MODELING OF URBAN GROWTH AND LAND COVER CHANGE:

AN IMPLEMENTATION OF THE SLEUTH MODEL

FOR SAN MARCOS, TEXAS

by

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1.0 INTRODUCTION

Within the past 20 years, Texas has become one of the fastest growing states in the United States. The Capital Areas Council of Governments' (CAPCOG) Assessment of Growth and Development (2010) describes counties in the central Texas region as having experienced unprecedented growth in recent years. Between 1990 and 2010, population doubled from 919,000 to 1.8 million, and increased nearly 43 percent between 2000 and 2011. This strong regional population growth trend is expected to continue at approximately 50,000 people per year, such that half of the region's counties are projected to have double-digit percent growth (CAPCOG 2010). At this rate, population totals are estimated to increase to 4.1 million in 2040. Satellite cities of major metropolitan areas have exhibited massive population growth as well. For example, Kyle, Texas, 32 km south of Austin on the IH-35 corridor had a population increase of 427 percent from 5,300 in 2000 to 28,000 in 2010 (U.S. Bureau of the Census 2012). Counties in the central Texas region do not have adequate land use administrative powers to ensure future urban development is suitable for the region's long-term needs. Consequently, cities, which do have land use control, often plan land use development in isolation (CAPCOG 2010). Despite this lack of coordination between city and county planning agendas, the rapid urban growth in the region has piqued the interest of governmental entities and non-governmental organizations.

Similar to many other large urban centers throughout the world, the in-migration of residents from throughout Texas, the United States, and immigration from other countries is responsible for the rapid growth of the Central Texas Region (CAPCOG 2010). Past trends in population growth in Texas suggest that more people are moving from rural to urban areas. Between 2000 and 2005, 11 Texas counties with one or more urban areas had at least 20 percent growth in population, while 93 rural counties experienced losses in population (Texas Comptroller of Public Accounts 2008). Residents of other states, such as California and New York, are drawn to Texas due to increased employment opportunities and economic advantages such as lack of state income taxes (Sager 2013). Additionally, many communities throughout the United States have struggled from recent economic downturns; however, the unemployment rate for the Central Texas region has remained two percent lower than the national average (CAPCOG 2012).

Agencies such as CAPCOG and The Trust for Public Land (TPL) have released assessments on the current growth trends of the area and expressing the need for sustainable urban growth management. Beyond the urban problems associated with population growth, there are additional environmental problems that should be considered regarding the overall effects of urbanization. Generally, environmental impacts of urbanization include habitat fragmentation (Scolozzi and Geneletti 2012; Shrestha et al. 2012), biochemical and physical changes to the hydrological system (White 2006), increased surface runoff and decreased aquifer recharge (Jacobson 2011; Pappas et al. 2008), reduction of CO_2 sequestration (Zhang et al. 2012), and urban heat island effects (Radhi et al. 2013). Impervious surfaces such as buildings, roads, and other paved surfaces prevent water infiltration into the soil and increase water runoff, thus resulting in increased erosion and potential for downstream flooding (Jacobson 2011; Pappas et al. 2008; White 2006). The non-contiguous conversion of native land cover creates a fragmented landscape that reduces viable habitat for native fauna and flora species (Scolozzi and Geneletti 2012; Shrestha et al. 2012). Additionally, the conversion of vegetated land to urban cover exacerbates urban heat island effects and inhibits local CO_2 sequestration (Radhi et al. 2013; Zhang et al. 2012).

Unanimously, CAPCOG and TPL reports agree that the most pressing issues for managing urban growth in the central Texas region include access to water, improvement to transportation, land use management, and preservation of green spaces as some of main factors to consider for promoting sustainable growth. Proper management and consideration of these resources and infrastructure may provide a solid foundation for the economic development necessary for continued population growth in this region.

The city of San Marcos, Texas is no exception to this unprecedented population and urban growth. San Marcos is situated off the IH-35 corridor, just 48 km south of Austin and 97 km north of San Antonio; two of the fastest growing metropolitan areas of Texas. From 2000 to 2010, the total population of San Marcos increased nearly 30 percent from 34,700 to 44,900, respectively (U.S. Bureau of the Census 2012). A great deal of this increase in population may be attributed to the growth in the student population of Texas State University located within the city. Enrollment at Texas State exhibited a steady increase throughout the past decade, with a notable increase of 4.7 percent in fall 2011 to 34,113 from 32,572 in fall 2010 (TXSU 2012b). This increase in student enrollment is significant compared to the 2.2 percent increase in enrollment at University of Texas at Austin for the same period (UT 2012).

1.1 Problem Statement

The urban coverage of San Marcos is expected to expand to permit the needs of a growing population and will warrant a greater expenditure of local resources. With the projected growth of population and urban coverage alike, local governmental and non-governmental organizations could benefit from information pertaining to the projected amount and location of urban growth. Models, such as the Cellular automata based SLEUTH model, are one such tool that can forecast urban growth patterns that can be utilized by decision-makers for urban planning considerations.

1.2 Objectives

This study will address two main objectives:

1. Describe regional changes in urban cover within the study area beginning in 2000 and ending in 2013, and

2. Implement the SLEUTH urban growth model to produce a probability map of urban coverage for San Marcos, TX in the year 2023.

1.3 Justification

Both Texas State and the city of San Marcos facilitate rapid population growth through policy and urban development. The city of San Marcos is encouraging economic development by offering new business incentives, development fee waivers, and tax waivers (City of San Marcos 2012). These incentives exist to attract new businesses investments, which in turn may result in property development and increased employment opportunities. Similarly, Texas State has invested over $585 million in improvements and new developments to the university campus (TXSU 2012a). These campus developments are designed to bring greater academic attention to the university, increase student enrollment, and, therefore, the overall population of San Marcos. Beyond the measurement of urban growth, the full impact of urban expansion can be realized by considering the need for water, building materials, food, and other goods pulled from the surrounding region to facilitate population and urban growth. As a result, the surrounding region is often converted from natural land to agricultural land (where permissible), and, through time, agricultural land is converted to urban cover.

Monitoring the expansion of urban areas is of critical importance to those involved in the study and management of the processes that influence such growth. Simply put, the greater the population within a region, the greater the impact on the environment through the consumption of food, energy, water, and land (Soltész 2010). As urban areas continue to expand to facilitate the population growth and resource needs, many areas previously used for agricultural or other green spaces are converted to urban cover (Bagan and Yamagata 2012; Li et al. 2010; Sezgin and Varol 2012; Yang 2002). Thus, accurate assessments of urban growth are important to understand the environmental impacts over time and to guide sustainable growth such that negative impacts on the environment are mitigated (Han et al. 2008).

2.0 LITERATURE REVIEW

2.1 Overview

Factors that influence growth of urban areas are complex with varying degrees of interdependence. Thus, simulating this complex process and accounting for key factors fostering such growth is challenging (Barredo et al., 2003). Models are a way of representing a process in reality composed of many complex relationships into a simplified version that is composed of the most significant factors perceived to influence a particular process (Liu 2009). Researchers construct models to represent the structure or process of a real system in an effort to understand, explain, or predict the behavior of the system (Liu 2009). A key feature and benefit of modeling is the ability to construct the model using key elements believed to influence a process. This selectiveness eliminates noise of other, less important factors and enables the real world to be simplified in a valid and understandable way. A challenge to constructing a model, however, involves the decision of the selecting elements of a real-world system to are perceived to be important and must be included and adequately interrelated to create valid results (Liu 2009).

The establishment of known relationships among elements included in a model enables researchers to make predictions of future conditions. As data used in models are generated from empirical observations, modeling results should be applicable to the real world. It should be noted here, however, that models are only approximations of reality and that any subsequent predictions can only be interpreted as generalizations of future conditions (Liu 2009). As many Earth processes are highly dynamic and complex, the use of geospatial models have been widely applied to help researchers gain more insight in to the causes of such phenomena. Common examples of geospatial modeling include hydrological (Remo et al., 2009), ecological (Silva et al., 2008; Zhao et al., 2006), land cover change (Araya and Cabral, 2010; Bagan and Yamagata, 2012; Yang, 2002) and urban development (Cheng and Masser 2003; Jantz et al., 2010, Liu, 2009; Yang, 2002). The adequacy of these models is highly dependent on the quality and accuracy of the data used. Currently, there is a great deal of research in determining the optimal methods of analysis to generate the most accurate output results.

Urban growth modeling is a common method used to help researchers attempt to understand the underlying factors influencing urban growth. Understanding the complexity of urban growth and expansion is a heavily researched topic (Barredo et al. 2003; Cheng and Masser 2003; Clarke et al. 1997; Cohen 2006; Geohegan 2001; Liu 2009; Santé et al. 2010; Soltész 2010). A review of this relevant literature reveals a set of characteristics describing urban expansion that are common among all cases. Developing urban systems can be characterized as self-organizing, complex emergent systems in which the collective interactions at the local-scale will shape and determine the ordered patterns at the large-scale (Tobler 1979; Wolfram 1984). Self-organization is defined as a process that typically involves emergent properties where coherent and organized patterns arise over time from the local interactions of an initially disordered system. The degree of interdependence of the processes within a system is not completely known; however, it is through these relationships that systems will tend to develop patterns (Barredo et al., 2003).

Geographic information systems (GIS) and remote sensing technologies are the most commonly utilized tools in geospatial modeling. GIS serves as a platform for quantitative and qualitative analysis of geospatial data. The application of GIS technologies is well known to be a means of efficiently analyzing large amounts of spatial data. However, in order to make predictions of future conditions, one must first have a good understanding of the historical patterns of change leading up to present conditions. Remotely sensed data are well suited for land cover land use (LCLU) change detection because of its repetitive acquisition capabilities and ability to cover a large spatial extent. Therefore, remotely sensed images are often used as the basis for LCLU maps analyzed within a GIS.

2.2 Remote Sensing for LCLU Change Detection

The U.S. Geological Survey (USGS) has long been on the forefront of studying land-use and land-cover changes. Since the 1970s with the development of a land-cover and land-use classification system by Anderson et al. (1976), the USGS has maintained an interest in monitoring the changes over the Earth's surface. In the 1990s, the USGS began the Human-Induced Land Transformations (HILT) project that was initially aimed at understanding the transitions of land to urban land-use, specifically in the San Francisco/ Sacramento area (Acevedo et al. 2010; Clarke et al. 1997; Kirtland et al. 2010). The results of the HILT project showed that the integration of historical maps and related geographic information with remotely sensed data can successfully map urban land characteristics, as well as provide a visual representation of such changes through time (Acevedo et al. 2010).

A good change detection study, as determined by Lu et al. (2004), should provide the following information: area change and change rate, spatial distribution of changed types, change trajectories of land-cover types, and accuracy assessment of change detection. Traditional methods of change detection began with repeat photography and, through timely technological advances, have eventually evolved to using digital remote sensing data. As technology continues to progress, the scientific community continues to develop new methods with increasingly accurate information on the changes to the Earth's surface.

There are many characteristics of remotely sensed data that make them particularly well suited for change detection projects. Currently, there are dozens of existing remote sensing platforms, all of which collect a variety of multispectral information at varying spatial scales (Jensen 2005). Satellite remote sensing platforms, such as Landsat Thematic Mapper (TM), Landsat Multi-Spectral Scanner (MSS), Landsat Enhanced Thematic Mapper Plus (ETM+), Satellite Pour l'Observationde la Terre (SPOT), Advanced Very High Resolution Radiometer (AVHRR), Moderate Resolution Imaging Spectroradiometer (MODIS), and Advanced Spaceborne Thermal Emission and Reflectance Radiometer (ASTER) are all major sources of data for change detection applications (Jensen 2005; Lu et al. 2004). These platforms are consistent and reliable sources of data with known temporal and spatial resolutions (Jensen 2005). Additionally, airborne (sub-orbital) remote sensing platforms, such as Compact Airborne Spectrographic Imager (CASI), are capable of capturing data at intervals that a particular satellite cannot (Jensen 2005).

The synoptic view of satellite and airborne sensors also allows for data to be collected over large areas, making it possible to detect changes over a large region. For example, Zhou et al. (2011) acquired five images from Landsat TM, MSS, ETM+, and SPOT HRV (high resolution visible image) to determine land-use changes and the human impacts on the land over 30 years in a region of China. Their results show that until the early 1990s human impacts were minimal, however, since then the area of cultivated farmland increased over five times, and continues to do so 30 percent annually. This research highlights the use of multitemporal remote sensing data sets for detecting changes across a large area over a relatively long period.

It is important to consider the sensor selected to obtain data for specific applications, as all sensors provide specific spectral and spatial data with varying resolutions (Jensen 2005). The digital format of remote sensing data makes it easy to store and is suitable for computer processing (Lu et al. 2004). After selecting the image data, the next step, selecting the appropriate change detection method, is perhaps the most important consideration for generating accurate results (Lu et al. 2004; Lu et al. 2005).

Lu et al. (2005) analyzed the differences in land-cover change detection accuracies generated from ten binary change detection methods using Landsat 5 TM imagery over a study site in the Amazon tropical region. Their results indicate that three of the ten techniques produce significantly better results. Furthermore, these results exemplify the importance of selecting the appropriate change detection technique to produce the best results for a specific study area.

Lu et al. (2004) and Singh (1989) provide in-depth reviews of the many available change detection techniques available at their respective times of publishing. These studies show the abundant methods available for comparing data between images for a diverse set of applications. Lu et al. (2004) identified the major categories of change detection applications using remote sensing technology, including LULC change, forest or vegetation change, wetland change, forest fire, urban change, environmental change, and many other applications. These reviews underscore the importance of monitoring the changes on the Earth throughout the years and the broad applicability of remote sensing data for change detection studies. It is not surprising that significant effort has gone into the development of new technology and methods for various change detection applications.

Change detection projects provide timely and accurate information on the changes of Earth's surface features and allow us to have a better understanding of the relationships among humans and our environment (Lu et al. 2004). Remote sensing technology has been utilized for many change detection studies throughout the years, fostering the advancement of change detection techniques for various applications. Despite this, characterizing the volumetric changes of target features using traditional photogrammetric methods is labor intensive and time consuming (Lefsky et al. 2002). Nonetheless, results of change detection studies are broadly applicable to anyone who is interested in any visible changes on the earth over time. Examples of applications include land-use and land-cover change, forest or vegetation change, forest fire, wetland change, urban change, environmental change, and many others.

2.3 Overview of Urban Growth Modeling

Most early applications of understanding the urban processes used transportation and land-use information to create models that were based on gravity theory or some form of optimized mathematics (Santé et al. 2010). However, among all urban modeling techniques, cellular automata (CA) are particularly well suited for modeling complex and dynamic natural phenomena such as urban areas (Tobler 1979; Wolfram 1984). Tobler (1979) identified the potential application of cellular space models to geographical processes. Tobler (1979) proposed that changes in the patterns on the Earth's surface are analogous to a game of chess in which the rules are simple, yet using these rules as strategy makes the game complex. In this context, given an initial state, a desired state, and a set of transition rules, one must determine if there is an identifiable path from one state to another (Tobler 1979). Wolfram (1984) demonstrated that CA are capable of modeling complex systems and are most appropriate in highly nonlinear processes, such as biological and physical systems, where growth inhibition effects occur.

More recent conceptual and technological advances have led to increased CA research and development of models applicable to real-world urban systems. CA models have the ability to simulate urban growth through the assumption that past urban development affects future urban growth patterns through neighboring interactions between land-uses (Santé et al. 2010).

Liu (2009) defines and explains the five basic elements of cellular automation: the cell, the state, the neighborhood, the transition rule, and the time. Cellular automata operate on a raster-format of discrete cells, each characterized by a state, where the state is representative of any one specific land cover or land use, such as rural or urban. This format allows for easy integration with GIS, and, consequently, operates at high computational efficiency at relatively fine spatial resolutions. The state of each cell is dependent on its previous state, the state of neighboring cells, and set of transition rules (Barredo et al. 2003; Garcia et al. 2012; Santé et al. 2010). The complexity of urban simulation requires considering particular behaviors of urban systems and modifying (or relaxing) the original structure of the CA to compensate for such complexity.

A major benefit of cellular automata is its ability to model complicated behavior, given its relatively simple construction (Wolfram 1984). A cellular automata system operates by dividing space into a regular cell spatial tessellation, where each cell is assigned a specific state. The status of each cell is determined by the state of the cell itself and the state of the other cells within a local neighborhood. Statuses of each cell change synchronously based on a defined set of local transition rules. All cells together, with the combined effect of single cell transition rules, define and generate the whole complex system where changes occur with each discrete time step (Liu 2009; Silva et al. 2008).

Another beneficial component of cellular automata is its ability to model the characteristics of a system that is capable of self-organization. Self-organization is a characteristic found in many complex systems, such as cities, in which local-scale interactions continue existing patterns, but also generate new patterns that participate in the next iteration; much like a feedback mechanism (Barredo et al. 2003). Cellular automata are able to accommodate this self-organization characteristic by allowing rules to change as the system grows (Clarke et al. 1997).

The concept of cellular automata can be easily applied to the organization and development patterns of urban areas. Consider that an urban area is represented by cellular space in which each cell is representative of a specific land parcel within the urban area. Each cell state can be defined as urban or non-urban at a specific point in time. The probability land development, or a cell's status changing from non-urban to urban, is influenced by the collective status of a local neighborhood of cells and a set of defined transition rules. These transition rules, usually expressed as "If-Then" statements, determine the process of a land parcel, or cell, transitioning from one state to another (Liu 2009).

For example, if three or more urban cells surround a non-urban cell, then the non-urban cell will likely convert to an urban cell through a growth cycle. This is, however, just a simple example of one transition rule. In the real-world most geographic phenomena, such as urban development, do not follow a uniform development process and requires developing multiple locally defined transition rules that take in to account multiple geographical conditions. Urban areas are composed of a complex mix of related units, but the degree and nature of the connections can be difficult to determine. The dynamics of urban land use in an urban area is directly attributable to the decisions of individuals, public, and private corporations acting together over time (Barredo et al. 2003). As a result, cities are continuously organized and shaped based on these influences. Barredo et al. (2003) identified five groups of factors that can influence the allocations and decision-making process of urban land-uses: environmental characteristics; local-scale neighborhoods characteristics; spatial characteristics of the cities (i.e. accessibility); urban and regional planning policies; factors related to individual preferences, level of economic development, socio-economic and political systems.

Santé et al. (2010) provides an in-depth review of many of the common modifications of CA for urban simulations and provides examples of the main urban CA models applied to real-world urban development processes. Additionally, CA-based models for urban growth simulation are grouped and compared based on the main characteristics of the model. Garcia et al. (2010) assesses the operational practicability of three common urban CA models to simulate the growth of a town in Spain. Their results showed that low growth in the area over the study period warrants more information with greater detailed data in order to identify growth dynamics within the area. However, including additional land-uses and extending the neighborhood of cell interactions could improve simulation results. This research provides context into the strengths and weaknesses of various models and underscores the application of a diversity of CA-based models for understanding various complex urban systems.

2.4 Incorporation of Remote Sensing LCLU Change Detection and Urban Growth Modeling

The systematic analysis of the dynamic changes between non-urban land cover to urban, or other land covers associated with urban expansion, can reveal trends that begin to explain past development patterns, as well as improve predictions of future growth. Remotely sensed imagery has been widely applied for the systematic analysis of changes in land cover and land use relative to changing urban growth characteristics. Bagan and Yamagata (2012) integrated Landsat MSS, TM, and ETM + derived land cover maps with population density to determine relationships between the land-cover and population density changes based on grid cells each covering 1 km^2. Population statistics were generated per grid cell by linking census data to the appropriate cell using latitude and longitude coordinates. Results demonstrated a decrease in growth within the metropolitan core area, a strong positive relationship between urban expansion and population density, and a strong negative relationship between urban expansion and cropland change. Additionally, urban growth exceeded population growth by a factor of approximately 2.6.

Hepinstall-Cymerman et al. (2009) developed a set of multi-date land cover maps for an urban area using Landsat TM images to examine the change in composition and configuration of land covers over a twenty-year time span. Images were classified using a combination of image classification techniques including image segmentation, spectral unmixing, and supervised classification. Image classification results were refined using multi-season imagery using landscape trajectory rules and ancillary GIS data. Changes in land covers through the study periods are described using landscape metrics of composition and configuration. Results from this study are similar to other findings; urban patches grow in size and become less dispersed with a subsequent decrease in the extent and homogeneity of grass, agriculture, and forest land cover.

An understanding of historic land cover change is a prerequisite to predictions of future urban land cover characteristics. Other studies have applied LULC maps derived from remotely sensed imagery to model and predict future conditions of class coverage. Tewolde and Cabral (2011) used eCognition to perform an object-based classification of Landsat 5 TM imagery into six basic land cover classes. Changes in urban sprawl were analyzed and quantified using post-classification change detection, land change modeler (LCM), and Shannon's Entropy, an urban sprawl index. Land cover maps were analyzed through the LCM to determine the main variables responsible for growth. The multilayer perceptron (MLP) neural network algorithm is used to create maps of cell transition potential that are subsequently used with Markov Chain modeler to simulate future land cover extents. The model simulation is validated by a comparative analysis of the predicted map to the reference map based on Kappa variations. Following the trends of similar studies, the study area has experienced, and is simulated to continue to experience rapid urban growth at the expense of valuable periphery resource lands.

Araya and Cabral (2010) conducted a comparable study with similar results. In this study, spatial metrics and Shannon's entropy were used to describe the spatial characteristics of class patches, class area, and the landscape. Modeling changes in classes was evaluated using a combination of Markov Chain and CA. The Markov Chain analysis is useful for describing the probability of land cover changes from one period to the next. The CA component allows for the integration of the transitional probabilities. This research highlights the utility of CA models to consider the dynamic transitional characteristics that will vary from one region to another.

Although there are several LULC modeling tools available, each with their own advantages and disadvantages, the SLEUTH model is capable of simulating changes in urban form independently, or in concert with LCLU data or socioeconomic variables. Development of the SLEUTH model comes from the modification of a wildfire model developed by Clarke et al. (1994) that established principles and growth rules to simulate organic growth based on CA research by Batty and Xie (1994), Couclelis (1985), and others. Based on these principles and rules, Clarke et al. (1996) developed SLEUTH, a CA-based urban growth simulation model as part of the USGS HILT project to estimate the regional impacts of urbanization. The SLEUTH model includes neighborhood transition rules that are typical of CA models, but operates with multiple data sources that are believed to be major influences on the process of urban growth including topography (slope and hillshade), road networks, existing settlements, excluded zones, and LCLU. These data sources are included as layers in the modeling process and all (except for hillshade) influence the way urban and other LCLUs change over time (Mahiny and Clarke 2012).

Clarke et al. (1996; 1997) and Clarke and Gaydos (1998) define and discuss five factors that control the behavior of the system and the four type of growth that all together create an urban growth simulation that is unique to an individual region of interest. The five factors controlling system behavior include: “a diffusion factor which determines the overall dispersiveness of the distribution both of single grid cells and in the movement of new settlements outward through the road system; a breed coefficient which determines how likely a newly generated detached settlement is to begin is town growth cycle; a spread coefficient which controls how much normal outward ‘organic’ expansion takes place within the system; a slope resistance factor which influences the likelihood of settlement extending up steeper slopes; and road gravity factor which has the effect of attracting new settlements onto the existing road system if the fall within a given distance of the road” (Clarke et al. 1997, 252). The growth rate of an urban area is the result of the combination of four different types of urban growth: spontaneous, diffusive, organic, and road influenced (Clarke et al. 1996, Clarke et al. 1997, Clarke and Gaydos 1998).

SLEUTH allows for predictive modeling under different scenarios matching urban planning objective, or lack thereof (Feng et al. 2012, Jantz et al. 2010). Jantz et al. (2010) developed a new version of the SLEUTH model (SLEUTH-3r) including a method to expand the utility of the SLEUTH model to include economic, cultural, and policy variables, as well as other modifications including new calibration statistics, decreased memory requirements, and enhanced scale sensitivity. Their study area covered encompassed 257,000 km^2 divided into 15 sub-regions of 7100 km^2 to 23,000 km^2, each with a unique set of calibration values. Urban growth, simulated for a twenty-year period, was forecasted under current growth trends for each sub-region and other model scenarios created to simulate urban growth under different economic, cultural, and policy regimens by relative changes in calibration values. Calibration results of the SLEUTH-3r model show a match within 10 percent of the simulated map to the control map. The Jantz et al. (2010) study demonstrates the capability of the SLEUTH-3r model to adapt to a range of local conditions, while at the same time facilitating the discovery of the impacts of the human socio-economic decision-making on urban development. Other studies cited by Mahiny and Clarke (2012) describe the ease of linking environmental data to model predictions by making appropriate changes to input layers to reflect study area conditions or urban planning objectives.

Measurement of urban area shape, size and configuration is important to for land-use planning and development. A systematic measurement of built-up area can aid in establishing relationships between growth and the process of such growth (Yeh and Li 2001). Furthermore, knowing the probability of land conversion of resource land (agriculture, forest) to residential, commercial, or industrial uses will guide development planning to seek alternative or preventative measure to protect resources (Araya and Cabral 2010, Hepinstall-Cymerman et al. 2009; Jantz et al. 2010, Tewolde and Cabral 2011). The spatio-temporal processes of urban development and the resulting social and environmental consequences of this development deserve a great deal of attention from urban geographers and policy makers (Liu 2009).

3.0 MATERIALS AND METHODS

3.1 Study Area

San Marcos, the county seat of Hays County, Texas (Figure 1) is located in the southeastern corner of the county along the IH-35 corridor between Austin and San Antonio, two of the fastest growing cities in the U.S. The city limits encompass approximately 4,700 ha and contains land east and west of IH-35. The main campus of Texas State, located within the city, covers 185 ha, nearly four percent of the land area within city limits. The city is positioned on the Balcones Escarpment separating the Edwards Plateau to the west and the Blackland Prairies to the east. This unique location at the foot of the Edwards Escarpment provides the headwaters for the spring fed Spring Lake and San Marcos River that transect the city. In fact, Native American artifacts found around Spring Lake are evidence that this area is one of the oldest and longest inhabited locations in the United States (Hickey 2011).

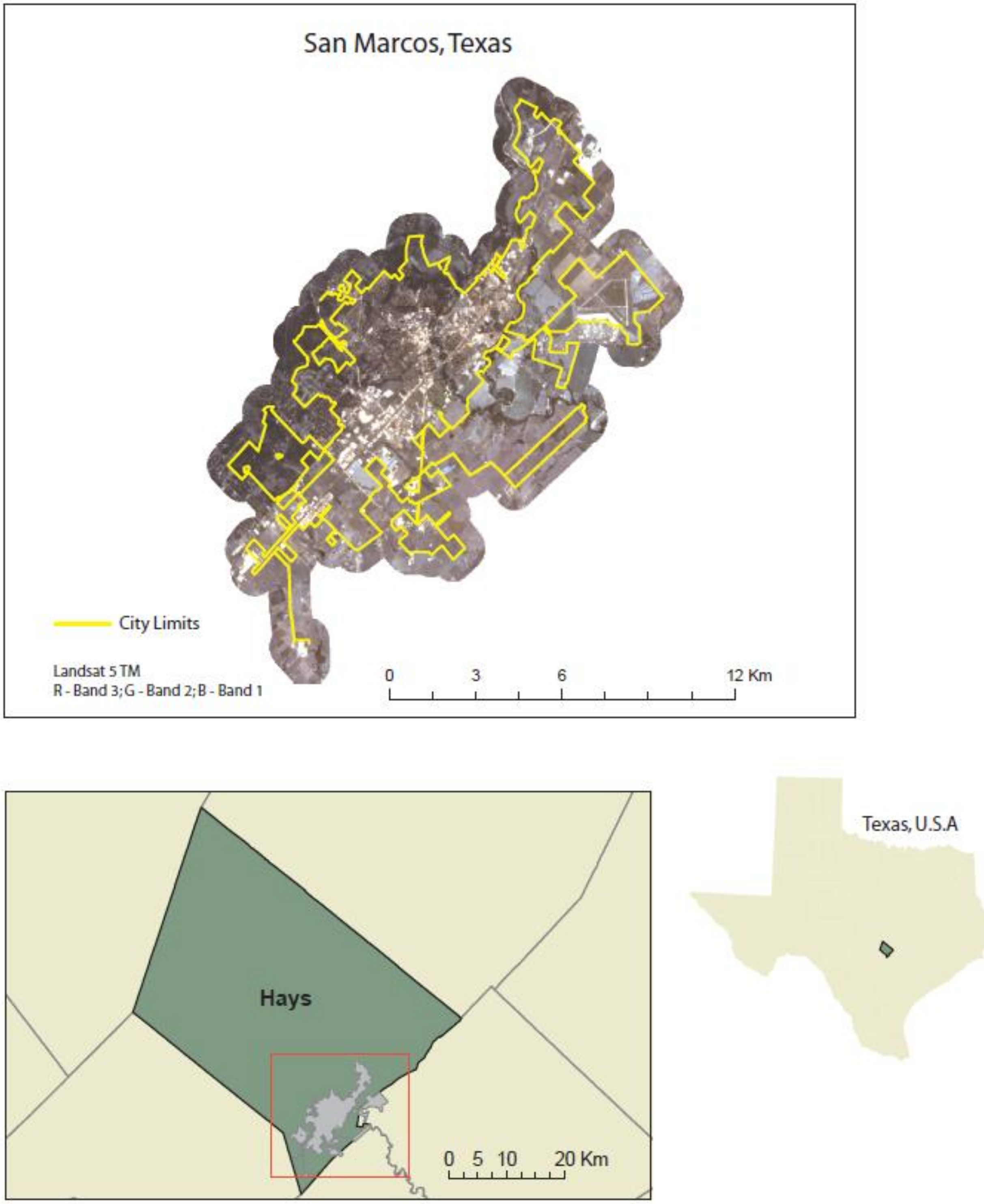


Figure 1. The study site, San Marcos, located within Hays County within the central region of Texas.

Within the context of urban growth, there are unique characteristics of San Marcos that make the city a good candidate for this study:

- San Marcos' close proximity to IH-35 is a source of continuous human and economic resources to the city. Beyond the historical trends of urban growth following main transportation lines, the location of the city between Austin and San Antonio intensifies capital resources.
- Since incorporation of San Marcos in 1877 and the opening of the Southwest Texas State Normal School in 1903, growth of the city and school are related. The influence of the university on economic and urban development within the city is a contributing factor not common in most developing cities.
- The local topography is not uniform across the entire study area. A dynamic range in slope will influence and produce unique growth patterns where new development must follow the path of least topographic resistance.
- San Marcos currently contains approximately 550 ha of parkland and local natural spaces, much of it sharing borders with the San Marcos River or its tributaries. These natural areas have and will continue to be a source of revenue for the city and can limit growth in certain areas that some would consider attractive for development.

These unique characteristics of San Marcos fit well with the data requirements of the SLEUTH model and will require case-specific consideration during model calibration.

3.2 Geospatial Data and Pre-processing

The SLEUTH model operates from six input grayscale gif images: urban extent, transportation, excluded areas from urbanization, slope, and hillshade are all required. The sixth layer, land use, is optional and is not used in this study. Additionally, there are format standards for all dataset images. For this study, all input images are projected to Texas State Plane Coordinate System using the Lambert Conformal Conic zone 4204 (meters) with the North American Datum of 1983. All images have a 30 m spatial resolution and are composed of 990 columns and 906 rows of pixels. Four discrete time periods of data are required for statistical calibration of the model.

3.2.1 Urban

Landsat 8 and Landsat 5 TM digital images at 30 m spatial resolution were collected for the study area for four time periods across the scope of the study; 2000, 2004, 2009, and 2013. Landsat 8 imagery was used for 2013 due to the decommissioning of Landsat 5 TM in 2011 and the Scan Line Corrector failure of Landsat 7 ETM+ in 2003. All images were collected from EarthExplorer, a USGS web-based repository for all Landsat and other sensor's imagery. An object-oriented supervised classification was performed in eCognition Definiens 8 to produce urban land cover datasets for each calibration year. eCognition is an object-oriented image analysis software that extracts features based on spectral and/or textural attributes. Object-based classification is advantageous compared to pixel-based classification as it allows the user to analyze imagery based on image objects rather than on a pixel level (Araya and Cabral 2010, Tewolde and Cabral 2011). eCognition operates by segmenting groups of image pixels that share similar properties based on a set of threshold values, or rules defined by the user. Additionally, classification results can be exported as raster or vector formats that are easily integrated into a GIS.

Supervised classification implemented the nearest neighbor classification algorithm. Extracted segments were classified based on user-specific samples and a set of spectral and textural conditions. These conditions are adjusted to best suit a specific land cover and are saved for use on subsequent images of the same area. Image segments were classified as urban and non-urban. The Multi-resolution Land Characteristics Consortium (MRLC) Level 1 classification scheme is used to distinguish different levels of urban cover intensity (Anderson et al. 1972). Low-density urban areas were not included in the urban extent layer. Low-density urban areas are found primarily outside of the city limits and consist of lots or developments with considerable acreage separating each house or areas with small groupings of multiple houses. These areas were difficult to distinguish from the surrounding areas during image segmentation due to their proportional coverage to the surrounding vegetation. Medium and high-density urban areas are both included in the urban cover layer. The study area was extended to a best-fit square around the San Marcos extraterritorial jurisdiction to allow for the forecasting of extended urban growth outside of San Marcos city limits and for consistency in the number of pixel columns and rows of each input image. Consequently, smaller municipalities that now fall within the study area, including Martindale, Staples, Uhland, Reedville, Redwood, Hunter, and Maxwell were also included in the urban cover layer.

Accuracy assessments of urban and non-urban land cover classifications were performed for classified image. Accuracy assessment is necessary due to the multiple applications of results for model simulation assessment and other data requirements for the model. Kappa statistics and confusion matrices were used to assess overall accuracies and to validate classification results. Only classified images with Kappa values greater than or equal to 0.8 were considered acceptable for use in further analysis. A Kappa score of 0.8 (80 percent) or higher is considered indicative of a strong agreement between the classified image and reference samples. A high Kappa score provides the user/producer assurance that land cover classifications are significantly better than if land cover classifications were made by chance (Jensen 2005). A stratified random sample of 24 samples per land cover was used to populate the confusion matrix. This sample size was calculated through a multinomial distribution with a 95 percent confidence level and ten percent precision (Jensen 2005).

The same Landsat 8 and Landsat 5 TM images were used for both the collection of samples for land cover classifications and for accuracy assessments. In-situ and high-resolution imagery were not used for gathering classification samples as the difference between high and medium-intensity urban and non-urban land covers are easily distinguishable from visual image interpretation. Moreover, accuracy assessments of image classifications warranted the use of the same imagery for the purpose of segmentation identification. The image segmentation is unique to the individual image and, therefore, requires reference to the originally segmented image during accuracy assessments for identification of the correct land cover class.

Each urban layer (Figure 2) was derived through the extraction of urban pixels from land cover classification of images for each period. The urban image used as the start date for the model, referred to at the seed layer, represents the initial conditions in which further expansion will occur in subsequent iterations. All classified urban/non-urban images were converted to grayscale GIF images using ArcGIS to make data compatible for model operation.

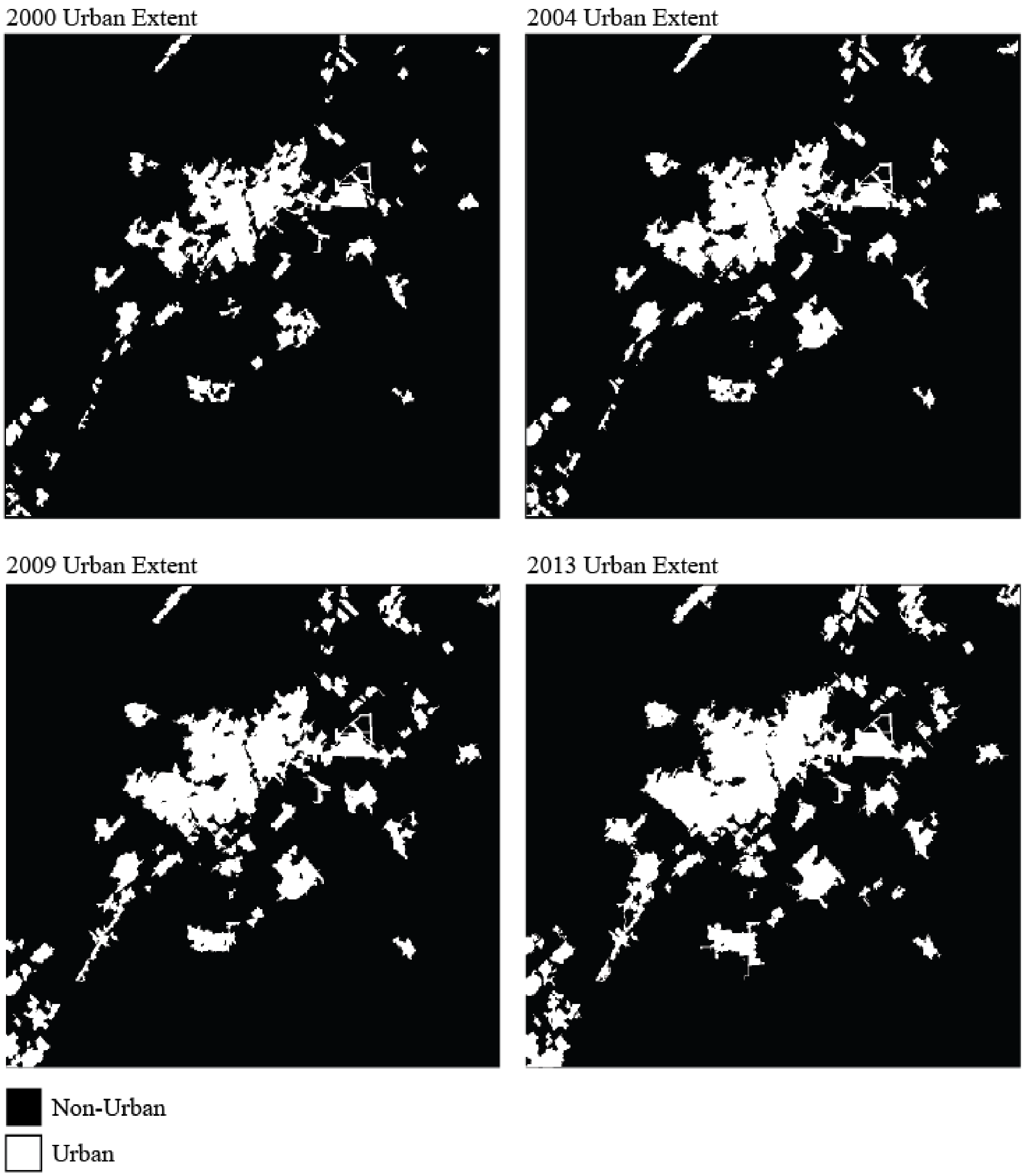


Figure 2. Input urban extent input images derived from satellite image classification. White represents urban, black represents non-urban pixels.

3.2.2 Excluded Area

The excluded area layer includes cells that represent areas protected from future urbanization. The excluded layer is composed of rivers, streams, water bodies, parks, railroads, and cultural areas. All data composing the excluded layer were obtained in vector format, merged together, and then converted to raster format. Parks, cultural areas, and railroads data were collected from CAPCOG. Hydrological datasets were gathered from the USGS National Hydrography Dataset. A 30 m buffer surrounding the rivers and streams was added to exclude these areas from any new urban development. These areas fall within the water quality zone of 30 m, per City of San Marcos' code of ordinances for new development and is prohibited or very limited to development. All water bodies smaller than 0.005 km^2 were removed from the excluded areas as any water body larger than that was believed to be beyond the cost benefit of infilling for new development. Nearly all water bodies removed as a result of this operation were small cattle ponds on the eastern side of the study area.

3.2.3 Transportation (Roads)

Roads are represented by an array of cells corresponding to roads present at each specific period and with pixel values relative to accessibility. For example, pixels with higher values represent roads with a tendency to attract urban growth. Road pixel values, or weighting, are determined by using the functional classification system developed by the U.S Department of Transportation Federal Highway Administration (2013). Roads are grouped into classes according to the level of service and accessibility they are intended to provide. This system provides an objective guideline for associating weights with each road. Each road was categorized into one of three classes: arterial, collector, or local roads. Arterial roads, given a pixel weight of 100, are the least common of the three road classes and are designed to provide the fastest route of travel. Collector roads, the second most common with a pixel weight of 50, are used as connections between arterial and local roads and are equally accessible and mobile. Local roads, with a pixel weight of 25, have high accessibility, but low mobility and are the most common class of roads.

Transportation networks can have a major influence on regional development. Thus, several road layers are desired to represent a change with the city's growth through time. These road layers (shown in Appendix A) were read into the model as time progressed to represent the most up-to-date transportation system for a particular period. Historic and current road data were collected as shapefiles from the City of San Marcos' GIS Department and U.S. Census TIGER/Line shapefiles. The vector road data were converted to GIF images with pixel values adjusted to represent road influence and accessibility.

3.2.4 Slope

The slope layer is used for establishing a slope-resistance weighting that determines the maximum change in elevation where urban expansion or new settlement can take place. To match the requirements of the SLEUTH model, slope values represent percent slope and were calculated from a 2009 USGS 7.5-minute digital elevation model (DEM).

3.2.5 Hillshade

The hillshade layer is a static background image included with image outputs of forecasted urban extent to provide a spatial perspective to changes in urban extent over time. Similar to slope, the hillshade image was generated using the 2009 USGS 7.5-minute DEM.

3.3 SLEUTH Model Calibration

A major component to SLEUTH implementation and accurate reproduction of past land cover changes is through calibration of parameter values to match local conditions of the study area. Thus, determining the best fit of appropriate parameter values is highly important with regard to simulating future conditions. Five coefficient values affect the simulated growth of a study area: diffusion, breed, spread, slope, and road gravity. The model was calibrated using the “brute force” Monte Carlo methodology in which a large number of coefficient values are generated and tested, resulting in an output of fit statistics for the user to evaluate. Output statistics include several Pearson r^2 statistics that compare measurements between known historical data and simulated data such as number of urban pixels, edges, clusters, and spatial match comparison. One such output statistic is a shape index named the Lee Sallee metric, which is a measure of spatial fit between the simulated urban growth and known urban growth (KantaKumar et al. 2011). While the Lee Salle metric has been used in previous studies for SLEUTH model calibration, studies have shown the Lee Sallee metric to have a relatively poor association with urban growth (Dietzel and Clarke 2007, KantaKumar et al. 2011). The Optimum SLEUTH Metric (OSM), a metric developed by Dietzel and Clarke (2007), produces a value based on compare, population, edges, clusters, slope, Xmean, and

Ymean metrics and “will provide the most robust results for SLEUTH calibration” (Dietzel and Clarke 2007, 43). OSM values are the product of multiple correlation coefficients, thus the resulting OSM values share the same minimum and maximum values ranging between zero and one. The highest OSM values can be used to narrow down the range of calibration values that creates the best fit between known and simulated urban growth.

Calibration begins with a set of starting coefficient values that are slightly modified by a process of self-modification through each calibration cycle. Calibration of coefficient values for this study were produced through a series of calibration phases, starting with coarse calibration. For coarse calibration, values for each parameter range from 1-100, and are incremented in steps of 25. Jantz et al. (2010) noted that any additional testing of parameter values than those tested through the coarse calibration warranted no additional gain at the cost of additional computing time. Coefficient values are changed to simulate accelerated or depressed growth relative to local urban development conditions for that point in time and result in a new set of coefficient values at the end. The resulting values of the coarse calibration are further narrowed down through fine and final calibration, where each set of refined coefficients are selected using the range of best-fit values determined by the top five OSM values of the antecedent calibration.

The final step of the calibration process is to determine the coefficient values that most accurately simulate historic growth trends. The top OSM values calculated after the final calibration are used to initialize the model for forecasting land cover conditions. Additionally, coefficient values used in predictions of urban extent for 2023 were run with 1,000 Monte Carlo iterations to account for any inherent variability in the modeling results.

3.4 Urban Growth Change Modeling

The SLEUTH model was applied to forecast and characterize the growth of urban land cover for a twenty three-year period. Growth was characterized by evaluating the conversion of non-urban to urban cover through time using urban growth maps, multivariate statistics, and landscape metrics. Figure 3 provides a basic graphical representation of a SLEUTH model simulation beginning with a set of initial conditions calibrated specifically for the study area, and run through a series of growth cycles. The model concludes when the required number of growth cycles are generated.

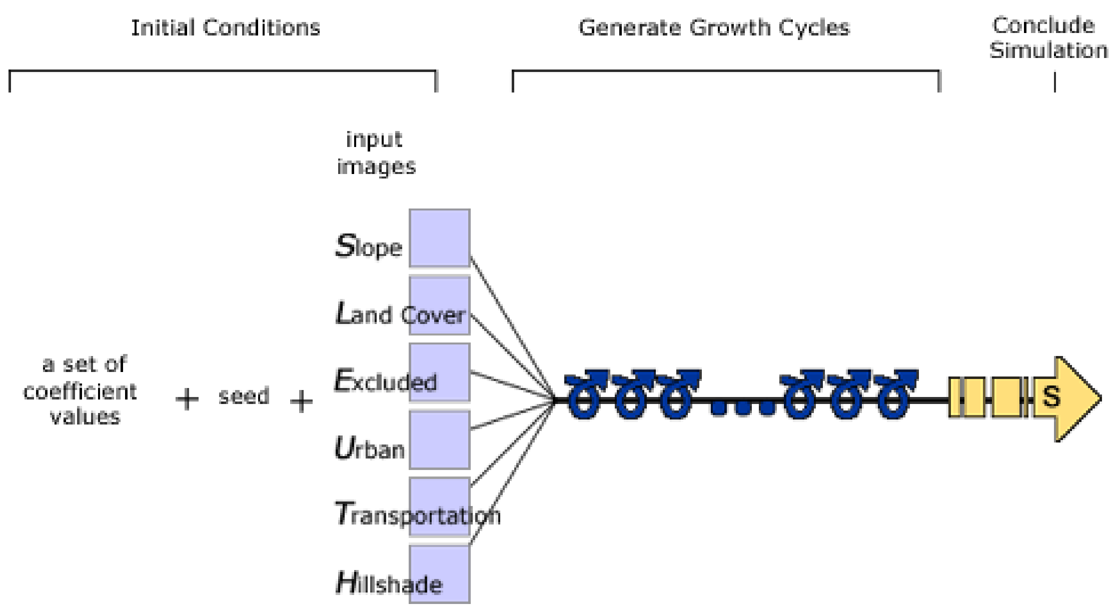


Figure 3. Conceptual representation of SLEUTH operational model including required input datasets (UCSB 2012).

3.4.1 Interpretation and Analysis of Results

Implementation of the SLEUTH model produces image and statistical output files, each with varying details about the growth resulting from each growth cycle. Land cover classification results were used as the control to test the calibration accuracy of simulated urban growth. The number and percentage of urban pixels, and the number of urban clusters were calculated for both the 2013 land cover classification and the 2023 simulated urban extent. The SLEUTH model conveniently outputs measurements of the number of urban pixels and clusters for each simulated growth cycle. A fractional difference metric was used to assess the difference between simulated and actual urban areas where negative values indicate underestimation, positive values for overestimation, and zero values for a perfect match.

Surface metrics are used to describe the spatial and non-spatial characteristics of an area of interest through quantification of existing relationships between features on the landscape. For example, the variability in the size of urban land-cover patches (non-spatial) and the arrangement and location of these patches throughout the landscape (spatial) (McGarigal et al. 2012). For this study, metrics were computed per land cover class describing the pattern and distribution per class, and by landscape, where the spatial structure of the entire surface may be described by a single metric. These metrics can be easily computed on categorical (i.e., land cover) grids in FRAGSTATS (McGarigal et al. 2012). Class and landscape metrics used in this study are provided in Table 1.

Table 1. Class and Landscape Metrics used to describe spatial and non-spatial characteristics

Metric	Definition
Class Metrics	
Total (Class) Area (CA)	Total (Class) Area (CA) is a measured sum of the landscape area composed of a specific class. The sum of the equation is divided by 10,000 to convert the calculated value to hectares (McGarigal et al. 2012).
Percentage of Landscape (PLAND)	Percentage of landscape (PLAND) equals the percentage of the landscape occupied by a particular class. Although this is similar to CA, the percentage values is relative to the entire landscape and is therefore more appropriate for comparative purposes (McGarigal et al. 2012).
Clumpiness Index (CLUMPY)	From McGarigal et al. (2012): $-1 \leqq \text{CLUMPY} \leqq 1$ Given any P_i , CLUMPY equals -1 when the focal patch type is maximally disaggregated; CLUMPY equals 0 when the focal patch type is distributed randomly, and approaches 1 when the patch type is maximally aggregated. Note, CLUMPY equals 1 only when the landscape consists of a single patch and includes a border comprised of the focal class.
Landscape Metrics	
Contagion Index (CONTAG)	From McGarigal et al. (2012): $0 < \text{CONTAG} \leqq 100$ CONTAG approaches 0 when the patch types are maximally disaggregated (i.e., every cell is a different patch type) and interspersed (equal proportions of all pairwise adjacencies). CONTAG = 100 when all patch types are maximally aggregated; i.e., when the landscape consists of single patch.

A visual analysis of the output images resulting from SLEUTH is also very illustrative of the model sensitivity to local conditions. Each forecasted growth cycle outputs images of simulated urban growth showing existing urban cells, as well as cells with associated probabilities of urbanization. These images are important for quantitative analysis, but also for visual analysis in illustrating the process of growth from an initial to final state. Thus, visual interpretation of image outputs was used to qualitatively describe the change in urban extent from 2013 to 2023.

After the final calibration values were selected, the SLEUTH model was implemented to produce future land cover maps to predict urban land cover in 2023. These maps demonstrate the expected patterns of urban growth if historic and current trends persist.

4.0 RESULTS

Accuracy assessments for land cover classifications, provided in Table 2, show adequate accuracies for the urban/non-urban land cover classifications. All classifications were found to have an overall Kappa statistic score of over 80 percent and overall accuracy of more than 90 percent, thereby making them suitable for use in further analysis. Lower Kappa values for urban classification in 2000 and 2013 suggest some confusion in segments classified as urban. This could be expected, as it can be difficult to assess if the proportion of urban to non-urban coverage is large enough within the segment to be classified as urban.

Table 2. Accuracy assessments results for all four images classifications

2000 Imagery

Class Name	Producer's Accuracy (%)	Users Accuracy (%)	Kappa Statistic (%)
Urban	95.45	87.50	76.92
Non-Urban	88.46	95.83	90.91
Overall Kappa Statistic	83.33%		
Overall Classification Accuracy	91.67%		

2004 Imagery

Class Name	Producer's Accuracy (%)	Users Accuracy (%)	Kappa Statistic (%)
Urban	100	91.67	84.62
Non-Urban	92.3	100	100
Overall Kappa Statistic	91.67%		
Overall Classification Accuracy	95.83%		

Table 2-Continued. Accuracy assessments results for all four images classifications

2009 Imagery

Class Name	Producer's Accuracy (%)	Users Accuracy (%)	Kappa Statistic (%)
Urban	100	91.67	84.62
Non-Urban	92.3	100	100
Overall Kappa Statistic	91.67%		
Overall Classification Accuracy	95.83%		

2013 Imagery

Class Name	Producer's Accuracy (%)	Users Accuracy (%)	Kappa Statistic (%)
Urban	100	83.33	71.43
Non-Urban	84.71	100	100
Overall Kappa Statistic	83.33%		
Overall Classification Accuracy	91.67%		

The parameter value sets used for each calibration phase for all five growth coefficients are summarized in Table 3. Each calibration phase was run with step values that tested at least five increments between the start and stop values or each parameter. Each combination of parameter values was run with five Monte Carlo iterations. Each calibration was successful in increasing the OSM value, with the final calibration significantly improving the OSM value by 0.066. The final calibration produced a top OSM value of 0.593, representing a moderate fit between modeled and known urban extent. The calibration accuracy results (Table 4) show that model simulations of the 2013 urban extent were slightly underestimated; -0.13 for urban pixels and -0.06 for urban clusters. The model achieved a fractional difference of 13 percent for urban pixels and 6 percent for urban clusters. Table 5 lists the forecasted amount of urban pixels and clusters for 2023. Urban coverage in 2023 is expected to increase 39,895 pixels to 164,282 urban pixels, composing 18.32 percent of the study area, along with the addition of 12 more urban clusters to increase the total to 72.

For the forecasting coefficient values, the highest score is found in the spread parameter suggesting a high probability of urbanization outward from existing urban centers. Similarly, a relatively high road growth coefficient suggests that urban growth has and will continue to be affected by road networks. The slope resistance value shows that the topography in this study area has a slight impact on limiting development, which is expected due to the highly variable topography in the study area. The low diffusion coefficient value indicates that, although most growth will expand from established urban areas – as indicated by the high spread coefficient, growth will be compacted around existing urban areas. The low breed coefficient suggests a low probability of a newly generated urban settlement outside of existing urban areas.

Table 3. Calibration and Prediction Parameter Sets (Start - Stop; Step)

Calibration	Diffusion	Breed	Spread	Slope	Road Growth	Top OSM Value
Coarse	0-100; 25	0-100; 25	0-100; 25	0-100; 25	0-100; 25	0.513
Fine	1-25; 5	1-25; 5	50-75; 5	1-25; 5	50-100; 10	0.527
Final	15-20; 1	1-6; 1	50-75; 5	19-24; 1	50-100; 10	0.593
Prediction Parameter Sets						
	18	4	75	21	50	

Table 4. Calibration accuracy results between 2013 known and simulated urban extent

	Pixels (%)	Clusters
2013 Known Urban	124,387 (13.87)	64
2013 Simulated Urban	107,753 (12.01)	60
Fractional Difference	-0.13	-0.06

Table 5. 2023 simulated urban pixels and clusters

	Pixels (%)	Clusters
2023 Simulated Urban	164,282 (18.32)	72

Tables 6 and 7 provide the results of the calculated class and landscape metrics. Calculated metrics for 2023 include all probabilities over 50 percent. Total urban area is forecasted to grow approximately 3,589.38 ha by 2023, increasing total coverage of the landscape from 13.87 percent to 18.32 percent. The Clumpiness Index value slightly increases from 0.95 in 2013 to 0.96 in the 2023. Similarly, the Contagion Index value drops slightly from 66.44 in 2013 to 61.38; which could be contributed to a greater amount of clusters in 2023. The minimal change in Clumpiness and Contagion index values is not ample to suggest that urban coverage will be any more or less fragmented across the landscape in 2023.

Table 6. Calculated Class and Landscape Metric Values for 2013 Urban Extent

2013 Urban Extent	
Metric	Value
Total Urban Area (CA)	11,196 ha
Percentage of Landscape (PLAND)	13.87%
Clumpiness Index (CLUMPY)	0.95
Contagion Index (CONTAG)	66.44

Table 7. Calculated Class and Landscape Metric Values for 2023 Urban Extent

2023 Predicted Urban Extent	
Metric	Value
Total Urban Area (CA)	14,785.38 ha
Percentage of Landscape (PLAND)	18.32%
Clumpiness Index (CLUMPY)	0.96
Contagion Index (CONTAG)	61.38

A visual interpretation of the forecasts of urban extent for 2023 (Figure 4) indicates that the majority of future growth in San Marcos is characterized by edge growth. Most urban growth is forecasted to occur outward from the city in conjunction with continued urban infilling between established urban areas. Spontaneous urban growth is minimal, with only a few pixels representing a relatively low probability of the occurrence of urban settlement in a new area without pre-existing urban coverage. It is difficult to interpret the impact of the road growth coefficient in this study area due to a low breed coefficient and with most pre-established urban cores surrounding main road networks, especially those associated with the highest gravity weighting.

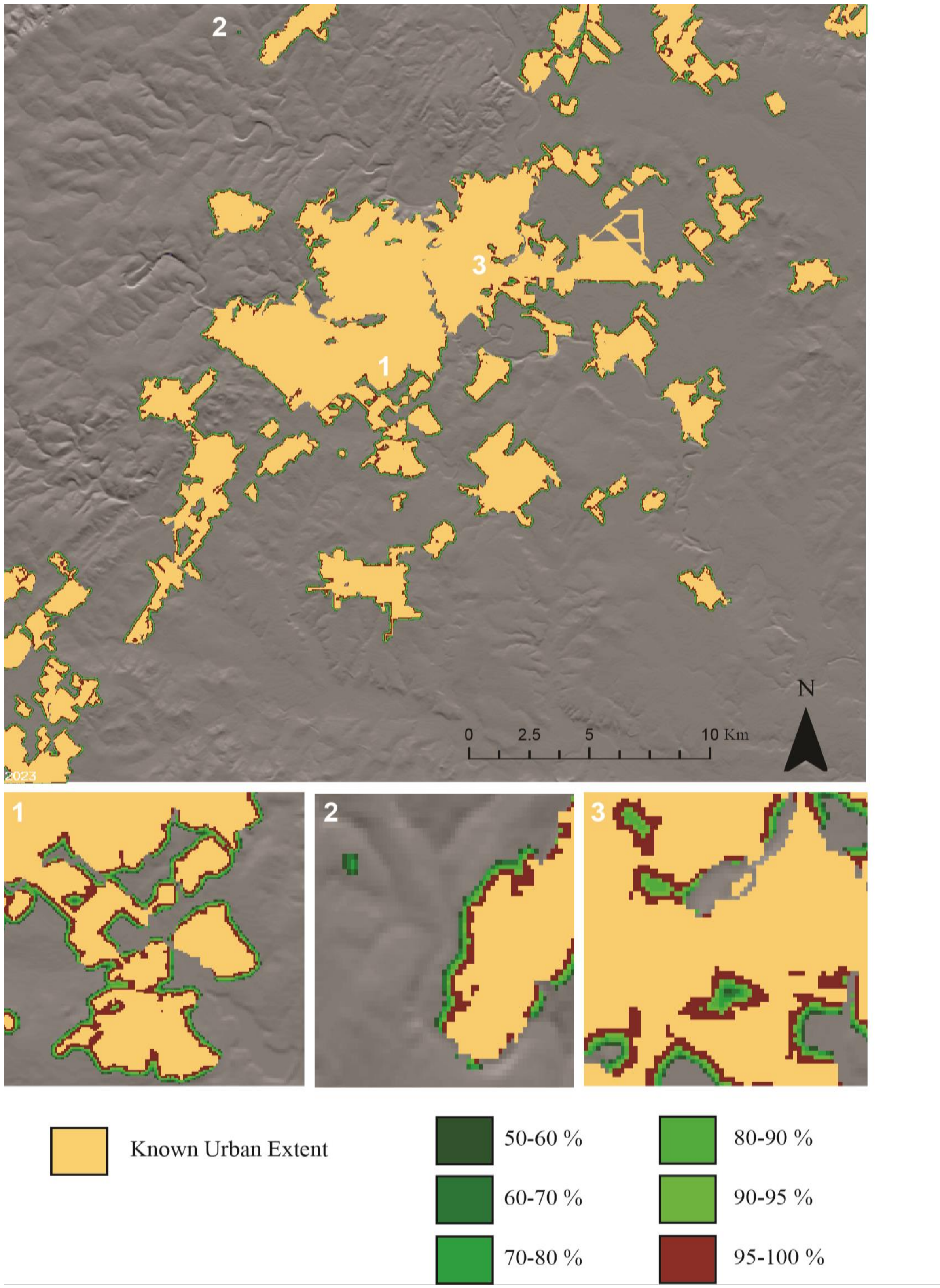


Figure 4. Probability maps of San Marcos urban extent in 2023. Probabilities are scaled from dark green representing lowest probability to dark red representing high probability.

5.0 DISCUSSION

5.1 Data and Calibration Modifications

Object-oriented image classification was adequate for classifying urban and non-urban areas and integration into the model; however, the segmentation of each image produced slightly different results. While the core of most urban clusters remained consistent, the segment boundaries of each urban cluster deviated slightly throughout each image classification. Deviation of urban cluster boundaries is exacerbated with the Landsat 8 image, likely due to its higher radiometric resolution (12-bit) compared to Landsat 5 TM (8-bit). Differences in known urban cluster boundaries could be a source of error during model calibration by creating artificial growth or loss of urban coverage. To compensate for deviations in urban cluster boundaries each urban extent layers were merged with the previous year. Thus, each subsequent urban layer will carry over the maximum urban extent from the previous years. This ensures that all urban clusters are expanding, eliminates the possibility of urban clusters getting smaller, and makes urban growth more consistent across all urban extent layers. This operation was not considered to have a significant impact on the results of the study with the expectation that urban sprawl in San Marcos has continued to grow rather than shrink during the scope of time this research has investigated.

SLEUTH implementation suggests resampling input image resolution for both coarse and fine calibration phases. However, resampling of input image resolution for these calibration phases had a considerably negative impact on OSM values and subsequent prediction results. Contrary to results of research by Silva and Clarke (2002), enhancing the spatial resolution of input images during calibration did not make the model more sensitive to local conditions for this study. Maximum OSM values for final calibrations using spatially resampled input data with the original and merged urban extent input layers were 0.341 and 0.382, respectively. Additionally, calibration coefficients generated through calibration with resampled input images generated urban predictions with nearly no urban growth. For this study, running all calibration phases with the full 30 m resolution imagery has produced more meaningful parameter values for the growth coefficients and urban extent predictions. Wu et al. (2009) opted to use full resolution for calibration along with other modifications to the model to improve simulation accuracy.

Poor calibration results from utilizing resampled input images suggest an issue of scale sensitivity. The drop in calibration performance when using finer resolution imagery could point towards SLEUTH's inability to capture the highly dispersed settlement patterns resulting from local scale factors (Jantz and Goetz 2005, Wu et al. 2009). Alternatively, this maybe due to a relatively short time span (2000-2013) of urban development used to calibrate the model. Jantz and Goetz (2005) conducted a study using 45 m imagery resampled to 90 m, 180 m, and 360 m to investigate the influence of input image resolution on the goodness-of-fit between modeled and known urban extent and the resulting coefficient calibration values. Their description on the behavior of urban growth for the 45 m spatial resolution shares many similarities with the results of this study. They found a dominance of edge growth, less dominance in spontaneous new growth and the spreading of center growth, and minimal development produced through road growth. Additionally, their results show SLEUTH consistently underestimating the number of urban edge pixels and urban clusters at a fine input resolution. This may be in part be due to finer resolution data's inability to fully capture the development patterns of an urban area, the particular time period chosen for model calibration, or from the difficulty in evaluating multiple metric-fit statistics (Jantz and Goetz 2005).

OSM values range between zero and one, where an OSM values closer to one represent a good fit between simulated and known urban extent and the opposite of that for values closer to zero. Obviously, it is ideal to have high OSM value for each calibration phase; however, there is no discussion within the literature that identifies a threshold of OSM values that should be met before initiating an urban growth prediction. Furthermore, there still remains no general consensus on the most appropriate method to be used for ranking the best fitting coefficient values. However, Dietzel and Clarke (2007) assert that the OSM is optimal for evaluating and selecting coefficient parameters for the best goodness of fit. Alternatively, Wu et al. (2009) suggest performing a thorough examination of the study area to identify consistent processes and patterns along with the crucial factors influencing urban growth for a study area. This information can lend insight into the most appropriate spatial resolution for input images and goodness-of-fit statistics.

5.2 2023 Forecasted Growth

The forecasts of urban growth made here continue the growth trends from the past thirteen years. It is clear from the class and landscape metric values and visual outputs of the model that San Marcos' urban coverage will continue to expand. The resulting values of the Clumpiness and Contagion index make sense when considering the prevalence of forecasted edge growth. Although infilling is projected to occur, the slightly higher Clumpiness value would suggest that, while the majority of growth would expand outward from urban centers, the 2023 urban extent will not be considerably more or less aggregated than urban coverage in 2013. Along the same lines with the Contagion Index value, the slight drop in value between 2013 and 2023 is not considerable enough to suggest that future urban coverage will be any more fragmented throughout the landscape than current conditions. Together, these indices indicate that, although growth is expected to occur, the general shape and distribution of urban sprawl in 2023 will remain similar to 2013.

The high value for the spread coefficient suggests that past growth has been extending out from the periphery of existing urban clusters. The likelihood of this trend continuing is further supported by the similarity in the class and landscape metric values for the Clumpiness and Contagion indices between 2013 and 2023. The coefficient value for road growth suggests that road networks are influential to urban growth in this study area. This would make sense as San Marcos is situated as a center point for the connection to many of the surrounding major highways to IH-35. Despite this, road influenced urban growth is not visually obvious in the results. Evaluating the effect of various road weight, or lack thereof, would likely provide more information on the influence of road weighting on urban growth patterns; however, this was not a focus of this study.

The low breed and diffusion values indicate that no significant new urban areas have developed in the area within the past decade and that the expansion of growth from existing urban areas has been relatively slow. These values are to be expected after further visual inspection of the urban input layers in which the majority of growth occurring between each image is through the expansion of currently existing urban areas rather than the development of new areas. Spontaneous growth was almost non-existent with the exception of a few dark green pixels in the top northwest and south-central regions of the output image (Number 2 in Figure 4). These small urban areas likely stayed small due to the low diffusion value. New urban centers may have occurred more frequently, however, the probability of such growth was not high enough to be displayed on the output probability map.

It is clear from the results of this study that scale influences coefficient parameters differently. This issue raises the question of the ability of certain parameters to function at certain image scales. Jantz and Goetz (2005) found that the highest fit score between simulated and known urban extents was reached when using the coarsest resolution input images, although it should be noted their study used different fit metrics from this study. With the results of this study, a potential for future research would involve investigating the changes in OSM and coefficient parameter values through calibration using coarser and finer resolution imagery. Utilization of finer resolution data on a relatively small study area may help connect modeled and simulated urban extent and reduce the Clumpiness index. Although this would increase processing time, the results may produce evidence that confirms or rejects methods of better performance suggested by the literature.

5.3 SLEUTH Performance

Considering that CA is raster based operation that relies on transitional neighboring cells to trigger a state change in surrounding cells, it makes sense that the dominance of urban growth trending towards edge growth in predictions is a common characteristic of SLEUTH (Jantz and Goetz 2005, Wu et al. 2009). This precedence to edge growth may limit the ability of model to simulate the development of new urban coverage from other influential factors (Wu et al. 2009). A major point of discussion over SLEUTH is in its simplicity of urban growth prediction (Chaudhuri and Clarke 2013, Wu et al. 2009). Principally, SLEUTH is a descriptive model and the transition rules do not allow for any analysis on the causes of the spatial patterns developed (Santé et al. 2010). In a real-world situation, there might be various regional developmental plans that could stimulate a leapfrog urban development throughout the region. Currently, however, the model is not capable of simulating the potential impacts regional developmental policies or incentives and the generations of urban extent forecasts are made without the direct influence of such planning and local-decision making.

The complex emergent behaviors of urban systems are very difficult to model. All models are abstract representations of this complex and dynamic behaviors and are flawed to some degree. For the most part, most CA-based urban models are simple in nature, yet these models are well suited for simulating certain components of the complex behaviors of urban systems. While SLEUTH is not adapted to the particular urbanism ideologies that exist in any particular city it is modeling, additional modifications or coupling with other models may produce results that consider the impact of other factors influencing growth (Clarke 2008).

SLEUTH is also computationally intensive and can take many hours to days to complete one of the three calibration phases. Calibration time is dependent on the calibration phase, cell resolution of input images, the number of coefficient parameters to be tested, the number of Monet Carlo iterations, and the size of the study area. In this study, with a relatively small study area and high-resolution input imagery, the combined completion time of all three calibration phases was just over three days. Although extensive research has gone into developing successful techniques for enhancing the computational efficiency of calibration (Candau 2000), time of operation continues to be an issue for SLEUTH (Al-shalabi et al. 2013, Jantz and Goetz 2005, Wu et al. 2009).

6.0 CONCLUSION

The results of this study suggest a high probability of continued urban growth from urban edges with continued aggregation of urban coverage in the gaps between existing urban areas in 2023. Effective forecasting of growth patterns will be useful tool in planning decision-making for local municipalities. Based on the results of this study, it may be recommended that decision makers prepare for aggregation of urban coverage at the city core with concurrent conversion of available land along the periphery of established urban areas. Perhaps most beneficial to local planning initiatives would include information on the predicted locations of newly developed urban centers and the preference of land use for conversion to urban coverage. This study, however, did not find any significant probability of such development within the near future or consider land use conversions.

The results of this study are derived from a standard SLEUTH implementation with very few model modifications, thus leaving the potential for pursing various avenues of research for urban modeling of the San Marcos area. These results may be considered as “business as usual” and could be used as a baseline for comparison to the results of different predictive scenarios. Other growth scenarios might include environmental protection parameters, preferential selection of lands for urban growth, or overall booming urban growth. These scenarios could be initiated through modifications of the excluded layer or the self-modification parameters and including land use data. Values for the self-modification parameters were left at the default values for this study. Many SLEUTH implementations have been conducted in the past, but few have changed their default values for these parameters (Clarke 2008, Wu et al. 2009). It is possible that modification of these parameters could produce more significant urban growth predictions and lend insight into the development process of the urban form of a particular city. This could help local decision-makers evaluate the impact to urban growth under various city urban planning, resource allocation, and environmental protection initiatives.

Beyond the results specific to San Marcos, this research has also opened up research opportunities for the SLEUTH model in general. For the calibration of coefficient values – if OSM is the best metric to use for the sorting and selection of values, then perhaps research could be done to investigate a threshold to which OSM values should not fall below in order to reliably forecast urban growth. Additionally, investigations on the optimal input image resolutions for various study area sizes would be beneficial to this study and to anyone interested in conducting a SLEUTH implementation. With the model's apparent issues of sensitivity to scale, future research could be applied towards developing a metric that determines the optimal size of input cell resolutions that produce coefficient growth values that most closely mimic the urban development of any particular study area.

APPENDIX SECTION

APPENDIX A

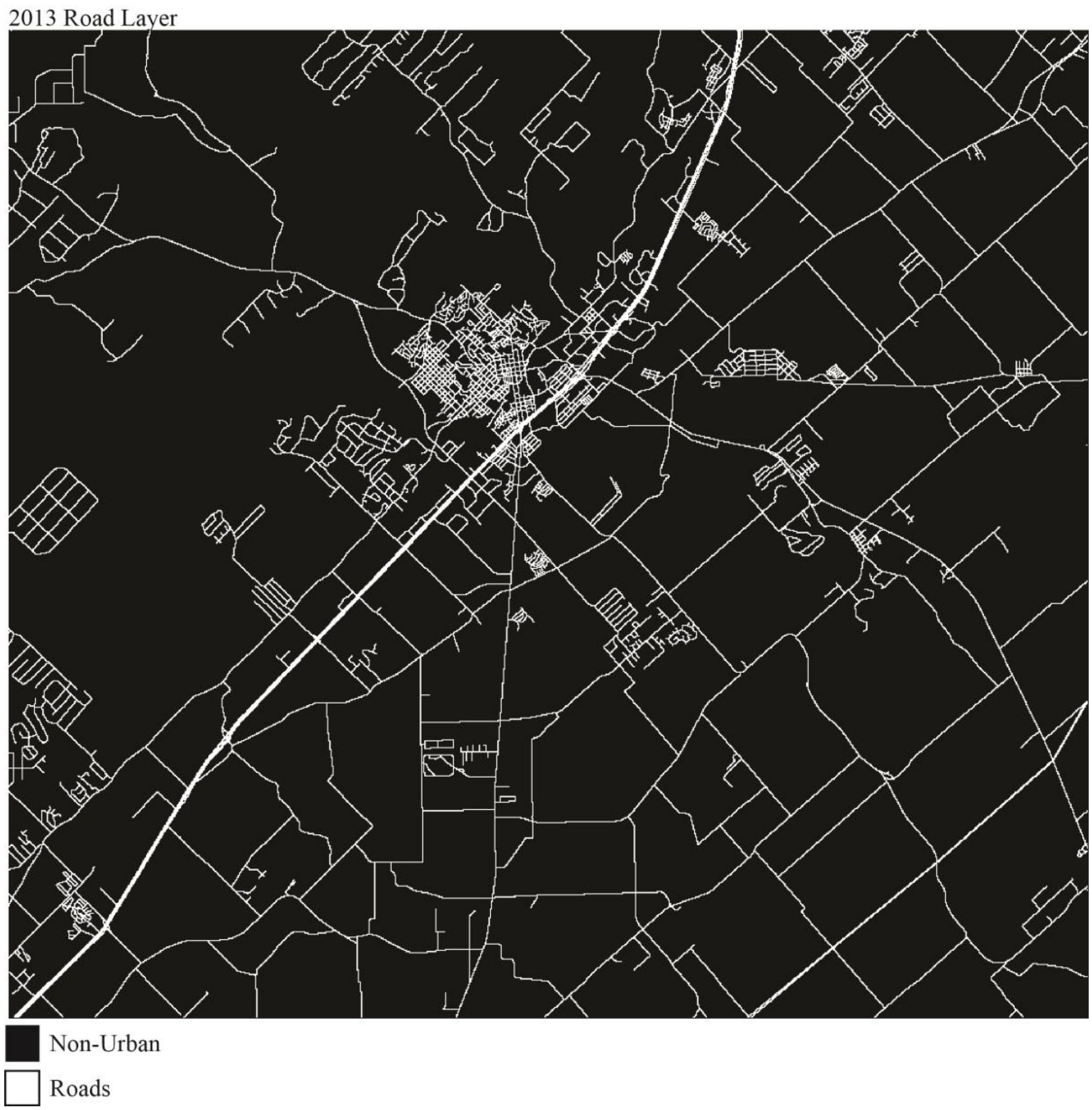


Figure 5. 2013 Transportation input image derived from the City of San Marcos' GIS Department and U.S. Census TIGER/Line shapefiles.

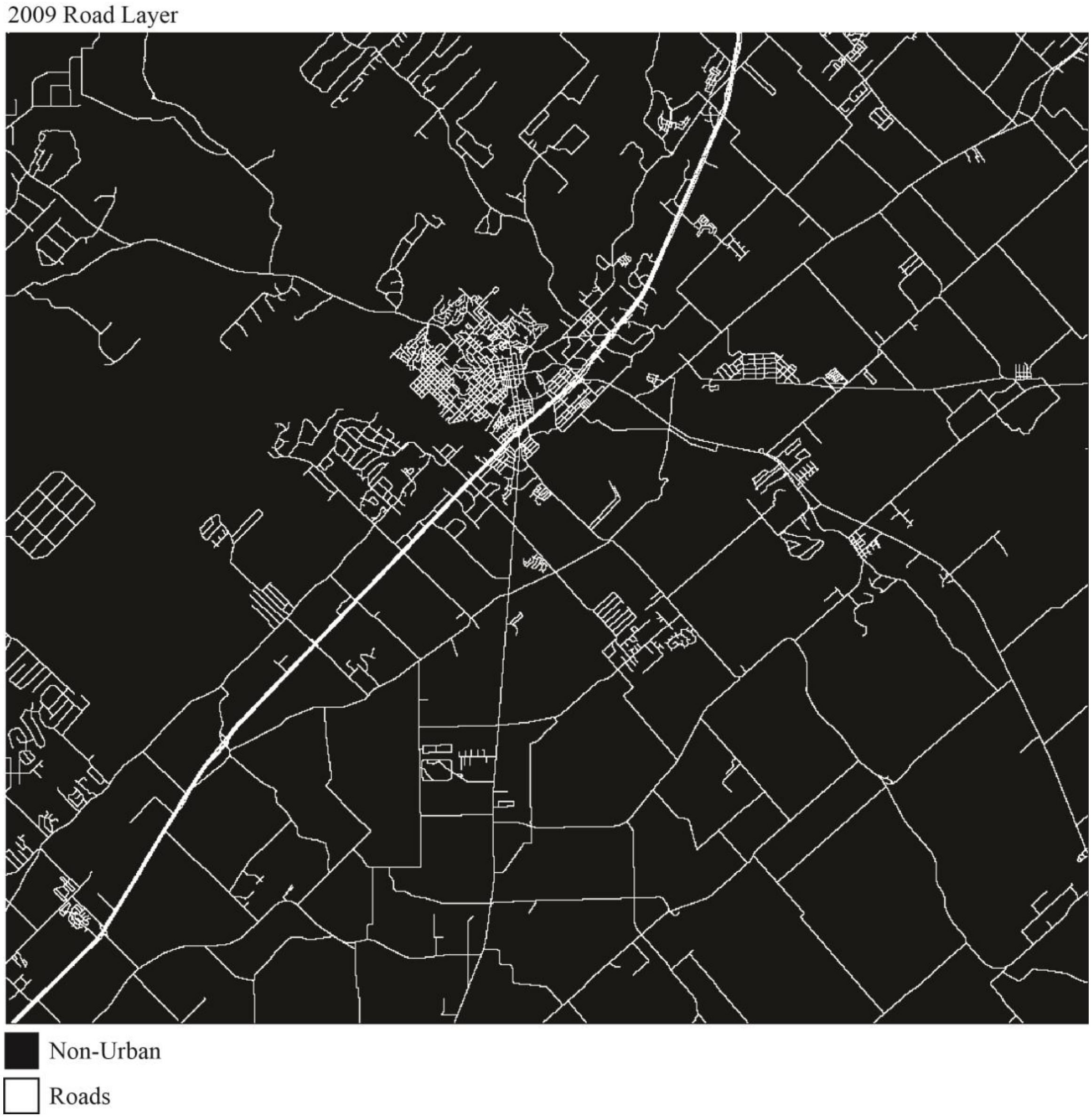
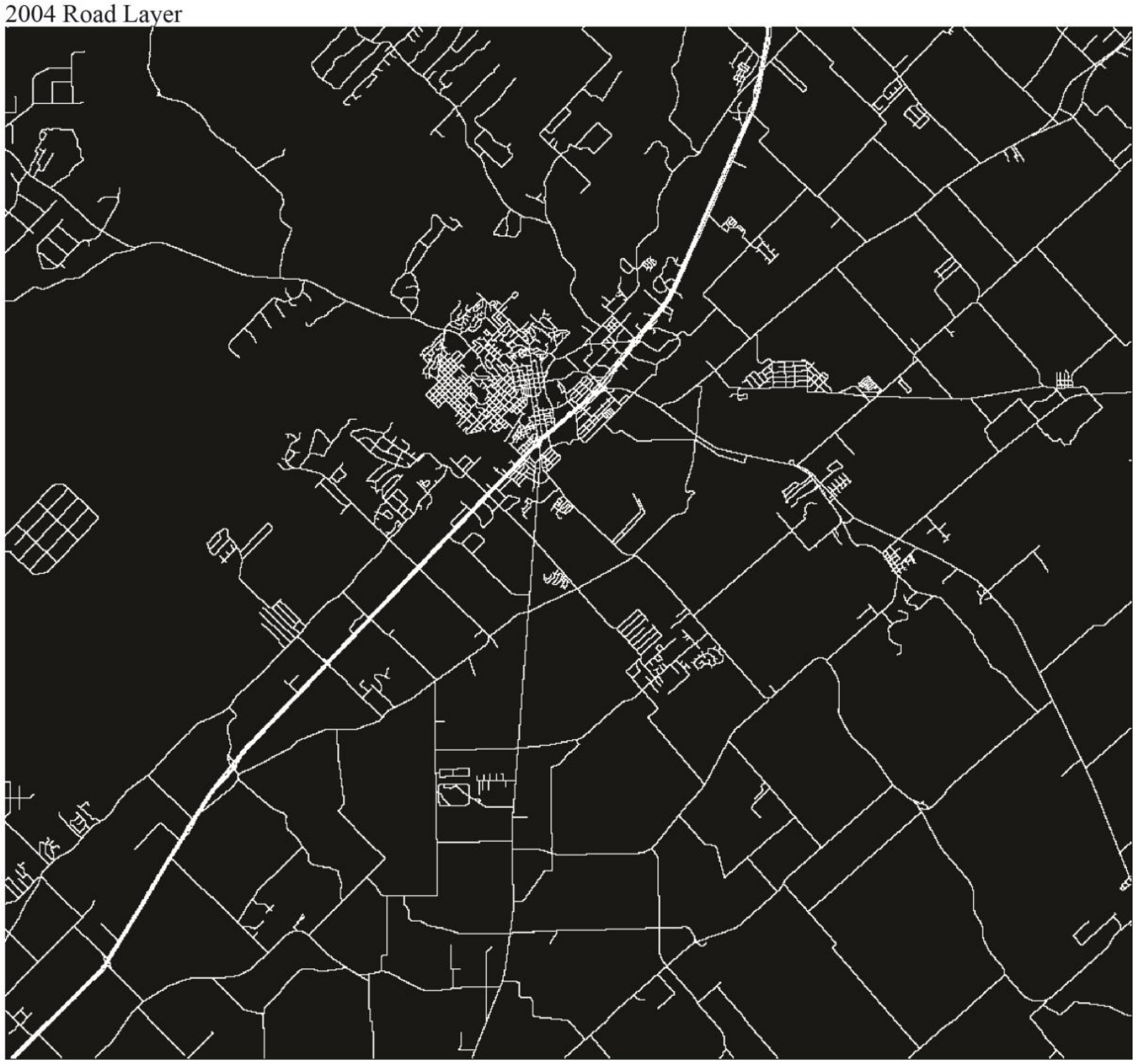


Figure 6. 2009 Transportation input image derived from the City of San Marcos' GIS Department and U.S. Census TIGER/Line shapefiles.

2004 Road Layer



Non-Urban

Roads

Figure 7. 2004 Transportation input image derived from the City of San Marcos' GIS Department and U.S. Census TIGER/Line shapefiles.

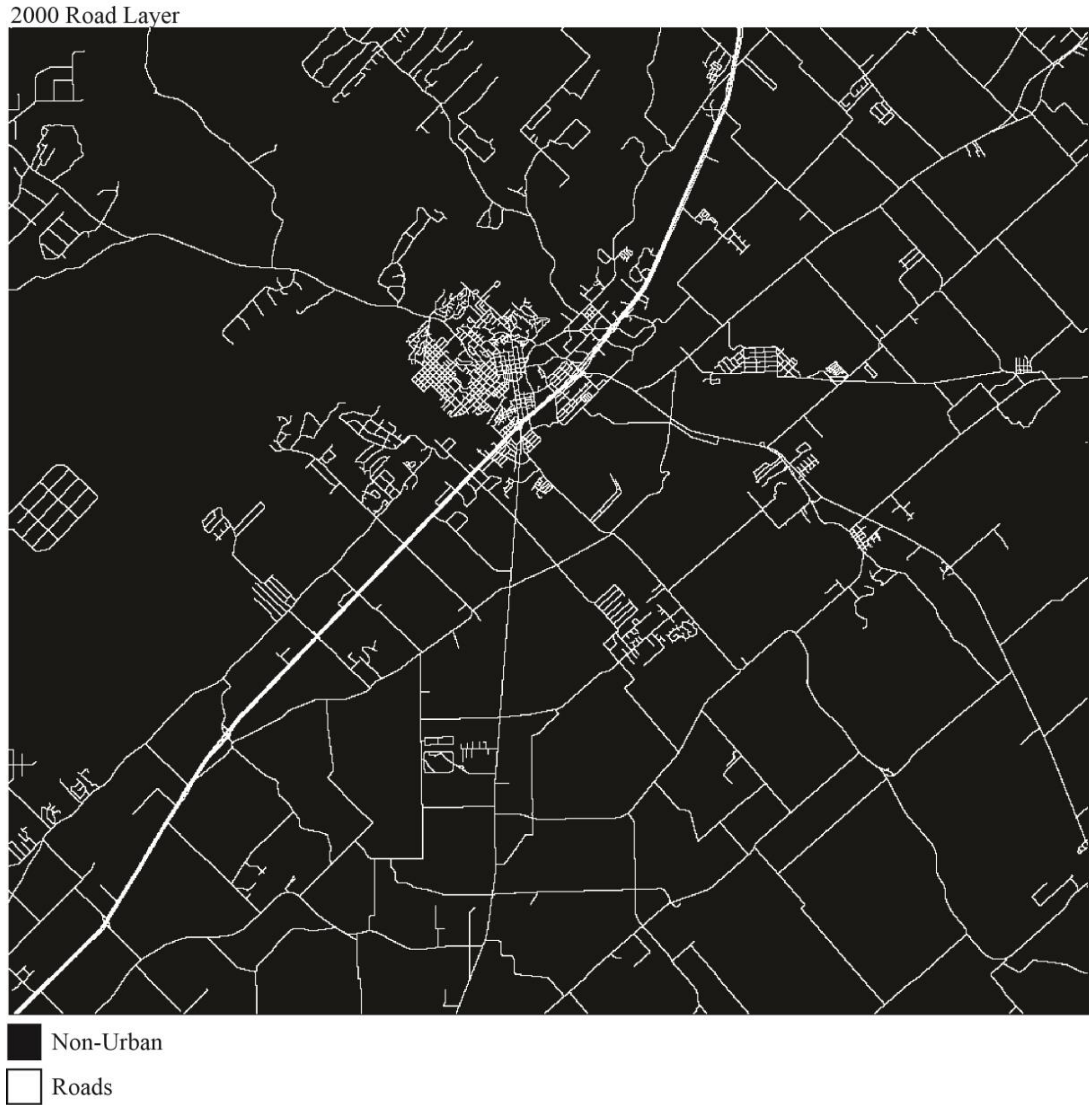


Figure 8. 2000 Transportation input image derived from the City of San Marcos' GIS Department and U.S. Census TIGER/Line shapefiles.

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