MODELING URBAN GROWTH AND LAND USE/LAND COVER CHANGE IN THE HOUSTON METROPOLITAN AREA FROM 2002 - 2030

A Dissertation

by

HAKAN OĞUZ

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

May 2004

Major Subject: Forestry

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ABSTRACT

Modeling Urban Growth and Land Use/Land Cover Change in the Houston Metropolitan Area from 2002 – 2030. (May 2004)

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The Houston-Galveston-Brazoria Consolidated Metropolitan Statistical Area (Houston CMSA) has experienced rapid population growth during the past decades and is the only major US metropolitan area with no zoning regulations. We use SLEUTH, a spatially explicit cellular automata model, to simulate future (2002-2030) urban growth in the Houston metropolitan area, one of the fastest growing metropolises in the United States during the past decades. The model is calibrated with historical data for the period 1974-2002 that are extracted from a time series of satellite images. The dataset consists of four historical urban extents (1974, 1984, 1992, 2002), two land use layers (1992, 2002), five transportation layers (1974, 1984, 1990, 2002, 2025), slope layer, hillshade layer, and excluded layer. Future growth patterns are predicted based on growth coefficients derived during the calibration phase. After calibrating the model successfully, the spatial pattern of urban growth of the Houston CMSA for the period from 2002 to 2030 is predicted.

Within SLEUTH, growth in the Houston CMSA is predominately "organic" with most growth occurring along the urban/rural fringe. Projected increases in urban area from 2002 to 2030 parallel projected increases in population growth within the Houston CMSA. We design three specific scenarios to simulate the spatial consequences of urban growth under different environmental conditions. The first scenario is to simulate the unmanaged growth with no restrictions. The second scenario is to project the moderate growth trend by taking into consideration environmental protection, specifically for agricultural areas, forests and wetlands. The last scenario is to simulate the managed growth with maximum environmental protection. Adjusting the level of protection for different land cover types was found to markedly affect the land use changes in the Houston CMSA. Without any protection on resource lands, Houston CMSA is estimated to lose 2,000 km^2 of forest land by 2030, about 600 km^2 of agricultural land, and approximately 400 km^2 of wetland. Approximately half of all resource land could be saved by the third scenario, managed growth with maximum protection.

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CHAPTER I

INTRODUCTION

The surface of the earth has been altered considerably over the past 50 years by humans especially through urbanization, deforestation, and agriculture. While conversion of available lands to agriculture and rates of deforestation vary across the world, the number of people residing in cities has been consistently increasing. Urbanization has been increasing since World War II, and has shown no sign of slowing and is likely to continue into the twenty-first century. In global scale, 2.5 billion people were living in urban areas in 1950, and the United Nations (1997) estimated that this number will reach to 3.25 billion by 2005.

U.S. cities have developed a different structure compared to their non-U.S. counterparts. Cities in foreign countries have grown more compact and more clustered; while U.S. cities have experienced accelerated outward growth with low density suburbs spreading beyond the boundaries of central cities to form larger metropolitan areas (Hartshorn, 1992). A series of federal and state government policies, massive road projects, and automobile dependent community planning has increased the growth of suburbs in U.S. It is estimated that suburbanization converts more than 22.26 km^2 of farmland and the open space into urban uses each day in the U.S. (Kostmayer, 1989). Continuing urban growth raises concerns over the degradation of the environmental and its ecological health.

This dissertation follows the style of *Remote Sensing of Environment.*

Understanding urban growth and change is critical to city planners and resource managers in these rapidly changing environments (Knox, 1993; Turner et al., 1993). Evaluating the impact of urban growth on the environment and understanding the dynamics of complex urban systems involves modeling and simulation which require innovative methodologies and robust techniques. A number of analytical and static urban models have been developed that are based on diverse theories such as urban geometry, size relationship between cities, economic functions and social and ethnic patterns with respect to city structures. However, these models explain urban expansion and evolving patterns instead of predicting future urban development. For understanding the spatial consequences of urban growth, a dynamic modeling approach is preferred (Meaille & Ward, 1990; Grossman & Eberhardt, 1993; Batty & Longley, 1994). In Geographical Information Science (GISci), dynamic modeling has rapidly gained popularity in recent years among urban planners and geographers as an urban simulation tool. Considerable research efforts have developed different dynamic models for urban and environmental applications (Turner, 1987; Meaille & Wald, 1990; Batty & Xie, 1994a and 1994b; Landis, 1995; Veldkamp & Fresco, 1996; Pijanowski et al., 1997; White & Engelen, 1997; Clarke & Gaydos, 1998; Wu & Webster, 1998, 2000; Li & Yeh, 2000; Sui & Zeng, 2001; Wang & Zhang, 2001). These models, mostly raster, have been developed as either stand-alone packages or subcomponents that are linked with GIS or urban planning software packages. These models can be categorized as either stochastic, such as cellular automata, Markov, and logit, or processes based, such as dynamic ecosystem model. All these models have some common features, such as the use of transition probabilities in a class transition matrix (Turner, 1987; Veldkamp & Fresco, 1996), cellular automata

(White & Engelen, 1997; Batty et al., 1999), and the GIS weighted overlay approach (Pijanowski et al., 1997).

Urban growth models based on cellular automata (CA) are probably the most impressive among all the documented dynamic models in terms of their technological evolution in connection to urban applications. A typical cellular automaton consists of four primary components: cells, states, neighborhoods, and transition rules. Cells are the smallest square units of states. A cell's state will change in regard to its neighboring cells when a set of transition rules is applied. Advantages of cellular automata are their flexibility, their simplicity to complex urban dynamics, their close ties to remote sensing data and GISci (Torrens, 2000). Much effort has been made to improve the construction of cellular automata models especially in the expansion of transition rules to include probabilistic expressions, self-modification, and stochasticity (Torrens & O'Sullivan, 2001). Because of these innovative technological advancements, cellular modeling has grown for an early game-like simulator and evolved into a promising tool for urban growth prediction and forecasting as demonstrated by recent research (Batty & Xie, 1994a; Couclelis, 1997; White & Engelen, 1997; Clarke & Gaydos, 1998; Wu & Webster, 1998; Li & Yeh, 2000; Sui & Zeng, 2001; Silva & Clarke, 2002; Yang & Lo, 2003).

This thesis focuses on modeling urban growth and land use/land cover change in the Houston metropolitan area using the SLEUTH urban growth model. For the past three decades, Houston has been one of the fastest growing metropolises in the U.S. emerging as a commercial, industrial, and transportation urban center of the south. Houston was 6th most populous city in U.S. in 1970, 5th in 1980, and 4th in 1990 and 2000 (U.S. Census

Bureau, 2001). The city has expanded greatly as suburbanization consumes large amounts of agricultural and forest land adjacent to the city, pushing the urban fringe away from the original urban boundary. This uncontrolled suburban sprawl has raised concerns over losses of large areas of primary forests, agricultural land, and open space, and the degradation of the quality of life in this region (Streutker, 2003). The Sierra Club's 1998 Annual Report cited Houston as the second most sprawl-threatened large city in the U.S (www.sierraclub.org, 1998). A lack of city zoning laws has led to large amounts of urban sprawl, resulting in a city of large land area and relatively low population density (Streutker, 2003). Although there are many definitions of sprawl, a central component of most definitions and of most people's understanding of sprawl is the outward spread of a city and its suburbs over more and more rural land at the periphery of an urban area. This involves the conversion of open space (rural land) into built-up, developed land over time. Thus, Houston is an ideal city in which to study environmental consequences of accelerating urban growth and its spatial pattern. This research reports the results of urban growth simulation carried out with a cellular automata model closely coupled with a land transition model. The primary objectives of this research is to simulate the spatial consequences of future urban growth under different planning scenarios considering specific environmental and development conditions so that the best scenario could be adopted for future planning.

A rigorous calibration is required by the model in order to predict future urban growth and land use/land cover change. The second chapter focuses on this calibration procedure undertaken prior to the prediction phase. The third chapter focuses on prediction of urban growth in the study area while the last chapter discusses the effects of predicted land use/land cover change from 2002 to 2030 in Houston CMSA.

CHAPTER II

CALIBRATION OF THE SLEUTH URBAN GROWTH MODEL FOR HOUSTON-GALVESTON-BRAZORIA CONSOLIDATED METROPOLITAN STATISTICAL AREA (HOUSTON CMSA)

The SLEUTH cellular automaton urban growth model has been applied to various metropolitan areas in the U.S. This research calibrated the SLEUTH model for the Houston-Galveston-Brazoria Consolidated Metropolitan Statistical Area (Houston CMSA), which has experienced rapid population growth during the past decades and is the only major US metropolitan area with no zoning regulations.

This study examines differences in the model's behavior when the only metropolitan area with no zoning regulations is captured in the data and modeled to simulate future urban growth. The SLEUTH model is developed with predefined growth rules and uses five parameters to calibrate the model to a particular city. Model input layers are composed of a set of land use, historical urban extents, exclusion, topographic slope, hillshade, and road transportation. Model calibration results show that Houston CMSA has been experiencing "organic" growth, occurring at the urban edges. We believe that lack of zoning regulations plays an important role on the outward growth of urbanization in Houston.

1. Introduction

Natural and human environmental activities such as fire, agriculture, and deforestation have profound impacts upon global systems but the most striking human-induced land transformation of the current era is that of urbanization. At global scale, urbanization is the conversion of natural to artificial land cover characterized by human settlements, workplaces, and other infrastructures such as roads. A complete definition of urbanization can be described as a massive unplanned global experiment affecting increasingly large acreages of the Earth's surface (Alig & Healy, 1987).

Since 1850, while total global population has increased six times, the earth's urban population has increased over 100 times (Hauser et al., 1982). Aided by the industrial revolution, cities have gone from being a minor feature on our planet to a major one. The impact of urban land on economic and environmental systems is immense compared with its spatial extent (Clarke et. al., 1997).

The world's urban areas are gaining an estimated 67 million people per year – about 1.3 million every week (UN, 2002). By 2030, approximately 5 billion people are expected to reside in urban areas – 60% of the projected global population of 8.3 billion (UN, 2002). Substantial growth in cities first occurred in Western Europe, America, Japan, and China but in the latter part of this century has spread throughout Asia, South America, and Africa. Urban growth at the global scale shows no sign of slowing and is occurring even in nations where population growth has stabilized (Clarke et al., 1997). From 1980 to 1990, eight of America's twenty largest metropolitan areas grew by at least 20% (Knox, 1993).

Measured urban extent underestimates the full impact of cities as they require building materials, food, water, goods and services from their surroundings, converting natural land to agriculture, and agricultural land to urban land uses. According to Pond and Yeates's (1994) estimation, in a growing country such as Canada, in addition to the actual urban area, 20% of the land was in the process of the urban transition and 2% was in ex-urban uses, fully dependent on the urban areas.

Communities across the nation are choosing to complement traditional planning approaches with analytical decision making tools to help them plan their sustainable futures. Today, with recent technological advances, a number of technologically-based tools are available for communities to use in assessing the impacts of various planning decisions and to help balance the demands of growth, environmental sustainability, and quality of life needs. Technologically-based tools such as models and geographic information systems (GISs) can provide increased clarity on probable or alternative outcomes, and thus enable decision makers to more effectively use traditional planning tools.

Regional growth management strategies involve planners, technical committees, and politicians. Planning agencies use urban modeling techniques to address growth management issues. Models can aid in evaluating future development scenarios and the potential consequences of those alternatives.

The modeling of urban development may serve as one part of a decision support tool, which is able to give insights in the consequences of the realization of particular plans to the city planners. For an assessment of environmental impact, the modeling of urban growth becomes important to both public institutions and industry. Modeling is essential for the analysis and particularly for the prediction of the urban growth (Silva & Clarke, 2002).

Population dynamics is quite important since a reallocation of land is required to accommodate the world's increasing population. In 1995, the number of people worldwide living in settlements of five thousand or more reached 51 percent, jumping from 29 percent in 1950 (Clarke & Gaydos, 1998). Regional, national, and worldwide land consumption rates will continue to increase as population numbers grow.

Before 1900, the City of Houston grew slowly, increasing to a population of 45,000 in that year. Throughout the nineteenth century, Galveston was the economic center of Texas. Houston's growth began with two events in early 1990s: the Galveston hurricane in 1900 and the discovery of large oil reserves at Spindletop in 1901, ninety miles east of Houston (Vojnovic, 2003). Today, Houston is the fourth largest city in the U.S. with a population of approximately 1.9 million. What makes the Houston metropolitan area an ideal place to do urban modeling is that even though Houston has many characteristics that are typical of large metropolitan areas, it also has distinctive qualities not generally associated with major U.S. urban centers, in particular its lack of zoning regulations.

2. Urban Modeling and SLEUTH

How global models reflect local characteristics is a major challenge if modeling is ever to move beyond case study comparisons (Silva & Clarke, 2002). Thus, an effort should be directed to an understanding of how increased spatial resolution improves sensitivity to local factors. The first generation of computer-based urban models was critical due to their specificity to the cities for which they were developed (Lee, 1973).

The current generation of computational models, including SLEUTH urban growth model, used very different methods to escape this legacy. The calibration step of SLEUTH involves a multistage optimization of the model to a specific parameter range so that we can learn about global properties from the local behavior of SLEUTH's parameters.

Growth dynamics have measurable dimensions. Urban sprawl is associated with suburbanization, automobile dependency, and highway investments. A set of variables and parameters supports urban and regional models. Depending on which variables are required by the model, elements can be defined and assigned behavior and significance, for example the importance of urban extent, parks, forests and agriculture. These general characteristics of urban change are incorporated by most urban and regional models.

General and known characteristics are usually accepted by urban models that include local variation for a specific area such as employment, transportation, and population growth. Alternatively, a model could also include these general characteristics but give the user the freedom to incorporate local variation in a way that allows the model to be reused from city to city. The problem would be how one could apply a model developed for a specific urban context in another. The answer to this is to develop a general-purpose model and to use a technique in modeling called "calibration."

Modeling geographic systems with cellular automata is relatively new. In the 1980s, the approach was first related to planning and has seen great interest in the last decade (Batty & Longley, 1994; Batty, Xie, & Sun 1999; Couclelis, 1985, 1997). Cellular automata are well suited to model complex dynamical systems composed of large numbers of individual elements linked by nonlinear couplings (Openshaw & Openshaw, 1997). The cellular automata's versatility is responsible for the growth in the applications to the diverse fields of urban growth analysis (Clarke & Gaydos, 1998; Clarke et al., 1997; Landis & Zhang, 1998), regional economics, demographics and land use (White & Engelen, 1997), and location choices (Roy & Snickars, 1998).

In essence, a model is a simplified representation of a real-life system. Ford (1999) defines a model as a simplified representation of part of the real world or its systems that retain enough aspects of the original system to make it useful to the modeler. In modeling, observations are generally transposed into a structure of model elements and their relations that are then converted into equations and coded in a manner amenable to running as a simulation. Understanding the complexity of urban landscapes and their behavior helps planned human interventions benefit society and the environment. The rapid spread of geographic information into planning is mostly caused by modeling and simulation (Birkin, Clarke, Clarke, & Wilson, 1996; Scholten & Stillwell, 1990; Stillwell, Geertman, & Openshaw, 1999).

3. Computation Approaches to Modeling Urban Growth

The implementation of regional growth management strategies involves technical committees, planners, politicians, and public participation. Urban modeling techniques are one method that is used by planning agencies to address growth management issues. Models can aid in evaluating future development scenarios and the potential consequences of those alternatives. Urban modeling is generally concerned with designing, building and operating mathematical models of urban phenomena, typically for cities and regions (Batty, 1976). According to Batty (1976) there are two main reasons for the development of urban models: first is their role in helping scientists to understand urban phenomena through analysis and experiment, and second is that their importance in helping planners, politicians and the community to predict, prescribe and develop the probable urban future.

A model is a simplified representation of a real-life system by representing reality with only those variables that truly affect the behavior of the system, and by clarifying the relationships and interdependences between those variables; the assumed "real world" is broken down into a form amenable to analysis (Taha, 1976). Modeling is essential for the analysis and the prediction of urban growth. Yet the successful application of a model in one particular geographical area does not necessarily imply its successful use in another area because of local characteristics, such as zoning regulations. Testing the efficacy of the model's algorithms at capturing and simulating the land transformations that are specific to a place is just as important to model urban growth across locales (Batty & Xie, 1994b; Clarke, Hoppen, & Gaydos, 1996; Li & Yeh, 2000). Many types of models have been used by a host of diverse professionals to simulate various aspects of the urban environments (EPA, 2000). Transportation engineers use models to project the number of commuters that will travel by car versus those who will make their trips by mass transit; economists use models to represent the flow of dollars within a regional economy; and biologists use models to describe the impact water pollutants will have on living organisms.

Traditional urbanization models have attempted to predict either the economic and size relationships between cities or the social and economic patterns within the city limits (Clarke et al., 1997). Christaller's central place theory, Zipf's rank-size rule, Alonso and

Muth's land-use transition model in landscape economics are of the first type (Wilson, 1978). Wong and Fotheringham have introduced a reinterpretation of the fractal model as a mechanism behind at least Zipf's rule. The Alonso and Muth model is spatial, modeling the demand curve relationship for land as a function of linear distance from a central marketplace. Other models have focused on social and ethnic patterns and less on geometry and economics as determinants of city structure (Jacobs, 1961). Many site-specific urban models have been developed for a particular region, mainly for use by urban planners. A well-known example is the BASS II which predicts urbanization at the regional scale for the San Francisco Bay area (Landis, 1992).

The SLEUTH cellular automaton urban growth model was developed by Keith Clarke to model and predict regional patterns of urbanization. The rules of the model are more complex than those of a typical cellular automaton (CA) and involve the use of multiple data sources such as road networks, topography, and existing settlement distributions (Clarke et al., 1997).

Although both BASS II and the SLEUTH model predict regional urban growth, they differ vastly in their level of detail, data requirements, and applications. BASS II is developed to the specifics of the San Francisco Bay Area; however the growth rules in the SLEUTH model are designed to be general enough to allow it to be applied to other regions.

A few theories have examined the rural to urban transition as a physical process, except for the outer edge expansion of the rural/urban boundary. For example, the urban edge is largely ignored in Christaller's model because the model seeks to predict the point provision of goods and services on a spatial tessellation of hexagonal market areas. The physical characteristics of urban expansion remained ill defined until the work of Batty who, together with his colleagues, used a dynamic systems model called "diffusion-limited aggregation" (DLA) to model urban expansion (Batty and Longley, 1994).

Batty's dynamic systems model also lends itself to the techniques of cellular automata (CA) which is a simple and easily automated method for generating simulations (Couclelis, 1985). Application of computational CA models to predict urban areas was pioneered by Roger White (White & Engelen, 1993). A classical CA approach is used by White's models. The modeling technique involves:

- reduction of space to a grid of square cells
- establishment of an initial set of conditions
- establishment of a set of transition rules between iterations
- recursive application of the rules in a sequence of iterations of the spatial pattern.

Development of such a model involves: (1) determining the rules from an existing system; (2) calibrating the CA to give results consistent with historical data; and (3) predicting the future by allowing the model to continue to iterate with the same rules (Clarke et al., 1997).

White used simple urban growth for some world cities and a more complex island model with self-modification and multiple land uses linked by rules. In self-modifying cellular automata however, the rules are allowed to change as the system grows or changes. For example, if all flat urban land is used by existing settlements, the rules penalizing building up slopes can be eased to reflect land pressure. During the last decade, urban modeling with cellular automata became widespread. White and Engelen (1992a) have extended their land use model to an entire island; Batty and Xie (1994) modeled the historical growth of Cardiff, Wales, and Savannah, Georgia using their DLA model. Cellular urban modeling is described in a recent work as a new school of urban modeling, although one with roots in the work of von Neumann (1966), Wolfram (1994), Hagerstrand (1967), and Tobler (1979). The research used here is a modified version of a CA which features the ability to modify parameter settings when the growth rate of the system exceeds or falls below critical threshold to model urban growth in the Houston Metropolitan area.

This paper focuses on calibrating the SLEUTH model, formerly the CLARKE Cellular Automaton Urban Growth Model (Clarke & Gaydos, 1998; Clarke, Hoppen, & Gaydos, 1997) for Houston-Galveston-Brazoria Cosmopolitan Metropolitan Statistical Area (Houston CMSA). SLEUTH is composed of first letters of the input layers: Slope, Land Use, Exclusion, Urban Extent, Transportation, and Hillshade. SLEUTH is a self-modifying cellular automaton model. Self modification of the rules changes the control parameters when modeled growth rates are exceeded (Clarke et al., 1997). In SLEUTH, self-modification is equivalent to adaptation or evolution, and the calibration method lets the model "learn" its local setting over time (Clarke et al., 1996). During the calibration of the five control parameters, this learning is quantified by the variation.

The United States Geological Survey (USGS) has a long tradition of studying land use and land cover, both current and potential. As a contribution to the U.S. Global Change Research Program, the USGS initiated a human-induced land transformations project (HILT) to understand the urban transition from a historical perspective and SLEUTH, was developed by Keith Clarke (Clarke et al., 1997) as part of this study.

The SLEUTH model was applied to the Houston-Galveston-Brazoria Consolidated Metropolitan Statistical Area (Houston CMSA). Houston CMSA consists of eight counties: Brazoria, Chambers, Fort Bend, Galveston, Harris, Liberty, Montgomery, and Waller. The urban pattern is mostly concentrated at the main nuclei, the City of Houston.

Urban expansion in SLEUTH is modeled in a spatial two-dimensional grid and the basic growth procedure is a cellular automaton. Five coefficients control the behavior of the cellular automaton. These are diffusion coefficient, breed coefficient, spread coefficient, slope resistance coefficient, and road-gravity coefficient. Four types of growth are possible in the model: spontaneous, diffusive, organic, and road influenced growth.

4. The Role of GIS in Urban Modeling

Despite the efforts to build cellular modeling functions into GIS directly (Takeyama & Couclelis, 1997; Park & Wagner, 1997) and the suitability both of specific GIS packages and of control languages and cellular automata, it is likely that most numerical modeling especially that requiring exhaustive or rigorous calibration, will need to parallel the GIS rather than work within software (Clarke & Gaydos, 1998). GIS is quite helpful in providing real-world environments for cellular automata, yet the full integration of cellular automata tools directly into GIS has not yet been achieved (Park & Wagner, 1999). Research on geographic modeling with cellular automata is still exploring and building upon modeling capabilities (Clarke & Gaydos, 1998; Li & Yeh, 2000).

The integration of GIS and modeling has been well documented (Wilson, 1995; Goodchild et al., 1996; Wagner, 1997). Anselin et al. (1993) classified and described the relation of modeling to GIS as one of "loose coupling." Park and Wagner (1997) implemented a tight coupling of several cellular automaton models including SLEUTH. GIS serves at least three important roles in the context of SLEUTH model that none of which could be called tight coupling.

The first of these roles is data integrator. In all initial applications, data were either already available as GIS coverages, or were captured by scanning and digitizing (Crawford-Tilly et al., 1996). Although the coverages existed, new map extents, projections, and grid resolutions were required, and the GIS ensured co-registered model input. All further modeling and analysis depended on this essential first step, what Chrisman has called a "universal requirement" for GIS (Chrisman, 1997). Data layers were each raster grids. Second, GIS allows the results to be visualized. This was the weakest part of the loose coupling. Third, the outputs were reintroduced into the GIS data sets available for application, allowing further analysis and decision making. This part favors the use of loose coupling.

5. The Role of Calibration in Modeling Urban Growth

One of the most important elements of successful model application is calibration (Silva & Clarke, 2002). Calibration allows users to narrow down the resulting values of the model to reflect the characteristics of locale. Birkin et al. (1996; p. 93) states that "the key component of the modeling process […] is calibration: the process by which numerical values are assigned to the model parameters in such a way that the model accurately reproduces the real patterns." The publications of calibration results document the importance of calibration (Batty & Xie, 1994b; Birkin et al., 1996; Clarke et al., 1996;

Landis & Zhang, 1998; Silva & Clarke, 2002). The model's applicability, verifiability and robustness are closely correlated by the calibration phase.

6. The SLEUTH Model

6.1. Introduction

The SLEUTH urban growth model is a cellular automaton (CA) model that has been widely used to model urbanization throughout various regions of the United States and the world (Solecki et al., in press; Yang & Lo, 2003; Esnard & Yang, 2002; Silva & Clarke, 2002; Clarke & Gaydos, 1998; Clarke et al., 1997). The model was originally developed by Keith Clarke, University of California at Santa Barbara (Clarke et al., 1997). The model has the ability to model urban/non-urban dynamics as well as urban/land use dynamics. Both abilities have led to the development of two subcomponents within the model; an urban growth model (UGM), and a land use/land cover change model (Land Cover Deltatron or LCD). The model uses same calibration routine for each of the subcomponent. If only urban growth is analyzed, then LCD is not activated by the model. LCD is activated when land use is being analyzed.

SLEUTH is a cellular automaton model written in the C programming language and developed with sets of predefined growth rules that are applied in a set of nested loops. The outer control loop executes each growth "history," retaining cumulative statistical data, while the inner loop executes the growth rules for a single year. The growth rules are applied on a cell-by-cell basis and the array is synchronously updated at the end of each year. The modified array forms the basis for urban growth in each succeeding year. Potential cells for urbanization are selected at random and the growth rules evaluate the properties of the cell and its neighbors such as whether or not they are already urban, what their topographic slope are, how close they are to a road. This study utilized Version 3.0 of the SLEUTH model obtained from the Gigalopolis website (http://www.ncgia.ucsb.edu/projects/gig/). The model's general structure is illustrated in Fig. 2.1. It has four main components: input, parameter initialization, growth rules application, and output. Similar to other predictive models, this model requires some input data in order to initiate the simulation. Version 3.0 of this model requires an input of six types of eight-bit GIF format data if land use change is being analyzed: urban extent, land use, road, excluded, slope, hillshade.

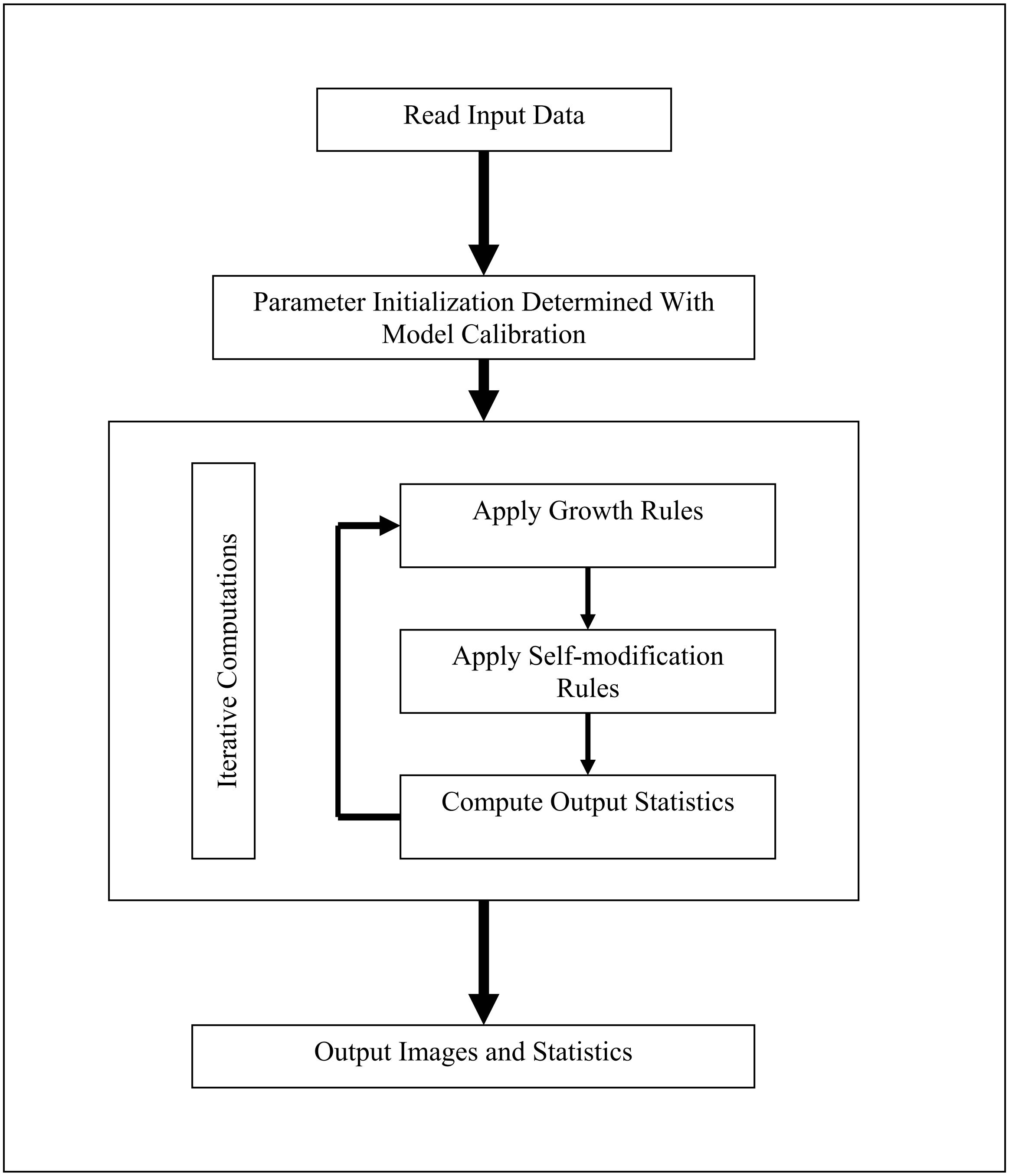

Fig. 2. 1 General structure of the SLEUTH model (Yang & Lo, 2003)

SLEUTH begins with a set of initial conditions. A set of growth or decision rules is then applied to the data in order to simulate urban growth (Gigalopolis, 2003). These rules are:

1) Spontaneous growth

2) Diffusive (New Center) growth

3) Organic (Edge) growth

4) Road-influenced growth

How these growth rules are applied depend on five growth control parameters (coefficients) (Gigalopolis, 2003):

1) Diffusion (dispersion) coefficient

2) Breed coefficient

3) Spread coefficient

4) Slope coefficient

5) Road-gravity coefficient.

The number of Monte Carlo iterations to be specified is a very important parameter in terms of determining the computation time and the simulation error level. The likelihood of urbanization throughout the growth process depends on two suitability measures. The suitability is defined by an exclusion layer (e.g. water) and by slope. Urbanization cannot occur on slopes above 21 percent (Gigalopolis, 2003).

Spontaneous growth defines the occurrence of random urbanization of land. This means that any unurbanized cell on the lattice has a certain (small) probability of becoming urbanized in any time step. New Spreading Center growth determines whether any of the new, spontaneously urbanized cells will become new urban spreading centers.

Organic or edge growth defines the growth that stems from existing spreading centers. This growth propagates both the new centers generated in New Spreading Center growth step, and the more established centers from earlier times. Road-Influenced growth is determined by the existing roads as well as the most recent urbanization (Silva & Clarke, 2002).

Diffusion (dispersion) coefficient controls the number of times a pixel will be randomly chosen for possible urbanization. Diffusion coefficient controls the spontaneous and road-influenced growth. Breed coefficient determines the probability of a spontaneous growth pixel becoming a new spreading center. This is used by new spreading center growth and road-influenced growth. Spread coefficient controls the probability that any pixel that is part of a spreading center will generate an additional urban pixel in its neighborhood. Slope coefficient influences the likelihood of settlement exceeding up steeper slopes. Slope coefficient affects all growth rules in the same way. Road-gravity coefficient attracts new settlements toward and along roads. This coefficient controls the road-influenced growth (Clarke et al., 1998).

The process of urban growth is not linear. This is easily demonstrated by looking at the number of homes built over time, there are clear cycles of booms and busts – largly tied to urban and regional economics. SLEUTH also utilizes a second level of growth rules termed self-modification rules to account for these cyclic periods of growth. The self-modifying rules of the model are prompted by an unusually high or low calculated growth rate. In SLETUH, the growth rate is computed by comparing the number of new cells urbanized to the total existing urban area during a single time period. Critical high and critical low growth thresholds, respectively, defined by the model, will initiate an increase or decrease in diffusion, breed, and spread coefficients. An increase in the diffusion, breed, and spread coefficients represents the tendency of an expanding urban system to grow even more rapidly (Fig. 2.2). A decrease in the diffusion, breed, and spread coefficients causes growth to slow (Fig. 2.2).

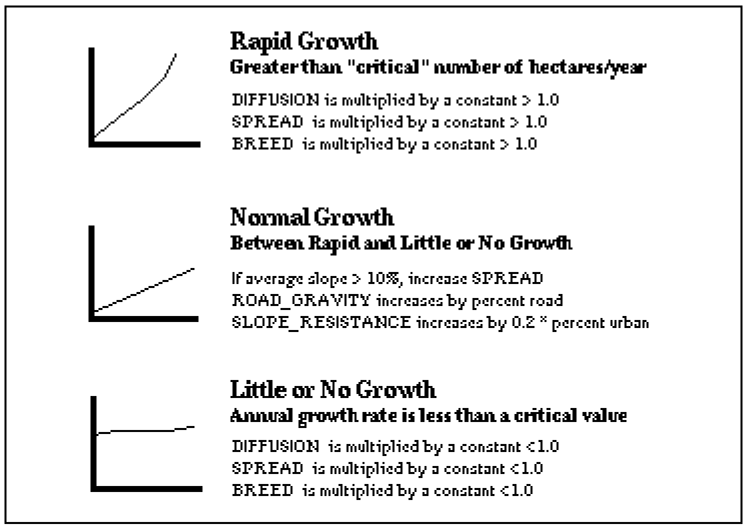

Fig. 2. 2 Growth patterns under the self-modification rules (Gigalopolis website, http://www.ncgia.ucsb.edu/projects/gig/)

The other two self-modification rules affect the road gravity coefficient and the slope resistance coefficient. The road gravity coefficient is increased as the road network enlarges, representing increased accessibility to the area. The slope coefficient is decreased as the percentage of land available for development decreases, allowing expansion to move up steeper slopes. Under self-modification, the coefficient values during a model run increase most rapidly in the beginning of a growth cycle, when many cells are open for urbanization, and decrease as urban density increases in the region and expansion declines (Clarke & Gaydos, 1998).

Both growth rules and self-modification rules are the core of the model. They reflect the universal understanding of the process of urbanization, but, to be successfully used, they need to be refined to the locale. To describe the behavior of the system correctly and predict its possible futures, the model needs to be calibrated (Silva & Clarke, 2002).

We installed and compiled the SLEUTH model (version 3.0) on a SUN UNIX workstation. Fig. 2.3 illustrates the procedure for the model implementation in this project, which consists of four main components: 1) developing input dataset, 2) model calibration, 3) model prediction (simulation), and 4) model output.

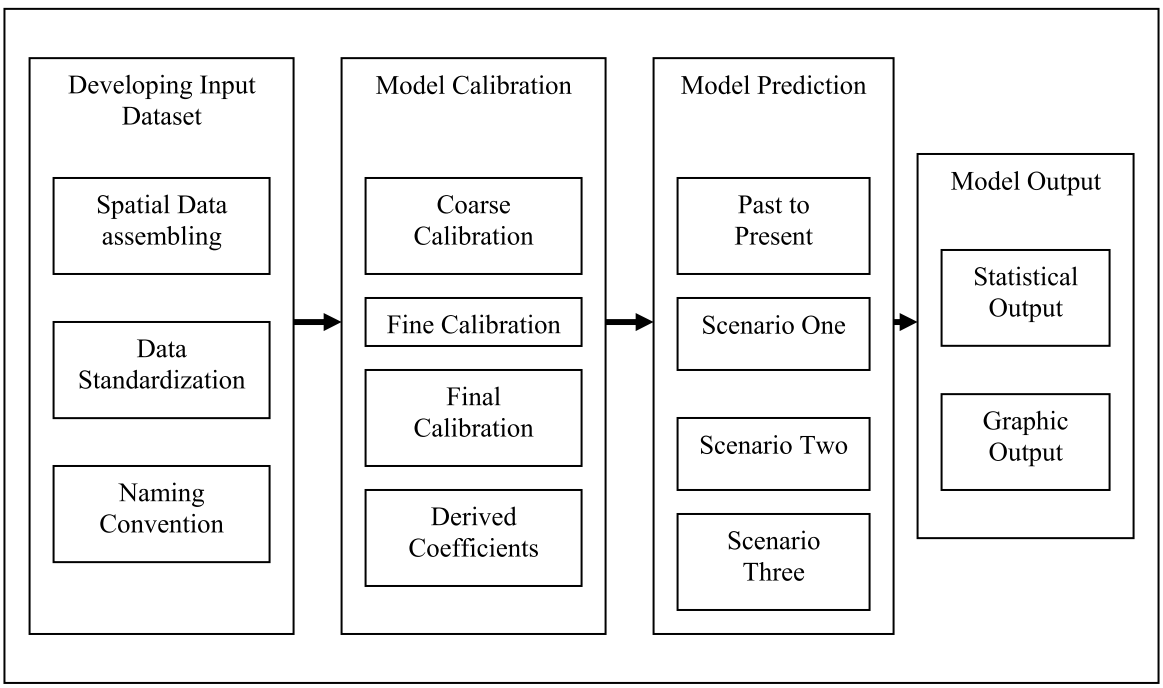

Fig. 2. 3 General procedures for the SLEUTH model implementation (Yang & Lo, 2003)

6.2 SLEUTH Inputs

Six types of input information are required to successfully run SLUETH. These include: 1) urban extent, 2) land use, 3) transportation, 4) excluded areas, 5) slope, and 6) hillshade. For statistical purposes, the model requires urban extent from at least four time periods. It also requires at a minimum transportation layers from two different years, a slope layer and a layer indicating which areas should be excluded from urbanization. A hillshade layer serves as a graphical background. Land use from at least two time periods is also required for the land use change analysis.

1992 land use data is downloaded from U.S. Environmental Protection Agency's (EPA) National Land Cover Dataset (NLCD) website. The data was in GeoTIFF format and had 30 meters spatial resolution. Original projection was in Albers Conical Equal Area. The downloaded GeoTIFF data covered all of Southeast Texas, so it was subset to our study area. The classification schema was recoded based on following format in order to match our 2002 land use classification schema (Table 2.1):

Table 2. 1
The NLCD classification scheme

11	-	Open water
12	-	Perennial Ice/Snow
21	-	Low Intensity Residential
22	-	High Intensity Residential
23	-	Commercial/Industrial/Transportation
31	-	Bare Rock/Sand/Clay
32	-	Quarries/Strip Mines/Gravel Pits
33	-	Transitional
41	-	Deciduous Forest
42	-	Evergreen Forest
43	-	Mixed Forest
51	-	Shrub land
61	-	Orchards/Vineyards/Other
71	-	Grasslands/Herbaceous
81	-	Pasture/Hay
82	-	Row Crops
83	-	Small Grains
84	-	Fallow
85	-	Urban/Recreational Grasses
91	-	Woody Wetlands
92	-	Emergent Herbaceous Wetlands

Following transformation is used to group NLCD classes into general 6-class Category I (Table 2.2):

Table 2. 2
The transformation table for NLCD classification

NLCD Classification		Category I
21, 22, 23	=======>	1 (urban)
51, 61, 71, 81, 82, 83, 84, 85	=======>	2(agriculture)
41, 42, 43	=======>	3 (forest)
11	=======>	4 (water)
91, 92	=======>	5 (wetland)
31, 32, 33	=======>	6 (other)

Because of the processing (CPU) time requirement of the SLEUTH model, we reduced the data resolution from 30 meters to 100 meters. The base resolution for the project was chosen as 100 meters due to CPU limitations. Thus, we resampled all of our data to 100 meters using Nearest Neighbor technique. Nearest Neighbor technique is chosen for the reason of not averaging the neighboring cells instead assigning the nearest cell to the target cell during resampling. The further data processing has been applied to the data. Using 7x7 kernel-size, we applied “majority” function to make the image smoother.

For 2002 land use data layer, we have purchased three Landsat ETM scenes (path25row39, path25row40, path26row39) from the United States Geological Service (USGS). The data were had 30 meters spatial resolution and were in Albers Conical Equal Area projection. Then the images were classified based on 6 general classes above (Table 2.2) utilizing ISODATA unsupervised classification technique and then mosaiced together to form one image.

Four Landsat MSS Triplicate scenes (path25row39, path25row40, path26row39, path26row30) were purchased from the USGS Land Processes Distributed Active Archive Center. From the triplicate data, only 1974 and 1984 MSS scenes were used. The original images were in UTM projection, so they are reprojected to Albers Conical Equal Area. The data have 60 meters spatial resolution. These images were then classified to urban/nonurban using ISODATA unsupervised classification technique and then mosaiced together to create urban extent layers for the study area.

1990 and 1999 road shapefiles are acquired from Houston-Galveston Area Council (H-GAC) for our study area. Using 1974, 1984, 1990, 2002 Texas Department of Transportation (TxDOT) highway maps, we filtered out roads that were not highway from the original H-GAC road shapefiles. Then these newly created shapefiles for above years were converted to raster format with 100 meters resolution. We also created a road layer for TxDOT's future road plan, Trans-Texas Corridor Plan. This Corridor is planned to be ready by 2025. A JPEG image of the Trans-Texas Corridor Plan was acquired from TxDOT. The image then was georeferenced using a Texas county map. The image then was subset to our study area. Using Geographic Information System (GIS), the image then was edited to create 2025 road layer.

National Elevation Data (NED) data for our study area counties were downloaded from Texas Natural Resources Information System website. Original data were in Arc Interchange (e00) format, so data were imported into GRID format, and then reprojected to Albers Conical Equal Area. Then these are resampled to 100 meters and mosaiced together to form Digital Elevation Model (DEM) for our study area. The SLEUTH model requires slope to be in percent, thus Percent Slope and Hillshade are derived from this DEM dataset.

Floodplain data was provided by Federal Emergency Management Agency. This dataset did not however include floodplain for Harris County. Floodplain data for Harris County was provided by Mr. John S. Jacob at Texas Coastal Watershed Program. The floodplain data was used in excluded layer. City and State Parks data were downloaded from the Texas General Land Office website. Forest, agriculture, wetland and water were acquired from 2002 land use layer to be used in excluded layer along with parks, floodplain data. Excluded layer is reclassified to weigh cell values to be used in calibration mode in SLEUTH model. Resulting excluded layer had following values for their respective classes as seen in Table 2.3:

Table 2. 3
Excluded layer with respective values to be used in calibration phase in SLEUTH model

	EXCLUDED FROM DEVELOPMENT (in percent)						
	Agriculture	Forest	Floodplain	Wetland	Parks	Water	Unclassified
Cell Values	40	40	40	60	90	100	100

1992 and 2002 land use/land cover data were reclassified as urban/non-urban to develop 1992 and 2002 urban extents to be used in the model along with 1974 and 1984 urban extents. Then we assigned 100 for urban pixels and 0 for non-urban for each urban extent year. For road data (1974, 1984, 1990, 2002, and 2025), we followed the same procedure above and assigned 100 for road pixels and 0 for non-road.

Following dataset was created when input dataset preparation step was finally over (see Table 2.4) and all data is in raster format.

Table 2. 4
Input data sources and years for SLEUTH model

SLEUTH Inputs	Input Data Sources	Data Types	Input Data Years
Urban	Landsat MSS, ETM	Raster	1974, 1984, 1992, 2002
Lulc	Landsat TM	Raster	1992, 2002
Road	Shapefiles	Converted to Raster	1974, 1984, 1990, 2002, 2025
Excluded	Landsat TM	Raster	N/A
Slope	NED	Raster	N/A
Hillshade	NED	Raster	N/A

However, the SLEUTH model requires all input data to be in grayscale 8-bit GIF format. Therefore, we converted all data into grayscale 8-bit GIF format using GIS and Image Processing Software. The model also requires a special naming format for the input dataset, so all input data was then applied to appropriate naming format.

1974 was the seed year, while the other years provided control data against which the model output was compared. Two land use layers 1992, and 2002; and five road layers 1974, 1984, 1990, 2002, and 2025 were used in this project. However, 2025 road data layer was not included during calibration phase; instead it was used in the prediction phase of the model.

An accuracy assessment has been made between our 2002 land use and Houston-Galveston Area Council's (H-GAC) 2002 land use for the study area. Table 2.5 illustrates confusion matrix (Congalton, 1991; Congalton & Mead, 1983) output based on the accuracy assessment for the Houston CMSA. As shown in Table 2.5, kappa coefficient and overall classification accuracy came out as 0.82 and 87.33% respectively. User's accuracy represents the probability that a given pixel will appear on the ground as it is classed (the percentage correct for a given column divided by the total for that column), while producer's accuracy represents the percentage of a given class that is correctly identified on the map (the percentage correct for a given row divided by the total for that row). User's and producer's accuracy can also be expressed in terms of commission and omission errors. Error of commission indicates pixels that were placed in a given class when they actually belong to another, while error of omission indicates the percentage of pixels that should have been put into a given class but were not (Congalton, 1991). This indicates that our 2002 land use map is within acceptable accuracy range.

Table 2. 5
Confusion matrix and kappa coefficient for the 2002 land use/land cover

	Reference Data Points (Houston Galveston Area Council LULC 2002 (HGAC LULC 2002))								
	Urban	Agriculture	Forest	Water	Wetland	Other	Row Total	Producers Accuracy	Users Accuracy
Urban	28	5	1	1	1	0	36	93.33%	77.78%
Agriculture	1	117	4	0	4	0	126	89.31%	92.86%
Forest	1	5	67	0	7	0	80	89.33%	83.75%
Water	0	0	1	35	0	0	36	97.22%	97.22%
Wetland	0	2	2	0	15	0	19	53.57%	78.95%
Other	0	2	0	0	1	0	3	---	---
Column Total	30	131	75	36	28	0	300		

Overall Classification Accuracy = 87.33%
Kappa (Khat) Coefficient = 0.82

HOUSTON CMSA LULC 2002

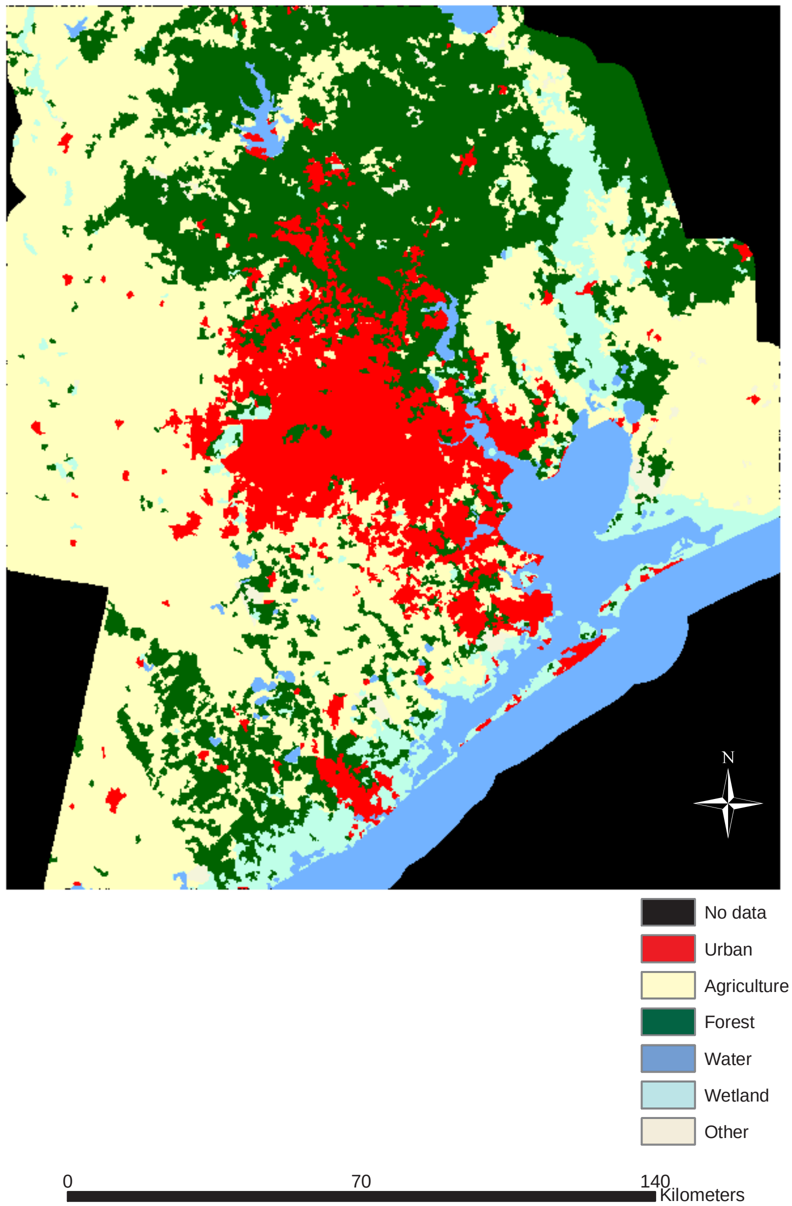

Fig. 2. 4 Our 2002 Houston CMSA land use/land cover

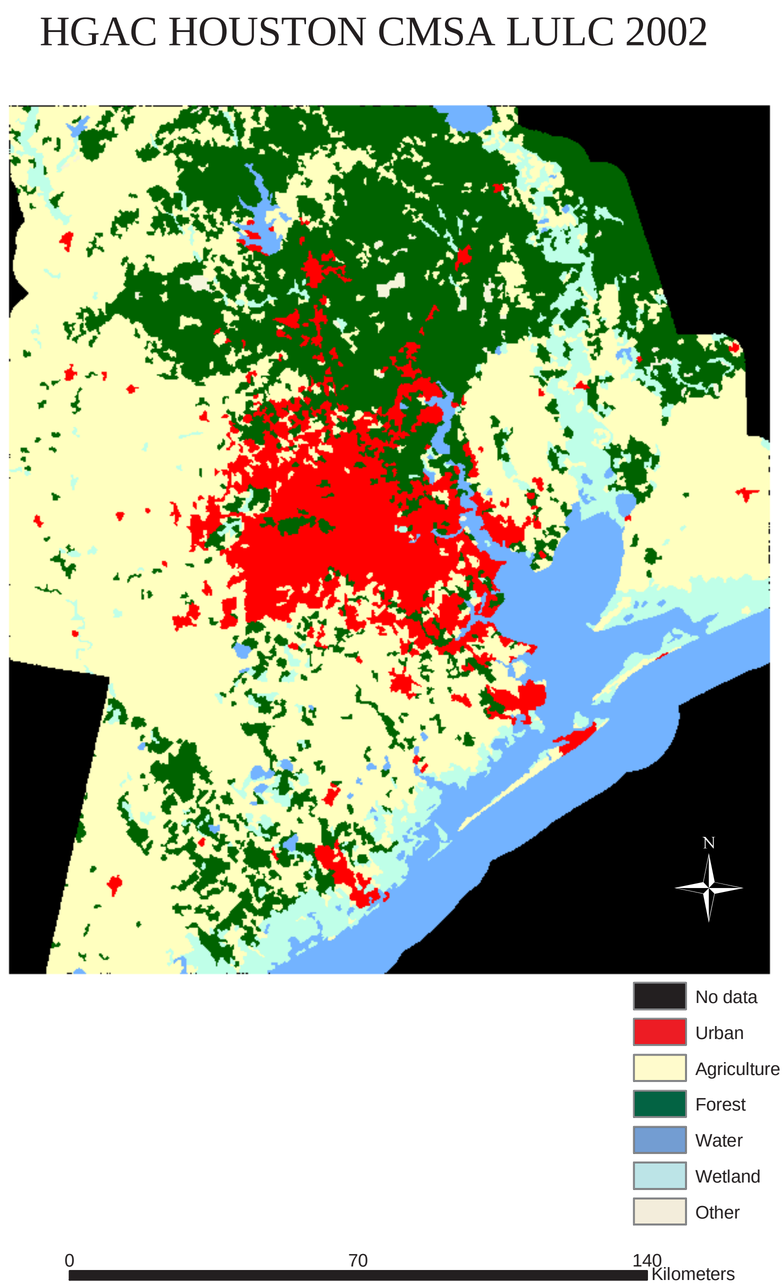

Fig. 2. 5 H-GAC's 2002 Houston CMSA land use/land cover

Figs. 2.4 and 2.5 illustrate our own 2002 land use/land cover map, and H-GAC's 2002 land use/land cover map respectively.

6.3 Calibration of SLEUTH

SLEUTH is a calibrated model. In order for it to successfully simulate the urban growth of a particular metropolitan area its general rules of urban growth must be adjusted to local conditions. Thus, calibration is the most important step in modeling urban growth using SLEUTH (Clarke & Gaydos, 1998; Silva & Clarke, 2002). SLEUTH utilizes a three phase (coarse, fine and final) approach to calibration. At each phase, the user tries to extract the values for each of the five coefficients controlling growth that provide the best match between the modeled and observed patterns of urban growth over the calibration period. For the Houston study presented here, the calibration phase encompassed the years 1974 to 2002 and utilized four urban extent maps (1974, 1984, 1992, and 2002).

The SLEUTH calibration process is automated with the "brute force method." In the calibration process, the model tests many combinations and permutations of the control parameters and performs multiple runs from the seed year, 1974, to the present (last) year, 2002. At each comparison year (1974, 1984, 1992, 2002), 13 different measures of the goodness of fit between the modeled and the real dispersion of urban pixels are used to assess how accurately the adjusted growth rules simulate observed urban growth. This calibration approach relies on the availability of significant computing power and benefits significantly from parallel processing and high performance computing methods. Results are sorted, and parameters of the highest scoring model runs are used to begin the next, more refined sequences or permutations over the parameter space. The first exploration of the parameter space uses a condensed, smaller (reduced resolution) version of the input data layers, and as the calibration closes in on the "best" run; the data are increased in spatial resolution.

Determining which coefficients provide the best match for observed growth is accomplished by computing 13 metrics (see Table 2.6) which represent either a determination of fit between actual and predicted values for the urban growth pattern such as number of pixels, number of edges, number of clusters; for spatial metrics, such as shape measures (Clarke & Gaydos, 1998).

Table 2. 6
Metrics that can be used to measure the goodness of fit in the SLEUTH model

Metric Name	Description
Product	All other scores multiplied together
Compare	Modeled population for final year / actual population for final year, or IF $P_{modeled} > P_{actual}$ { 1 - (modeled population for final year / actual population for final year)}.
Pop	Least squares regression score for modeled urbanization compared to actual urbanization for the control years
Edges	Least squares regression score for modeled urban edge count compared to actual urban edge count for the control years
Clusters	Least squares regression score for modeled urban clustering compared to known urban clustering for the control years
Cluster Size	Least squares regression score for modeled average urban cluster size compared to known average urban cluster size for the control years
Lee-Sallee	A shape index, a measurement of spatial fit between the model's growth and the known urban extent for the control years
Slope	Least squares regression of average slope for modeled urbanized cells compared to average slope of known urban cells for the control years
% Urban	Least squares regression of percent of available pixels urbanized compared to the urbanized pixels for the control years
X-Mean	Least squares regression of average x_values for modeled urbanized cells compared to average x_values of known urban cells for the control years
Y-Mean	Least squares regression of average y_values for modeled urbanized cells compared to average y_values of known urban cells for the control years
Rad	Least squares regression of average radius of the circle which encloses the urban pixels
F-Match	A proportion of goodness of fit across landuse classes. { #_modeled_LU correct / (#_modeled_LU correct + #_modeled_LU wrong)}

SLEUTH calibration relies on maximizing spatial and other statistics between the model behavior and the known urban extent at specific calibration data years, 1974, 1984, 1992, and 2002, for this particular project.

A variety of different goodness of fit measures (see Table 2.6 above) can be used to narrow the five growth parameters (coefficients) range. There is not one sole metric that has been shown to be the most effective. Traditionally the Lee and Sallee (Lee & Sallee, 1970) metric has been used to determine which parameter sets best describe the replication of the historical datasets. Therefore, we have chosen Lee-Sallee metric as our primary goodness of fit measure in this project. The Lee-Sallee shape index is a measurement of spatial fit between the model's growth and the known urban extent for the control years. This simple measure of shape was adjusted to describe distributions, and was computed by overlaying the observed and the predicted maps of urban extent, computing the union and the intersection of their total areas on a pixel by pixel basis, and then dividing the intersection by the union. For a perfect match, the Lee-Sallee measure gives a value of 1.0 and for all others a smaller number, similar to an r-squared value.

A Monte Carlo approach used to test the full range of coefficients, and averages of the 13 comparison metrics are computed across multiple runs to ensure robustness of the solutions. The three calibration phases are performed at successively higher and higher spatial resolution. Coarse calibration mode runs at ¼ of original spatial resolution, fine calibration mode at ½ and the final calibration phase utilizes the entire spatial resolution of the input data. By using different spatial resolutions and a sequential multistage optimization of the coefficients that control the system, the model is carefully adapted to local characteristics throughout calibration and the user can select parameter set that best simulates growth in the urban area under study and that best enable the model to predict future urban expansion.

The current version of the SLEUTH can drive a land use/land cover change model (land cover deltatron or LCD), although the urban growth model can run independent of the LCD model. The general structure of LCD model could be explained: select a pixel at random. This pixel cannot be one of following pixels: urban, water, no-data. Get this pixel's land cover class. Select two transition classes randomly. These classes should not be no-data, urban, water, or current land cover class. Compare the slope of the selected pixel with the average slope of the two transition classes. The transition class whose mean slope is closer to the slope of the selected pixel is then assigned as the new class. Draw a number at random. If this value is smaller than the transition probability for the transition class, then the program will take the following actions: apply land cover transition to the selected pixel, then create land cover transition cluster of neighborhood pixels through a random walk, and assign "ALIVE" to corresponding pixels in "deltatron space." In deltatron space, apply cellular automata growth rules to "ALIVE" pixels (Gigalopolis, 2003).

7. Study Area: Houston CMSA

Houston, Texas, is located on the flat upper Gulf coastal plain 50 miles from the Gulf of Mexico (Figs. 2.6-2.7). The city itself has a population of 1.9 million people making it the fourth most populous city in the nation, trailing on New York, Los Angeles and Chicago and the largest in Texas. Houston is also the only metropolitan city that functions without zoning regulations or plans (Vojnovic, 2003).

While most of the region's population is concentrated in and around the city of Houston proper, which is also serves as the Harris county seat, the The Houston-Galveston-Brazoria Consolidated Metropolitan Statistical Area (Houston CMSA) encompasses Primary Metropolitan Statistical Areas (PMSAs) in eight counties (Fig. 2.6) on the Texas Gulf Coast. The Houston PMSA occupies six counties Chambers, Fort Bend, Harris, Liberty, Montgomery, and Waller Counties. The Galveston-Texas City PMSA and Brazoria PMSA each occupy a single county, Galveston and Brazoria, respectively

The total population of the Houston CMSA's is 4.8 million making it the 10th largest U.S. metropolitan statistical area.

Fig. 2. 6 The Houston CMSA counties

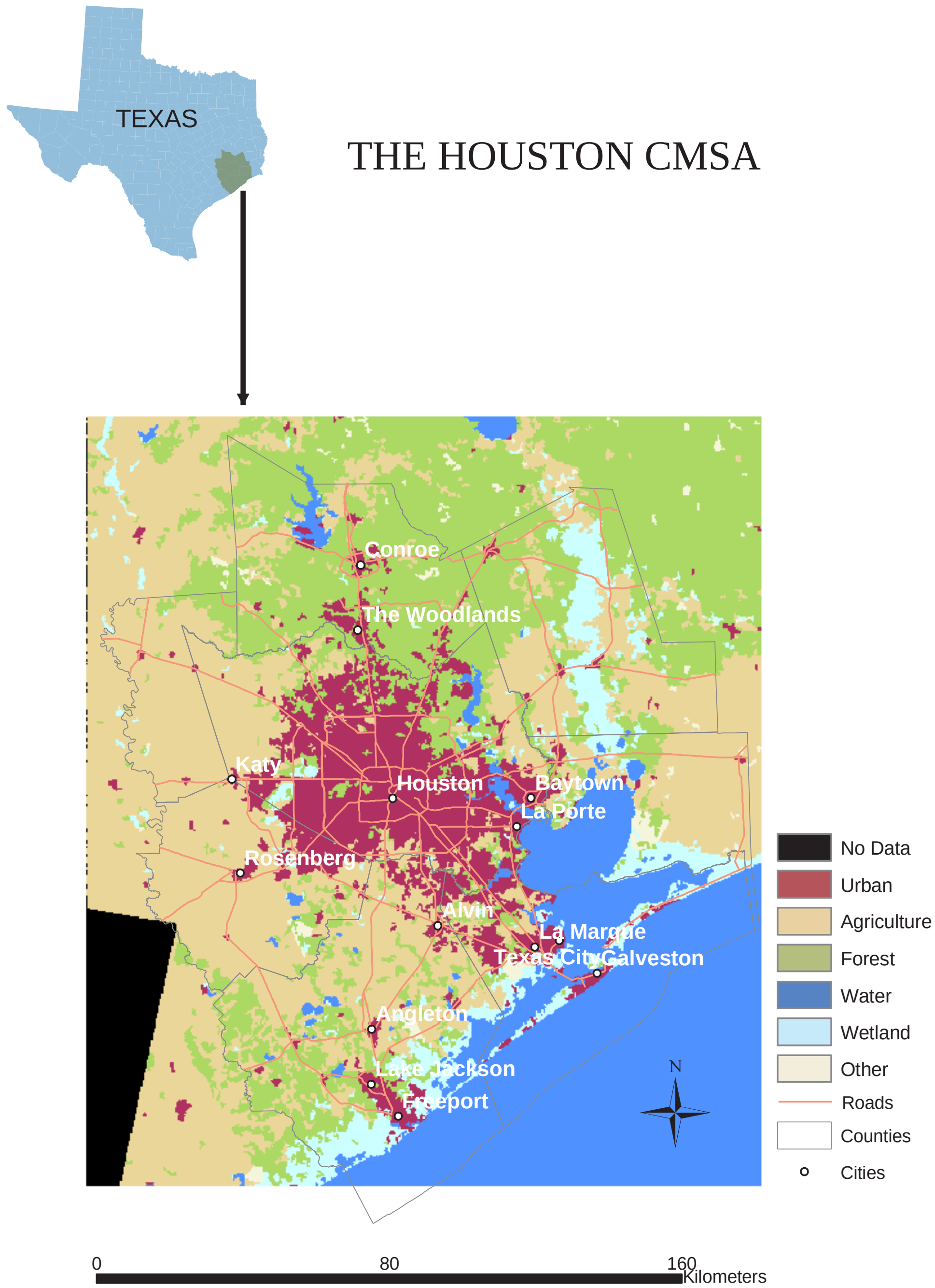

Fig. 2. 7 Study area (Houston CMSA)

Table 2. 7
Study area (Houston CMSA)

NAME	AREA COVERED (km^2)
Houston CMSA	22,735.80
Houston PMSA	16,328.09
Brazoria PMSA	4,137.61
Galveston PMSA	2,270.02
Harris County	4,604.71
City of Houston	1,538.79

The City of Houston proper occupies three counties: Harris (1,511 km^2) (see Table 2.7), Fort Bend (21 km^2), and Montgomery (7 km^2). Under Texas' Municipal Annexation Act of 1963, cities have certain powers over surrounding unincorporated areas which is termed Extraterritorial Jurisdiction (ETJ). The ETJ is a function of population, for cities over 100,000, it can cover all unincorporated area within 8 kilometers of any point on the city limits. Houston's ETJ encompasses 3,397.93 km^2, excluding the area of incorporated areas that lie within it. For example Houston's ETJ would not include the 35 incorporated areas lying wholly or partially in Harris County.

The Houston CMSA lies in the northern portion of the northern Gulf coastal plain in a 64- to 80-kilometer-wide swath along the Texas Gulf Coast. The topography of the area is flat with altitudes typically only rises approximately 19 centimeters per kilometer inland. The northern and eastern portions of the Houston CMSA are largely forested, southern and western portions are predominantly prairie grassland while coastal areas are prairie. Surface water in the Houston region consists of lakes, rivers, and an extensive system of bayous and manmade canals that are part of the rainwater runoff management system. Because of its low lying topography and proximity to the Gulf of Mexico, flooding is a major problem to Houston and is an impediment to urban growth. Some 25%-30% of Harris County lies within the 100-year flood plain.

Houston's land surfaces are unconsolidated clays, clay shales, and poorly-cemented sands extending to depths of several kilometers that have deposited by a river networks carrying material eroding from the Rocky Mountains to the sea. From an economic standpoint these interbedded sands and clays deposited also contain significant amounts of organic matter that over time have decayed and been transformed into oil and natural gas.

The City of Houston was founded in 1836 and incorporated in 1837. The city grew slowly, increasing in population to only about 45,000 by 1900. During the 1800's Galveston, located on the Gulf of Mexico some 80 kilometers south of Houston, was the economic center of Texas throughout the nineteenth century and a key commercial port for cotton in the U.S. (Vojnovic, 2003).

Two events early in 1900s stimulated Houston's first phase of significant growth. First, in 1900 a hurricane destroyed much of Galveston and left approximately 6,000 dead. A year later oil reserves were discovered at Spindletop 145 km east of Houston. These two events led to Houston's rapid growth (Vojnovic, 2003). In the 19th century, new investment on transportation infrastructure in Houston began with new railroad and the construction of the Houston Ship Channel. Waterway improvements made it possible for ships to dock directly in Houston and taking its principal product directly to Europe (Vojnovic, 2003).

In the 20th century, federal and state intervention in the Houston economy expanded to include the funding of petrochemical plants, gas pipelines, refineries, and research and development in the petrochemical industry. The decision to locate the National

Aeronautics and Space Administration (NASA) complex was another boost to the Houston area in the 1960s.

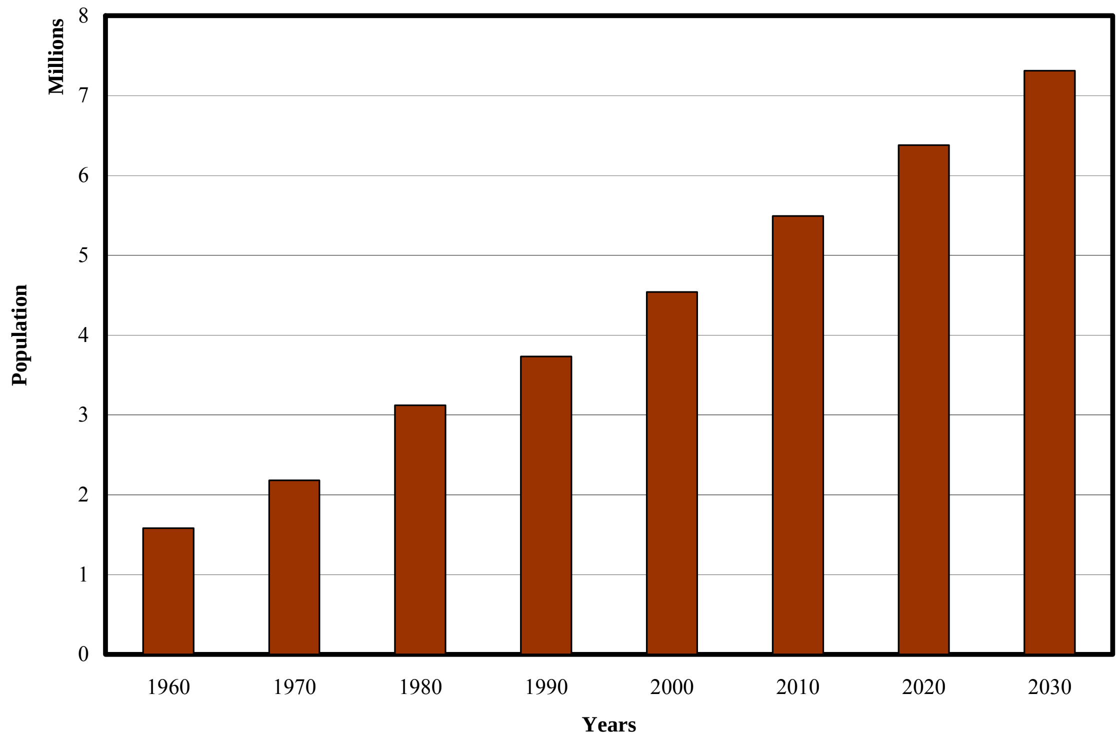

Fig. 2. 8 Past and projected population growth in Houston CMSA

The population grew from approximately 1.5 million in 1960 to 4.5 million in 2000. Fig. 2.8 illustrates the past population growth in Houston CMSA from 1960 to 2000 (The Perryman Group, 2002) and also illustrates the projected population increase till 2030 (Texas State Data Center, 2003).

Several factors combine to make the Houston CMSA an ideal urban area to study urban growth using SLEUTH. The first is that in recent decades Houston has rapidly expanded and current population projects suggest this growth trend will continue. Secondly, because of its location on the flat Texas Gulf Coastal Plain topography presents a minimal barrier to urban expansion. Lastly because the city of Houston lacks comprehensive zoning regulations, urban expansion can be expected to be both less fettered and less influenced by government regulations. From this perspective, Houston represents one possible endmember of urban growth – a city with few barriers either natural or governmental to growth.

Following Figs. 2.9-2.16 illustrate land use, urban extent, and roads that are used as input to SLEUTH.

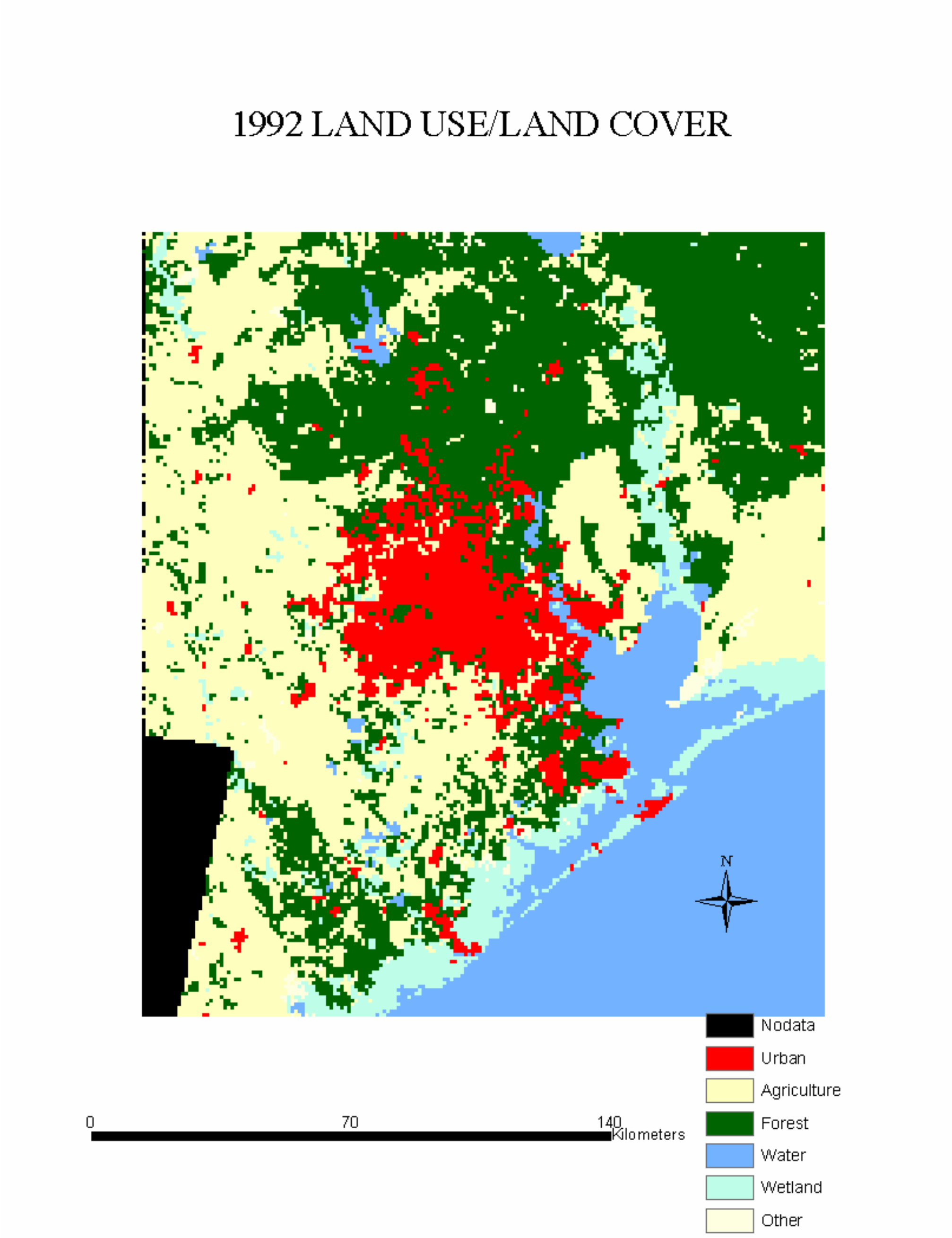

Fig. 2. 9 The Houston CMSA 1992 land use/land cover

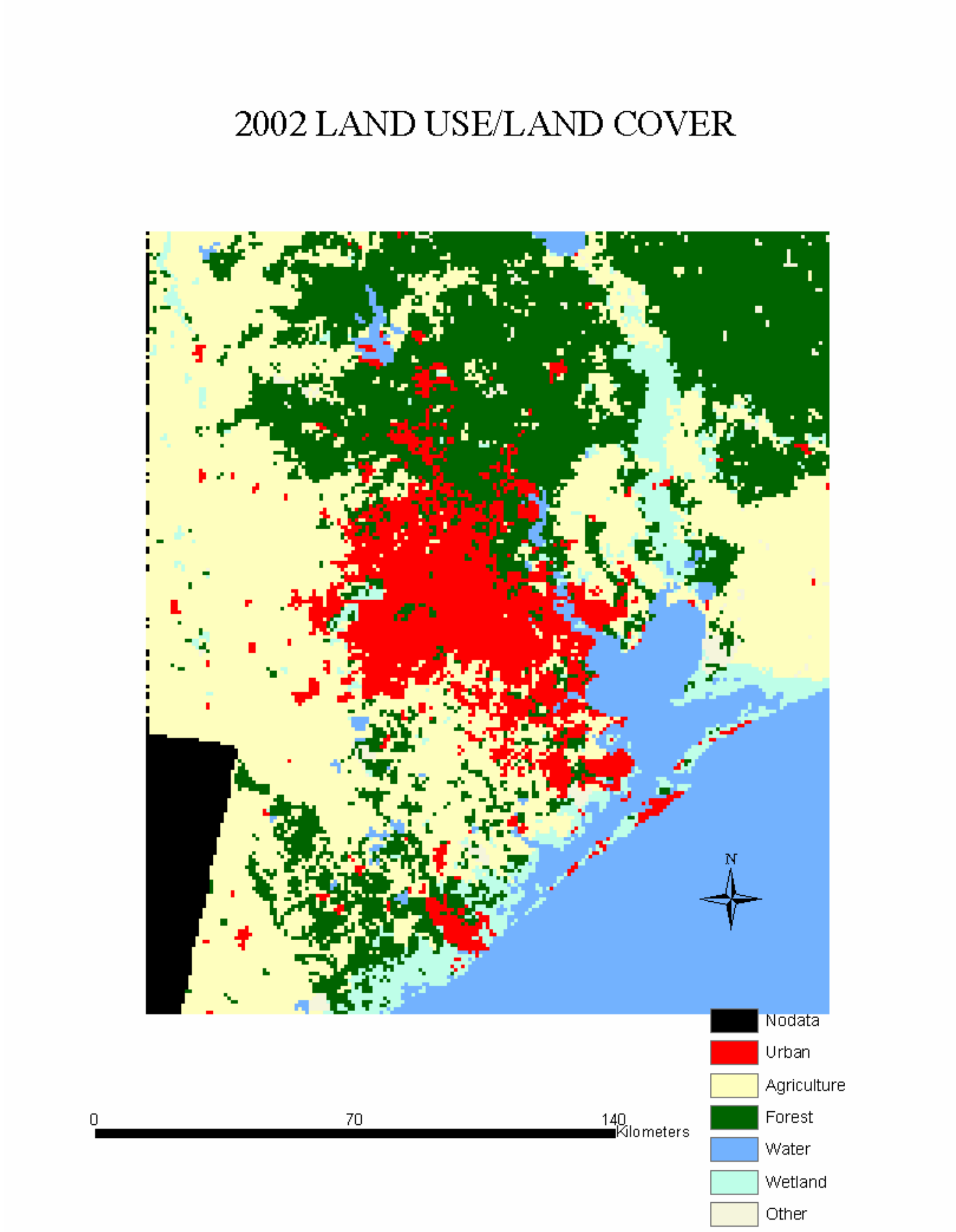

Fig. 2. 10 The Houston CMSA 2002 land use/land cover

SLEUTH INPUT URBAN EXTENTS

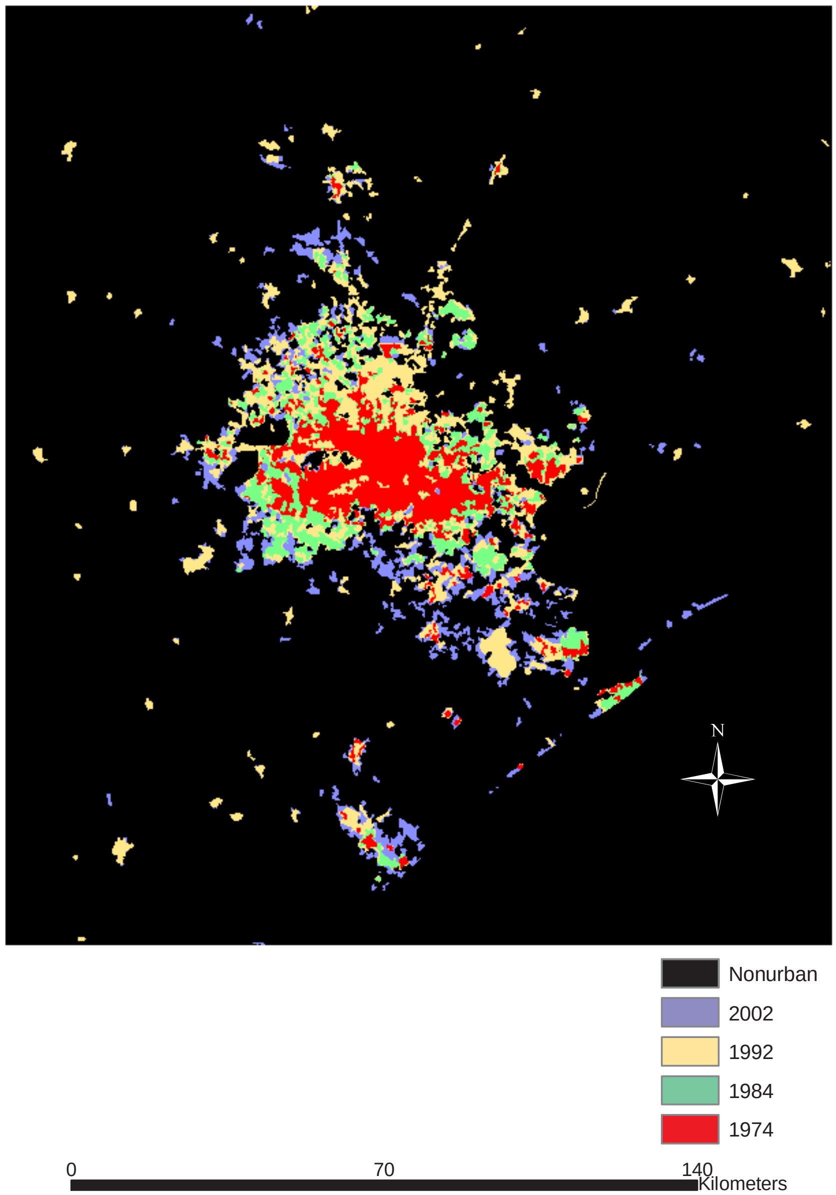

Fig. 2. 11 The Houston CMSA urban extents

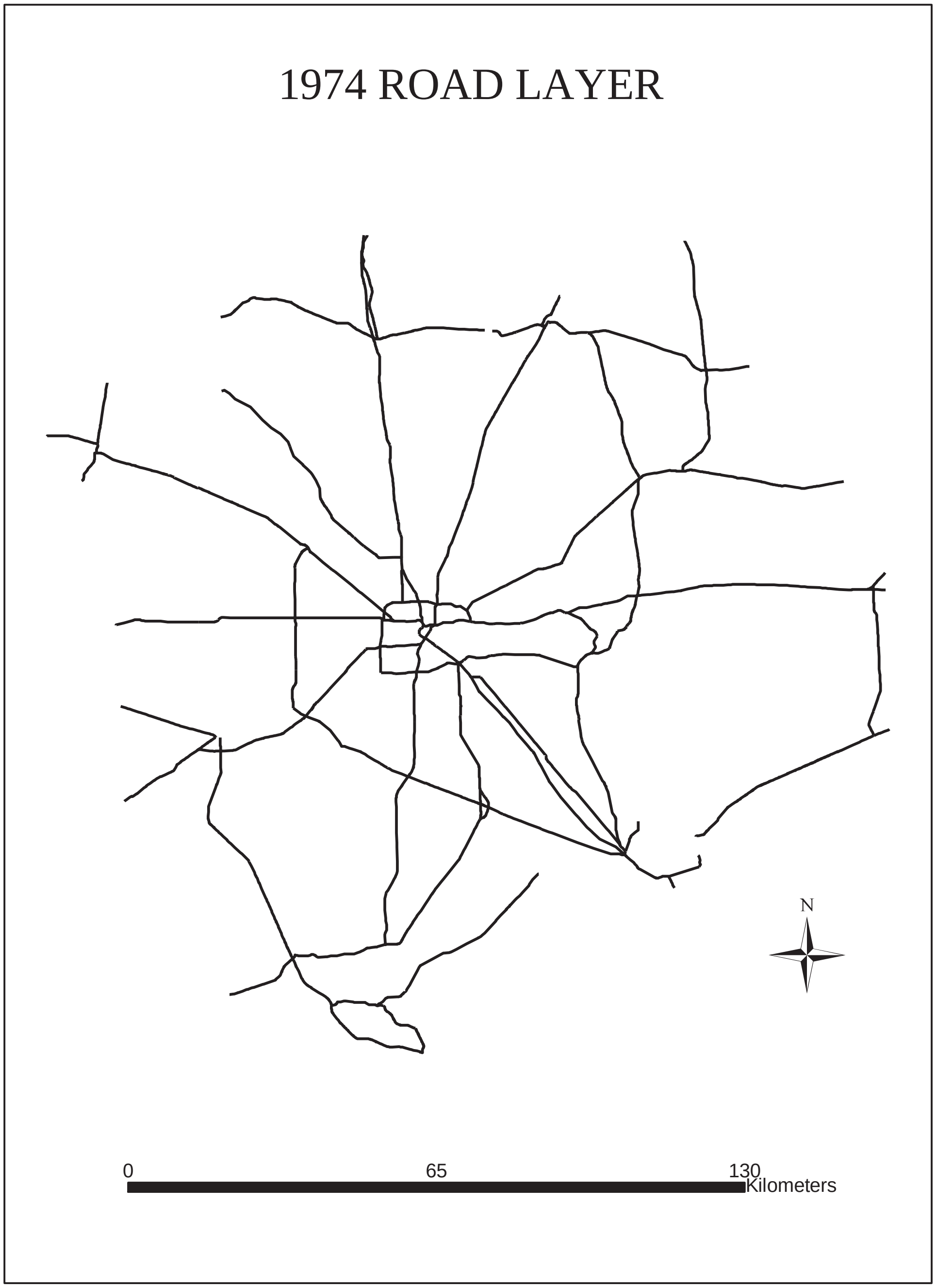

Fig. 2. 12 1974 road network used as input to SLEUTH during calibration phase

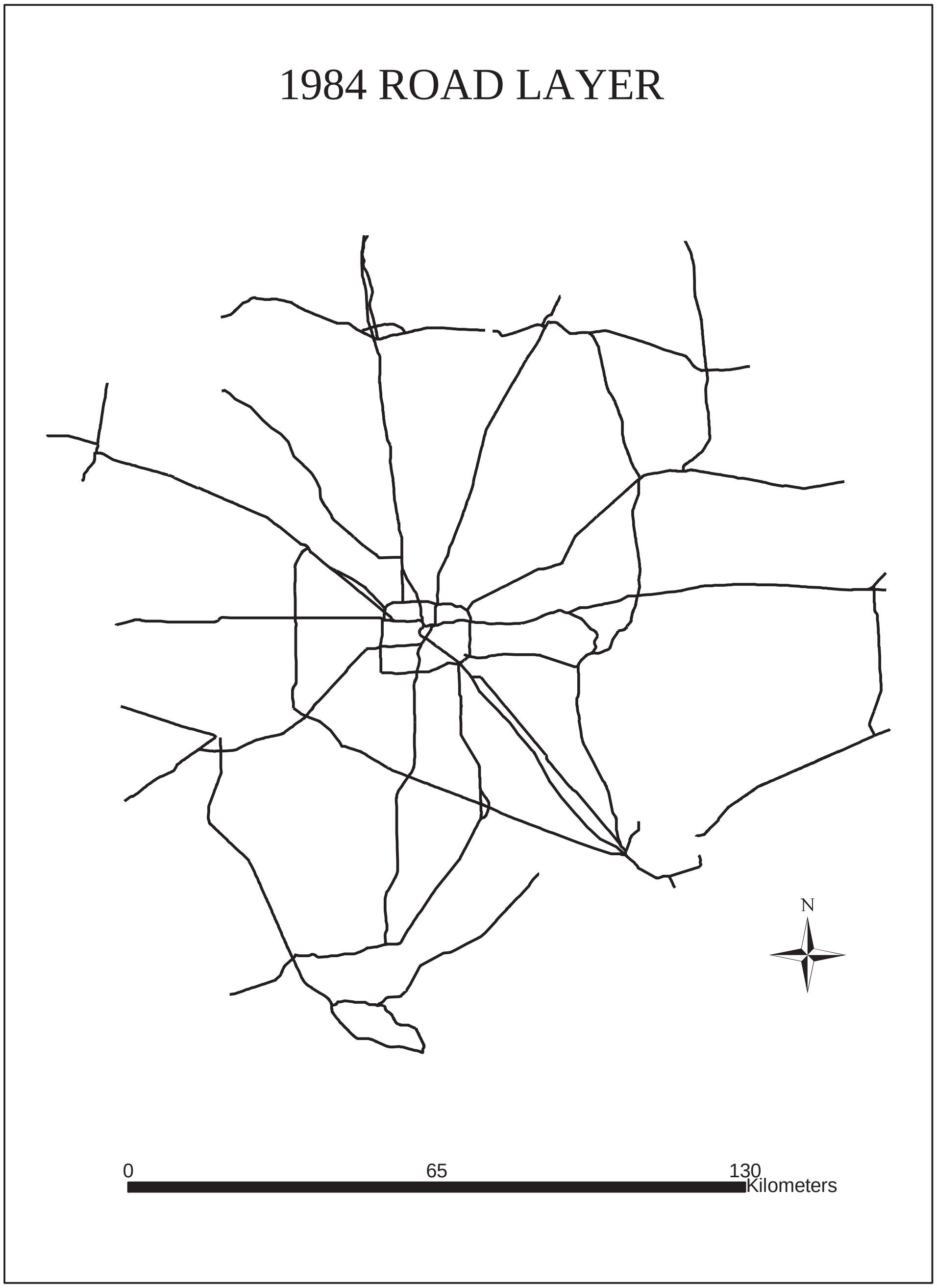

Fig. 2. 13 1984 road network used as input to SLEUTH during calibration phase

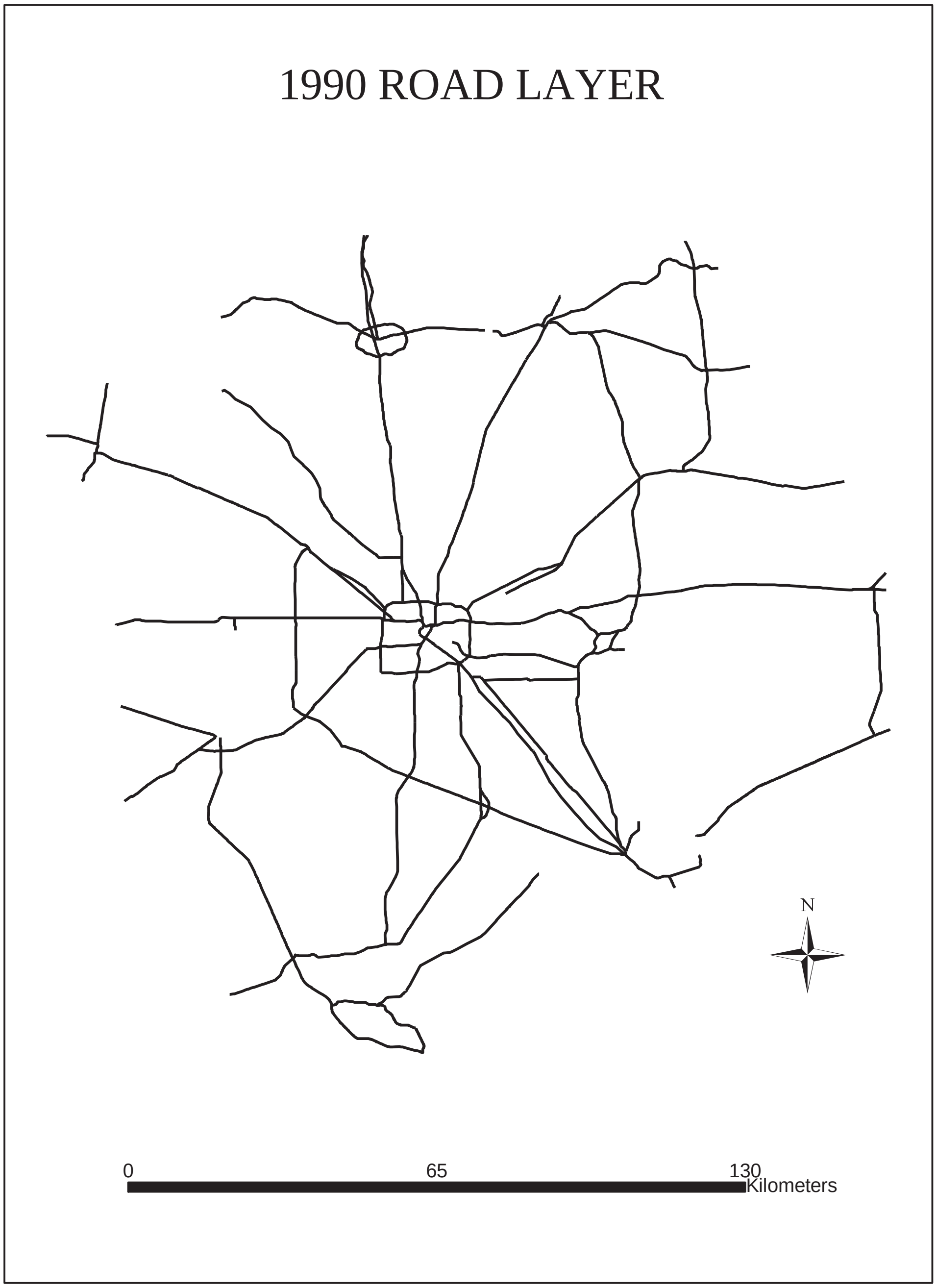

Fig. 2. 14 1990 road network used as input to SLEUTH during calibration phase

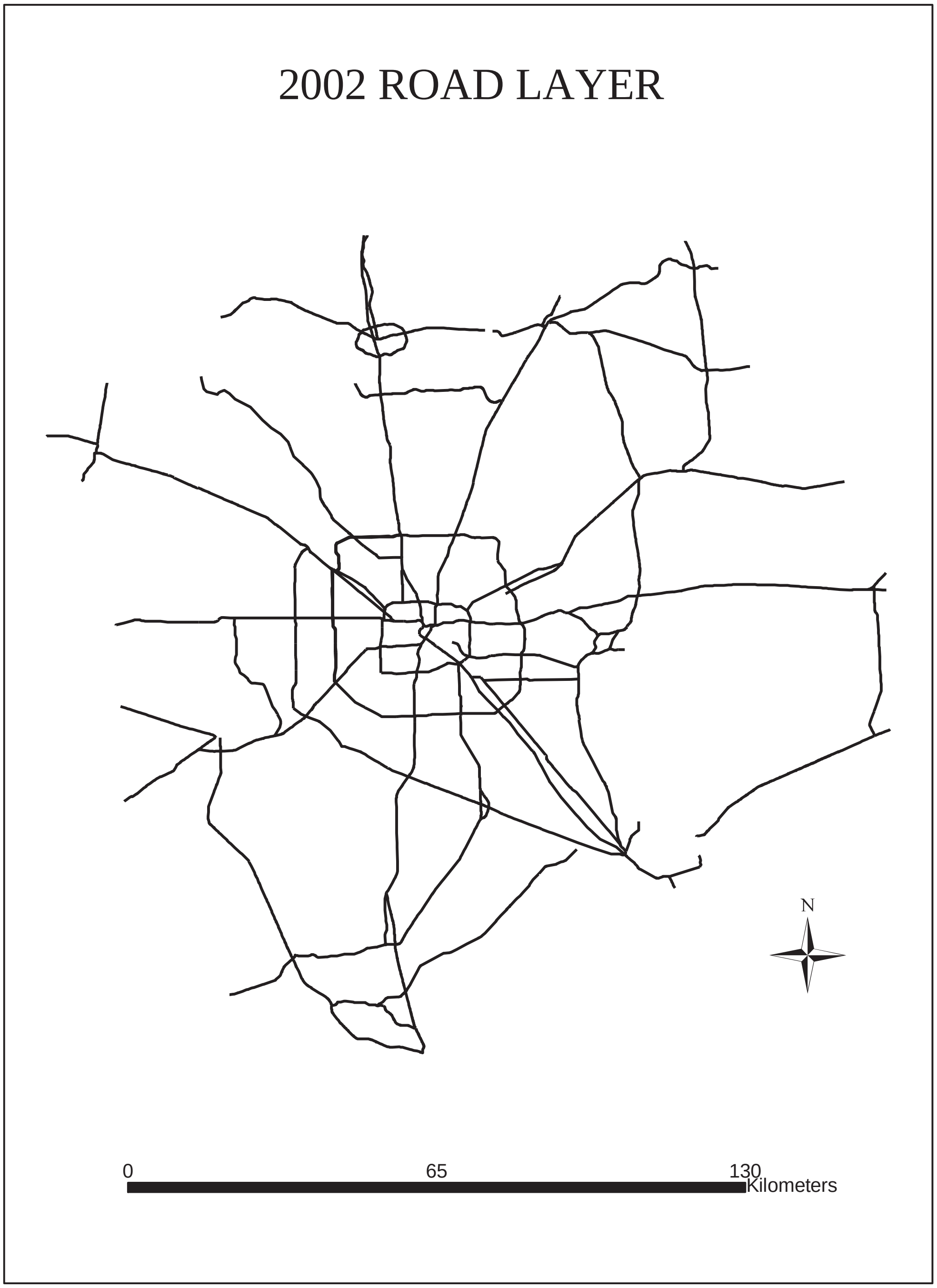

Fig. 2. 15 2002 road network used as input to SLEUTH during calibration phase

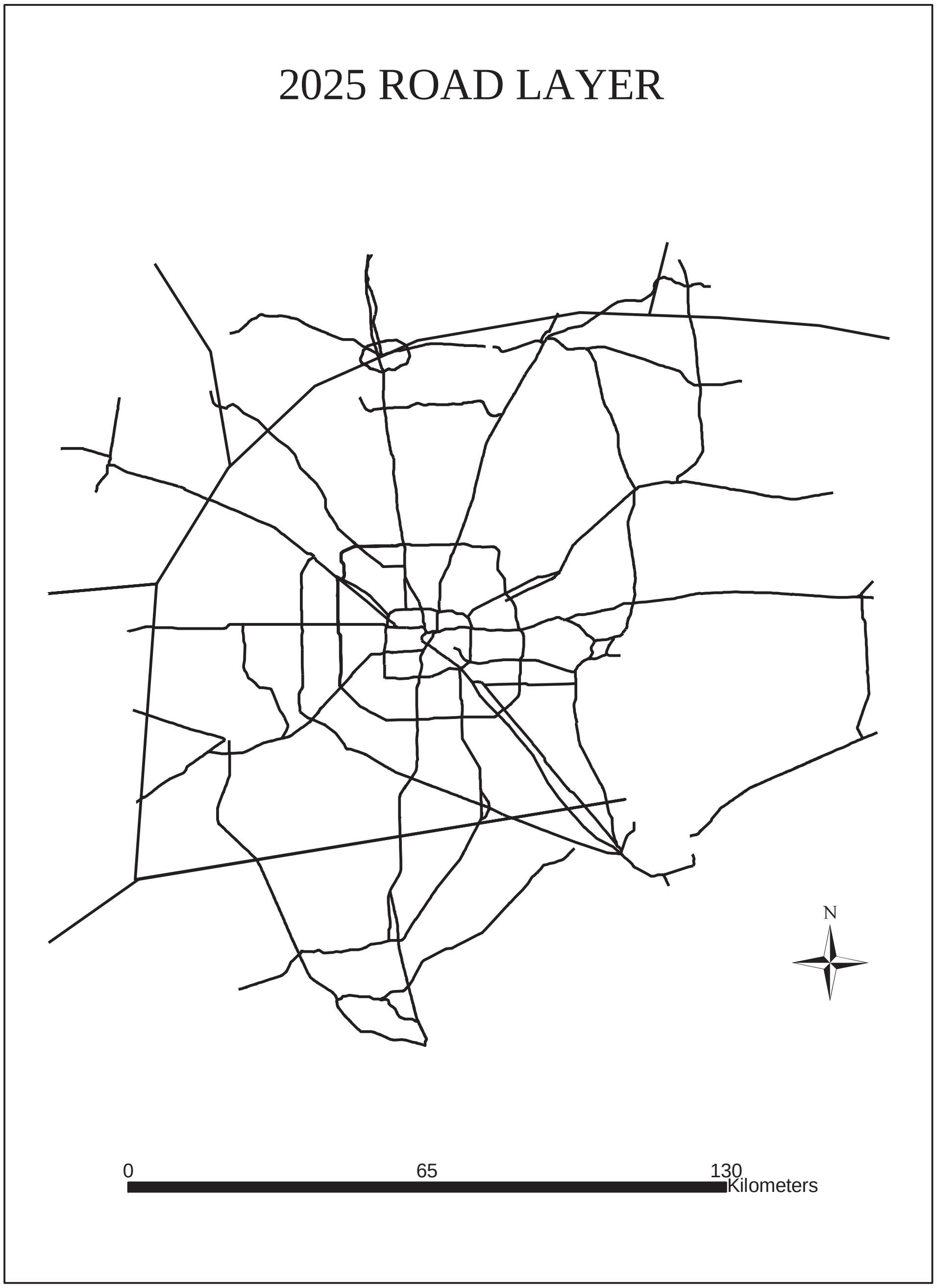

Fig. 2. 16 2025 road network used as input to SLEUTH during prediction phase

8. Calibration Results for the Houston CMSA

By running the model in calibration mode, the control parameters are refined in the calibration phases: coarse, fine and final calibrations (Silva and Clarke 2002). The model was calibrated using hierarchical spatial resolutions, beginning with data of coarser resolution, narrowing the range of parameter that most accurately described the growth of the system, and then using a finer resolution to narrow the parameter values to one distinct set. Thus, we resampled all input data which are in 100 meters resolution into 400 meters to be used in coarse calibration phase, into 200 meters to be used in fine calibration phase. We used data sets with 100 meters (full resolution) resolution in final calibration phase.

The coarse calibration process ran from April 10, 2003 to April 16, 2003. The fine calibration ran from April 17, 2003 to May 05, 2003. Both coarse and fine calibrations were run on a Linux machine with 1.3 GHz CPU and 1.2 GB RAM. We have made two attempts to run final calibration with our Linux machine but the process would take extremely long time to finish (about over 2 months). Both attempts were unsuccessful because of the random local power outages. I would like to thank to Mr. Mark Feller, who is a research scientist at USGS. He accepted to run the final phase of the calibration for us on USGS's 16-node Beowulf PC Cluster. The final calibration began to run on May 29, 2003 and continued until June 09, 2003.

The coarse calibration began with parsing the parameter space into five areas and using the values of 1, 25, 50, 75, and 100 for each of the five parameters. This gives 3,125 (5^5) different parameter sets that are tested to determine which range of parameter the one parameter set that best describes the data is located within. Results from the coarse calibration (see Table 2.8) are examined to determine the goodness of fit for each of the parameter sets. We used LeeSallee metric as goodness of fit measure throughout this project in order to narrow down the parameter set. After coarse calibration was done, the output statistics file was sorted by descending order using LeeSalle metric. Then three highest scoring LeeSallee values and respective parameter values were selected. These optimum parameter values were then used to form input parameter ranges in fine calibration. Table 2.8 illustrates the resulting parameter values after the coarse calibration phase.

Table 2. 8
Coarse calibration, 526 x 462 (rows x columns)

Run	Product	Compare	Population	Edges	Cluster	Cluster Size	Leesalee
70	0.00148	0.78558	0.99959	0.89401	0.61675	0.37173	0.54257
66	0.00448	0.78437	0.99950	0.92294	0.62635	0.38578	0.54219
60	0.00753	0.78066	0.99973	0.91913	0.97203	0.45256	0.54217
Slope	%Urban	Xmean	Ymean	Rad	Fmatch		
0.99494	0.99899	0.70073	0.02839	0.99878	0.85617		
0.99115	0.99886	0.89536	0.06230	0.99864	0.85618		
0.99772	0.99920	0.89767	0.05749	0.99899	0.85608		
Diffusion	Breed	Spread	Slope resist	Road gravity			
1	1	50	100	1			
1	1	50	75	25			
1	1	50	50	1			

For the fine calibration, same procedure was followed. The dataset that were used here had 200m spatial resolution. Therefore, this process took more time than coarse calibration. Table 2.9 illustrates the output parameter values after fine calibration phase.

Table 2. 9
Fine calibration, 1051 x 923 (rows x columns)

Run	Product	Compare	Population	Edges	Cluster	Cluster Size	Leesalee
167	0.00032	0.64802	0.99942	0.76536	0.89472	0.47960	0.53129
153	0.00462	0.64451	0.99943	0.82819	0.62212	0.57374	0.53115
174	0.00514	0.64463	0.99927	0.82730	0.91520	0.52199	0.53115
175	0.00514	0.64463	0.99927	0.82730	0.91520	0.52199	0.53115
176	0.00514	0.64463	0.99927	0.82730	0.91520	0.52199	0.53115
154	0.00412	0.64626	0.99924	0.82067	0.74215	0.57311	0.53110

Slope	%Urban	Xmean	Ymean	Rad	Fmatch
0.96311	0.99854	0.05125	0.06652	0.99819	0.86134
0.96918	0.99856	0.86135	0.06371	0.99821	0.86145
0.97311	0.99831	0.71654	0.06345	0.99793	0.86193
0.97311	0.99831	0.71654	0.06345	0.99793	0.86193
0.97311	0.99831	0.71654	0.06345	0.99793	0.86193
0.92966	0.99828	0.61884	0.06968	0.99791	0.86081

Diffusion	Breed	Spread	Slope resist	Road gravity
1	1	60	80	25
1	1	60	60	15
1	1	60	100	1
1	1	60	100	5
1	1	60	100	10
1	1	60	60	20

The final calibration is the most time consuming procedure in SLEUTH due to its full resolution dataset. The procedure is same for the final calibration. See Table 2.10 below for the output of final calibration phase.

Table 2. 10
Final calibration, 2100 x 1843 (rows x columns)

Run	Product	Compare	Population	Edges	Cluster	Cluster Size	Leesalee
485	0.00541	0.53550	0.99910	0.84385	0.99834	0.43084	0.51069
226	0.00501	0.53286	0.99927	0.86201	0.99666	0.38350	0.51061
215	0.00502	0.53284	0.99928	0.84966	0.99898	0.39583	0.51053
Slope	%Urban	Xmean	Ymean	Rad	Fmatch		
0.97246	0.99765	0.90340	0.07230	0.99719	0.86400		
0.98400	0.99790	0.95309	0.06932	0.99746	0.86366		
0.97344	0.99791	0.90037	0.07293	0.99747	0.86367		
Diffusion	Breed	Spread	Slope resist	Road gravity			
1	2	77	40	15			
1	1	77	35	12			
1	1	77	25	15			

The last section of Tables 2.8-2.10 defines the composite results of the optimum values for the control parameters (diffusion, breed, spread, slope, and road gravity) (see Table 2.11). Tables 2.8-2.10 show successive improvement in the parameters that control the behavior of the system. Parameter values range from 1 to 100. In the coarse calibration, the resulting values were narrowed to 1, 1, 50, 100, 1; and with fine calibration values became more sensitive to locale having 1, 1, 60, 80, 25. In the final calibration, values even became more sensitive to the locale with results presenting, respectively, values of: 1, 2, 77, 40, and 15. This extensive automated exploration of the parameter space shows the importance of this multistage optimization throughout the selection of the different scores, which allowed narrowing to actual values that better reflect the characteristics of the metropolitan area.

Table 2. 11
Coefficients defined in the Tables 2.8-2.10

Coefficients	Definitions
Diffusion	determines the overhaul dispersiveness of growth, for both single grid cells and of the movement of new settlements outward through the road systems
Breed	determines how likely a newly generated detached settlement is to begin its own growth cycle
Spread	controls the amount of outward "organic" expansion
Slope resistance	influences the likelihood of settlement extending up steeper slopes
Road gravity	encourages new settlements to develop near or along the road network

The comparison of the model final “population” gives very high correlation of 0.99. On the other hand, “compare” presents average value of 0.53. These scores state that the prediction of the model based on the initial seed year of the present urban pattern using those refined values in similar to what happened in reality. “Edges” and “cluster” scores are used to evaluate the shape and form of urbanization. For the final calibration correlation was 0.84 in the case of the score “edges.” In the case of the score “cluster”, the correlation was 0.99.

The spread coefficient value of 77, shows that the urbanization of the Houston CMSA tended to occur from the main nucleus. It indeed grew from the main nucleus of City of Houston and growing to outward. The low values of diffusion and breed coefficients state that the opportunity for new urban center is very small, and more and more people are moving out from urban centers to suburbs. This tendency also helps the organic growth of the Houston CMSA. Because of heavy urbanization, slope coefficient allows new urbanization into upper slopes. Road gravity has relatively less effect on urbanization due to the high spread coefficient and they are being located in the already urban centers.

The final results of the calibration process are coefficient values that best simulate historical growth for a region. However, due to SLEUTH's self-modification qualities, the values of the five growth coefficients at the start of the calibration period may differ substantially from those at the end of the calibration period. To achieve the best simulations, the coefficient values from the end of the calibration period are desirable.. Using the best coefficients derived from calibrating and running SLEUTH for the historical calibration period will produce a single set of finishing date coefficients to initialize forecasting. However, due to the random variability of the model, averaged coefficient values taken from multiple Monte Carlo-iterations will produce a more robust forecasting coefficient set than those taken from the single best simulation.

The result of this sorting and averaging was reflected in a change in coefficients that control the model over the duration of the calibration period as is illustrated for the three comparison years in Table 2.12. The increase in the spread coefficient and decrease in slope resistance over the calibration period are the most obvious changes. Spread coefficient values jumped from 77 to 100 after self-modification. Slope resistance values nearly halved from 40 to 22. One possible interpretation of these values is that the Houston CMSA is susceptible to intense boom phases as evidenced in the high increase seen in the spread coefficient over the calibration period and as urbanization continued to increase from the main nucleus in the study area – the city of Houston. The Houston CMSA has relatively low slopes and as the urban areas continue to expand, less space remains for urbanization. Thus, self-modification causes slope resistance to decrease.

Table 2. 12
Averaged coefficient values after "derive forecasting coefficients phase"

Year	Diffusion	Breed	Spread	Slope resistance	Road gravity
1984	1	2	84	36	15
1992	1	2	91	31	16
2002	1	3	100	23	17

During the prediction phase, an error was discovered involving the misnaming of the 1974 and 1984 extents. These were incorrectly given the years, 1970 and 1980 respectively. The problem was how the model treats time in SLEUTH modeling. In order to see if this misnaming would affect the outcome, we have rerun the final phase of calibration, deriving forecasting coefficients phase (see Tables 2.13-2.14).

Table 2. 13
"Derive forecasting coefficients" results before the misnaming

Year	Diffusion	Breed	Spread	Slope resistance	Road gravity
1980	1	2	84	36	15
1992	1	2	95	29	16
2002	1	3	100	22	17

Table 2. 14
"Derive forecasting coefficients" results after the misnaming

Year	Diffusion	Breed	Spread	Slope resistance	Road gravity
1984	1	2	84	36	15
1992	1	2	91	31	16
2002	1	3	100	23	17

The results show almost perfect similarity. We have found that the temporal spacing of control data sets does not drastically affect the final parameter values in SLEUTH modeling. Based on these results, misnaming error did not cause serious problems.

An additional statistical validation of the models predictive performance was undertaken. This was accomplished by running the model in prediction mode using the 1974, 1984, and 1992 urban extents to predict 2002 urban extent for the study area. We will call the resulting output image "Predicted Urban Extent." Since we have an independently derived estimate of 2002 urban extent from remote sensing, we can undertake a statistical comparison between our 2002 predicted urban extent and the 2002 observed urban extent. This comparison is illustrated in Figs. 2.17-2.18 and an error (confusion) matrix (Congalton, 1991; Congalton & Mead, 1983) and kappa coefficient (Table 2.15) were computed to quantify the degree comparison accuracy.

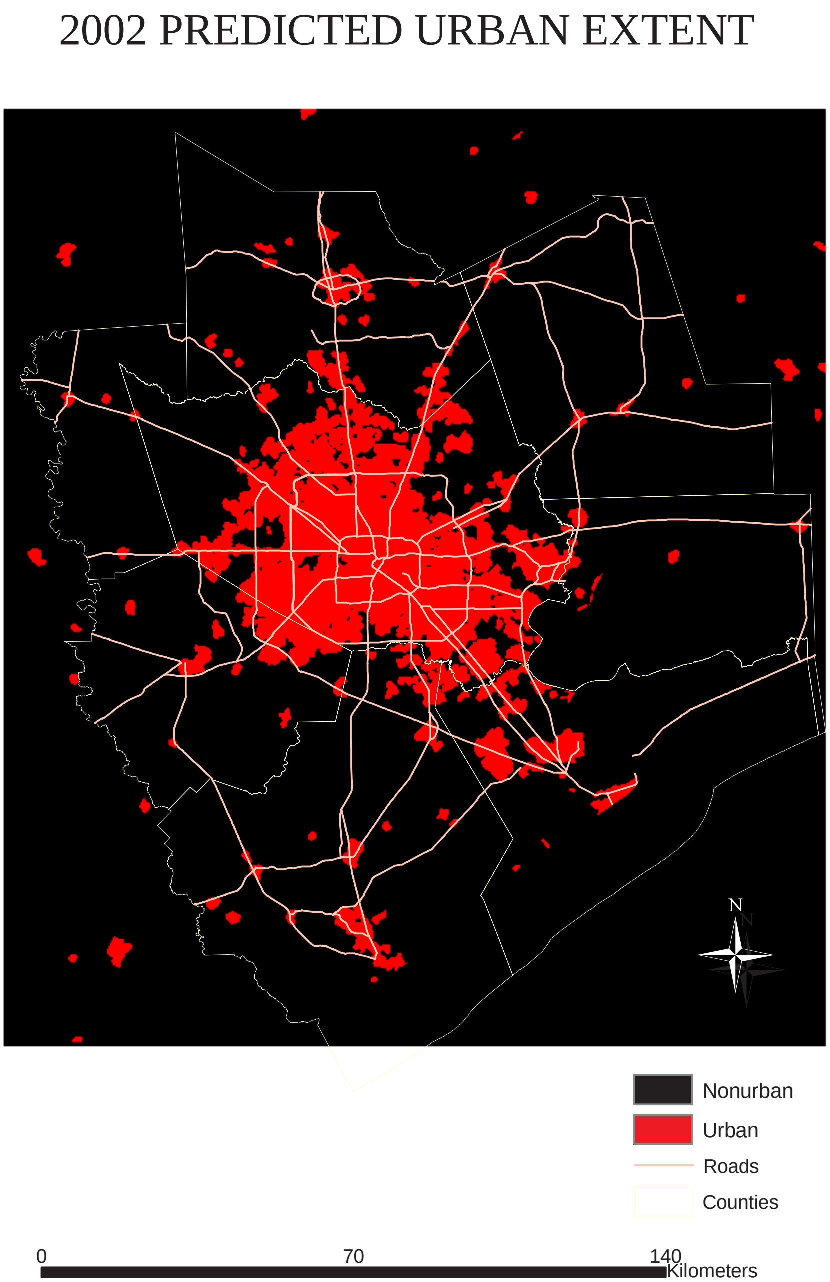

Fig. 2. 17 The Houston CMSA 2002 predicted urban extent

2002 OBSERVED URBAN EXTENT

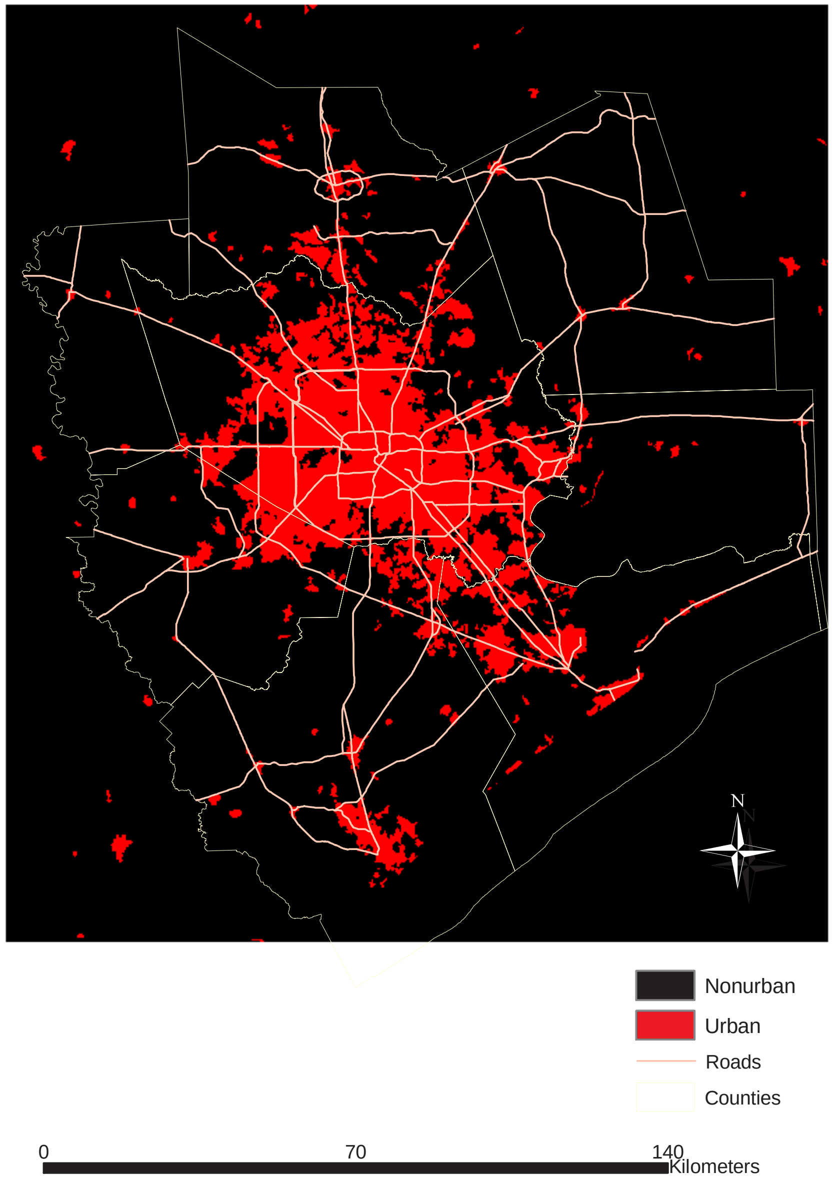

Fig. 2. 18 The Houston CMSA 2002 observed urban extent

Table 2. 15
Confusion matrix and kappa coefficient for the 2002 predicted urban extent

Classified Data Points		Reference Data Points (OBSERVED URBAN 2002)				
		Nonurban	Urban	Row Total	Producers Accuracy	Users Accuracy
	Nonurban	227	3	230	99.13%	98.70%
	Urban	2	24	26	88.89%	92.31%
	Column Total	229	27	256		

Overall Classification Accuracy = 98.05%
Kappa (Khat) Coefficient = 0.89

We obtained a 98% overall accuracy with kappa coefficient of 0.89. Kappa values are also characterized into 3 groupings: a value greater than 0.80 (80%) represents strong agreement, a value between 0.40 and 0.80 (40 to 80%) represents moderate agreement, and a value below 0.40 (40%) represents poor agreement (Congalton, 1996). Our kappa coefficient value came out as 0.89, which represents a strong agreement. Based on high overall classification accuracy and kappa coefficient value, we can say that the model predicts in high accuracy.

9. Results and Discussion

Despite some minor setbacks, through simulation of observed urban growth in the Houston CMSA from 1974 – 2002 a thorough calibration of SLEUTH was undertaken. Through the process of calibration, several important conclusions concerning SLEUTH's ability to successfully model growth in the Houston Metropolitan area can be drawn. It is important to recognize that compared to urban growth in many other cities, urban growth in Houston is largely unimpaired by topography and zoning restrictions. The population of the Houston CMSA increased from 1.5 million in 1960 to 4.5 million in 2000, it simply tripled. It is projected that Houston CMSA's population will increase to 7.5 million by 2030 (The Perryman Group, 2002). The study area has a total of 20,019 km^2 of land area. Of this land, only 5 percent was occupied by urban settlements in 1974. However, in 2002, the urbanized area in Houston CMSA accounted for 19 percent of the total CMSA land, a nearly quadruple increase.

The performance of the SLEUTH calibration in the Houston CMSA was improved with increased spatial resolution. As the calibration process progressed, the five coefficient values were successfully adjusted to accurately reflect the study area. The slope resistance coefficient value dropped substantially indicating that slope was not a factor of urbanization in at least the Houston CMSA due to the area's low slope. The spread coefficient, on the other hand increased substantially showing that infill and edge growth are major factors on urban development in Houston CMSA. Lack of zoning regulations, suitable topography, and warm environment are expected to be the main factors that affect spread coefficient to be high.

Coarse calibration phase has made the initial improvement in model performance. Values that were fed to coarse calibration had a starting value of 1 and finishing value of 100. After the coarse calibration was done, the values for five coefficients were 1, 1, and 50 for diffusion, breed, and spread coefficients respectively. For slope resistance, resulting values ranged from 50 to 100. For road gravity, however, it ranged from 1 to 25. Out of five coefficients, the values for the three coefficients, spread, slope resistance, and road gravity, showed the most improvement from coarse to fine, and from fine to final calibration. The intensity of the values of this improvement varied with the local environmental and urban characteristics of Houston CMSA. The study area presented a regular transition from coarse, fine, and final calibration (see Fig. 2.19); the values tend to adjust to local characteristics gradually. The possible explanation of this could be that the input dataset with higher resolution produce better results (Yang & Lo, 2003).

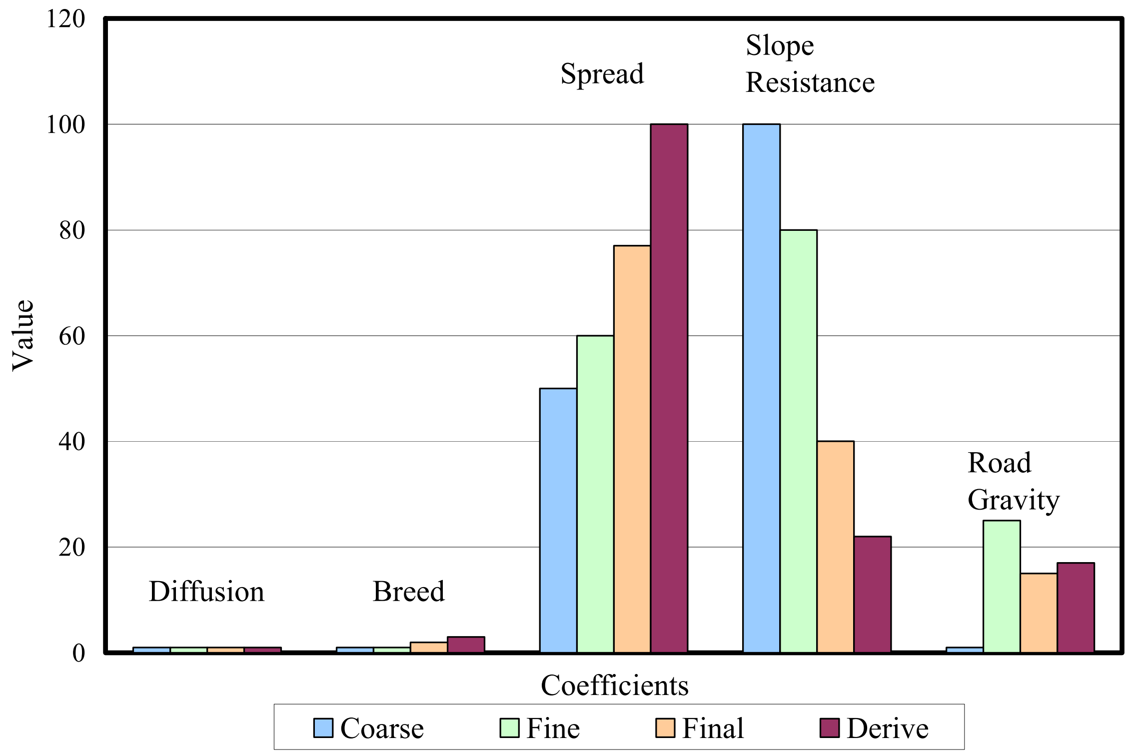

Fig. 2. 19 The behavior of the study area, Houston CMSA, to the growth coefficients

The LeeSallee metric was chosen our primary goodness of fit measure during the SLEUTH model run. In this study, the LeeSallee score, which is a shape index metric, defined as a ratio of the AND to the OR of the actual and predicted urban images as binary layers (Keith et. al., 1996), is used to rank the growth scenarios and select an appropriate suite of coefficient values to model Houston's future growth. Let say "A" is our predicted urban image for calibration year, and "B" is observed (or actual) urban extent image. Then, the LeeSallee shape index is calculated by following formula: $(A \cap B) / (A \cup B)$. The degree of shape match between the modeled growth and the known urban extent for the control years is measured through LeeSallee score. If the model grows in different ways or in different directions this index will reflect that. The predicted urban extent in 2002 after final calibration and compared to that obtained independently from a remotely-sensed land use/land cover map had a shape index of 0.51 for Houston CMSA. Even though SLEUTH widely popular modeling urban growth; there are only a few published results that show output statistics. Silva & Clarke (2002) modeled urban growth in Lisbon and Porto, Portugal using SLEUTH urban growth model. They achieved a LeeSallee value of 0.35 for Lisbon, and 0.58 for Porto. Clarke & Gaydos (1998), however, achieved a LeeSallee value of 0.30, and they emphasized that even a 30 percent (0.30) match was quite good for their study.

Houston CMSA presents a very low value of diffusion and breed and very high spread coefficient and low slope coefficients. This indicates that growth clearly occurs at the urban-rural fringe. The increase in suburbs and exurbs has increased organic growth. Another reason that Houston CMSA may present a very high value of spread is that Houston is the only metropolitan area that functions without a zoning plan (Vojnovic, 2003). The outward growth occurs from every direction in Houston CMSA because development outward from the existing urban centers is unrestricted by zoning.

Road gravity presents low value because expansion of the highway network in the Houston metropolitan area from 1974 to present consisted primarily of upgrading existing roads rather than developing roads in areas where non existed before. However, a new major transportation construction, Texas Corridor, is planned to be finished in 2025 by Texas Department of Transportation (TXDOT) and will be included in predicting Houston's future growth.

10. Conclusions

Concerns over the degradation of our environment are raised because of increasing urban growth through the world. Modeling and simulation are required to understand the dynamics of complex urban systems and to evaluate the impacts of urban growth on environment. Dynamic modeling has gained popularity in recent years among city and urban planners as a useful tool for urban modeling. Cellular automaton has technologically advanced in the last decade as a popular dynamic modeling method.

We used Houston CMSA as our case study due to its rapid change in urban development during the past 30 years. This study has examined the spatial consequence of urban growth for Houston CMSA, only metropolitan area in the U.S. that has no zoning regulations (Vojnovic, 2003). The cellular automaton modeling has been found to be the most suitable for use in simulating urban growth in a metropolitan area. The calibration results clearly show that the growth occurs at the urban fringe and it grows outward in every direction due to lack of zoning regulations.

Self-modification rules were found to play an important role in controlling urban growth in the study area, Houston CMSA. The coefficient values that control the system capture the essence of the study area. Population grew constantly starting from 1960s in Houston CMSA, and this certainly influenced new developments in the metropolitan area.

This study is unique in several ways: first, it represents the first modeling of urban growth of a Consolidated Metropolitan Statistical Area using SLEUTH. Moreover, the city of Houston is the only major metropolitan area operating without a zoning plan and with very little topographic control on urban expansion. Therefore, this study represents calibration of the SLUETH model under the case where growth is virtually unrestricted by either natural barriers or governmental controls.

The rigorous calibration process has resulted in the determination of a set of diffusion, breed, spread, slope resistance, and road gravity growth coefficients that enable SLEUTH to quite accurately simulate the observed growth in the Houston CMSA over the period 1974 to 2002. Because Houston CMSA is located upon relatively flat topography, and having no zoning regulations, the study area has been experiencing a steady population and urban growth increase. Our results indicate a very high spread coefficient indicating an edge growth in Houston CMSA. Slope coefficient also was relatively low because the topography is clearly less of a constraint to growth in the Houston CMSA. Just as importantly, the high values of the spread coefficient relative to the others, indicates that the calibration process has successfully captured the organic nature of the Houston's growth. Clarke & Gaydos (1998) have modeled urban growth in San Francisco and Washington/Baltimore, reporting spread coefficients as 19 and 21 respectively. Slope resistance coefficients were 31 for San Francisco and 10 for Washington/Baltimore. Yang and Lo (2003) also modeled urban growth in Atlanta, Georgia, using the SLEUTH urban growth model, and they reported their spread coefficient and slope coefficient as 41 and 95 respectively. This gives extra strength to the model's own ability to automatically calibrate itself. For Houston CMSA, the calibration presented a set of starting parameter values in 1974 of: 1, 3, 100, 22, and 17, for diffusion, breed, spread, slope resistance, and road-gravity respectively.

11. Recommendations for Future Research

This paper introduces an exhaustive and rigorous calibration of the SLEUTH model to data from the Houston-Galveston-Brazoria Consolidated Metropolitan Statistical Area (Houston CMSA). As, the current literature provides little guidance in which metrics to use in the selection of SLEUTH's growth coefficients, in this research, the leesalee, shape index, metric which is defined as a ratio of the AND to the OR of the actual and predicted urban images as binary layers was used to select among the possible alternatives. However, additional metrics and an increased number of Monte Carlo iterations may improve the coefficients obtained from the calibration phase. Time constraints precluded performing an exhaustive comparison among leesalee, population, edges, and clusters or some composite of these.

The coefficient values that are computed here during rigorous calibration phases are going to be used in predicting urban growth in Houston CMSA and also land use/land cover change will be simulated throughout 2030.

CHAPTER III

PREDICTING URBAN GROWTH IN HOUSTON-GALVESTON-BRAZORIA CONSOLIDATED METROPOLITAN STATISTICAL AREA (HOUSTON CMSA)

The Houston-Galveston-Brazoria Consolidated Metropolitan Statistical Area (Houston CMSA) has experienced rapid population growth during the past 3 decades and it is projected to reach approximately 7.5 million by 2030. Houston also is the only major US metropolitan area with no zoning regulations. Using SLEUTH, a spatially explicit cellular automata model, the spatial pattern of future urban growth within the Houston CMSA is predicted for the 2002 to 2030 period. The SLEUTH model is calibrated for local conditions in Houston using four historical urban extents, two land use layers, four transportation layers, slope layer, and excluded layer for the period from 1974 to 2002. The modeled SLEUTH, growth in the Houston CMSA is predominately "organic" with most growth occurring along the urban/rural fringe. Projected increases in urban area from 2002 to 2030 parallel projected increases in population growth within the Houston CMSA. From 1990 to 2000, the population of Houston CMSA more than doubled from approximately 2,000,000 to 4,600,000 and it is expected to grow by an additional 2,800,000 people by 2030. Secondly, urban growth in Houston over the past 30 years has epitomized the term urban sprawl because the urban area has quadrupled, growing from 941 to 3,724 km^2 from 1974 to 2002, and it is predicted to double by 2030, reaching 6,621 km^2.

1. Introduction

Urban planners and other academics focused their attention on urban growth models in order to help understand, and potentially lower the negative effects of large-scale urbanization. Planning agencies have recently been integrating analytical decision making tools with traditional planning approaches to improve planning for their communities. Technologically based tools such as urban models and geographic information systems (GIS) can provide insight into different growth scenarios, enabling policy makers to more effectively use traditional planning tools (EPA, 2000). Geographic information developed to support growth management strategies can be incorporated into planning activities and environmental analysis.

Sprawl has been in effect with the exurban growth in our cities. Middle-class and wealthy residents are drawn out of the inner city into the suburbs and exurbs (Beale, 1977; Hodge & Qadeer, 1983; Davies, 1990). Higher taxes on farmland, demand for better public services, trespassing on farmlands, and displacement of farm families to the city are some of indirect impacts of exurban growth (Rodd, 1976; Bryant & Russwurm, 1979; Bryant, 1981).

Between 1900 and 1970 net migration in the USA was predominately from rural areas to urban centers (Wardwell & Brown, 1980). Since then, the nation's rural population fluctuated between 50 and 60 million, while the urban population increased nearly seven-fold to approximately 150 million in 1970 (Fuguitt et. al., 1989). During the 1970s, the trend of net migration to urban centers reversed with large cities losing population to non-metropolitan rural areas and small cities with populations less than 25,000 residents laying on the urban fringe (Wardell & Brown, 1980). The largest net population growth rates in the 1970s were in the non-metropolitan counties adjacent to at least one metropolitan county (Johnson, 1989). A metropolitan county contains a city with at least 50,000 people or is part of an urbanized metropolitan area with a population of at least 100,000 (Myers, 1992). During the 1980's, the nation returned to the historical norm of rapid metropolitan population growth with net out-migration from rural areas to metropolitan areas (Fuguitt et al., 1989). However, population continued in non-metropolitan counties located adjacent to metropolitan ones (Johnson, 1989).

Population dispersion from city centers to the outwards in the USA and in other industrialized nations has been facilitated by advances in transportation and communication technologies, changes in labor-force composition, increases in personal affluence, and a reduction in rural-urban differences (Wardwell, 1980; Fuguitt et al., 1989). The lessening distance brought about by technological changes and by the expansion of transportation infrastructure has made rural landscapes in both metropolitan and adjacent non-metropolitan counties accessible for residential development. Because of the diversity of residential locations urbanization decisions are increasingly influenced by the quality of public services (Anas, 1982) and by the spatial distribution of environmental amenities and disamenities (Diamond & Tolley, 1982; Knapp & Graves, 1989).

During the last 50 years, these migration patterns to and within metropolitan areas in the United States have caused rapid growth, transforming farmland, wetland, and forests into extensive urban landscapes. Research scientists and policy makers are paying attention to the consequences of urbanization as a result of the environmental impacts it produces. The widespread expansion of urban areas has been especially evident in regions that are undergoing rapid economic development. In such areas, problems arise when urbanization is poorly planned. Unplanned and uncontrolled urbanization results in sprawl, conversion of prime agricultural land to urban uses, and habitat fragmentation.

Houston, Texas, is an archetypical example of rapid expansion of an urban area in the United States. The Houston-Galveston-Brazoria Consolidated Metropolitan Statistical Area (hereafter referred to as the Houston CMSA) is among the nation's most dynamic and rapidly growing metropolitan areas. Between 1900 and 2000, the region's population more than doubled growing from approximately 2,000,000 to 4,600,000 (U.S. Census Bureau, 2000a). The population is projected to grow by an additional 2,800,000 by the year 2030 (The Perryman Group, 2002). Because Houston's areal growth over the past 30 years has been a prime example of urban sprawl and there is no reason to assume this growth mode will not continue in the future.

Any substantial increase in population usually has a negative effect on land because it requires the land, which is employed for other uses, to be converted to urban land. There has been a movement recently to develop urban simulation models that are designed to help understand the spatial expansion of urban areas (White & Engelen, 1993; Batty & Xie, 1994; Cecchini, 1996; Batty et al., 1997; Clarke et al., 1997; Clarke & Gaydos, 1998; Semboloni, 1997; White et al., 1997; Li & Yeh, 2000). These urban growth models follow in the long and distinguished tradition of the mapping and quantifying spatial patterns of urban growth (Tobler, 1970). Urban models have been developed to predict, describe, and analyze the spatial expansion of urban areas for research and policy purposes (Lee, 1973; Batty, 1976; Landis, 1994; Couclelis, 1997; Guhathakurta, 1999; Klosterman, 2000).

One of these new urban growth simulation models is the SLEUTH model. The acronym, SLEUTH, was compiled from the image input requirements of the model: Slope, Land cover, Exclusion, Urbanization, Transportation, and Hillshade. The SLEUTH model has been designed for easy portability to diverse regions throughout regional and global scale and SLEUTH has successfully predicted urban expansion in the San Francisco Bay area, the Washington-Baltimore corridor and in Lisbon-Porto, Portugal (Clarke et al., 1997; Clarke & Gaydos 1998; Silva & Clarke 2002). SLEUTH is currently being used to model urban growth in Chicago-Milwaukee, Portland-Vancouver, the Philadelphia-Wilmington and New York metropolitan areas (Gigalopolis, 2003). The model's validity can be evaluated by its ability to generate realistic urban patterns useful for scenario planning and various types of regional analysis. In this research, SLEUTH model is used to predict the future urbanization patterns in the Houston CMSA for the period 2002 to 2030.

2. The Houston-Galveston-Brazoria CMSA

Houston, Texas, presents an ideal metropolitan area for modeling spatial patterns in urban growth using SLEUTH model. First, from 1990 to 2000, the population of Houston more than doubled from approximately 2,000,000 to 4,600,000 and it is expected to grow by an additional 2,800,000 people by 2030. Secondly, urban growth in Houston over the past 30 years has been epitomized by the term urban sprawl. The urban area has quadrupled; growing from 941 to 3724 km^2 from 1974 to 2002. Thirdly, compared to many other cities, urban expansion in Houston is largely unconfined. Outside of water bodies and floodplains, there are few physiographic limits to Houston's growth. Because

Houston is the only major city without a zoning plan (Vojnovic, 2003), urban growth there faces much less regulatory constraints than urban growth in many other cities in the United States. Texas political columnist Molly Ivins succinctly summarized Houston's climate, topography and rapid urban sprawl in her description of "Houston is Los Angeles with the climate of Calcutta"

Houston lies largely in the northern portion of the Gulf coastal plain along a 64 to 80 km. wide swath along the Texas Gulf Coast. The northern and eastern portions of the eight-county study area are largely forested, while the southern and western portions are predominantly prairie grassland. Perhaps the largest physiographic obstacle to growth in the Houston metropolitan area is surface water. The study area contains lakes, rivers, bays and an extensive system of bayous and manmade canals that are part of the rainwater runoff management system. Approximately 25%-30% of Harris County, which contains most of the city of Houston, lies within the 100-year flood plain.

The Houston-Galveston-Brazoria Consolidated Metropolitan Statistical Area (Houston CMSA) forms the basic areal unit of this study. The Houston CMSA (see Fig. 2.6) contains eight counties and three Primary Metropolitan Statistical Areas (PMSAs): The Houston PMSA encompasses Chambers, Fort Bend, Harris, Liberty, Montgomery, and Waller Counties while the much smaller Galveston-Texas City PMSA and Brazoria PMSA each comprise a single county, Galveston and Brazoria, respectively. The Houston CMSA's population of 4.8 million is the 10th largest among U.S. metropolitan statistical areas. The city of Houston has a population of 1.9 million and is the 4th most populous city in the nation trailing only New York, Los Angeles, and Chicago.

The City of Houston lies in three counties: Harris (1,511.13 km^2), Fort Bend (20.92 km^2), and Montgomery (6.73 km^2) (see Table 3.1). Under Texas' Municipal Annexation Act of 1963, the city of Houston (as can all cities over 100,000) also can exert certain powers over unincorporated areas lying within 8 km of any point on the city limits, which is termed the Extraterritorial Jurisdiction (ETJ). Houston's ETJ encompasses 3,397.93 km^2, excluding the area of cities that lie within it. In addition to Houston, Harris County contains part or all of 35 individual incorporated areas which lie outside of Houston's ETJ.

Table 3. 1
Spatial extent of Metropolitan Statistical Areas and counties and the City of Houston

NAME	AREA (km^2)
Houston CMSA	22,736
Houston PMSA	16,328
Brazoria PMSA	4,138
Galveston PMSA	2,270
Harris County	4,605
Chambers County	1,551
Fort Bend County	2,266
Liberty County	3,004
Montgomery County	2,704
Waller County	1,335
City of Houston	1,539

The City of Houston was founded in 1836 and incorporated in 1837, but grew slowly prior to 1900 when it reached a population of only 45,000. The Galveston Hurricane of 1900 and the discovery of large oil reserves at Spindletop in 1901, 145 kilometers east of Houston, led to Houston's rapid growth. Transportation improvements in the 19th and

20th centuries including the creation of the Houston Ship Channel which enabled oceangoing vessels to reach Houston itself also fueled Houston's growth. In the 20th century, federal and state intervention in the Houston economy expanded to include the funding of petrochemical plants, gas pipelines, refineries, and research and development in the petrochemical industry. The decision to locate the National Aeronautics and Space Administration (NASA) complex was another boost to the Houston area in the 1960s. Vojnovic (2003) provides a good review of the factors fueling Houston's growth.

3. Population Growth and Urbanization

Globally, the world's population is becoming more urbanized. In 1995, 51 percent of the world's population lived in settlements of at least five thousand people, an increase of 29 percent from 1950 (Clarke & Gaydos 1998). It is expected that the equivalent of 1,000 cities, each of three million inhabitants, will have to be constructed worldwide by the year 2040 (Binde, 1998). According to U.S. Census Bureau projections (U.S. Census Bureau 2000b), which rely on assumptions about future fertility, mortality, and international migration rates, suggest a doubling of the U.S. population by 2100 to approximately 570 million people (U.S. Census Bureau 2000c).

Texas's population has also increased dramatically since the 1960's, and in 2003 totaled approximately 22 million making Texas the 2nd most populous state after California (MERIC, 2003; U.S. Census Bureau, 2000a).

Detailed population predictions for the period 2000 to 2040 have been performed on a county level basis for the state of Texas by the Texas Office of the State Demographer and The Department of Rural Sociology at Texas A&M University. These projections utilize a state of the art methodology cohort-component projection technique with existing demographic patterns taken into account (Texas State Data Center, 2003). Three population projection scenarios have been developed. The population projection used here represents the one-half 1990-2000 Migration scenario which assumes that net migration will occur at a rate one-half that observed during the 1990s (see Appendix). These projections are those recommended for most applications (Texas State Data Center, 2003). Table 3.2 below illustrates the population projections from 2005 to 2030 for each Houston CMSA county, Houston CMSA, and Houston PMSA (Texas State Data Center, 2003).

Table 3. 2
Population projections from 2005 to 2030 for the Houston CMSA counties

	2005	2010	2015	2020	2025	2030
Brazoria	263,631	285,850	308,656	331,731	354,258	375,664
Chamber	28,637	31,375	34,261	37,328	40,256	42,867
Fort Bend	401,710	449,811	501,218	557,407	615,222	670,032
Galveston	259,872	268,714	277,238	284,731	290,522	294,218
Harris	3,674,011	3,951,682	4,240,026	4,541,661	4,853,680	5,17,4691
Liberty	75,876	81,930	88,354	94,898	10,1220	107,335
Montgomery	335,176	379,363	426,858	478,187	531,570	585,111
Waller	36,644	41,137	46,142	51,175	56,654	62,352
Houston PSMA	4,552,054	4,935,298	5,336,859	5,760,656	6,198,602	6,642,388
Houston CMSA	5,075,557	5,489,862	5,922,753	6,377,118	6,843,382	7,312,270

Fig. 3.1 illustrates population projections for counties in the study area, excluding Harris for the 2005 - 2030 period. Fort Bend and Montgomery counties have the highest

population among the seven counties and also they are projected to have the highest growth rate between 2005 and 2030. Chambers, Waller, and Liberty counties have low population amount and also have low growth rate relative to Fort Bend and Montgomery. Galveston also shows a trend close to send group, Chambers-Waller-Liberty, based on a lower growth rate especially after 2015.

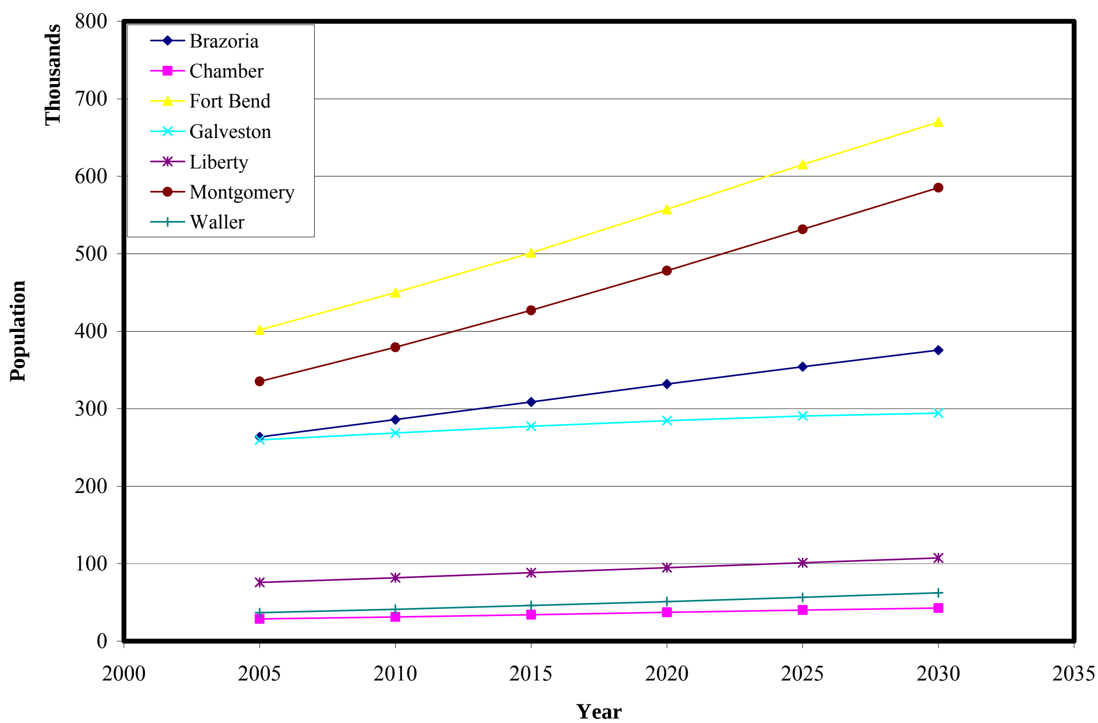

Fig. 3. 1 Population projections for counties in the study area, excluding Harris, for the 2005-2030 period

Fig. 3.2 plots population growth for Harris county, Houston PMSA and Houston CMSA. Houston PMSA and Houston CMSA are similar in terms of their growth rate. This indicates that population is concentrated on Houston PMSA. Harris, Fort bend, and Montgomery counties have the highest population growth rate and population amount.

Therefore, Houston PMSA shows parallel growth rate to Houston CMSA. The rest of the counties; such as Galveston, Waller, and Liberty; do not account much for the study area in terms of population growth and growth rate.

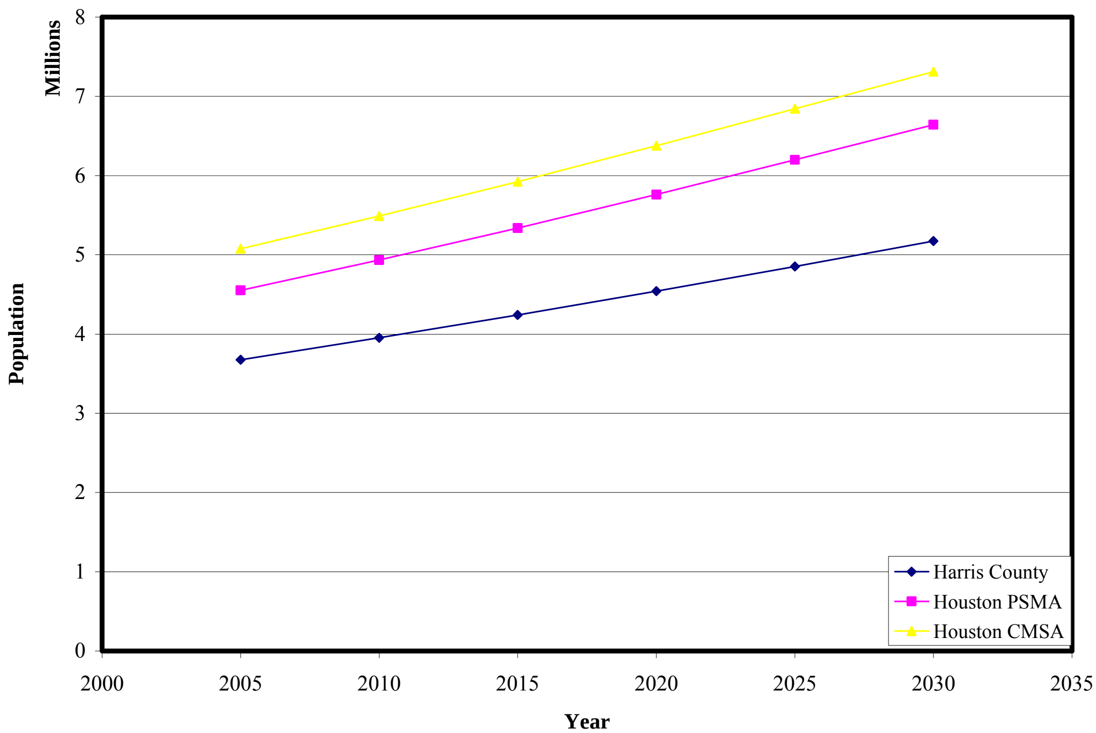

Fig. 3. 2 Population projections for Harris County and the Houston Primary (PMSA) and Consolidated (CMSA) Metropolitan Statistical Areas for the 2005-2030 period

Population dynamics are important because land is required to accommodate the world's rapidly increasing urban population. In Texas, the major urban growth form is sprawl, occurring as a result of a surging state population.. Urban sprawl such as has occurred in Houston is characterized by (1) low density development that extends outward from city centers, (2) a heavy dependence on automobiles for transportation and (3) single-use zoning that separates one type of land use from another (EPA, 2000). As a result of urban sprawl, farmland and natural habitats are being replaced with low density single family dwellings and sprawling retail shopping complexes, deteriorating the environment and outpacing the economic benefits of growth. As outlying growth centers continue to develop, such as Houston's edge cities (Garreau, 1991) of the Galleria and Greenspoint, people and businesses then begin to move away from the central city, which can lead to urban decay and the isolation of disadvantaged populations (EPA, 2000).

4. Urbanization and Modeling

Urban modeling is generally concerned with designing, building and operating mathematical models of urban phenomena, typically for cities and regions to help scientists understand urban phenomena through analysis and experiment and aid planers politicians and the community to predict, prescribe and invent the urban future (Batty, 1976). The role of models in the planning process is to help understand the behavior of urban systems. Hester (1970) identifies two objectives for the use of models in urban planning. One is to uncover the dynamics of urban development, as a means of advancing the theory of urban growth, and making theory operational so that it can be refined and tested. The second objective for the use of models in urban planning is to provide a method for projecting the future state of the systems they describe, in order to anticipate or influence the course of urban development in accordance with public policy.

According to Guhathakurta (1999), the renewed optimism of large-scale urban models stems from two sources: (1) the power of personal computers and (2) the promise of geographical information systems (GIS) as a communicative platform for testing and applying urban models. This new technology must be integrated with a new planning philosophy. Guhathakurta (1999) argues that it is essential to forge a symbiotic relationship between planning theory and the urban modeling efforts and the validity of urban modeling can be demonstrated through successful use by the planning community. The role of models in the planning process has increased in relation to their greater acceptance in the planning community.

5. Urban Models

Modeling has been used to study the demographics, economic activity and spatial organization of urban areas using both descriptive and predictive approaches. Computer models used in community planning traditionally have focused on regional economic trends or transportation related impacts on economic growth (EPA, 2000). Demographic models are used for the analysis and projection of population dynamics and are useful for planning purposed because they can examine the effect of population grown on land requirements for housing and other urban activities and the influence of population growth on investment decisions and on public policy (Masser, 1972; Oppenheim, 1980). Economic activity models (i.e. inter-industry relationships, economic base, input-output analysis) are techniques for analyzing economic activity in relation to urban planning and can aid in the formulation of planning policies and provide insights into the structure of the local economy (Masser, 1972). Finally, spatial organization models such as gravity models, the Lowry model, and operational urban models, attempt to explain the spatial organization of population and economic activity within regions and urban areas.

Since all urban activities influence one another, a model that considers the spatial relationships represents an improvement in modeling urban growth. Gravity models have long been used for analyzing spatial relationships in regions and urban areas more than any other form of mathematical model (Lee, 1973; Masser, 1972). Gravity models analyze the interaction between various urban activities, and are so called because the gravity concept of human interaction is based on the Newtonian concept of gravity (Lee, 1973). Main urban modeling, the gravitational pull exerted by two bodies is interpreted as the amount of interaction between two areas, and the mass of the bodies is measured in terms of size and attractiveness of the urban areas (Lee, 1973). Even though gravity models have been widely within the planning community, they have problems and limitations. The main criticism is the lack of a sound theoretical base. Lee (1973) states that gravity models are not based on any theory of urban system behavior and lack explanatory behavior. Gravity models may describe the interaction between activity centers; however, they fail to explain the interactions.

One of the most widely applied urban models is the Lowry model which depicts well the relationships between transportation and land use. The core assumption of the Lowry model assumes that regional and urban growth (or decline) is a function of the expansion (or contraction) of the basic sector. This employment is in turn having impacts on the employment of two other sectors, retail and residential. The Lowry model introduced two major innovations into the urban modeling field: (1) it incorporated within its structure both a forecasting land use distribution and intensity of land use activities and (2) it related three elements of the urban system (population, employment and transportation) within one model framework (Lee, 1973). According to economic base theory, the major force driving changes in the structure of an urban region is employment change in the region's industries, and this affects population and employment levels directly and indirectly (Lee, 1973). The model has been widely applied and has proved useful in a variety of studies, but it also has been criticized because it is a static model (Lee, 1973).

Recently there has been renewed interest in the development of operational urban models to aid in understanding the adverse effects of urban expansion. This renewed interest in urban models stems from a increases in computer computational power, software developments such as Geographic Information Systems (GIS), plentiful digital data and increasing environmental concerns. The emphasis on "smart growth" which attempts to balance the needs for development with quality of life has put an increasing emphasis on spatially explicit models that address the environmental consequences of land use/land cover (LULC) change. "Smart growth" places emphasis on town-centered development, mass transit and pedestrian oriented planning, and seeks to achieve a balanced mix of housing, commercial and retail uses (EPA 2000). Operational urban models can be applied at multiple locations and generate results that address relevant planning issues. Table 3.3 summarizes the type of operational urban models currently available (Klosterman 2000) where "model type" refers to aspects of the models such as operational method, underlying math structure and thematic scope. Although a number of urban models have been developed, only a few are actually available, and even fewer are freely available. The LUCAS, Markov, SLEUTH, Smart Growth Index, UPLAN, and UrbanSim are the only free models available for academic research.

Table 3. 3
Type of operational urban models

Model	Spatial Interaction	GIS (Planning Requirements)	GIS (Calibration)	Other
Community Viz		X		
CUF, I		X		
CUF, II			X	
CURBA			X	
DELTA				X
DRAM/EMPAL	X			
GSM		X		
INDEX		X		
IRPUD	X			
LTM				X
LUCAS			X	
Markov				X
MEPLAN	X			
METROSIM	X			
SAM-IM		X		
SLEUTH				X
Smart Growth Index		X		
Smart Places		X		
TRANUS	X			
Ugrow				X
UPLAN		X		
UrbanSim	X			
What if?		X		

6. Complexity of Urban Environments

Urban areas have complex land use patterns. This complexity is meaningful as it represents the information-rich nature of the system, and is necessary for the successful functioning of the city (White et al. 1997). Work by White and Engelen (1993) on the theory of dynamics and evolutionary systems provides support for the idea that complexity is an inherent and necessary characteristic of cities. These complex urban patterns can by capture by a GIS for use in models. The integration of Cellular Automata (CA) with GIS provides an approach to modeling spatial dynamics that both retains and utilizes the spatial complexity of cities (White at al. 1997). Clarke and Gaydos (1998) believe CA models are ideally suited to modeling urban systems, because of more unknown than measurable variables. The number of variables involved in the urban growth process has not been concretely established. The SLEUTH model attempts to simplify the process by modeling the complex nature of urban areas solely by the physical controls to development.

7. Limitations of Modeling in GIS

GIS requires improvement and advancement of analytical capabilities. Solutions are required for problems that address both the performance and the modeling problems of contemporary GIS (Wagner, 1997). Contemporary GIS has serious deficiencies as a platform for urban modeling including poor performance for many operations (especially for large data volumes), poor ability to handle dynamic spatial models, and poor handling of the temporal dimension (Park & Wagner, 1997). Research has focused on improving the analytical capabilities of spatial modeling within GIS (Park & Wagner 1997; Fotheringham & Rogerson, 1994; Semboloni, 1997). In these efforts the focus is on the incorporation existing spatial models into GIS and to a lesser extent the development of a more suitable GIS-based framework for spatial modeling (Wagner 1997).

Sui (1998) claims that the integration of urban modeling with GIS must proceed with the development of new models for inherently complex cities, the incorporation of multi-dimensional concepts of space and time with GIS, and through extension of the feature-based model to implement these new urban models and spatial-temporal concepts. One means to overcome the performance constraints of current generation of GIS for urban modeling is through the use of cellular automata (CA).

The integration of CA and GIS is not only feasible, but provides many advantages. Cecchini (1996) concluded that CA and other techniques from within the artificial intelligence paradigm are useful for representing socioeconomic and urban development phenomena which are shaped by individual choices and decisions. Current research on coupling CA with GIS has improved the analytical capabilities for dynamic spatial modeling (Wagner, 1997; Park & Wagner, 1997; Clarke & Gaydos, 1998). Park and Wagner (1997) have shown significant advantages of CA in data analysis and modeling. The abilities of CA to perform spatial dynamic modeling, to handle time explicitly, and the ease with which CA models can be constructed are all valuable benefits (Wagner, 1997). Couclelis (1997) argues that the integration with GIS has helped move cellular automata-based urban and regional models from the realm of instructive metaphors to that of potentially useful quantitative forecasting tools.

8. Cellular Automata

CA belongs to a family of discrete, connectionist techniques that are currently being used to investigate fundamental principles of dynamics, evolution, and self-organization (White & Engelen, 1993). Essentially, a cellular automaton model is composed of a finite set of grid cells, the current state of each cells, a set of transition rules for the cells, and the neighborhood of a cell. In a strict cellular automaton the rules must be uniform and must apply to every cell, state, and neighborhood. Every change in state must be local implying that there is no action at a distance (Batty et al., 1997). There are many renditions of CA, but the current ones that have applicability to urban systems follow Conway's logic (Batty & Xie, 1994).

9. Urban Modeling Using CA

The application of CA to dynamically model urban systems can be traced back to CA's beginnings. The first attempts to build mathematical CA models of urban systems originated with Hagerstrand's (1967) spatial diffusion models. This was followed with work accomplished by Tobler (1970) formulating a demographic model based on the cell-space concept in the Detroit region. Tobler (1979) continued his pioneering efforts by formulating models for geographic problems following strict CA principles. Couclelis (1985, 1989, and 1997) followed using CA to explore theoretical issues such as complexity and structure formation of urban systems.

A number of studies applied CA to practical problems in urban modeling and land use planning starting in the early 1990s. White and Engelen (1993) used a cellular modeling approach to investigate the dynamics, evolution, and self-organization of urban land use patterns. Batty and Xie (1994) formulated a CA model to simulate historical development in Savannah, Georgia and this was followed by Batty and Xie (1997) who established a generic framework for urban simulation using CA. Cecchini (1996) implemented an urban modeling scheme through a system called urban automata, conceptually developed by the CAVE (Cellular Automata in VEnice) research group. White et al. (1997) developed a cellular automaton model that generated a spatially detailed representation of the evolution of urban land use patterns. Semboloni (1997) developed an urban and regional model based on CA and economic theory, structure and policy parameters, and population. Wu (1998) developed a fuzzy-logic-controlled CA to simulate urban encroachment on rural land in the context of sustainable development. Webster and Wu (1999) used cellular automata simulations to explore the impact of alternative systems of pollution property rights on urban morphology and performance. More recently, Li and Yeh (2000) attempted to model sustainable urban development with a cellular automaton model and GIS.

The basis of the SLEUTH CA model used in this research had traces its heritage to Clarke et al. (1997) who used a self-modifying cellular automaton to model historical development in the San Francisco Bay area. This initial work was followed by Clarke and Gaydos (1998) who applied the same model to the Washington-Baltimore corridor in the Eastern United States. This research by Clarke et al. (1997) and Clarke and Gaydos (1998) demonstrated that urban growth in these two quite different regions could be successfully predicted using loose-coupling of a cellular automaton model in concert with GIS. The developed model is scale independent, which allows local, regional, and continental scale processes to be described in a single context. The model functions similarly to the way in which a city expands; i.e. every single part acts as part of an ensemble to collectively urbanize a region. The complex aggregate behavior of CA modeling results from many interacting self-motivated agents, which has great value for both urban modeling and for the data rich environment of GIS (Clarke & Gaydos 1998).

The theoretical advance of the represented by this model is its incorporation of self-modifying rules. The control parameters of the model are allowed to self-modify; that is, the CA adapts itself to the circumstances it generates (Clarke et al. 1997). The self-modification rules account for periods of rapid growth or economic stagnation. As time progresses, the factors controlling real-world urbanization change and this is represented by the model's self-modifying rules. Without these rules, the model produces linear or exponential growth as long as new land remains available for urbanization. Self-modification generates the typical S-curve growth rate (see Fig. 2.2) of urban expansion observed within a region (Clarke & Gaydos, 1998). Clarke and Gaydos (1998) identify the need for the model to be ported to, and repeatedly applied to, new study areas and at different map scales. Applying the model to different study areas will test the reliability and applicability of the model.

10. Materials and Methods

10.1. The Basics of the SLEUTH Model

The SLEUTH model, formerly known as the Clarke Cellular Automaton Urban Growth Model (Clarke & Gaydos, 1998; Clarke et al., 1997) is a CA model written in the C programming language and selected for predicting urban growth in the Houston CMSA. SLEUTH is an acronym created from its six required input layers: Slope, Land

Use, Exclusion, Urban, Transportation, and Hillshade. SLEUTH is a self-modifying cellular automaton model whose control parameters change when modeled growth rates exceed or fall below critical threshold values (Clarke et al., 1997). In SLEUTH, self-modification is equivalent to adaptation or evolution, and the calibration method enables the model to "learn" its local setting over time (Clarke et al., 1996).

Urban expansion in SLEUTH is modeled on a two-dimensional grid. SLEUTH's sets of predefined growth rules are applied in a set of nested loops. The outer control loop executes each growth "history," of the two-dimensional grid and retains cumulative statistical data, while the inner loop executes the growth rules for a single "year." The growth rules are applied on a cell-by-cell basis and the array is synchronously updated at the end of each year in the simulation. The modified array forms the basis for urban growth in the succeeding year. Potential cells for urbanization are selected at random and the growth rules evaluate the properties of the cell and its 8 successive neighbors such as whether or not they are already urbanized, what their topographic slope is, and their proximity to a road.

Four types of urban growth are possible in the model: 1) spontaneous, 2) new spreading center (diffusive), 3) organic (edge), and 4) road influenced growth (Table 3.4). Spontaneous growth occurs when a randomly chosen cell falls adjacent to an already urbanized cell. It simulates the influence urban areas have on their surroundings. New spreading center growth permits the urbanization of cells which are flat enough to be desirable locations for development, even if they are not located adjacent established urban cells. Organic growth spreads outward from existing urban centers and represents the tendency of cities to expand. Road influenced growth encourages urbanized cells to develop along the road network.

Table 3. 4
SLEUTH growth types

SLEUTH GROWTH TYPES	DEFINITION OF GROWTH TYPES
Spontaneous Growth	Simulates the random urbanization of land
New Spreading Centers	Simulates the development of new urban areas
Edge (Organic) Growth	Stems from existing urban centers
Road-Influenced Growth	Simulates the influence of the transportation network on development patterns

Five coefficients control the behavior of the cellular automaton, 1) the diffusion coefficient determines the overall outward dispersiveness of the distribution; 2) the breed coefficient specifies how likely a newly generated detached settlement is to begin its own growth cycle; 3) the spread coefficient controls how much organic expansion occurs from existing settlements; 4) the slope resistance coefficient influences the likelihood of settlement exceeding up steeper slopes; and 5) the road gravity coefficient attracts new settlements toward and along roads.

SLEUTH's second level growth rules are its self-modification rules which are prompted when growth rates exceeds critical high values or critical low value. Crossing a critical high or low threshold, defined by the model will initiate an increase or decrease in diffusion, breed, and spread coefficients. An increase in the diffusion, breed, and spread coefficients represents the tendency of an expanding urban system to grow even more rapidly while a decrease represents declining growth in a depressed or saturated urban system. The self-modification rules also affect the road gravity coefficient and the slope resistance coefficient. The road gravity coefficient is increased as the road network enlarges which represents increased accessibility to the area. As the amount of land available for development decreases as urbanization progresses, the slope resistance coefficient will decrease as well allowing expansion to encroach upon steeper slopes which are less desirable for urbanization. Typically under SLEUTH's self-modification rules, the coefficient values increase most rapidly in the beginning of a growth cycle, when many cells are open for urbanization, and decrease as urban density increases in the region and expansion declines (Clarke & Gaydos 1998).

10.2. SLEUTH Inputs

SLEUTH is a scale independent model and can be used to model the spatial patterns of urban growth at a variety of spatial scales in different regions. Successful initialization of SLUETH for the eight-county Houston CMSA requires five input layers: urban extent, transportation, areas to be excluded from urbanization (e.g., water bodies), slope and a hillshade image (for visualization only). For statistical purposes, model requires at least four urban extent layers. It also requires at least two transportation layers of different years, a single layer of slope, one layer with areas excluded from urbanization and a hillshade layer for use only as a background with the graphical version of the model (Gigalopolis, 2003).

The development of the required thematic information for calibrating the growth coefficients for the Houston CMSA based on observed urban growth during the 1974-2002 calibration period and for predicting urban growth in the Houston CMSA over the 2002-2030 prediction period is described in detail in Chapter II. A summary table of the SLEUTH inputs is described in Table 3.5.

Table 3. 5
SLEUTH input dataset

SLEUTH INPUT DATASET						
# of Layers	Layer Type	Years				
4	Urban	2002	1992	1984	1974	
2	Lulc	2002	1992			
5	Road	2025	2002	1990	1984	1974
1	Excluded					
1	Slope					
1	Hillshade					

The SLEUTH model domain for the eight county Houston CMSA study area (which is approximately 22,736 km^2.) was 1843 pixels east-west and 2100 pixels north-south. The spatial resolution of each grid cell in the model domain was 100 m x 100 m.

10.3. SLEUTH Calibration Results

In chapter II, we have successfully calibrated the SLEUTH model using historical urban extent, land use, and road layers. Table 3.6 shows coefficient values that were obtained in calibration phase. Five coefficients that control the behavior of growth are derived after the rigorous calibration process. These coefficient values are used in prediction mode in the model to predict urban growth till 2030 for the study area, Houston CMSA.

Table 3. 6
Averaged coefficient values after the “derive forecasting coefficients phase”

Year	Diffusion	Breed	Spread	Slope resistance	Road gravity
1984	1	2	84	36	15
1992	1	2	91	31	16
2002	1	3	100	23	17

The values that will be used in prediction mode are laid out in year 2002. As seen from the table above, spread coefficient is the single dominant coefficient, which states that the metropolitan area has been experiencing an “organic” growth.

11. Results

Future urban growth of the Houston CMSA is predicted from 2002 to 2030. The predicted growth is outputted individual years from 2003 to 2030. For this particular paper, predictions from only three years, 2010, 2020, and 2030 are illustrated in Figs. 3.3. 3.4, and 3.5 respectively.

The growth is concentrated on the urban-rural fringes and the calibration of the model helped us reach the best values. The model was accurate in modeling Houston CMSA’s organic growth and this gives extra strength to the model’s own ability to automatically calibrate itself.

Predicted population estimates (Texas State Data Center, 2003) are used to compare with urban growth predictions. The results indicate that urban growth rate is slightly higher than population rate as shown in Fig. 3.6.

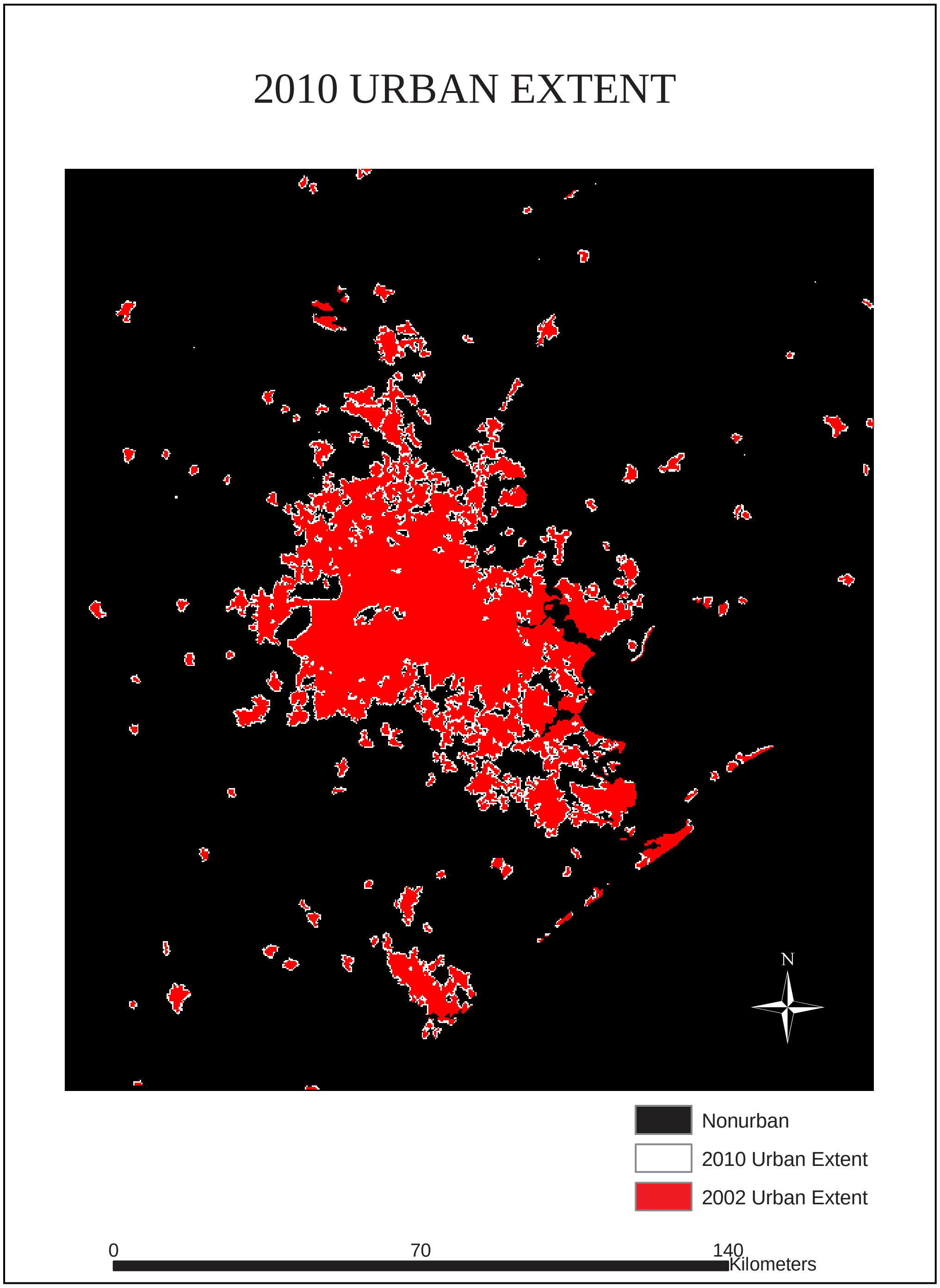

Fig. 3. 3 Predicted urban extent in 2010 for Houston CMSA

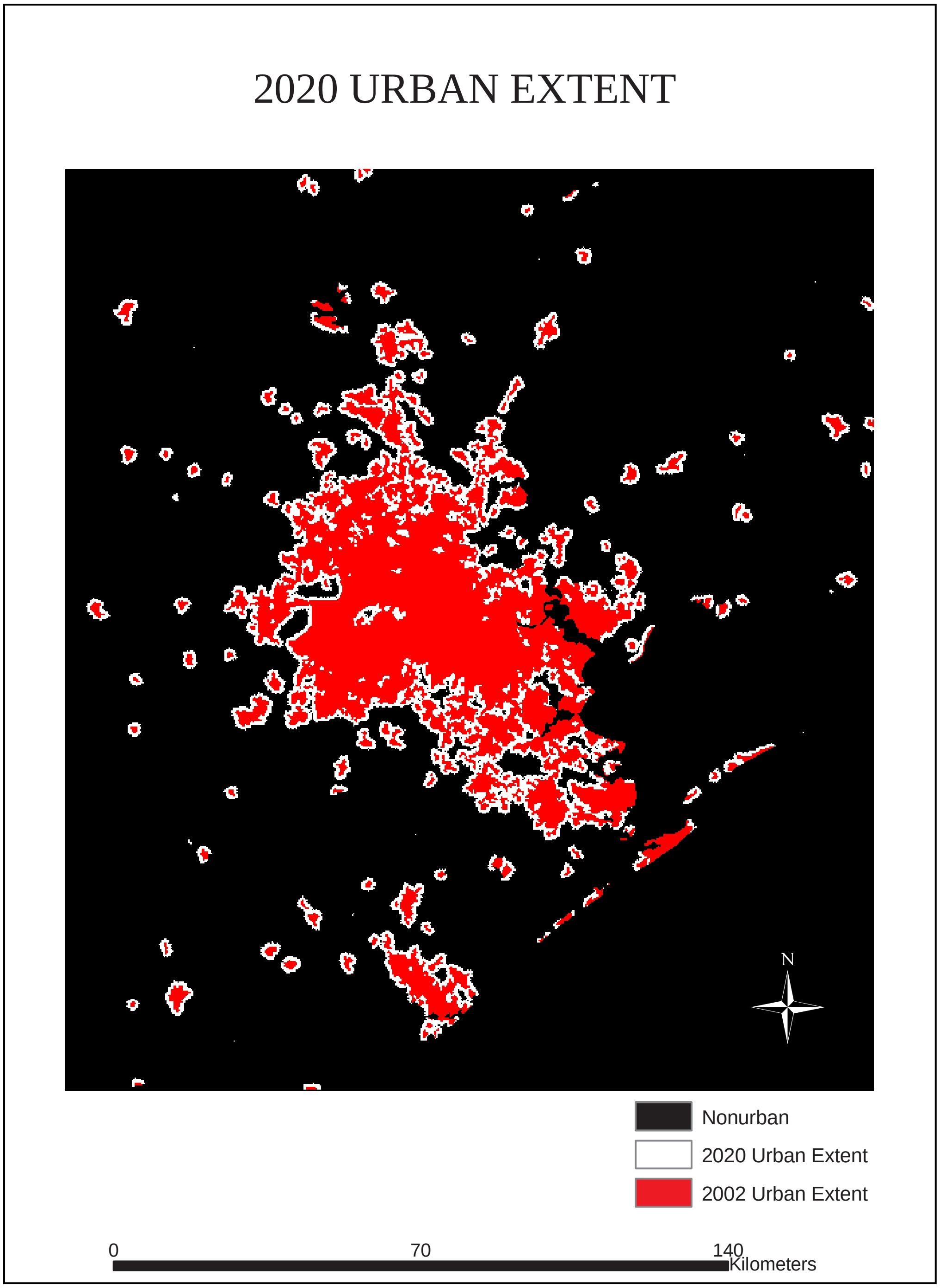

Fig. 3. 4 Predicted urban extent in 2020 for Houston CMSA

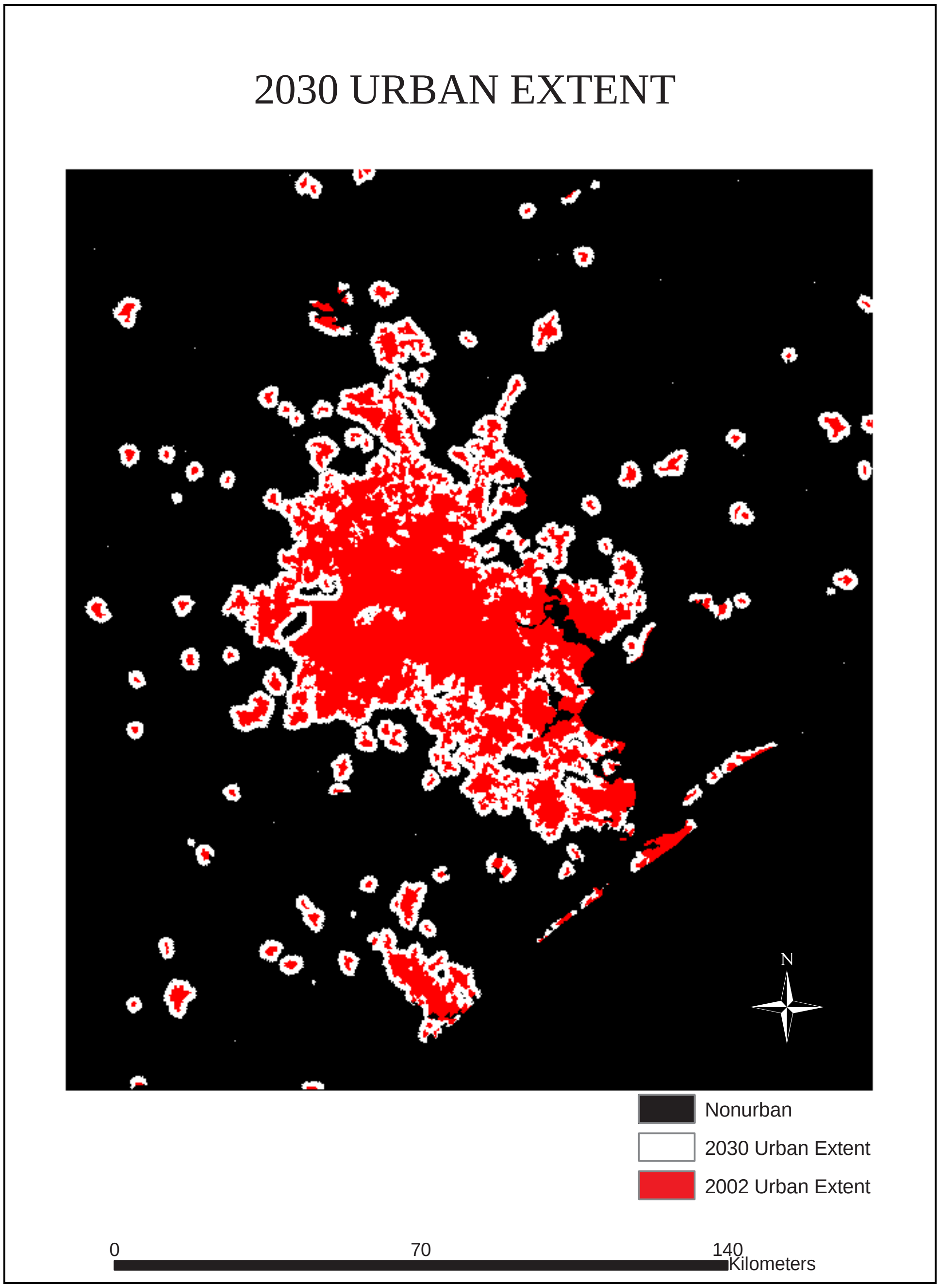

Fig. 3. 5 Predicted urban extent in 2030 for Houston CMSA

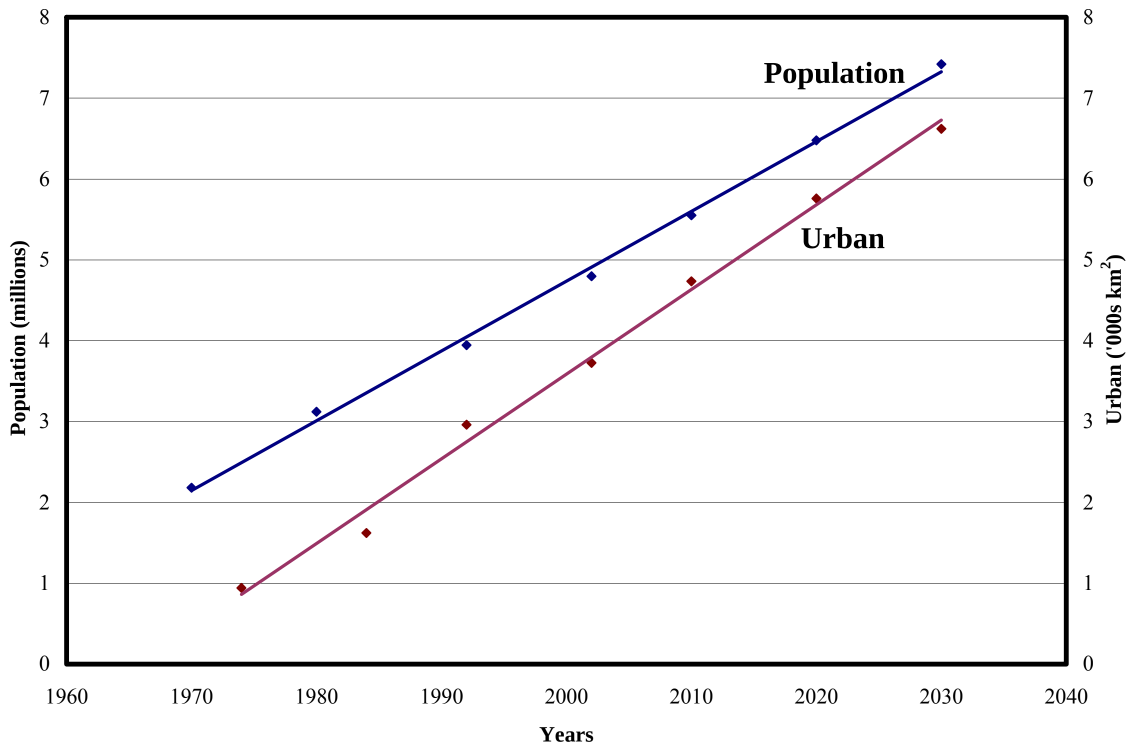

Fig. 3. 6 Population vs. urban growth in Houston CMSA

Past and future urban growth predictions in the three PMSAs that form Houston CMSA are presented in Fig. 3.7. It is easy to see that major urban growth occurs in Houston PMSA rather than other two PMSAs.

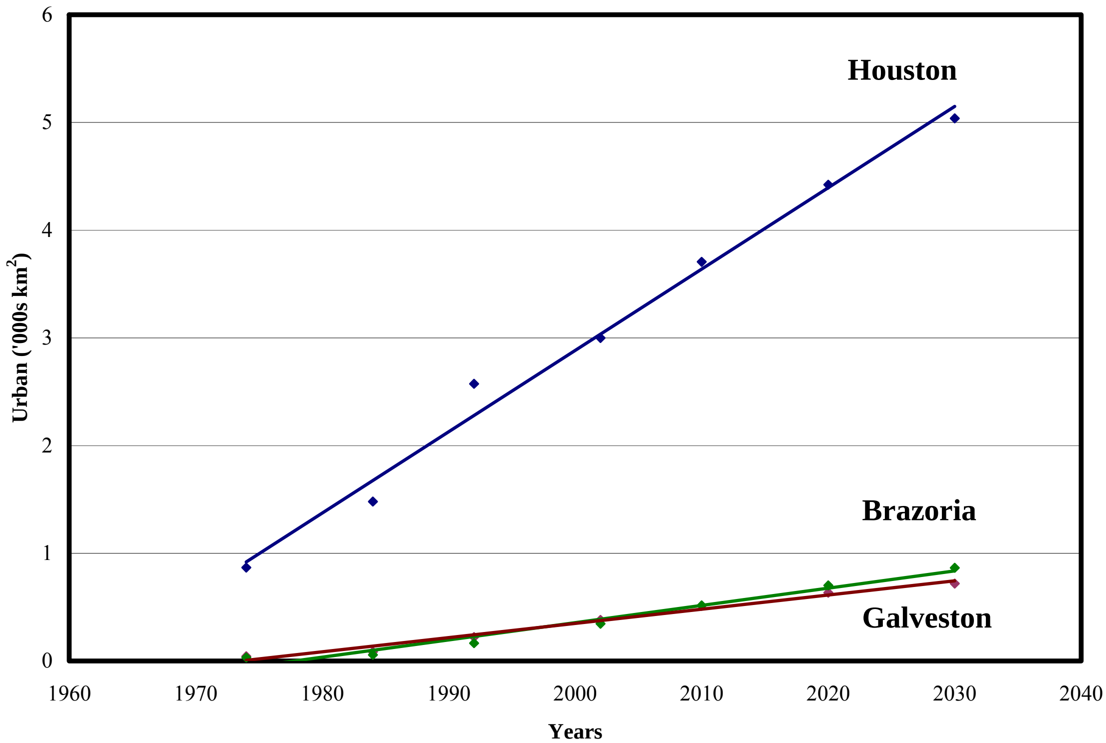

Fig. 3. 7 Urban growth in Houston, Galveston, and Brazoria PMSAs

Urban growth by the percentage of land portion of county is a good measure to illustrate how much of the urban development account for the whole county area. Fig. 3.8 exhibits that Harris and Galveston counties account for most of the urban based on their county size.

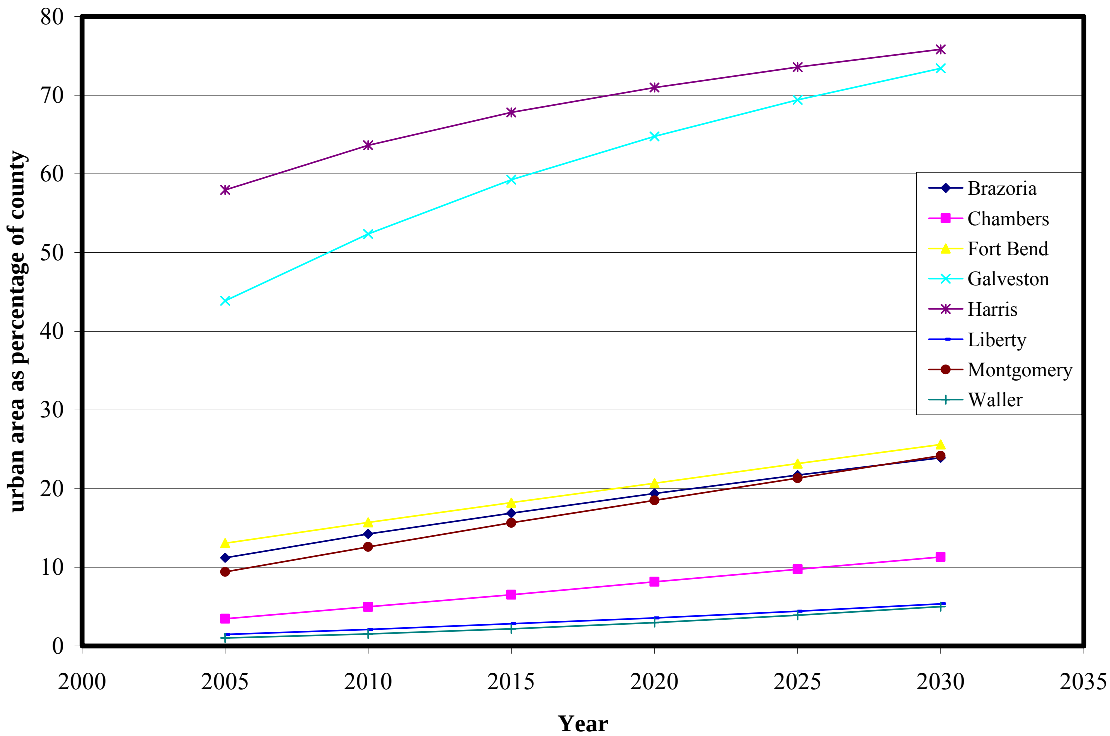

Fig. 3. 8 Urban area growth (% of Land portion of county)

Fig. 3.9, depicts an interesting result, such that, Harris and Galveston counties' growth rates have been in decline more than the other counties in Houston CMSA. This could be due to following two reasons: either growth rate is declining because available land also is declining for both of the counties, Harris and Galveston (see Fig. 3.8); or these two counties might have implemented a smart growth policy.

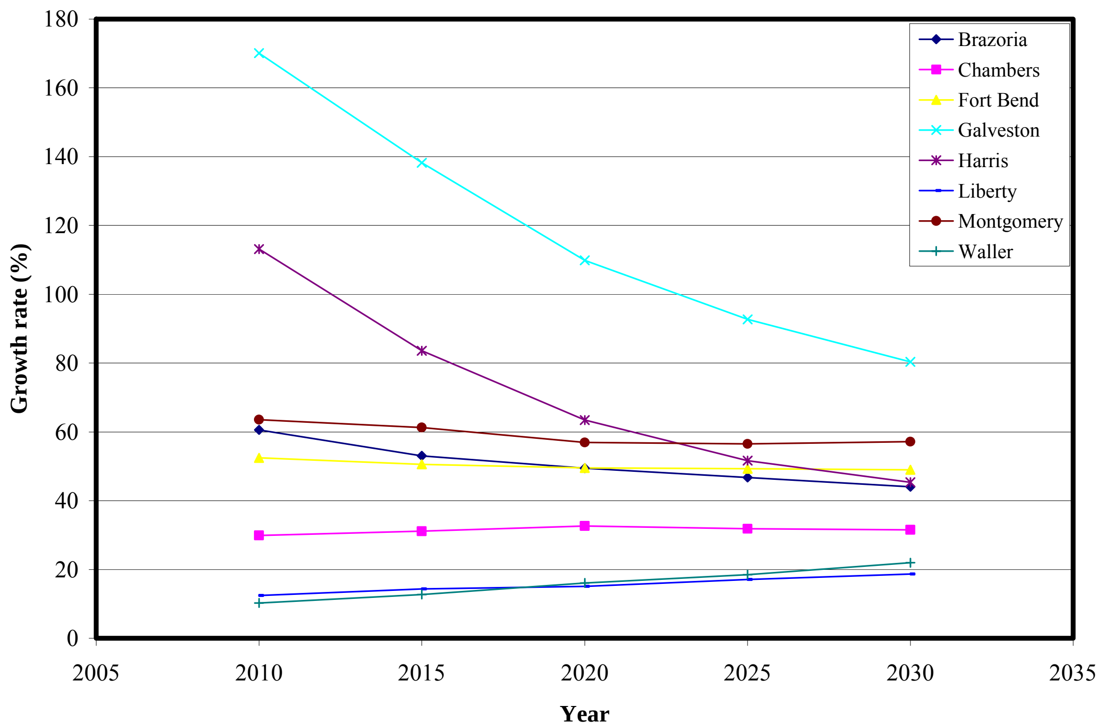

Fig. 3. 9 Growth rates [(year2-year1)/5] for CMSA counties

Fig. 3.10 illustrates the urban growth for each county, plotted in logarithmic scale. It is clear that Harris County is the most urbanized county in our study area.

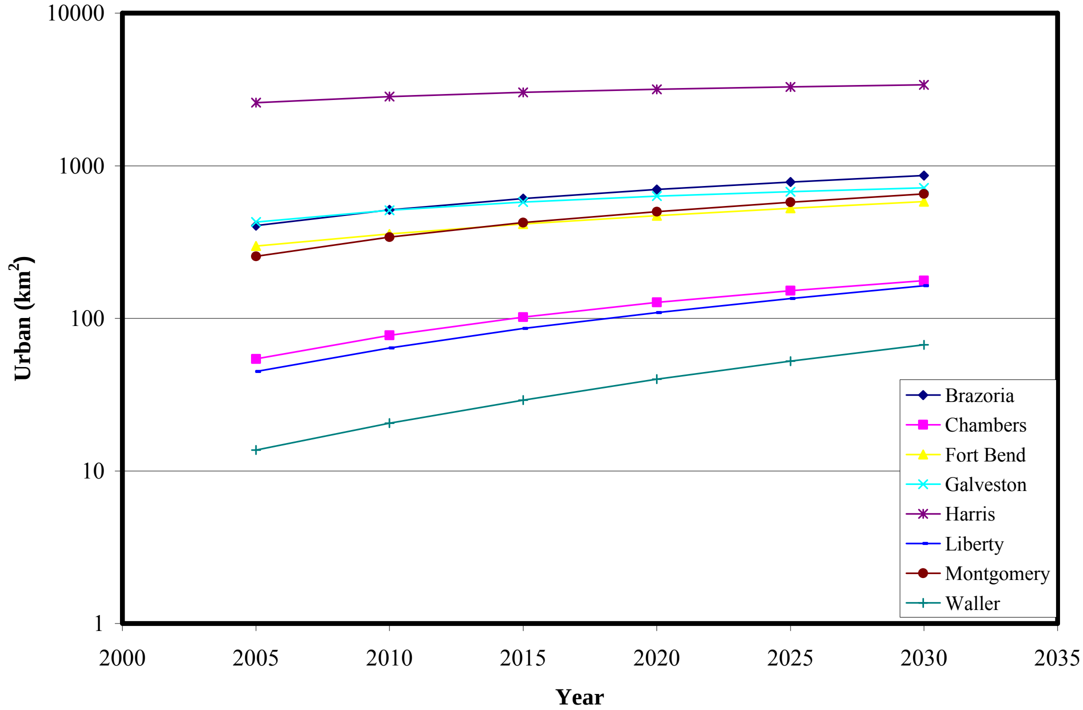

Fig. 3. 10 Urban growth in each county (logarithmic scale)

12. Conclusions

The uniqueness of this study is twofold: first, it is the only Consolidated Metropolitan Statistical Area that is modeled for urban growth and second, it is the only metropolitan area that functions without zoning and a plan. Most increase in urban and population growth in Houston CMSA occurred between 1970s and 1990s. This trend however had slowed down in both urban and population by 2002. Results reveal that urban growth is concentrated on the urban/rural fringes in the Houston CMSA. Predicted results also indicate that urban growth for the period from 2002 to 2030 is in almost parallel with the population growth prediction.

Among Houston PMSAs, Houston was the major metropolitan area that drove the population and urban growth in Houston CMSA. Galveston and Brazoria PMSAs did not show increase in both and they reflect very small part of Houston CMSA.

CHAPTER IV

USING THE SLEUTH URBAN GROWTH MODEL TO SIMULATE THE IMPACTS OF FUTURE POLICY SCENARIOS ON URBAN LAND USE IN THE HOUSTON-GALVESTON-BRAZORIA CMSA

We used the SLEUTH urban growth model, closely coupled with a land transition model, to simulate future urban growth in the Houston metropolitan area, one of the fastest growing metropolises in the United States during the past three decades. The model was calibrated with historical data extracted from a time series of satellite images. Three specific scenarios are designed to simulate the spatial pattern of urban growth under different environmental conditions. Then first scenario depicts an unmanaged growth with no restriction on environmental areas, such as forest, agriculture, and wetland. The second scenario assumes a managed growth with moderate protection. The last scenario simulates a managed growth with maximum protection on forest, agricultural areas, and wetland. The third scenario demonstrates the most conserved natural land with the least urban development. This scenario should be the most desirable for the future urban growth of Houston.

1. Introduction

In industrialized countries, the current pattern of urban development is increasingly taking the form of low-density, decentralized residential and commercial development. This form of development, the environmental and quality-of-life impacts of which are becoming central to debates over land use and land cover in urban and suburban areas is now commonly known as "sprawl." Many classic symptoms are loss and fragmentation of the natural resource, declining water quality, and traffic congestion (Burchell et al, 1998). "Smart growth," a land use policy orientation embodied by a suite of policies aimed at natural resource and agricultural preservation, transit-oriented development, and "brownfield" redevelopment, is becoming a reality for some areas within the Houston CMSA.

Land cover is an important element of ecological function, especially in terms of hydrological processes (Wickham et al, 2000). While urbanization has occurred, natural resource lands, such as forest, wetlands and agriculture, have been replaced by land uses with more impervious surfaces. Predicting future environmental consequences requires being able to predict the spatial pattern of land use change.

In recent years, spatially explicit simulation models of urban growth patterns have emerged. The economic versions of these models estimate land use transition probabilities using discrete choice methods based on the behavior of agents making land use decisions (Bockstael, 1996). The spatially explicit model of Landis (1995) for the San Francisco Bay and Sacramento areas is an example of a micro-level model that makes use of data from a geographic information system (GIS) to generate spatially disaggregated predictions of land use change. These modeling efforts require detailed parcel-level and GIS data that are often not widely available. This limits the ability to expand the models to a broader region or transfer them to other areas together.

A relatively simple class of models, cellular automata (CA), has gained attention from researchers attempting to simulate and predict spatial patterns of urban development. CA models require that space should be represented as a grid of cells that can change state as the model iterates. These changes are regulated by rules that specify a set of neighborhood conditions to be met before a change in state can occur (O'Sullivan, 2001). CA models are not only conceptually elegant but also they have the potential to simulate the complex behavior of systems, such as cities (Torrens et al, 2001). CA models have been used to simulate different types of urban forms (Yeh et al, 2001) and development densities (Yeh et al, 2002), and to investigate the evolution of urban spatial structure over time (White et al, 2000). Although pure CA models have been quite successful at recreating patterns of urban development, they have been criticized for their seeming inability to account for processes driving urban change. Recently, advances have been made in developing hybrid CA that can incorporate process-based factors.

Webster et al (2001), for example, incorporate microeconomic urban theory into a spatially explicit CA to investigate the effects of alternative planning regimes on land use patterns. As planning tools, CA urban models have several benefits: they are interactive, potential outcomes can be visualized and quantified, they can be closely linked with CIS, and raster based spatial data derived from remote sensing platforms are easily incorporated into the CA modeling environment (Couclelis, 1997).

In order to assess the potential effectiveness of smart growth policies in the Houston CMSA, our study area for this particular research (see Fig. 2.6), our objective was to develop a predictive modeling system capable of depicting the impacts of different land use and land management policies within the Houston CMSA. The design and development of the model were specifically focused on a number of criteria: (1) the model should be policy driven to facilitate discussion and testing of the effects of different land use management policies; (2) the model assumptions, implementation methodology, and results should be transparent to the average citizen; and (3) the model should be modular to facilitate the inclusion of additional scenarios and impact assessments.

The amount of urbanized land in the USA increased by 47% to 307,500 km^2, while the population grew by 17% between 1982 and 1997 (Fulton et al., 2001). The conversion of land for development was estimated to have increased from about 5,000 km^2 per year between 1982 and 1992 to 13,000 km^2 per year between 1992 and 1997 (NRCS, 1999). In general, urban sprawl in the south has been aggravated by a decline in population density in urban centers (Fulton et al., 2001).

Population growth has been especially rapid in the states along the USA-Mexico border (USCB, 1993). In Texas, population is projected to increase from 19 to 33 million by 2030, with over 70% of the growth expected to occur along the central and southern portions of the I-35 highway corridor and in the Lower Rio Grande Valley (Conner & James, 1996). Houston was the fastest growing city in the United States in the 20th century (American City Business Journals, 1999). Houston has also become one of the fastest growing metropolitan areas in the USA, experiencing a 20% increase in population from 1990 to 2000, reaching approximately 2 million in 2000 and now being the fourth largest city in the country (Demographia, 2000). This growth can be attributed to a steady growth in employment in the Houston area, and less expensive housing among 20 metropolitan areas with populations of more than 2 million (ACCRA, 2000), and low cost of living (ACCRA, 2001).

This population growth is increasingly impacting rural areas, especially those close to major urban centers in the southern part of Texas, by accelerating land subdivision and reducing the average size of land parcels (Conner & James, 1996). In addition, increase in urban sprawl generally leads to greater traffic volumes, increased pressure on local resources, less open space (Holtzclaw, 1999), and such land use changes often have a significant negative impact on the affected ecosystems and the goods and services that they provide. Ecosystem services represent the benefits that living organisms derive from ecosystem functions that maintain the earth's life support system, and include nutrient cycling, carbon sequestration, air and water filtration, and flood amelioration, to name a few (Costanza et al., 1997).

Changes in land use may significantly affect ecosystem processes and services. Monitoring and processing the impacts of such land use changes are difficult for several reasons. Impact of land use changes on ecosystems often become noticeable at the regional scale however monitoring changes is difficult because of the large volume of data and interpretation required. In addition, accurately quantifying the impacts of urban sprawl on changes in ecosystem services is difficult because of the lack of information about the contribution of alternate landscapes to these services.

The objectives of this study are: (1) to quantify land use change in Houston CMSA from 1992 to 2002; and (2) to predict land use change in study area from 2002 to 2030.

2. Materials and Methods

Houston, the seat of Harris County, Texas, is located on the upper Gulf coastal plain at 80 km from the Gulf of Mexico. The Houston-Galveston-Brazoria Consolidated Metropolitan Statistical Area (Houston CMSA) consists of three Primary Metropolitan Statistical Areas (PMSAs): Houston (Chambers, Fort Bend, Harris, Liberty, Montgomery, and Waller Counties), Galveston-Texas City (Galveston County), and Brazoria (Brazoria County) (see Fig. 2.6). The Houston CMSA's population of 4.8 million is 10^{th} largest among U.S. metropolitan statistical areas. The population is concentrated mainly around the city of Houston. The city of Houston has a population of 1.9 million and is the fourth most populous city in the nation (trailing only New York, Los Angeles, and Chicago), and the largest in the southern U.S. and Texas. Houston is the only metropolitan U.S. city that functions without a zoning plan (Vojnovic, 2003). Houston CMSA encompasses an area of 22,735.80 km^2.

The City of Houston lies in three counties: Harris (1,511.13 km^2), Fort Bend (20.92 km^2), and Montgomery (6.73 km^2). Harris County contains part or all of 35 individual incorporated areas. Under Texas' Municipal Annexation Act of 1963, cities have certain powers over surrounding unincorporated areas, termed the Extraterritorial Jurisdiction (ETJ). The ETJ is a function of population, for cities over 100,000, it can cover all unincorporated area within 8 kilometers of any point on the city limits. Houston's ETJ encompasses 3,397.93 km^2, excluding the area of cities lying within it.

Houston lies largely in the northern portion of the Gulf coastal plain, a 64- to 80-kilometer-wide swath along the Texas Gulf Coast (Fig. 2.7). Typically, elevation rises approximately 0.19m per kilometer inland. The northern and eastern portions of the area are largely forested, while the southern and western portions are predominantly prairie grassland. Surface water in the Houston region consists of lakes, rivers, and an extensive system of bayous and manmade canals that are part of the rainwater runoff management system. Approximately 25%-30% of Harris County lies within the 100-year flood plain. Elevation ranges for each county as follows: Brazoria 0-45m, Chambers 0-30m, Fort Bend 4-48m, Galveston 0-13m, Harris 0-94m, Liberty 0-82m, Montgomery 13-133m, and Waller 24-109m.

Houston's land surfaces are unconsolidated clays, clay shales, and poorly-cemented sands extending to depths of several kilometers. The region's geology developed from stream deposits from the erosion of the Rocky Mountains. These sediments consist of a series of sands and clays deposited on decaying organic matter that, over time, was transformed into oil and natural gas.

The City of Houston was founded in 1836 and incorporated in 1837. The city grew slowly, increasing in population to only about 45,000 by 1900. Galveston, located on the Gulf of Mexico, 80 km south of Houston, was the economic center of Texas throughout the nineteenth century. Galveston was a key commercial port for cotton in the U.S.

Two events early in 1900s stimulated Houston's first phase of significant growth. First, the Galveston Hurricane of 1900 that killed about 6,000 people destroyed much of Galveston, contributing to its decline as the commercial center of the State. Second, the discovery of large oil reserves at Spindletop in 1901, 145 km east of Houston, led to Houston's rapid growth. In the 19th century, new investment on transportation infrastructure began with the railroad and port projects. In the 20th century, federal and state intervention in the Houston economy expanded to include the funding of petrochemical plants, gas pipelines, refineries, and research and development in the petrochemical industry. The decision to locate the National Aeronautics and Space Administration (NASA) complex was another boost to the Houston area in the 1960s. Houston ship channel and its port were the two areas that received considerable attention in the 19th and 20th centuries. Major improvements were needed along Buffalo Bayou, the San Jacinto River and Galveston Bay if Houston would like to have central role as a shipping port in Texas. With the improvements of the waterway, large ships were pulling into Houston and taking its principal product directly to Europe. In addition to that, combustion engine production demanded petroleum and oil began to play an increasing important role in the Houston economy (Vojnovic, 2003).

2.1. SLEUTH Model

The Urban Growth Model (UGM) is a C program running under UNIX that uses the standard gnu C compiler (gcc) and may be executed in parallel. The land cover transition model is included within the code and will be called and driven by the UGM. The land cover transition model is tightly coupled with the urban code, but the UGM can run independently of it. Together, these coupled models are referred to as SLEUTH. The name SLEUTH is an acronym for the input image requirements of the model (Slope, Land use, Exclusion, Urban extent, Transportation, Hillshade) (U.S. Geological Survey, 2003).

SLEUTH is adopted because of its success with regional scale modeling, its ability to incorporate different levels of protection for different areas, and the relative ease of computation and implementation (U.S. Geological Survey, 2003). Each cell in the study area for urban extent layer had only two possible states: urbanized or non-urbanized. The land use layer had seven different possible states: unclassified, urban, agriculture, forest, water, wetland, other. The transportation layer had four possible states: non-road, 2-lane roads, 3 or 4-lane roads, more than 4-lane roads. Whether or not a cell becomes urbanized is determined by four growth rules, discussed below, each of which attempts to simulate a particular aspect of the development process. In their original application of the Clarke urban growth model, a predecessor to SLEUTH, in the San Francisco Bay area, Clarke et al (1997) stressed the utility of the model in simulating historic change, the description of which can help in the explanation of growth processes at a regional scale, and in predicting future urban growth trends. The model was successful in simulating urban change between 1900 and 1990 for the San Francisco area, and was later applied to the Baltimore/Washington corridor (Clarke et al, 1998), where calibrations and long term predictions for both San Francisco and Baltimore/Washington were presented, allowing for an effective comparison to be made between the growth patterns and processes of the two urban systems.

SLEUTH simulates four types of urban land use change: spontaneous growth, new spreading center growth, edge growth, and road-influenced growth. These four growth types are applied sequentially during each growth cycle, or year, and are controlled through the interactions of five growth coefficients: dispersion, breed, spread, road gravity, and slope (Table 4.1). Each coefficient has a value that ranges from 0 to 100. The exact value assigned to each coefficient was, in our case, derived through a rigorous calibration procedure, described in detail in section 2.3. In conjunction with the excluded layer probabilities, the five growth coefficients determine the probability of any given location becoming urbanized. The user-defined excluded layer specifies areas that are completely or partially unavailable for development. Water and unclassified areas, for example, would have an exclusion value of 100, indicating that it is 100% excluded from development. If a cell that is chosen for potential urbanization has an exclusion-value of 50, it has a 50% probability of being urbanized in any given simulation.

Table 4. 1
Summary of growth types simulated by the SLEUTH model

Growth Cycle Order	Growth Type	Controlling Coefficients	Summary Descriptions
1	Spontaneous	Dispersion	Randomly selects potential new growth cells
2	New Spreading Center	Breed	Growing urban centers from spontaneous growth
3	Edge	Spread	Old or new urban centers spawn additional growth
4	Road-Influenced	Road-Gravity, Dispersion, Breed	Newly urbanized cell spawns growth along transportation network
Throughout	Slope Resistance	Slope	Effect of slope on reducing probability of urbanization
Throughout	Excluded Layer	User-Defined	User specifies areas resistant or excluded to development

Spontaneous growth simulates the random urbanization of single pixels, which has the potential to capture low density development patterns and is not dependent on closeness to existing urban areas or the transportation infrastructure. The overall probability that a single non-urbanized cell in the study area will become urbanized is determined by the dispersion coefficient.

New spreading center growth models the emergence of new urbanizing centers by generating up to two neighboring urban cells around areas that have been urbanized through spontaneous growth. The breed coefficient determines the overall probability that a pixel produced through spontaneous growth will also experience new spreading center growth.

A newly urbanized cluster can then experience edge growth, which simulates outward growth from the edge of new and existing urban centers. Edge growth is controlled by the spread coefficient, which influences the probability that a non-urban cell with at least three urban neighbors will also become urbanized.

The final growth step, road influenced growth, simulates the influence of the transportation network on growth patterns by generating spreading centers adjacent to roads. When road influenced growth occurs, newly urbanized cells are randomly selected at a probability level determined by the breed coefficient. For each selected cell, the existence of a road is sought within a search radius defined by the road-gravity coefficient. If roads are found near the selected cell, a temporary urban cell is placed at the closest location adjacent to a road. This temporary urban cell then searches along the road for a permanent location. The direction of the search along the road is random and the search is determined by the dispersion coefficient. The permanent location becomes a new spreading center, so up to three cells along a road can be urbanized at this point.

The slope coefficient accounts for the influence of topography on development patterns and is applied as a suitability test before any location is urbanized. A high slope coefficient value will decrease the likelihood that development will occur on steep slopes.

SLEUTH also has a functionality termed “self-modification” (Clarke et al, 1997), which allows the growth coefficients to change throughout the course of a model run and which is intended to more realistically simulate the different rates of growth that occur in an urban system over time. When the rate of growth exceeds a specified critical threshold, the growth coefficients are multiplied by a factor greater than one, simulating a development “boom” cycle. Likewise, when the rate of development falls below a specified critical threshold, the growth coefficients are multiplied by a factor less than one, simulating a development “bust” cycle. Without self-modification, SLEUTH will simulate a linear growth rate.

Implementation of the model occurs in two general phases: (1) calibration, where historic growth patterns are simulated, (2) prediction, where historic patterns of growth are projected into the future. For calibration, the model requires inputs of historic urban extent for at least four time periods, at least two historic land use layers, a historic transportation network for at least two time periods, slope, and an excluded layer.

2.2. Input Data

Unsupervised classification (ISODATA) is applied to Landsat Thematic Mapper (TM) and Multispectral Scanner (MSS) imagery. This allowed us to map urban extent for 1974, 1984, and land use for 2002. 1992 land use map is acquired from EPA MRLC National Land Cover Data (NLCD) website. The original data were at 30m resolution in TM and 60m in MSS imagery. Because high resolution TM images produced an array that exceeded the available computational resources of our Linux PC and SUN UNIX machine, the data were therefore resampled to a lower resolution of 100 meters to reduce the size of the array while maintaining the spatial extent of the study area.

Five time steps for transportation were also prepared (Table 4.2). Roads layers for 1974, 1984, 1990, and 2002 were developed using the primary road network and TXDOT road maps. 2025 road map is developed by using TxDOT Texas Corridor Plan. Slope and hillshaded are created from National Elevation Dataset (NED) which was downloaded from Texas Natural Resources Information System (TNRIS) website. For the calibration phase, the excluded layer consisted of water, which was 100% excluded from development, as well as federal, state, and local parks, which were 90% excluded from development. All input files were rasterized at a 100-meter resolution to the spatial extent of the study area.

Table 4. 2
Input dataset for SLEUTH

SLEUTH Inputs	Input Data Types	Input Data Years
Urban	Landsat MSS, Landsat TM	1974, 1984, 1992, 2002
Lulc	Landsat TM	1992, 2002
Road	Shapefiles	1974, 1984, 1990, 2002, 2025
Excluded	Landsat TM	
Slope	NED	
Hillshade	NED	

2.3. Model Calibration

The goal of calibration is to derive a set of values for the growth parameters that can effectively model growth during the historic time period, in this case from 1974 to 2002. This was achieved in the SLEUTH modeling environment through a brute force Monte Carlo method, where the user indicates a range of values and the model iterates using every possible combination of parameters. For each set of parameters, simulated growth is compared to actual growth using several least squares regression measures, such as the number of urban pixels, urban cluster edge pixels, the number and size of urban clusters, and other fit statistics, such as Leesallee metric. The model calculates these statistics internally and writes the results to a log file that can be manipulated by the user to evaluate the performance of different parameter sets. For each set of parameter values in a Monte Carlo iteration, the model calculates measurements of simulated urban patterns for each control year in the time series. These measurements are then averaged over the set of Monte Carlo iterations and compared to measurements calculated from the actual historic data to produce least squared regression measures (U.S. Geological Survey, 2003). The Leesallee metric (Lee et al, 1970) is the only metric that specifically measures spatial fit. SLEUTH model calculates a modified Lee and Sallee index by taking a ratio of the intersection and the union of the simulated and actual urban areas (Clarke et al, 1998). A perfect spatial match would result in a value of 1. As Clarke et al (1998) point out, achieving high values for this index is challenging. With an earlier version of the model, Clarke et al, (1998) did not report values of the Lee and Sallee statistics that exceeded 0.3, although recent applications of SLEUTH have achieved values that approach 0.6 (Silva at al, 2002). We achieved a value of 0.51 for leesallee for this particular research.

Calibration was performed in three phases: coarse, fine, and final. Coarse and fine calibration phases are done on our Linux machine, however, final calibration was done at USGS Rocky Mountain Mapping Center in Denver, CO by Mark Feller. It was done on a Beowulf PC Cluster with a 16-node system. All calibration (coarse, fine, final) process took approximately 2 months.

Leesallee metric was used as primary metric to evaluate the performance of the model. After each calibration phase, the top set of leesallee scores determined the range of values used in the subsequent phase of calibration.

To perform a spatial accuracy assessment, the model was initialized with 1974 urban extent and growth was predicted out to the year 1992. One hundred Monte Carlo iterations were performed, and an urban extent of 2002 was produced (Fig. 2.17). This is compared with 2002 observed urban extent (Fig. 2.18).

The confusion matrix is calculated for the observed versus predicted urban areas in 2002. As you can see in the Table 2.15, we have found high overall classification accuracy, 98%, and a high kappa coefficient, 0.89, between observed urban area and predicted urban area.

2.4. Prediction

SLEUTH requires the following inputs for prediction phase: urban extent, land use/land cover (LULC), roads, excluded layer, slope, and a hillshade. Three future growth scenarios were simulated: Unmanaged growth, managed with moderate protection, and managed with maximum protection. The excluded layer served as the primary instrument to differentiate between three policy scenarios. The future transportation network, Texas Corridor, which is planned to be completed in 2025, was also created and incorporated into the model for the year 2025.

3. Results

The unmanaged trend scenario reflects that there is no protection against development. Natural resource land was not protected except city and county parks. Unclassified pixels, water and parks are fully excluded from development. However, wetland, agricultural land, forest, and floodplain were not protected. The managed growth with moderate protection scenario, however, reflects a stronger commitment to spatially focused growth and resource protection. In the excluded layer higher levels of protection were assigned to wetlands, agricultural land, forest land, and floodplain. The third and last scenario, managed growth with maximum protection, implies a more extreme set of protection on resource land. The data elements for the excluded layer are similar to those in the managed growth with moderate protection case, but protection levels are higher.

Data layers and probabilities of exclusion or levels of protection, for each scenario are summarized in Table 4.3 below.

Table 4. 3
The growth scenarios and levels of protection

Growth Scenarios	Excluded From Development (in percent)						
	Agriculture	Forest	Floodplain	Wetland	Parks	Water	Unclassified
Unmanaged	0	0	0	0	100	100	100
Managed with Moderate Protection	40	40	40	60	100	100	100
Managed with Maximum Protection	60	60	60	80	100	100	100

The results of the scenario predictions (Figs. 4.1 - 4.3) show higher dispersed development patterns for the unmanaged than the managed growth scenario with moderate protection, while the managed growth with maximum protection scenario shows highly constrained growth over the whole region, with most occurring in and around existing urban centers. Unmanaged growth trend shows similar to low-density development patterns. This is predicted to lead to substantial land consumption throughout the study area with a simultaneous loss of resource lands. Due to the higher levels of protection, the growth rates for the managed growth scenarios are reduced, producing a much lower predicted loss of resource lands as illustrated in Figs. 4.1 - 4.3.

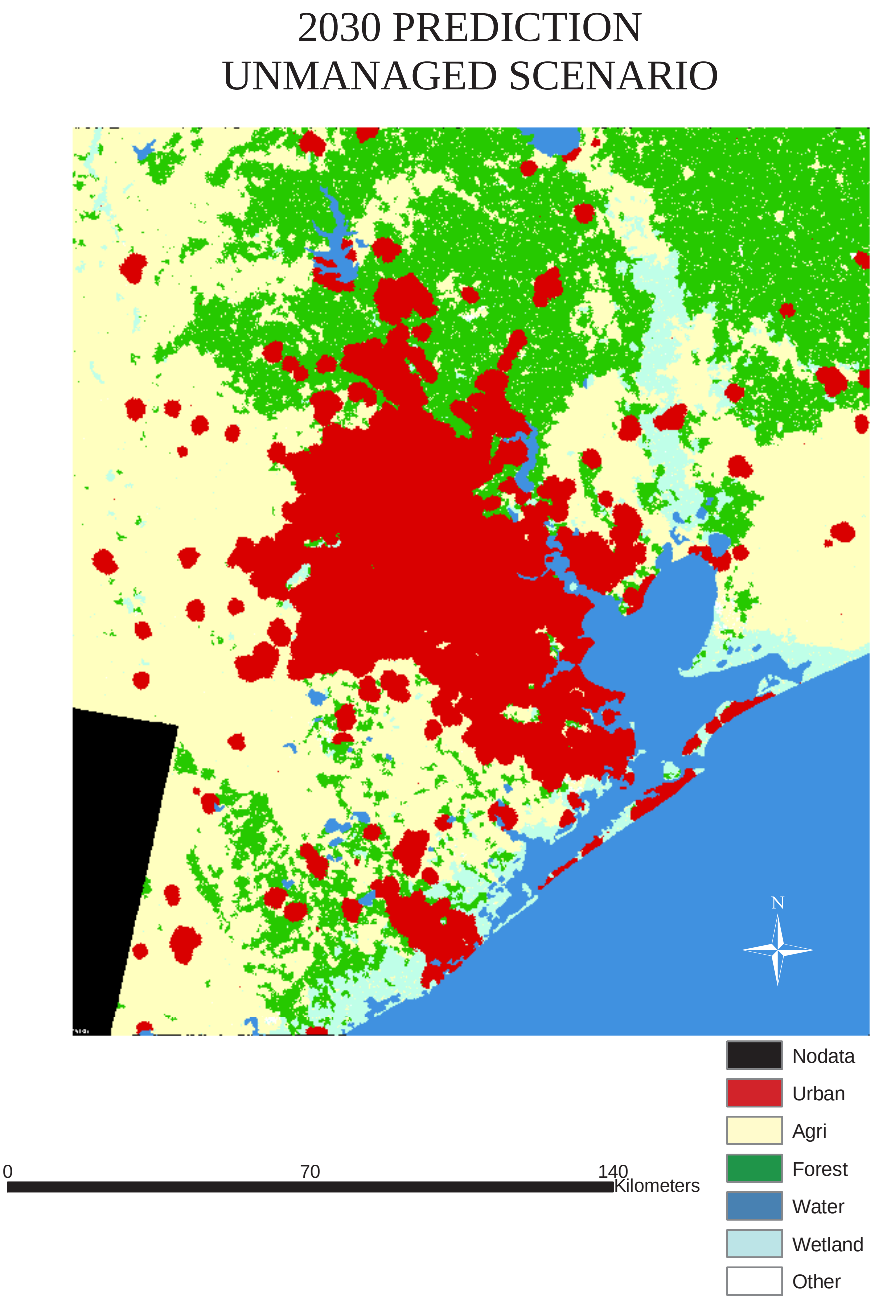

Fig. 4. 1 Unmanaged growth scenario prediction

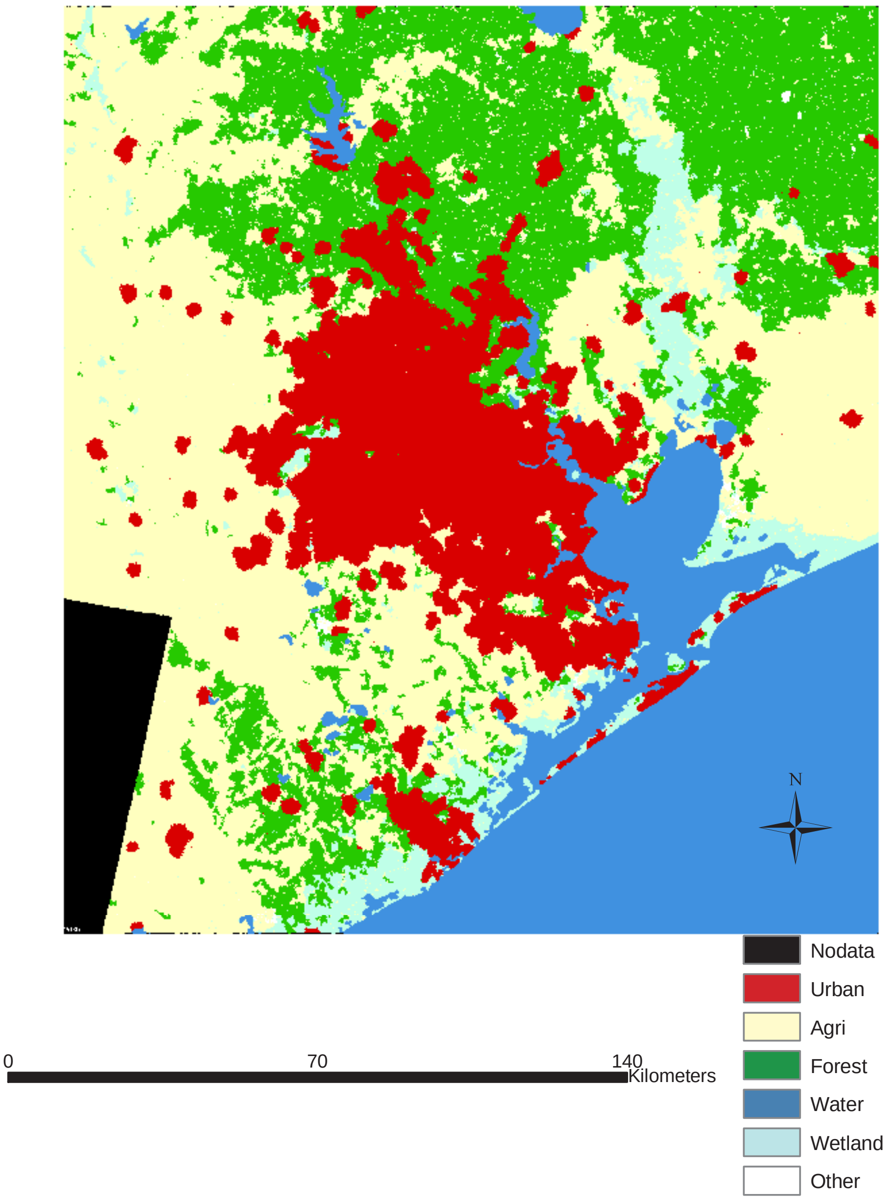

Fig. 4. 2 Managed with moderate protection scenario prediction

2030 PREDICTION
MAXIMUM PROTECTION SCENARIO

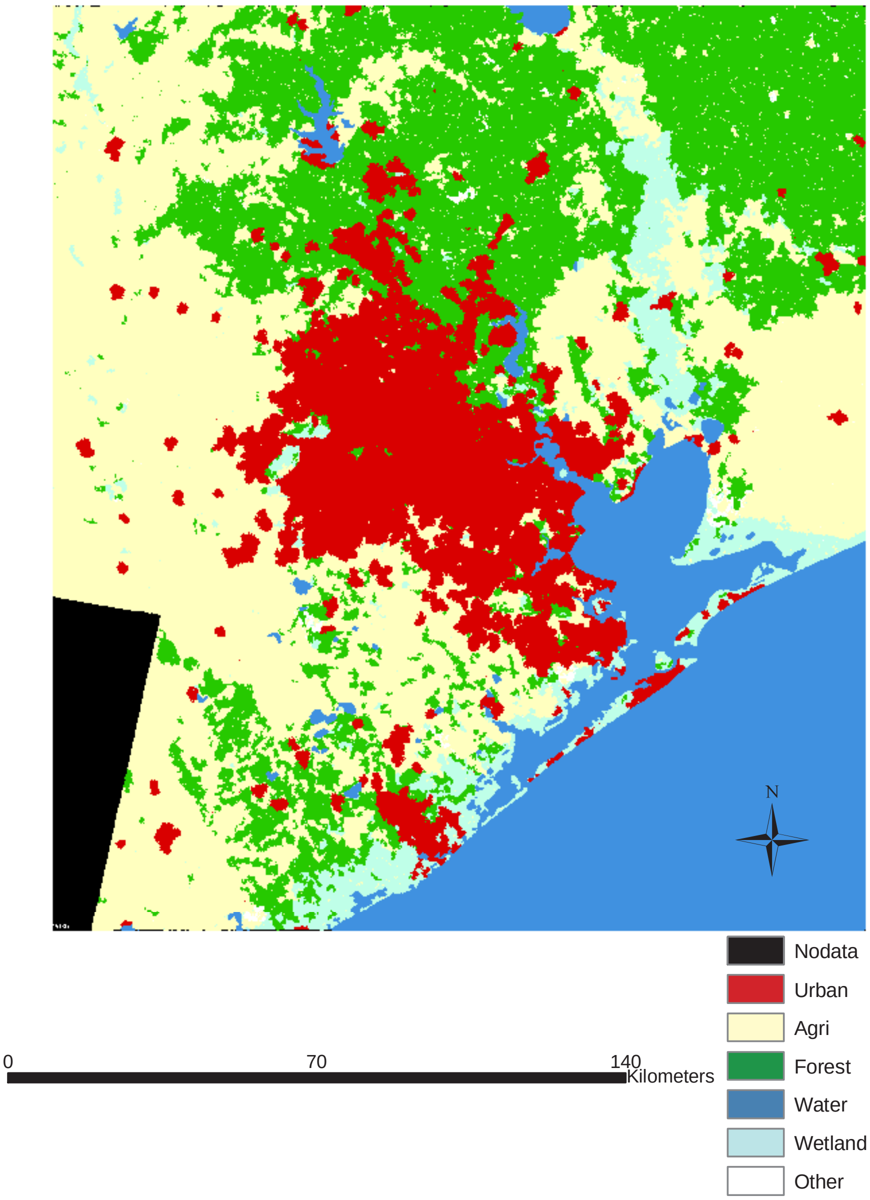

Fig. 4. 3 Managed with maximum protection scenario prediction

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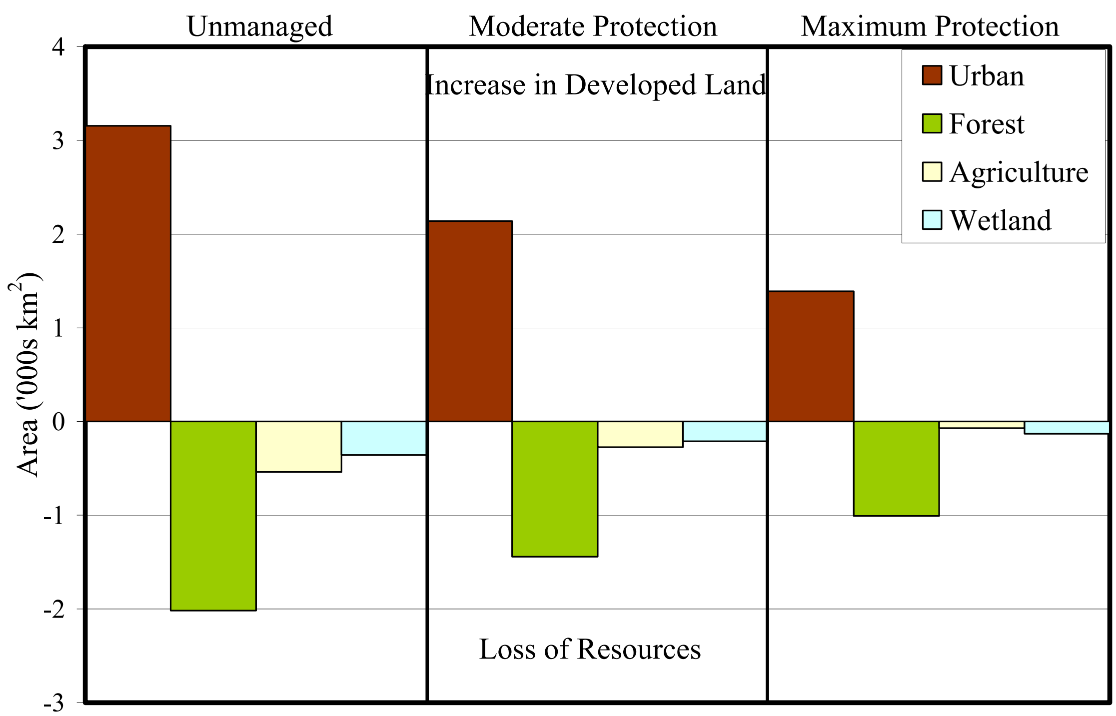

Fig. 4. 4 Comparison of three scenarios for future predictions in Houston CMSA

As seen from Fig. 4.4, third scenario would save 1000 km^2 forest land compare to unmanaged scenario, and about 500 km^2 compare to moderate scenario. Urban sprawl seems to affect forested land more than other resource lands. Spatial distribution of the predicted forest loss is illustrated in Figs. 4.5, 4.6, 4.7 for unmanaged growth scenario, managed growth with moderate protection scenario, and managed growth with maximum protection scenario respectively.

PREDICTED FOREST LOSS
UNMANAGED GROWTH SCENARIO

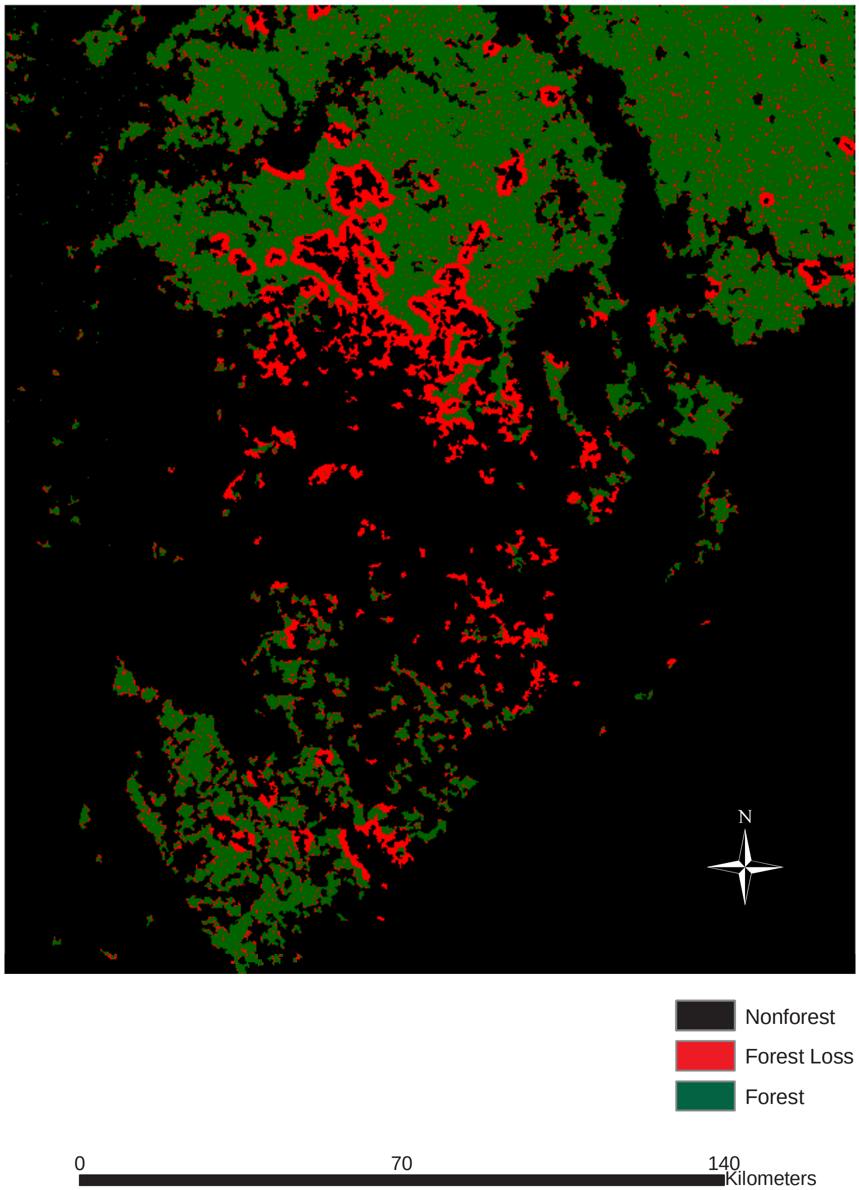

Fig. 4. 5 Predicted forest loss in unmanaged growth scenario by 2030

PREDICTED FOREST LOSS
MODERATE PROTECTION SCENARIO

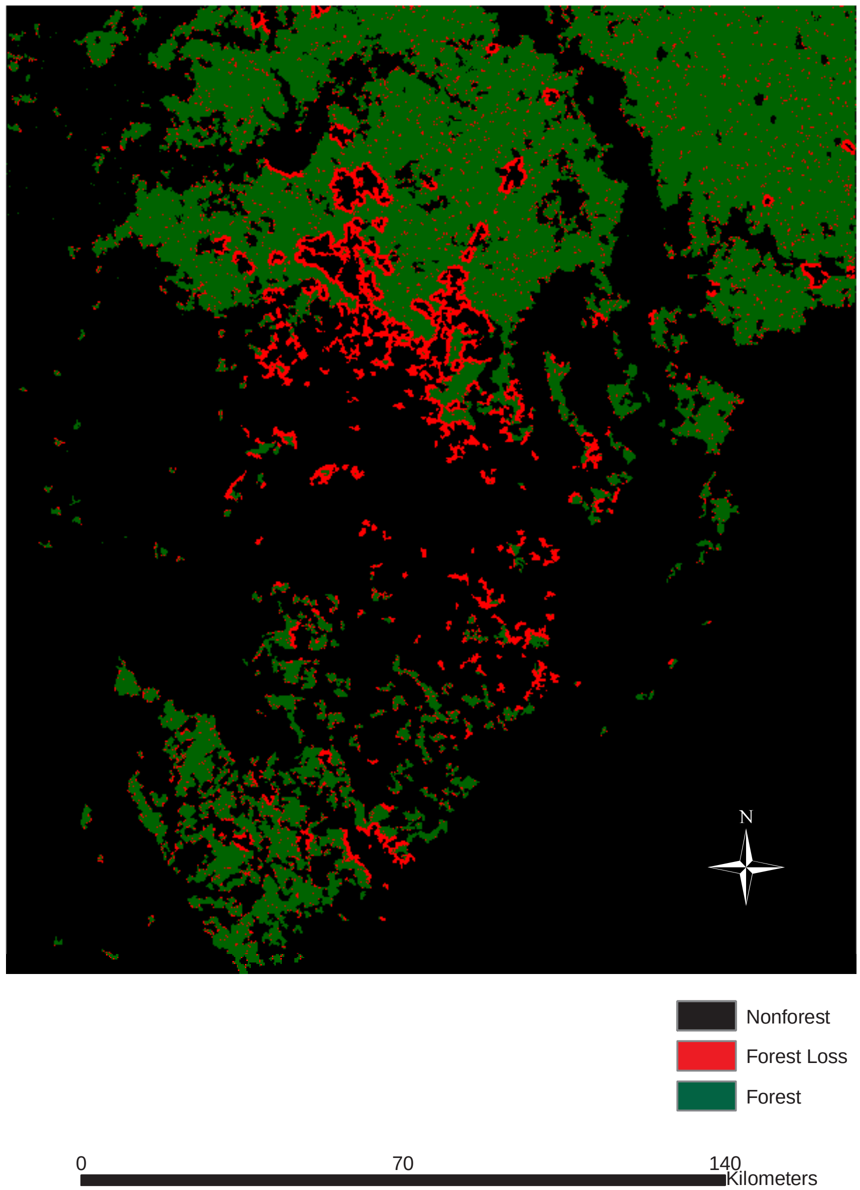

Fig. 4. 6 Predicted forest loss in moderate protection scenario by 2030

PREDICTED FOREST LOSS
MAXIMUM PROTECTION SCENARIO

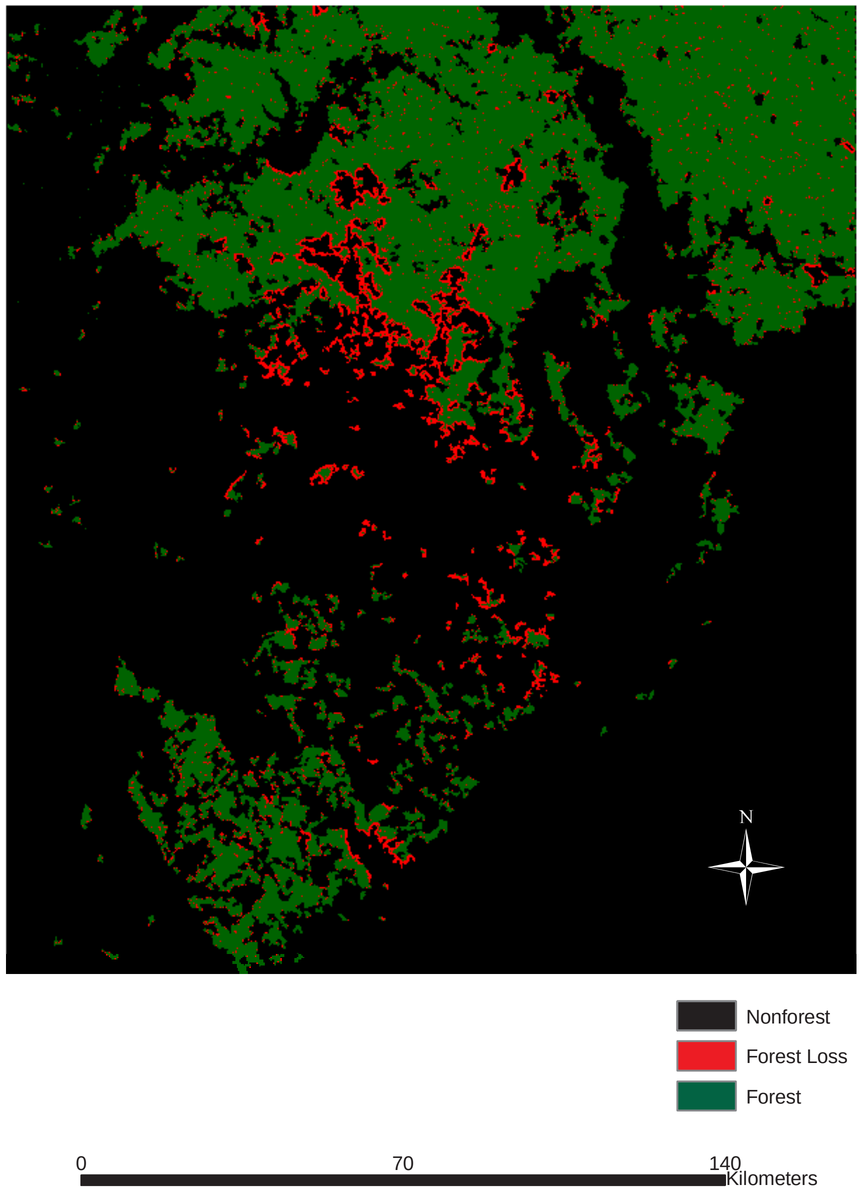

Fig. 4. 7 Predicted forest loss in maximum protection scenario by 2030

The predicted forest loss area by each Houston CMSA county is illustrated in Fig. 4.8.

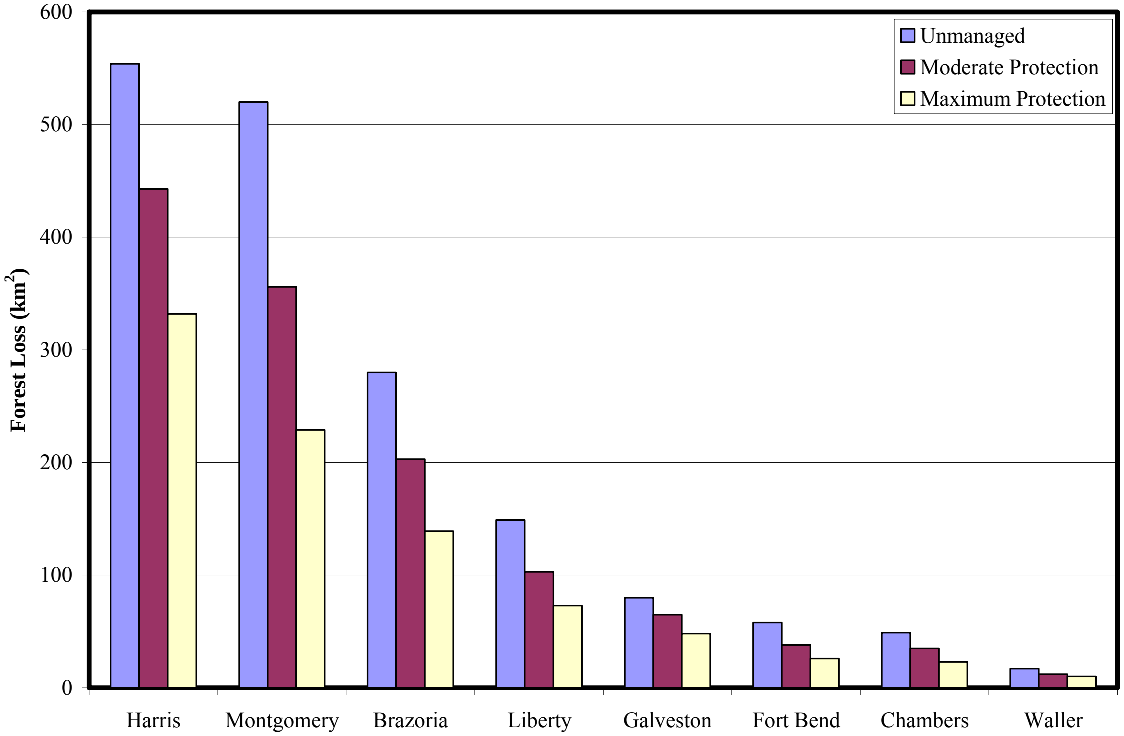

Fig. 4. 8 Predicted forest loss by 2030 for Houston CMSA counties for the three growth scenarios

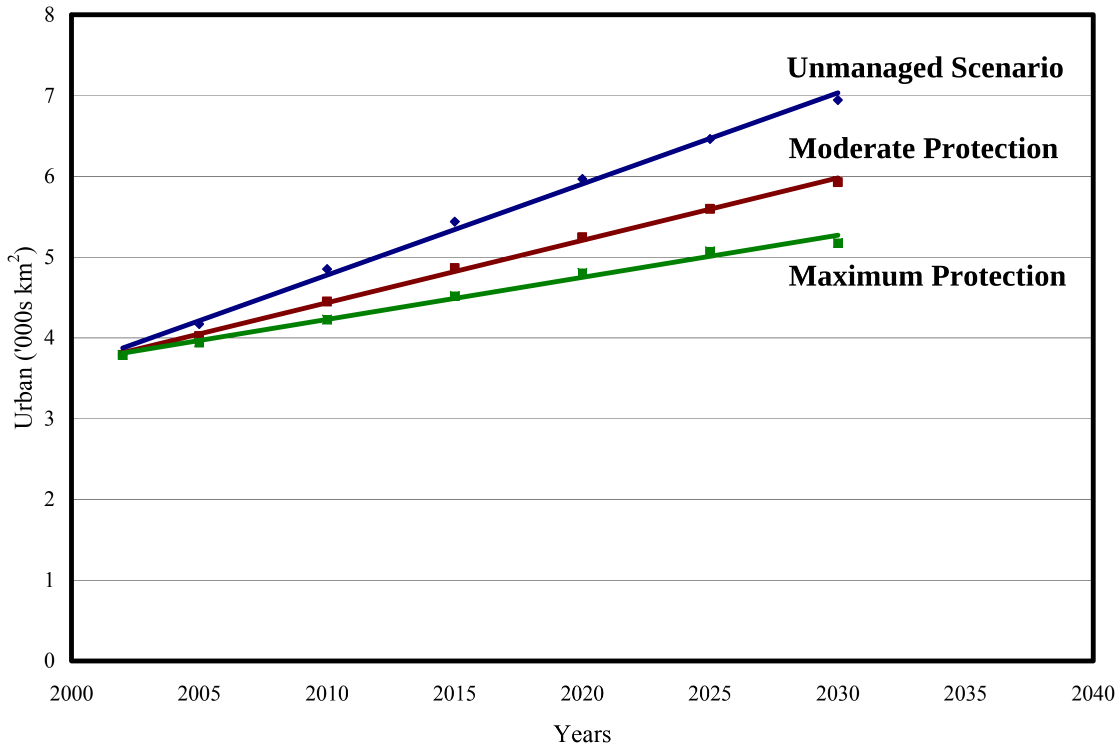

Fig. 4. 9 Comparison of urban areas in the Houston CMSA for the three growth scenarios

It's predicted that urban area will cover approximately 7,000 km^2 by 2030 in unmanaged scenario in the Houston CMSA. With the maximum protection scenario, around 2,000 km^2 of land could be saved from development (Fig 4.9).

4. Discussion

The results from this regional scale assessment have provided interesting insights into the future of the region. Given these findings, SLEUTH could be an appropriate model for regional assessments of urban land use change, the results of which could be used to guide more localized modeling efforts. The visualization of potential land use change has proven to be a powerful tool for raising public awareness and facilitating discussion.

Reports about this research were published in several well-known media sources, such as the Washington Post newspaper (Huslin, 2002), and appeared on the website for the Chesapeake Bay Foundation, a prominent regional environmental group. The results for the unmanaged trends scenario are especially important to public discussion since they demonstrate the potential losses in resource lands that could occur if the observed rates of land use change were to continue into the future. Moreover, as efforts to improve the health of the Houston CMSA progress, the need for the regional-scale land use change assessments is becoming critical. SLEUTH may be a tool that can meet these needs and this has been recognized by state and regional agencies to explore the use of SLEUTH as a potential tool for modeling environmental vulnerability.

The excluded layer proved to be an effective tool for exploring different policy scenarios, and illustrates the advantages of linking the modeling process to a GIS. All data integration and manipulation was performed within GIS, allowing for the precise designation of target conservation areas, such as wetlands. For each scenario, all land within the study area was ranked in terms of conservation using a grid-based model. The resulting excluded layer was easily integrated into the model. Translating various policies into exclusion probabilities was done by Mid. Atlantic RESAC (2003), and was not an intuitive process. It consisted of an informed qualitative ranking of each conservation policy. These rankings of low, medium, or high were then translated into generalized exclusion probabilities. In our scenarios, we have used Mid Atlantic RESAC's policy exclusion probabilities.

Although the excluded layer is ideal for simulating the effects of conservation or regulatory policies, SLEUTH does not have an adequate mechanism to simulate the potential impacts of incentive policies. By encouraging denser and more compact development in areas that have existing urban infrastructure, it is hoped to decrease the amount of new development occurring in outlying areas (Northrup et al, 1997).

We also obtained significantly higher values for the Leesallee measure than Clarke et al (1998), but this is likely due to the fact that we were working with a shorter time series, 28 years compared to 200 years. We also worked with land cover data that were obtained from a single source, satellite imagery, while Clarke et al (1998) had obtained data from variety of cartographic sources. The satellite data is more advantageous to the SLEUTH modeling environment, and probably contributed to the higher values we obtained for the Leesallee metric.

5. Conclusions

Increasing urban growth through the world has aroused concerns over the degradation of our environment. Therefore, understanding the dynamics of urban systems and evaluating the impacts of urban growth on the environment are needed and they involve modeling. In regions where regional approaches to land use management are being developed, a realistic modeling system that can be used to explore different regional futures is critically needed. Because of an ability to simulate the complex behavior of urban systems, CA models represent a possible approach for regional scale modeling. Furthermore, consistent, regional data sets derived from satellite imagery and other sources can be readily integrated into the CA modeling environment. Our research explored the suitability of utilizing one CA, the SLEUTH model, for regional planning applications.

The Houston metropolitan area was used as our study area. The study indicated the usefulness of cellular modeling and geographical information systems for urban scenario planning. Three scenarios have been designed and simulated in this research. The first scenario simulated the continued growth (unmanaged) trend if the urban sprawl is allowed to continue. The second scenario projected the growth trend with moderate environmental protection. The last scenario simulated the development trend with maximum environmental protection. The three scenarios of future urban growth simulation predict the general trends under different conditions nicely. Results from first scenario indicate that Houston metropolitan area would lose considerable amount of open space and natural land, such as forest. The second scenario results are not encouraging as much as the last scenario. The growth rate is controlled and natural land is conserved most with the last scenario. The results are encouraging, although more accurate simulations could be achieved if more growth constraints were considered. The role of remote sensing and GIS in cellular automata-based urban modeling is necessary, especially for input data preparation, model calibration and verification, urban pattern analysis, and also growth impact assessment.

SLEUTH provides key functionalities like interactive scenario development and the ability to visualize and quantify outcomes spatially. The availability and consistency of historic data sets, especially those that are earlier than satellite availability, is a potential issue for some applications. Empirical calibration of the model using Landsat TM image maps of past change aided the model predictions of future change. Calibration at high level of spatial detail remains a computationally intensive process, requiring sufficient use of a parallel computing environment, and may prevent the use of the model by local or nongovernmental agencies where computing resources may be a limiting factor. Despite these considerations, we found SLEUTH to be a useful tool for assessing the impacts of alternative policy scenarios.

CHAPTER V

CONCLUSIONS

Concerns over the degradation of the environment we live in are raised because of an increasing urban growth throughout the world. Modeling and simulation are required to understand the dynamics of complex urban systems and to evaluate the impacts of urban growth on environment.

Houston was selected as the study site because Houston is the only major metropolitan area in the U.S. that functions without a zoning. This research focuses on modeling urban growth and land use/land cover change in Houston metropolitan area using SLEUTH urban growth model. For the past 3 decades, Houston has been one of the fastest growing metropolises in the U.S. and has emerged as commercial, industrial, and transportation urban center of the south.

Calibration of the SLEUTH model for Houston indicates a very high spread coefficient, which means that the predicted mode of growth in Houston is "organic" or edge growth. Houston has been experiencing "organic" or edge growth. Among Houston PMSAs, Houston PMSA was the major metropolitan area that drove the population and urban growth in Houston CMSA. The Galveston and Brazoria PMSAs did not show increase in both and they reflect very small part of Houston CMSA. According to our county level analysis, Harris and Galveston counties contain the highest percentage of urban land in proportioned their area. Urban growth rates for Harris and Galveston are higher than other six counties in Houston CMSA. We also developed three environmental scenarios in our study area. The third scenario provides the best protection for Houston CMSA, and protects most of the resource land. Without any protection on resource lands, Houston CMSA is estimated to lose 2,000 km^2 of forest land by 2030, about 600 km^2 of agricultural land, and approximately 400 km^2 of wetland. Approximately half of all resource land could be saved by the third scenario, managed growth with maximum protect.

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