_i^b + e_i \]  \hspace{1cm} (12)

Since the surface is created by OLS regression, the usual assumptions of normality, independence and zero mean must be made:

\[ e_i \sim \text{NID}(0, \sigma^2) \]  \hspace{1cm} (13)

That is, only if the error terms are independent, normally distributed, random variables, with expected value of zero and a constant variance will the regression coefficients be the best, linear, unbiased estimators of the parameters. Accordingly, each set of HPF residuals was tested to assure the assumptions were satisfied. In the presence of multicollinearity, however, this is not enough. As shown by Greene (1990) and Johnston (1984), the OLS estimators under multicollinearity remain unbiased and the best available, but because of inflated variance are unreliable, i.e. the best are none too good. The models were therefore tested for inflated variances as well, and it was found necessary to limit the use of the second order and higher TSA models, as discussed in the next chapter. The results of the iterative estimation of (12) at various values of \((m)\), in comparison with the estimate of (8) from the same data, are discussed in Chapter V.
In this study, data problems were minimized by the use of a large dataset with values extending over several years. While multicollinearity is unavoidable, and thus prevents the use of the response surface methodology for explanatory purposes, no such limitation appears in the use of the technique for forecasting. Accordingly, two approaches to analysis of the data were selected, 1) a comparison of hedonic pricing models with and without spatial attributes and, 2) a test of various response surfaces against a hedonic model for forecasting power.
CHAPTER IV

METHODOLOGY

Given the current state of research into the hedonic pricing of real estate, a natural extension would explicitly consider location either as an extension of, or substitute for, the set of variables now generally in use. This follows from the fact that the implicit importance of location is so universally recognized. Also, a natural extension of the application of response surface methodologies to questions of land economics would be the further exploration of spatially-based valuation models. The combination of both the hedonic method and response surface methodologies appear to fit both of these goals.

The hedonic pricing function and the various response surface methodologies are well-established techniques, though not often combined in an economic context (see: Schroeder and Sjoquist 1976, Jackson 1979, Johnson and Ragas 1987, Sharkawy 1990). The scarcity of attempts to do so is likely a result of the unavoidable multicollinearity produced by the calculation of the various power and crossproduct terms required for the estimation of the response surface, making OLS regression inappropriate for many estimation purposes. Lack of data, of course, is a frequent problem in all areas of real estate research, and
may be the reason why response surface methodologies have not been used in forecasting, either.

**Dataset**

The data are provided through the courtesy of DRESCO, Inc., of Dallas, via the DRESCO RealTrac™ Data System. RealTrac™ is a computerized commercial database incorporating all public records as well as proprietary information on actual sale prices gathered and verified by DRESCO employees. Besides being a very large data base, the DRESCO data have the advantage of including verified sales prices instead of the more typical appraisal estimates.

Fully one half of the eighteen pricing studies referred to above used value estimates based on appraisal data, with four limited to tax appraisals only. Of the seven using unofficial or unverified sales prices (one of them from questionnaires) four used sources such as transfer tax records or multiple-listing service data and other reliable estimates. Only two, including Peiser (1987), made use of actual prices such as are included in this dataset.

The data consist of 2,788 actual sales of vacant or unimproved land occurring within Dallas County, Texas, from January 1, 1983, through October 31, 1990, for which actual sale prices are available, excluding foreclosure sales or other public (auction) sales under court order. Potential sources of selection bias exist due to these selection
criteria. There is no basis for anticipating any systematic deviation from actual values, however, and thus errors should cancel. In addition, the large number of observations tends to reduce the influence of such bias. The possibility, however, must be noted.

All location variables are measured in miles linearly between the reference points which are presumed to be located in the center of the map grid in which the reference is located. These grid locations were obtained from commercial maps produced by MAPSCO, Inc. The entirety of Dallas County is covered in a series of 126 maps or pages in the MAPSCO Street Guide--1991 (Mapsco, Inc. 1991) with each page made up of twenty-four equal (3,000 ft. by 3,200 ft. or approximately 220 acre) grids. Thus, a total of 3,024 points, each slightly more than one half mile apart are defined on a regular grid system covering an area slightly larger than the county.

Locational references for property sales are obtained from the DRESCO RealTrac™ data. The MAPSCO Street Guide--1991 includes references for major buildings, shopping centers and malls. All other locations were obtained by visual examination of the MAPSCO product. Computer programs were written to convert MAPSCO grids into Cartesian coordinates and to calculate the locational variables.
FIGURE 1

DALLAS COUNTY HIGHWAY SYSTEM
Hedonic Pricing Function—Model

The variables for the pure hedonic model used in this research fall into three categories of attributes. The working model is:

\[ V_i = f(S_s, L_l, U_u) \quad (s + l + u = k) \]  (14)

Where:

- \( V_i \) = Observed sale price.
- \( S_s \) = Site-specific characteristics.
- \( L_l \) = Access (location) characteristic.
- \( U_u \) = Land use (zoning) characteristics.

Peiser (1987) chose as a functional form a logarithmic model, on the grounds that the contribution of a particular attribute would be expected to be in the form of a percentage of value rather than an absolute amount (Peiser 1987, p.346). This is consistent with most of the published hedonic studies of real estate value. A logarithmic model in the following form is used in this study:

---

The functional form for the model is a frequent subject of discussion. MacDonald et al. (1987), and others, argue that there is no theoretical basis for the preference of one form over another and recommend the use of a Box-Cox transformation. The principal models used in this study were estimated for linear, log-linear, linear-log and log-log transformations, and the appropriateness of Peiser's selection of the log-log was confirmed for use here based on adjusted \( R^2 \):

<table>
<thead>
<tr>
<th>Transformation</th>
<th>Std. HPF</th>
<th>Aug. HPF</th>
<th>Ext. HPF</th>
</tr>
</thead>
<tbody>
<tr>
<td>log-log</td>
<td>0.5574</td>
<td>0.5924</td>
<td>0.5954</td>
</tr>
<tr>
<td>log-linear</td>
<td>0.4745</td>
<td>0.4919</td>
<td>0.5203</td>
</tr>
<tr>
<td>linear-log</td>
<td>0.3974</td>
<td>0.3995</td>
<td>0.4112</td>
</tr>
<tr>
<td>linear</td>
<td>0.1557</td>
<td>0.1571</td>
<td>0.1803</td>
</tr>
</tbody>
</table>
\[ V_i = B_0 S^{B_1} L^{B_2} U^{B_3} \epsilon_{v_i} \]  

(15)

Taking the log of both sides, the value \((V_i)\) is estimated as:

\[ \ln V_i = B_0 + B_1 \ln S + B_2 \ln L + B_3 \ln U + \ln \epsilon_v \]  

(16)

with each term representing a vector of regression coefficients \((B_n)\) and a vector of natural logs of attribute quantities, with the intercept \((B_0)\), of course, being a constant. The intercept term, consistently with Edmonds (1984), may be construed as including the common characteristics or those with insufficient variation to be the subject of separate expenditure.

**Hedonic Pricing Function—Variables**

The variables selected were not in any way intended to exhaust the possible proxies for location, nor is any attempt made to suggest that only the selected factors may be relevant. The variety of such potential influences is evident. If the proximity of a community college campus is a positive value influence in some cases, for example, what then might be the effect of a high school or elementary school? It is clear that the list of potential variables can quickly become unmanageable. Such is, of course, one of the problems addressed by this research.

Each of the following are theoretically appropriate
under Edmonds' (1984) application of Lancaster in that each
may be the subject of conscious choice by the consumer. The
anticipated sign for each coefficient is specified, but no
basis for any expectation with regard to magnitude exists.

Site Characteristics (S_i)
The dataset was limited to sales of land. As
generally used in the real estate literature, the term
"land" refers to vacant or unimproved real estate, rather
than improved or income-producing properties. The specific
characteristics or attributes of land are thus relatively
few in number, there being by definition no improvements to
consider. Moreover, it is appropriate to limit
consideration to land since the presence of improvements
significantly affects the costs of some potential uses of a
particular parcel and thus constrains the value of the
zoning classification (itself a constraint on the value of
the parcel, as discussed below). In addition, as noted by
Peiser (1987) and many others, the effects of marketing
decisions, managerial skill and other agency issues, as well
as functional and economic depreciation and similar factors,
are minimized by exclusion of improved properties.

Most hedonic pricing studies are limited to cash
transactions on the basis that financing conditions may be
capitalized into the sale price, thus distorting the "true"
value. Although exclusion of financed sales is common in
real estate pricing studies, it is uncertain whether this is necessary since the effect might be captured in a dummy variable. Accordingly, a variable named CASH was included in the data set to designate observed sales which were not associated with recorded financing instruments.5

Given that the topographic conditions of the observations are unavailable, these potentially interesting variables were reluctantly consigned to the error term. Since, however, the general topography of Dallas County is uniformly flat, with few natural boundaries, wetlands or the like, it may be that this characteristic is captured in the intercept rather than showing up as misspecification. A natural follow up to the results discussed below would be to determine whether including a measure of the topography would produce any improvement in performance.

The site-specific variables and their anticipated signs include PRICE, the dependent variable, being the observed selling price calculated on a square foot basis and adjusted for inflation (dependent variable), CASH a dummy variable designating whether a sale was financed or was a cash sale, and ACRE, the size of parcel in acres. A

5 Any security arrangement will be unenforceable if the financing instruments are not properly recorded. This has resulted in a universal practice of simultaneous recording of title and security instruments which thus assures financed sales may be accurately identified. Actual terms of financing are not always discernible from the financing documents and were therefore not used.
positive sign was anticipated for CASH, since leveraged transactions, being more risky, should be associated with higher prices. A negative sign, representing lower unit price for large parcels was forecast for ACRE.

**Access (Location) Characteristics (L₁)**

In line with the hedonic studies of real estate, the linear distance to specific amenities from each observed sale was included as a proxy for access. Actual driving distances and condition of roads would, of course, be a more precise measure, but such information was not available for each observation. In the absence of significant barriers (except for the Trinity River and certain highways) and given the intensively developed study area, linear distance is likely to be an adequate proxy. The variables chosen were facilities or destinations to which access is likely to be valuable. The list is clearly not exhaustive. Inclusion of every possible factor would be unworkable.

Each observation was assumed to be located at the center of the map grid in which it falls in order to preserve the regularity of the spacing of the points of measurement, and all values and distances were thus measured with reference to the same set of regularly spaced points. The minimum distance was set at 0.01 mile representing observations which fell in the same map grid as the amenity (each grid measuring approximately 0.57 by 0.61
miles) and avoiding the computational problems of taking the natural log of a zero value. Johnson and Ragas (1987) recommend establishing a maximum range of influence for such a variable in order to reduce multicollinearity. Peiser (1987) used a negative exponential relationship with an arbitrarily selected decay parameter and a maximum of six miles in this context. For this study, no such truncation was found necessary.

The total study area (Dallas County, Texas) is nearly square, with sides of slightly more than 31 miles. The longest dimension (31.6 miles) was tested as a divisor to scale both the locational variables ($L_n$) and the spatial attributes or coordinates (see Box and Draper 1987) but, there being little multicollinearity, was found unnecessary for either the HPF or the Augmented HPF models. In order to ease interpretation of the regression coefficients, then, the variables are not scaled or transformed except for the logarithmic function.

The locational variables can be separated, for convenience, into activity centers, transportation nodes and destinations. A brief description of each follows. Figures 2 through 10 are plots of the location of the suspected value influence measured by each such variable. These variables are:
Activity centers:

CBD
Central business district of the City of Dallas, being roughly one mile square and centrally located in the county.

LBD
Nearest local business district, defined as any MAPSCO [c] grid containing three or more major (200,000 sq. ft. or larger) office buildings.

Transportation nodes:

AIR
Nearest commercial airport entrance (north and south entrances at D/FW International Airport and Mockingbird Lane entrance of Love Field).

GENAIR
Nearest general aviation airport.

HWY
Nearest entrance ramp to a limited access freeway or interstate highway.

Destinations:

SHOP
Nearest shopping center, including strip centers of 10,000 retail square feet and larger.

MALL
Nearest of the largest ("regional") shopping malls.

MEDIC
Nearest hospital with emergency room facilities (trauma center).

COLL
Nearest college or university, including community colleges.

The following figures, showing the 3,024 grids in the study area, indicate the relative location of the foregoing factors. The entirety of Dallas County is covered by the grid pattern, and each grid containing one or more of the locational factors is shown in solid color in the appropriate figure. In order to assist in visualizing the
location of these grids in relation to figure 1, the
variable coding for limited access highway ramps (HWY) is
also plotted, but in a lighter shading (see figure 6).
These figures are to scale, with North to the top of the
page.
FIGURE 2

LOCATION OF CENTRAL BUSINESS DISTRICT (CBD)
FIGURE 3
LOCATION OF LOCAL BUSINESS DISTRICTS (LBD)
FIGURE 4
LOCATION OF COMMERCIAL AIRPORT ENTRANCES (AIR)
FIGURE 5
LOCATION OF GENERAL AVIATION AIRPORTS (GENAIR)
FIGURE 6
LOCATION OF LIMITED ACCESS HIGHWAY RAMPS (HWY)
FIGURE 7
LOCATION OF LOCAL SHOPPING CENTERS (SHOP)
FIGURE 8

LOCATION OF SHOPPING MALLS (MALL)
FIGURE 9
LOCATION OF TRAUMA CENTERS (MEDIC)
FIGURE 10

LOCATION OF COLLEGE/UNIVERSITY CAMPIUSES (COLL)
Land Use Characteristics

A significant function of municipal government is the establishment of controls on the use of land within its jurisdictional area. The most common of such systems of control is the zoning ordinance, a comprehensive plan for controlling the externality effects of the use of land by dividing the jurisdiction into areas or zones of presumptively compatible permitted uses. The theory of zoning is that by restriction of uses which may be nuisances in proximity to other types of use (i.e., create negative externalities), the overall efficiency of land use is improved.

The necessary result of the adoption of zoning restrictions is the establishment of artificial constraints. By this set of constraints, a particular property may be used only for those purposes included on a list of permitted uses within the classification. These constraints are may be modified only through the political process (rezoning) or by a quasi-judicial means of obtaining exceptions to the rules (variances). Both processes are costly and time-consuming and neither is considered a matter of right under the law, therefore the zoning categories may be considered fixed in the relevant time period.

In general, the permitted uses fall into several broad categories: residential; commercial, such as shopping centers; office; industrial uses; and mixed, multiple or
"planned development" uses (which may include a combination of the foregoing). The nonresidential and residential use categories are often incompatible, except where specific planning criteria are established and rigorously enforced, thus the term "planned development" for mixed-use areas designed to maintain the value of each use.

Within each permitted use category, several levels of intensity may be designated by the zoning authority. As a result, each observation was examined to determine the appropriate zoning variable. This was a necessary step since the data could come from any of the twenty-five separate municipalities in Dallas County, each with its own zoning ordinance establishing its unique scheme of classification with as many as thirty-six subclassifications within the main use categories.

Rather than coding the dummy variables either one or zero, these (as well as CASH) were set equal to either the base of the natural logarithm (e) or one, so that the log transformations could be used directly. To avoid singularity, the "planned development" (ZONED_PD) category was selected as the "leave-out" variable. Since the zoning classification was known prior to sale, purchasers were most likely to have been willing to pay a premium for the right to use the property and thus the coefficients were all expected to be positive.
The land use variables were:

**ZONED_C**

Commercial: Retail; shopping center; local business; freeway commercial; and general business

**ZONED_O**

Office: Office

**ZONED_I**

Industrial: Light, medium or heavy manufacturing; mineral extraction; warehousing or shipping terminal

**ZONED_PD**

Multiple or planned development uses including CBD (City of Dallas central business district only) Multi-use (MU) designations and approved Planned Unit Developments (PUDs).

**Response Surface (TSA)—Variables**

Other than the spatial attributes (Cartesian coordinates), the variables used in the expanded hedonic pricing function were identical to those used in the traditional model. The spatial attributes consist of the (x,y) Cartesian coordinates of the observed sales. For the higher order TSA models used in the forecasting tests, the same variables, of course, are used. The crossproduct and power terms, as needed, are specified by (12).

The origin for the Cartesian coordinate system was placed at the southwest corner of the study area to keep all values in quadrant I (all positive). A preliminary test of the CBD as the origin produced no difference in results. The range of both variables was 0.01 to 30.1 miles.
The spatial attributes are:

**EAST**
Distance in miles east of the center of the MAPSCO \(c\) grid located in the extreme southwest corner of Dallas County (81W) to the center of the grid in which the target is located. With the concentration of high intensity uses in the area between Dallas and Fort Worth, West of the CBD, this coefficient was expected to be negative.

**NORTH**
Distance in miles north of the center of MAPSCO \(c\) grid 81W to the center of the target grid. Much of the area to the South of the Trinity River (e.g. Oak Cliff) is residential, while a high concentration of commercial and office uses is located along I675 (LBJ Freeway) North of the CBD. This was therefore expected to have a positive coefficient.

Since dummy variables are frequently used in standard hedonic studies to code for various two-state conditions, a hedonic model, called Expanded HPF, was formed using the center of the Dallas CBD as a dividing line for the designation of spatial attributes in the form of binary (dummy) variables. Thus, the observations were classified as to whether they fell in the East or West half of the county and whether they were located in the North or south half as well. The East-West location was recorded in the dummy variable \(E\_DUM\), and North-South was recorded in \(N\_DUM\).

This Expanded HPF model represents less of a departure from standard hedonic pricing formulations than the Augmented HPF model, while still capturing the essence of the spatial attributes. The use of dummy variables is well
understood, and it appears that it may be possible to capture the effects of spatial attributes, at least in a general sense, by doing so. The same tests were performed on this Expanded HPF as were on the Standard HPF and Augmented HPF models to determine whether there would be any significant differences.

The E_DUM variable was coded zero for West of the CBD and unity for East, and the N_DUM was similarly valued zero for South of the CBD and unity for North. The effect of taking these dummies together, of course, is to designate location on the basis of the quadrant of the County in which the observation is located. This use of dummy variables is functionally equivalent to measuring the spatial attributes on a scale of zero to one units, rather than zero to approximately thirty miles. Alternatively, it may be seen that the use of the spatial attributes EAST and NORTH results in dividing the County into 3,024 areas into which an observation might fall while the use of the dummy variables divides it into four such areas. In either case, the use of binary spatial attributes was anticipated to produce similar results to the use of the measured spatial attributes, with the combination designating the Northwest quadrant of the County associated with higher values.

**Multicollinearity In Response Surface Models**

When higher orders of the spatial attributes are
calculated for use in the response surface models, multicollinearity immediately becomes troublesome. This econometric problem results in a violation, or near violation, of the OLS requirement that the model be of full rank, that is, that no variable be the same as any other variable or linear combination of variables. Where variables are identical, multicollinearity (or collinearity of any pair of variables) is said to be perfect, and there is no unique solution for the vector of regression coefficients (Johnston 1984). Where two or more variables are systematically close in value, the multicollinearity is said to be high. This latter condition is more common.

Johnston shows that in the case of perfect collinearity, the model is not of full rank. In such a case, there being an infinite number of possible solution vectors, the variance of the coefficients would be infinite. The sum of the coefficients, however, no matter which set is chosen, remains the same (Johnston 1984, p. 242). Thus, while there is no unique answer, the function remains estimable.

In the case of high, but not perfect, multicollinearity, both Johnston and Greene (1990) observe that three problems might occur. First, small data changes might result in large changes in the parameter estimates. That is, the variance of the OLS estimates will be extremely high. Second, as a result of this high level of variance,
coefficients may be nonsignificant in spite of a high level of significance when considered jointly with others and in spite of a high Adj. $R^2$. Third, the extreme variance might result in "wrong" signs or magnitudes of the OLS coefficients.

Clearly, where the intent of the model is to describe a pricing process, even moderate levels of multicollinearity are impossible to accept. Moreover, as Greene shows, typical methods of correction for multicollinearity, such as ridge regression, intentionally produce biased estimators which have been manipulated to reduce variance while maintaining Adj. $R^2$. The satisfaction of reducing mean squared error is spoiled by the realization that the ridge estimator is a function of unknown parameters and thus the direction of the bias is unknown (Greene 1990, p. 278).

In the case of the Standard HPF model used in this study, no serious multicollinearity is present according to the variance inflation factors. As discussed below, the variables all tended to be significant and of the expected signs, with only a few interesting deviations. The variances of the estimators are thus not suspect. Most importantly, no difference is found when the spatial attributes EAST and NORTH are included in the formulation of the Augmented HPF model nor is any detected in the Expanded HPF using dummy spatial variables E_DUM and N_DUM. It may be concluded that multicollinearity is not a problem for any of the Standard
HPF, Expanded HPF or Augmented HPF models.

Such is not the case for the TSA models used in this research, however. The variance inflation factors for even the first set of power and crossproduct terms (calculated for the second order model called TSA2), are unacceptable for explanatory purposes. This problem only increases with increasing orders. Clearly, the forced interrelation of the variables in the model resulting from the calculation of these terms produces variables which, as order increases, become closer in value. It was found, for example, that rounding error renders the seventh order model (TSA7) undefined for this reason. The differences become so small at that point that the SAS system finds many of the variables to be identical (within the precision available to the SAS software) and declares the model not to be of full rank.

The effect of this unavoidable mathematical result is to render TSA models meaningless for descriptive use, given standard econometric methods. The use of various models for forecasting purposes, however, is unaffected by the multicollinearity-induced unreliability of the individual coefficients (see Johnston 1984, p. 239 et seq.).

The measures of reliability for forecasting models do not require reference to the individual coefficients. Instead, such tests are based on the differences between actual and estimated values of the dependent variable (i.e.
the regression residuals) and not the coefficients of the regressor variables themselves. Johnston clearly establishes that the estimate is unaffected. Thus, a model which suffers from a high degree of multicollinearity but which predicts observed values more consistently can be justifiably called "better" for that narrow purpose than a poorer performing model which shows no multicollinearity at all.

Accordingly, the forecasting tests were performed on the Standard HPF, Expanded HPF and Augmented HPF models as well as a series of TSA models of orders zero through six, corresponding to integer values of 0 through 6 for \( m \) in (12). In each model, the \( \{a_t\} \) vector consisted of the site specific and land use variables ACRE, CASH, ZONED_C, ZONED_I and ZONED_O. Thus, TSA0 included those variables only, while TSA1 also included the spatial attributes EAST and NORTH and so forth. The models for each order are specified in Appendix B.

**Computational Methods and Hypotheses Tested**

The research questions addressed were: whether the hedonic approach to pricing land can be improved in explanatory power, forecasting capability, or both, by the consideration of the explicit spatial attributes of the observations as explanatory variables, either directly or as dummy variables, and, how such improvement might be measured.
The tests of both these questions were generally straightforward, except for the measurement of spatial autocorrelation in the residuals. The relative merits of two models may be compared by examining the results of spatial autocorrelation tests in addition to the traditional measures such as Adj. \( R^2 \).

Due to the nature of the TSA function, extreme levels of multicollinearity (as predicted by Johnson and Ragas 1987) make the OLS coefficients of the TSA of orders greater than one unusable for explanatory purposes due to their extreme variances and associated unreliability. This problem, in fact, led Johnson and Ragas to omit reporting of their TSA coefficients on the grounds that they were meaningless. Thus, the TSA method cannot be used for usual econometric explorations of the land pricing process. This does not, however, mean that spatial elements cannot be considered. The use of the simple spatial attributes, EAST and NORTH or their binary counterparts, E_DUM and N_DUM, does not raise the multicollinearity problem, and thus was pursued.

On the other hand, the forecasting power of a model is unaffected by multicollinearity. Therefore, the forecasting ability of the Standard HPF function can be compared with that of the various orders of TSA to assist in distinguishing the models. In all cases, the spatial autocorrelation in the residuals is measured to determine
whether the Moran Coefficient is consistent with the more familiar indicators, and the residuals are tested for satisfaction of the standard OLS assumptions.

Thus, the principal hypothesis tested is that hedonic land pricing models which use limited versions of spatial attributes as additional explanatory variables are superior to a model using the traditional hedonic pricing variables alone in explaining the pricing of land. The second hypothesis is that either, or both, the augmented or expanded HPF model has greater forecasting power than the Standard HPF. Superiority is tested by reference to familiar statistical tests as well as the measurement of spatial autocorrelation in the residuals from the models examined.

The first hypothesis was tested by constructing a model in the form of a Lancastrian hedonic pricing function for real estate, using the variables described above. This model is referred to as the Standard HPF. The variables are specified in table 4. The Standard HPF model was then augmented by inclusion of the spatial attributes of each observation as additional explanatory variables. The variables in this latter model, referred to as the Augmented HPF model, are shown in table 5. An alternative version of the spatial attributes, measured as dummy variables, were included in the third model tested, the Expanded HPF, table 6. The test applied was an F-test of the restriction that
the spatial attributes were equal to zero. The critical value was one, and any larger value calls for failure to accept the restriction. In addition, the Root Mean Square Error (RMSE) or standard deviation and the Adj. \( R^2 \) were calculated for each model.

To test the second hypothesis, that of improved forecasting power, the restricted and unrestricted models as well as a series of response surface models were compared for forecasting power using a variety of statistical measures. These included the familiar Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Adj. \( R^2 \), as well as Theil's \( \bar{U} \) Statistic, a measure of the effectiveness of a forecast model which compares predictions using coefficients calculated from a portion of the sample with the actual values from a different portion.\(^6\)

The MAE and RMSE statistics were calculated by estimating the coefficients for the model for half the data, the estimation sample, then substituting these values into the models and calculating the resulting prediction errors in the remaining half, or forecasting sample. Evaluation

\(^6\)The formula for Theil's \( \bar{U} \) is:

\[
\bar{U} = \sqrt{\frac{1}{n^o_I} \sum_{i=1}^{n^o} (y_i - \hat{y}_i)^2} - \sqrt{\frac{1}{n^o} \sum_{i=1}^{n^o} y_i^2}
\]

where \((n^o)\) is the number of observations in the forecast period.
criteria for the RMSE and MAE were their absolute values, with reduction in these measures indicating a lower variance between actual and predicted values of COST. An increase in Adj. (R²), conversely, was held to indicate an improvement by reason of the increase in the amount of variation explained in the forecasting sample.

Theil's U statistic is related to R², but is not restricted to values between one and zero. As the value of Theil's U increases, a poorer forecasting performance is indicated (Greene 1990). The values were calculated for each model using the same estimation and forecasting samples.

The various ordinary least squares regressions were computed using the SAS System PROC REG. The residuals were separately analyzed with PROC UNIVARIATE using the NORMAL option. Reported statistics from the REG procedure include the Adj. (R²) as a measure of explanatory power, F value for the significance of the model, T statistics for the significance of each variable, collinearity diagnostics and the variance inflation factor (VIF) which, as the reciprocal of tolerance (1-R²), signals multicollinearity problems. The UNIVARIATE procedure produces descriptive statistics, a test of whether the mean is zero, and the Kolmogorov-Smirnov D statistic to test whether the residual comes from a distribution which is a good fit for a normal distribution with the same mean and variance. No procedures in SAS are
available for the computation of the Moran Coefficient, so a program was written to make this computation.

Monthly average residuals were used for calculation of the Durbin-Watson "D" statistic since the observed sales were unevenly distributed over the time period of this study. Lower bounds for both the one percent and five percent significance levels are reported.

**Measurement of Spatial Autocorrelation**

The availability of spatial attributes (Cartesian coordinates) for the observations allowed the measurement of the spatial autocorrelation of the residuals from the various models in addition to the standard statistical tests. This measurement, called the Moran Coefficient or Moran's (I) statistic, indicates the level of spatial autocorrelation in the residuals and also indicates the extent to which the spatial process underlying the model has been captured.

Past hedonic studies of land pricing have not measured spatial autocorrelation. Although most appear to have considered (and found insignificant) the presence of time-series or temporal autocorrelation, none have attempted to measure autocorrelation in the plane. Even if there is no apparent problem with temporal autocorrelation, there is no guarantee that harmful autocorrelation may not exist in spatial data.
The assumption of independently distributed residuals from the OLS regression requires that there be no systematic relationship defining one observed error term in terms of any other. If any value is defined, even partially, by another, then the Ordinary Least Squares estimation of the data will be biased. Individual values will be assumed to contain more information than they actually do (some of the information is captured in the correlated value) and thus the error terms will be underestimated, causing a consequent overestimation of the \( R^2 \). In the case of time series, or temporal autocorrelation, a residual is thus described, at least in part, as a function of time and all the preceding residual values.\(^7\) Such temporal autocorrelation is recognized as a problem in time series models, of course, and a number of techniques have been devised to remove it.

Cliff et al. (1975) point out that spatial patterns are discernible in most physical and social systems and identification of the patterns provides insights into the underlying processes. Such spatial trend indicates the existence of a pattern in location. It is important, however, to distinguish between spatial autocorrelation (or pattern) in the observed dependent (and even independent)

\(^7\)Spatial autocorrelation in the residuals is a function of significantly different variables: the value of all other residuals (not just the preceding ones) and the untransformed spatial attributes of each individual residual. See, discussion following.
variables, which is a subject of study, and spatial autocorrelation in the residuals, which is an indication of possible bias in the statistical results.

If, after removing the trend captured by a model, there are spatial trends remaining in the data, the residuals should exhibit spatial autocorrelation. That is, the residual values should be mathematically related to each other according to some function of their spatial attributes or coordinates. If such spatial autocorrelation exists in the pure HPF residuals and is reduced by the introduction of spatial attributes (Cartesian coordinates), either in the augmented or expanded models or via methodologies such as TSA, the idea that explicit consideration of spatial attributes is appropriate for such models is given support. A measure of this spatial autocorrelation, then, must be developed as an additional test of the models in this study.

Cliff and Ord (1981) introduce the concept of spatial autocorrelation by citing Tobler's First Law of Geography: "Everything is related to everything else, but near things are more related than distant things." (Cliff and Ord, p. 8, quoting Tobler). A model of a reality which follows Tobler's Law must of necessity omit some sources of spatial autocorrelation; otherwise it would be a complete description rather than a model.

The measurement of spatial autocorrelation is based on the notion that if high values of a measure in one area are
regularly associated with high values in another area, that association may be detected by applying statistical tests. If it is assumed that the population in each area represents an independent or separate population, then Cliff et al. (1975) define spatial autocorrelation as present when, for any pair of areas, drawings from each population are pairwise correlated. Since the models to be considered are spatial in character, however, the potentially complex interaction of other locations must be accounted for.

In the simplest case of spatial autocorrelation, measures of some value are taken at regular points and the influence of each measurement on the others is considered. The relationship of the eight "nearest neighbors" to a single point may be diagrammed as shown in figure 11. It is evident that the value in cell 5 can be influenced by the values in all eight adjoining cells. Moreover, if the value is a direct function of physical distance, it is evident that the center of cell 3 is not the same distance from the center of cell 5 as are the centers of cells 4 and 8, and may therefore not have the same effect on the value in cell 5. This assumes, of course, that only distance is relevant. Thus, the actual effect \( w \) of the value in one cell (i) on that in another (j) may be derived from two sources:
FIGURE 11

NEAREST NEIGHBOR RELATIONSHIPS
where \((d_{i,j})\) is the distance between the points, and \((R)\) is some function describing the nature of their relationship, if there is a factor other than distance which relates them.

An interaction effect represented by \((R)\) may result from physical access considerations including the number and quality of linkages (transportation routes), or barriers such as unbridged rivers or freeways. That is, the effect of communication over simple linear distance may be complicated by the inability to take the shortest route, resulting in the need for the \((R)\) term to account for such factors.

For this research, the topographical homogeneity of Dallas County and the high degree of development of infrastructure justifies the assumption that access is generally unimpeded from one point to another. There is thus no \((R)\) variable to consider, and therefore a simple function of distance alone is satisfactory.

Most commonly, the weighting factor is presumed to be a reciprocal function of distance (Ebdon 1985). Following Ebdon, the simplest form of weighting factor, the reciprocal of the linear distance between the points was used as the weighting function \((w^*)\):

Given the foregoing, a plausible measure of the spatial autocorrelation in a set of points on a plane would
be in the form of a typical correlation coefficient, that is, the covariance of the points in question divided by the variance of the function, but adjusted by the weighting function to reflect interaction effects. Such a measure applicable to the residuals from (16) is Moran’s (I) statistic.

Moran’s (I), also called the Moran Coefficient, takes the effect of distance and other functional relationships into account by including a weighting coefficient such as (18) in the classical form of correlation coefficient. The statistic as proposed by Moran in 1950 for binary weights, and generalized to provide for any weighting scheme by Cliff and Ord, is specifically stated (Cliff and Ord 1981):

$$I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \theta_i \theta_j}{\sum_{i=1}^{n} \theta_i^2}$$  \hspace{1cm} (19)$$

where

$$S_o = \sum_{i=1}^{n} \sum_{j=0}^{n} w_{ij}$$  \hspace{1cm} (20)$$

The nature of the Moran Coefficient as an expanded correlation coefficient form is made clear by examining a
special case. If only one dimension is considered, that is if all observations had the same value for one spatial attribute, and if the relationship for the weighting function were such that only the value in the cell to the immediate "left" of each observation has any effect on its neighbor, and each observation is the same "distance" from the next, it is evident that this special case is identical to a time series. If each individual weight is then defined to be unity, the sum of the weights \((S_n)\) will be equal to \((n)\), and this equation reduces to:

\[
I = \frac{\sum_{i=1}^{n} e_i e_{i-1}}{\sum_{i=1}^{n} e_i^2} \quad (21)
\]

which is easily recognized from Johnston (1984, p. 320) as the serial autocorrelation coefficient of OLS residuals.

When measuring the spatial autocorrelation of residuals, however, it is useful to statistically test whether a significant degree of such correlation is present. The variance of Moran's (I) Coefficient can readily be determined as can the expected value \((E(I))\), and a simple \(z\)-statistic may be calculated to test whether the residuals appear to be related spatially. The test statistic is:

\[
z = \frac{I - E(I)}{\sqrt{\sigma_I^2}} \quad (22)
\]
CHAPTER V

ANALYSIS OF THE RESULTS

The analysis of the data provides uniform and consistent statistical support for both the principal hypothesis (that the introduction of spatial attributes or geographic coordinates into a hedonic pricing function (HPF) will reduce spatial autocorrelation in the residuals) and the secondary hypothesis (that forecasting performance of the hedonic model so augmented or extended will be improved). In addition, it is shown that the Moran Coefficient, as a measure of spatial autocorrelation, provides evidence which is consistent with standard measures of performance for hedonic pricing models.

Spatial autocorrelation in residuals, as measured by the Moran Coefficient, is reduced in both the Augmented HPF and Extended HPF models from the level exhibited in the Standard HPF, indicating that the models including spatial attributes capture more of the spatial trend. In addition, the augmented and extended models are shown to be superior to the Standard HPF model at a statistically significant level both in terms of explanatory power and forecasting ability, although only a modest improvement is achieved in either case.

Unexpected results were also obtained. A comparison
of the regression coefficients from the Standard HPF and Augmented HPF models shows that the set of statistically significant variables differs between the models in a manner which may be systematic. Also, unanticipated differences appear across zoning classifications. These findings suggest topics for further research which may provide a better understanding of the spatial nature of the land pricing process.

In addition, extremely high levels of spatial autocorrelation were found in all of the hedonic models. Since the serial autocorrelation levels found in this data and as reported in the hedonic pricing literature were not such as to justify a great amount of concern, it is likely that this econometric problem has not been adequately considered in the past.

Tests of Explanatory Power

Because of the multicollinearity inherent in the TSA methodology, the usual statistical tests of explanatory power could be applied only to the three hedonic models. These statistics, the standard deviation (RMSE) and Adj. (R²), are, however, reported for all the models for comparison purposes. The coefficients for all variables and complete statistical results are reproduced in Appendix B.

In the tables and the following discussion, the response surface models are referred to by their order, with
order zero (TSA0) representing a model including only the site specific characteristics (ACRE and CASH) and the zoning classifications. The first order model (TSA1) also includes the spatial characteristics, EAST and NORTH, and higher order TSA models include the appropriate cross-product and power terms of these variables. The full specification of each model is indicated in Appendix B.

The Moran Coefficient is not affected by multicollinearity. This is true because the estimated value of the dependent variable is unaffected by multicollinearity (Johnston 1984, p. 241 ff.). The residual, of course, is merely the difference between the estimated value and the observed value and the calculation of Moran's Coefficient requires only the EAST and NORTH variables and the value of the respective residual. The regression coefficients do not enter into the calculation, and thus the Moran Coefficient is meaningful for all the models reported in table 1 regardless of multicollinearity.

It is important to note that the Moran Coefficient does not depend at all on the use of spatial attributes in the regression model for which it is calculated. This statistic is a function of the location of the observation and its associated residual, and thus may be calculated for any model, so long as the distance from each observation to all other observations is known, even if those distances are not used in the regression.
By all criteria, the addition of spatial attributes to the Standard HPF model produces improved performance. The increase in Adj. \( R^2 \) indicates that the augmented and extended models account for more of the observed variation in the data, and the decrease in standard deviation (RMSE) shows that this is achieved with a lower level of variance. These criteria alone would indicate a preference for either the Extended HPF or the Augmented HPF model.

The Moran Coefficient may also be used to rank the various TSA models relative to the Standard HPF since, as noted, it is unaffected by the multicollinearity which renders the regression coefficients on the higher order power and crossproduct terms unreliable. Thus, the fourth order TSA surface (TSA4) is shown to be roughly equivalent to the Standard HPF in terms of the capture of spatial trend. This finding is in line with the observation of Johnson and Ragas (1988) that the sixth order TSA appeared to be a better predictor of value than their "behavioral" model (which resembles a Standard HPF).

To confirm that the apparent improvement resulting from the inclusion of spatial attributes in the hedonic pricing function is meaningful, additional tests were performed by restricting the Augmented HPF and Extended HPF models and performing an F-test of the restriction that the coefficients on the spatial attributes, the EAST and NORTH variables, or E_DUM and N_DUM variables, respectively, were
TABLE 1

TESTS OF MODELS

<table>
<thead>
<tr>
<th>MODEL</th>
<th>RMSE</th>
<th>ADJ R-sq</th>
<th>MORAN COEFF.</th>
<th>Z-TEST</th>
<th>D-VALUE</th>
</tr>
</thead>
<tbody>
<tr>
<td>HPF</td>
<td>0.9503</td>
<td>0.557</td>
<td>0.0414</td>
<td>54.70</td>
<td>0.0662</td>
</tr>
<tr>
<td>Aug.HPF</td>
<td>0.9125</td>
<td>0.592</td>
<td>0.0289</td>
<td>38.34</td>
<td>0.0644</td>
</tr>
<tr>
<td>Ext.HPF</td>
<td>0.9087</td>
<td>0.595</td>
<td>0.0242</td>
<td>28.76</td>
<td>0.0721</td>
</tr>
<tr>
<td>TSA0</td>
<td>1.5616</td>
<td>0.345</td>
<td>0.1094</td>
<td>143.64</td>
<td></td>
</tr>
<tr>
<td>TSA1</td>
<td>1.0740</td>
<td>0.435</td>
<td>0.0924</td>
<td>121.36</td>
<td></td>
</tr>
<tr>
<td>TSA2</td>
<td>1.0042</td>
<td>0.506</td>
<td>0.0537</td>
<td>70.79</td>
<td></td>
</tr>
<tr>
<td>TSA3</td>
<td>0.9732</td>
<td>0.536</td>
<td>0.0494</td>
<td>65.19</td>
<td></td>
</tr>
<tr>
<td>TSA4</td>
<td>0.9463</td>
<td>0.561</td>
<td>0.0382</td>
<td>50.42</td>
<td></td>
</tr>
<tr>
<td>TSA5</td>
<td>0.9289</td>
<td>0.577</td>
<td>0.0325</td>
<td>42.98</td>
<td></td>
</tr>
<tr>
<td>TSA6</td>
<td>0.9127</td>
<td>0.592</td>
<td>0.0237</td>
<td>31.49</td>
<td></td>
</tr>
</tbody>
</table>
equal to zero. The critical value for rejecting the null hypothesis that the restriction was valid was unity. The calculated F-values of 119.86 for the Augmented HPF and 105.86 for the Extended HPF model leave no question but that the added variables do, in fact, contribute to the regressions.

Since the usual statistics used to compare the standard and Augmented HPF models rely on the results of OLS regressions, the residuals from the Standard HPF, expanded HPF and Augmented HPF regressions were tested for normal distribution. The test used was the Kolmogorov-Smirnov D Statistic. The results are reported in the last column of table 1, and show no significant differences between the calculated residuals and normal distributions with a mean of zero and the same variance. It may therefore be presumed that the OLS results are the best, unbiased estimates of the parameters.²

Given the size of the sample, all of the statistical tests performed are highly meaningful. The contention that the addition of spatial attributes to the standard hedonic pricing function for land will improve the explanatory power of the technique may not be rejected on this evidence.

²These tests are not reported for the TSA models since they are not presented as explanatory models. They all demonstrated similar results, however.
Residual Autocorrelation

Although the reduction in the Moran Coefficient is consistent with improved performance resulting from the inclusion of the spatial attributes (Cartesian coordinates), the amount of autocorrelation revealed by the level of the coefficient in all the models raises a potentially serious econometric problem.

The apparent reduction in the Moran Coefficient reflects a corresponding reduction in residual spatial autocorrelation. This indicates that the Augmented HPF and Extended HPF models capture more of the spatial trend than does the Standard HPF. However, the residual levels of spatial autocorrelation signal the possibility of an important source of bias which may have gone undetected in past hedonic studies of land. If the Standard HPF is even fairly typical of the hedonic pricing models, the high level of spatial autocorrelation suggests the possible presence of equally high levels in prior studies.

To confirm the absence of the traditionally-recognized problem with autocorrelation in time-series data, a Durbin-Watson test was performed on the residuals from the hedonic models. Since the data were observed on unequal intervals, the residuals were grouped into monthly averages and the resulting values were tested for autocorrelation over time, or temporal autocorrelation.

As may be seen from table 2, there is an indication of
the presence of a small potential problem with temporal autocorrelation. At the five percent level, all the models cluster closely around the lower bound, indicating the possible presence of a problem. At the one percent level, however, all are relatively well above the lower limit. It may or may not be necessary to correct for this level of autocorrelation.

What is important here, however, is to note that the existing hedonic pricing literature for land relies on tests of just this sort, if at all. Few, if any, of these prior studies report any problem with autocorrelation, perhaps as a result of calculations such as those shown in table 2. None of these studies appear to have considered the possibility of autocorrelation on a spatial, as well as temporal, basis.

Although it is possible that the use of the Rosen formulation of the Hedonic model will eliminate the small amount of serial autocorrelation found here, it is unknown whether the spatial measurement will be affected by the inclusion of supply and demand shift variables.

The Z-statistic, calculated as in (22), indicates that while the Moran Coefficient values represent an improvement over the standard HPF on the part of both the Augmented and Extended HPF models, there is an extremely high level of spatial autocorrelation in the residuals for all the models. It must be noted, however, that the data are not weighted to
### TABLE 2

**DURBIN-WATSON STATISTICS**

<table>
<thead>
<tr>
<th>MODEL</th>
<th>DURBIN-WATSON</th>
<th>CRITICAL VALUES (LOWER BOUND)</th>
</tr>
</thead>
<tbody>
<tr>
<td>HPF</td>
<td>0.9992</td>
<td>dL (5%) = 1.029, dL (1%) = 0.893</td>
</tr>
<tr>
<td>Aug. HPF</td>
<td>0.9996</td>
<td>dL (5%) = 0.951, dL (1%) = 0.822</td>
</tr>
<tr>
<td>Ext. HPF</td>
<td>0.9990</td>
<td>dL (5%) = 0.951, dL (1%) = 0.822</td>
</tr>
<tr>
<td>TSA5</td>
<td>0.9998</td>
<td>dL (5%) = 0.836, dL (1%) = 0.716</td>
</tr>
</tbody>
</table>
assure even distribution over space or transformed to remove effects from cycles in sales volume or similar problems.

The nature of this residual spatial autocorrelation is an important subject for future investigation. Questions to be considered, as suggested in the preceding paragraph, include the effect of spatially clustered observations on both the measurement of spatial autocorrelation and the determination of its level of significance, the dual effect of spatial and temporal observations (i.e. the effect of using data which is both cross-sectional and time series) and other potential complications.

If spatial autocorrelation does, indeed, represent an econometric problem similar to that of the more familiar temporal form of autocorrelation, it would appear that the prior hedonic pricing literature for land should be reconsidered in the light of the nature and extent of the potential bias in results. Before such a determination is made, of course, the problem must be more specifically defined and quantified.

**Forecasting Tests**

The forecasting capabilities of the various models were tested by randomly dividing the dataset into two equal parts and using one for estimation and the other for forecasting. Due to the large size of the dataset, this could be done without concern for loss of degrees of
freedom. The results of the several tests are given in table 2. The Augmented and Extended HPF models again consistently outperformed the standard model. The TSA models also exhibit steadily improving performance as the order of the polynomial surface increases although at a decreasing rate.

The most informative test of predictive ability among those reported is Theil's $U$-statistic. This value indicates the correlation between the actual and predicted values, and is similar in form to Adj. $R^2$. Perfect correspondence, however, is indicated by a value of zero rather than one. That is, higher values indicate poorer performance (Greene 1990).

The results of Theil's $U$-statistic show that the forecasting power of both of the two spatially-sensitive hedonic models is superior to that of the Standard HPF. The Augmented HPF model (which uses variables that measure the location more precisely than the Extended HPF) is actually the best of the three. In this instance, possibly because of the greater precision of the measurements of the NORTH and EAST variables (as opposed to E_DUM and N_DUM), the Augmented model appears to slightly outperform the Extended HPF model. As discussed below, this may be a basis for selection between the two. It is interesting to note that once again the fourth order TSA (TSA4) is shown to be roughly equivalent to the Standard HPF, generally confirming
<table>
<thead>
<tr>
<th>MODEL</th>
<th>THEIL (U)</th>
<th>ADJ R-sq</th>
<th>MAE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>HPF</td>
<td>0.0885</td>
<td>0.581</td>
<td>0.7183</td>
<td>0.9453</td>
</tr>
<tr>
<td>Aug.HPF</td>
<td>0.0847</td>
<td>0.610</td>
<td>0.6818</td>
<td>0.8664</td>
</tr>
<tr>
<td>Ext.HPF</td>
<td>0.0859</td>
<td>0.589</td>
<td>0.6820</td>
<td>0.8866</td>
</tr>
<tr>
<td>TSA0</td>
<td>0.1060</td>
<td>0.363</td>
<td>0.8836</td>
<td>1.3558</td>
</tr>
<tr>
<td>TSA1</td>
<td>0.0988</td>
<td>0.453</td>
<td>0.8106</td>
<td>1.1799</td>
</tr>
<tr>
<td>TSA2</td>
<td>0.0927</td>
<td>0.524</td>
<td>0.7497</td>
<td>1.0369</td>
</tr>
<tr>
<td>TSA3</td>
<td>0.0897</td>
<td>0.547</td>
<td>0.7213</td>
<td>0.9713</td>
</tr>
<tr>
<td>TSA4</td>
<td>0.0866</td>
<td>0.566</td>
<td>0.6980</td>
<td>0.9065</td>
</tr>
<tr>
<td>TSA5</td>
<td>0.0853</td>
<td>0.583</td>
<td>0.6826</td>
<td>0.8796</td>
</tr>
<tr>
<td>TSA6</td>
<td>0.0843</td>
<td>0.600</td>
<td>0.6717</td>
<td>0.8575</td>
</tr>
</tbody>
</table>
the observation of Johnson and Ragas (1987).

The MAE and RMSE values in this table represent the prediction error in the forecasting sample, given coefficients calculated from the estimation sample. The MAE and RMSE calculations, as with the general tests of the models given in table 1, show a trend towards reduced variance between actual and predicted values as the order of the response surface increases. The Adj. \(R^2\) increases, as well, indicating improved explanatory power. Of course, the comparisons between the Standard HPF and the Augmented HPF and Extended HPF models again show the superiority of the extended and augmented models.

The statistical tests uniformly indicate the principal hypothesis cannot be rejected. Given the large sample size, the tests are significant. Both the Augmented HPF and Extended HPF models therefore may be capable of statistically forecasting the land pricing process better than the Standard HPF model. Since the only difference is the inclusion of the spatial attributes (Cartesian coordinates) in the augmented and extended models, any such improvement in forecasting power may be ascribed to these variables alone.

The choice between the Augmented HPF and the Extended HPF, however, is not nearly as clear. From table 1 it may be seen that the Extended HPF model outperforms the Augmented HPF model for explanatory purposes in all
categories, although ever so slightly. Given the familiarity and acceptability of dummy variables in the same context, however, it appears there is a preference for the Extended HPF model for explanatory uses.

For forecasting, however, table 3 reveals a clear edge in favor of the Augmented HPF model. The higher error and increased Theil's U associated with the Extended HPF model reflect poorer forecasting performance than the Augmented HPF model, and thus favor the latter. It is probable that the greater precision of the measurements of EAST and NORTH is the cause. In any event, it is evident that additional research into the relative merits of these approaches is indicated.

Also, although the results of the Moran Coefficient calculations are fully consistent with the other statistical tests, the presence of extreme levels of spatial autocorrelation raises important questions about hedonic pricing models for spatial phenomena. Exploration of the use of this potentially valuable tool in pursuit of the autocorrelation problem is clearly justified.

**Analysis of Regression Coefficients**

The production of a hedonic land pricing model was not, in itself, a principal purpose of this research. Such models, however, were formulated in order to obtain the statistical results discussed above, and their comparison
provides interesting, and even surprising, information.

Prior hedonic pricing studies of real estate are not generalizable to different markets, nor can they be directly compared with other studies for reasons already stated. Some expectations, however, can be formed based on these studies and compared to the results obtained in this research.

The results obtained from any of the models, each examined individually and without reference to the others, can be considered generally consistent with prior research. That is, examined out of context none of the findings are so far out of line as to attract undue attention. Since the models are estimated from the same large data set, however, the fact of differences among them is useful information, indicating the possible presence of real, spatially-related processes associated with the valuation of land. Since the spatial attributes are the only differences among the models, their role in exploring land pricing becomes potentially of great significance.

Unlike in prior studies, the models here were estimated from the same data, and thus may be closely compared. Such a comparison, for the most part, supports and validates prior findings by being consistent with the expectations formulated from those studies. A few surprising and potentially interesting deviations, however, do appear.
Some generalized predictions may be proposed from prior research. All of the hedonic pricing studies of real estate predict that the variables associated with positive value influences such as central business district, transportation nodes and the like, should show an inverse relationship between value and distance. The significance of a particular locational variable is not readily predictable in advance, but once determined should not change from model to model. Similarly, the sign of the coefficient of a locational variable should be the same among the various models.

The effect of zoning classifications should be constant across models with regard to sign and significance. Leveraged transactions are almost universally expected to involve higher purchase prices, reflecting the value to the buyer of the financing. Finally, the per unit price of larger parcels is generally expected to be inversely related to the size of the parcel, if for no other reason than that the largest parcels tend to be the farthest away from population concentrations associated with high per unit value.

A comparison of the results shows that most of these expectations from prior work are met. A few anomalies, however, exist. These may possibly be related to the spatial nature of the augmented and extended models, thus suggesting a course for future research which may uncover
the nature of the spatial process. In addition, an unexplained difference in the effect of zoning classifications was revealed suggesting that fundamentally different pricing functions may apply to different land uses.

The regression coefficients are given in tables 4, 5 and 6. The numbers in parentheses are the T-values. As can be seen, the variables which were shown to be significant tended to be highly significant, with only the CASH variable falling into the 5% category. The intercepts are highly significant in all models and are of similar values. Positive intercepts indicate, according to Edmonds (1984), that apparently many of the value influences on the parcels in the dataset are shared by all observed sales and thus not separately priced.

Negative coefficients on the ACRE variables in all models show that as the size of the parcel increases, its unit price tends to decrease, supporting the observation that smaller parcels tend to be more costly, an apparent result of the "agglomeration effect" described by Peiser (1987). ACRE is highly significant in all models, further supporting the importance of parcel size.

The CASH dummy variable is only marginally significant in two models, and insignificant in the Extended HPF model, indicating there may be a leverage effect, but it appears to be weak. Positive coefficients are found, suggesting a
<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>COEFFICIENT</th>
<th>T-VALUE</th>
<th>VARIANCE INFLATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>11.8720*</td>
<td>136.621</td>
<td>0.0000</td>
</tr>
<tr>
<td>ACRE</td>
<td>-0.2762*</td>
<td>-21.469</td>
<td>1.4862</td>
</tr>
<tr>
<td>CASH</td>
<td>0.0824**</td>
<td>2.188</td>
<td>1.0408</td>
</tr>
<tr>
<td>ZONED_C</td>
<td>0.5954*</td>
<td>12.098</td>
<td>1.8593</td>
</tr>
<tr>
<td>ZONED_I</td>
<td>0.0710</td>
<td>1.293</td>
<td>1.7976</td>
</tr>
<tr>
<td>ZONED_O</td>
<td>0.5541*</td>
<td>6.451</td>
<td>1.2768</td>
</tr>
<tr>
<td>AIR</td>
<td>-0.1980*</td>
<td>-5.869</td>
<td>1.6901</td>
</tr>
<tr>
<td>CBD</td>
<td>-0.0994*</td>
<td>-4.278</td>
<td>2.2133</td>
</tr>
<tr>
<td>COLL</td>
<td>-0.0883*</td>
<td>-2.545</td>
<td>2.5700</td>
</tr>
<tr>
<td>GENAIR</td>
<td>-0.0153*</td>
<td>-0.587</td>
<td>1.0870</td>
</tr>
<tr>
<td>HWY</td>
<td>-0.0152</td>
<td>-1.722</td>
<td>1.1813</td>
</tr>
<tr>
<td>LBD</td>
<td>-0.2435*</td>
<td>-16.190</td>
<td>2.1452</td>
</tr>
<tr>
<td>MALL</td>
<td>-0.1512*</td>
<td>-6.827</td>
<td>1.4067</td>
</tr>
<tr>
<td>MEDIC</td>
<td>-0.0151</td>
<td>-0.770</td>
<td>1.3216</td>
</tr>
<tr>
<td>SHOP</td>
<td>-0.0515*</td>
<td>-4.562</td>
<td>1.2683</td>
</tr>
</tbody>
</table>

N = 2788

ADJ. $R^2 = 0.5576$

* Significant at the 0.01 level
** Significant at the 0.05 level
TABLE 5

REGRESSION COEFFICIENTS (Augmented HPF)

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>COEFFICIENT</th>
<th>T-VALUE</th>
<th>VARIANCE INFLATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>11.0436*</td>
<td>110.973</td>
<td>0.0000</td>
</tr>
<tr>
<td>ACRE</td>
<td>-0.2555*</td>
<td>-20.512</td>
<td>1.5043</td>
</tr>
<tr>
<td>CASH</td>
<td>0.0821**</td>
<td>2.268</td>
<td>1.0410</td>
</tr>
<tr>
<td>ZONED_C</td>
<td>0.5779*</td>
<td>12.225</td>
<td>1.8601</td>
</tr>
<tr>
<td>ZONED_I</td>
<td>0.0723</td>
<td>1.369</td>
<td>1.8100</td>
</tr>
<tr>
<td>ZONED_0</td>
<td>0.5029*</td>
<td>6.092</td>
<td>1.2792</td>
</tr>
<tr>
<td>AIR</td>
<td>0.0272</td>
<td>0.706</td>
<td>2.4044</td>
</tr>
<tr>
<td>CBD</td>
<td>-0.0297*</td>
<td>-11.367</td>
<td>2.8934</td>
</tr>
<tr>
<td>COLL</td>
<td>0.0414</td>
<td>1.188</td>
<td>2.8142</td>
</tr>
<tr>
<td>GENAIR</td>
<td>-0.1088</td>
<td>-4.211</td>
<td>1.1639</td>
</tr>
<tr>
<td>HWY</td>
<td>0.0436*</td>
<td>-5.013</td>
<td>1.2550</td>
</tr>
<tr>
<td>LBD</td>
<td>-0.1440*</td>
<td>-9.078</td>
<td>2.5702</td>
</tr>
<tr>
<td>MALL</td>
<td>-0.1409*</td>
<td>-6.599</td>
<td>1.4161</td>
</tr>
<tr>
<td>MEDIC</td>
<td>0.0714*</td>
<td>-3.589</td>
<td>1.4727</td>
</tr>
<tr>
<td>SHOP</td>
<td>-0.0600*</td>
<td>-5.056</td>
<td>1.2782</td>
</tr>
<tr>
<td>EAST</td>
<td>0.0190*</td>
<td>-6.161</td>
<td>1.9827</td>
</tr>
<tr>
<td>NORTH</td>
<td>0.0488*</td>
<td>15.336</td>
<td>2.2948</td>
</tr>
</tbody>
</table>

N = 2788

ADJ. R² = .5920

* Significant at the 0.01 level
** Significant at the 0.05 level
TABLE 6

REGRESSION COEFFICIENTS (Extended HPF)

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>COEFFICIENT</th>
<th>T-VALUE</th>
<th>VARIANCE INFLATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>11.0841*</td>
<td>113.662</td>
<td>0.0000</td>
</tr>
<tr>
<td>ACRE</td>
<td>-0.2554*</td>
<td>-20.474</td>
<td>1.5104</td>
</tr>
<tr>
<td>CASH</td>
<td>0.0481</td>
<td>1.332</td>
<td>1.0445</td>
</tr>
<tr>
<td>ZONED_C</td>
<td>0.5632*</td>
<td>11.937</td>
<td>1.8666</td>
</tr>
<tr>
<td>ZONED_I</td>
<td>0.0499</td>
<td>0.924</td>
<td>1.8161</td>
</tr>
<tr>
<td>ZONED_O</td>
<td>0.5039*</td>
<td>6.114</td>
<td>1.2840</td>
</tr>
<tr>
<td>AIR</td>
<td>0.0617</td>
<td>1.640</td>
<td>2.2958</td>
</tr>
<tr>
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<td>-0.1922*</td>
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<td>2.3019</td>
</tr>
<tr>
<td>COLL</td>
<td>-0.0455</td>
<td>-1.343</td>
<td>2.6282</td>
</tr>
<tr>
<td>GENAIR</td>
<td>-1.1164*</td>
<td>-4.307</td>
<td>1.2832</td>
</tr>
<tr>
<td>HWY</td>
<td>-0.0404*</td>
<td>-4.708</td>
<td>1.2286</td>
</tr>
<tr>
<td>LBD</td>
<td>-0.1666*</td>
<td>-10.903</td>
<td>2.4047</td>
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<tr>
<td>MALL</td>
<td>-0.1069*</td>
<td>-4.972</td>
<td>1.4396</td>
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<td>MEDIC</td>
<td>-0.0489*</td>
<td>-2.505</td>
<td>1.4235</td>
</tr>
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<td>SHOP</td>
<td>-0.0600*</td>
<td>-5.532</td>
<td>1.2747</td>
</tr>
<tr>
<td>E_DUM</td>
<td>-0.2573*</td>
<td>-5.592</td>
<td>1.7537</td>
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<td>1.9780</td>
</tr>
<tr>
<td>N</td>
<td>2788</td>
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</tr>
<tr>
<td>ADJ. R²</td>
<td>0.5954</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Significant at the 0.01 level
** Significant at the 0.05 level
higher price is, indeed, commanded for financed transactions as suggested by many researchers.

In view of the uncertainty of the effect of leverage on the pricing of land, most researchers exclude financed sales, exacerbating an already serious data problem. Since the effect of leverage may be captured with a dummy variable, however, some support is found here for reconsideration of this practice of using only cash sales. In view of the scarcity of data for real estate research and the increased possibility of selection bias, it would be appropriate to investigate this point in future studies to determine if it is, in fact, necessary to truncate the data.

All three dummy variables for the zoning classifications have positive coefficients. The fourth category, left out to avoid singularity, is the mixed use or Planned Development classification (ZONED_PD). The effect of this variable, of course, is captured in the intercept. The positive coefficients indicate that a premium is paid for a particular use category. This is no surprise since relatively few purchases of income property should be consummated in cases where the land cannot be put to productive use.

What is surprising, however, is that the industrial zoning category is not significant in any model. There is no clear a priori explanation for this difference. A potential reason might lie in some unique aspect of the
Dallas County market, but it might also be suggested that some factor besides location governs the choice of industrial sites. That is, the pricing process for industrial land may be fundamentally different from that of commercial or office property.

In general, the locational variables are significant and carry negatively signed coefficients (the exceptions are discussed at length below). Since the variables are linear distances and the value relationship, based on prior studies, is expected to be inverse, this is consistent with prior research. A brief discussion of each variable is appropriate.

Access to commercial aviation facilities (AIR) is negative and significant in the Standard HPF model, but not the augmented or extended models. This finding, discussed in the next chapter, is surprising and important. Signs and significance should be the same among models, but here both are reversed. Although the expected sign is negative, theoretical support might be proposed for a positive sign, for example that airport noise may be a negative externality for some uses. The lack of significance may have a plausible explanation also, such as that the ready availability of airport shuttles and other transportation services make distance less relevant to access. The difference in results, however, can only be related to the inclusion of the spatial attributes.
Similarly, the difference in the sign and significance of access to higher education facilities (COLL) is another surprise. This variable, like AIR, is negative and significant in the Standard HPF model, but not the Augmented HPF model, while it is negative and insignificant in the Extended HPF model. Plausible explanations are somewhat more difficult to formulate, but still possible. Noise and traffic, for example, may render a college campus a nuisance. Purchasers of income property may not obtain utility from the closeness of the campus and may therefore not place any value on this factor, and so forth. There is no such ready explanation, however, for why these differences should be revealed only when the spatial attributes or geographic coordinates are included in the regression.

The situation is reversed in the case of access to freeway ramps (HWY) and trauma centers (MEDIC) which are significant in the Augmented HPF and Extended HPF models but not the Standard HPF. Further research is clearly called for to determine whether there may be a discernible and quantifiable process underlying these differences. This question is considered in the next chapter.

The predicted inverse relationship and high level of significance for the value of distance to the central business district (CBD) is found in all models. This is, of course, consistent with traditional hedonic pricing studies.
which all include distance to the CBD as an explanatory variable. The negative sign for this coefficient confirms that land becomes less costly as distance to the central business district increases.

Closeness to office building clusters, or local business districts (LBD), also carries a premium of high statistical significance. If, as may well be the case, this results from Peiser's "agglomeration effect" (Peiser 1987), the LBD variable should have an effect analogous to the CBD variable, as it does appear to have. Care must be taken in interpreting this finding, however, in view of the fact that nearly all the LBD sites were located in the north half of the County (see, figure 3).

The two measures for access to shopping, MALL (regional centers) and SHOP (local shopping centers) are negatively signed and have similar coefficients in all models. Several specific explanations for this anticipated result are found in the literature, including the effect of a concentration of commercial activity (Peiser's "agglomeration effect," again).

Finally, the spatial attributes used to expand the Augmented HPF and Extended HPF models are essentially the same in the two models. Both models show both attributes to be highly significant, and both tell the same story. As might be anticipated from a physical examination of the market area, they both suggest that there is a premium for
location in the Northwest quadrant of the County. This finding, of course, is completely in line with expectations based on the economic geography of Dallas County, Texas. Confirmation of this empirical fact, however, is of more than passing interest; as obvious as it is to the casual observer, this information cannot be obtained from a Standard HPF analysis. The importance of this is discussed in the next chapter.

Graphic Representations of Response Surface Models

For some purposes, particularly in exploratory research, a graphic representation of a response surface will aid in identifying trends or other important features. Although the visual comparison of surface plots is not a reliable indicator of statistical differences, it may often aid in understanding the process under investigation and even provide insights which give direction to statistically valid investigations.

To illustrate this use of graphic representations, surface plots were prepared showing the response surfaces obtained by treating each individual variable as the sole determinant of value as expressed in (1). The response shown on the z-axis is predicted value given only the specific variable and its spatial attributes plotted on the x-axis (EAST) and the y-axis (NORTH). The square formed by the x and y axes thus neatly corresponds to the nearly
square outline of Dallas County.

The most striking observation to make from the collection of surfaces is the preponderance of high values in the northwest and north areas of the graph, as expected from both the Augmented and Extended HPF models as well as a physical examination of the locale. The visual impact of the strong slopes to the southeast on most of the plots underscores the relatively lower value of land in that part of the study area somewhat more forcefully than the numerical results.

A few comments might be made about these plots. In particular, the anticipated conic shape of the plot of \( \text{COST} = f(\text{CBD}) \) is interesting as an example of the Von Thünen-Burgess concentric circle model. If CBD, alone, were the factor from which land values are derived the negative exponential model would look like figure 12. Evidence of Hoyt's sector theory in operation, on the other hand, is less clear from the surface plots than from more typical maps.

Many of the plots clearly indicate the relatively high valuation of the north and northwest areas of the county. It is clear from the plots, though not from the data or the numerical results, that many of the value factors are located in those areas. Thus, AIR, LBD, GENAIR and MALL are all consistent with the mathematically derived valuation pattern but provide an additional informational input in
terms of concentration of valuation factors. This concentration is discernible from NORTH and EAST with some effort, and easily identified by N\_DUM and E\_DUM. It cannot be isolated from a standard HPF result.

The relative flatness of the surface for HWY is worthy of note. This might be an indication that the HWY variable is of relatively local effect, while such variables as CBD and AIR have regional or at least market-wide effects. If this is the case, there may be some methodology for classification of land valuation variables on this basis.

The surface plots of the full regression models, figures 21, 22 and 23, show the cumulative effect of the locational variables. Figure 24 is a plot of the fifth-order trend surface, showing the remarkable similarity, graphically as well as mathematically, of this model to the HPF models. It is difficult to draw clear distinctions from these plots, which of course is to be expected given the similarity of the numerical results.

Of equal interest are figures 25 through 28, giving the surface plots of the residuals from the hedonic and fifth-order TSA models. The similarity of the hedonic models to the TSA model is further evidence of the extremely high level of residual spatial autocorrelation shown by the Moran Coefficient. While it might be expected that the three HPF models would have similar residuals, the residuals from the TSA function should be markedly different, given a
random distribution of their values. The similarity of the plots is evidence that both classes of model are failing to include some as yet unidentified underlying process. This similarity is most evident from comparison of the contour plot of the residuals from the standard HPF, shown in figure 29, with the contour plot of the fifth-order TSA residuals, figure 30.
FIGURE 12

SURFACE PLOT OF COST=f(CBD)
FIGURE 13

SURFACE PLOT OF COST=f(LBD)
FIGURE 14

SURFACE PLOT OF COST=$f(AIR)$
FIGURE 15
SURFACE PLOT OF COST=f(GENAIR)
FIGURE 16
SURFACE PLOT OF COST=f(HWY)
FIGURE 17
SURFACE PLOT OF COST=f(SHOP)
FIGURE 18
SURFACE PLOT OF COST=f(MALL)
FIGURE 19

SURFACE PLOT OF $\text{COST}=f(\text{MEDIC})$
FIGURE 20
SURFACE PLOT OF COST=f(COLL)
FIGURE 21
SURFACE PLOT OF STANDARD HPF
FIGURE 22
SURFACE PLOT OF AUGMENTED HPF
FIGURE 23
SURFACE PLOT OF EXTENDED HPF
FIGURE 24
SURFACE PLOT OF FIFTH ORDER TSA
FIGURE 25

SURFACE PLOT OF RESIDUALS FROM STANDARD HPF
FIGURE 26
SURFACE PLOT OF RESIDUALS FROM AUGMENTED HPF
FIGURE 27

SURFACE PLOT OF RESIDUALS FROM EXTENDED HPF
FIGURE 28

SURFACE PLOT OF RESIDUALS FROM FIFTH-ORDER TSA
FIGURE 29

CONTOUR PLOT OF RESIDUALS FROM STANDARD HPF

RESID
-4.33
-2.93
-1.52
-0.11
FIGURE 30

CONTOUR PLOT OF RESIDUALS FROM FIFTH-ORDER TSA
CHAPTER VI
CONCLUSIONS

A first glance at the foregoing results might prompt a suggestion that the traditional location variables (such as CBD) in hedonic studies should be discarded in favor of models which rely solely on spatial attributes or geographic coordinates as access proxies. Such a conclusion, however, is not supported by the results of this analysis. In particular, the differences in signs and significance of some of the variables must be resolved before the precise role of the spatial attributes in hedonic pricing of land may be settled.

The Standard HPF is widely accepted as a useful, even reasonably good, model of land valuation without the addition of spatial attributes (Cartesian coordinates). These models have been successfully used for fifteen years. The methodology is well understood, even though controversial in some aspects, and there is much room for further research. It is not suggested that the prior work should be discarded or even discounted in view of the results of this study.

This research was intended to do no more than inquire into whether the spatially sensitive analysis techniques of the regional sciences deserve consideration in financial
analysis of land. That question has been answered in the affirmative, at least to the extent that further exploration is justified. There is no support here, however, for any significant deviation from the groundwork laid in the past fifteen years. Rather, new avenues of research have been opened, many of which being suggested above, which may lead to such a substitution or, more likely, to new models of land valuation which include some aspects of both traditional HPF models and response surface models.

Spatial Analysis in Hedonic Pricing

This research provides some clear, and other not so obvious, reasons for pursuing the notion of spatial analysis in land pricing studies. As shown, the spatial attributes have the capacity of improving certain hedonic pricing models. How great and how useful such improvements might be remains to be clarified in future research.

The improvement added by the spatial attributes, while real, is not so great as to justify immediately discarding the traditional locational variables entirely in specifying hedonic models. This is clear from a comparison of the Standard HPF model with the first order TSA model (TSA1) which represents exactly such an exchange. Either the locational variables must be retained or higher order TSA surfaces must be calculated to achieve the same level of usefulness as the Standard HPF model. The question remains
as to which should be done, or whether some blending is more appropriate.

It is, however, reasonable to conclude that the spatial attributes have a potentially important role in hedonic pricing studies. The evidence is unequivocal that the spatial attributes add to the Standard HPF model's ability to predict prices from the data, and to describe the pricing process itself. A greater proportion of the variance is accounted for when these values are considered, and the overall variance is reduced.

These achievements could possibly be duplicated by the selection of some variables other than the spatial attributes, it is true. But there are justifications for preferring the spatial attributes or other forms of geographic coordinates. The potential number of other variables is unbounded. There is no clear theoretical basis for selection among such potential influences. Furthermore, the other potential variables all are recognized as no more than proxies for access or some other spatial relationship.

There is only one set of true spatial attributes or geographic coordinates possible for any single observation. In this study, in order to maintain the grid for computational purposes, the set of possible pairs of spatial attributes was restricted to 3,024 combinations for EAST and NORTH and four possible combinations for E_DUM and N_DUM. In reality, each observation can be located precisely, resulting in an infinite number of unique locations.
observation describes its location and thus is unique and cannot be shared by any other parcel of land. These attributes are relatively easy to measure.

Theoretically, the spatial attributes may capture all possible locational effect, or at least all effects resulting from stationary influences. Also, the spatial attributes have the capability of more directly measuring an underlying spatial process, being two dimensional, and thus should be more effective at doing so.

That the spatial attributes might replace any one or even all of the specific amenities is supported by the evidence that the fifth and higher order TSA surfaces appear to outperform the Standard HPF for forecasting purposes by all the criteria used in this research. The spatial attributes are easily and cheaply calculated, compared with the difficulty of measuring the distance from each observation to each of several specific amenities. It is true that the distances can readily be calculated if the location of both the observation and each amenity are known, but since the location of the observation is its spatial attribute, there should be no need to take the additional steps of locating each amenity and calculating the distances. Fewer measurements and calculations, of course, means less overhead cost for doing research and fewer opportunities for measurement error.

Each market will be unique in the identity and pattern
of location of the amenities used for hedonic pricing models. Physical barriers such as rivers or lakes are not found in all urban settings. Some amenities, such as the Superdome or the Bourbon Street district in New Orleans which were considered by Johnson and Ragas (1987), have no analog in some other markets. Thus, the particular set of specific amenities is likely to be unique to each market, or at least incapable of comparison with another. Such would not necessarily be true of a response surface, particularly if the surface is calculated from only the spatial attributes and such site-specific factors as acreage.

The comparison of response surfaces was shown by Sharkawy (1990) to be possible and informative even where the data used to produce the surface are incompatible. In that study of the Atlanta market, Sharkawy used data from three separate sources compiled with different sub-boundaries and using completely different techniques and observations. It would not have been possible to directly compare the datasets, even though they were descriptions of the same metropolitan area.

Sharkawy's TSA technique, however, allowed the estimation of a surface from each of the three sets of response values since all were stated in the same units and described the same response. The spatial attributes related to the market, and thus were the same for all the sources examined even though the observations those sources relied
upon were different. Sharkawy was able to show that the results from the three sources were apparently inconsistent. This information was not discernible using standard techniques since the data sources could not be generalized. The development of spatial valuation techniques thus has the potential of providing useful comparisons not before available.

Another important result of the use of spatial attributes in land pricing is the possibility of obtaining information which cannot be obtained using traditional techniques. The data show that the land values in Dallas County tend to be higher in the Northwest part of the County. This simple fact is readily confirmed by direct observation but cannot be discerned from a standard hedonic pricing study.

None of the distance measurements used in standard hedonic analysis have any directional content, rather they are given as linear values only. The calculated value effect of distance from the central business district, or any other of the specified amenities, given by the coefficient on the variable does not reveal where any of these amenities are located. Nor does it show for the Dallas County market that a large, perhaps even disproportionate number, of these amenities are located in the Northwest part of the County. This information, however, is easily obtained from the response surface, and
to a lesser extent from the binary variables.

Furthermore, such analysis can be performed even where none of the individual amenities are specified in the model since the information describing the surface can be obtained from the spatial attributes alone.10 Such clustering is specifically addressed by the measurement of spatial autocorrelation, as well. It cannot be measured with traditional hedonic methodologies.

Much additional study is needed, however, before the concepts of spatial analysis may be confidently and routinely applied to hedonic pricing studies of land. Problems with multicollinearity in explanatory models must be overcome, perhaps by application of more sophisticated statistical techniques. The measurement of spatial autocorrelation which appears to be relevant to the question of the power of the models has only been examined in terms of Moran's (I) Statistic. This criterion might be improved by the use of other mathematical techniques. The opportunities for additional research are clear and compelling.

A question of some interest, for example, lies in the finding that the significance of the AIR and MEDIC variables

---

10That is, from the measured form such as EAST and NORTH. The binary (dummy variable) form of spatial attributes is not precise enough to provide any usable information regarding either the underlying response surface or spatial autocorrelation.
is reversed between the Standard HPF and the Augmented HPF and Extended HPF models. Pursuit of this issue might lead to an answer to the question of which of the competing measures, locational influences or spatial attributes, is the proxy and which is the true factor. Or, such study might show that both are reflections of some common, underlying, cause.

The AIR variable proxies airport access by measuring the distance to the closest commercial airport entrance. These three locations all fall in the northwest quadrant of the County. The several trauma centers constituting the locational influences measured by MEDIC are widely dispersed. Such facilities would logically be located in such a manner as to provide equal access, at least qualitatively, to the entire county. If spatial autocorrelation in the regression residuals is a stock quantity which can be reduced by more efficient modeling of the regression, it appears that the use of variables representing more highly concentrated value influences should do so.

The AIR variable, therefore, should capture a greater amount of the spatial autocorrelation in the residuals since the locational influences it measures are relatively concentrated. The opposite might be expected of MEDIC. The widely dispersed HWY variable, similarly, would be expected to capture less spatial autocorrelation. Nearly three
hundred on and off ramps serving the various limited access highways assure a relatively narrow range of values for this variable.

The EAST and NORTH variables in the Augmented HPF function dominate the AIR variable, compared with the Standard HPF, while they do not so dominate the scattered MEDIC or HWY variables. This may be because of some effect of spatial autocorrelation. And, in fact, the Moran Coefficient for the residuals of a model including the AIR variable and the first five (site specific and land use) variables in the HPF models is only 0.0791, while that of the same model substituting MEDIC is 0.1082 and for HWY a relatively large 0.1110 (see table 5). This pattern should be investigated for an explanation of when the spatial attributes of an observed sale might dominate the measured locational influences and should be the subject of future research. The discovery of these differences, of course, would not have been possible without the use of the spatial attributes in the regression.

Conclusion

The results of the data analysis support the contention that the use of spatial attributes (Cartesian or geographic coordinates) provides a statistically significant improvement in land valuation models. The effects of the inclusion of the spatial attributes as variables in a
### TABLE 7

**MODELS LIMITED TO SINGLE VARIABLES**

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>AIR ONLY</th>
<th>MEDIC ONLY</th>
<th>HWY ONLY</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>12.1807*</td>
<td>11.0531*</td>
<td>10.8350*</td>
</tr>
<tr>
<td></td>
<td>(147.294)</td>
<td>88.219</td>
<td>(184.976)</td>
</tr>
<tr>
<td>ACRE</td>
<td>-0.3680*</td>
<td>-0.4037*</td>
<td>-0.4213*</td>
</tr>
<tr>
<td></td>
<td>(-27.767)</td>
<td>(-28.762)</td>
<td>(-31.021)</td>
</tr>
<tr>
<td>CASH</td>
<td>0.0660</td>
<td>0.0458</td>
<td>0.0500</td>
</tr>
<tr>
<td></td>
<td>(1.540)</td>
<td>(1.013)</td>
<td>(1.105)</td>
</tr>
<tr>
<td>ZONED_C</td>
<td>0.5717*</td>
<td>0.5245*</td>
<td>0.4800*</td>
</tr>
<tr>
<td></td>
<td>(10.535)</td>
<td>(9.174)</td>
<td>(8.388)</td>
</tr>
<tr>
<td>ZONED_I</td>
<td>-0.1207*</td>
<td>0.0414</td>
<td>0.0231</td>
</tr>
<tr>
<td></td>
<td>(-1.979)</td>
<td>(0.647)</td>
<td>(0.362)</td>
</tr>
<tr>
<td>ZONED_O</td>
<td>0.8590*</td>
<td>0.8229*</td>
<td>0.8414*</td>
</tr>
<tr>
<td></td>
<td>(9.023)</td>
<td>(8.185)</td>
<td>(8.391)</td>
</tr>
<tr>
<td>AIR</td>
<td>-0.6190*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-19.815)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MEDIC</td>
<td></td>
<td>-0.1817*</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-8.454)</td>
<td></td>
</tr>
<tr>
<td>HWY</td>
<td></td>
<td></td>
<td>-0.0884*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-8.948)</td>
</tr>
<tr>
<td>N</td>
<td>2788</td>
<td>2788</td>
<td>2788</td>
</tr>
<tr>
<td>R²</td>
<td>0.4260</td>
<td>0.3613</td>
<td>0.3632</td>
</tr>
<tr>
<td>ROOT MSE</td>
<td>1.0825</td>
<td>1.1418</td>
<td>1.1400</td>
</tr>
<tr>
<td>MORAN COEFFICIENT</td>
<td>0.0791</td>
<td>0.1082</td>
<td>0.1110</td>
</tr>
</tbody>
</table>

* Significant at the 0.01 level
** Significant at the 0.05 level
standard hedonic analysis of land prices appear to be reduction in variance, increase in explanatory power and reduction in spatial autocorrelation in the residuals. These effects, though modest, are statistically significant. Further research aimed at determining the optimal method of taking advantage of this approach is clearly justified.

When spatial attributes are used as explanatory variables, it is possible to obtain information about the distribution of values across the market area which was previously unobtainable from land pricing studies. The measurement of such patterns has long been undertaken in the geographic sciences, and appears to have promise in financial analysis as well, at least where the assets to be studied have a fixed location. The response to be analyzed, however, need not be limited to the residuals used in this study. Response surface analysis has application in many economic contexts for the study of any financial characteristic which is spatially distributed.

Response surface analysis has been shown to have potential for the comparison of incompatible markets. Previously, it has been impossible to generalize hedonic pricing studies at all. Where reliance is not placed on whether or not certain amenities are present in a particular market, however, generalization is apparently possible. The use of response surface techniques opens this avenue for consideration.
Even when spatial attributes are not used as explanatory variables, if the location of the observation is known, the measurement of spatial autocorrelation can provide useful information. It has been shown that the evidence of the Moran Coefficient is consistent with common measures of the efficiency of the model, for example. The analysis of spatial autocorrelation may reveal important information about the distribution of valuation factors and about the response under analysis. This information, like the spatial trend measured by the spatial attributes, is not obtainable from standard methodologies.

This research into the analysis of spatial autocorrelation in land pricing data has also revealed an intriguing question about the possible effect of clustering of the hedonic pricing factors. It appears possible that the spatial distribution of some variables may be related systematically to their effect on the pricing of land. If such a process is identified and quantified, it may provide theoretical basis for selection of variables or for further improvement of the hedonic technique by identifying the variables or classes of variables which should be dropped and others which should be included in a response surface analysis of land pricing.

In the process of identifying these surprising results, it was also found that one zoning classification, industrial use, was generally insignificant. This
unexpected result may suggest the existence of a completely
different pricing process for this type of land. It may
also, however, only reflect the economic makeup of the
Dallas market which does not rely on "smokestack"
industries. In either event, this intriguing finding
deserves further examination.

The use of spatially sensitive analysis in land
valuation has another less obvious benefit which, as a
practical matter, may be of no little importance. By
validating and quantifying the universally held, and
strongly believed, empirical expectation that location has a
major role in land pricing, theory approaches practice in a
manner which does no harm to either. By more closely
aligning theoretical specification of land pricing models
with the actual market practices, the theoretical process is
enhanced by both increased explanatory power and greater
acceptance by those who, after all, are the intended
ultimate beneficiaries of research.
APPENDIX A

MATHEMATICAL NOTATION
MATHEMATICAL NOTATION

The following mathematical notation was used throughout this paper, except where specified otherwise in the text.

Variables

\[ a_{i,z} \]

quantity \((a)\) of some attribute \((z)\) of a parcel of land \((i)\) capable of being measured and used in pricing the land.

\[ d_{i,j} \]

linear distance between points \((i)\) and \((j)\).

\[ p_z \]

price of attribute \((z)\) for a unit quantity.

\[ V_i \]

observed market price of parcel \((i)\)

\[ w_{i,j} \]

weighting factor describing the effect of the value of point \((j)\) on the value of point \((i)\), assuming a spatially autoregressive function.

\[ x_i \]

east-west spatial attribute of point \((i)\); distance east (if negative, west) of the fixed, but arbitrarily chosen origin in a uniform grid, or Cartesian coordinate system.

\[ y_i \]

similarly, the north-south spatial attribute of point \((i)\).

\[ e \]

residual from an Ordinary Least Squares regression.
Index Variables

Observations:

- \( n \) number of observations.
- \( i \) one of \( n \) observations.
- \( j \) one of \( n \) observations.

Variables:

- \( k \) number of explanatory (independent) variables in the hedonic pricing model.
- \( r \) number of terms (explanatory variables) in the trend surface model.
- \( z \) one of \( k \) variables.
- \( s \) a site-specific variable.
- \( l \) a locational variable.
- \( u \) a land use variable.

Note: \( k = s + l + u \)

- \( m \) degree of trend surface polynomial.
- \( q \) exponent of \((x)\) coordinate in a trend surface polynomial.
- \( s \) exponent of \((y)\) coordinate in a trend surface polynomial.

Functions
\[ H = f(x, y) \] the trend surface function, a polynomial of degree \((m)\) in the \((x)\) and \((y)\) coordinates of the observed value of the function in a uniform grid system.

\[ R = r(.) \] spatially autoregressive relationship between points on a plane; a measure of the nature of the interaction between the values, presumed to be uniform as to any pair of values, but also affected by the distance between the points according to \((w)\).

\[ w_{i,j} = (.) \] the weight function in a spatially autoregressive model, specifying the relationship between points \((i)\) and \((j)\) as a function of \((R)\) and their distance.

\[ V_i = (.) \] land value (pricing) function for parcel \((i)\).
APPENDIX B

CALCULATION OF THE MORAN COEFFICIENT
CALCULATION OF THE MORAN COEFFICIENT

Although the formulation of the Moran Coefficient given in (19) appears straightforward, the inclusion of the weighting function creates complications in its calculation as well as the calculation of variance for statistical testing purposes. A brief discussion of the matrix formulations for (19) and the calculation of the test statistic (22) are appropriate.

Beginning with the classical OLS model with (n) observations, each denoted as \( (Y_i) \), (k) explanatory variables contained in matrix \( (X) \) and the OLS coefficients designated as \( (\beta) \), the OLS model provides:

\[
E(Y) = X\beta
\]  

(23)

The OLS estimators \( (b) \) are determined as:

\[
b = (X'X)^{-1}X'Y
\]  

(24)

In the absence of autocorrelation (and of other econometric deficiencies) the \( (b) \) are the best, linear, unbiased estimators of the \( (\beta) \). Extending this result to spatial models including a function describing the spatial process (rho) (given as \( w_{i,j} \) in (17)) and the matrix of weights \( (W) \), Cliff and Ord (1981, p. 231) state the model as

\[
Y = \rho NY + X\beta + \epsilon
\]  

(25)

where the first term represents the spatially autoregressive
component. In the absence of spatial autocorrelation, this term will be equal to zero and the model will be the same as (23).

In such a model, error may arise from both the regression coefficients, (6), as well as the spatial component. Thus, the unobservable error is given by Cliff and Ord as:

$$\epsilon = \rho W \epsilon + \mu$$

(26)

with the first term representing the spatial component and the last ($\mu$) the error from the regression. The variance of (26) is shown by Cliff and Ord to be

$$VAR(\epsilon) = E(\epsilon \epsilon')$$

$$= \sigma^2 [ (I - \rho W') (I - \rho W)]^{-1}$$

(27)

If there is no autocorrelation, the ($M$) will be an identity matrix ($I$). Thus, testing for autocorrelation involves testing the independence of the error terms, i.e., whether ($M$) differs from an identity matrix ($I$). This is done by measuring the correlation of the spatially weighted error terms (Moran's Coefficient):

$$I = \frac{n}{S_o} \frac{\epsilon' W \epsilon}{\epsilon' \epsilon}$$

(28)

with ($S_o$) being the sum of the weights. The expected value (Cliff and Ord 1981, p. 202) is:
\[ E(I) = -\frac{n \text{tr}(\mathbf{A})}{(n-k)S_o} \]  

(29)

with variance

\[ \text{VAR}(I) = \frac{n^2}{S_o^2(n-k)(n-k+2)} \left[ S_1 + 2 \text{tr}(\mathbf{A}^2) - \text{tr}(\mathbf{B}) - \frac{2[\text{tr}(\mathbf{A})]^2}{n-k} \right] \]  

(30)

where

\[ \mathbf{B} = 4(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{D}^2\mathbf{X} \]  

(31)

\[ \mathbf{D} = \frac{1}{2}(\mathbf{W} + \mathbf{W}') \]  

(32)

\[ \mathbf{A} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{WX} \]  

(33)

The z-test given in (22) measures whether the points are pairwise correlated, that is, whether the spatial distribution of the residuals appears to be random.

Computational problems for large data sets may be severe, however, since \((\mathbf{W})\) is an \((n \times n)\) matrix. Nearly eight million elements are required for the present data set \((n^2 = 7,772,944)\), exceeding the capacity of computer resources capable of handling matrices. The computations were therefore made using an iterative method after Ebdon (1985, p. 161).

After calculation of the mean of the data, for each pair of points in the entire dataset the weights (reciprocal of distance) were calculated \((w_{i,j})\), then, separately, squared \((w_{i,j})^2\) and multiplied by the residuals \((w_{i,j}e_i e_j)\).
Next, the sum of all weights was calculated and squared to obtain \((\Sigma w_{i,j})^2\). It was then possible to calculate \(I\) from Ebdon (1985, p. 160):

\[
I = \frac{n \Sigma \Sigma w_{i,j}(x_i - \bar{x})(x_j - \bar{x})}{(\Sigma \Sigma w_{i,j}) \Sigma (x_i - \bar{x})^2}
\]

The expected value of \(I\) is:

\[
E_I = -\frac{1}{n-1}
\]

and the standard deviation of the expected value of \(I\) is:

\[
\sigma_I = \sqrt{\frac{n^2 \Sigma \Sigma w_{i,j}^2 + 3(\Sigma \Sigma w_{i,j})^2 - n(\Sigma \Sigma w_{i,j})^2}{(n^2 - 1) \Sigma \Sigma w_{i,j}^2}}
\]

under the assumption of normal distribution. These values may then be used in the calculation of the Z-statistic (22).
APPENDIX C

CODE FOR CALCULATION OF MORAN'S I
/* Calculation of Moran's I statistic **/
/* according to Ebdon (Iterative method) **/

#include <math.h>
#include <fcntl.h>
#include <alloc.h>
#include <float.h>
#include <stdlib.h>
#include <stddef.h>
#include <ctype.h>
#include <string.h>
#include <stdio.h>

/**************************
/* global declarations */
/**************************

struct ei_rec_def {
    float _ei, e, x, y;
} ei_rec[3200];

double dij, wij=0, wije=0, wij2=0, swij=0, swij2=0;
double kurt, moran, emoran, nmoran;
double rtop1, rtop2, rbot, rmoran, zn, zr;
double ei2, xi, yi, e2, e3, e4, tempe;
int nceil, count, curri, currj, numei, gap, i, j;

double ndble, n2dble;
double ei, edble, ebar=0, std=0, z0=0;
float nflt, high=0, low=0, sume;

char ch [2], dset[20], model[20], file1[20], file9[20],
    temp[20];
int done, i, ip, np,j, jp;
char obstr[20], estr[20], xstr[20], ystr[20];
char analhead[10], modelhead[10];

FILE *fp9;  /*** output file ***/

/*****************************/
/** main program **/
main()
{
    /** begin main **/
    void calcvalues();
    void readinput();
    void prtrpt();

    /** init before calculations **/
    numei = 0;

    /** output file **/
    printf("\n\t OUTPUT File Name ");
    gets(file9);

    if ( (fp9 = fopen(file9,"wb") ) == NULL) {
        printf("Cannot open output file, file9\n");
        exit(1);
    }

    done = 0;

    /** keep processing until Q entered **/
    do { /** processing loop **/
        /** determine variable headings **/
        printf("\n\t Variable or Residual or Quit ? V/R/Q ");
        gets(ch);
        ch[0] = toupper(ch[0]); /** convert to upper case **/
        switch(ch[0])
        {
            case 'V': /** variable **/
            
            
        }
    } /** begin switch on ch **/
```c
strcpy(analhead,"Variable");
strcpy(modelhead,"Variable");
readinput(); /** read input file **/
calcvalues(); /** do calculations **/
prtrpt(); /** print report **/
break;

case 'R': /** residual **/
    strcpy(analhead,"Residual");
    strcpy(modelhead,"Model ");
    readinput(); /** read input file **/
calcvalues(); /** do calculations **/
prtrpt(); /** print report **/
break;

case 'Q': /** quit **/
    printf(" QUIT \
");
done = 1;
break;

default:
    printf(" error on input \
");
break;

} /** end switch on ch **/

} while(!done); /** end processing loop **/
fclose(fp9); /** close output file **/

} /*** end main ***/

/*****************************/
/***** perform calculations *****
/*****************************/

void calcvalues()
```
{ /** begin calc values **/
  
  /***** initialize before calculations ****/
  e2 = 0;
  e3 = 0;
  e4 = 0;

  wij = 0;
  wije = 0;
  wij2 = 0;
  swij2 = 0;

  ndble = numei; /* n as double precision */
  n2dble = pow(ndble,2); /* calc n squared once */
  ebar = sume / ndble;

  for (curri = 1; curri<=numei; curri++)
    ei_rec[curri].ei = ei_rec[curri].e - ebar;
    /** deviation **/
  count = 0;
  printf("\n");

  for (curri = 1; curri<=numei; curri++)
  {
    /** process outer ei record loop **/
    ei2 = pow(ei_rec[curri].ei, 2); /** e squared **/
    xi = ei_rec[curri].x;
    yi = ei_rec[curri].y;

    e2 = e2 + ei2; /** first moment **/
    e3 = e3 + ( pow( ei_rec[curri].ei, 3 ) );/**second ,
            moment**/
    e4 = e4 + ( pow( ei_rec[curri].ei, 4 ) ); /**third
            moment**/
    swij = 0;

    for (currj = 1; currj<=numei; currj++)
    {
      /** process inner ei record loop **/

      }  

      }
if (currj == curri)
    dij = 0.0;

else
    dij =
    { sqrt (  
         ( pow((xi-ei_rec[currj].x),2) +  
         pow((yi-ei_rec[currj].y),2)  )  
    )};

if (dij != 0)
    swij = swij + (1.0/dij);

if (currj > curri )
{
    /* skip if j<=i */
    count = count +1;

    if (dij != 0) {
        wij = wij + ( 1.0/ dij ) ;
        wij2 = wij2 + (1.0/ pow(dij,2));
        wije = wije +  
               ((1.0/dij) * ei_rec[curri].ei * 
               ei_rec[currj].ei);
    } /* end dij not zero */

    ** gets(ch);**/
    
    } /* end skip if j<=i */

/**gets(ch);**/
/** end inner ei record loop **/

swij2 = swij2 + pow(swij,2);
}

/* end outer ei loop */

std = sqrt(e2/ndble);  /** std deviation **/

z0 = ebar /std;
kurt = (e4/ndble) / pow((e2/ndble),2);  /** kurtosis **/

moran = (ndble * wije) / (wij * e2);

emoran = -1.0 / (ndble-1.0);
nmoran = ((n2dble * wij2) + 
(3.0 * pow(wij,2)) - 
(noble * swij2)) / 
((n2dble-1.0) * 
(pow(wij,2))) ;

rtop1 = noble * ( 
( (n2dble + 3.0 - (3.0 * noble)) * wij2) + 
(3.0 * pow(wij,2)) - 
(noble * swij2) 
);

rtop2 = kurt * 
(((n2dble - noble) * wij2) + 
(6.0 * pow(wij,2)) - 
(2.0 * noble * swij2));

rbot = (noble-1.0) * 
(noble-2.0) * 
(noble-3.0) * 
pow(wij,2);

rmoran = (rtop1 - rtop2)/rbot;

zn = (moran-emoran)/ sqrt(nmoran);

zr = (moran-emoran)/ sqrt(rmoran);

} /** end calc values **/

void prtrpt()
{
/** begin prt report **/

/*** display report /**/

printf("\n Analysis of %s \n",analhead);

printf(" Dataset: %s %s: %s \n",dset,modelhead,model);
printf("\n Spatial Autocorrelation:\n\n\n");
printf("\t Moran Coefficient:\t I = %f \n", moran);
printf("\t Expected Value:\t E(I) = %f\n\n\n",emoran);
printf("\n Test for Normality: \n");
printf(" Variance = %f \t Z = %f \n", nmoran,zn);
printf(" Test for Randomization: \n");
printf(" Variance = %f \t Z = %f \n", rmoran,zr);

/*** write report to output file ***/
fprintf(fp9, "\f\r\n Analysis of %s \r\n\",analhead);
fprintf(fp9, " Dataset: %s %s: %s ,\r\n",dset,modelhead,model);
fprintf(fp9, "\r\n Spatial Autocorrelation:\r\n\n\n");
fprintf(fp9, "\t Moran Coefficient:\t I = \n\n", moran);
fprintf(fp9, "\t Expected Value:\t E(I)=%f\r\n\n\n",emoran);
fprintf(fp9, "\r\n Test for Normality: \r\n\n");
fprintf(fp9, " Variance = %f /t Z = %f \r\n\n", nmoran,zn);
fprintf(fp9, " Test for Randomization: \r\n\n");
fprintf(fp9," Variance = %f \t Z = %f \r\n\n", rmoran,zr);
}

/*******************************************************************************/
/********* read input file  ************
/*******************************************************************************/

void readinput()
FILE *fpl; /** input file **/

/** input dataset name for report **/

printf("\t DATASET Name? ");
gets(dset);

/** input name of model for report **/

printf("\t MODEL Name? ");
gets(model);

/** open input file **/

printf("\t INPUT Dataset Name ");

gets(file1);
if ((fpl = fopen(file1,"rb") ) == NULL) {
printf("Cannot open input file, file1\n");
ext(1);
}

/** read e x y as string variables from input file **/

ip = 0;

while (! feof(fpl)) { /** begin read input loop **/
ip=ip+1;
fscanf(fpl,"%s %s %s %s",
obstr, xstr, ystr, estr);

/** remove blanks & convert to floating point **/
i = 0;

while (isspace(estr[i])) i = i+1; /** search for non-blank **/

strcpy(temp,estr);
ei_rec[ip].e = atof(temp); /** convert to float **/
i = 0;

while (isspace(xstr[i])) i = i+1; /** search for non-blank **/

strcpy(temp,xstr);
ei_rec[ip].x = atof(temp); /** convert to float **/

i = 0;

while (isspace(ystr[i])) i = i+1; /** search for non-blank **/

strcpy(temp,ystr);

ei_rec[ip].y = atof(temp); /** convert to float **/

} /** end read input loop **/

numei = ip - 1;
sume = 0;
for (curri = 1; curri<=numei; curri++)
{
    sume = sume + ei_rec[curri].e;/**sum e values **/
}
fclose(fp1);

} /** end read input **/
APPENDIX D

REGRESSION RESULTS AND ANOVA
REGRESSION RESULTS AND ANOVA

The following SAS output tables for the ANOVA and OLS coefficients were obtained using the entire dataset for each model. The results have been analyzed in chapter VI. Variable names are the same as described in Chapter IV except for the spatial attributes. In the following, NORTH is represented by Y and EAST is represented by X in order to permit the use of meaningful labels for crossproduct terms as well as to save space.
Model: MODEL1
Dependent Variable: COST

Analysis of Variance

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
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<th>Mean Square</th>
<th>F Value</th>
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Root MSE = 0.95045
R-square = 0.5598
Dep Mean = 10.89854
Adj R-sq = 0.5574
C.V. = 8.72092

Parameter Estimates

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**Model:** MODEL1  
**Dependent Variable:** COST

### Analysis of Variance

<table>
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<th>F Value</th>
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- **Root MSE:** 0.91215  
- **R-square:** 0.5949  
- **Adj R-sq:** 0.5924  
- **C.V.:** 8.36943

### Parameter Estimates

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<tr>
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<th>T for HO: Parameter=0</th>
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Root MSE 1.15614, R-square 0.3463, Dep Mean 10.89854, Adj R-sq 0.3452, C.V. 10.60822

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Dependent Variable: COST

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Root MSE   1.00420  R-square  0.5077
Dep Mean 10.89854  Adj R-sq 0.5060
C.V. 9.21408

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Dependent Variable: COST

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Root MSE = 0.94623, R-square = 0.5643, Dep Mean = 10.89854, Adj R-sq = 0.5614, C.V. = 8.68219

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