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16. Abstract

This report is part of an ongoing research on Texas Triangle megaregion, which refers to the region delineated by the metropolitan areas of Dallas/Fort Worth, San Antonio/Austin, and Huston. As the region expects a population growth by approximately 10 million in the next 40 years, it is important to understand the land use/land cover (LULC) implications of the vast growth. Even more important is to understand how public policies and investments (in infrastructure, for example) will influence LULC. The study reported here focuses on the effect of highway construction on LULC through a case study of the Austin, TX area. The methodologies developed from the Austin case may be applied to the entire Triangle to understand the effects of state-wide transportation strategies, for example, the Trans-Texas Corridor (TTC), on urban development outcome in the region. The Austin case study included three parts. First, historical data on highway constructions in the Austin area are collected and visualized in GIS. Next, land use/land cover maps are derived from classifying LandSat images. A binary logit model is then formulated, quantifying the impacts of transportation accessibility and neighborhoods on the likelihood of LULC change.

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ABSTRACT

This report is part of an ongoing research on Texas Triangle megaregion, which refers to the region delineated by the metropolitan areas of Dallas/Fort Worth, San Antonio/Austin, and Huston. As the region expects a population growth by approximately 10 million in the next 40 years, it is important to understand the land use/land cover (LULC) implications of the vast growth. Even more important is to understand how public policies and investments (in infrastructure, for example) will influence LULC. The study reported here focuses on the effect of highway construction on LULC through a case study of the Austin, TX area. The methodologies developed from the Austin case may be applied to the entire Triangle to understand the effects of state-wide transportation strategies, for example, the Trans-Texas Corridor (TTC), on urban development outcome in the region. The Austin case study included three parts. First, historical data on highway constructions in the Austin area are collected and visualized in GIS. Next, land use/land cover maps are derived from classifying LandSat images. A binary logit model is then formulated, quantifying the impacts of transportation accessibility and neighborhoods on the likelihood of LULC change.

EXECUTIVE SUMMARY

Land use/land cover (LULC) changes result from interactions among social, economic, and environmental systems. There has been a long tradition of modeling LULC change for the interest of understanding and predicting the LULC trend associated with natural and human factors. This report is part of an ongoing research on Texas Triangle megaregion, which refers to the region delineated by the metropolitan areas of Dallas/Fort Worth, San Antonio/Austin, and Huston). In the next 40 years, the Texas Triangle is expected to grow in population by approximately 10 million. For community development and resource management, it is important to understand the LULC implications of the vast amount of population growth. Even more important is to understand how public policies and investments (in infrastructure, for example) will influence LULC. The study reported here focuses on the effect of highway construction on LULC through a case study of the Austin, TX area.

A number of modeling tools are available for LULC analysis. The study reviewed statistical and econometric models, spatial interaction models, integrated models, agent-based models, and others built upon geographic information systems (GIS). Each has specific advantages and limitations in terms of theoretical strengths, analytical capacities, data requirements, and operational complexities. The study applied the Markov-Chain method, GIS overlay analysis, and logit modeling to understand LULC as it related to highway construction in the Austin area.

Data used for this study include historical records of highway construction obtained from TxDOT and LandSat satellite imageries for the year of 1979, 1987, and 2002. The highway data came in table forms showing types, locations and years of completion. They were digitized in ArcGIS. The satellite imageries data were obtained from the Texas Synergy and Global Land Cover Facility (GLCF) data center.

Supervised classification was performed on the 1979, 1987, and 2002 satellite imagery. Changes in LULC during the three time periods were then analyzed by three approaches: the Markov-Chain analysis, GIS overlay, and binary logit modeling of land use conversion. The Markov-Chain analysis confirmed that LULC in the Austin area from 1979 to 2002 exhibited a Markov Process. GIS overlays enabled visual analyses of spatial evolution and patterns of urban expansion in the Austin area. The logit modeling analysis allowed us to build direct links between the dependent variable (i.e., LULC) and the explanatory variables (i.e., highway construction, along with others). A model was estimated and applied for 2005 LULC forecasting for the Austin area.

These three analyses provide the following results regarding LULC development patterns in the Austin area:

- Over 80% of urbanized area is within three kilometers of highway in the Austin area.
- Urbanized proportion decreases by nearly 45% per one kilometer increase of the distance from the highway;
- A 1% increase of road length is associated with approximately 5% increase of urbanized area;

- Neighboring land cells have great impacts on the likelihood of development of any chosen cell; i.e. an urbanized cell tends to be a seed expediting urban growth around it. If more than two neighboring cells in a Moore neighborhood are urbanized, their contribution to the urbanization of that cell is even larger than an existing road within three kilometers.

Future efforts may be directed towards improving the logit model of LULC change by incorporating additional contextual and policy variables, for example, population and employment density, land suitability for development, local zoning control and macro economic conditions.

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Chapter 1 Introduction

1.1 Research Objectives

Land use/land cover (LULC) changes result from interactions among social, economic, and environmental systems. Land cover is the physical state of the earth surface, for instance, water, forests, grassland, and the built-up area. In contrast, land use emphasizes the function or purpose for which the land is consumed. Human activities play a critical role in shaping the land use pattern. Land use and land cover are closely related; the status of land cover indicates the type of land use. In urban areas, however, land cover features may not provide sufficient details to distinguish among various land uses. There has been a long tradition of modeling LULC change for the interest of understanding and predicting the LULC trend associated with natural and human factors. Improved understanding of the trend and its driving factors will better inform decisions and policy-making on rural-urban development and conservations.

This report is part of an ongoing research on Texas Triangle megaregion, which refers to the region delineated by the metropolitan areas of Dallas/Fort Worth, San Antonio/Austin, and Huston). In the next 40 years, the Texas Triangle is expected to grow in population by approximately 10 million. For community development and resource management, it is important to understand the LULC implications of the vast amount of population growth. Even more important is to understand how public policies and investments (in infrastructure, for example) will influence LULC. The study reported here focuses on the effect of highway construction on LULC through a case study of the Austin, TX area. Our objective is to explore and develop study methodologies that may be applied to the entire Triangle for studying the effects of state-wide transportation strategies on urban development outcome. An immediate example of such state-wide strategies is the Trans-Texas Corridor (TTC).

1.2 Scope of Research

This study intends to explore methodologies suitable for the analysis of LULC change in response to highway construction; meanwhile to obtain both qualitative and quantitative relations between highway development and urban expansion. The analysis is conducted based on satellite images, at both aggregate level and disaggregate level. Spatial dimension of urban growth is explicitly addressed in the proposed pixel level model. The temporal dimension of road and urban interaction is not of major concern due to the lack of historical land cover images. It does not take into account many other factors for the sake of simplicity and less data requirement, which are favored in the modeling of regional level development.

1.3 Organization

Chapter 2 presents an overview of LULC modeling techniques and introduces the methodologies employed in this report. Chapter 3 mainly discusses the data preparation procedures, including

the processing of highway and satellite images, followed by a brief introduction of the initial preparation results. Chapter 4 analyzes the data with three approaches: (1) based on Markov theory, to test the applicability of Markov theory in explaining LULC change; (2) applying GIS to explore the spatial patterns of urbanization; (3) formulate two models representing the relationship between road development and urbanization process at both aggregate and disaggregate levels. Chapter 5 concludes this report in regards to the methodologies, major findings and future work.

Chapter 2 Literature Review

This chapter describes a representative collection of land use models. As elaborated in the previous chapter, the need to understand land use change patterns drives researchers developing a considerable number of models, serving a variety of purposes, assuming different underlying theories, at various aggregation levels, with different data requirements. To present an overview of the land use modeling development, a composite criterion, based on modeling tradition, was applied to classify those models. The modeling tradition refers to the dominant features used to derive the model and its corresponding solution techniques which reflect the spatial aggregation level, temporal dimension and data requirements. Based on this aggregate criterion, this chapter will describe land use models by the following classifications:

a. statistical and econometric models
b. spatial interaction models
c. integrated models
d. agent-based models, and
e. other models

2.1 Statistical and Econometric Models

Application of statistical techniques to investigate the mathematical relationships between a dependent variable and a set of independent variables are common in modeling socio-economic phenomena. Multivariate analysis and multiple regression analysis are the most commonly used empirical analysis techniques in building statistical and econometric models. With the emphasis on analyzing explanatory spatial data in terms of data reduction and structure detection, multivariate analysis is realized by conducting principal component analysis, factor analysis, canonical correlation analysis, and cluster analysis (Lesschen et al., 2005). The focus of multiple regression analysis is to solve problems involving systems of equations that represent the relationships between demand and supply, which give rise to the "econometric models". Figure 2.1(Lesschen et al., 2005) shows the statistical techniques for the analysis of spatial patterns of land use.

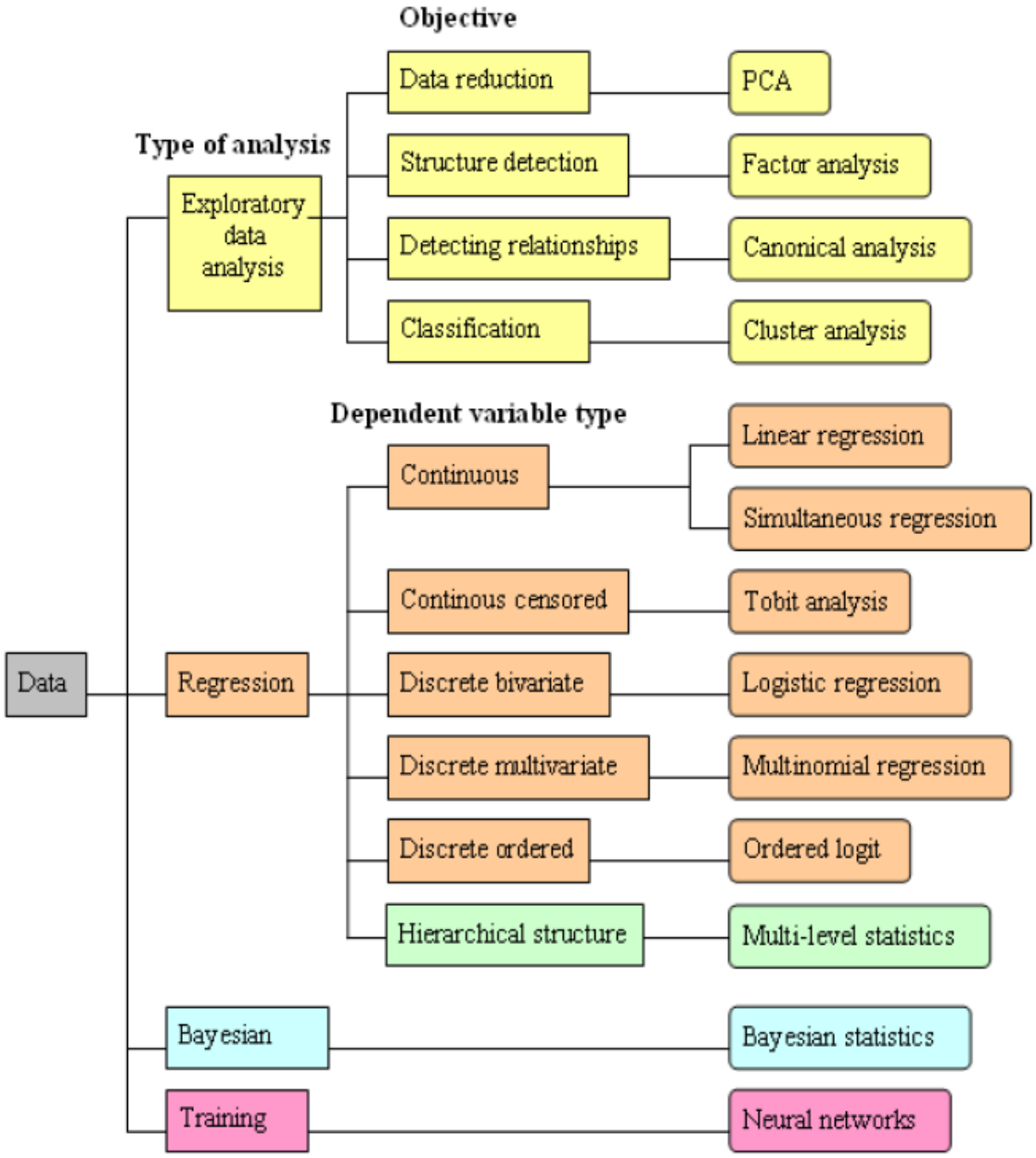


Figure 2.1: Classification of empirical analysis techniques for LUCC based on objective and data structure

Statistical models are frequently used as a component of a larger model of land use change (Veldkamp and Fresco, 1996a, Verburg et al., 1997), or sometimes are applied directly as the whole model (Chapin and Weiss, 1968). There are two types of dependent variables in a statistical land use model: continuous and discrete variables. In a continuous model, the dependent variable is continuous (the area devoted to a land use type); while in a discrete model, land use is treated as a discrete variable and the model result would indicate the type of the land that would likely be given a set of explanatory variables.

In general, in a statistical land use model, the study area is divided into a number of zones (e.g. traffic analysis zones), whose size and shape depends on the level of aggregation and the data available (Briassoulis, 2000). As is commonly perceived, land use change is the result of active interactions among demographic, economic, environmental and cultural issues. With no underlying theories, the continuous model takes a general form of:

$$LU_j = \alpha + \sum_i \beta_i X_i + \varepsilon \qquad (2.1)$$

Where the dependent variable *(LU_j)* stands for the area of land occupied by land use type *j*, X_i represents independent variables such as population, employment, housing prices etc., α and βs are coefficients estimated from historical data, and ε is the error term of the model.

Examples of this type of continuous model can date back to the 1960s. Chapin and Weiss (1968) applied a linear model to predict residential growth by using (1) accessibility of a zone to work areas, (2) availability of sewerage in a zone, (3) accessibility of a zone to a nearest major street, and (4) accessibility of a zone to a nearest elementary school. A linear regression is used to test the correlation between census dwelling data and residential densities (Chen, 2002); another example is to predict urban expansion using population growth in Morelia, Mexico (López et al., 2001); the CHANGE module of the CLUE model also applied linear regression to estimate the area change of a certain type land corresponding to the change of socio-economic factors (Veldkamp and Fresco, 1996a, Verburg et al., 1997). However, these linear regression models can be applied to the analysis of land use patterns only if continuous land use data are available.

Discrete choice models are widely used to represent choice situations in general (McFadden, 1978). In the land use modeling area, discrete choice concepts are also widely accepted to describe the potential change of land use. In the case of a discrete statistical model, the study area is divided into a number of zones or cells; for each cell, its socio-economic conditions correspond to the utility of a certain type of land use, which indicates the associated change potential. The general form for this type of model is:

$$V_{ij} = C_j + \sum_k \beta_{kj} X_{ik} \qquad (2.2)$$

$$P_{ij} = \frac{\exp(V_{ij})}{\sum_k \exp(V_{ik})} \qquad (2.3)$$

Where:

V_{ij} the utility of land type *j* in cell *i*;

X_{ik} the k^{th} independent variable in cell *i*;

β_{kj} the coefficient associated with the k^{th} independent variable for land type *j*;

C_j the constant for land type *j*;

P_{ij} the proportion of land type *j* in cell *i*;

The above formulation calculates the utility of each land use type which is determined by a set of explanatory variables, and then derives the probability (proportion) of each land use type using logistic functions. This formulation is frequently used in modeling land use/land cover change, especially in the modeling of forest and farming system (Serneels and Lambin, 2001, Schneider

and Pontius, 2001, Geoghegan et al., 2001, Gobin et al., 2002, Bockstael, 1996). For example, Verburg et al. (2004) used a logistic regression to estimate the proportions of five types of land use (forest, arable land, grassland, residential area and industrial area) by soil properties and distance to town and open water. Gobin et al. (2002) adopted a nest structure to predict the probabilities of local agricultural land use, in which agricultural fields are first distinguished by land management system, and then subdivided by cultivation strategies (e.g. continuous cultivation, grass follow and bush follow etc.). Müller and Zeller (2002) developed a multinomial logit model to estimate the probability of a certain land use type for a given cell using historical data for two districts in the Central Highlands of Vietnam. Chomitz and Gray (1996) used soil properties, distance to road, slope and climate information to predict the likelihood a piece of land of being a natural vegetation, subsistence agriculture and commercial agriculture.

The purpose of statistical models is generally to describe and explain the land use mechanism as a function of a set of independent variables, such as population, employment, economic and environmental data. These models do not emphasize rigorous grounding theories, rather they share a common belief in the process of socio-economic-environmental interactions. Exceptions are the discrete statistical models which consider individual decision making processes based on micro-economic theories. However, the linearity assumptions of either the direct regression or the utility function are not necessarily true in all cases, which result in an inherent flaw of the statistical models. Models are usually operating on a coarse level, such as national or regional level, depending on the level of detail of the available data. As for the temporal dimension, generally static models or quasi-static models are used by introducing certain lagged values (Irwin and Bockstael, 1999). Statistical models commonly employ multivariate techniques to manage data (data reduction, structure detection, correlation analysis etc.) before getting into the model developing stage.

Econometric models of land use are not frequently seen in the literature. This type of model usually models land use implicitly; first estimates activities (production, employment, housing demand, etc.), and then converts the activities into land use requirement (Briassoulis, 2000).Hill (1965) and Rothenburg-Pack (1978) described a regional activity allocation model-EMPIRIC, which is a well known econometric model for impact assessment and policy analysis.

EMPIRIC consists of three main components: (1) activity allocation module, (2) forecast monitoring module, and (3) land consumption module. Though it has various applications, EMPIRIC bears a lot of criticisms, such as “Although certain lags are built into the system, their explanation is also largely statistical” (Batty, 1976) and the lack of theoretical or behavioral grounding makes its specification difficult to rationalize (Rothenburg-Pack, 1978). In summary, econometric models do not give rise to a promising solution to land use change modeling.

2.2 Spatial Interaction Models

Spatial interaction models rely on theories of socio-physics, taking the analogy from the Law of Gravity, or the Second Law of Thermodynamics (entropy law) to explain social phenomena. The logic for gravity-type of spatial interaction model is that the attractiveness of locations is in

proportional to the "mass" (production activities, employment, recreation, commercial, or residential densities), and inversely proportional to the impedance of activities to take place; therefore, it realizes the interactions between spatial locations and human activities. For entropy maximizing type of models (Wilson, 1967, 1970 & 1974), the logic is that the final state of a system should be the one with maximum likelihood after the random interactions of each micro system; in other words, the most probable state of the urban system should correspond to the largest number of possible microstates that a system can have. General form of a gravity type model is:

$$G_i = \sum_k \beta_k X_{ki} \qquad (2.4)$$

$$A_{ij} = \frac{1}{imp_{ij}} \qquad (2.5)$$

$$G_{ij} = G_i \frac{A_{ij}}{\sum_j A_{ij}} \qquad (2.6)$$

Where:

G_i the total activities in zone *i*;

G_{ij} the activity interaction between zone *i* and *j*;

A_{ij} the activity interaction potential, inversely proportional to the impedance (distance, time, and cost etc.) between zone *i* and *j*;

X, β the characteristics of zone *i* and their associated coefficients.

The above formulation addresses the spatial interaction explicitly by employing some simple behavioral assumptions regarding human activities and location characteristics. However, gravity models bear various criticisms:

1. Lack of theoretical base. Even though the analogy is taken from physics theory, it does not provide a solid foundation for interpreting spatial interaction;
2. Aggregation level depends on the number of zones of the study area, and there is no consensus on the proper number and the shape of the zones;
3. Zones are treated as points, resulting in the ignorance of the impacts that development densities of a zone have on activities;
4. model can only represent the interactions between a pair of zones, without an overall representation of the web of interactions among all land use types, as mentioned in Briassoulis (2000): "spatial interaction models can deal with only two land uses at a time; hence, their capacity to cover the complete pattern of land uses in urban, rural and other regional contexts appear to be limited";
5. Model prediction largely depends on the functional form of the impedance function;
6. It has high data requirement due to its spatially explicit nature, especially if a higher level of land use detail is pursued.

To address these limitations, entropy maximizing models were developed. Entropy models made progress in the representation of disaggregated behavior; however, it still employs the analogy of physics, which are not necessarily applicable to interpret complex social phenomena. In

conclusion, both gravity models and entropy maximizing models are limited by their weak theoretical foundation and have a limited ability to represent the complex interactions among land use, socio-economic-environmental factors and human activities. To what extent spatial interaction models can address the variety and multitude of land use change patterns remains a question.

2.3 Integrated Models

Generally, integrated models are large-scale models with emphasis on the integration of their components which represent economic activities, regions, transportation and land use. Land use change models are usually accounted as a component of an integrated model, rather than the integrated model itself (Briassoulis, 2000). More recently, integrated models whose direct purpose is the analysis of land use/land cover change are frequently addressed in the literature of agent-based LUCC models (Manson, 2000, Parker et al., 2003), which will be discussed in detail in the next section. Here a brief discussion will be provided about the integrated models which contain a land use change module, where land use change is either considered directly or implicitly.

Integrated models commonly consist of several separate modules which are integrated by a system of interaction mechanisms. As Briassoulis (2000) noted, there are five types of integration: spatial integration, sector integration, land use integration, economy-society-environment integration and sub-market integration, which depending on the purpose of the model. If the temporal dimension is incorporated, it becomes a dynamic integrated model. The following section will present the major two groups of integrated models which are classified by their dominant features.

2.3.1 Spatial Interaction Type Integrated Models

The most well known model from the family of gravity/spatial interaction type integrated model is the Lowry model (Lowry, 1964) for the Pittsburgh metropolitan region. It is built on economic base theory, and takes gravity formulations to allocate the secondary employment to zones according to the distance to other zones and population in other zones. Meanwhile, population is allocated based on distance and employment. The key relationship is population and employment, which is solved in an iterative manner and interacts with land use constraints (total land, unused land, basic industrial land, residential land and service land). The Lowry model is widely used in modern planning. It introduced a multiplier to improve the explanation of the urban structure. But it was not a dynamic model. It referred to employment in industrial activities and their location as exogenous variables at the moment of simulation.

Other applications of the Lowry model include Time Oriented Metropolitan Model (TOMM) for Pittsburgh Community Renewal Program, Projective Land Use Model (PLUM) for San Francisco Region, and Activity Allocation and Stocks-Activities Models which introduces floor space to represent location attraction (Batty, 1976). These models are based on the Lowry model

framework and incorporate various modifications and improvements on technical details, such as zonal size, land constraints, activity rates and population disaggregating.

To briefly conclude, these spatial interaction type models share the same main purpose "to forecast (or, predict) future changes in the distribution of the population, employment and land uses in urban (mostly) areas given exogenous changes in basic employment. In other words, they are basically demand-driven models in which the supply side of land is under-represented in the best case"(Briassoulis, 2000). However, these models were born with some inherent drawbacks:

1. Land is a special commodity; in most cases, land supply plays a more important role in determining the interaction mechanism;
2. They are static in nature;
3. Land use change is treated in a linear fashion; however, nonlinearity is much closer to the reality.

2.3.2 Simulation Integrated Models

Many integrated models can be classified as simulation models. When the system is too complex, it is difficult to derive explicit expressions to represent the behavior of the system. In such circumstances, we resort to simulation techniques, which employ a set of predefined rules, operate on a set of related data and then arrive at a decision. Based on the level of spatial detail, simulation integrated models can be grouped into (1) urban/metropolitan simulation models, (2) regional simulation models, and (3) global simulation models.

The San Francisco CRP, NBER, HUDS (see details in Kain, 1986), CUFM (Landis, 1994, Landis, 1995), Dortmund (Wegener, 1982), ITLUP (Putman, 1983), TRANUS (de la Barra, 1989) and CATLAS (Anas, 1982) models are all from the group of urban/metropolitan simulation models. These urban simulation models mostly take some versions of micro-economic theory as their theoretical basis; the interaction between population and employment is the major driving force for land use change, involving mainly residential and commercial land use. They bear with the same criticisms for early urban economic models, even though improvements have been made regarding the diversity of explanatory variables and interaction processes.

Different from urban level models, regional level simulation models focus on a higher level of spatial scale, which implies a broader scope of driving force (environment, macro-economy and policy), participating agent and/or entities, and land use types (agriculture, forestry). Several regional level simulation frameworks which address land use change directly were developed in the past decade, for example, the Conversion of Land Use and its Effects (CLUE) (Veldkamp and Fresco, 1996a, 1996b, Verburg et al., 1997), Integrated Model to Predict European Land Use (IMPEL) (Rounsevell, 1999) and the Cellular Automata Modeling Framework (White and Engelen, 1994, de Almeida et al., 2003). It is worth mentioning the cellular automata approach briefly here.

The cellular automaton is a concept borrowed from social physics, which is widely applied in the modeling of comprehensive, dynamic, socio-economic phenomena. "A cellular automaton consists of an array of cells in which each cell can assume one of k discrete states at any one time.

Time progresses in discrete steps, and all cells change state simultaneously as a function of their own state, together with the state of the cells in their neighborhood, in accordance with a specified set of transition rules"(Engelen et al., 1995). Cellular methods have been incorporated into many land use change models (Alonso and Sole, 2000, Li and Reynolds, 1997, Manson, 2000). As indicated by the definition, its strength lies in its capability to integrate macro and micro levels of spatial and temporal details, and its relatively realistic representation of the real world; however, its ability largely depends on the predefined stationary transition rules. In addition, cellular models do not consider transportation system explicitly, which makes it less appropriate if the main purpose is to simulate interactions between land use patterns and the transportation system.

Global level simulation models generally aim at predicting and evaluating global environmental change, such as climate change, deforestation, and desertification etc. Therefore, these type of models typically do not focus on modeling land use change. Readers may refer to Liverman (1989) for details about the IFS model and to Alcamo et al. (1994a, 1994b) and Rotmans (1990) for the IMAGE model.

2.4 Agent-Based Land Use/Land Cover Models

Agent-based models have become popular in simulating land use/land cover change in recent years. Before going any further, the concept of "agent" needs to be clarified. Agents share some common features: "they are autonomous; they share an environment through agent communication and interactions; and they make decisions that tie behavior to the environment" (Parker et al., 2003, pp 317). Various entities can be regarded as agents, such as organizations, people (for example, land owners and land developers) and animals.

The two key components of an agent-based LUCC model system are: (1) a cellular model to represent the landscape, (2) an agent-based model to simulate human decision making processes over the landscape under study (Parker et al., 2003). These two components are integrated through a series of interaction mechanisms between agents and their environment. It is believed that multi-agent based LUCC models offer a promising means to represent human-environment interdependencies; in particular to represent small-scale individual decision making on land change (Janssen, 2003). Many applications can be found in the recent literature, as listed by Parker et al. (2003, pp 310):

Table 2.1: Characteristics of a number of Land-use/cover change studies that use the combinations of agents and cellular models

Publication(s)	Type(s) of Land Use	Issue	Time Period	Type(s) of Agents	Type(s) of Decisions	Geographic Location
Balmann (1997); Balmann et al. (2002)	Agriculture	Diffusion of new practices	2001–2020	Farms	Investment, production, land-renting	Hohenlohe, Germany
Berger (2001)	Agriculture	Diffusion of new practices	1997–2015	Farm households	Investment, tenure, production	Chile
Rouchier et al. (2001)	Rangelands	Emergent relationships between farmers and herdsmen	400 units of time	Herdsmen, farmers, and village leader	Negotiations on location for herding, selling animals	North Cameroon
Dean et al. (2000)	Settlements	Societal collapse	800–1360	Households	Location to farm, harvest, store harvest, marriage	Long House Valley, Arizona, U.S.
Hoffmann, Kelley, and Evans (2002)	Forests, agriculture	Trends in deforestation and reforestation	1850–present	Landowners	Farm, fallow, harvest timber	Indiana, U.S.
Kohler et al. (2000)	Settlements	Settlement pattern	900–1300	Households	Agricultural production decisions, marriage, choice of new residential location	Mesa Verde Region, U.S.
Ligtenberg, Bregt, and van Lammeren (2001)	Urban	Modeling spatial planning	30 years	Stakeholders	Voting for preferred land use	Nijmegen, the Netherlands
Lim et al. (2002)	Forests	Trends in tropical deforestation	1961–present	Farmers	Cropping decisions	Brazilian Amazon
Lynam (2002)	Savanna	Sustainability of agricultural practices	30 years	Households	Cropping decisions	Kanyurira Ward, Zimbabwe
Manson (2000; forthcoming)	Forests, agriculture	Trends in tropical cultivation and deforestation	1960–2010	Households, institutions	Crop/land allocation	Yucatán Peninsula, Mexico
Polhill, Gotts, and Law (2001)	Not specified	Study of imitation strategies	200 years	Land managers	Land-use decisions and land market	No specific location
Rajan and Shibasaki (2000)	Forests, agriculture, urban	Land-use/cover change at the national level	1980–1990	Decision maker on spatial grid	Land use and migration	Thailand
Sanders et al. (1997)	Urban	Evolution of settlements	2000 years	Spatial entity	Transition rules for settlement type change	No specific location
Torrens (2001)	Urban	Residential location dynamics	Not specified	Home sellers and home buyers	When to sell and buy	No specific location

There are two approaches to applying multi-agent based LUCC techniques: the explanatory approach and the descriptive approach. The explanatory approach is to provide insights that will lead to macroscopic phenomena. Given an empirical phenomenon, users propose a set of rules, specifications (about the agent behaviors and interactions), and then apply them into simulated scenarios in the hope that the generated results will resemble the target phenomenon. Basically, the explanatory approach is to test theory, new hypothesis and explore possible outcomes. The descriptive approach attempts to mimic the real world scenarios. It makes full use of available data by making the model fully parameterized as permitted by the data. It does not require outcomes to arrive at an equilibrium state, which make it more flexible in modeling nonlinear discrete behaviors. These two approaches are not mutually exclusive; rather the choice depends on the data availability and the modeling purpose.

To summarize, major advantages and disadvantages are listed below:

- It is flexible, which makes it a more powerful tool when modeling large scale complex systems.
- It is adaptive; both the individual level decision and macro-level evolution strategies can be built into the modeling framework.
- Dynamic mechanisms are relatively more realistic, flexible and clear.
- Its flexibility makes it less theoretically grounded.
- It is complex.
- Lack of open computing source for LUCC modes and modeling platform.
- Model verification and validation are challenging tasks, which are critical to the successfulness of the models.

2.5 Other Models

There are other types of models which can not be easily classified into the groups mentioned above. These non-traditional models may provide potentials for addressing the limitations of conventional modeling methods. Two types of models are presented below.

2.5.1 GIS-based Modeling Approaches

A Geographic Information System (GIS) is a powerful tool for the management and manipulation of spatial data sets. Data storage, retrieval, analysis and display are the main functions of GIS. These functions make it a possible tool to track historical land use change and predict future land use patterns based on certain rules. Currently, many models use GIS to input spatial data and/or display model outputs (Manson, 2000, Veldkamp and Fresco, 1996b, Logsdon et al., 1996, Johnston and de la Barra, 2000). However, GIS-based models refer to a close-coupling of GIS and spatial modeling techniques, which means that GIS is not used only as a spatial data manipulation and display tool, but also an indispensable component of the overall model structure performing analytical tasks. Four types of approaches can be integrated into GIS (Aspinall, 1994):

- Rule-based
- Knowledge-based

- Inductive-spatial, and
- Geographic

rule-based approach employ rules to weight spatial data sets, which can be used to describe land use change by conducting map overlay analysis, and also to predict possible land use change by performing the rules over spatial data. Knowledge-based approaches employ a set of predefined (developed outside of GIS) equations to manipulate and analyze spatial data inside of GIS. To develop a meaningful integrated model, this approach offers a potential when coupling with spatial interaction models, agent based models, and other spatially explicit model techniques. Inductive-spatial approaches employ spatial statistical techniques to identify the spatial pattern of the data set, and geographic approaches focus on the location distribution patterns. The last two approaches are not widely recognized as promising means for land use change modeling.

2.5.2 Artificial Neural Network Approaches

Artificial neural networks were first developed to model neural tissues and to simulate cognitive processes, and now are used for pattern recognition, prediction and classification in a variety of disciplines. An artificial neural network is made up of several layers, which are linked sequentially through input processing units, hidden processing units and output units. Then the whole model can be described by equations between the processing units of each pair of successive layers. The relationships between layers are derived by a training procedure over a subset of data via trial and error. Naturally, artificial neural networks bring benefits in terms of flexibility and nonlinearity, especially when dealing with large complex system. However, the relationships derived are invisible to the modelers, and thus we lose the opportunity to understand the land use change mechanisms. That is the biggest drawback of artificial neural networks. Several attempts have been made to model land use change by artificial neural networks (Li and Yeh, 2002, Pijanowski et al., 2002).

Other types of models include Markov analysis (Lein, 1989, Logsdon et al., 1996, Muller and Middleton, 1994), participatory models (Grimble and Wellard, 1997, Luz, 2000, Craig et al., 2002) and some natural science oriented models (e.g. landscape ecology models, stochastic landscape models). These models have their own features and suited for special aspects of the socio-economic phenomena.

2.6 Concluding Remarks

In conclusion, for the modeling of land use/land cover change there is no single, perfect method or approach. The selection of modeling techniques should be based on the research question and available data. Considering the available resources and model objectives, this report will employ Markov-based, GIS-based and statistical approaches to analyze and model land use/land cover change in response to road development.

Chapter 3 Data Preparation

3.1 Data Source

Based on the research question, the required data include land use/land cover data (satellite imagery) and historical highway construction data. Historical highway construction data were available from TxDOT in table forms showing types, locations and years of completion, which were manually digitized on the current maps of the study area. As shown from Table 3.1, LandSat data are available only after 1972; though it is preferred to have images in 1960s when the national highway system was initiated, to detect the interaction between highway and land use/land cover, the images used were solely LandSat data, to avoid errors that could be introduced in the georeferencing and digitizing of aerial photographs. Land use land cover data were obtained from the Texas Synergy and Global Land Cover Facility (GLCF) data center.

Table 3.1: LandSat series information

Satellite	Start	End	Bands	Sensor	Pixel Size
LandSat-1	1972	1978	4,5,6,7	MSS	57 x 79 m
LandSat-2	1975	1982	4,5,6,7	MSS	57 x 79 m
LandSat-3	1978	1983	4,5,6,7,8	MSS	57 x 79 m
LandSat-4	1982	1993	4,5,6,7/ 1,2,3,4,5,6,7	MSS/ TM	57 x 79 m/ 30m reflective 120m thermal
LandSat-5	1984	present	4,5,6,7/ 1,2,3,4,5,6,7	MSS/ TM	57 x 79 m/ 30m reflective 120m thermal
LandSat-6	1993	Failed			
LandSat-7	1999	present	1,2,3,4,5,6,7,8	ETM+	30m reflective 60m thermal

Source: http://landsat.usgs.gov/project_facts/history/index.php

3.2 Data Processing

3.2.1 Study Area

The study area (Figure 3.1) is located between 30°3'44.178"N and 30°37'16.363"N, 98°3'15.114"W and 97°27'59.208"W, with total area of 3444 km2. This area consists of Travis County, and parts of Williamson, Hays and Bastrop Counties.

This study area was selected based on consideration of data availability and real applications. Firstly, it is reasonable to study an area with significant land use development over years, in order to develop an applicable method that may be further applied to other mega-regions.

Secondly, from the data aspect, only Austin area highway construction data are available; moreover, satellite images for this area are also available for a long time span including 1979, 1987, and 2002, which helps to make the LULC change detection and analysis better grounded.

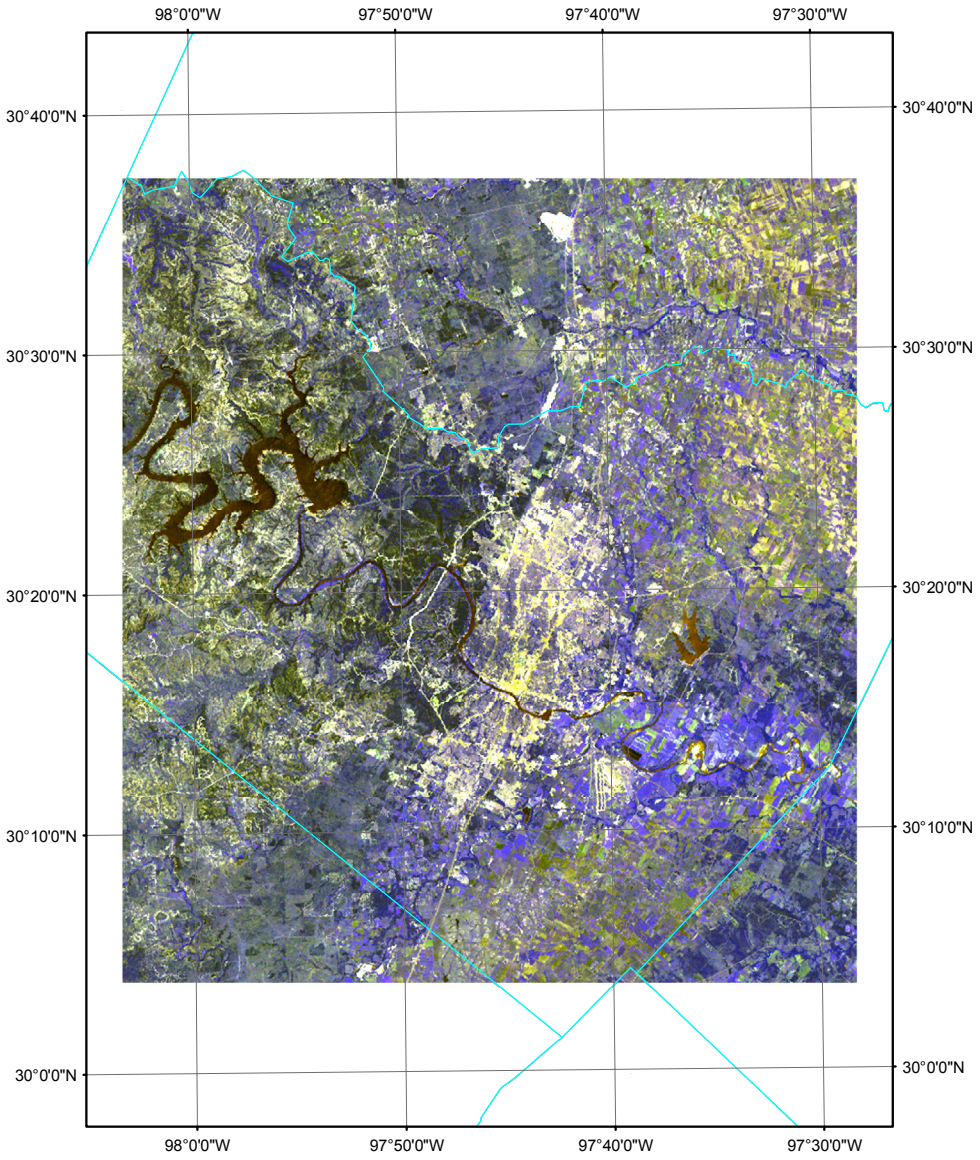


Figure 3.1: Study area satellite image (MSS, 1979) and location

3.2.2 Highway Data

As mentioned in the previous section, highway data were manually digitized by utilizing historical maps, which inevitably resulted in some inaccuracy. But based on the following three considerations, this approach is still acceptable and applicable:

Highways were digitized on a current GIS base; hence, errors in the location and length of highways were controlled.
The resolutions (See Table 3.1) of satellite images are relatively low, which leaves room to accommodate small variations of ground features.
The analysis focuses more on the impacts of the existence of roads on urbanization, rather than road attributes.

The final outcome of highway data processing is a shapefile (.shp) that includes road location (start and end points), completion year, road categories and length information.

3.2.3 Satellite Image Data

A satellite image is a spectral representation of everything that covers the land surface; different types of materials (such as water, vegetations, soils and cultural features) have their own reflectance, which are captured by satellite sensors and thus indicate a certain pattern of land cover. Figure 3. is an example of a satellite image. To identify land cover patterns, image classification procedures are needed.
Classification is a process to sort pixels into a number of individual categories based on their data file values. These categories or classes correspond to LULC types. There are two ways to classify images, unsupervised classification and supervised classification.

Unsupervised classification uses the Iterative Self-Organizing Data Analysis Technique (ISODATA), a widely used clustering algorithm to uncover the statistical pattern of the data. Users set the parameters (number of classes, maximum iterations and convergence threshold) and then computer programs can finish the classification automatically (e.g. ERDAS Imagine 9.1). Supervised classification is more controlled by users, although it also needs certain clustering algorithms. Users select signature samples to represent individual class, and the computer will classify the image according to the signatures. Supervised classification requires the analyst's knowledge of the study area, more time, and yields more accuracy in comparison with unsupervised classification. While if no information is available about the study area, unsupervised classification is the only option.

The three images covering Austin area were taken at June 11, 1979 (MSS), October 11, 1987 (TM) and November 23, 2002 (ETM+).

After comparing the results from unsupervised classification and supervised classification, supervised classification was finally selected and applied to those three images. Table 3.2 (Lillesand et al., 2004) shows the strength of each spectral band on feature identification. Considering the main research objective-- to identify urbanized area, Band 1, 2, 3 and 4 are used in the supervised classification.

Table 3.2: TM & ETM+ spectral bands

Band	Wavelength (μm)	Nominal Spectral Location	Principle Applications
1	0.45-0.52	Blue	Designed for water body penetration, making it useful for coastal water mapping. Also useful for soil/vegetation discrimination, forest-type mapping, and cultural feature identification.
2	0.52-0.60	Green	Designed to measure green reflectance peak of discrimination and vigor assessment. Also useful for cultural feature identification.
3	0.63-0.69	Red	Designed to sense in a chlorophyll absorption differentiation. Also useful for cultural feature identification.
4	0.76-0.90	Near IR	Useful for determining vegetation types, vigor, bodies, and for soil moisture discrimination.
5	1.55-1.75	Mid IR	Indicative of vegetation moisture content and soil moisture. Also useful for differentiation of snow from clouds.
6	10.4-12.5	Thermal IR	Useful in vegetation stress analysis, soil moisture discrimination, and thermal mapping applications.
7	2.08-2.35	Mid IR	Useful for discrimination of mineral and rock types. Also sensitive to vegetation moisture content.

Another question needs consider is the classification scheme. The determination of classification system (level of details) is in accordance with the research question. Table 3.3 shows the classification system adopted in this study. The classification is mainly based on Anderson's Level I classification scheme, excluding its other four classes: wetland, barren land, tundra and perennial snow on ice (not typical in Austin area).

Table 3.3: Land use and land cover classification

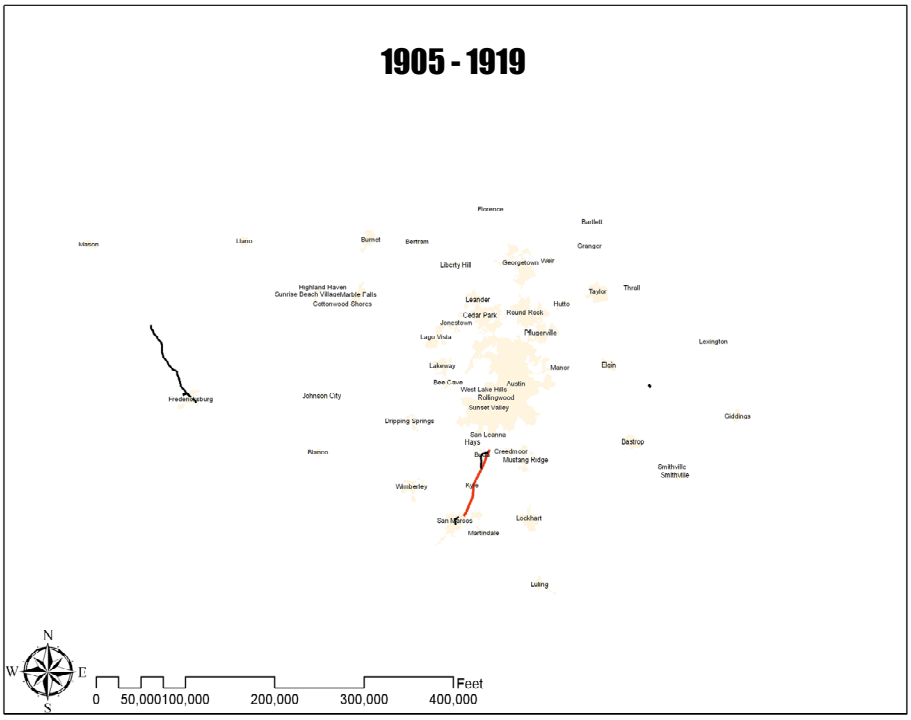
Class	Definition
Urban or build-up land	Residential, commercial, industrial, transportation, and other mixed urban or built-up land
Agricultural land	Cropland, pasture, Orchards, groves, vineyards, nurseries, and ornamental, and other agricultural land
Rangeland	Herbaceous, shrub, brush and mixed rangeland
Forest land	Deciduous, evergreen and mixed forest land
Water	Streams, canals, lakes, reservoirs, bays and estuaries

Source: http://courses.washington.edu/urbdp467/html/classify.html

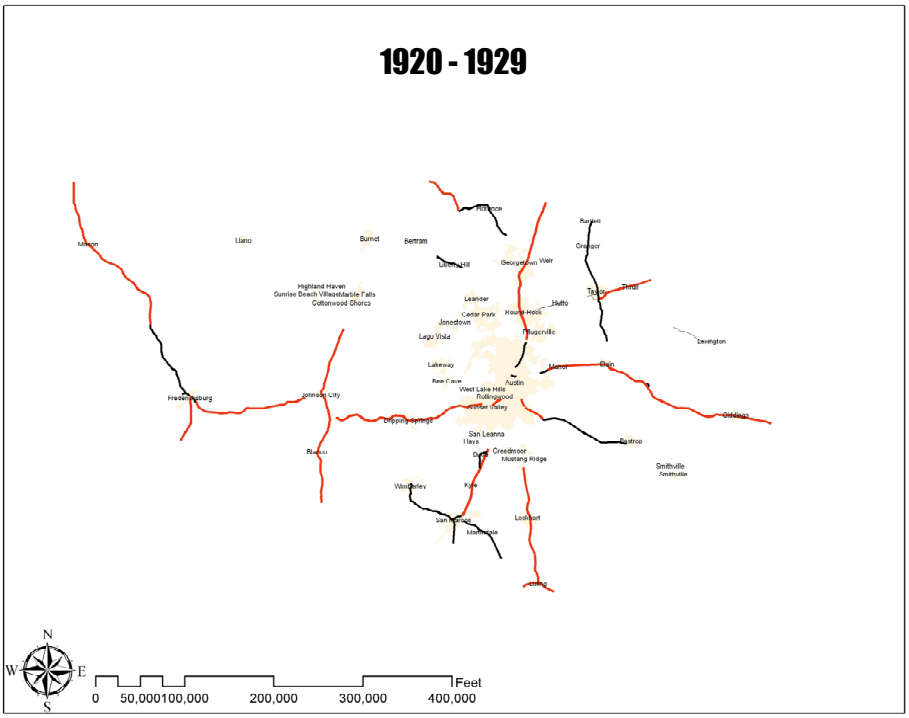
3.3 Results of Data Processing

3.3.1 Historical Road and Austin Maps

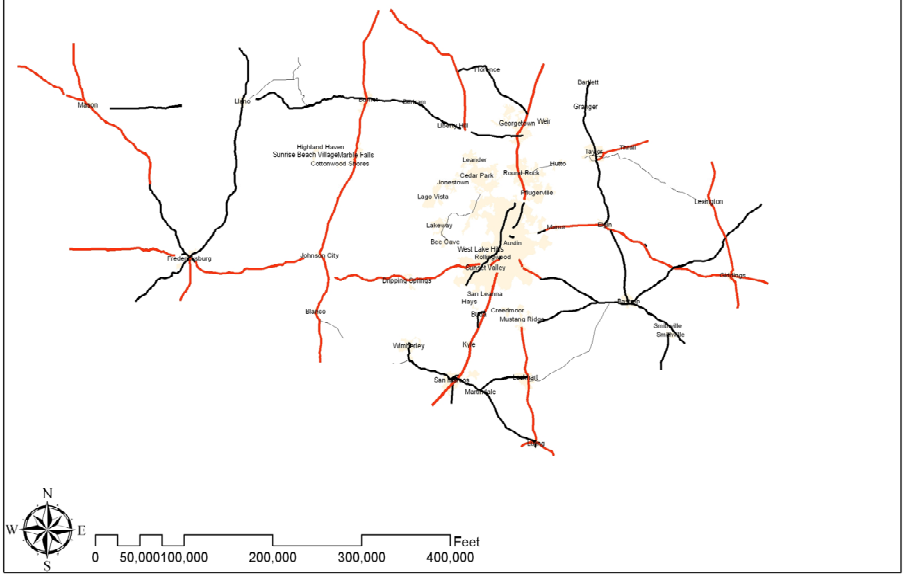
Using ArcGIS 9, historical road maps were digitized on a current GIS base map. Figure 3.2 shows the development of the urban/ built-up area and roads during the period of 1901-1967. Visual examination suggests a strong correlation between urban expansion and roadway extension in the Austin area.

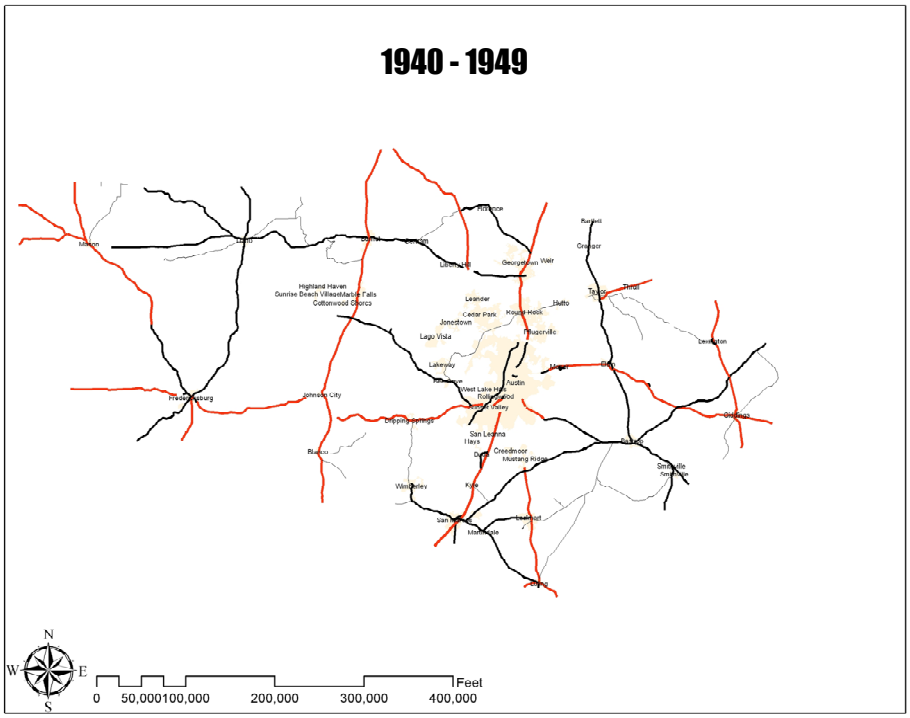


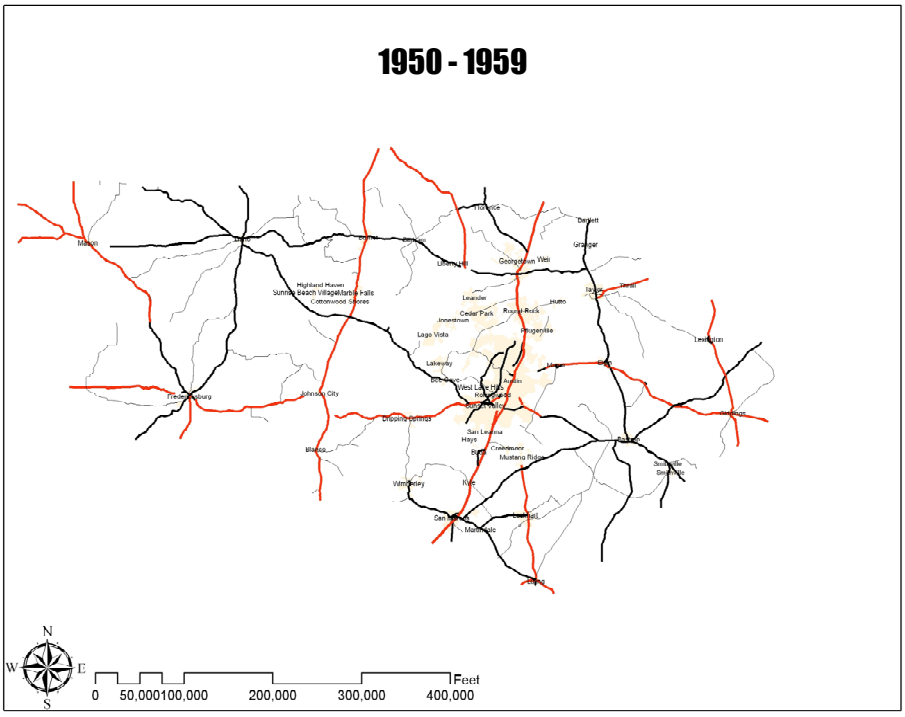
1920 - 1929

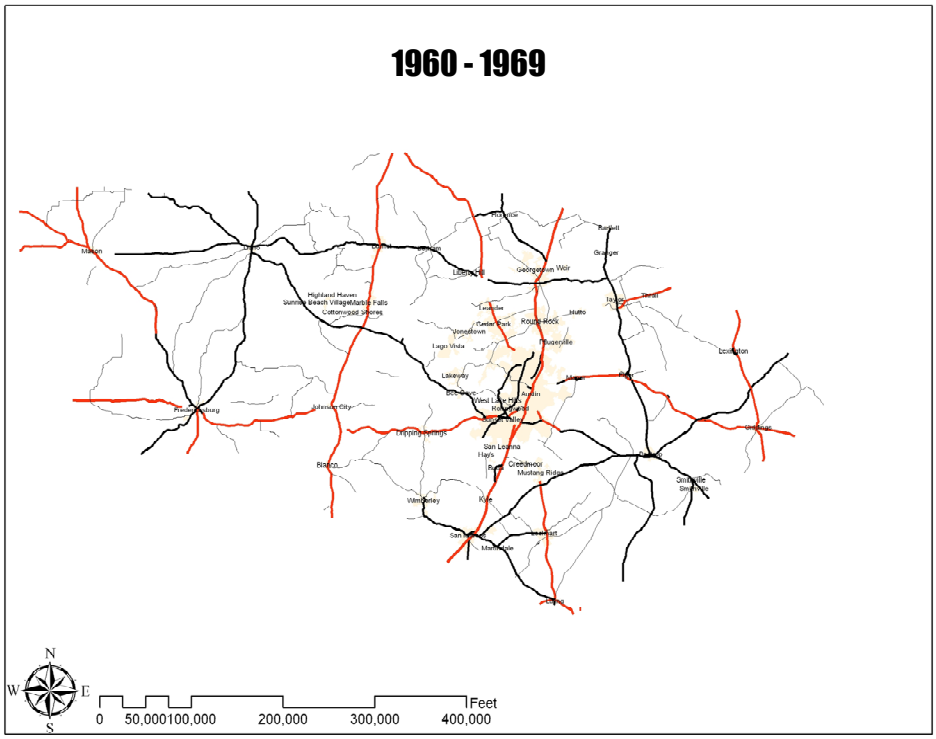


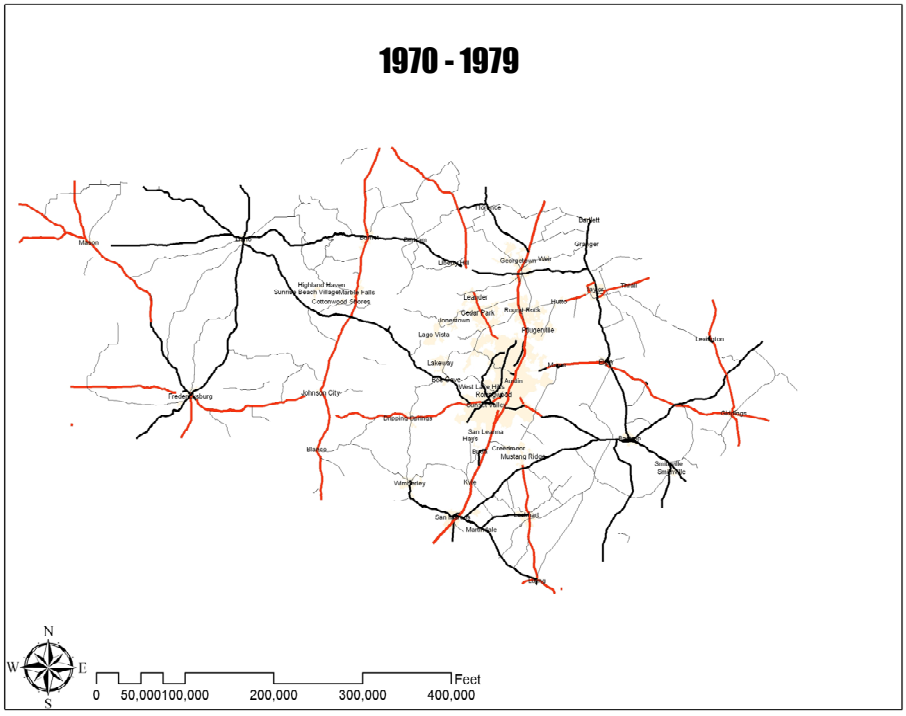
1930 - 1939

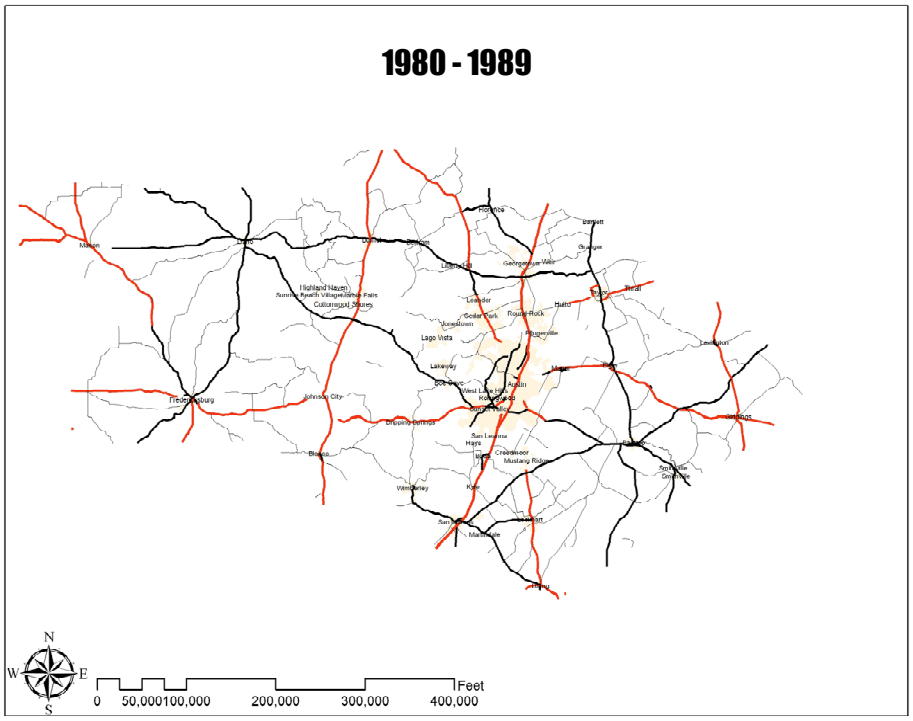


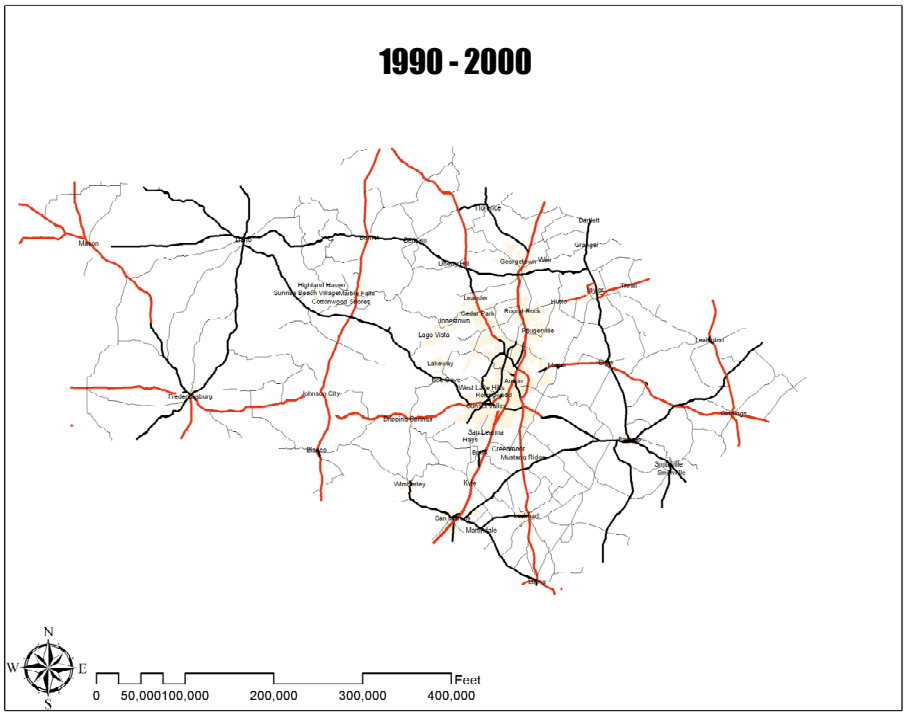

1940 - 1949
N
W
E
S
0 50,000100,000 200,000 300,000 400,000
Feet


1950 - 1959
N
W
E
S
0 50,000100,000 200,000 300,000 400,000
Feet


1960 - 1969
N
W
E
S
0
50,000
100,000
200,000
300,000
400,000
Feet


1970 - 1979
N
W
E
S
0
50,000
100,000
200,000
300,000
400,000
Feet


1980 - 1989
N
W
E
S
0 50,000100,000 200,000 300,000 400,000
Feet


1990 - 2000
N
W
E
S
0 50,000100,000 200,000 300,000 400,000
Feet

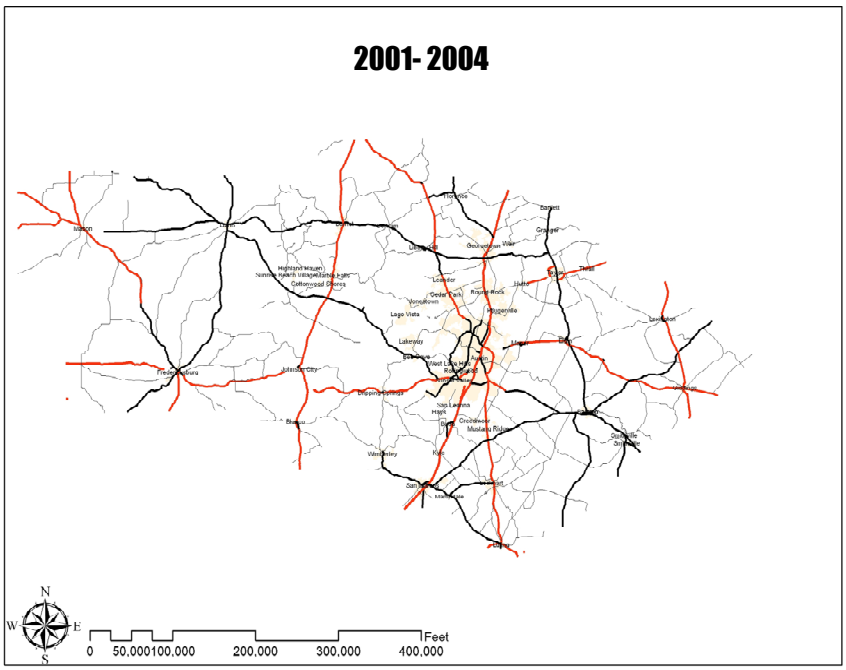
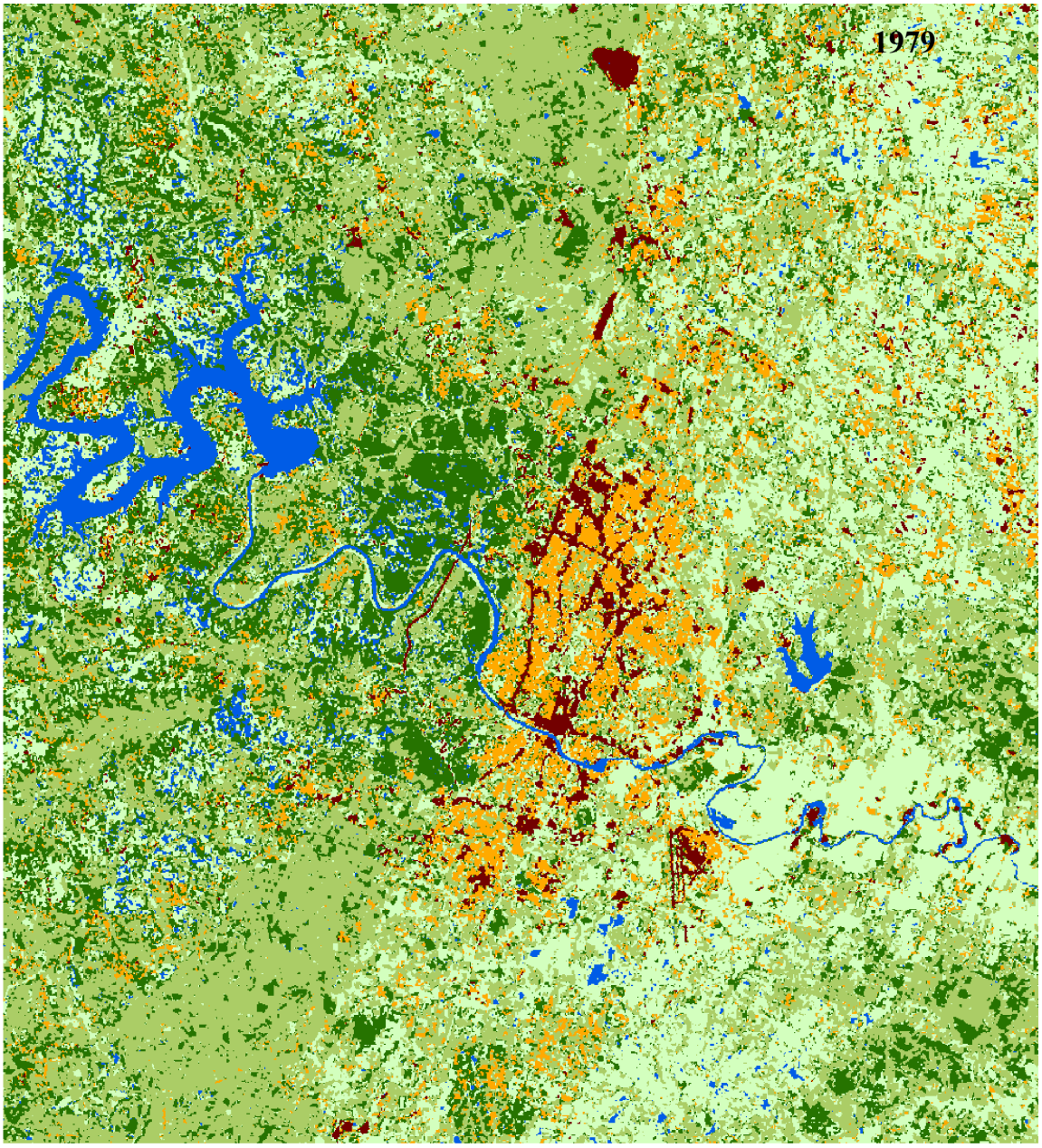


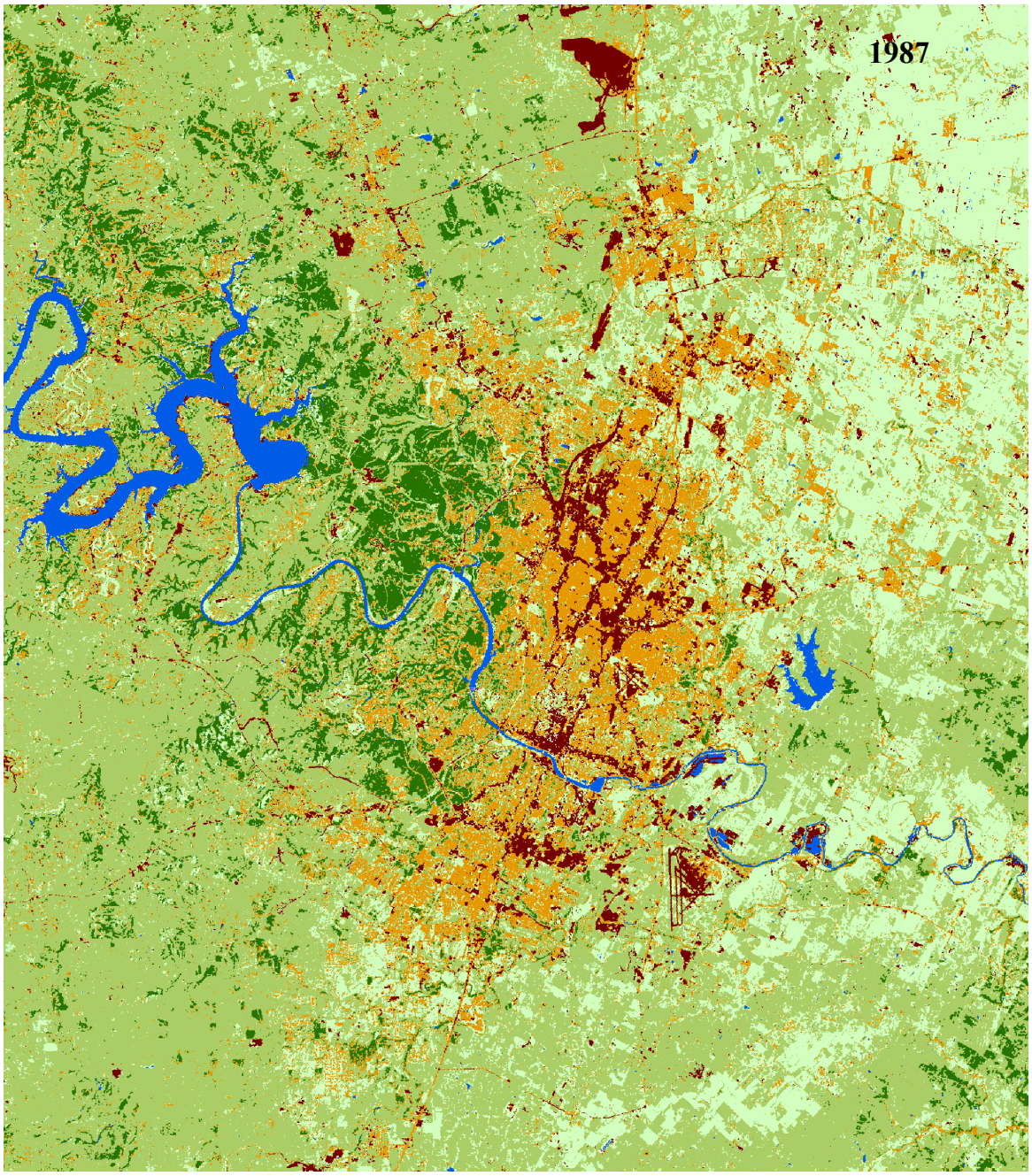
Figure 3.2: Historical records of highway constructions in the Austin, TX area

3.3.2 LULC Classification Images

Supervised classification was performed on 1979, 1987, and 2002 satellite images according to the classification scheme listed in Table 3.3. Residential and commercial land use was shown separately in the following classified images (Figure 3.3a, b and c).



3.3a: 1979



3.3b: 1987

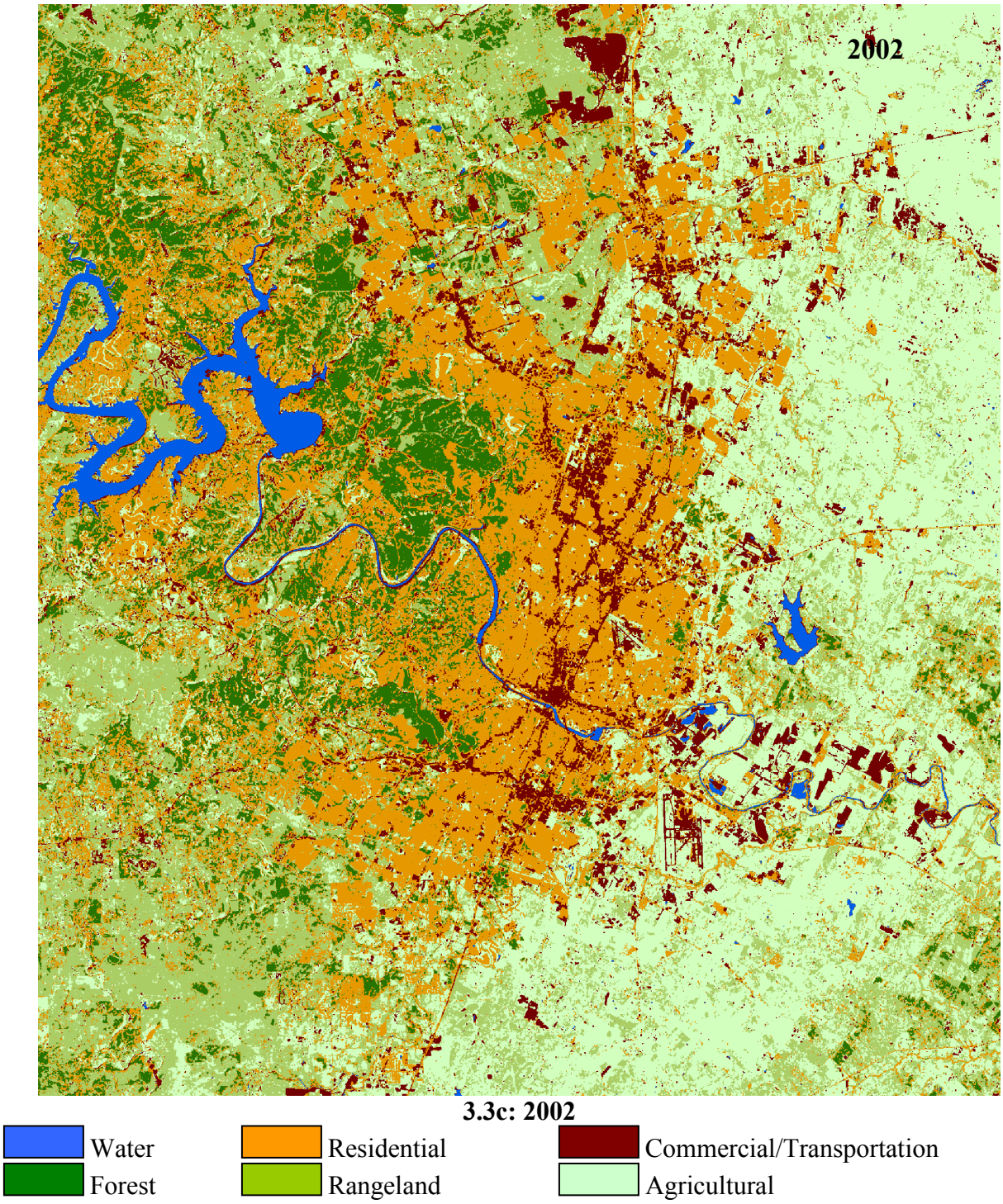


Figure 3.3: Land use classification map (1979, 1987 and 2002)

Chapter 4 Data Analysis and Model Development

4.1 Markov Process

A Markov process has been used to explain land use land cover change for many years. More recently, it has been incorporated in the cellular automata modeling process to make the cellular automata transition rules more reliable. Markov LULC models share one basic assumption: land use land cover change is a stochastic process, and every land use land cover state is regarded as a state of a Markov chain, whose value depends on the state at previous time points.

This section conducts a brief Markov analysis to the observed LULC data, to test the applicability of Markov chain theory to the land use change analysis in this study.

Assuming the land use change is a homogeneous first-order Markov chain, which means that the next state only depends on the previous state and the transition probabilities over time are constant. The transitional probabilities can be estimated by the observed data, which can be expressed as:

$$p_{ij} = \frac{n_{ij}}{n_i} \qquad (4.1)$$

Where, p_{ij} is the one-step transition probability from state *i* to state *j*, n_{ij} is the observed number of land units changed from state *i* to state *j*, and n_i is the number of total land units at state *i*.

The transition probabilities were calculated for time period 1979-1987, 1987-2002, and 1979-2002. Table 4.1 shows the transition probabilities between 1979 and 2002. For example, the transition probability from agricultural to urban is 0.2856, from rangeland is 0.3004 and from forest is 0.3608. Those probabilities are in accordance with people's perception of real world; however, the transition probabilities from urban to other types of land use appear not quite reasonable, which may be due to classification errors and thus some areas were misrepresented.

Table 4.1: Land use transitional probabilities 1979-2002

1979	2002				
	Urban	Agricultural	Rangeland	Forest	Water
Urban	0.5906	0.2823	0.1182	0.0071	0.0018
Agricultural	0.2856	0.5122	0.1622	0.0373	0.0028
Rangeland	0.3004	0.2556	0.3505	0.0926	0.0009
Forest	0.3608	0.1918	0.2444	0.2012	0.0018
Water	0.2916	0.1221	0.0584	0.1478	0.3801

The expected transition probabilities from 1979 to 2002 shown in Table 4.2 were calculated using the Chapman-Kolmogorov equation (Eq. 4.2). The Chapman-Kolmogorov equation calculates n-step transitional probabilities of a Markov process.

$$p_{ij}^{(n)} = \sum_{r \in S} p_{ir}^{(k)} p_{rj}^{(n-k)} \quad (4.2)$$

Table 4.2: Expected LULC transitional probabilities under Markov hypothesis 1979-2002

1979	2002				
	Urban	Agricultural	Rangeland	Forest	Water
Urban	0.4698	0.3099	0.1740	0.0419	0.0042
Agricultural	0.3275	0.3847	0.2227	0.0612	0.0040
Rangeland	0.3249	0.3157	0.2747	0.0826	0.0023
Forest	0.3327	0.2508	0.2347	0.1774	0.0045
Water	0.2565	0.1758	0.1264	0.0992	0.3421

In other words, the transition probabilities from the period 1979-2002 should equal to the multiplication of transition probabilities from the periods 1979-1987 and 1987-2002, if the land use change is a Markov process. To test if the observed occurrences (shown in Table 4.) follow Markov process frequencies (shown in Table 4.), Karl Pearson's chi-square test is used.

$$\chi^2 = \sum_i \sum_k \frac{(O_{ik} - E_{ik})^2}{E_{ik}} \quad (4.3)$$

Where, O_{ik} and E_{ik} are the observed and expected frequencies, respectively. This test statistic χ^2 follows a chi-square distribution with $(m-1)^2$ degrees of freedom; m is the dimension of the transition matrix.

A null hypothesis is made that the data follows a Markov process. If $\chi^2 > \chi^2_{1-\alpha,(m-1)^2}$, the null hypothesis will be rejected. The calculated χ^2 is 0.2988. The value of $\chi^2_{0.95,16}$ is 7.9616, which is greater than χ^2. Therefore the null hypothesis cannot be rejected at 95% confidence level; that is to say, the observed transition probability is not significantly different from the expected probability, which suggests that the transition can be regarded as a Markov process at a risk of 5%.

This is a brief discussion about applying Markov theory to discover the land use transition mechanism. The chi-square test indicates that Markov theory may apply to these data and those transition probabilities can provide the magnitude of potential changes in a simple fashion. However, two problems remain to hinder the direct application of Markov to the LULC field. One is noticed in this study that some specific transition probabilities appear not reasonable, possibly due to the original image quality and classification errors. The other is that this method

does not provide an explicit explanation of what makes the transition happen. Therefore, the Markov approach may be more appropriate to be employed with other methods for modeling LULC change.

4.2 GIS Overlay Analysis

GIS is powerful in its ability to represent spatial features and associating locations with their attributes. Relying on GIS, this section uncovers the spatial patterns of urbanization process in response to road development.

First, residential and commercial/transportation land uses were combined into one category called urban/built-up, and all the other types were considered non-urban type. Percentages of urban/built-up area (see Figure 4.1) are calculated based on the three classified images in Chapter 3. The urban area had experienced a huge change from 11% of the total study area in 1979, to 17% in 1987 and 34% in 2002. The next step was to identify the spatial pattern of urbanization.

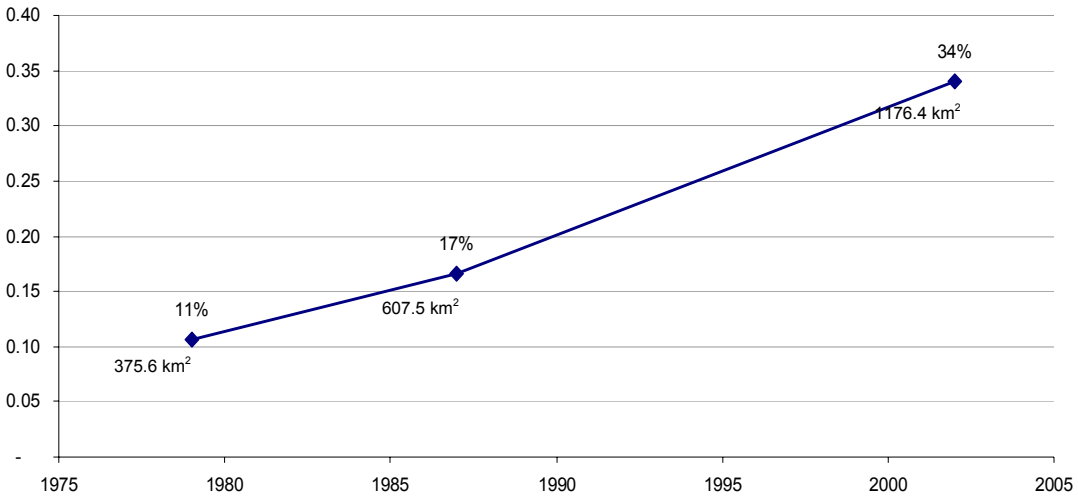


Figure 4.1: Urban/built-up area change 1979-2002

As is generally believed, urbanization occurs along roads and roads extend to wherever they are needed. Figure 4.2 shows the 2002 urbanized area, highway network, and 2km and 3km highway buffers. Apparently, the highway buffers cover most of the urbanized areas. A detailed discussion will be presented below.

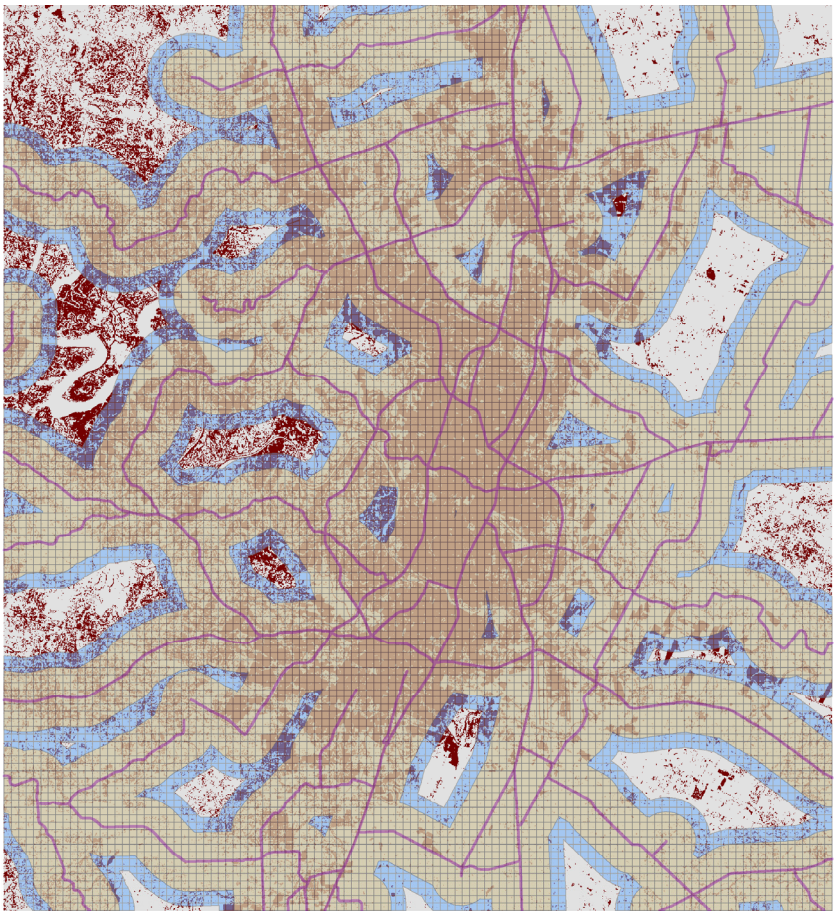


Figure 4.2: 2002 urban area, highways and highway buffers (2km & 3km)

As is shown in Figure 4.3, the urbanized area within the 1km highway buffers (1km each side of the roads) makes up 45% of the total urban area in 1979, 46% in 1987 and 50% in 2002; as the buffer is broadened to 3km, this proportion increases dramatically to 85%, 87%, and 90%, respectively. Within each buffer, the proportion experiences a slight increase over time, which implies that urban growth is not only an outward expansion, but also an increasing of development density. It is also interesting to see that over 85% of the urbanized area is within the 3km distance of highways.

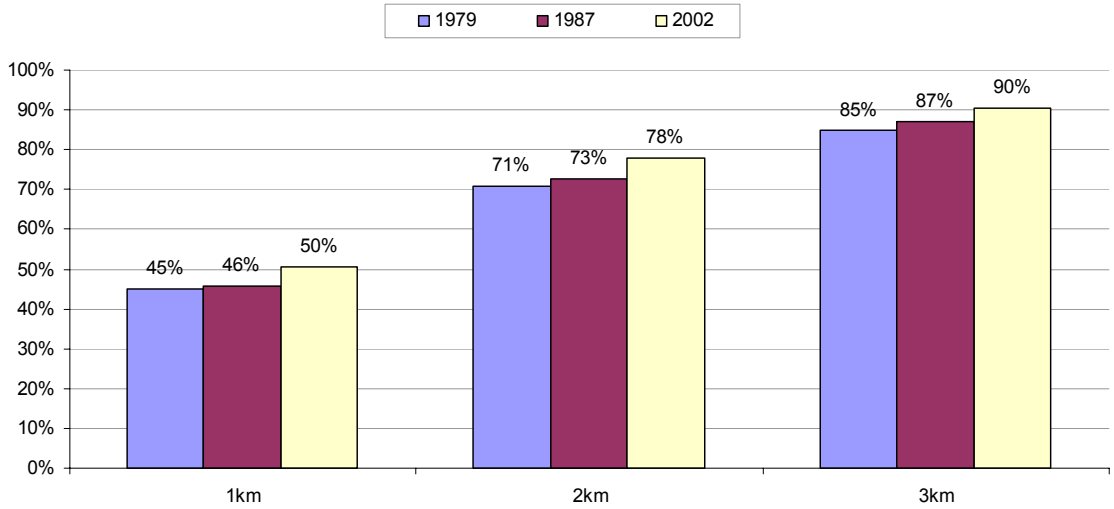


Figure 4.3: Urbanized proportion of total urbanized areas within buffers

In addition, as the distance from highways increases, the rate of increase of the urbanized proportion slows down, as clearly shown in Figure 4.4. The comparison is based on the total study area. Three years data indicate similar patterns both spatially and temporally:

- The urbanized proportion decreases for each of the bands which are successively from the roads. For instance, the 1979 urbanized proportion within 0-1km, 1-2km, 2-3km bands are 4.6%, 2.6%, and 1.4%, respectively. The proportion decreases by 43.5% from 4.6% for the 0-1km band to 2.6% for the 1-2km, and further decreases by 46.1% from 2.6% for the 1-2km band to 1.4% for the 2-3km band. Similar numbers can be calculated from 1987 and 2002 data.
- The rate of urbanization is slowing down with time (see Table 4.3).

Table 4.3: Annual increase rate of the proportion of urbanized area

Buffer	1979-1987	1987-2002
0-1km	6.5%	5.6%
1-2km	6.8%	5.2%
2-3km	7.0%	3.8%

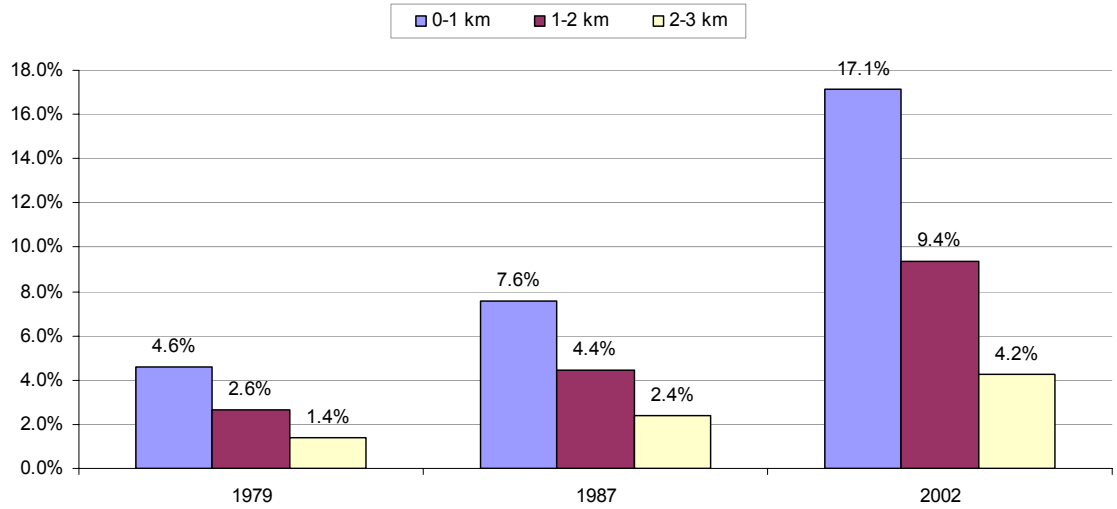


Figure 4.4: Proportion of urbanized area to total study area

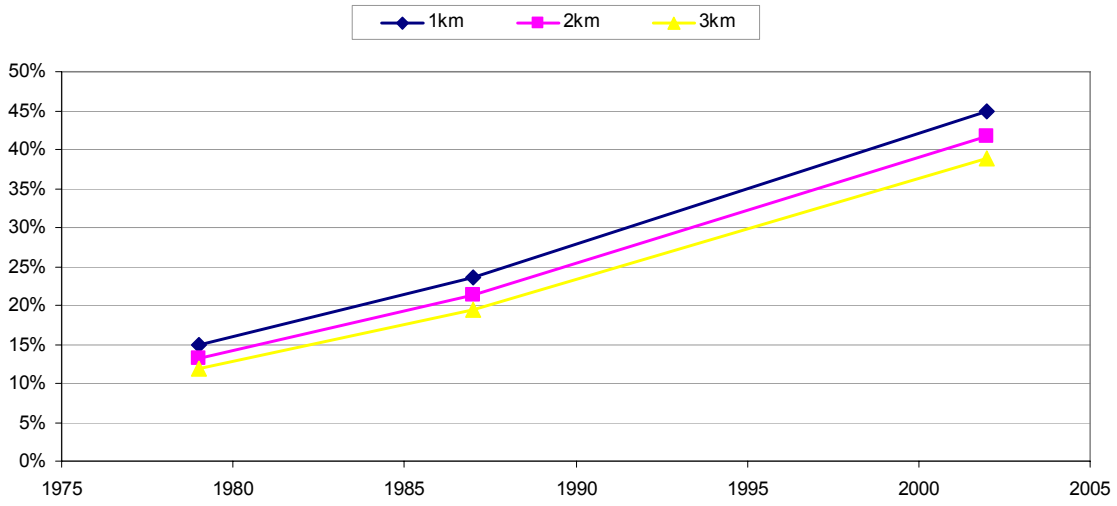


Figure 4.5: Urbanized proportion to the area within each buffer over time

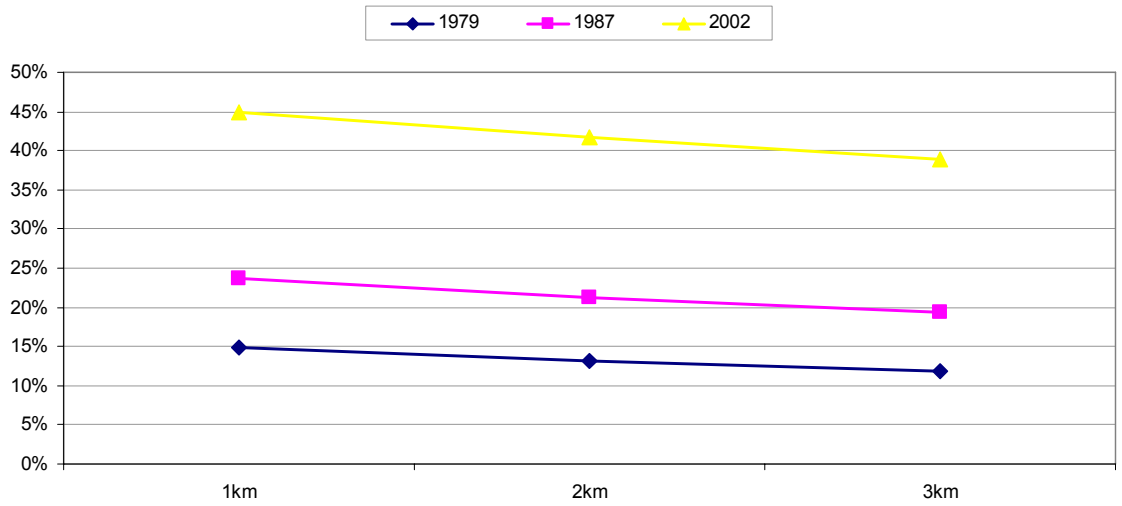


Figure 4.6: Urbanized proportion of the area within each buffer based on distance

The urbanization percentage within each highway buffer is calculated to provide information on development density. Figure 4.5 suggests similar patterns in the urbanized proportion within 1km, 2km and 3km buffers in comparison to the total area within those buffers, which experienced similar increase rates around 6% during 1979-1987 and 4% during 1987-2002. Figure 4.6 indicates that the urbanized proportion of each buffer area decreases approximately 2% per kilometer away from the highways, and this same pattern is seen in 1979, 1987, and 2002.

Three-year data are not enough to draw a safe conclusion regarding the specific increase or decrease rate; however, it is clear enough to indicate the spatial patterns of urbanization in response to the highway network.

4.3 Model Development

4.3.1 An Aggregate Model

A GIS overlay presents the direct spatial relationship between the road network and the urbanized area. The historical roads and jurisdiction maps were digitized to estimate the overall magnitude of road and urban development (see Table 4.4), which provides an opportunity to model the direct relationship between the two from an aggregate level. According to Table 4.4, Figure 4.7 is plotted to identify the scatter pattern of these two variables. Apparently, road length and urban area have a strong correlation. Using the MATLAB 7.0 statistical toolbox, the data were fitted using five functional forms. The results are shown in Figure 4.8 and Table 4.5.

Table 4.4: Historical urban area and road length

Year	1901	1915	1939	1955	1961	1967	1977	1983	1991	1997	2000
Road Length (km)	15	62	1606	2723	3265	3499	3799	3989	4425	4638	4753
Urban Area (ha)	1294	2940	6454	11622	16793	20015	25526	31362	50130	70094	80650

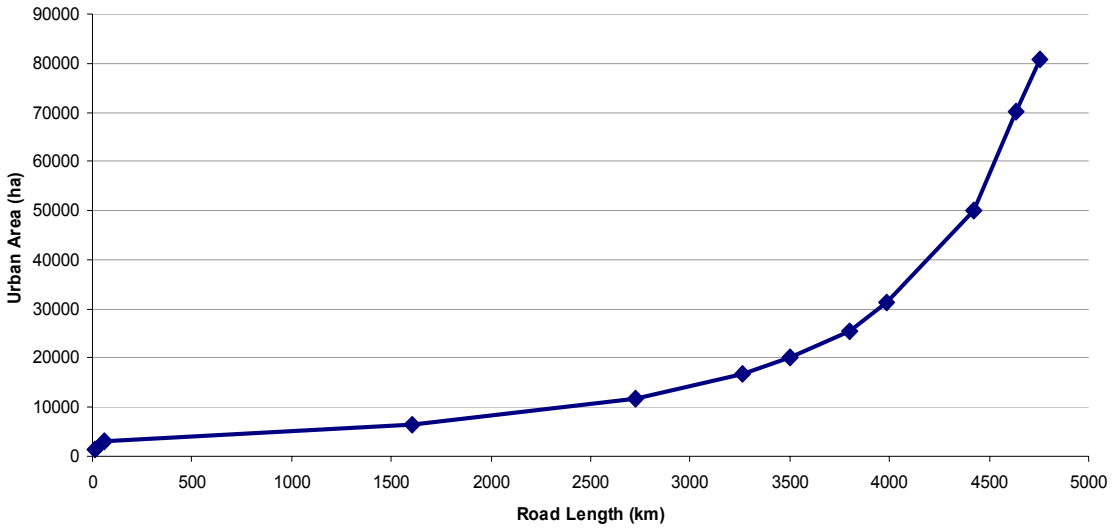


Figure 4.7: Road development vs. urban area 1900-2000

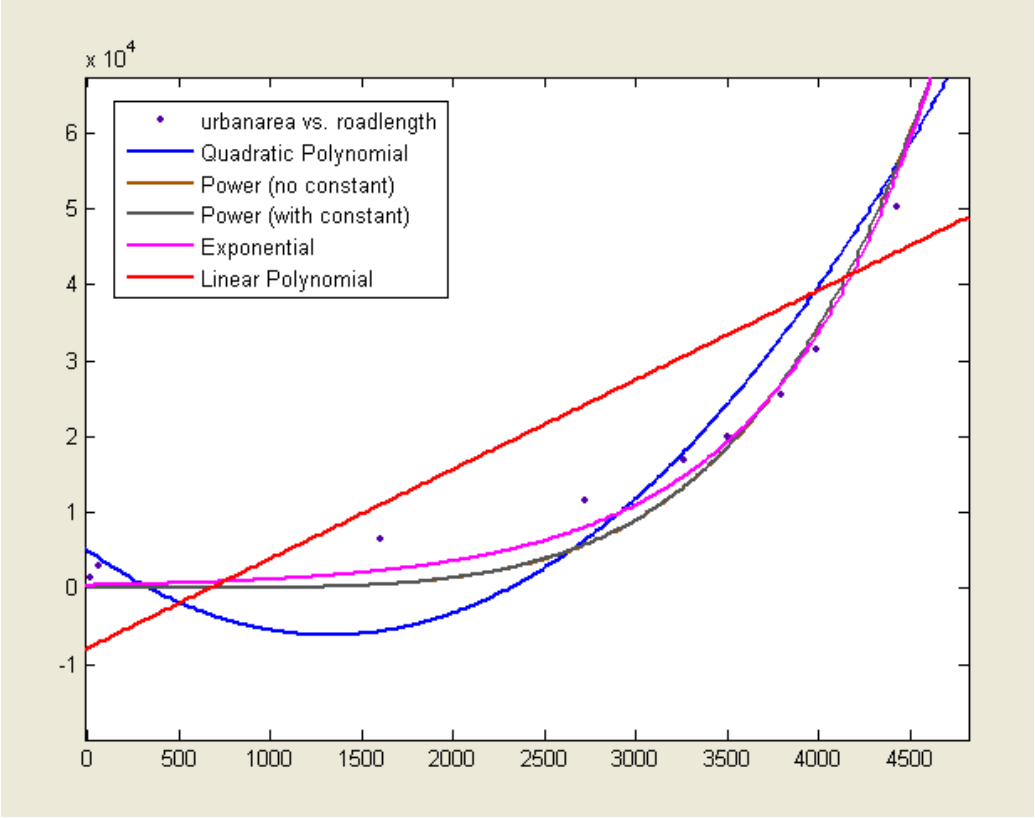


Figure 4.8: Data fitting graph

Table 4.5: Estimated parameters

Function Form	p1/a	p2/b	p3/c	Adjusted R^2
f(x) = p1*x + p2	11.79	-7875	--	0.5042
f(x) = p1*x^2 + p2*x + p3	0.006426	-17	5052	0.8966
f(x) = a*x^b	5.366e-013	4.667	--	0.9751
f(x) = a*x^b+c	5.337e-013	4.667	0	0.972
f(x) = a*exp(b*x)	384.1	0.001119	--	0.9871

Note: f(x) = urban area (ha), x = road length (km)

Both a power function and an exponential function fit the data very well. The parameter *b* in the power function is the elasticity of the dependent variable (Eq. 4.4), so the estimated power function (without constant term) indicates that a 1% road length increase is associated with a 4.667% urban area increase.

$$\varepsilon(y) = \frac{x}{y} \cdot \frac{dy}{dx} = \frac{x}{ax^b} \cdot abx^{b-1} = b \qquad (4.4)$$

$$UrbanArea(ha) = 5.366 \cdot 10^{-13} \cdot RoadLength(km)^{4.667} \qquad (4.5)$$

It is recommended to use Equation 4.5 to estimate the total urban area. This aggregate model can provide the magnitude of urban area change in response to the road length change; however, the spatial pattern of urbanization is not reflected, which will be addressed in the following binary logit model.

4.3.2 A Binary Logit Model

To predict the potential of land use change at a finer scale, a binary logit model is proposed. Considering that one of the purposes of this study is to explore an approach to modeling regional level land use change with emphasis on the involvement of highway development, this model requires few variables and these are readily available.

First, the study area was subdivided into cells with identical size so that each cell could be regarded as a case and modeled individually. The cell size is 500m by 500m, considering that the land development unit was generally a half mile grid so that the distance from grid center to its boundary was approximately within walking distance (quarter mile) (Zhang and Kukadia, 2005) . Second, the explanatory variables are identified. It is believed that the development of a land cell relates to not only its own attributes but also the state of its neighboring cells. This model employed the 3 x 3 Moore neighborhoods, in which the target cell's development is affected by its 8 neighbors (See Figure 4.9). The number of neighboring urban cells is set to 0 for all the boundary cells of the study area to simplify the counting of neighbors. Also, road accessibility and flood plain area are generally believed to have impacts on land development. Incorporating these basic variables, the probability of a particular state of a land cell is formulated as Equation 4.6 and Equation 4.7:

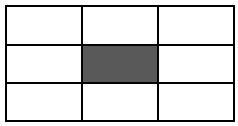


Figure 4.9: 3 x 3 Moore neighborhoods

$$P(Y=1 \mid \mathbf{X}) = \frac{\exp(V)}{1+\exp(V)} \qquad (4.6)$$

$$V = \alpha + \beta_1 \cdot Road + \beta_2 \cdot Neighbor + \beta_3 \cdot Flood \qquad (4.7)$$

Where:

Y: the state of a cell; 1, urbanized; 0, otherwise.

Road: road accessibility indicator; 1, if a road is within 3 km of the cell; 0, otherwise.

Neighbor: number of urbanized neighboring cells.

Flood: flood plain indicator; 1, if the cell is in 100 year flood plain; 0, otherwise.

$\alpha, \beta_1, \beta_2, \beta_3$: estimated parameters.

The model parameters are estimated using 1979 and 1987 classified images by SPSS 13.0 for Windows. Table 4.6 is the estimation results including all variables including the flood plain variable. All the signs of the parameters are in line with expectations in explaining land

development. For example, road accessibility has positive effects in urbanization, the more neighbors that are urbanized the more likely it develops, and land developers avoid flood plains. One might note that the Wald statistic shows that the Flood variable is not of high significance, so the model was estimated again without using the Flood variable. The result is shown in Table 4.7.

Table 4.6: Estimated binary logit model parameters (with flood plain variable)

Variables	B	S.E.	Wald	df	Sig.	Exp(B)
Road	.982	.100	96.565	1	.000	2.669
Flood	-.140	.063	4.933	1	.026	.870
Neighbor	.637	.023	753.232	1	.000	1.891
Constant	-3.503	.100	1216.547	1	.000	.030

Table 4.7: Estimated binary logit model parameters (without flood plain variable)

Variables	B	S.E.	Wald	df	Sig.	Exp(B)
Road	.980	.100	96.287	1	.000	2.665
Neighbor	.634	.023	751.179	1	.000	1.886
Constant	-3.568	.096	1369.743	1	.000	.028

SPSS provides the Nagelkerke Pseudo-R^2 for the logit models (see Eq. 4.8), and both models have the same Pseudo-R^2 of 0.15. Therefore, the final model uses the parameters from Table 4., which uses one less variable while maintaining the same results.

$$R^2 = \frac{1-\left[\frac{-2LL_{null}}{-2LL_k}\right]^{2/n}}{1-\left(-2LL_{null}\right)^{2/n}} \qquad (4.8)$$

The estimated parameters suggest that road accessibility has significant impact on urbanization; however, the neighborhood variable can influence the probability even more due to its wide value range from 1 to 8, which implies that the more neighboring urban cells, the more likely it will change to urban land.

4.3.3 Model Prediction

To test model accuracy, the proposed logit model was applied to 1979 and 1987 land use images with corresponding road networks. Since the model's result is a probability of the cell state which will never be 0 or 1, a threshold of change must be identified. The assumed threshold is set to 0.25, which means that a cell is regarded as likely to be urbanized (Y=1) if the probability is greater than 0.25. Table 4.8 and Table 4.9 show the results. The predictions for 1987 and

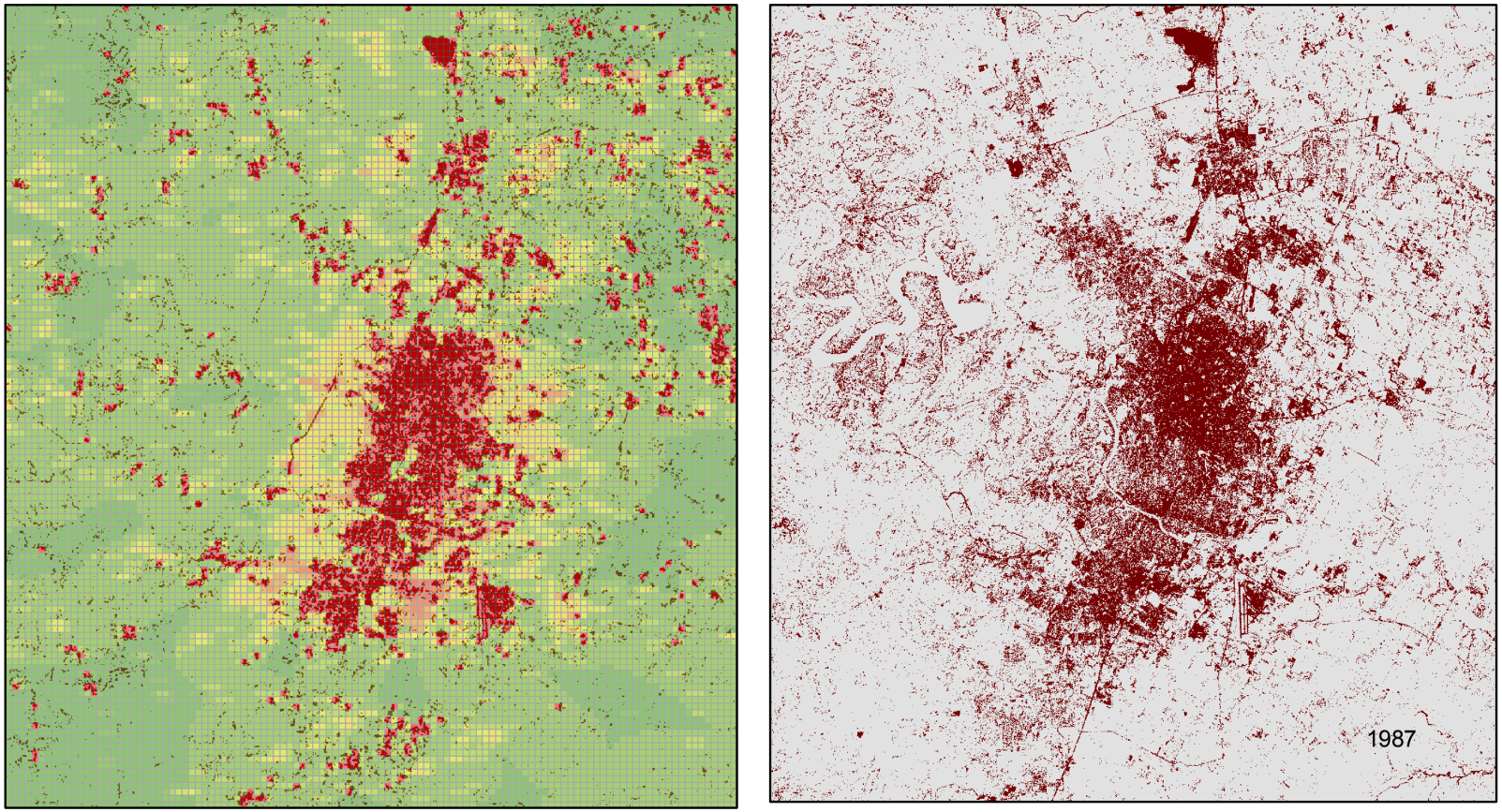
2002 produced an accuracy rate of 86.8% and 78.6%, respectively; while the accuracy rate is the percentage of right predictions (e.g. the sum of the diagonal elements over the sum of all elements). Figure 4.10 and Figure 4.11 compare the model predictions with the observations. With the color changes from green to yellow to red, the probability of a cell being an urbanized cell increases. The threshold does not apply to Figure 4.10 and Figure 4.11. Figure 4.10 and Figure 4.11 demonstrate that roads and developed cells work as seeds of further growth.

Table 4.8: Model prediction vs. observation (1987)

1987		Predicted		Total
		0	1	
Observed	0	10618	885	11503
	1	930	1343	2273
Total		11548	2228	13776

Table 4.9: Model prediction vs. observation (2002)

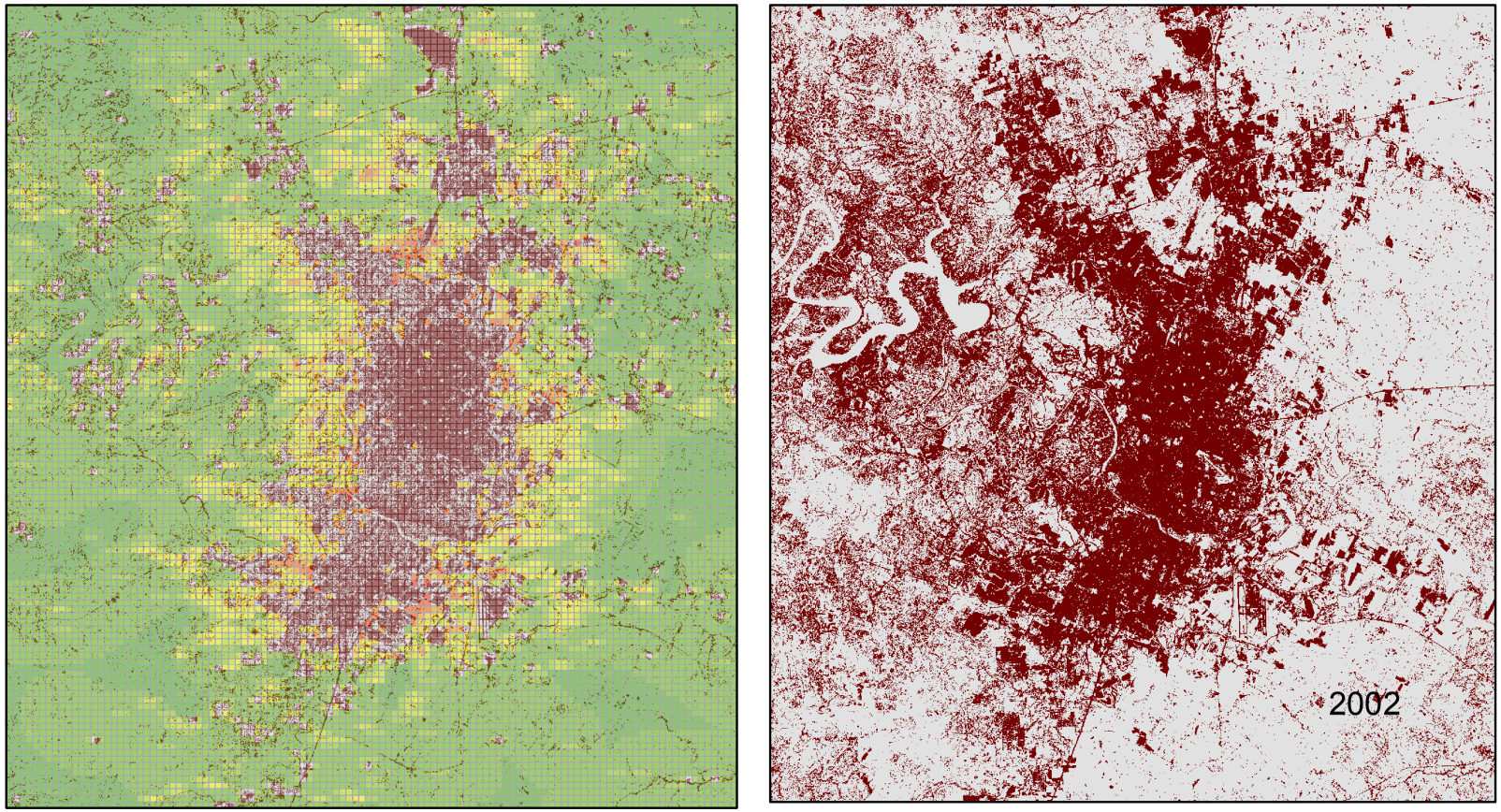
2002		Predicted		Total
		0	1	
Observed	0	8218	1116	9334
	1	1835	2607	4442
Total		10053	3723	13776



Predicted Land Use (1987)

Observed Land Use (1987)

Figure 4.10: Predicted vs. observed urban area (1987)



Predicted Land Use (2002)

Observed Land Use (2002)

Figure 4.11: Predicted vs. observed urban area (2002)

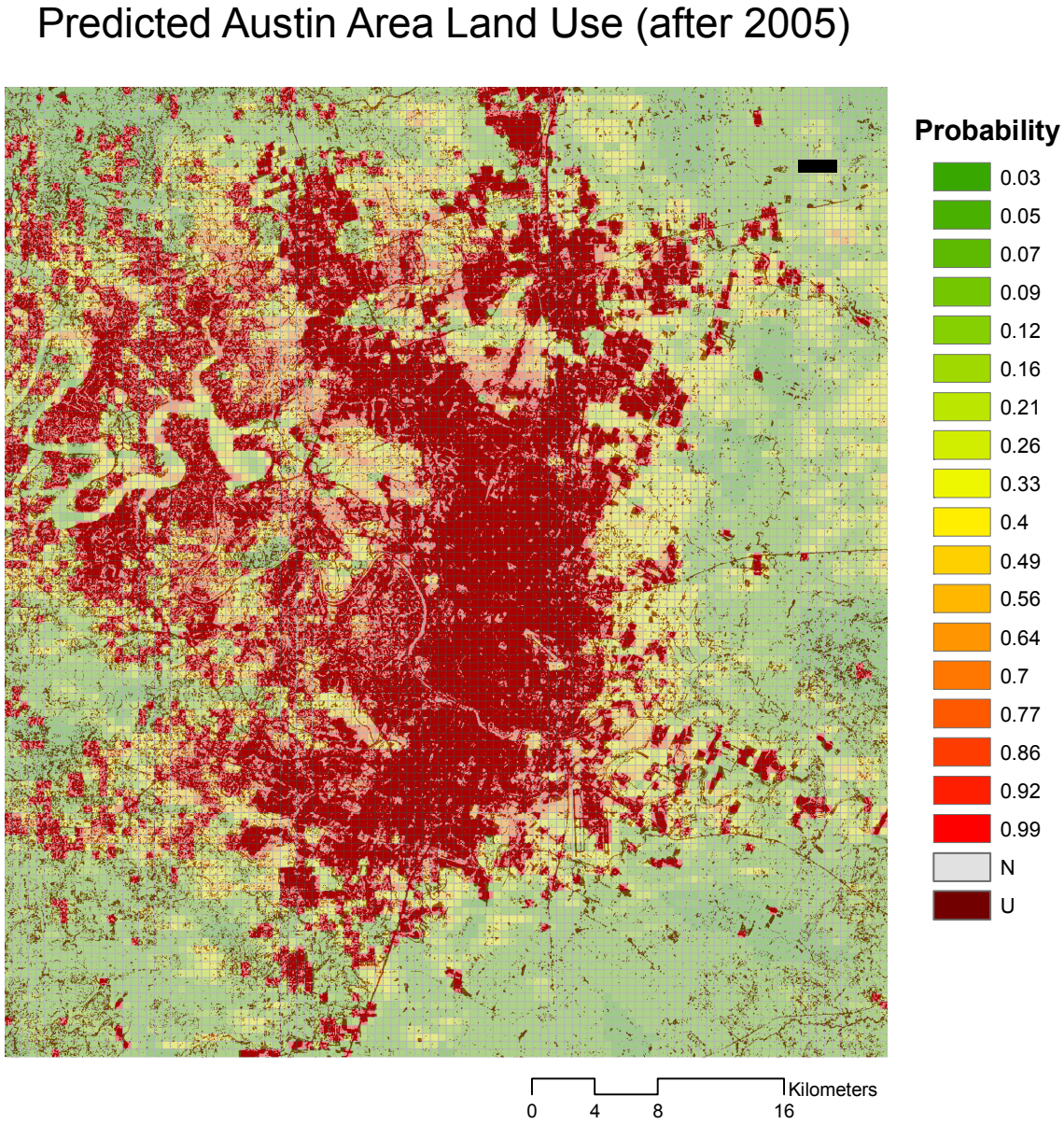


Figure 4.12: Predicted Austin area urbanized area based on 2005 road network

The model does not incorporate time variables, and so it cannot show exactly how much time will be required for the land change, but it does show the trend relating to the road network. Figure 4. presents the predicted urbanized area based on 2005 road network. The urban area grows toward the northwest and southwest, which is in line with the development of Austin's high-tech industry. There is a slight development potential on the east side of the current urban area, but not as impressive as the northwest and southwest side. The total urban area is predicted to be 59% under the same probability threshold based on the 2002 neighborhoods and 2005 roads.

This chapter discussed the relationships and patterns urban growth discovered in the data, from both a non-spatially aggregate perspective and a spatially disaggregate perspective, and it presented two models to represent these patterns. Markov theory was tested on the processed data for applicability; GIS overlays showed the spatial relationship in a direct and relatively aggregate way; a power function was derived to link the urban area and road length directly. Finally, a binary logit model was formulated to predict the potential of urbanization of each land cell. All the relationships obtained are within a reasonable range, and work in a simple manner.

Chapter 5 Conclusions

5.1 Major Findings

This study simulated urban expansion as it related to highway development in the Austin, TX area. The study methodology involved multiple steps of data processing and modeling. First, we collected and digitized historical data on highway construction in the region from 1905 to 2004. Next, we classified land uses using Landsat satellite images for Year 1979, 1987, and 2002. Changes in LULC during the three time periods were then analyzed by three approaches: the Markov-Chain analysis, GIS overlay, and binary logit modeling of land use conversion. The Markov-Chain analysis confirmed that LULC in the Austin area from 1979 to 2002 exhibited a Markov Process. It suggests that the LULC of Austin in the future time point could be reasonably predicted from its immediately preceding status of LULC.

GIS overlay analysis offers a direct view over the spatial changes and patterns of urban expansion, which is recommended for initial pattern recognition and basic aggregate level data calculation. The logit modeling analysis allowed us to build direct links between the dependent variable (i.e., LULC) and the explanatory variables (i.e., highway construction, along with others). A model was estimated and applied for 2005 LULC forecasting for the Austin area.

These three analyses provide the following results regarding LULC development patterns in the Austin area:

- Over 80% of urbanized area is within 3 km of highway in the Austin area.
- Urbanized proportion decreases by nearly 45% per 1 kilometer increase of the distance from the highway;
- A 1% increase of road length is associated with approximately 5% increase of urbanized area;
- Neighboring land cells have great impacts on the likelihood of development of any chosen cell; i.e. an urbanized cell tends to be a seed expediting urban growth around it. If more than 2 neighboring cells in a Moore neighborhood are urbanized, their contribution to the urbanization of that cell is even larger than an existing road within 3 km.

5.2 Future Work

Future efforts may be directed towards improving the logit model of LULC change by incorporating additional contextual and policy variables, for example, population and employment density, land suitability for development, local zoning control and macro economic conditions. In this study, only the satellite images in three time points were collected and processed. In the next step of study, additional images in more frequent time points should be processed, which will help improve LULC modeling. It is the project purpose to simulate, with the methodology piloted in the Austin, LULC change in the Texas Triangle. The simulation

analysis will help assess the likely consequences of transportation investment schemes being considered by the State and local governments in Texas.

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