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GIS and Spatial Analysis of Housing and Mortgage Markets

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Abstract

This article provides a spatial analytical framework for using Geographic Information Systems (GIS) technology in housing and mortgage market research. It discusses the nature of neighborhood effects and their influence in residential market behavior and outcomes. It then discusses how GIS can aid with empirical research investigations.

GIS, coupled with spatial analytical tools, offers an ideal research environment for processing, analyzing, and modeling housing and mortgage data sets. GIS offers powerful data mapping and visualization functionality to facilitate spatial explorations of the data. It also allows data from multiple sources and disparate formats to be integrated. Its powerful spatial querying and overlay capabilities greatly facilitate the organization and management of data sets to fit research needs. Finally, GIS is especially significant for constructing spatial variables.

Keywords: GIS; Spatial research; Neighborhood effects

Introduction

The importance of neighborhood in the operation of housing and mortgage markets is indisputable because housing is fixed in geographic space. The geographic location of a house determines access to employment, shopping, and recreation; neighbors and neighborhood characteristics; proximity to environmental amenities; and the level and quality of public services. Geographic location is a major determinant of household residential satisfaction and the resulting patterns of household mobility and neighborhood change. The process of location choice leads to geographic segmentation of the housing stock along various dimensions, including type, quality, ownership, and price, as well as along household characteristics, especially income, race and ethnicity, and lifestyles.

The importance of geographic location is inherent in many business practices concerning housing supply, marketing, and financing. Real estate practitioners know that "location, location, location" determines the premium that households are willing to pay for comparable properties. Appraisers take into account locational factors and recent sales in assessing the market value of properties. Mortgage lenders and insurers know that the geographic location of the property that secures a loan is a major determinant of their credit risk exposure. Policy makers are interested in targeting programs to neighborhoods where the

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housing investment is most likely to lead to desirable outcomes. Laws such as the Home Mortgage Disclosure Act (HMDA) and Community Reinvestment Act (CRA) ensure that industry practices are responsive to the housing and mortgage credit needs of low-income neighborhoods.

Despite the recognized importance of geographic location for business, policy, and regulatory practices, its incorporation into housing and mortgage market research has been limited. An explicit spatial treatment is needed to measure and quantify accurately the role of neighborhood in housing and mortgage market behavior and outcomes. Although appropriate methods are available in spatial statistics and spatial econometrics to facilitate such treatment, there has been limited awareness of their availability in the housing research community. Only a few recent studies have applied spatial analytical tools to examine neighborhood effects on housing prices (e.g., Can 1990, 1992b; Can and Megbolugbe 1997; Dubin 1992; Pace and Gilley 1997), in population density models (Griffith and Can 1995), or in mortgage market outcomes (Anselin and Can 1995).

The lack of software tools, limited availability of accurate and comprehensive information on residential properties and neighborhoods, and lack of research computing environments to facilitate the geoprocessing needs of spatial data have further hindered the spatial treatment of housing and mortgage markets. Geographic Information Systems (GIS) technology is emerging as a significant contributor to overcome the operational impediments that hindered empirical work with a spatial focus. Today, high-end GIS research computing platforms offer an ideal environment for researching the role of neighborhood in housing and mortgage markets. GIS capabilities not only facilitate the organization and management of geographic data, but they also enable researchers to take full advantage of locational information contained in these databases to support the application of spatial statistical and spatial econometric tools. The combination of GIS research infrastructure and recent advances in spatial research thus offer tremendous opportunities for investigating the neighborhood context in housing and mortgage market research.

GIS has also been an impetus behind the development of specialized software tools that are needed in spatial research. Complex questions faced in the analysis and modeling of neighborhood effects cannot be sufficiently addressed by off-the-shelf GIS software. Depending on the purpose of the research application, the commercial analytical functionality of GIS needs to be complemented by external analytical tools (Anselin, Dodson, and Hudak 1993; Anselin and Getis 1992). A recent focus in the spatial research community has therefore been the development of external software tools that are either embedded in or interface with existing GIS software environments (Can 1992a, 1996). The availability of these tools has in turn facilitated the application of spatial analytical tools in housing and mortgage research.

This article provides a spatial analytical framework for the investigation of neighborhood effects in housing and mortgage market research with the aid of GIS technology. After a discussion of the types and sources of neighborhood effects in the second section, a two-stage research approach is outlined in the third section for spatial analysis and modeling of housing and mortgage markets. The fourth section defines GIS and presents its functional capabilities to support spatial research. In the next section, selected spatial research examples are presented and the contribution of GIS is discussed. The final section offers concluding remarks.

Importance of Location in Housing and Mortgage Markets: Neighborhood Matters

There is increasing awareness of the important role neighborhood plays in social and economic outcomes for individuals and the resulting housing market processes and institutional behavior. Goodman, for example, identifies this as one of the major research areas for microeconomic analysis of housing markets and reinforces the notion that neighborhood does "matter" in housing research:

> Perhaps because neighborhood is difficult to measure, and more difficult to model, economists have often asserted that it does not make much difference. If such is the case, then the observed ethnic and racial enclaves that obviously exist have no economic meaning. Further, this assumption implies that realtors, home buyers, and the general public are misguided or misinformed in their statements that neighborhood is important, and in their perceived willingness to pay premiums for at least some neighborhood amenities. It is thus necessary to examine both the modeling and empirical concerns of neighborhood as part of the housing purchase. (Goodman 1989, 53)

Two unique qualities of housing—spatial fixity and durability—inextricably link housing purchase and subsequent residential satisfaction to its geographic location. In addition to the physical characteristics of the residential structure and its immediate site, a wide array of neighborhood characteristics enter into the housing bundle due to the geographic location of the structure.

In terms of individual- and market-level behavior and outcomes, the role of geographic location can be examined in two interrelated ways. One form of geographic influence involves localized externalities associated with the absolute location ("site") of the house. These types of externalities are called *adjacency effects* because they capture the spatial spillover effects on a given structure of neighboring structures. For example, a dump site would be a source of negative externality to adjacent properties. In addition to spillovers from neighboring structures, overall neighborhood characteristics—known as *situation*—such as accessibility, socioeconomic context, and so on, will also enter into decision-making activities and resulting market outcomes. These kinds of influences can be labeled as *neighborhood effects.* In this article, the discussion of neighborhood effects covers both types of influences associated with geographic location.

Neighborhoods can be defined as discrete spatial entities ("physical areas") that contain households and housing structures with similar characteristics. Typically, households exhibit similar social, economic, and demographic characteristics within neighborhoods. Similarities among housing structures are observed in tenure type (owner-/renter-occupied), ownership (private/public), type of structure (single-family/multifamily), and design (colonial, rambler, town house), as well as the general quality of the stock. The extent of similarity—that is, spatial continuity among households and housing units—varies across neighborhoods, making some neighborhoods more homogeneous than others.

Types and Sources of Neighborhood Effects

Four major differentiating factors across neighborhoods may lead to positive or negative externalities on residents: (1) accessibility; (2) physical environment; (3) social, economic, and demographic context; and (4) public-service provision. Accessibility is perhaps the most important differentiating factor. The second, physical environment, concerns the physical characteristics of the residential stock as well as proximity to environmental hazards. Third, neighborhoods are typically stratified on the basis of social, economic, and demographic characteristics of residents. Finally, neighborhoods differ in the type, level, and quality of public services they offer.

Accessibility Characteristics of Neighborhoods. The relative geographic position of a neighborhood determines access to employment and transportation opportunities.[1] Limited accessibility to suburban employment opportunities from inner-city neighborhoods is well known to have serious economic consequences for low-income and otherwise disadvantaged households. Neighborhoods with easy access to public transportation are at a relative advantage. In addition to access to jobs, the relative location of a neighborhood will determine access to amenities. Being within easy reach of shopping malls, parks, recreational facilities, public libraries, and medical centers has a positive effect on neighborhood residents.

Physical Neighborhood Environment. As a result of historical patterns of development, the physical character of the residential stock varies substantially across the urban landscape. The type, density, and architectural style as well as physical characteristics of the landscape differentiate neighborhoods. For example, the post–World War II Levittown period involved mass production of tract housing in suburban land and created a distinct spatial and social imprint. Customer preferences, ease and cost of land assembly, construction technology, and prevailing economies of scale determine the extent of spatial clustering in housing production by housing type. Because the majority of new housing is constructed on the urban periphery, there is a decrease in dwelling age in a concentric fashion moving outward from the city center. Of course, as the aging process depreciates the quality of the housing stock, rebuilding and revitalization become important in altering the spatial distribution of the physical stock. The aging process is also nonuniform due to variations in initial construction quality and affects the rate of deterioration as well as household desire to renovate and maintain the structure.

Certain neighborhoods, because of their topography and physical characteristics, are more prone to environmental hazards such as fire, flood, and earthquakes than others. This is a source of negative externality and lower housing demand for these neighborhoods and increases the risk of lending there. The location of a house also determines proximity to sites that are often considered undesirable, such as landfills, brownfields, toxic waste sites, airports, highways, and subsidized housing projects. Usually the presence of such sites is associated with neighborhood decline and instability and makes the neighborhoods that house them relatively unattractive.

Accessibility and the physical patterns of neighborhood landscape, housing production, and redevelopment are the starting points of social and economic variation across neighborhoods within urban areas.

[1] Differential access to workplaces has been the foundation of microeconomic theories of land use and residential location and the resulting rent/house price gradients (see, for example, Alonso 1964; Muth 1969). These models are quite useful in explaining the major spatial regularities observed in the allocation of urban residential land—for example, high-rise, high-density development near the city center and low-rise, low-density development in the peripheral locations. As Straszheim (1975) argues, however, these models are insufficient for investigating the considerable spatial detail in housing and neighborhood characteristics at different locations. In fact, this limitation has been the major motivating factor for subsequent econometric investigations of housing markets.

Social, Economic, and Demographic Context. Neighbors and neighboring structures are major sources of spatial externalities that affect household residential satisfaction and housing values in a neighborhood. The occupants and the quality and uses associated with the neighboring structures greatly influence one's residential satisfaction and resulting residential mobility decisions. First, neighbors, through their social, cultural, economic, and demographic characteristics, serve as role models/peers to young children and can positively or negatively influence the development of their value systems and behaviors. The literature suggests that exposure to poverty-stricken racially and economically segregated neighborhood environments might negatively influence social and economic opportunities for urban youth, especially educational attainment, criminal involvement, and employment prospects.[2] Therefore, households may perceive neighborhoods with certain income and racial and ethnic mixes to be more desirable than others.

Second, neighbors are the foundation of neighborhood-based social networks that unite residents around shared values, interests, or problems. It has been posited that neighborhoods with strong cohesive social networks have a stronger sense of community and are politically better positioned to take collective action when confronted with social problems such as crime and violence (Temkin and Rohe 1998). Residents in such communities are known to become more civically and politically engaged as shown in activities such as voting, taking a position on neighborhood issues with elected officials, participating in neighborhood associations, and volunteering. Although the literature is limited in terms of linking strong social networks with neighborhood stability, social networks are found to play an important support role in terms of social and economic advancement opportunities for households through information exchange about job opportunities, services, and other resources (Ellen and Turner 1997; Galster and Killen 1995). Neighborhoods with stronger social networks are therefore expected to offer positive benefits to residents.

A third major influence of neighbors involves their effect on the property maintenance and improvement behavior of households. Neighbors who take care of their property are a positive influence to surrounding households. Households try to keep up with their neighbors in maintaining and improving their property. In addition to a behavioral impact, well-kept structures have positive spatial spillover effects on the surrounding properties and raise their value. Finally, the uses associated with neighboring structures can be a source of externalities. For example, being next to noisy neighbors or abandoned or foreclosed properties is a nuisance and may be an incentive to consider moving.

Local Public-Service Provision. Considerable variations exist in the type, level, and quality of public services as well as in residential property taxes across neighborhoods and jurisdictional boundaries. Public school quality and crime protection have been the most important services that households consider because of their both short- and long-term economic and social consequences. The impact of educational quality is expected to be disproportionately greater on low-income households because more affluent households can afford to send their children to private schools. Given that education is the foundation for future social and economic advancement, public school quality plays a critical role in households' housing search, purchase, and mobility decisions. Effective public safety and crime-control measures can have stabilizing influences on residential turnover and mobility. An important compo-

[2] See Galster and Killen (1995) and Ellen and Turner (1997) for detailed reviews of the impact of neighborhood effects on families and children.

nent of public-service provision involves municipal services (such as trash collection and street maintenance) that influence the general quality of the neighborhood and its attractiveness. In addition to public-service provision, the availability and quality of public institutions such as religious centers, community facilities, child care, and medical care constitutes an important resource. Given that variations in public service provision and residential taxes largely occur at the jurisdictional level, households typically first choose a jurisdiction and then further differentiate locations on the basis of neighborhood-level variations.

Neighborhood environment, singly or jointly through a combination of these conditions, has positive or negative effects on the social and economic well-being of households. Subject to income constraints, households make trade-offs between different housing and neighborhood characteristics when they make decisions about where to buy, how much to pay, whether to maintain or improve, and whether to move or stay. It should be emphasized that the extent to which households differentiate neighborhoods along these dimensions determines the extent of spatial externalities. Household preferences, perceptions, and knowledge about neighborhood differentials greatly influence resulting neighborhood effects in market processes.

Market-Level Influences of Neighborhood Effects

The four differentiating factors (accessibility; physical environment; social, economic, and demographic context; and public-service provision) influence the larger market-level processes in housing and mortgage markets. The outcome of neighborhood differentials along these dimensions is systematic spatial variation in the distribution of housing demand, production, distribution, and financing. The following briefly discusses the impact of neighborhood differences on major market processes and outcomes as well as resulting spatial structure.

Spatial Variation in the Demand and Supply of Housing and Mortgage Credit. Home purchase is for most households the single largest lifetime economic and social investment. In addition to preferring certain housing types, households search for neighborhoods with the overall goal of minimizing economic risk and social conflict. To the extent that neighborhoods are spatially differentiated, this results in spatial variation in the structure of housing demand—houses in certain neighborhoods are in higher demand than others. Because of the reciprocity between household mortgage demand and housing and residential choice, the spatial structure in housing demand translates into similar spatial patterns in mortgage demand. The result is systematic spatial variations in mortgage demand in terms of both its level and type.

Conversely, decisions to supply housing are largely based on anticipated housing demand by price and location in addition to cost considerations. Therefore, household locational preferences enter into the decisions of builders and developers. At the same time, financial institutions are sensitive to locational differences in their underwriting decisions to provide housing construction loans because of the market risk involved. Zoning, land use, and building regulations may act as additional spatial constraints to housing suppliers and may reinforce existing spatial clustering in housing production by housing type and price.

The cost and availability of mortgage credit have significant influences on housing outcomes, especially for low-income and underserved households. Mortgage lending institutions have been under increasing public and regulatory scrutiny to ensure that their lending decisions are based on economic safety and soundness considerations, not on racial composition or income levels of neighborhoods. Research on mortgage redlining has sought to measure spatial bias in the distribution of mortgage funds resulting from noneconomic considerations (see, for example, Canner and Gabriel 1992; Holmes and Horvitz 1994; Munnell et al. 1996).

Spatial Variation in Housing Prices. Regardless of neighborhood differentials, housing prices are expected to vary systematically across the urban landscape as a result of spatial variations in the physical qualities of the residential stock—type, style, quality, density, and so on. Spatial externalities associated with neighbors and neighborhood conditions are expected to enter as an additional "premium" (if positive) or "discount" (if negative). There can be substantial differences in the selling prices of houses with similar structural characteristics—for example, age, number of bathrooms, and lot size—depending on geographic location and neighborhood context. An important question is whether the observed transaction prices are significantly different from the expected market prices of houses once structural and neighborhood differentials are accounted for. Such discrepancies would point in the direction of localized aberrations, that is, market inefficiencies, and result in "bargains" or "losses" in housing transactions.[3]

In addition to the effect of local market conditions (e.g., high or low turnover rates), one source of discrepancies between expected and observed market prices is the influence of prior sales on current sales. Homeowners and investors assess the value of their property by looking at the going prices of the immediately surrounding properties. They perceive the value of their property to be increasing if the neighboring properties are selling for more than the expected market value on the basis of structural, accessibility, and neighborhood characteristics. Conversely, if households perceive that the prices of nearby properties are in decline, they fear that the value of their property will go down too. Therefore, it is easily conceivable that once the pattern of price inflation (or deflation) starts in a neighborhood, it can very quickly become a contagious and self-perpetuating process and take over the entire neighborhood. The spread of this process would in most cases be tempered by the prices of similar houses in adjacent neighborhoods.

Spatial Variation in Mortgage Default/Foreclosure. An integral aspect of mortgage allocation decisions by primary and secondary lenders is the anticipated mortgage default/foreclosure risk. Research has shown that mortgage default is highly dependent on the loan-to-value ratio (LTV) (the outstanding mortgage loan to the market value) of the house. Given that house prices vary spatially, it is expected that credit risk associated with default will also vary across neighborhoods. In assessing the market value of houses for underwriting or portfolio management decisions, mortgage lending institutions consider recent house price movements in neighborhoods because of their effect on the nature and direction of prevailing house values. Additional local economic factors such as unemployment, vacancy rates, and rental occupancy rates can be used by lending institutions to further gauge future housing

[3] An important policy concern is whether these market inefficiencies coincide with certain neighborhood types and household groups (e.g., low-income minority neighborhoods). A politically sensitive issue in the literature has been whether minorities pay (or are charged) more than others due to institutional discrimination.

demand and prices. This may further reinforce the nonuniform distribution of credit risk across the urban area to the extent that certain attributes are spatially concentrated in certain neighborhoods.

An important aspect of foreclosures is their spatially contagious nature. An abandoned property resulting from foreclosure in a neighborhood acts as a catalyst by reducing the expected return on investment on surrounding properties. Homeowners and investors adjacent to abandoned or vacant properties are less likely to invest because of the anticipated spillover effects of these properties on the value of their property. This will start the familiar self-fulfilling prophecy of less investment, leading to lower quality, lower demand, lower price, higher LTV, and finally foreclosure and abandonment. The result is large-scale accelerated neighborhood decline and housing abandonment in a neighborhood. This emphasizes the importance of early loss mitigation efforts by mortgage lenders to minimize the spread of default/foreclosure in metropolitan areas. Of course, the primary explanation for foreclosure is the household economic characteristics; the spillover effects of surrounding foreclosures is an additional factor. A large number of foreclosed properties in a neighborhood, by raising the supply of properties for sale, would also likely reduce prices.

Spatial Variation in Housing Maintenance and Upgrading. In addition to depreciation associated with the aging process, housing maintenance and improvement play an important role in maintaining the quality of the physical stock. Most people prefer to live in neighborhoods where they think the return for their housing investment in a dwelling with given characteristics is the highest. For the same reason, people are willing to invest in maintaining dwellings where the return for such expenditures will be sufficiently high. Household perceptions regarding future returns on investment are major determinants in the decisions to maintain and upgrade. For example, a household might not invest in the construction of a deck if it thinks that the outcome would not sufficiently raise the value of the house. An additional consideration in maintenance and upgrade decisions is the household's expectations that the neighbors would or would not do the same. As the well-known prisoner's dilemma posits, the natural tendency for households is not to act but to wait for the neighbors to act in order to reap the economic benefits resulting from the spillover effects of neighbors' actions. This is the primary reason for an accelerated rate of disinvestment in residential stock and resulting neighborhood decay when the neighborhood is perceived to be in decline. The direction and pace of neighborhood change varies greatly across the urban landscape.

Residential Segmentation and Segregation. Differences in household incomes and preferences, along with systematic spatial variations across neighborhoods, lead to spatial segmentation. Differing segmentation can be found in household income, race and ethnicity, and lifestyle preferences within a given metropolitan area. For example, households with young children may prefer single-family to multifamily housing. Those with modest incomes may face a limited set of locations that fit their needs and preferences and may need to settle for cheaper rental units in inner-city neighborhoods with easy access to public transportation. Those with higher incomes, on the other hand, may be able to afford single-family structures in suburban settings with better educational quality. To the extent that income correlates with race and ethnicity, spatial segmentation results in residential segregation in an urban area. In addition to market forces, institutional barriers—including redlining and discrimination by landlords, real estate agents, and building/housing codes and zoning regulations—reinforce spatial segregation by limiting the entry of certain racial and ethnic groups to certain neighborhoods. In some cases, public policies and programs further promote spatial differentiation when they target certain neighborhoods or certain household groups in housing and social service delivery. Limited information about neighborhood conditions may further restrict the locational choices of minority households.

Understanding and revealing the complex mechanisms that lead to segmentation in socioeconomic space has been a major preoccupation of social science research. Because alterations to the housing stock are expensive and there are high costs involved in settlement and movement, neighborhood effects can have long-lasting influences on the social and economic outcomes for households, especially for those with financial constraints and those that are subject to discrimination or have limited information about housing and neighborhood choices. Therefore, an important policy concern has been to ensure that households facing such constraints not become spatially trapped in undesirable neighborhoods but instead have neighborhood choices and opportunities similar to those of households with better economic means.

How Do We Handle Neighborhood Effects in Housing and Mortgage Market Analysis?

In order to achieve desirable household, business, and policy outcomes, there is a great need for a systematic understanding of the sources, nature, and extent of neighborhood effects. An explicit spatial analytical treatment is necessary to examine and model accurately the operation of housing and mortgage markets. Although appropriate spatial analytical tools and methods are available in spatial statistics and spatial econometrics, their application to housing research has been quite limited. There are a number of reasons for this. First and foremost, researchers in the housing community have been unaware that such tools are available. Second, the examination of neighborhood context requires detailed and up-to-date neighborhood-level data, which are often difficult to obtain. The limitations of decennial census data for measuring neighborhood changes are well known (available every 10 years; boundaries of spatial units—e.g., tracts, block groups—change between census counts; limited information on neighborhood characteristics). Interim estimates of household and housing characteristics by the U.S. Bureau of the Census are only available at higher levels of aggregation, such as at the city, county, or state levels. Data on certain neighborhood characteristics such as crime and school quality are intermittently available and come in different geographic scales and data formats, making them difficult to use in conjunction with the census data. Third, the application of spatial analytical methods in housing research demands a research technology platform to accommodate the special processing requirements of geographic data that was not available until recently.

The combination of spatial analysis and GIS technology provides the optimal environment for investigating neighborhood effects in housing and mortgage markets. Spatial analysis provides the necessary methods and GIS serves as the research platform both to manage spatial data and to implement the spatial methods. The following section outlines a general spatial analytical framework and the subsequent section discusses how GIS can assist with statistical and econometric investigations in housing research.

A Spatial Analytical Framework

The investigation of neighborhood effects requires spatial analytical methods that are specifically designed for the analysis and modeling of geographically referenced data. These methods formally incorporate the spatial structure—that is, spatial arrangement and spatial relationships (e.g., adjacency, proximity, contagion, and interaction)—among geographic entities as additional information to measurements of their selected attributes. In contrast to traditional mathematical and statistical analysis where spatial structure is discarded, spatial analysis builds upon this information to analyze and model spatial phenomena in order to provide an understanding of the underlying causal processes and mechanisms.

A two-tier approach is recommended for the investigation of spatial structure in geographical data (Haining 1990). The first stage is called the exploratory spatial data analysis (ESDA) and focuses on the measurement and quantification of spatial structure. This stage is important for hypothesis formulation to feed into the next stage. The second stage is called confirmatory data analysis (CDA) and involves modeling the impact of spatial structure on behavior and outcomes in addition to economic considerations.

Exploratory Spatial Data Analysis. The first stage is the *spatial pattern identification* stage. This involves a careful investigation of spatial structure in geographic data sets in addition to their standard distributional properties. Figure 1 illustrates three distributions with identical distributional properties but with distinctly different spatial arrangements.[4] Pattern (a) exhibits clustering of similar values by location, which is known as positive spatial autocorrelation. Pattern (b), on the other hand, exhibits clustering of dissimilar values, which is known as negative spatial autocorrelation. Pattern (c) exhibits what is known as a random spatial arrangement, which is the underlying assumption of traditional statistical and econometric methods.

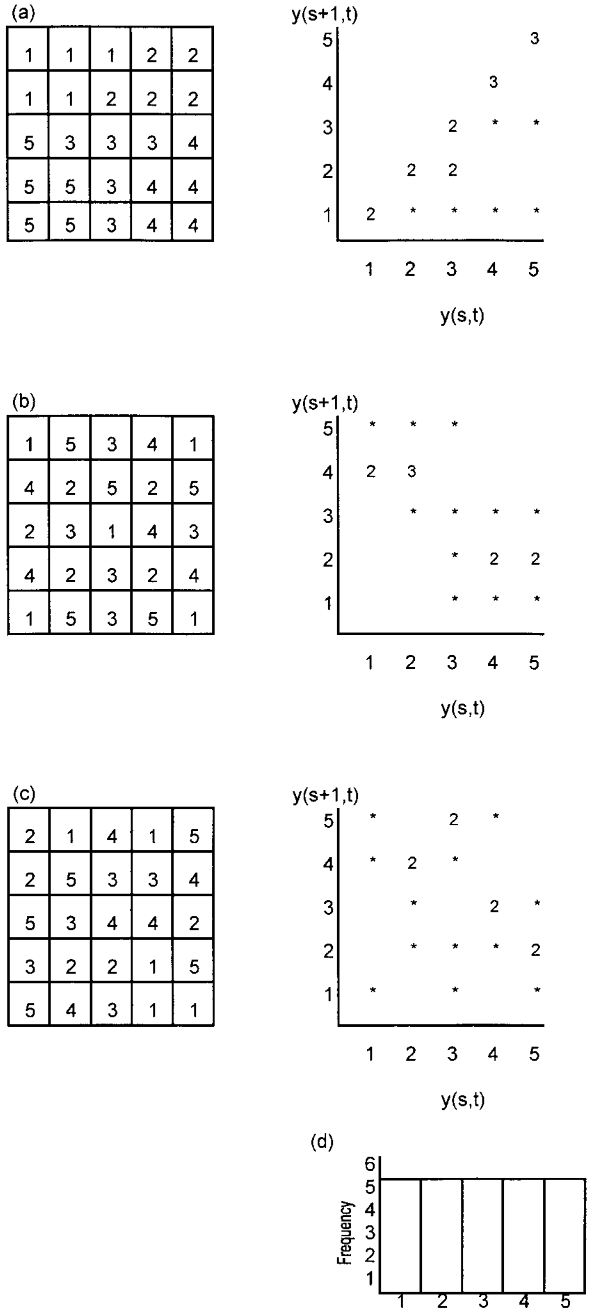
Formal measurement of trends in spatial patterns can be done using what are known as spatial association (or autocorrelation) statistics. These statistics quantify the extent and direction of spatial clustering in attribute values (e.g., positive and strong, negative and weak) as well as its statistical significance.[5] The interpretation of spatial association statistics is similar to simple correlation statistics. The main difference is that correlation statistics measure the strength of similarity between the values of two variables whereas spatial association statistics measure the extent of similarity in the values of the same variable across space. Spatial association statistics can be used either to measure spatial clustering in the whole system or to determine whether a given observation value is significantly different from its neighbors in space. Such observations are called *spatial outliers*. Identification of spatial outliers is very useful for data cleaning and error checking as well as for the interpolation of missing values in spatial data sets. An example is provided later in the GIS section.

ESDA, therefore, explores, summarizes, and exploits the informational content of geographical data sets and as such concerns itself with description rather than explanation. Detection

[4] The set of graphs in the middle column of figure 1 plots the value observed at each location (grid cell) against the value of its immediate row-neighbor. If there is more than one occurrence of the same value pair, then the number of occurrences is indicated. For example, in pattern (a), there are three occurrences in which a grid cell with a value of 5 also has an immediate row-neighbor with a value of 5. If (s,t) denotes position on the map (s = row number, t = column number), then these could be identified as the following: [(s,t), (s + 1,t)] pairs: [(1,1), (2,1)]; [(1,2), (2,2)]; and [(2,1), (3,1)]. The right-hand column, on the other hand, plots the values observed at each grid cell against its column-neighbor. Using the (5,5) value pair, this time there are only two grid cells whose immediate column-neighbors also contain a 5. These are locations [(1,1), (1,2)] and [(2,1), (2,2)]. These graphs strongly indicate the presence of spatial similarity in data values both across columns (east-west) and rows (north-south).

[5] For a theoretical treatment of spatial autocorrelation, see Cliff and Ord (1981); Anselin (1988); and Griffith (1988).

Figure 1. **Alternative Spatial Configurations for a Distribution**



Three maps with identical distributional properties but with different spatial arrangement properties: y(s,t) denotes the value at position (s,t) on the map; (a) clustered arrangement of values (similar values together); (b) alternating arrangement of values (different values together); (c) random arrangement of values; (d) histogram of data values for cases a, b, and c.

Source: Haining (1990, 28). Reprinted by permission from Cambridge University Press.

of spatial autocorrelation by means of exploratory data analysis can provide important insights about the nature of localized processes and spatial externalities in housing and mortgage market research. It is often very difficult to find a precise quantitative explanation of how neighborhood enters into household and market behavior and processes even with highly sophisticated mathematical and statistical models. This stage gains more importance during the hypothesis formulation phase of housing market research.

There are, of course, definite limits to the utility of geographic information and its contribution to understanding certain processes. As Openshaw (1991) warns, a map is a wonderful communication device but it can also mislead. Therefore, it is essential to place these geographical explorations within appropriate theoretical and conceptual frameworks from urban housing economics.

Confirmatory Data Analysis and Modeling. The second stage in spatial analysis is *spatial process exploration,* which uses CDA methods to explore systematically the structural relationships among geographic distributions of selected attributes. CDA is similar to the traditional econometric framework in terms of the emphasis on hypothesis testing, estimation, and prediction, but it also provides tools for the formal incorporation of spatial structure into functional relationships. The most crucial input at this stage is urban economics theory because it is the foundation on which researchers can build models to explain underlying structural relationships. A spatial econometric framework simply enables the researcher to combine economic theory with spatial information.

A major concern of CDA is testing for spatial autocorrelation in regression residuals. As explained previously, the presence of spatial autocorrelation indicates that there is a systematic pattern in the spatial distribution of data values. Spatial autocorrelation in regression residuals implies nonrandomness in their distribution and violates the statistical assumption of independence in regression analysis. Spatial autocorrelation in regression residuals can arise for two reasons. First, spatial structure can result from the presence of localized externalities in housing processes such as in mortgage default and housing renovation behavior. In other words, where you are in space and who your neighbors are makes a difference in terms of output. This kind of spatial autocorrelation is usually referred to as spatial dependence because there is functional interdependence among nearby observations. Spatial autoregressive models are available for the explicit incorporation of this type of spatial dependence in housing and mortgage processes (for examples, see Can 1990, 1992b; Can and Megbolugbe 1997).

In addition to functional interdependence, spatial autocorrelation in regression residuals may result from omitted variables. Since it is quite difficult if not impossible to have a fully specified econometric model that can comprehensively model the underlying neighborhood processes, the omitted variables may lead to spatial autocorrelation because in most situations they will be spatially nonrandom. In addition, systematic spatial variation resulting from measurement-related errors in sampling, data collection, or data analysis can lead to spatial autocorrelation in regression residuals. Common sources of sampling and data collection errors include systematic spatial differences in data collecting and recording—for example, the skipping of a group of houses in a dilapidated area by census takers or the use of an incorrect areal unit for surface partitioning in collecting or analyzing socioeconomic data (Haining 1990). The latter, known as the spatial aggregation (or modifiable areal unit) problem, is of great importance in social science research because most socioeconomic information—such as census data—is available in aggregate form that may not necessarily correspond to the "true" scale at which spatial variations exist. If, for example, the "true" spatial scale of the phenomenon under study is different from the one for which data are collected, then it is certain that measurement errors will spill over the boundaries of spatial units and result in systematic spatial variation (Anselin 1988).

Recent research in spatial statistics and econometrics has shown that ignoring spatial autocorrelation in econometric modeling might lead to incorrect inferences in statistical and econometric modeling because spatial structure violates the underlying assumption of spatial randomness in traditional methods. Methods are now available to detect spatial structure in geographic data and to incorporate this information in the most appropriate way into spatial data analysis and modeling (see, for example, Anselin 1988, 1990; Anselin and Griffith 1988; Cliff and Ord 1981; Griffith 1988). Although a parametric approach has been predominant, robust nonparametric approaches are also available for CDA within a spatial context, such as the spatial bootstrap in Anselin (1990).

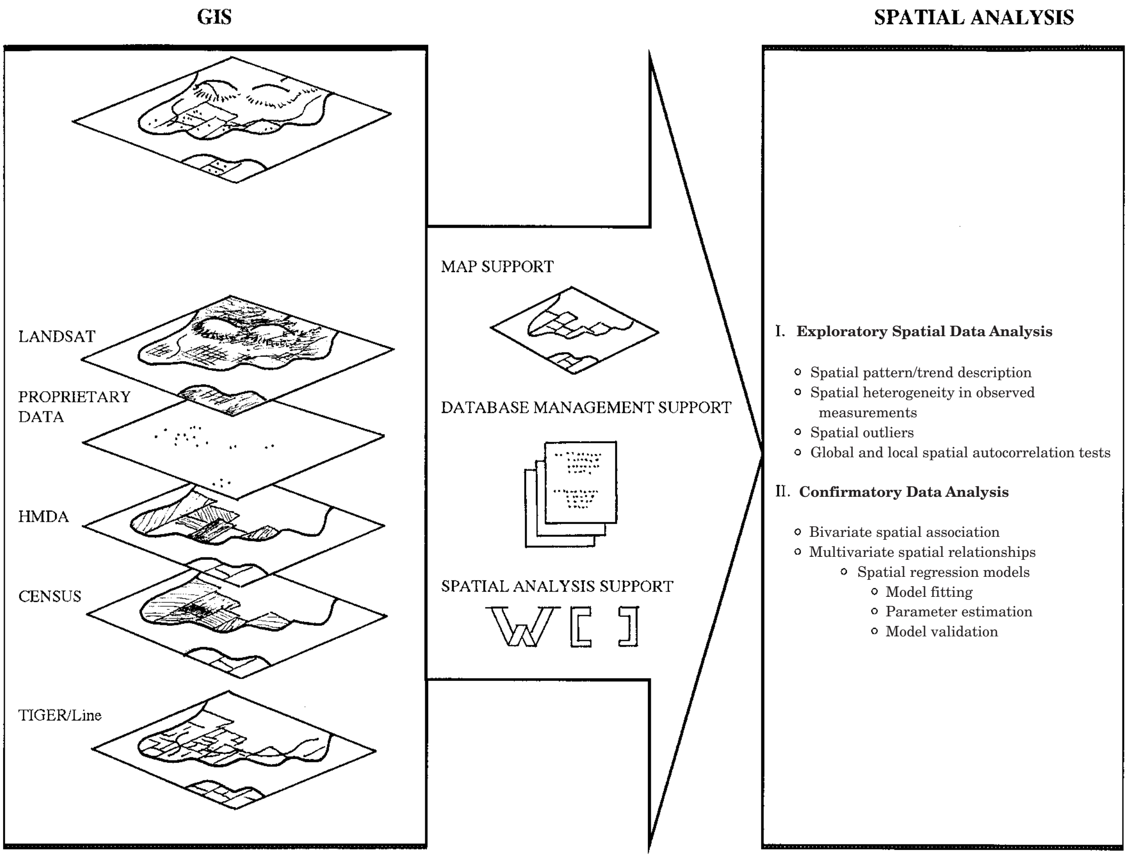
How Can GIS Support Spatial Housing and Mortgage Market Research?

GIS not only provides the means for geographically sensitive business application development, but it also provides an ideal environment for conducting spatial research that would ultimately feed into the development of such applications[6] (figure 2). First, GIS enables the researcher to organize, visualize, and analyze data in a map form. The visualization of geographic data familiarizes the researcher with the area of investigation and the underlying spatial context. Second, GIS provides the medium for the integration of multiple geographical data sets typically used in housing and mortgage market research. Third, GIS provides analytical support for spatial data analysis by providing explicit information on spatial relationships. The ability of GIS to offer functionality in these areas together is what makes GIS a very powerful analytical tool for spatial data analysis and modeling.

GIS as a Map Maker and Visualization Aid. The common saying that "one picture is worth a thousand words" nicely conveys the importance of a map as a communicator of information. GIS now routinely offers tremendous functionality for graphic and cartographic visualization of data. GIS technology offers enormous capabilities for not only displaying but also querying geographical databases from within a graphical user interface. A relatively new technology in this area is the use of multimedia techniques for enhanced visualization of geographic information. These techniques make it possible to integrate picture support and voice support into databases using object level data structures, which enhances the integrated use of the information content of spatial databases. This technology makes it possible to envision a system whereby the user would speak into a microphone and state a property address and several windows would subsequently display relevant information in different scales and formats. In such a system, one window would display a picture of the house, another one would list the property characteristics, and another would show the property highlighted on the street network. The graphical and cartographic display capabilities of

[6] For a detailed discussion of geographic data, GIS functionality, and business applications of GIS in mortgage finance, see Belsky, Can, and Megbolugbe (1998).

Figure 2. **GIS and Spatial Analysis of Housing and Mortgage Markets**



GIS are therefore very important for spatial orientation as a first step for any research investigation.

GIS as a Medium for Aggregation, Data Integration, and Exploration. Geographic information requirements vary widely depending on the purpose of the research investigation. The major distinction in this requirement is the spatial aggregation level required, primarily whether individual-level or aggregate-level data are needed. Some research requires the handling of individual transaction data (e.g., acquisitions), whereas others use transaction data in an aggregated form over selected geographic entities that are important in the delivery of mortgage services and products (e.g., census tracts, central cities, or metropolitan statistical areas [MSAs]).

The street address of properties in business data sets provides a unifying element and the least common denominator for the geoprocessing needs of research. GIS geocoding and spatial overlay operations permit use of the property address as the linkage mechanism for spatial aggregation of individual transaction data at desired levels of geographic entities (e.g., tracts, MSAs) by organizing information on the basis of the property address. Thus, GIS allows the use of a given database at different levels of geography (vertical integration).[7]

Because GIS organizes data by geographic location, it allows the integration of data from multiple sources that come in disparate formats, scales, and levels of resolution (e.g., satellite imagery with census data). As depicted in figure 2, it is possible to integrate most commonly needed neighborhood information from HMDA, census, and other relevant data in a GIS framework. A related issue is spatial interpolation. This is an empirical issue that arises when geographical data are collected at different aggregation levels (e.g., school districts, census geographic areas, postal codes, topographic surveys, and administrative units). The need to use geographic information from disparate sources simultaneously requires the interpolation of data from an original aggregation unit into common units. There are various strategies for spatial interpolation, ranging from very simple heuristic solutions to sophisticated ones that exploit the spatial structure in data sets.[8]

Through its spatial querying capabilities, GIS also enables researchers to generate variables and indexes based on spatial relationships—for example, the average price of housing transactions within the three-kilometer radius of a current listing that occurred within the last six months. This provides additional information by tapping into the locational information that already exists in data sets. The querying functions are especially important for the management of large spatial data sets in housing market research. Because GIS uses the geographic location of entities as the storage and linkage mechanisms, it facilitates flexible organization of data and helps detect errors in the management of large transaction-based data sets.[9]

GIS as a Spatial Analytical Support Tool. Although the visualization and database management capabilities of a GIS are sufficient for queries about the spatial distribution of attribute values, the investigation of neighborhood effects that underlie such spatial outcomes is the forte of spatial analysis.

One of the major requirements for spatial analysis in both ESDA and CDA is the formal definition and identification of neighbors. Definition of neighbors can be done in one of two ways. The first and the most commonly used definition uses spatial contiguity as the basis for determining neighbors. In this definition, spatial entities are considered to be "neighbors" if they share a common boundary. For example, in figure 1, the immediate row- and column-neighbors of a grid cell would be considered neighbors based on this definition. A second approach is to use distance among spatial entities. This definition is based on the spatial interaction theories that posit that the strength of interaction is a function of distance among spatial entities; the closer entities will exert a larger influence on each other than distant ones. Information on neighbors is formally stored in what is known as a *connectivity* or

[7] The major data input into the geocoding process and subsequent spatial aggregation are digital street network files (or geographic base files). For a detailed discussion of street network files, see Can (1993).

[8] Because there are no theoretical guidelines for the selection of the correct interpolation method, GIS can be instrumental in a comparative analysis of various methods (see Flowerdew and Green 1994 for a detailed discussion of GIS use in spatial interpolation research).

[9] In fact, an emerging trend in the development of marketing information systems is the use of geographic location as the unifying element. This trend has been facilitated by the availability of powerful, easy-to-use desktop GIS software, such as ArcView (ArcView is a registered trademark of the Environmental Systems Research Institute), that facilitates linkages between GIS and other database management systems, such as Oracle.

weight matrix (W), which has dimensions of N by N (where N is the number of spatial entities in the study area such as houses, census tracts, etc.). Elements of W, w_{ij}, are the proximity values either based on adjacency or distance.

Although the construction of W can be done simply for small data sets, when large spatial data sets are used, complex spatial relationships exist and need to be identified. A GIS with a topological vector model is the most suitable one for spatial analysis as it provides an explicit representation of spatial relationships—namely, connectivity and adjacency—to facilitate the construction of weight matrices (see Can 1993, 1996 for a detailed discussion).

GIS provides the geographic information needed for the application of spatial analytical methods, but it does not provide the necessary tools for their application. Therefore, a growing focus in the research community is the interfacing of commercial GIS with external software tools, especially for spatial statistical and econometric analysis (Anselin, Dodson, and Hudak 1993). A "close coupling" is typically promoted for the link between GIS and external software for the purposes of ESDA. This involves embedding user-developed algorithms within a GIS environment through the macro languages provided (e.g., AML or Avenue, which are macro language facilities provided by ARC/INFO and its desktop mapping product). This type of interfacing enables researchers to get results in the most efficient manner from a geographical data set. For CDA, however, "loose coupling" is considered more suitable. This involves file transfer between GIS software, such as ARC/INFO, and other software (e.g., Gauss, SpaceStat, and S-Plus).[10] Recent developments in desktop GIS are opening up other interfacing options (see Anselin 1998 for a detailed discussion of research infrastructure needed to complement existing commercial GIS environments in order to effectively employ GIS and spatial analytical tools in real estate analysis).

Selected Research Examples

This section illustrates via selected research examples how GIS can assist with spatial analytical research investigations of housing and mortgage markets. Three research examples are given. The first example illustrates how GIS can be used to construct spatial variables. The second demonstrates the utility of GIS in error checking and data cleaning in large spatial data sets. The final example uses GIS to examine the spatial structure in mortgage originations.[11]

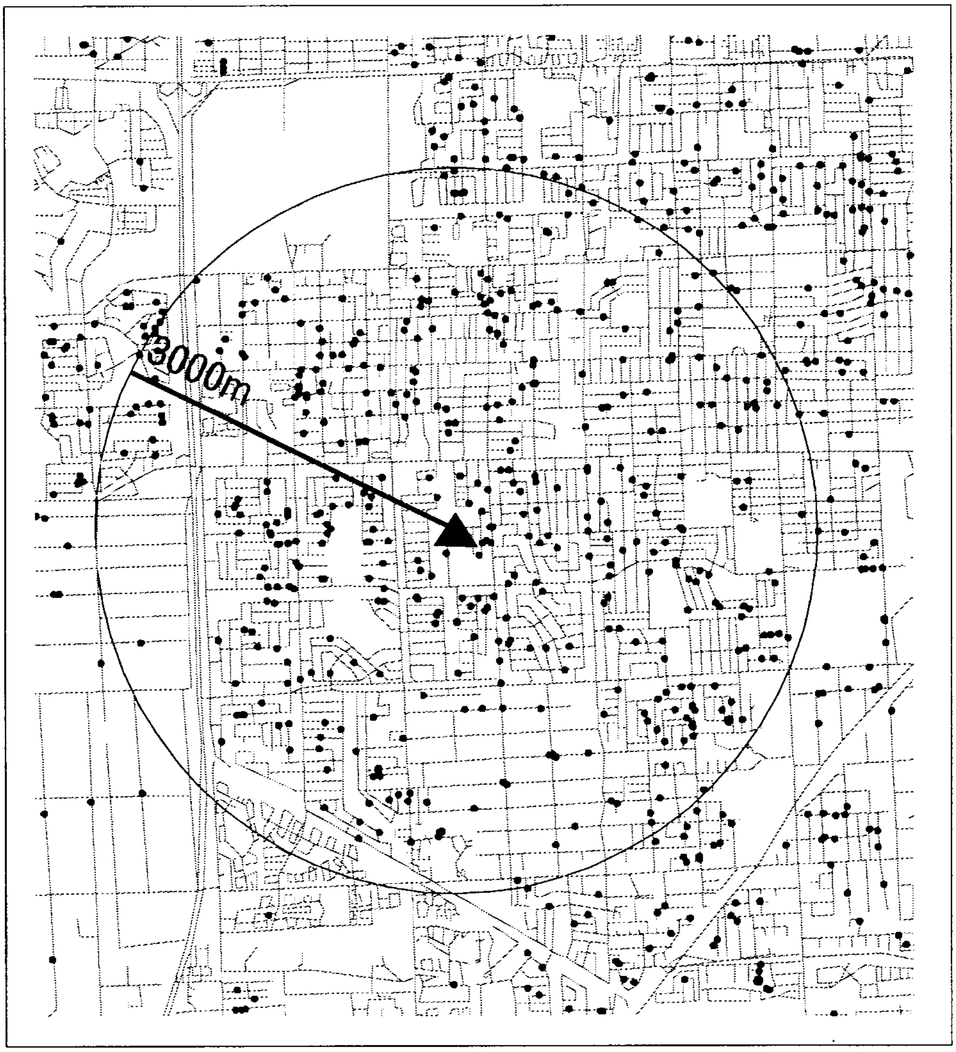
Construction of Spatial Variables

This research example demonstrates how GIS can be used to generate additional variables based on spatial relationships. As discussed previously, prior selling prices are taken into account by homeowners, real estate agents, and appraisers when appraising residential property values. GIS can assist with the examination of prior sales by constructing a spatially weighted average price of prior transactions within specified spatial ranges of a given

[10] ARC/INFO is a registered trademark of the Environmental Systems Research Institute, Gauss is a registered trademark of Aptech Systems, and S-Plus is a registered trademark of Mathsoft, Inc.

[11] ARC/INFO and SpaceStat (Anselin 1992, 1995b) are used to support the research investigations reported in this section.

Figure 3. **Construction of Spatially Lagged Price Variables**



This figure depicts the prior sales that occurred in the last six months within the three-kilometer range of a house indicated by the arrow.

Source: Can and Megbolugbe (1997, 208). Reprinted by permission from Kluwer Academic Publishers.

sale (see figure 3). Alternative definitions of neighbors (e.g., all houses within a three-kilometer range) and different time frames (e.g., sales that occurred within the last six months versus three months) can be used. Also, one can hypothesize varying influence of neighbors based on distance.

Can and Megbolugbe (1997), for example, construct three alternative spatially weighted average prices of prior sales in their examination of the house price determination process in Miami. Using 1990 housing transaction prices, they construct the following spatial variables:

$$\text{LAG\_D\_3} = \Sigma_j\, [(1/d_{ij})/\Sigma_j\, 1/d_{ij}]P_{j,}\, ,\ d_{ij} \leq 3\text{km} \tag{1}$$

$$\text{LAG\_D2\_3} = \Sigma_j\, [(1/d_{ij}^{\,2})/\Sigma_j\, 1/d_{ij}^{\,2}]P_{j,}\, ,\ d_{ij} \leq 3\text{km} \tag{2}$$

$$\text{LAG\_NGH} = \Sigma_j\, [(1/d_{ij})/\Sigma_j\, 1/d_{ij}]P_{j,}\, ,\ j = 1{,}2{,}3 \tag{3}$$

Here, d_{ij} is the distance between a given sale and its neighbor j; P_j is the selling price of a prior sale j that occurred within the last six months of the current sale. The first specification assumes uniform distance effect in that all neighbors within a three-kilometer range are assumed to have the same influence. The second specification, on the other hand, gives a higher weight to nearby houses by using an inverse distance squared function. The third specification resembles the comparable sales approach in that it includes the three closest prior sales. Spatial comparisons of sales prices against their neighbors can provide insights about the underlying spatial externalities (see figure 4).

Subsequent use of spatially weighted averages of prior sales in a hedonic house price analysis would enable the researcher to determine the expected absolute price impact of nearby sales on each other. For example, Can and Megbolugbe (1997), using LAG_D_3, found that a $1,000 increase in the selling prices of nearby houses would raise the value of a given sale by about $219. In addition to this extremely useful information, the resulting models were much better in terms of model fit and predictive performance (see Can and Megbolugbe 1997 for details).

Error Checking and Data Cleaning of Large Spatial Data Sets

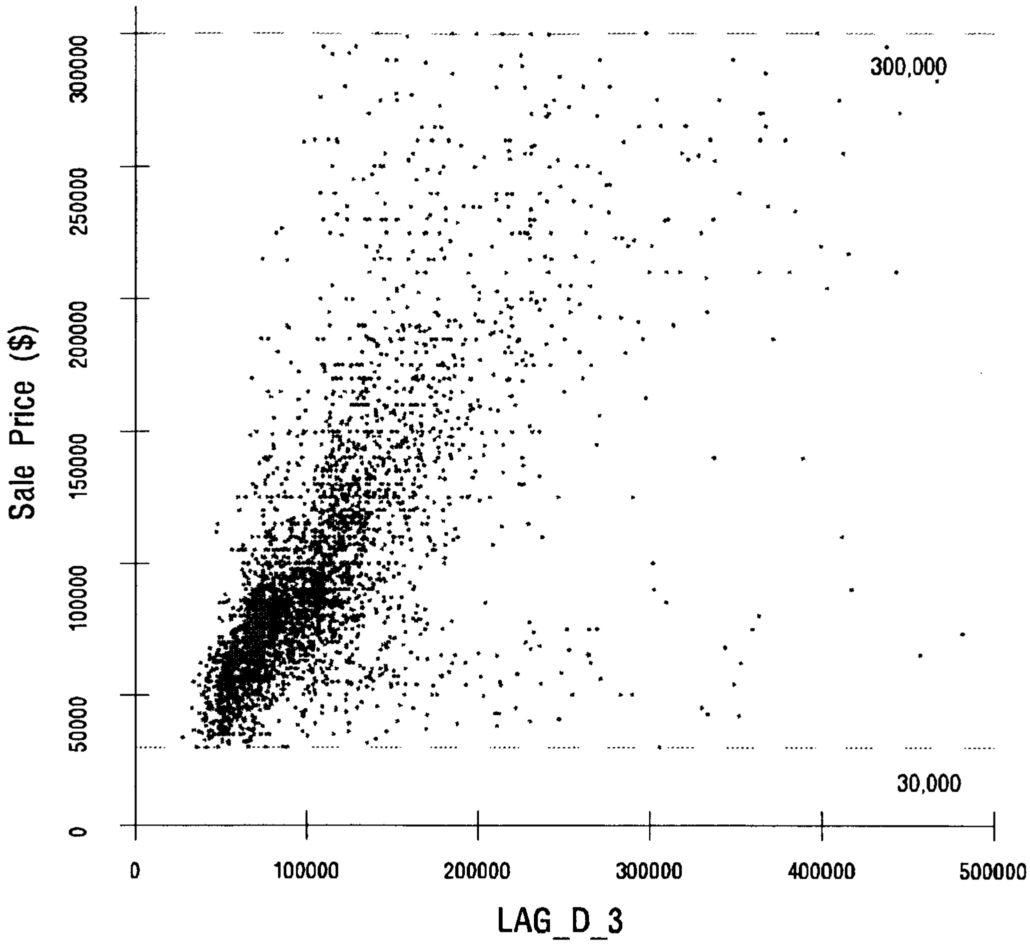
As stated earlier, a spatial outlier is an observation whose value is drastically different ("too high" or "too low") in comparison with its neighbors. The spatial variables constructed in the previous example can also be used to identify spatial outliers in data sets. Figure 5 depicts a transaction of over $1 million on a property (indicated by the arrow) surrounded by neighbors (within 500 meters) with selling prices ranging from $19,000 to $31,000 as computed by LAG_NGH and LAG_D_3. Although it is not unlikely to find a transaction price of this type in Miami, it is quite unlikely to find it located within close spatial proximity to low-priced housing. This probably indicates an error in data collection and/or recording. Therefore, the construction of these lagged sales values is very helpful in isolating these cases. This could not have been identified by just examining the distributional properties of selling prices.

Measurement of Spatial Structure in Mortgage Originations

A common research concern in mortgage finance is the comparison of mortgage originations in reference to the spatial distribution of minority and low-income households. Public concern that the allocation of mortgage credit may be biased on the basis of racial and income composition of neighborhoods has largely prompted this interest.

Anselin and Can (1995) use an exploratory spatial approach to the examination of spatial structure in 1990 mortgage originations for Dade County, FL. Specifically, local spatial association statistics are used to identify areas that exhibit statistically significant clustering of high and low levels of mortgage activity (i.e., "hot spots"). An additional interest is to

Figure 4. **Transaction Prices against Spatially Lagged Prices**



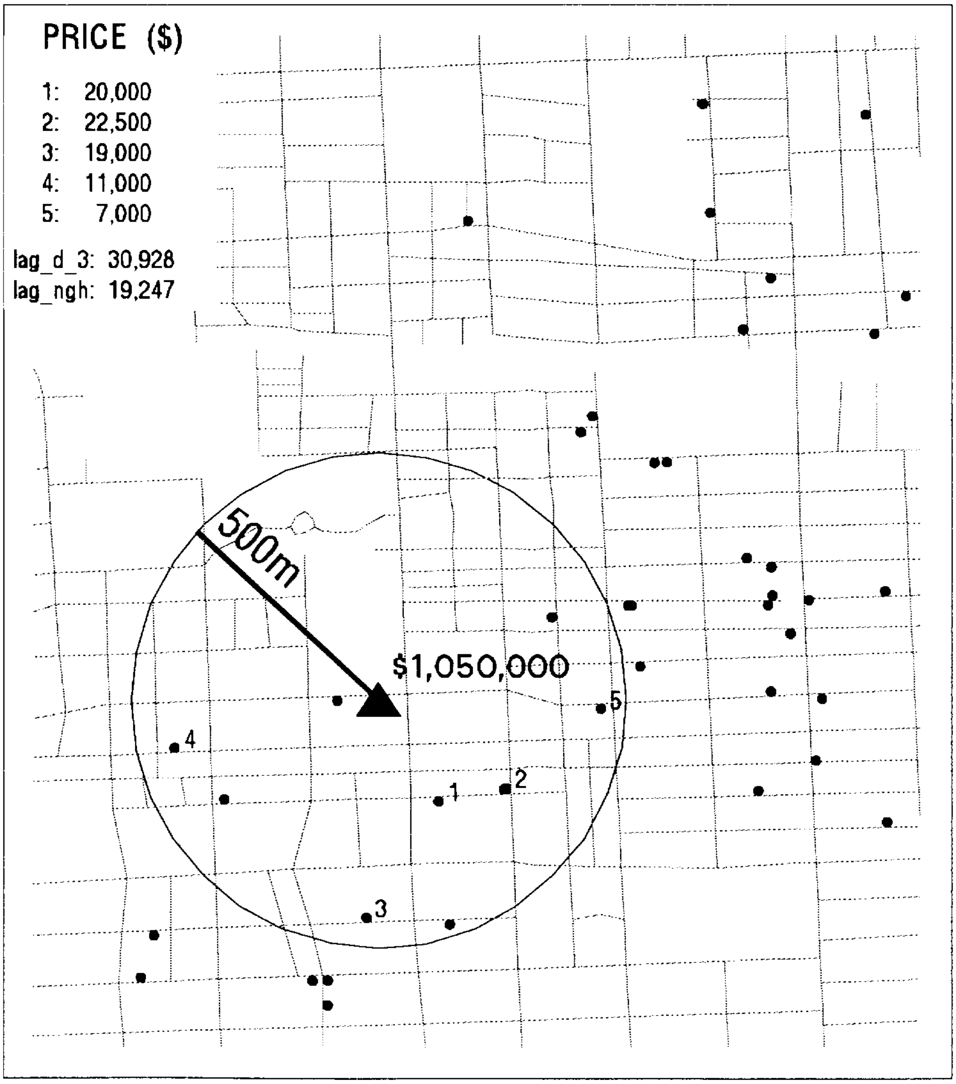
This figure plots LAG_D_3 values against the selling prices of single-family transactions. The data come from a 25 percent random sample of 1990 third-quarter sales ($30,000 to $300,000 range) in Dade County, FL.

Source: Can and Megbolugbe (1997, 210). Reprinted by permission from Kluwer Academic Publishers.

detect spatial outliers (i.e., areas that have significantly different values from their neighbors in space).

The selected local spatial association statistic in this research is the Gi* statistic (see Getis and Ord 1992; Ord and Getis 1995). This statistic is designed to measure the extent of spatial association in attribute values within a specified distance of a given location. Using this statistic, one can tell if the observed attribute value for a given observation is statistically significant in its similarity to its neighbors. The Gi* statistic distinguishes between spatial concentrations of high values and low values. Therefore, it is an extremely useful analytical tool for identifying spatial trends in geographic distributions. The results of the application of the Gi* statistic to 1990 Dade County mean mortgage values ($) (by census block group)

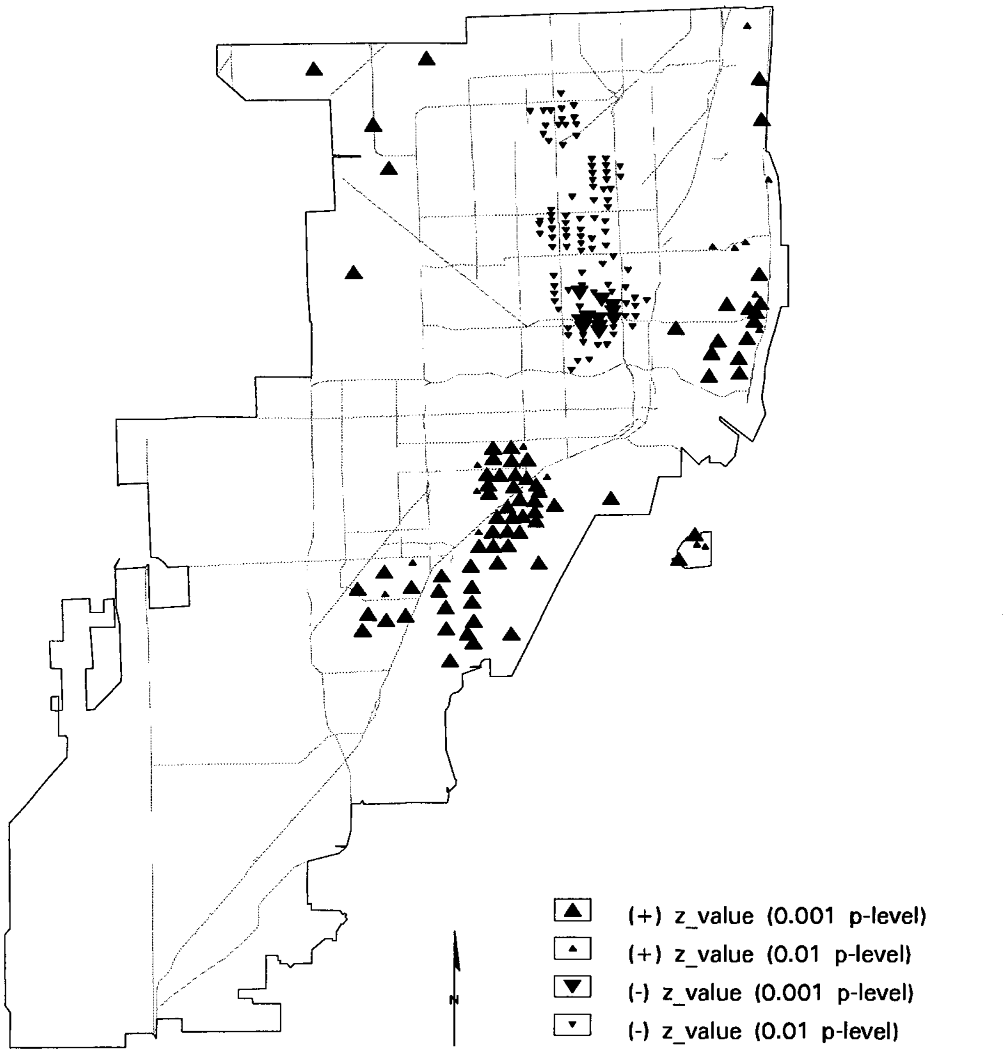
Figure 5. **Identification of Spatial Outliers**



This figure illustrates the large discrepancy between the selling price of a house indicated by the arrow ($1,050,000) and five prior sales within a 500-meter radius ($7,000 to $20,000). The expected selling price for this house would be $30,928 using prior sales within three kilometers of its range and $19,247 using the three most recent sales. Prior sales include all sales that occurred within the last six months.

Source: Can and Megbolugbe (1997, 208). Reprinted by permission from Kluwer Academic Publishers.

Figure 6. **Gi* Statistic for Mean Mortgage Value**



This figure depicts the census block groups in Dade County, FL, that exhibit statistically significant values of the Gi* statistic. The variable is the 1990 average mortgage origination value ($) by census block group.

is displayed in figure 6. The upward-pointing triangles represent the clustering of statistically significant positive values. These indicate significant high mortgage activity clusters. Downward-pointing triangles represent the areas with a statistically significant concentration of low levels of mortgage activity. The most important contribution of these maps is that, starting out with the original distribution of mortgage activity, these are the only areas (census block groups) where there is statistically significant spatial clustering of mortgage activity. The geographic distribution of mortgage activity for the rest of the study area exhibits a more or less random distribution.

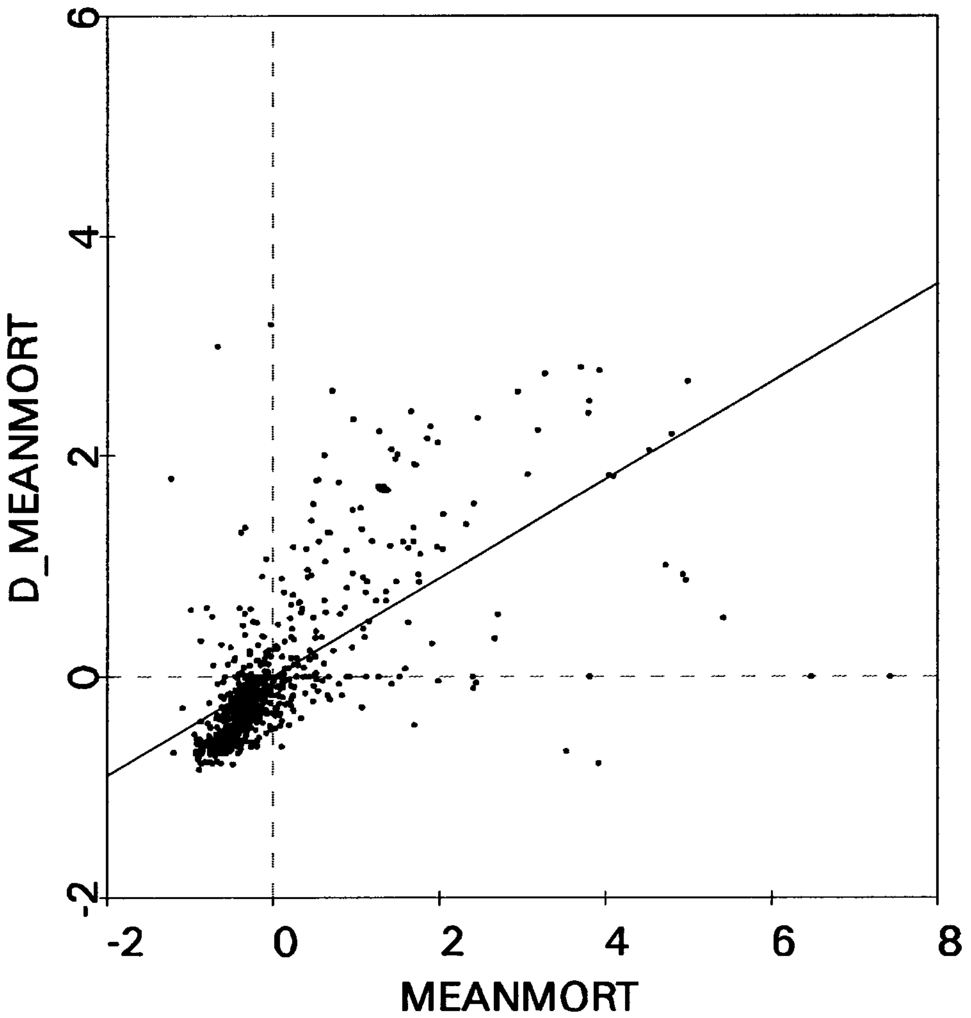
Although the Gi* statistic is useful for identifying local pockets of high and low levels of mortgage activity, it is also of interest to determine if there are any areas that exhibit significantly different levels of activity from their neighbors. An additional spatial analytical tool known as a Moran scatterplot is used for this purpose (Anselin 1995a). A Moran scatterplot uses the standardized values of a local Moran statistic—another local spatial association statistic. The local Moran statistic is conceptually similar to the Gi* statistic with the exception that it distinguishes spatial clustering of similar values (either high or low) from spatial clustering of dissimilar values (e.g., an observation with a high value surrounded by neighbors with low values). A Moran scatterplot arranges the values of local Moran statistics into quadrants of high-high, high-low, low-high, and low-low. Because the values are standardized, this tool is highly useful for identifying outliers (values greater than and less than two standard deviations) for further investigation. Figure 7 shows a Moran scatterplot for the distribution of mean mortgage activity (dollar amounts) for census block groups. The high-low quadrant (lower right) displays observations with high attribute values that are surrounded by systematically low attribute values, whereas the low-high quadrant (upper left) contains low-level observations surrounded by high-level observations. Using this, we can identify census block groups that are surrounded by unusually high or low activity levels. These block groups can be treated as spatial outliers. Careful examination of the Moran scatterplot reveals that spatial clustering is stronger for block groups with low levels of activity than for those with higher levels of activity. This may point to the presence of structurally different processes in high and low mortgage activity regions in the mortgage origination process.

Conclusion

GIS greatly facilitates the spatial analysis of housing and mortgage markets by offering an optimal research environment for exploiting the information content inherent in geographic data sets. As illustrated by the selected research examples, the power of GIS for spatial analysis lies in the integrated research environment it offers for different stages of data analysis and modeling. GIS offers tremendous functionality for visualization of geographic data and greatly facilitates the organization and management of data through its spatial operators, such as spatial overlay and spatial comparisons. The contribution of GIS is especially significant in the data preparation stage in terms of constructing variables on the basis of selected levels of spatial aggregation (e.g., area-based mortgage activity measures from original point distributions). The spatial querying capability of GIS also offers great benefits for visual examinations, error identification, and analytical purposes.

GIS also facilitates the construction of spatial variables on the basis of neighboring attribute values, such as spatial averages of attributes for their neighboring blocks. The ability to

Figure 7. **Moran Scatterplot of Mean Mortgage Values**



This figure plots the standardized local Moran statistic values for census block groups (MEANMORT) against their neighbors within two kilometers (D_MEANMORT). The variable used is the 1990 average mortgage origination value ($) by census block group for Dade County, FL.

compare the distribution of attribute values against their neighbors in geographic space (and time) can provide insights for hypothesis generation as well as for spatial explorations of data sets. This information can be especially useful in investigations of "contagious" processes in neighborhood change. In addition, spatial variables can be used in econometric models as proxies for omitted variables that may be spatially autocorrelated. This can be very important for investigating market dynamics, especially geographic segmentation in housing and mortgage outcomes.

GIS provides the prerequisite locational and topological information for spatial statistical and econometric data analysis and modeling. This information is an essential input for the application of spatial exploratory methods as well as for detecting spatial structure in regression analysis, estimating spatial autoregressive models, and predicting spatial outcomes. As recent research has shown, the incorporation of locational effects improves the precision of coefficient estimates and increases the predictive power of models (see, for example, Can and Megbolugbe 1997). This is especially important for policy formulation because it enables researchers and policy analysts to evaluate the effectiveness of alternative policy tools for controlling undesirable spatial outcomes.

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