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Modeling Urban Growth and Land Use Change in Albuquerque using SLEUTH

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Dedication

To Marisa.

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ABSTRACT

This research examines the urban growth and land use pattern of Albuquerque in the next 20 years, for the year 2035, based on past urbanization and land use. Additionally, it compares possible urban growth and land use patterns for two scenarios i. Business as usual scenario, where urbanization pattern of Albuquerque is based on historic data without any explicit definition of areas specifically designated for development and ii. Expansion scenario, where three areas around Albuquerque specifically designated for development (Mesa del Sol, Volcano Mesa and Santolina) is explicitly defined in the model. The two scenarios are further examined based on possible high and low growth rate to expose the upper and lower bounds of future development. SLEUTH, a cellular automata based dynamic urban growth model, was used in the analysis and future urban growth prediction. The SLEUTH model was first calibrated for Albuquerque and its input variables (specifically exclusion layer), and self-modification rule were modified to simulate the two scenarios and the growth conditions respectively. The results indicated, with a very high certainty, that for any scenario in any growth rates, urban expansion would occur in the in-fills fringes of the current urban extension of the city. Among the areas designated for urban development, results showed a high probability of urban growth occurring primarily in Volcano Mesa, followed by Mesa del Sol and with a low probability of urban growth occurring in Santolina. This was true for both scenarios in high and low growth rate.

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1. Introduction

The number of people living in urban areas has increased at a rapid rate over the past few decades. According to a recent report by the United Nations (UN), 54 percent of the world's population now live in urban areas, and, this number is expected to increase to 66 percent by the year 2050 (UN, 2014). Growth of urban areas is even more drastic in the US where 80 percent of the population currently live in urbanized areas (Auch, Taylor and Acevedo, 2004). The rapid growth of urban population centers has led to an increased pressure on land and resources to support this growth. The socio-economic development and improvement in the quality of life that comes with urbanization have been the anthropogenic drivers for conversion of undeveloped land into the urban landscape of cities and towns (Clarke et al., 1997). Even with these urban landscapes occupying only a small fraction of the world's total land area, their rapid rate of expansion has caused significant impacts on the environment; resulting in the loss of natural vegetation, encroachment of land for urbanization (Tan et al., 2005), reduced biodiversity (Zimmermann et al., 2010), and has contributed to local and regional climate change (Kaufmann et al., 2007).

Most of the urban growth in the US has been characterized by an outward growth, extending beyond the core city centers and into low density sub-urban neighborhoods (Hartshorn, 1992). Suburban growth exploded post World War II due to the construction of Federal Interstate Highways that connected urban areas (Auch et al., 2004). By the 1970s, there were more people living in the suburbs than in the city centers (Abbott, 1981). Suburbs that were previously "bedroom communities" had transformed into hubs of urban economic activity with residential, retail, service, and entertainment establishments (Auch et al., 2004).

Albuquerque, NM, the focus of this study, experienced a similar pattern of urban growth; urban development in Albuquerque has been extending outward from the center of the city towards its fringes. Historically agricultural land, such as those in the South Valley and the outskirts of the city, are being gradually transformed into sub-urban areas with residential and commercial developments (Skaggs et al., 2011). Additionally, vast tracts of land have been specifically acquired by the city of Albuquerque for large scale urban development projects to be completed over the next 30 to 50 years. Currently, the three major tracts of land that have been designated for large scale urban development in Albuquerque and its immediate surroundings are:

- Volcano Mesa development: located in the north western side of Albuquerque covering an estimated 3,532 acres,
- Mesa del Sol development: located in the south eastern side of Albuquerque covering about 12,900 acres, and
- Santolina: a recently approved, third major urban development project located just outside the city of Albuquerque covering about 13,851 acres.

These developments are designed as urban communities that would serve as commercial centers, with mixed used neighborhoods and residential areas. Each of the three development areas is expected to house around 100,000 residents. It stands to reason that the development of these large-scale expansion projects would significantly affect the rate, pattern, and nature of future urban growth in Albuquerque.

The purpose of this research is to address the question, “How will the three major urban development projects planned in and around the City of Albuquerque affect the pattern of urban growth and land use of Albuquerque over the next 20 years?” This question is addressed by modeling urban growth under and comparison of two scenarios:

a. Business as usual scenario: where prediction of urban growth and land use was based on the current growth pattern of Albuquerque without any explicit definition of areas allocated for the three development projects and,

b. Expansion scenario: where prediction of urban growth and land use of Albuquerque includes the explicit definition of the three development projects as areas specifically allocated for expansion of the city.

Furthermore, to expose upper and lower bounds of future development, the research will examine these urban growth patterns and land use based on the current, relatively low, growth rate and a possible high growth rate, like that experienced by some other southwestern sunbelt cities such as Phoenix, Denver and Las Vegas (Auch et al., 2004; Koebler, 2011; Parker, 2011).

Understanding these trends of urban growth and land use patterns will allow policy makers and stakeholders to develop, adopt and examine plans and projects to enable more sustainable growth of the city and its surrounding communities (Li, 2014).

Over the years, various models have been developed to examine historical land use change and, based on it, infer likely land use patterns and rates into the future. Among these, models that are based on Cellular Automata (CA) have been shown to be versatile, simple and flexible (Torrens, 2000; Sevik, 2006). The SLEUTH urban land use model, developed by Keith Clarke at the University of California, Santa Barbara is one such CA model (Clarke et al., 1997). SLEUTH, like most land use change models, leverages observed historical urban growth trends to predict the rate and pattern of the urban expansion that might occur in future. SLEUTH is a tried and tested model that is versatile, scale independent, transportable and transparent (Clarke et al., 1996; Clarke and Gaydos, 1998; Jantz et al., 2003) and is used in this research to predict patterns of urban growth and land use change of Albuquerque, NM.

2. Study Area

The City of Albuquerque, according to US Census, is the 32nd largest city in the US based on population (US Census Bureau, 2014). It was founded in 1709, incorporated in 1891 and falls within the Bernalillo county with an approximate location of of 35°06′39″N and 106°36′36″W (City of Albuquerque, 2015).

2.1. Topography of Albuquerque

The city of Albuquerque is situated within the Rio Grande Valley. There are three mountain ranges on the eastern edge of the city: The Sandias, Manzanitas and Manzanos; the highest of which rise to 10,679 feet above sea level (City of Albuquerque Planning Department, 2013). These ranges are a part of Cibola National Forest and have open forest with sparse population. Either side of the valley is surrounded by mesas. The characteristics of East mesa is mostly defined by smooth and steep slopes starting at around 3 to 10 percent grade at the base whereas West mesa is characterized by high cliffs or escarpments that consist of volcanic cinder cones, basaltic lava flows, sandy soils and sand dunes (City of Albuquerque Planning Department, 2013).

The Rio Grande, cuts through Albuquerque making an S-shape (City of Albuquerque Planning Department, 2013). The flood plains along its banks have historically been used for mostly agricultural purposes, as well as for flood control. The Bosque, which is the natural wooded area along the edge of the river, acts a green belt and a place for riparian habitat (City of Albuquerque Planning Department, 2013).

2.2. Land Use of Albuquerque

Based on the 2013 comprehensive plan by the City of Albuquerque Planning Department, the land use of the city has been broadly categorized into Open Space Network, Reserve Areas, Rural Areas, Semi Urban Areas, Developing or Established Urban areas and Activity Centers.

For the purpose of this research, these categories have been combined into two broad categories: Areas where development is not allowed and Areas where development is allowed.

2.2.1. Areas where development is not allowed

In Albuquerque, areas where development is not allowed include all the areas that have been categorized as Open Space Networks. These are areas that have remained undeveloped and are designated as being undevelopable land because of their natural value, archeological significance, or simply because of its characteristics that makes it unsuitable for development (City of Albuquerque Planning Department, 2013). The undeveloped open space has been a big part of Albuquerque's planning strategy. The comprehensive plan for Albuquerque proposed in 1975 mandates a total of 76.9 square miles for open space (City of Albuquerque Planning Department, 2013). The Petroglyph National Monument, along with other opens spaces that have been acquired over the years as a part of the open space network, so far accounts for 31 square miles within the City of Albuquerque (City of Albuquerque Planning Department, 2013).

These open spaces are complemented by a number of parks scattered throughout the city that are also excluded from development. As of 2013, there are a total of 30 developed county parks and 175 developed city parks that account for about 800 acres and 38 undeveloped parks that account for 400 acres within the city of Albuquerque (City of Albuquerque Planning Department, 2013).

2.2.2. Areas where development is allowed

Excluding the open spaces and city and county parks, development is allowed in the rest of Albuquerque. Within these areas where urban development is allowed, the Reserve areas hold a special significance. Reserve areas within Albuquerque are areas that have been committed for future urban development. These areas have potential to be developed as either planned communities, where the city's plans, policies and goals dictate the construction and development of these areas, or as conventional development, where Rural Area policies of Bernalillo County and its subsequent zoning policies are applicable during construction and development (City of Albuquerque Planning Department, 2013).

There two areas within the city limits of Albuquerque that have been designated as reserve areas: Mesa del Sol, which is located south of Tijeras Arroyo, and the Volcano Mesa development, located on the upper West Mesa. While, Santolina, a third large tract of land reserved for development is located outside the city limits to the west (See Fig. 1.1).

2.3. Urban Growth of Albuquerque

Albuquerque is the largest metropolitan region in New Mexico. When it was designated as a metropolitan area in 1950, it had a population of 96,815 and covered a total of 48.27 sq. miles (City of Albuquerque Planning Department, 2013). Over the last few decades the 'Duke city' has seen an explosion in population; going from 384,734 in 1990 to 447,961 in 2000 and to 543,383 in 2010 (US Census Bureau, 2012), a compounded 41.23 percent increase in population over the last three decades. The 2010 census indicates that out of the 381 Metropolitan Statistical Areas (MSA) Albuquerque is the 53rd fastest growing MSA in the United States (New Mexico Bureau of Economic Research and Analysis, 2012). With this growth in population, the urban areas of the city have expanded substantially.

Albuquerque has exhibited a typical urban growth pattern of a city, where the growth has extended from city centers towards the edges and has extended further towards the suburbs. Areas located around the outskirts of Albuquerque that were historically used for agriculture and farmlands are being developed for urban, residential and commercial uses. South Valley, traditionally an agricultural community, has seen a 20 percent decrease in agriculture land use over the past 25 years and a 33 percent increase in urban land use (Skaggs et al., 2011). Based on historical development patterns, future urban growth of Albuquerque is likely to take place in the outskirts of the city and in urban in-fills. The addition of sizable tracts of land approved for large scale development projects seems likely to alter this historical pattern of development.

It should be taken into consideration, however, that the population growth of Albuquerque has been slowing down since 2010; the growth rate has been less than 0.5 percent per year from 2012 to 2014 (Real Estate Center at Texas A&M, 2014). During the year ending 1st July 2014, the growth rate of Albuquerque was only 0.1% (Provost and Bienvenu, 2014). This decline in population growth is likely to impact the development of the three large areas that have been targeted for development and the urban growth pattern of the city at large.

2.3.1. Mesa del Sol Development

Mesa del Sol, as shown in Fig. 1.1, covers about 12,900 acres and is the largest tract of flat undeveloped land within one city limit in the US (Chamberlin, 2007). It lies adjacent to I-25, just west of Kirkland Air Force Base, north of the Isleta Pueblo and east of Broadway Boulevard. It is proposed to be developed as a mini city within the city of Albuquerque (Calthrope Associates, 2005; Chamberlin, 2007). The concept for this project started in the early 1980s, initiated by the government, using city, state and federal funds, though a public-private partnership, with the idea of minimizing the extent of urban sprawl and limiting the development of residential exurbs deep in the desert by providing a tract of land that would offer housing potential for around 100,000 residents within the city limits (Alcorn, 2013). The 12,900 acres of land for the project was annexed by the City of Albuquerque in 1993 (Calthrope Associates, 2005). The project officially broke ground in 2007 (Provost and Bienvenu, 2015).

Mesa del Sol has been envisioned by its designer, Calthrope Associates, as an ambitious project that is aimed to be developed over the next 35 to 50 years, intended to provide an environmentally sustainable community with economic opportunities, employment centers, areas for civic and institutional use, walkable neighborhoods and mixed use areas (Calthrope Associates, 2005).

During the last few years of the project, the development of Mesa del Sol has been turbulent. This project that initiated its planning phase in the 1980s and began construction of housing units in 2013, has only recently started seeing some home sales,;

a process that has been hindered by recession and slow recovery of the economy (Scott, 2014; Hilf, 2015). Furthermore, foreclosure action filed against the major developers of the project, Forest City Enterprise Inc., and news of the company trying to sell its share of 3,000 acre has brought about a loss of confidence among investors and potential homebuyers (Domrzalski, 2014; Metcalf, 2015). Lately, however, there has been some progress and a boost in confidence for the stakeholders of the project with capital coming into to Mesa del Sol in the form of corporate investments (Mayfield, 2015). But on the whole, after boom and eventual bust of the real estate market in the 2000s, the massive development project has been a “Zombie Subdivision” (Provost and Bienvenu, 2015) where in certain sections of the development, roads and other infrastructure to support houses exist, but no houses have yet been built and as a result no taxes are being generated from these areas (Provost and Bienvenu, 2015). Defenders of this development project nevertheless consider these vacant lots and subdivisions as being “intentionally slowed” due to the decline in housing markets in Albuquerque and nationally (Provost and Bienvenu, 2015).

2.3.2. Volcano Mesa Development

Volcano Mesa, as shown in Fig. 1.1, is the second reserve area within Albuquerque that has been allocated for urban development. It was originally mapped in the 1960s and was annexed by the City in 1981 (City of Albuquerque, 2015). The area is located in the North West side of Albuquerque adjacent to Petroglyph National Monument and alongside a series of dormant volcanos that have been designated as public open spaces. The area is serviced mainly by Paseo del Norte, Unser Blvd, University Blvd and Rainbow Blvd (City of Albuquerque, 2013). The concept and planning of the Volcano Mesa development started in 2004 (City of Albuquerque, 2014). The proposed area for this development covers 3,532 acres and is expected to accommodate about 100,000 residents (City of Albuquerque, 2014). This project is expected to complete its build out by 2035 (City of Albuquerque, 2013).

Development of this area is divided into three sectors that have been designed to take into consideration the requirements put forward by the stakeholders and property owners of the Volcano Mesa area (City of Albuquerque, 2014):

- Volcano Cliff sector: with a total of 2,327 acres, this sector is focused on low density residential development with individually owned houses and small lots (City of Albuquerque, 2014).
- Volcano Heights sector: with a total of 446 acres, this sector focuses on larger tracts of land that would be designated for mixed use with employment and commercial areas, along with high to medium density residential developments (City of Albuquerque, 2014).
- Volcano Trail sectors: with a total of 570 acres, this sector is aimed at developing medium density single family residence with consolidated ownership and large tracts of land (City of Albuquerque, 2014).

2.3.3. Santolina Development

Santolina, as shown in Fig. 1.1, is the third major development around Albuquerque that covers a total of 13,851 acres and sits just outside the Albuquerque city limits. The master plan for this project was recently approved on July 16th, 2015 (WALH, 2015). This area lies on the South West Mesa; surrounded by I-40 on the north, 118th Street on the east, Pajarito Mesa grant boundary on south and Rio Puerco valley on the west. The area, based on market demand and the economy, is expected to be developed over the next 40 - 50 year time frame (WALH, 2015). Santolina is expected to have a total of 38,045 dwelling units, housing nearly 100,000 residents, with a combination of residential villages, urban centers, town centers, business parks, industrial areas as well as open spaces, included in the development (WALH, 2015). The area designated for development currently houses large government and private facilities along with the Cerro Colorado Landfill (WALH, 2015).

The Santolina development has also wrought with crisis and controversy. Planning for this development project initially started in 2007 under SunCal real estate developers, which later went bankrupt. Barclays, the lender, foreclosed on the property and set up Western Albuquerque Land Holdings (WALH) which now, along with two new investors, holds the right to develop the area (Provost and Bienvenu, 2015).

Moreover, there has also been opposition from local residents and environmental groups regarding the development of the area. The opposition has mostly been concerning the viability of the development due to the amount of water that would be required for the project and its long term consequences on surrounding irrigation and communities (Lusk, 2014; Provost and Bienvenu, 2015). Furthermore, questions regarding the necessity of another urban development project at such a massive scale, when there already are other such projects underway which have not lived up to their potential, has also been a constant source of controversy for the project (Lusk, 2014; MacMillan, 2014).

3. Modeling Land Use Change and Urban Growth

A model provides a "representation of a real life system" (Oguz, 2004). Elements of real life are represented in the model as variables that allow for analysis of these selected variables, and explore the relationships, and the interdependencies between them (Oguz, 2004). Models offer a platform to investigate historical data, virtually manipulate these variables, and assess potential implications of current or future policies and programs on these variables.

Land use change and urban growth is one such real life event that has been analyzed and modeled using a variety of different techniques. Understanding the changes in land use and urban growth patterns enable forecasting and prediction of effects of human behavior as well as natural phenomenon. It allows for simulation of programs and policies and predict its impact on future land use of a given area (Hedge et al., 2008). Awareness of such possible urban growth patterns and land use change is critical to a variety of stakeholders including city planners, resource managers, environmentalists, and policy makers, to name a few. Having knowledge of how land could change differently under various polices, programs and scenarios allow these stakeholders to engage in knowledgeable and productive planning, policy, and informed decision making (Hedge et al., 2008).

3.1. Early Urban Growth and Land Cover Change Modeling

The earliest spatial models explaining urban land use and urban growth can be seen in the writings of Johann Heinrich von Thunen in 1826. Von Thunen's theory stated that the agricultural land use decreases as the distance from the city increases in a pattern of rings that radiate out from the city center (Onsted, 2007). In this model, land use of a particular area is indicated as being influenced by the distance of the area from the markets and its geographic conditions (Rodrigue, 2015). This was originally used in the analysis of agricultural land use patterns in Germany and was driven on principles of economics, where the most productive agricultural actives yielding higher prices would be closest to the market, hence minimizing transportation cost and maximizing profits (Onsted, 2007; Rodrigue, 2015).

"Concentric Urban Land Use Pattern" published by Burgess in 1925, was one of the first models that specifically investigated land use patterns of urban areas (Qi, 2012; Rodrigue, 2015). This model emphasized the importance of transportation and mobility and was also based on concentric circles extending outward, with each ring representing specific socio economic urban landscapes (Rodrigue, 2015). Burgess' model of land use and urban growth could be considered as an adaptation of von Thunen's model (Rodrigue, 2015). "Central Place Theory" published by German urban geographer Christaller and economist Losch in 1930 and 1940 (Qi, 2012), and "Centripetal and Centrifugal Force Theory" published in 1931 by Colby at the University of Chicago (Batty, 2011; Qi, 2012) also employ a similar static model conceptualizing urban expansion.

The major drawback of the concentric model was that it overlooked the influence of transportation on urban growth and did not allow for the possibility of having multiple city centers and nuclei of growth (Rodrigue, 2015). This drawback was addressed by emergence of polycentric and zonal land use models in the late 1930s and 1940s (Rodrigue, 2015). A model proposed by Hoyt (1939), based on a study of residential areas of North America, stated that land use pattern and growth were not sharply defined as concentric circles but rather were sectors within a circle and major transportation corridors were responsible for defining these sectors (Rodrigue, 2015). Harris and Ullman (1945) proposed a model which also stated that cities did not grow around central business district but rather developed as nodes. These nodes were further differentiate and specialized based on factors such as accessibility, proximity interactions with other similar or different areas, as well as location suitability based on price, rent and so on (Rodrigue, 2015). Following these concepts of land use and urban growth, hybrid models, such as that by Isard (1955), were developed in the latter half of the 1950. These models amalgamated the behaviors of various concentric, sector, and nuclei models into one model to explain land use change and urban growth (Rodrigue, 2015). The limitations of these traditional models have been their static and linear nature, which made it difficult to encompass and generate certain parameters such as complex surface features. Furthermore, these models focus mostly on large geographic units such as administrative regions which provided insufficient spatial information for setting up detailed land use and growth models (Qi, 2012).

The start of modern urban growth modeling can be traced to the late 1950s, with the development of a large number of theories of urban expansion based on urban geometry, size relationships, economics, and growth patterns (Oguz, 2004; Rafiee, Mahiny and Gholamalifard, 2007; Mahiny, Khorsani and Darvishsefat, 2009). One of the major developments that occurred in the late 1960s was the advancement of dynamic urban modeling. This included development of kinetic models that were based on differential equations and the development of discrete kinetic models that employed cellular automata (Qi, 2012). Dynamic modeling with differential equations had been the dominant trend, which involves the use of variables representing social and economic trends and relies on the process of interaction and feedback between these variables for computation (Qi, 2012). The drawback of these type of dynamic models was their limited ability to represent complex systems with large numbers of factors affecting the urban dynamics. This resulted in a poor performance of these models when calculating future land use and growth trajectories (Batty and Xie, 1994).

3.2. Cellular Automata based Urban Growth and Land Use Modeling

A revolution in spatial modeling and prediction was seen after the development of Cellular Automata in the 1940s by Ulam and its implementation by Von Newmann to investigate the logical nature of self-reproducible systems (Li and Yeh, 1998; Hedge et al., 2008). The CA model is a discrete dynamic model capable of handling complex systems. The basic elements of a CA system includes: cell, state, neighborhoods and the rules. The relationship between the elements can be seen with the state of the cell changing based on transition rules which are further dictated by the nature of its neighborhood cells (Sevik, 2006).

CA models have been applied to a wide range of problems involving spatially complex systems, including: modeling of discrete entities such as for ecological systems and population dynamics, modeling of emergent phenomenon such as evolution, earthquakes and spread of wild fire, for pattern recognition such as prediction of traffic, land cover land use and urban growth patterns and so on (Sevik, 2006; Hedge et al., 2008). For this research, CA is applied to modeling urban growth and land use change.

One of the most influential researchers in the application of CA for urban growth modeling, Michael Batty, described the concept of modeling using CA as "a process of understanding cities through their local properties, which would then be aggregated to reveal naturally forming properties of the city" (Batty and Xie, 1994). CA provides a means to represent a complex system like the urban environment in a single model (Li, 2014). In contrast to other models that employ a top-down approach, CA models implement a bottom-up approach (Batty and Xie, 1994; Batty, 2011). Rather than being dictated by overarching equations and functions, the CA method relies on a combination of rules that command the state of the cell, transition of the cell, and the impact of its neighboring cells (Qi, 2012). In addition to CA, other discrete dynamic models that have been used for land cover change analysis include the Diffusion Limited Aggregation model, Percolation model, and Multi-agent model (Qi, 2012, Hua et al., 2014).

CA is particularly well suited for modeling land cover and urban growth because of the regular, two-dimensional grid of identical cells (i.e., raster grid) on which it is based. These cells provide an excellent representation of zonal geography of the area of study, with each cell representing the attributes present in the area at that particular location of the cell (O'Sullivan and Torrens, 2000). Additionally, use of CA provides the ability to apply transition rules through local neighborhood interactions between surrounding cells and allows the model to take into account global external constraints on the area of study due to various anthropogenic or environmental factors (O'Sullivan and Torrens, 2000).

Moreover, as CA develops over the allotted time steps, it exhibits a bi-fractal structure which is characterized by the development of two or more zones, with the inner core comprising of compact built areas and the outer zone characterized by a sprawl. This feature of CA is indicative of bi-fractal structure also exhibited by an expanding city that has a well-developed central core and a sprawling outer fringes where urban growth is still occurring (Torrence, 2000).

Rapid development of GIS applications, their availability, and increased computing power have helped enable extensive application of CA in the study of urban dynamics and land use. Linking CA to GIS has allowed for a development of a symbiotic relationship, where use of CA has alleviated some of the limitations by providing a tool within the current GIS application to preform fast iterative computations (Sevik, 2006). GIS has provided a sophisticated system for data management, definition of transition rules and constraints, and an overall frame work for programming and executing spatial CA models (Sevik, 2006).

Following an extensive literature review, Qi (2012) segmented CA models focused on urban dynamics into three categories: i) pure theoretical urban evolution research based on CA models; ii) urban expansion simulation based on CA models; and iii) urban planning schemes based on CA model (Qi, 2012). SLEUTH falls into Qi's second category of models that simulate urban expansion, along with others land change models such as Dynamic Urban Evolution Model, Multi Criteria Evaluation-CA model, multi-agent system-CA model, Geo-CA model, and Markov-CA (Hua et al., 2014).

3.3. Modeling using SLEUTH

Among the various CA models that have been developed, SLEUTH has been one of the most prominent, well-established and well-researched (Oguz, 2004; Clarke et al., 2007; Onsted, 2007; Jantz et al. 2014). The SLEUTH urban land use model was developed by Dr. Keith C. Clarke of University of California Santa Barbara. It evolved from a model used for simulating spread and behavior of wildfire, also developed by Dr. Clarke (Clarke et al., 2007; Chaudhuri and Clarke, 2012). The acronym SLEUTH is derived from an abbreviation of the inputs required for the model, which are: Slope, Land use, Exclusion, Urban extent, Transportation, and Hillshade. These input parameters can be manipulated to interact with the model in order to set limitations and boundaries to reproduce various real world development scenarios within the model (Silva and Clarke, 2002). SLEUTH uses these inputs in its urban growth and land cover deltatron sub-models to determine the rules that dictate the transition between states of individual cells within the CA for a particular location (Chaudhuri and Clarke, 2014).

Based on the research by Dietzel and Clarke (2006), SLEUTH has the capability of merging detailed high resolution land use data with a tried and tested urban growth model. It has been widely applied to a variety of different places with in US, including in San Francisco, CA and Washington Bay areas to examine historical urbanization (Clarke et al., 1997); in Sioux Falls, SD to compare calibration strategies for the SLEUTH model (Goldstein, 2004); in Atlanta, GA (Yang and Lo, 2003; Yang 2004), Detroit, MI (Richards, 2002), and Albuquerque, NM (Hester, 1999; Hester and Feller, 2002) for modeling land use change. And has also been implemented internationally in multiple cities in China (NCGIA, 2015), Hyderabad, India (KantaKumar et al., 2011), Lisbon, Portugal (Silva and Clarke, 2002), Cape Town, South Africa (Watkiss, 2008), and Younde, Cameroon (Sietchiping, 2004).

4. The SLEUTH model

The basic structure of the SLEUTH model consists of the inputs required for the model, the two sub-models within SLEUTH – Land Cover Deltatron and Urban Growth Model, the calibration process that is needed to customize the model for area of study (in this case Albuquerque), and the self-modification or feedback process.

4.1. Inputs for the SLEUTH model

SLEUTH requires a particular set of inputs in a predefined format to execute. All of the inputs in the model must be provided as 8-bit raster - GIF format, with each input having the same number of row and columns. These inputs should be located in a designated "Input" directory and must follow the naming conventions dictated by the model (Al-shalabi, 2013). The inputs required for SLEUTH include: Slope, Land use, Exclusion (excluded areas), Urban extent, Transportation and Hillshade.

4.1.1. Slope

The slope input provides the topographic information for the model. Since urbanization of an area can be directly linked to topography, with greater urbanization and urban sprawl taking place in flatter and broader areas than in areas with higher gradients, slope is considered as one of the essential parts of the model (Qi, 2012). The slope of the area being considered is unlikely to change drastically over the modeling period, so only one static slope layer is sufficient for the model (NCGIA, 2015). This layer can be derived using a digital elevation model. The cell values within the layer must be in percent slope instead of degrees and the pixel value ranges from 0 to 100 (NCGIA, 2015).

4.1.2. Land use

The land use input, as the name suggests, provides land use information of the area. It is used to predict the transition probability of a cell between various land use classes based on its neighborhood cells and historic transition probabilities (Clarke, 1997; Chaudhuri and Clarke, 2012). This input, however, is not necessary for simulating the urban growth patterns of a given area (Dietzel and Clarke, 2007), but in order to simulate land use change, at least two land use layers with consistent classification from two different time periods is required (Dietzel and Clarke, 2007). The pixel value for the input ranges from 0 to 255 (NCGIA, 2015)

4.1.3. Exclusion

The exclusion layer is used to specify areas such as water bodies and designated open areas that are prohibited from urban development. Additionally, this layer can be used as a resistance layer to allow variation in the rate of urbanization for defined locations based on the weights provided for the locations (Dietzel and Clarke, 2007). The weights provided for the excluded layer range from 0 to 100, with values closer to 0 having the highest probability of urbanization, and with values closer to 100 having little or no probability of urbanization (Qi, 2012). The ability to manipulate the weights in the exclusion layer permits for delineation of specific areas that might be more or less prone to urbanization. This exclusion layer therefore allows for integration of various policies, programs and scenarios to be represented by the model. For example, an area that has been designated for further urban development can be represented by a value closer to 0 as compared to an area that has been protected from development, which can be represented by a value closer to 100 (Qi, 2012). The pixel values for the layer ranges from 0 – 255 however, all values that are greater than 100 are read as100 (i.e., areas with no probability of urbanization) (NCGIA, 2015).

4.1.4. Urban extent

The urban extent is one of the most data-intensive inputs; requiring map layers from four different points in time periods. This input provides information on urbanized area for a given location and serves as a reference for the calibration of the model and a basis on which the goodness of fit of the model is determined (Dietzel and Clarke, 2007). The urban extent layer that is at the earliest point in time is considered the “seed” layer from which the start of urban growth and change occurs (Clarke et al., 1996; Dietzel and Clarke, 2007; NCGIA, 2015). The rest of the layers are known as the "Control Years" that are used in assessing the least square best fit values in the calibration process (NCGIA, 2015; Dietzel and Clarke, 2007). The urban extent layer only requires a binary classification of urban and non-urban pixels. The pixel values for the layer ranges from 0 to 255 with 0 being non-urban areas and the rest of the non-zero values being defined as urban areas (NCGIA, 2015).

4.1.5. Transportation

The transportation layer is another data-intensive input requiring at least two input layers from different points in time characterizing the growth in transportation network. This allows for the simulation of higher intensity of urban growth in areas that are accessible by roads (NCGIA, 2015). This layer can be classified as either binary (road/no-road) or with relative values. The pixel value for the layer ranges from 0 to 255 with 0 value indicating no roads (NCGIA, 2015). Road networks with relative values in the transportation layer are defined in a weighted hierarchal fashion, with roads such as Interstates and US highways getting higher values and local roads (e.g., rural roads) getting low values. Roads with higher values, such as highways, allow for a larger distance to be travelled along the road for urbanization, and hence allows for urbanization to occur further along the road network, whereas roads with a lower value have a more localized effect on urbanization (NCGIA, 2015)

4.1.6. Hillshade

Hillshade is the only input that does not affect the behavior of the model. Although, as with slope, it provides information about the topography of the area, it is only used for visualization purposes (Dietzel and Carke 2007). Only one hillshade layer is required as an input.

4.2. SLEUTH Sub-Models

SLEUTH is a CA model that couples two sub-models: the Land Cover Deltatron (LCD) Model, used for the simulation of transition between various land use states and Clark's Urban Growth Model (UGM), used for the simulation of urban growth (Clarke, 1997; KantaKumar, Sawant and Kumar 2011; NCGIA, 2015;).

4.2.1. Land Cover Deltatron (LCD) Model

The Land Cover Deltatron (LCD) model, also known as the Deltatron Land use Model (DLM) (Candau et al., 2000), is an optional sub-model within SLEUTH that may or may not be executed based on the preference of the user. The LCD model is used in the land use change analysis for the area of study. This sub-model implements deltatrons cells, which do not change themselves but rather are "bringers of change" to stimulate the transition of its neighboring cells to some other land use class (Candau and Clarke, 2000). The model uses the following three factors along with some degree of randomness to determine these deltatron cells: probability of a cell transitioning into another land cover type, influence exerted by the local topography in the area and, urban and historical drivers influencing the area (Candau and Clarke, 2000; Clarke, 1997). Two land use layers are used in the LCD model to calculate the probability of class-to-class transitions (Chaudhuri and Clarke, 2012). This model is only triggered if land use is activated and is being analyzed but is not triggered if only urban growth is being examined (Oguz, 2004).

4.2.2. Urban Growth Model (UGM)

The Urban Growth Model (UGM) determines the probability of urbanization of a particular cell within the CA using a set of four predefined growth rules that simulate urban expansion, which are further governed by five growth coefficients or control parameters, it's relationship is illustrated in Fig. 2.1 (Clarke et al., 1996; Clarke and Gaydos 1998; Oguz, 2004; KantaKumar et al., 2011; Chaudhuri and Clarke, 2014).

4.2.2.1. Growth Rules

The four growth rules that are applied in the prediction of urban growth are as follows: i) Spontaneous, ii) Diffusive (New Center), iii) Edge (organic) and iv) Road influenced growth. These growth rules are further determined by five growth coefficients discussed in the next section.

Spontaneous growth simulates urban growth in low density areas that are not close to any existing urban centers or transportation infrastructure (Oguz, 2004). For spontaneous growth to occur, the model requires only for a cell to have a desirable location. The desirability of a location for urbanization in SLEUTH is based on the exclusion layer and slope input layers. Urbanization is not possible in certain areas of the exclusion layer, such as bodies of water, and in locations with slope greater than percentage specified by the user with the default being 15 percent (Clarke et al., 1996; Oguz, 2004). Barring areas excluded from urbanization, every other individual cell has a small probability of transitioning into an urbanized cell by means of spontaneous growth if it meets the urban growth criteria (NCGIA, 2015).

Diffusive (New Center) growth simulates growth around a new urban center. It defines if a cell would become a new center of growth from which urbanization spreads (Oguz, 2004). For a cell to be defined as a center for new urbanization, based on growth coefficients, two adjoining cells would have to be available for urbanization (NCGIA, 2015).

Organic or the edge growth simulates urban growth that spreads from an already existing or newly formed urban center outwards toward the edges, representing the expansion of the urban area (Clarke et al., 1996; Oguz, 2004).

Road-influenced growth simulates urban growth that takes places due to transportation infrastructure leading to increased accessibility and connectivity. This growth is highly influenced by urbanization occurring as a result of the three previously mentioned growth types (Clarke et al., 1996; Oguz, 2004).

4.2.2.2. Growth Coefficients

The behavior of growth rules for urbanization is further influenced by a set of five control parameters or coefficients values: 1) dispersion coefficient, 2) breed coefficient, 3) spread coefficient, 4) road gravity, and 5) slope resistance factor, each with a value ranging from 0 to 100 (Oguz, 2004; Qi, 2012; Chaudhuri and Clarke, 2014). Through the calibration process, SLEUTH aids in calculation of the optimal combination of these growth coefficients for the growth rules based on the characteristics of the inputs for the study area (Qi, 2012).

In the model, dispersion, also known as diffusion coefficient, defines the number of times a cell is randomly chosen for possible urbanization (NCGIA, 2015). It is responsible for initiating spontaneous growth by randomly selecting potential cells for urbanization (Oguz, 2004) and also controls the behavior of road influenced growth by determining the pixel in or around the road network that would be urbanized based on "random walks" along the road network (Oguz, 2004; Qi, 2012; NCGIA, 2015).

The breed coefficient is responsible for predicting the probability of a cell being urbanized during spontaneous growth. It influences diffusive growth by determining the spreading point of urbanization and provokes road influenced growth by determining the spread along the road (Oguz, 2004; Caglioni et al., 2006).

Spread coefficient influences the edge growth where it determines the probability of a cell generating additional urban cells in the neighborhood of an already urbanized cell (Qi, 2012).

Slope coefficient determines the likelihood of urbanization for a particular cell based on the steepness of the slope, and has equal impact on all the growth rules. For any cell, if the slope gradient exceeds the critical slope defined by the user, then urbanization does not take place regardless of the favorability of other (Hui-Hui, 2012).

Finally, the road gravity coefficient impacts road-influenced growth and determines the maximum radius along the road network within with urbanization is probable (Oguz, 2004; Qi, 2012; Chaudhuri and Clarke, 2014).

4.3. Calibration of SLEUTH

The process of calibration can be compared to the process of "learning" by the model based on the available information and data (Clarke, 2008). Calibration is the process of training the general purpose SLEUTH model to represent a specific urban area that is being analyzed, such as Albuquerque (Oguz, 2004). The calibration of parameters within SLEUTH is complex, time consuming, and is considered one of the most crucial phases of the simulation process (Oguz, 2004; Qi, 2012). Calibration is preformed using statistical and spatial information of the past to predict a known future, then comparing this prediction produced by the model with the actual observed information for the location being studied and using this information to adjust the next phase of calibration to further fine-tune the replication of the actual observation within model (Clarke et al., 1996; Oguz, 2004; Clarke-Lauer and Clarke, 2011; KantaKumar et al. 2012).

The standard method of calibration of SLEUTH is known as "Brute Force" calibration. The alternative to brute force calibration is a user developed variant of SLEUTH that uses a separate Generic Algorithm in the calibration process. As compared to genetic algorithm calibration, brute force calibration is a well-defined, documented and researched process. So, for the purpose of this research brute force calibration process will be used.

4.3.1. Brute Force Calibration

The brute force method of calibration utilizes a Monte Carlo simulation to produce coefficient values for the five urban growth coefficients (Oliveri, 2004; Clarke-Lauer and Clarke, 2011). It is a sequential method of calibration that is completed in three phases – Coarse, Fine, and Final. Starting from a coarse phase, the number of Monte Carlo iterations are increased at every phase while the range of the coefficients are narrowed based on the calibration results from the previous phase (Oguz, 2004; Oliveri, 2004;

Dietzel and Clarke, 2007).

In the “Coarse” phase, the entire range of possible coefficients values from 0 to 100 with an interval step of 25 units is used for all the five growth coefficients. The range of best fit values derived from the “Coarse” calibration phase is used to narrow down the range of coefficients used in the “Fine” phase of the calibration process. In the “Fine” phase, coefficient values that had been narrowed down using results derived from “Coarse” phase are used as input with step increments of 5 – 10 units between the lowest and the highest predicted coefficients. Lastly, the range of best fit values derived from the “Fine” phase is used to further narrow down the range of the coefficients and step interval of 1 – 3 units between the lowest and the highest predicted coefficients is used to determine the “Final” value for the calibration (NCGIA, 2015). Each phase of the calibration produces thirteen goodness of fit metrics of the current run (See Table 1.1) (Dietzel and Clarke, 2007).

Selecting the ideal goodness of fit metrics for narrowing the coefficient ranges in the process of calibration has been an ongoing discussion among the users of SLEUTH (NCGIA, 2015). Over the years, researchers have used various metrics to evaluate the coefficient ranges in the calibration process: Jantz et al. (2004) used the *compare*, *population* and *Lee-Sallee* statistics; Jantz et al. (2014) used *cluster, edge* and *area*; Yi and and Lo (2003) created a weighted sum of all the metrics (Dietzel and Clarke, 2007), but the most popular has been the stand-alone *Lee-Sallee* metric as the best fit metric (Dietzel and Clarke, 2007). Some researchers that have used the *Lee-Sallee* metric include Sylva and Clarke (2002), Jantz et al. (2003), Dietzel and Clarke (2004), Oguz (2004, 2007), Qi (2012), and Hui-Hui (2012). The Lee-Sallee metric is defined as the “ratio of the intersection and the union of the simulated and actual urban areas” (Dietzel and Clarke, 2007; Qi, 2012) or,

$$\text{Lee-Sallee} = (A \cap B) / (A \cup B) \tag{1}$$

It measures the degree of match between the growth predicted by the model with the actual extent of urban growth that has been seen in the control years (Silva and Clarke, 2002). This index is comparable in interpretation to the r-square value used in statistics, with a range from 0 to 1 and 1 being a perfect fit (Clarke et al., 1996).

Using either a single metric or a combination of multiple metrics as the best option to determine a robust goodness of fit has been a controversial subject. When using a combination of the thirteen metrics, there have been a number of metrics that appear to be correlated with each other, leading to a bias in the best fit result (Dietzel and Clarke, 2007). Subsequently, omissions of certain metrics from the analysis have led to a low goodness of fit results (Dietzel and Clarke, 2007).

The Optimal SLEUTH Metrics (OSM) created by Dietzel and Clarke (2007) addresses the issue of creating the best goodness of fit results for the SLEUTH model based on the available metrics. To create OSM, Dietzel and Clarke (2007) identified and eliminated redundant metrics and maintained metrics that are most influential in determining the accuracy level of the predicted urban growth. This metric developed as a result of the research has been formulated as a product of *compare, population, edges, cluster, slope, x-mean, and y-mean* metrics (Dietzel and Clarke, 2007). Since its inception, OSM has served as the de facto calibration metric. The drawback of calibration metrics that have been derived from a combination of other metrics, such as OSM, has been the inconsistency of results when comparing it with other metrics produced in the calibration process (Jantz and Goetz, 2005). These inconsistencies have led to an increased difficulty in interpreting the results of these combined metrics (Jantz and Goetz, 2005).

4.4. Self-Modification in SLEUTH

Another important aspect of the SLEUTH model is self-modification. In addition to the four growth rules (spontaneous, diffusive, organic and road influenced), the self-modification process has been considered as a second level or “meta” growth rule providing a feedback for the SLEUTH model (Herold et al., 2002; Chaudhuri and Clarke, 2012; NCGIA, 2015). This can be compared to the process of adaptation or evolution within the model (Oguz, 2004) that allows for a more realistic simulation of growth by avoiding linear and exponential urban growth (Jantz et al., 2010; Chaudhuri and Clarke, 2012).

The process of self-modification comes into play when the growth rate exceeds a particular predefined critical threshold and affects three growth parameters – diffusion, breed, and spread (Sietchiping 2004; Jantz et al., 2010; NCGIA, 2015). The growth rate is defined as the sum of the four growth types for each time step (Charke and Hoppen, 1997; NCGIA, 2015). When the growth rate exceeds a predefined Critical High level, it initiates a Boom cycle or an expansion in urban growth (Jantz et al., 2010). This is simulated in the model by multiplying the three growth coefficients by a predefined factor greater than one (NCGIA, 2015). This in turn encourages diffusive, organic and road influenced growth to occur (Clarke and Hoppen 1997). Over the growth cycle of an expanding city, the growth rate increases more rapidly at the beginning of the growth cycle as urban development starts taking up more land, the availability of land for urbanization gets saturated and the growth rate slows down until it reaches a Critical Low (Sietchiping 2004). This growth rate, if it falls below a predefined Critical Low levels, a Bust cycle is initiated by the model (Jantz et al., 2010). This Bust cycle is simulated by multiplying the three growth coefficients by a predefined factor of less than one, causing the growth to taper off (Jantz et al., 2010; NCGIA, 2015). The predefined default values of Critical Low, Critical High and the corresponding multiplier for Boom and Bust within SLEUTH are set by examining the historical growth rates of the cities through a process of trial and error (Clarke, 2008; C. Jantz, personal communication, September 20, 2015).

4.5. Execution of SLEUTH

The structure of the SLEUTH model, as shown in Fig. 2.2, can be divided in to three parts: Initial Condition, Growth Cycles and Concluding Simulation. Initial condition includes the input files, which contains the seed layer from which the urban growth is predicted and the preliminary set of coefficient values for the growth rules derived through calibration. The growth cycle is the core of the SLEUTH model. The number of growth cycle iterations corresponds to the number of time steps, or number of years, between the initial year and the final year for which the simulation or forecast is performed. During the growth cycle, the two sub-models, UGM and LCD, and the self-modification processes, are executed. The conclude simulation phase consists of applying the final values computed during the growth cycle and using these values for simulation and prediction to produce statistical data and raster maps representing urban growth forecasts and land use change.

The SLEUTH model is executed in three different modes sequentially: test mode, calibration mode and the prediction mode. The test mode is executed prior to calibration and prediction modes. It is mainly used to verify the correctness and specificity of the data as required by the model and gauge the initial reaction of the model to the data (Sevik, 2006). During the test mode, only one growth cycle is executed and no calibration of coefficients takes place. The final stage of this mode generates statistical data as well as image files representing annual land cover change (NCGIA, 2015).

The calibration mode is used for the purpose of determining the best fit value for the growth coefficients so that it accurately represents the real growth pattern that is occurring in the area of interest (Sevik, 2006). In this mode, during each phase of brute force calibration, UGM and the LCD sub-models are executed for the specified number of Monte Carlo iterations. The growth cycle ends after all three brute force calibration phases are completed and the final best fit value for the coefficients has been derived. The last stage of this mode produces several output statistics and provides an option of producing image files based on the preferences defined by the user.

The final prediction mode is used in forecasting the future of urban growth and land use change for the study area. During the execution of SLEUTH in this mode, the best fit value for the coefficients derived during calibration is used for the forecast. The final stage of this mode, based on the preference of the user, creates data files producing statistics on the goodness of fit metrics, value of growth coefficients during each Monte Carlo iteration, memory storage and system performance along with image files representing the forecasted urban growth and land use (NCGIA, 2015).

4.6. Advantages of SLEUTH

There are certain elements within SLEUTH that make it particularly attractive for the purpose of investigating and predicting land use change and urban growth of Albuquerque. First, SLEUTH is specifically geared toward modeling and predicting urban growth based on historical trends. It uses the Urban Growth Model developed by Dr. Keith Clarke in conjunction with the cellular automata-based Land Cover Deltatron model that explores land cover change (Clarke, 1997) to model the urban dynamics within the area. Second, the model can be applied to any geographic system at any extent and resolution using a wide array of input data resolutions (Rafiee et al., 2009), as demonstrated by the broad application of the model in various parts of the U.S., including Albuquerque, and worldwide from India to Portugal to Cameroon and Egypt (NCGIA, 2015). Third, the model has seen a constant refinement over the years either by the developers or by independent researchers, and is still regularly being used for research and modeling. The latest version of the model, SLEUTH-3r, published in 2005, has addressed problematic issues from previous versions of the model. Additionally, other models based on SLEUTH have also been developed that have customized the base SLEUTH model as per the requirements of the researchers. Fourth, there is a well-established online support group for the users of the model through discussion boards and forums (Rafiee et al., 2009). Finally, SLEUTH is a shareware and allows researchers free access to the software (Rafiee 2009; NCGIA, 2015).

4.7. Limitation of SLEUTH

Models are abstract representations of reality. Subsequently, all models suffer from certain limitations and drawbacks in their abstraction of reality. SLEUTH is no exception. Though SLEUTH is a tried and tested model with a relatively high rate of accuracy in predicting urban growth and land use change, there have been numerous criticisms and limitations associated with it.

One of the major limitation of this model, as with all other forecast models, is its ability to predict changes occurring in the near future with a higher accuracy than those occurring in the more distant future (Chaudhuri and Clarke, 2014). Research by Chaudhuri and Clarke (2014) indicates that SLEUTH prediction for 10 years tend to be within the tolerable levels of accuracy of 0.7 or more (i.e., ????) but beyond 10 years the prediction becomes more uncertain. Goldstein et al. (2004) concludes that the prediction accuracy and capability of SLEUTH is largely a product of the number of years for which historical data is available for calibration. There has also been debate on where the inaccuracies in the outcome predicted by the model mainly lie. Literature indicates SLEUTH exhibiting inaccuracies in both location (Wu et al., 2009) and quantity prediction (Pointus et al., 2008). Research show that SLEUTH has a tendency to over fit and exaggerate the prediction by forecasting higher levels of growth than what actually would have occurred, thus leading to these inaccuracy (Pointus et al., 2008).

Another limitation of SLEUTH is the subjective nature of the model while choosing best fit metrics. The inaccuracy of location or quantity for the model tends to be sensitive to the type of best fit metrics chosen during the calibration phase and the number of Monte Carlo iterations preformed (Wu et al., 2009). However, it should be noted that extending the number of Monte Carlo iterations has diminishing returns as almost all variance is captured in the first few iterations (Clarke, 2008).

The accuracy of the SLEUTH model also tends to depend on the spatial scale of the input data. When coarser scale land use data are used as the input, even though the spatial resolution of the overall output goes down, the location accuracy and the neighborhood relationship seems to improve (Jantz and Goetz, 2005; Wu et al., 2009; Otis, 2012). A bias within SLEUTH favoring edge (organic) growth while using finer resolution data also limits the ability of the model to simulate urban growth from less organic and a more random origins. This is expected to be a factor contributing to errors in prediction (Wu et al., 2009; Jantz et al., 2010).

The other prominent drawback cited for SLEUTH has been the computation time required for the model in the calibration phase. Depending on the size of the area being investigated, the time required for the calibration process can range anywhere from 27 hours (Chaudhuri and Clarke, 2012) to several months (Clarke-Laure and Clarke 2011); a product of inefficient use of computer memory by the program (Chaudhuri and Clarke, 2012).

4.8. Evolution of SLEUTH

The SLEUTH model has been in a constant process of evolution, development, and refinement since its inception as the Urban Growth Model (Clarke et al., 2007; Chaudhuri and Clarke, 2012). The latest version of the model, SLEUTH 3-r model, also known as SLEUTH3.0 beta, was released in 2005 (NCGIA, 2015). The SLEUTH 3-r version has tried to address some of the reoccurring issues within SLEUTH. The tendency of the SLEUTH model to preference edge growth, especially for finer resolution data, while the spontaneous growth remains relatively dormant, has been acknowledged by allowing the diffusion growth multiplier to be interactive rather than a constant as in the previous version (Jantz et al., 2010; Chaudhuri and Clarke, 2012). This has allowed the users to manually set the multiplier value before the calibration is initiated based on observation and historical growth rates.

Additionally, the problem with inefficient use of memory was also addressed by modifying SLEUTH’s source code. The changes made in the new version improved on the allocation of memory for internal cell grids and created a more efficient algorithm for road growth, the most time-consuming activity in growth simulation (Jantz et al., 2010). This reduced the overall memory use of the model by approximately 65% (Jantz et al., 2014) and increased the processing speed. It also upgraded the calibration statistic options by adding new goodness of fit metrics and addressed the issue of scale sensitivity using an interactive platform to set model coefficients (Jantz et al., 2010). New fit metrics that were not available in the previous version include Compare, Edge, Cluster, Cluster size, Slope, % Urban, X-Mean, Y-mean, and Radius (See Table 1.1 for description of each metric) (Jantz et al., 2010).

Independent researchers have taken the basic model of SLEUTH and specifically tailored it based on their particular requirements. Some of the other versions of SLEUTH that have been developed since its inception include p-SLEUTH, developed by Qingfeng (Gene) Guan of University of California, Santa Barbara (Guan, 2008). Customization of the original SLEUTH model for P-SLEUTH came from introduction of parallel raster processing programming language that allowed the new model to further improve processing speed in the calibration process hence, providing the ability to execute a more detailed calibration processes efficiently (Guan and Clarke, 2010). The SLEUTH-GA was another variation of SLEUTH developed by Goldstein that involved calibration employing a Genetic Algorithm (GA) instead of the traditional brute force mechanism (Goldstein, 2004). The SLEUTH-GA models tested by Goldstein (2004) and Clarke-Lauer and Clarke (2011) indicated a decrease in calibration time without a significant change in the goodness of fit of the model (Chaudhuri and Clarke, 2012).

The SLEUTH model has also been used in combination with other models representing social and physical scenarios to analyze various environmental dynamics. To name a few: SLEUTH has been coupled with an urban runoff model by Arthur (2001) to study the effect of urbanization in local microclimate and surface hydrology. It has been used in conjunction with Multi-Criteria Evaluation to examine land fill suitability in Iran and Brazil (Siddique et al., 1996; Mahiny and Gholamalifard, 2011), SLEUTH has been coupled with the LANDIS landscape model to look at the effects of urban development in fire frequency (Syphard et al., 2007).

Even with the SLEUTH model being close to 20 years old, continuous application and modification, along with online support, has kept this model relevant, functioning and effective.

5. Methodology

The primary aim of this research was to examine the historical urban growth of Albuquerque, NM over the past 20 years and, based on it, use the SLEUTH model to predict the trend and pattern of urban growth and land use change for the next 20 years, till 2035. In particular, this research investigated two scenarios: ‘Business as usual scenario’ and ‘Expansion scenario’.

In the business as usual scenario, the prediction of urban growth and land use change of Albuquerque was be based on the historic and current patterns of urban expansion of Albuquerque. Here, land designated for the three development projects were not explicitly defined. Instead, the growth was expected to follow the current pattern of urbanization providing information on how urban growth pattern would have looked like if the three development areas had not been commissioned.

In the expansion scenario, prediction of urban growth and land use change of Albuquerque was based on the historic rate of urban expansion pattern but with an explicit definition for the three development areas. This allowed SLEUTH to model these areas as being more receptive to urban growth and having a high probability of transitioning into an urban land use state over the next 20 years. This scenario was based on the assumption that over the next two decades there will be substantial construction and development of the reserve areas.

Additionally, the research examined urban growth and land use change based on two growth rates. Firstly, a low growth rate, based on population growth of the last 10 years and, secondly, a high growth rate based on prediction by Mid-Region Council of Governments of New Mexico for 2040.

5.1. Data

Data used for inputs in the SLEUTH model along with some of its attributes are shown in Table 1.2. Data downloaded from the sources listed in the table was further processed and prepared based on the specifications for the model. The input data for Slope (See Fig. 3.1 a) and Hillshade (See Fig. 3.1 b) was derived from a 30 meter DEM acquired from the RGIS website, a part of Earth Data Analysis Center at UNM. The Land use data for 2001 and 2011 as shown in Fig. 3.2 was acquired from Multi-Resolution Land Characteristics Consortium's (MRLC) National Land Cover Database (NLCD) website. The NLCD land cover data was derived from LANDSAT images, with 20 land cover categories (Multi-Resolution Land Characteristics Consortium, 2015). For the purposes of this research, these categories were reclassified into five broad categories namely: Vegetation, Urban, Barren, Agriculture and Water bodies. The process of reclassification is shown in Table 1.3.

Urban extent data, as shown in Fig. 3.3, for the model was derived from NLCD land use data and was reclassified to urban/non-urban. To produce the urban extent data, classification of areas identified as urban under the new classification scheme (See Table 1.3) was retained whereas all other categories were reclassified as non-urban. Areas classified as urban were given a value of 100 and those classified as non-urban were given a value of 0. Transportation data, as shown in Fig. 3.4, originally a vector layer, was derived from the Topologically Integrated Geographic Encoding and Referencing (TIGER) data and rasterized to the NLCD grid. The road pixels within the rasterized data were weighted based on the type of the road. Pixels that were identified as US interstate highways, interstate off and on ramps, and interstate frontage roads were given a higher relative value of 75 based on the accessibility whereas rest of the roads within Albuquerque were given a lower relative value of 20 to produce a more localized effect (NCGIA, 2015).

The Exclusion layers, shown in Fig. 3.5 a and Fig. 3.5 b, designated the attractiveness of a particular pixel to convert into urbanized pixel. Pixels with a value of 100 were excluded from development and were not allowed to convert to urban pixels, whereas pixels with value of 0 were not excluded from development and had the freedom to convert to urban pixels. Jantz et al. (2010), in the paper "Designing and implementing a regional urban modeling system using the SLEUTH cellular urban model", utilized the exclusion layer to define the degree attractiveness of a pixel for urbanization. Instead of having zero as the default base value for areas where urbanization is allowed, a value of 50 was designated as the base value allowing for additional flexibility in the calibration and forecasting using this method. Pixels having a value of less than 50 were considered as pixels with a higher affinity to urban growth and thus were more likely to be developed. Whereas pixels with values greater than 50 were considered as pixels having a lower affinity to urban growth and development and were less likely to be developed (Jantz et al., 2010).

In the exclusion data layer for the business as usual scenario (See Fig. 3.5 a), pixels within areas marked as opens spaces, water bodies, airports and army bases, i.e. areas excluded from development, were given a value of 100. Pixels for rest of Albuquerque, where development was allowed, were given a base value of 50.

For the expansion scenario, pixels in areas corresponding to Mesa del Sol, Volcano Mesa and Santolina were given a value of less than 50, indicating that these areas had a higher affinity to urban growth when compared to all the other areas. Additionally, since Mesa del Sol was the only development area of the three where construction of residential or commercial areas had taken place, the probability of further development taking place in this area was perceived as being higher compared to the other two projects. Therefore, based on these criteria Mesa del Sol was given the lowest exclusion value of 20 (See Fig. 3.5 b). This signified that even within the three areas, based on the historical and current development status, Mesa del Sol would have a higher likelihood for urban growth than the other two areas. Furthermore, due to the historically slow development of these massive construction projects, the values of the remaining development areas were justified to be higher than that of Meas del Sol and closer to 50. Based on their current development status, pixels within Volcano Mesa were given a value of 30 and those within Santolina were given a value of 35 (See Fig. 3.5 b).

The GIS data required for Mesa del Sol, Volcano Mesa and Santolina areas were requested from the Bernalillo County and Albuquerque City officials but were not obtained. So, these areas were digitized using available maps (See Fig. 1.1).

5.2. Analysis

All the processes involved with execution of the model was controlled by what is known as a "scenario file". A generic scenario file that was provided with the model was edited in order to personalize the model to fit and run the data for Albuquerque. Major portions of the scenario file that were edited will include: `I. PATH NAME VARIABLES` that defined the path pointing towards the input and output directories; `IV. Log File Preferences` that indicated which information to create logs of; `VII. MONTE CARLO ITERATIONS` that stated the number of Monte Carlo iteration to run, `VIII. COEFFICIENTS` that delineated the five growth coefficients after each brute force calibration process and during the prediction phase of the model; `IX. PREDICTION DATE RANGE` that showed the range of dates for which the model would be predicted, `X. INPUT IMAGES` that defined the input images; `XII. COLORABLE SETTINGS` used for defining the colors for the input and output maps, and `XIII SELF-MODIFICATION PARAMETERS` that defined the Boom and Bust criteria.

The initial run of the model was executed in the test mode to determine the compatibility of the data with the model. After the initial run, the process of brute force calibration was started and the model was executed in the coarse mode. As indicated by Jantz and Goetz (2005), using a combination of two or more goodness of fit metrics, such as the OSM, has shown to produce contradicting results when compared to using individual goodness of fit metrics. However, a further review of the literature and comparison between various goodness of fit metrics by Dietzel and Clarke (et al. 2007) revealed OSM to be a relatively robust metric compared to others for SLEUTH calibration. As a result, OSM was used in the calibration process for this research. The `control_stats.log` log file produced after running the coarse calibration, was used to narrow the range of `start` and `stop` values of the five growth coefficients based on the calculated OSM metrics. Using these values, the "fine" calibration phase was executed. A similar process was run to determine the values used for "final" calibration phase. The range of `start` and `stop` values resulting from the "final" calibration phase, was used to derive the `avg.log` file and extract the final coefficient values for the five growth coefficients. The result for the final values of the five growth coefficients yielded from the calibration process is illustrated in Table 1.4. The final calibration results indicate a very high breed and spread coefficients that directly influence diffusive and edge (organic) growth respectively, a relatively low diffusion coefficient and an extremely low road growth and slope coefficients. The SLEUTH model applies these five growth coefficients derived in the calibration process to the four growth rules to predict the growth pattern of Albuquerque.

To simulate these varying growth rates on which these growth patterns are based, the `BOOM` value and the `Critical High` values under `SELF-MODIFICATION PARAMETERS` in the scenario file were manipulated in the prediction mode. These self-modification values were based on trial and error to match the growth rate of Albuquerque (C. Jantz, personal communication, September 20, 2015). To simulate the current low growth rate, established from last 10 years of data, the Boom value was adjusted to 1.00, and the Critical High value was kept at the default of 1.30. To simulate a high growth rate, as shown in the forecast of Bernalillo County by Mid-Region Council of Governments of New Mexico for 2040, the Boom value was adjusted up to 1.2, providing a higher multiplier and the Critical High value was lowered to 1.2, providing a lower threshold for the boom multiplier to take effect.

5.3. Validation

There is a paucity of rigorous validation and performance evaluation in many studies that have applied the SLEUTH model (Wu et al., 2009). The implicit validation method for the SLEUTH model involves visual comparison, least sum square regression, and other goodness of fit statistics (Wu et al., 2009). But even with the "face validity" provided by the extensive use of the model by many researchers at various locations nationally and internationally, there are only few research examples where the model has been explicitly validated (Jantz et al., 2014).

One of the few explicit verification processes that have been investigated by researchers for the model includes the Relative Operation Characteristic (ROC) that was initially used by Pontius (2001) for land use change evaluation (Zhou et al.). ROC provides a method that “compares the likelihood of a given class occurring in a given location to a reference layer that denotes whether the class exists in reality” (Wu et al., 2009). Wu et al.’s (2008) implemented the ROC validation process to investigate the most robust goodness of fit metrics for SLEUTH and concluded that the index used during the calibration of the model is dependent on the specific goals of the research.

For the purpose of this research, initially, a statistical validation of the model was performed based on the process implemented by Jantz et al. (2003, 2014), Oguz (2004) and Al-Shalabi et al. (2012). Here, the model was initialized using 2006 urban extent data in the business as usual – low growth scenario to predict the growth for year 2011. Since only three years of historic data was used, as compared to the four years required by the model, the Self-modification function of SLEUTH was not initialized and thus the model simulated a linear growth (Jantz et al., 2010). Results that were predicted as urban areas by the SLEUTH model for 2011 were compared with the actual urban areas for 2011 using the Cohen’s Kappa Coefficient to analyze the degree of agreement between the actual and the predicted urban areas (McHugh 2012, PennState, 2015).

Cohen’s Kappa is defined by

$$\kappa = \frac{p - p_e}{1 - p_e} \tag{2}$$

Where κ is Cohen’s Kappa Coefficient, p is the proportion of units where there is actual agreement and p_e is the proportion of units where it is expected to agree by chance (McHugh, 2012). The value for the coefficient ranges from 0 to 1, with 1 indicating perfect match and 0 indicating perfect mismatch (McHugh, 2012).

However, based on Pontius and Millones’ (2011) research, Death to Kappa, that highlighted the misleading nature of this statistic and their recommendation of using quantity disagreement and allocation disagreement criteria for accuracy assessment and map comparison, the Lee-Salle metrics, a shape index metric, that looks at the spatial intersections between the simulated urban area and actual urban area, hence providing a location match (Lin et al., 2008), and, the F-Match metric, that looks at the ratio of number of pixels categorized into correct land use to the total sum of pixels categorized into correct and incorrect land use, consequently providing a quantity match (Lin et al., 2008), were used for comparison during validation.

6. Prediction and Results

6.1. Validation Results

Results for validation using Lee-Sallee and F-match metrics were derived as an outcome of the calibration process. Here, Lee-Sallee metrics value of 0.61 indicated a relatively high location match between the simulated and actual urban areas, and a high F-Match metrics value of 0.79 indicated a high of quantity match between the pixels.

For the purpose of statistical validation, the SLEUTH model was executed in the Predict mode with the starting prediction year of 2006 and end prediction year of 2011 for business as usual – low growth scenario. The results, as illustrated by Fig. 4.1, were used to compare the areas that were correctly predicted by the model as being urban and areas that were incorrectly predicted by the model as being urban. The area values produced through the confusion matrix, as shown in Table 1.5, were used to calculate the kappa coefficient.

Results from the confusion matrix comparison revealed a p value of 0.94, a p_e value of 0.53 producing a kappa coefficient of 0.88. This kappa value shows a strong agreement between the predicted and actual urban growth areas for 2011.

Outcomes of these validations suggested that the calibration results from the SLEUTH model derived for Albuquerque (i.e. the growth coefficients) produced a high degree of fit with the real world scenario and is likely to produce a relatively high level of accuracy during the prediction phase. As SLEUTH simulated a linear growth for validation, this, if continued would have sustained urban growth in the region until all areas available for development was urbanized. Use of four years of historic data allows for application of the Self-modification rule that initiates a Bust cycle, based on the specification provided by the user for a more realistic non-linear prediction of future urban growth pattern. Although validation of future prediction, in this cause for year 2035, is not possible, this explicit validation for year 2011 provides an indication of the predictive power of the model.

6.2. Prediction for 2035

The prediction of urban growth of Albuquerque for 2035 was based on two scenarios: Business as Usual and Expanded Growth. These scenarios were further analyzed for two possible growth rates: current or low growth rates, established using data from last 10 years, and a possible high growth rate, based on the forecast of Bernalillo county by Mid-Region Council of Governments of New Mexico for 2040.

The SLEUTH model was executed in the Predict mode with the starting prediction year of 2011 and end prediction year of 2035, first, for the business as usual scenario using high and low growth rates, then, for expansion scenario using high and low growth rates.

6.2.1. Current low growth rate

If the current low growth rate persists, the urban extent of Albuquerque for the year 2035 as predicted by the model showed most of the development occurring around the fringes and the in-fills of the current urban areas for both businesses as usual and expansion scenarios as shown in Fig. 4.2 b and Fig. 4.2 d. As expected, urbanization within the three areas that have been designated for development is clearly higher for the expansion scenario as compared to business as usual scenario. However, for the three areas, Santolina was predicted to have the least amount of urban growth for both the scenarios, followed by Mesa del Sol, while Volcano Mesa was predicted have the highest amount of urban growth. Additionally, probability outputs indicated that the likelihood of urbanization occurring in Volcano Mesa, which was initially given a lower value in terms of attractiveness for development compared to Mesa del Sol, to be higher than the other two development projects for both business as usual and expansion scenario during low growth rate. This high probability of development and urban growth in Volcano Mesa region can most likely be attributed to the existing urbanized areas present in the North, South and West boundaries of the region in 2011 (See Fig. 4.3). These urbanized surrounding areas are likely to influence the development of the Volcano Mesa area. Furthermore, with the suburbs of Albuquerque already present around the region, Volcano Mesa is expected to be the logical progression of urban expansion in

Albuquerque.

In support of the results yielded from the calibration process (See Table 1.4), the map output produced by the SLEUTH model predicted the spread coefficient to be the primary factor contributing in urban growth of Albuquerque for both scenarios in case of low growth rate (See Fig. 4.4 b and Fig. 4.4 d). The spread coefficient is directly and solely responsible for edge (organic) growth. With a high value of 100 for the spread coefficient derived during calibration, edge growth has been shown to be the dominant type of growth in the urban expansion pattern of Albuquerque. Other elements of growth such as diffusion, breed and road influenced are also visible within the area of study area, but are minimal in comparison.

In terms of land use, the most prominent observations predicted by the model for 2035 was a decrease in total percentage of agricultural land use area compared to the rest of the land use categories as illustrated in Fig. 4.5. The cause of this change in land use pattern can be attributed to the expansion of urban land use along the fringe of the current urban extent instigated by edge (organic) growth of the city as a result of the spread coefficient as seen in Fig. 4.4 b and 4.4 c. This trend seems to be present in both the business as usual and expansion scenarios for low growth. The model estimates that the decrease in agricultural land to be higher for the expansion scenario when compared to business as usual scenario. As indicated in Table 1.6, the agricultural land use within Albuquerque is expected to go down from 12,922.26 acres in 2011 to about 4,400.36 acres in 2035 for business as usual – low growth scenario, a decrease of about 65.94 percent. And likewise, the agricultural and is expected to decrease to about 3,380.69 acres for expansion - low growth scenario, showing a 73.85 percent decline. This indicates a general trend of change in land use that is expected to occur in the coming years in Albuquerque. This decrease in agricultural land as a result of urban encroachment was especially prominent around the Mesa del Sol development area.

Calculation of total area for all locations that were expected to show urban growth in 2035 was generated using method implement by Watkiss (2008) where only those areas that were indicated to have 80 to 100 percent probability of being urbanized in 2035 were taken into consideration. As shown in Table 1.7, this produced a total of 31,594.32 acres as area predicted for urban growth in a business as usual scenario and 39,134.24 acres as area predicated for urban growth in an expansion scenario in case of low growth rate for 2035. Among the three development areas, 80 to 100 percent probability of urban growth for both scenarios was predicted to be very high for Volcano Mesa, followed by Mesa del Sol and Santolina (See Table 1.8 for comparison of the three development areas with 80 – 100 percent probability of urbanization for business as usual and expansion scenarios for 2035). Fig. 4.7 a, b, c and Fig. 4.9 a, b, c provides a map comparison between the three development areas for areas with 80 to 100 percent probability of urbanization during low growth rate - business as usual and expansion scenario respectively predicted for 2020 and 2035.

6.2.2. High growth rate

In case of a high growth rate in years leading to 2035, the urban growth pattern for the business as usual scenario and expansion scenario follows a similar trend as described in the previous section but, somewhat obviously, at a higher rate. As with low growth rate, most of the urban growth outside of the three development areas is predicted to occur around the infill and fringes for both scenarios but at a more aggressive rate (See Fig. 4.2 a and Fig. 4.2 c). Also similar to the low growth scenario, the 80 to 100 percent probability of urban growth is predicted to be very high for Volcano Mesa, followed by Mesa del Sol and Santolina (See Table 1.8 for comparison of the three development areas with 80 – 100 percent probability of urbanization for business as usual and expansion scenarios for 2035). Fig. 4.6 a, b, c and Fig. 4.8 a, b, c provide a map comparison between areas with 80 to 100 percent probability of urbanization for business as usual and expansion scenario during high growth rate for 2020 and 2035 for the three development areas.

As illustrated by Fig.4.4, similar to low growth rate, most of the growth during high growth rate has been predicted due to spread coefficient leading to edge (organic) growth.

Occurrence of possible spontaneous growth and new spreading growth are visible but are extremely low and are not drastically different from previous low growth prediction for both scenarios.

In terms of land use, the decrease in agricultural land use has been predicted to be higher when compared to low growth case for both scenarios. However, the percentage decrease in agricultural land for 2035 does not seem to be significantly different between expansions scenario and business as usual scenario for high growth rates. As illustrated in Table 1.6, the agricultural land use within Albuquerque is expected to go down from 12,922.26 acres in 2011 to about 3,300.32 acres in 2035 for business as usual – high growth scenario, a decrease of about 74.45 percent. And similarly, agriculture land use is expected to decrease to about 3,132.27 acres for expansion - high growth scenario, showing a 74.36 percent decline. As during the low growth rate, this decrease in agricultural land use is contributed by the growth of urban land use along the fringe of the current urban extent instigated by edge (organic) growth (See Fig. 4.4). As expected, land use prediction also shows high levels of urbanization all three development areas, but is especially prominent in Volcano Mesa followed by Mesa del Sol.

When considering calculation of urban areas with 80 to 100 percent probability of being urbanized, the results as shown in Table 1.7 indicated 38,679.06 acres as predicted urbanized area for business as usual scenario and 39,515.26 acres as predicated urbanized area for expansion scenario in case of high growth rate.

7. Discussions

The results from the analysis indicate that the three areas, if and when developed over the next 20 years, is expected to have a substantial impact on the pattern of urban growth and land use of Albuquerque. Specifically, among the three development areas, comparing business as usual scenario with the expansion scenario for areas with 80 – 100 percent probability to urbanize (illustrated in Table 1.8), Mesa del Sol was shown to have the most impact over the next 20 years as a result of it being defined and built as a development areas. The result from the model also indicated that, during low growth rate for 2035, if Mesa del Sol had not been established as a development area, only 396.16 acres would have been predicted to be urbanized (See Fig. 4.7 b) as compared to 1,139.29 acres when it was defined as a development area (See Fig. 4.9 b), implying a significant impact on the pattern of urban growth for the Mesa del Sol region. This impact on urban growth pattern as a result of the establishment of development areas was lower under the high growth rate scenario but was still significant for Mesa del Sol (See Table 1.8).

Currently, Mesa del Sol is finally seeing some infusion of investment from the commercial sector and is seeing some homes being developed and sold (Scott, 2014; Hilf, 2015, Mayfield, 2015).

Volcano Mesa showed minimal changes when comparing business as usual and expansion scenario. Here, for the low growth rate business as usual scenario, 1,262.29 acres was predicted to be urbanized with 80 – 100 percent probability (See Fig. 4.7 a) and 1,676.55 acres was predicted for expansion scenario (See Fig. 4.9 a). For the high growth rate business as usual scenario 1,542.35 acres was predicted (See Fig. 4.6 a) and 1,693.92 acres was predicted for expansion scenario (See Fig. 4.8 a). The small difference between total area predicted for the business as usual and expansion scenarios imply that establishing Volcano Mesa as a development area did not have a significant impact on the pattern of urban growth leading to the conclusion that Volcano Mesa area would have been developed regardless of it being defined as a development area. This is most likely due to the increased pressure from the surrounding areas that have already been developed as suburbs of Albuquerque and have started its move into the Volcano Mesa (See Fig. 4.3) as a result of edge (organic) growth occurring in the area.

Finally, Santolina also showed some impact on the pattern of urban growth for the region as a result of it being established as a development area. Here, the model predicted a more significant impact on urban growth pattern during low growth rate over the next 20 years. The result showed that if Santoliona had not been established as a development area, for low growth rate areas with 80 – 100 percent probability to urbanize, only 162.31 acres of land would have been urbanized (See Fig. 4.7 c), as compared to 348.68 acres when it was established as a development area (See Fig. 4.9 c). In both business as usual and expansion scenario for high and low growth rates, that amount of land predicted by the model to be urbanized within Santolina was minimal (See Table. 1.8).

Among the three development areas, Santolina is the latest and the largest region to be established as a development area. Based on future prediction by the model, even during a high growth rate in the expansion scenario Santolina is only expected to see about 394.60 acres of urban development with 80 – 100 % probability of urbanization (See Fig. 4.8 c). Based on this poor performances of Santolina for the future prediction of urban growth of the region, questions regarding the financial and economic viability of the project as big as Santolina when there already is another ongoing massive development project, Mesa del Sol, that is still yet to be completed and populated, and more importantly the environmental sustainability of Santolina development area need to be raised.

Santolina, having similar design plans with Mesa del Sol, adopting mixed used neighborhoods with part commercial and part residential area, it can be assumed that the two development areas will be in direct competing for businesses in both residential and commercial sector, as both will be attracting similar customer base. Furthermore, considering that it took Mesa del Sol, more than 20 years to get off the ground since its inception, it can be argued that Santolina will most likely take a similar time frame for any substantial development to start, especially when taking into account the declining population growth rate of Albuquerque (Provost and Bienvenu, 2014). This, along with the size of the development, with the number of planned housing within Santolina comparable to Rio Rancho, New Mexico's third largest city, the probability of this project reaching its full potential even within its predicted time frame of 40 to 50 years is still questionable.

Santolin will also be competition for the water resources with the local farmers and residents, initially for the amount of water that would be required to build the massive project and later, if developed, for the supply of water necessary for its residents and businesses within the development area (Lusk, 2014). With the local population as well as the environmental activists citing degradation and constrain of water supply and the lack of transparency on use of water by Santolina (McKay, 2015; Peters, 2015) the environmental feasibility of this project is also a big concern.

8. Conclusion

It is understood that the future is uncertain. But having the ability to factor in specific areas within the uncertainty grants key insights that can prove to be critical for making vital decisions when considering the future. As the City of Albuquerque expands, understanding the current patterns of urban growth and land use and predicting the possible future patterns of growth of the city empowers stakeholders and policymakers by provides them with information and support that would prove to be essential for future policies and development decisions.

Comparing the growth pattern of Albuquerque using the Business as Usual and Expansion scenarios provides the understanding of possible difference and similarities in patterns of urbanization of the city as a result of large scale planned urban development projects. It offers a method to distinguish between areas that would have been urbanized regardless of these development projects and, areas that are most likely developed due to the direct influence of these projects. Additionally, estimating these scenarios through a low and high growth rate offers a range of probabilities within which possible future expansion patterns of Albuquerque could lie.

The SLEUTH model, identified in-fills and fringes around the current urban area of Albuquerque as regions where most of the urban expansion is expected to occur as a result of edge (organic) growth, regardless of the availability of the three targeted development areas for expansion. When considering land use change, agricultural areas within Albuquerque were predicted to experience the largest percentage decrease as a consequence of encroachment from urban areas.

Examining the expansion scenario, the results indicated Santolina, as having the lowest probability of urban growth. Mesa del Sol was predicted to show a relatively steady rate of urban growth, whereas Volcano Mesa was expected to have the highest probability of urban growth for both growth rates.

As a result of this analysis, it can be concluded that the urban growth in Albuquerque in the next 20 years will mostly be seen around fringes and the infill of the current urban areas. Additionally, as a result of this urban expansion a decline in agricultural land use due to encroachment from urbanization is also predicted. Establishment of the three-development area will play a significant role in the urban growth pattern of Albuquerque especially for Mesa del Sol region. Moreover, with the Volcano Mesa area already being surrounded in three sides by urban development, and the increased pressure to expand region as indicated by the creeping development of the area over the years, Volcano Mesa is predicted to be the next logical step in a major expansion of the Albuquerque. As for Santolina, from the results of the analyses it can be concluded that the project is questionable at best. The model did not predict a substantial future urban growth within the region. Additionally, Santolina, with its massive size and being in direct completion with other major development in the area the financial feasibility of the project is uncertain and with possible harsh environmental consequences.

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9. Tables

Table 1.1 Metrics to evaluate goodness of fit for SLEUTH model

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

Source: Oguz, 2006

Table 1.2 Input dataset for SLEUTH

Data	Resolution	Year	Source	Format
Slope	30 meters	2002	Resource Geographic Information System Earth Data Analysis Center, UNM	Raster
Land Use	30 meters	2001	National Land Cover Database Multi-Resolution Characteristics Consortium	Raster
	30 meters	2011	National Land Cover Database Multi-Resolution Characteristics Consortium	Raster
Excluded Areas		2013	Opens Spaces City of Albuquerque	Rasterized from Vector
Urban Extent	30 meters	1992	National Land Cover Database Multi-Resolution Characteristics Consortium	Raster
	30 meters	2001	National Land Cover Database Multi-Resolution Characteristics Consortium	Raster
	30 meters	2006	National Land Cover Database Multi-Resolution Characteristics Consortium	Raster
	30 meters	2011	National Land Cover Database Multi-Resolution Characteristics Consortium	Raster
Transportation		1994	Resource Geographic Information System Earth Data Analysis Center, UNM	Rasterized from Vector
		2006	Resource Geographic Information System Earth Data Analysis Center, UNM	Rasterized from Vector
		2010	Resource Geographic Information System Earth Data Analysis Center, UNM	Rasterized from Vector
		2014	Topologically Integrated Geographic Encoding and Referencing, US Census Bureau	Rasterized from Vector
Hillshade	30 meters	2002	Resource Geographic Information System Earth Data Analysis Center, UNM	Raster

Table 1.3 Reclassification of NLDC land cover classification

New Classification	NLDC Classification
1 Water Bodies	11 Open Water
	12 Perennial Ice/Snow
2 Urban	21 Developed, Open Space
	22 Developed, Low Intensity
	23 Developed, Medium Intensity
	24 Developed High Intensity
3 Barren	31 Barren Land (Rock/Sand/Clay)
4 Vegetation	41 Deciduous Forest
	42 Evergreen Forest
	43 Mixed Forest
5 Shrub/Grassland	51 Dwarf Scrub *
	52 Shrub/Scrub
	71 Grassland/Herbaceous
	72 Sedge/Herbaceous *
	73 Lichens *
	74 Moss *
	90 Woody Wetlands
	95 Emergent Herbaceous Wetlands
6 Agriculture	81 Pasture/Hay
	82 Cultivated Crops

* Indicates found only in Alaska

Table 1.4 Results for the coarse, fine, final and derive phase of the brute force calibration process used to produce the end values for the five growth coefficients

	Monte	**Diffusion**		**Breed**		**Spread**		**Slope**		**Road Growth**	
Calibration	**Carto**	Range	Step	Range	Step	Range	Step	Range	Step	Range	Step
Coarse Phase	5	0 - 100	25	0 - 100	25	0 - 100	25	0 - 100	25	0 - 100	25
Fine Phase	8	25 - 100	15	25 - 100	15	50 - 100	10	1 - 75	15	1 - 100	20
Final Phase	10	25	1	55 - 100	9	70 - 100	6	16 - 61	9	1 - 61	12
Derived	100	25	1	91 - 100	1	88 - 100	1	34 - 61	1	1 - 61	1
Final results from Calibration		***30***		***98***		***100***		***1***		***13***	

Table 1.5 Confusion Matrix with for total urban and non-urban areas as it actually appears in 2011 and as predicted by SLEUTH for 2011.

		Actual		
		Urban (acres)	Non-Urban (acres)	**Total (acres)**
Predicted	Urban	100910.23	12945.35	113855.57 *(38.37 %)*
	Non-Urban	3205.99	179666.54	182872.53 *(61.63%)*
	Total	104116.22 *(35.09%)*	192611.89 *(64.91%)*	296728.13 *(100%)*

Table 1.6 Total land use areas predicted by SLEUTH for business as usual and expansion scenarios during high and low growth rates for 2035

	Initiation Year 2011 (acres)	**Business As Usual Scenario (2035)** High Growth (acres)	Low Growth (acres)	**Expansion Scenario (2035)** High Growth (acres)	Low Growth (acres)
Water Body	1095.02	1004.60	1048.97	1030.33	1028.35
Urban	104062.97	157546.88	138657.55	163000.74	151599.49
Barren	1044.11	450.02	580.75	468.41	481.88
Vegetation	2708.50	2574.23	2595.16	2568.66	2579.61
Shrub Grassland	174867.78	131821.39	149414.34	126315.68	137627.10
Agriculture	12922.26	3300.32	4400.36	3313.27	3379.69

Table 1.7 Total urban growth areas with 80 – 100% probability of urbanization for business as usual and expansion scenarios during high and low growth rates for 2035

	Business As Usual		**Expansion**	
	High (acres)	Low (acres)	High (acres)	Low (acres)
Predicted Urban growth with 80 - 100% probability	38679.06	31594.32	39515.26	39134.24

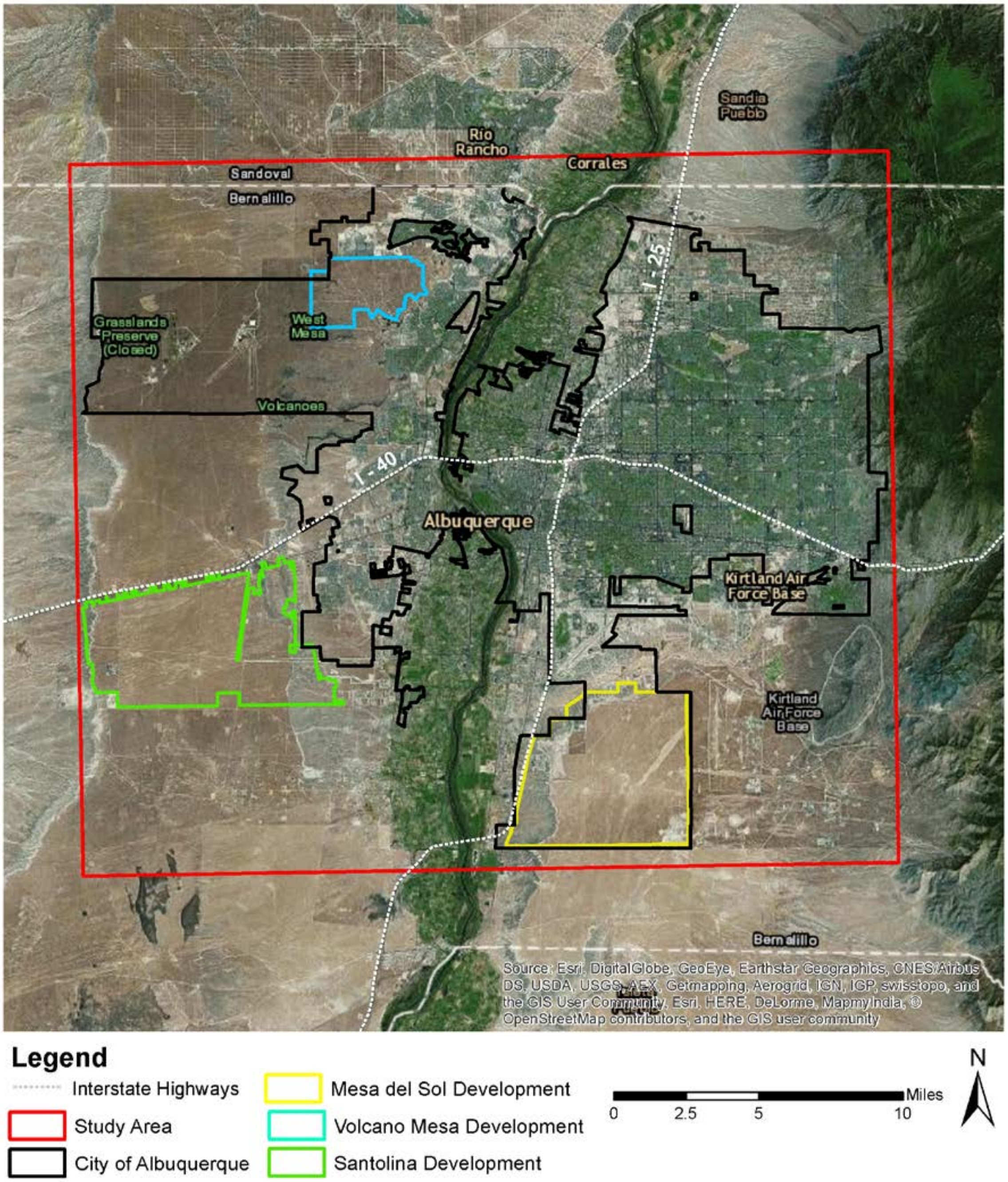
Table 1.8 Comparison of the three development areas with 80 – 100 percent probability of urbanization for business as usual and expansion scenarios during high and low growth rates for 2035

	High Growth		Low Growth	
	Business As Usual (acres)	Expansion (acres)	Business As Usual (acres)	Expansion (acres)
Mesa del Sol	684.77	1217.00	396.16	1139.29
Volcano Mesa	1542.35	1693.92	1262.96	1676.55
Santolina	282.27	394.60	162.31	384.68

10. Figures

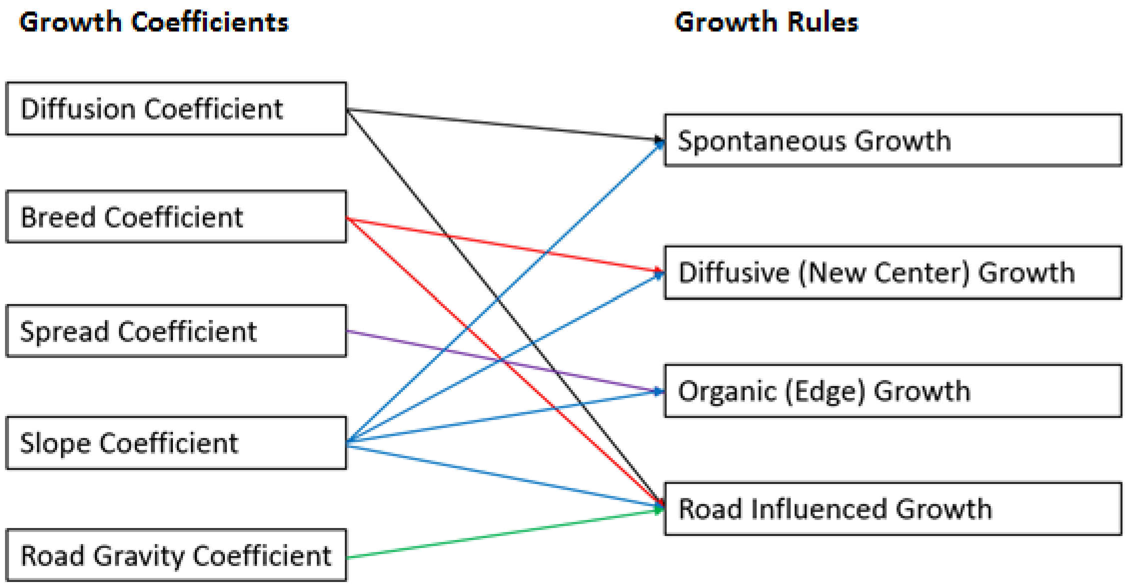
10.1. Study Area

Fig. 1.1 Three Developments Areas (Mesa del Sol, Volcano Mesa, Santolina) within the study area



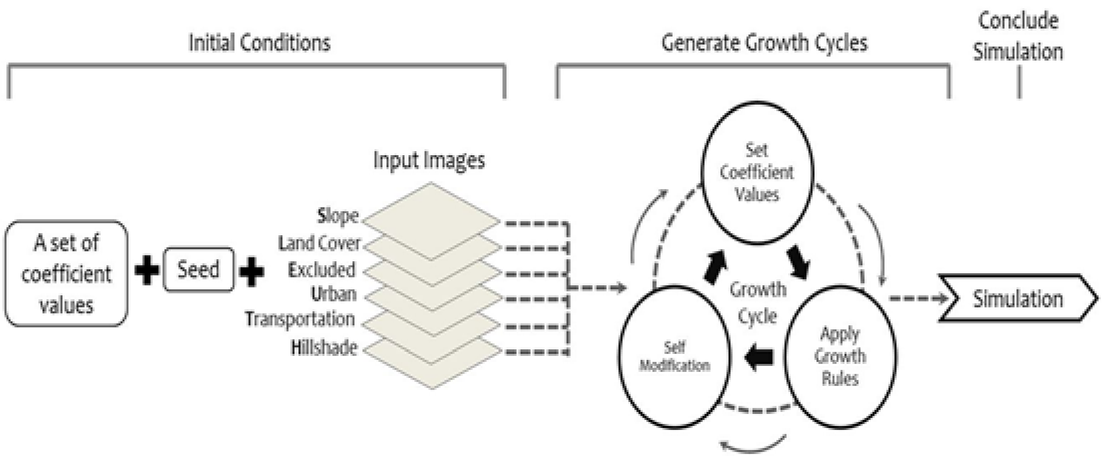
10.2. The SLEUTH Model

Fig. 2.1 Relationship between Growth Coefficient and Growth Rules



Source: Ding and Zhang, 2007

Fig. 2.2 Structure of the SLEUTH Model



Source: Chaudhuri and Clarke, 2012

10.3. SLEUTH Inputs

Fig. 3.1 SLEUTH input for a. Slope layer and b. Hillshade layer

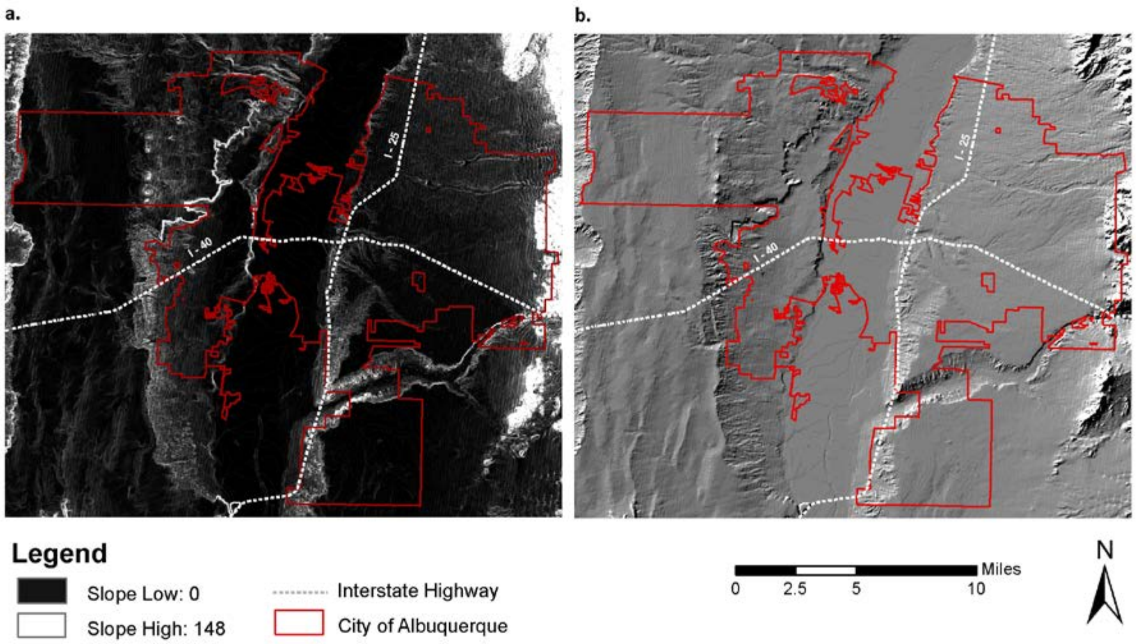


Fig. 3.2 SLEUTH input for Land Use layer for year: a. 1992; b. 2001; c. 2006 and d. 2011

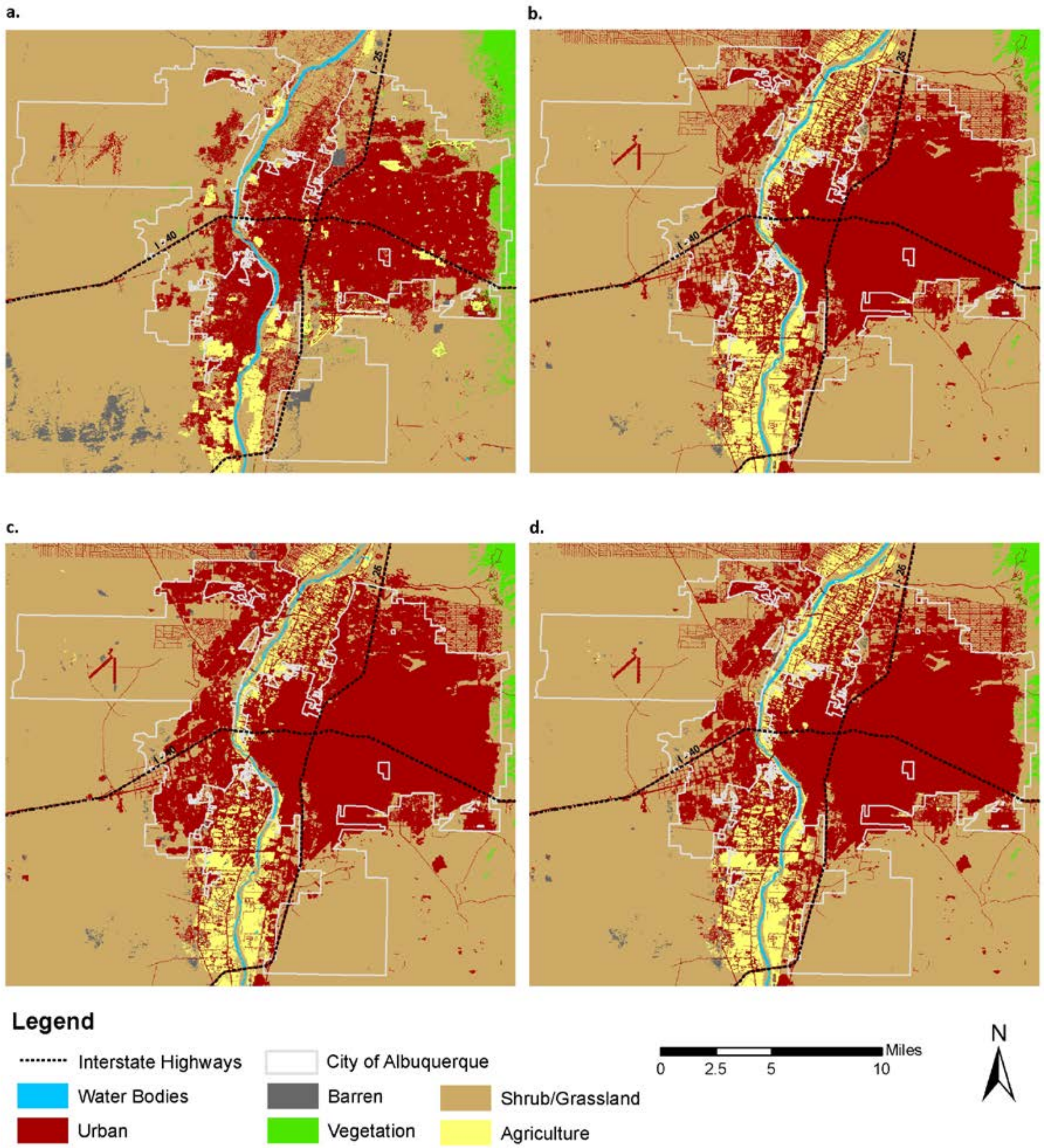


Fig. 3.3 SLEUTH input for Urban Extent layer for year: a. 1992; b. 2001; c. 2006 and d. 2011

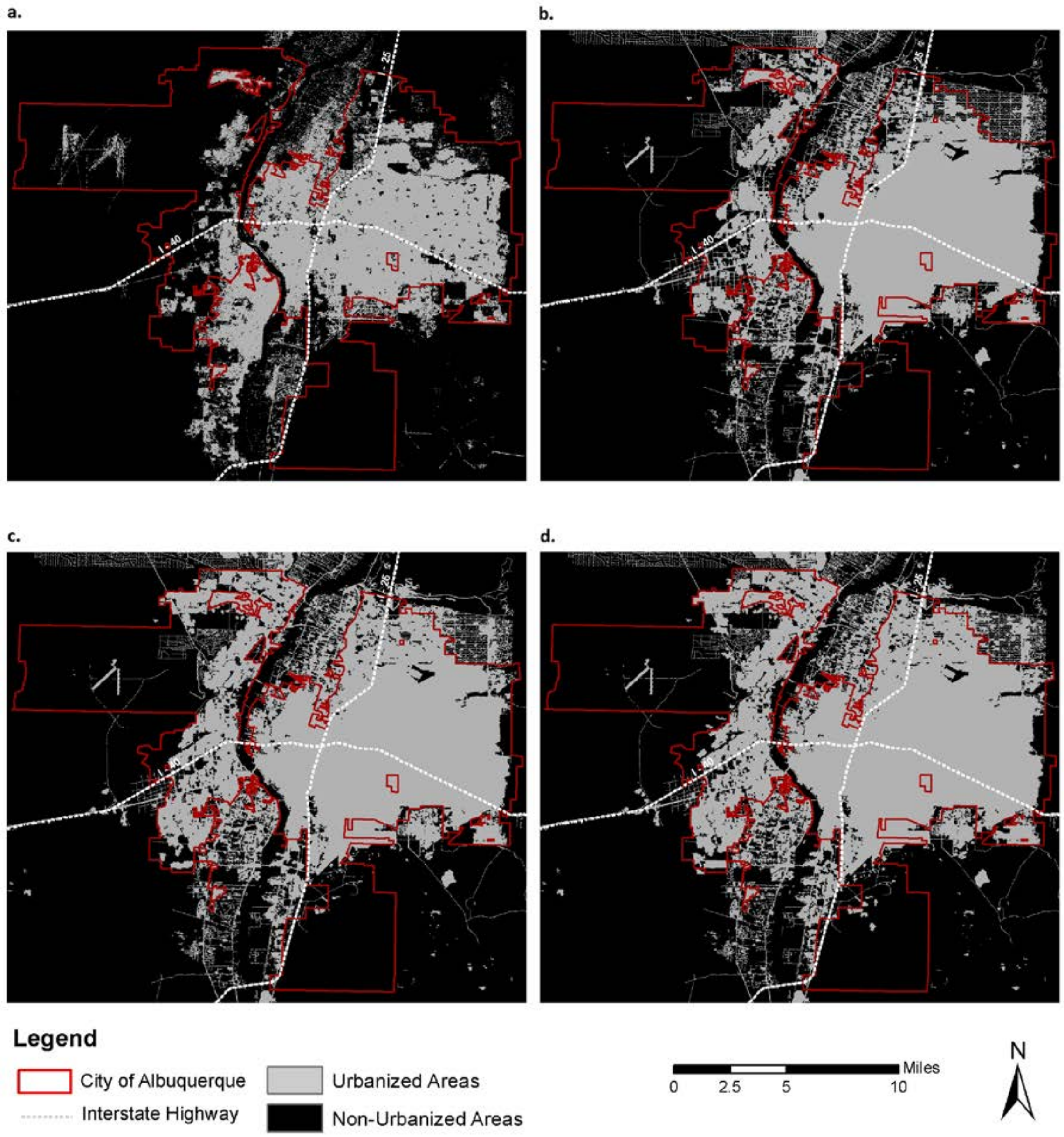


Fig. 3.4 SLEUTH input for Transportation layer for year: a. 2001; b. 2006; c. 2010 and d. 2014

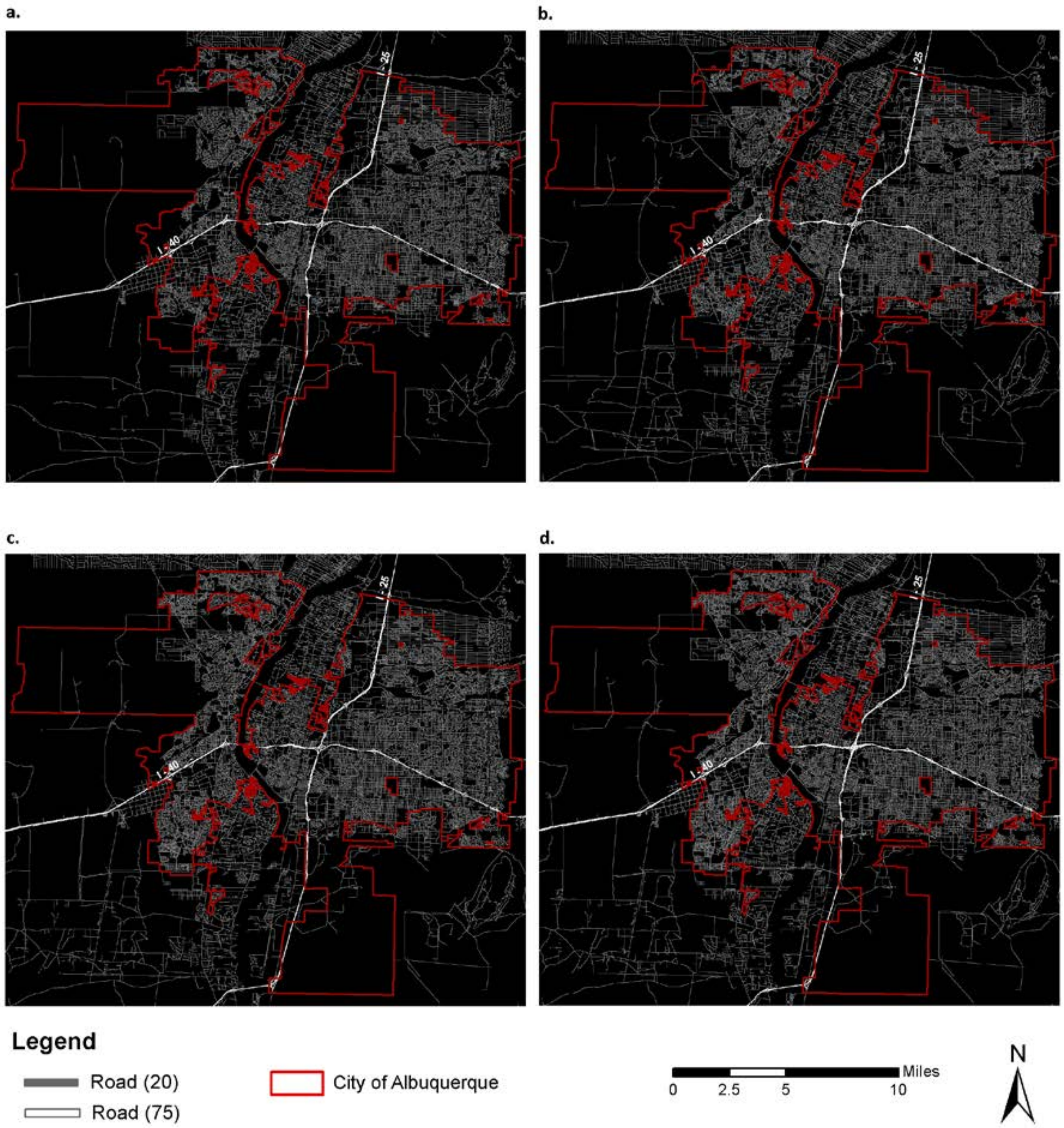
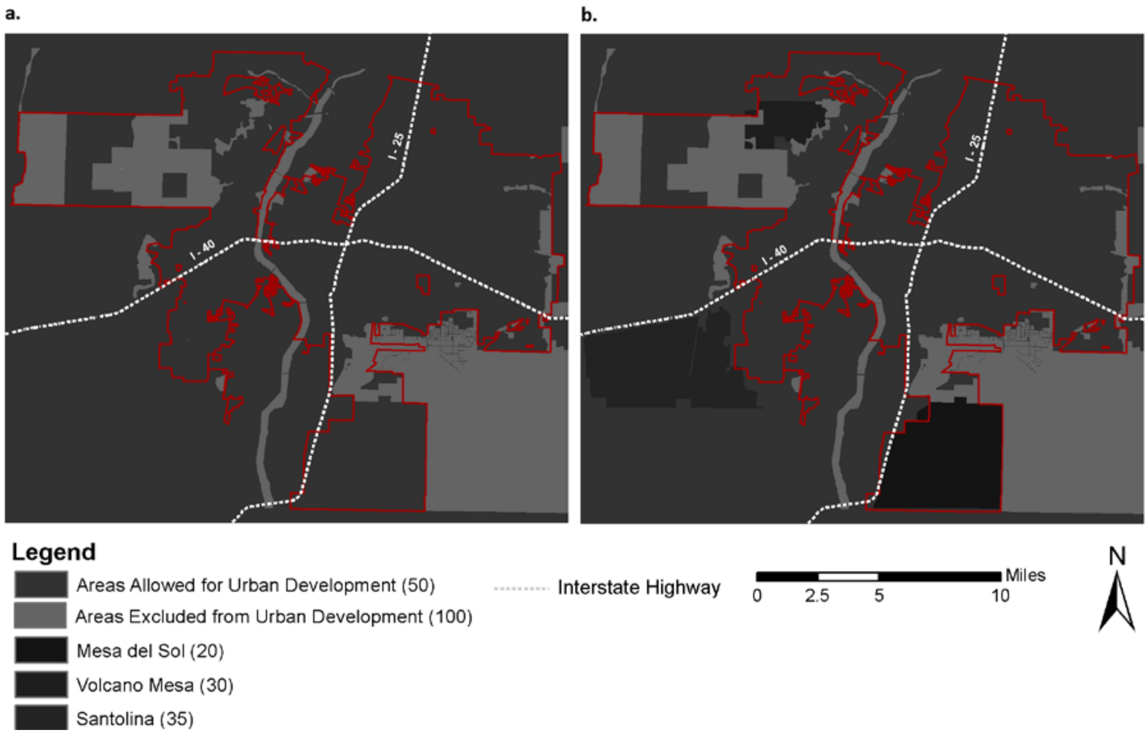


Fig. 3.5 SLEUTH input for Exclusion layer for a. Business as Usual Scenario and b. Expansion Scenario



10.4. SLEUTH Output

Fig. 4.1 Correctly and Incorrectly predicted areas by SLEUTH for 2011

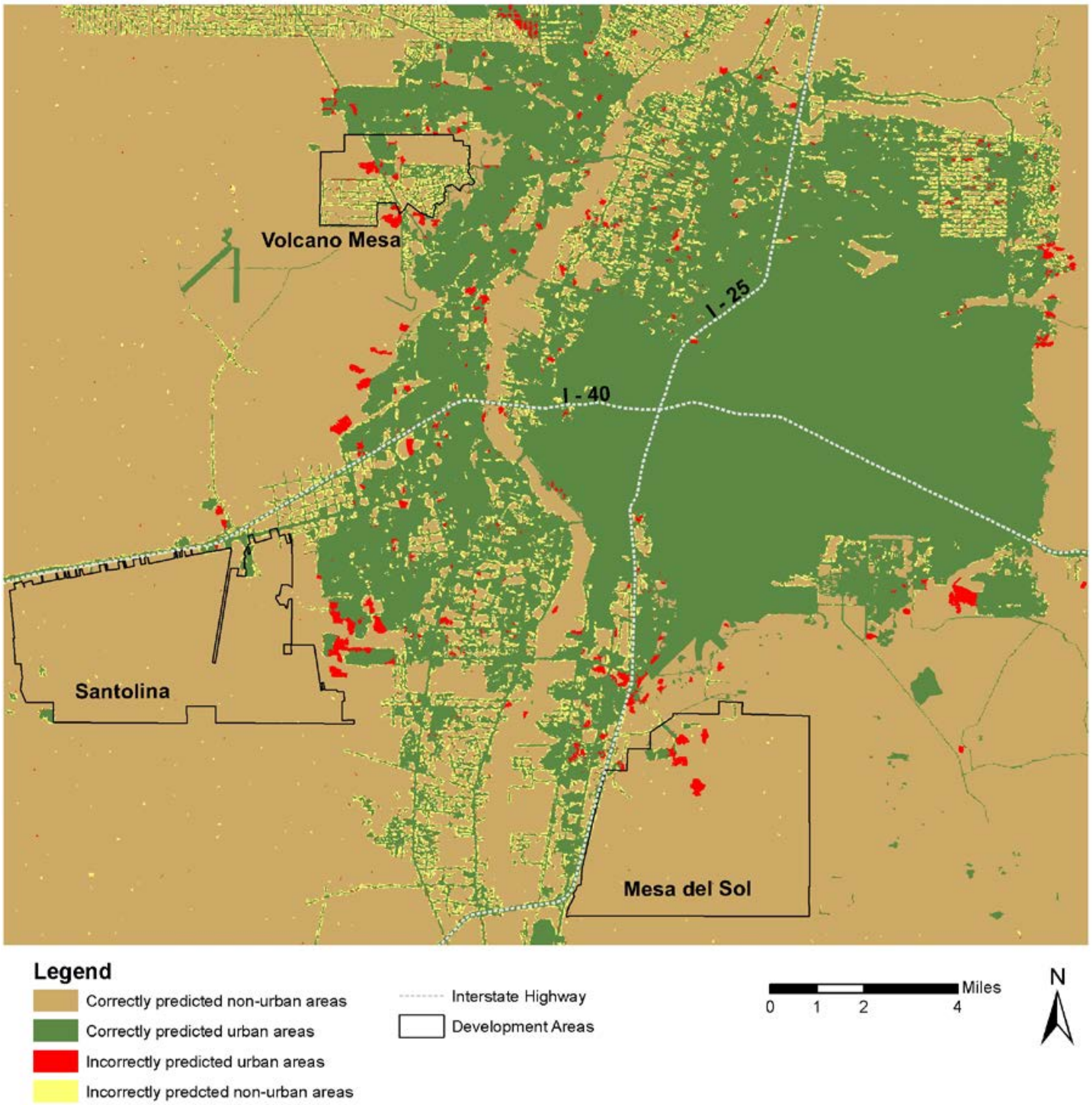


Fig. 4.2 Areas Predicted for Urbanization for 2011, 2020 and 2035 during:
a. Business as Usual Scenario – High Growth Rate;
b. Business as Usual Scenario – Low Growth Rate;
c. Expansion Scenario – High Growth Rate;
d. Expansion Scenario – Low Growth Rate

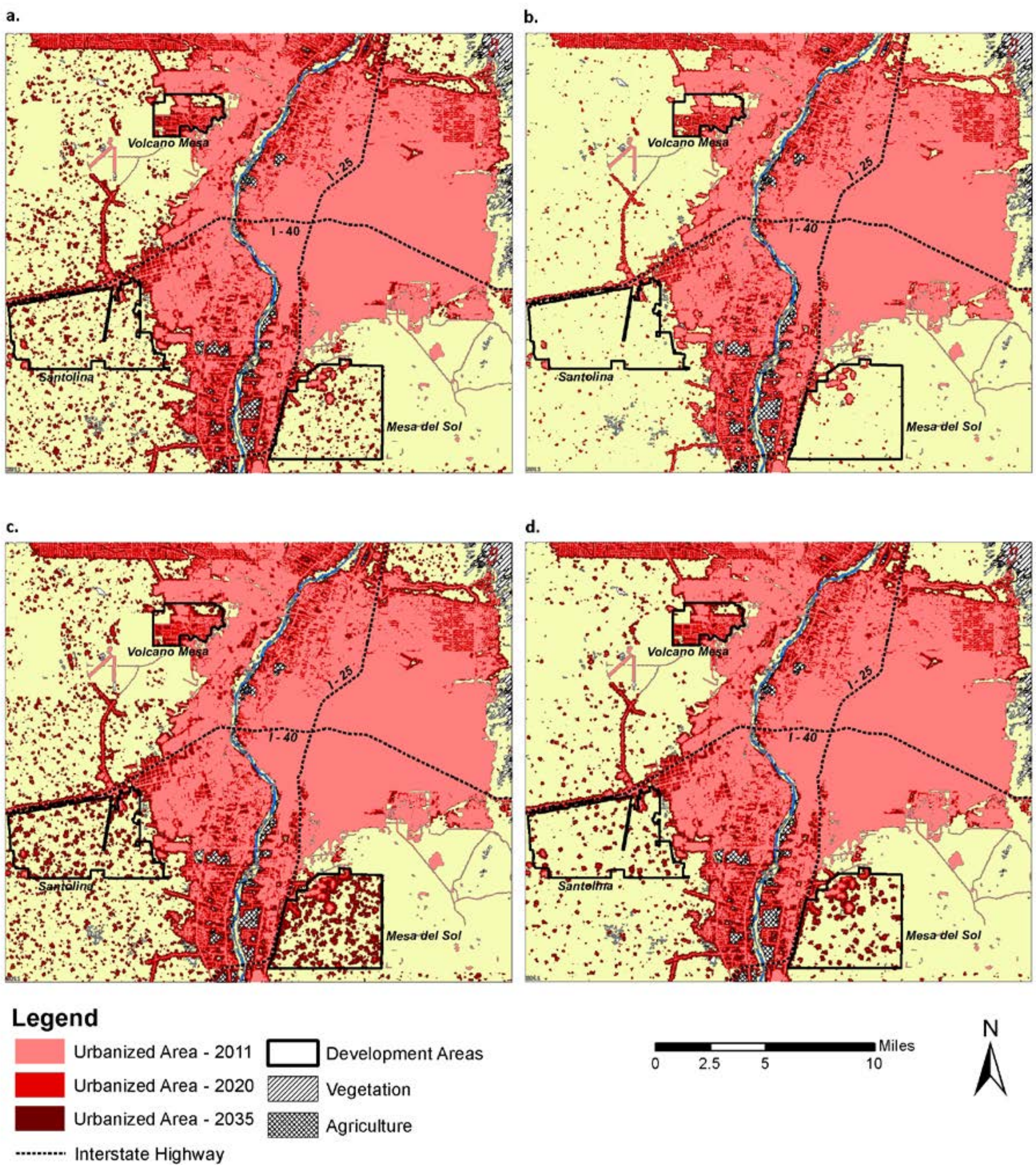


Fig. 4.3 Urbanized Areas around Volcano Mesa Development Area in 2011

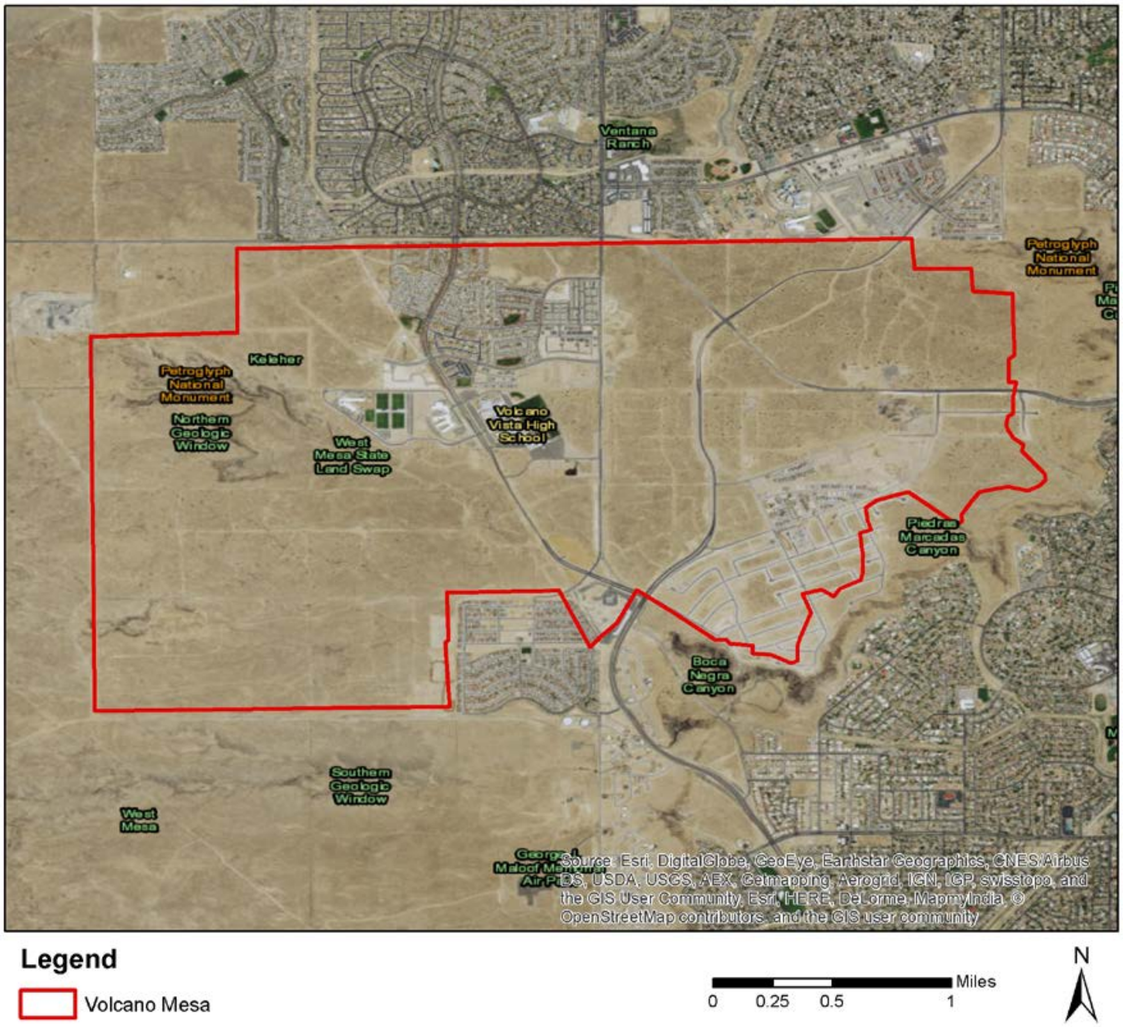


Fig. 4.4 Predicted Growth Type for 2035 for:

a. Business as Usual Scenario – High Growth Rate;
b. Business as Usual Scenario – Low Growth Rate;
c. Expansion Scenario – High Growth Rate;
d. Expansion Scenario – Low Growth Rate

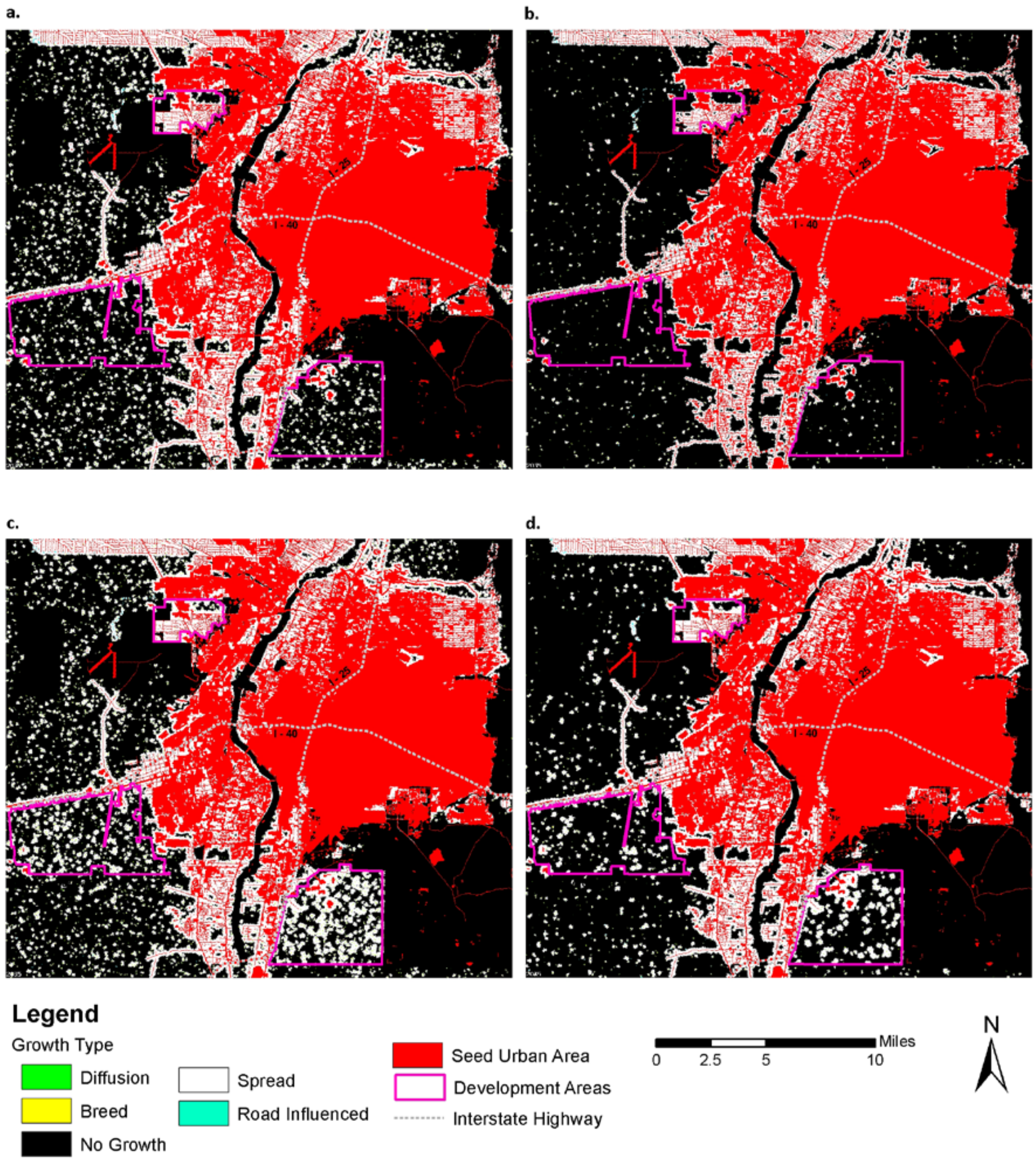


Fig. 4.5 Change in Land Cover Area

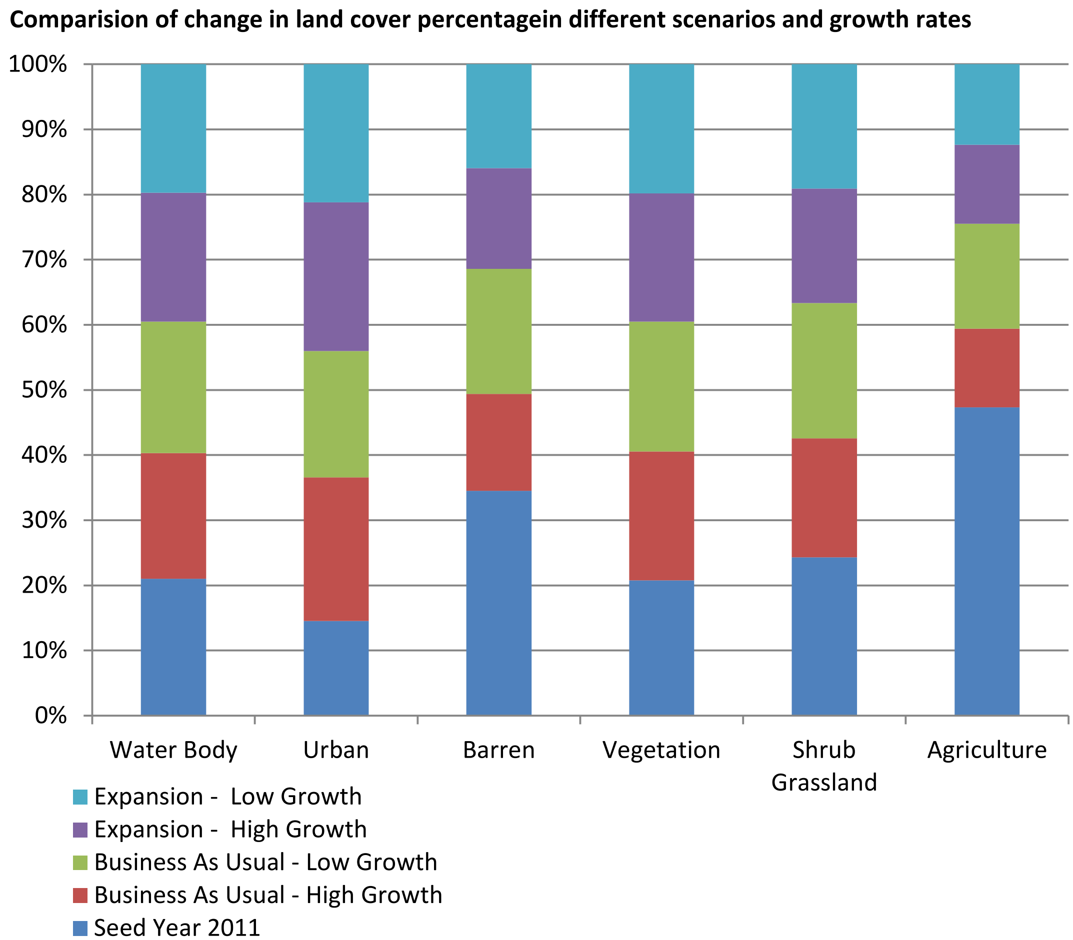


Fig. 4.6 Areas with 80 to 100% Probability of Urbanization for Business as Usual Scenario during High Growth Rate for a. Volcano Mesa; b. Mesa del Sol and c. Santolina

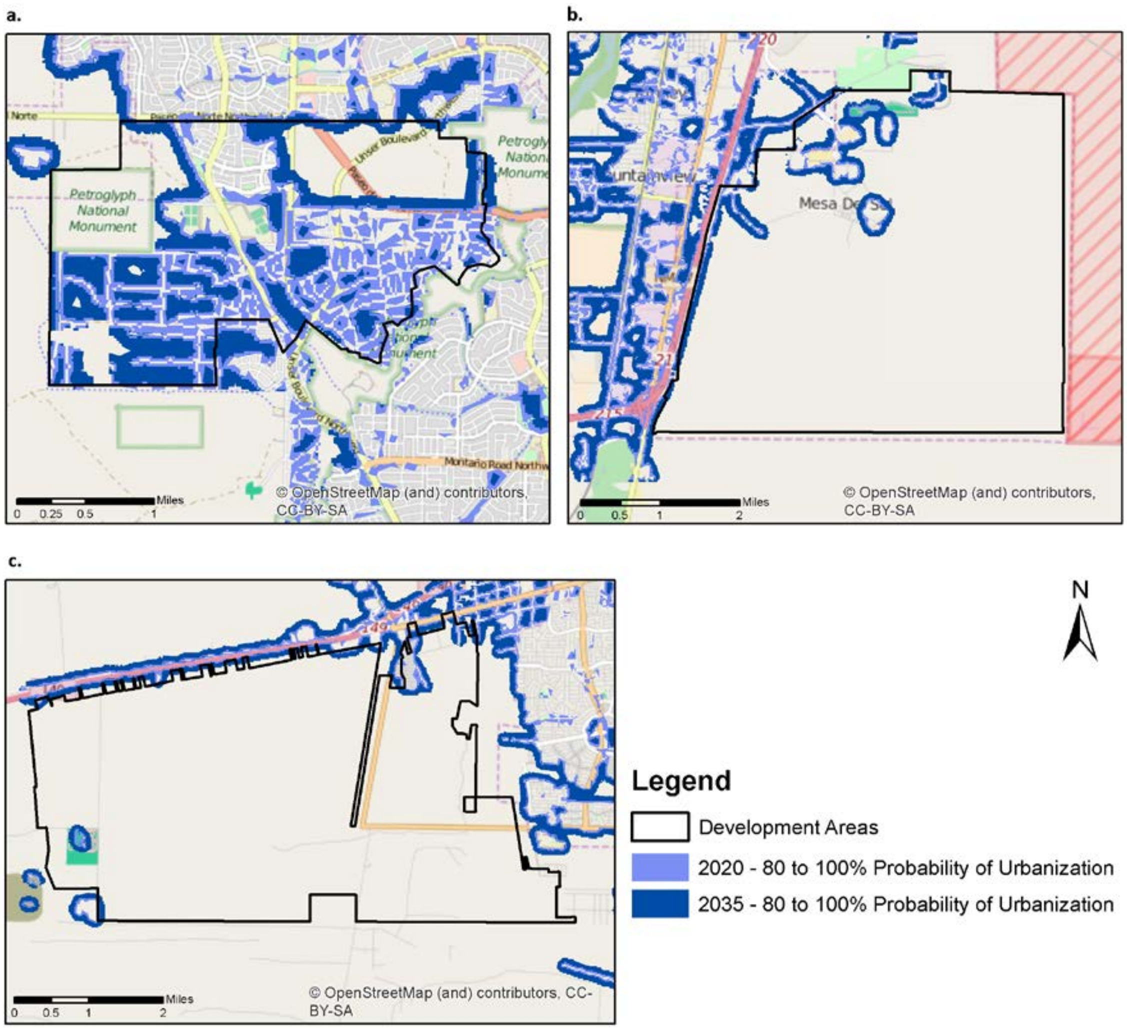


Fig. 4.7 Areas with 80 to 100% Probability of Urbanization for Business as Usual Scenario during Low Growth Rate for a. Volcano Mesa; b. Mesa del Sol and c. Santolina

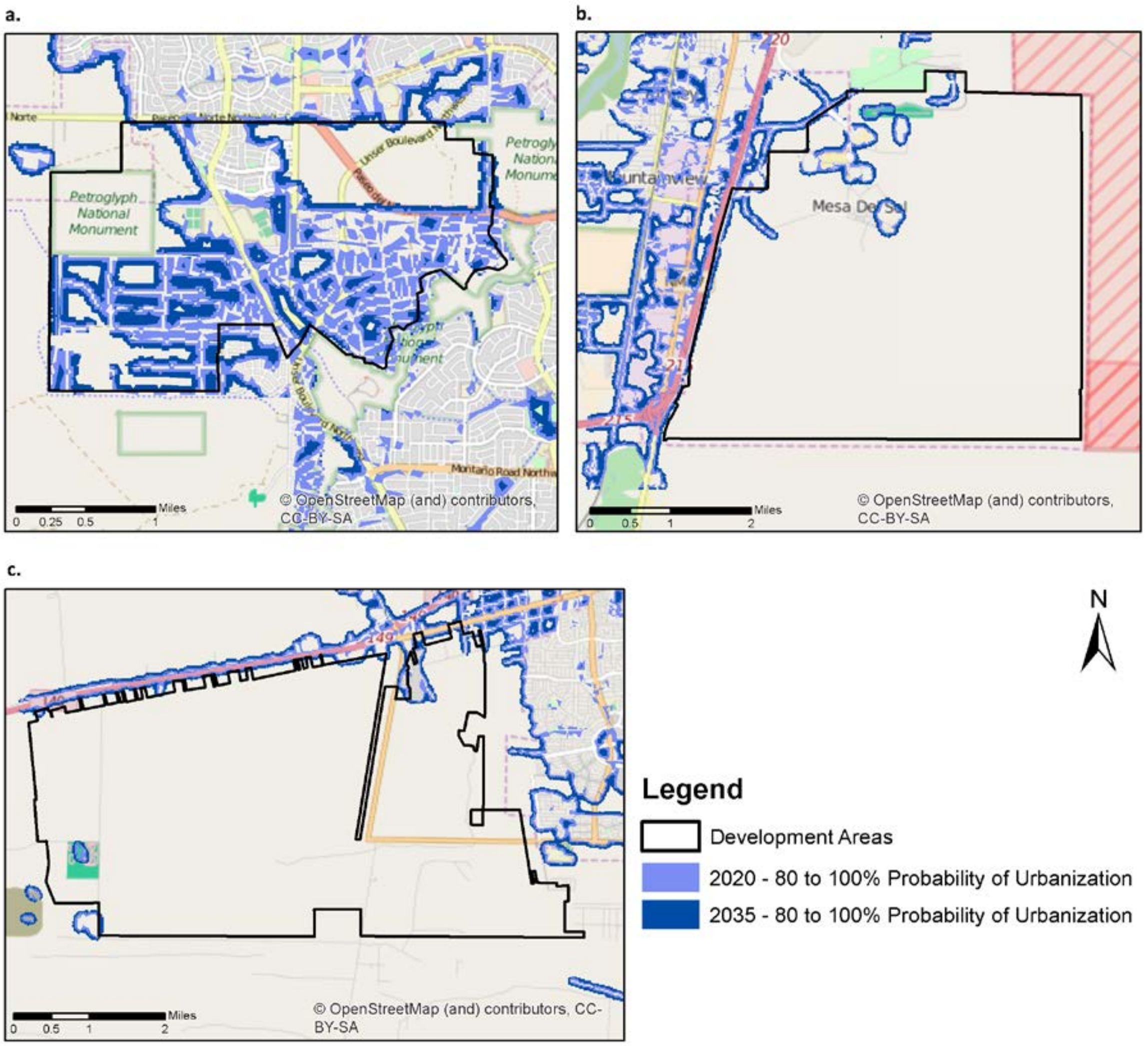


Fig. 4.8 Areas with 80 to 100% Probability of Urbanization for Expansion Scenario during High Growth Rate for a. Volcano Mesa; b. Mesa del Sol and c. Santolina

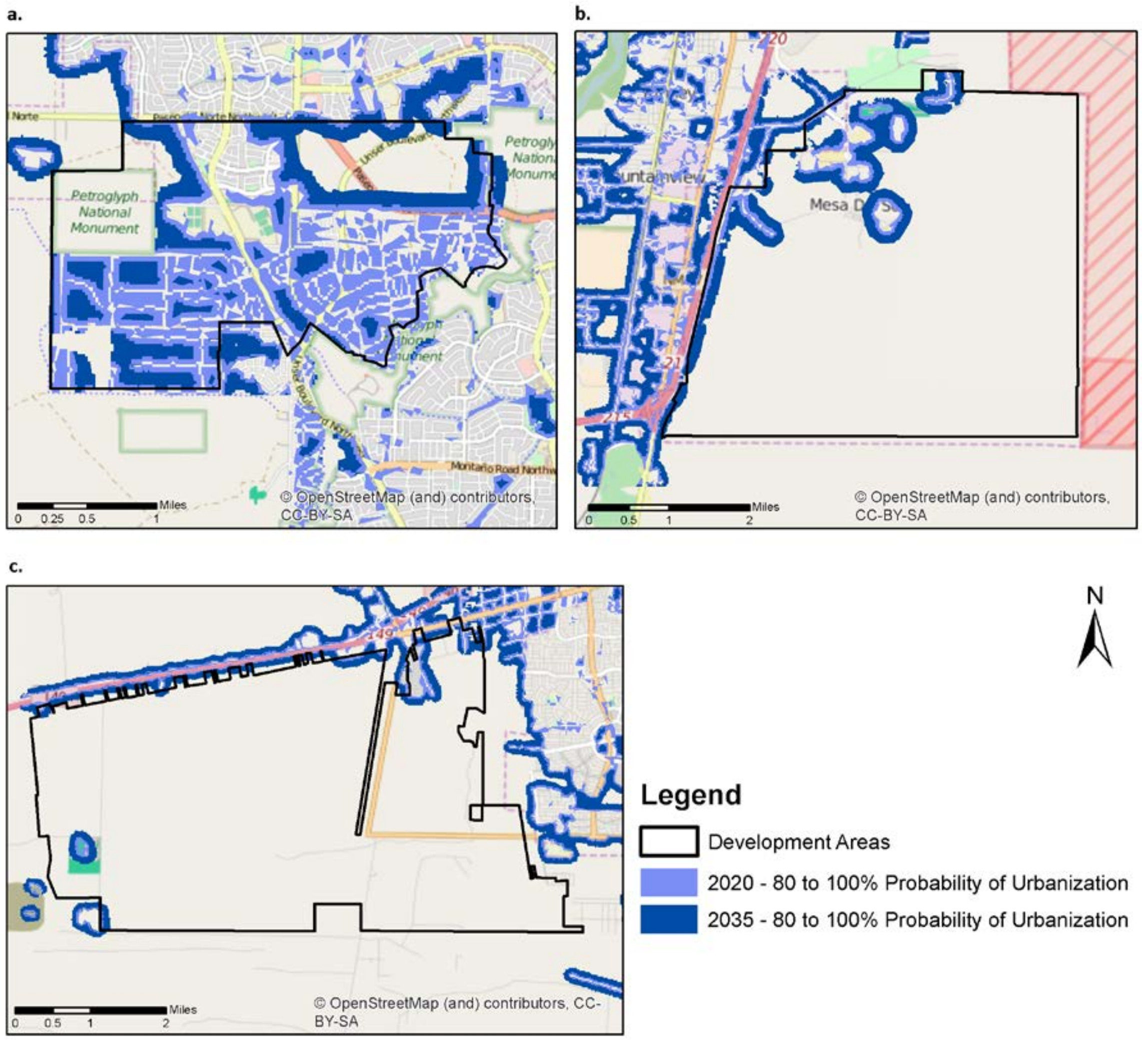
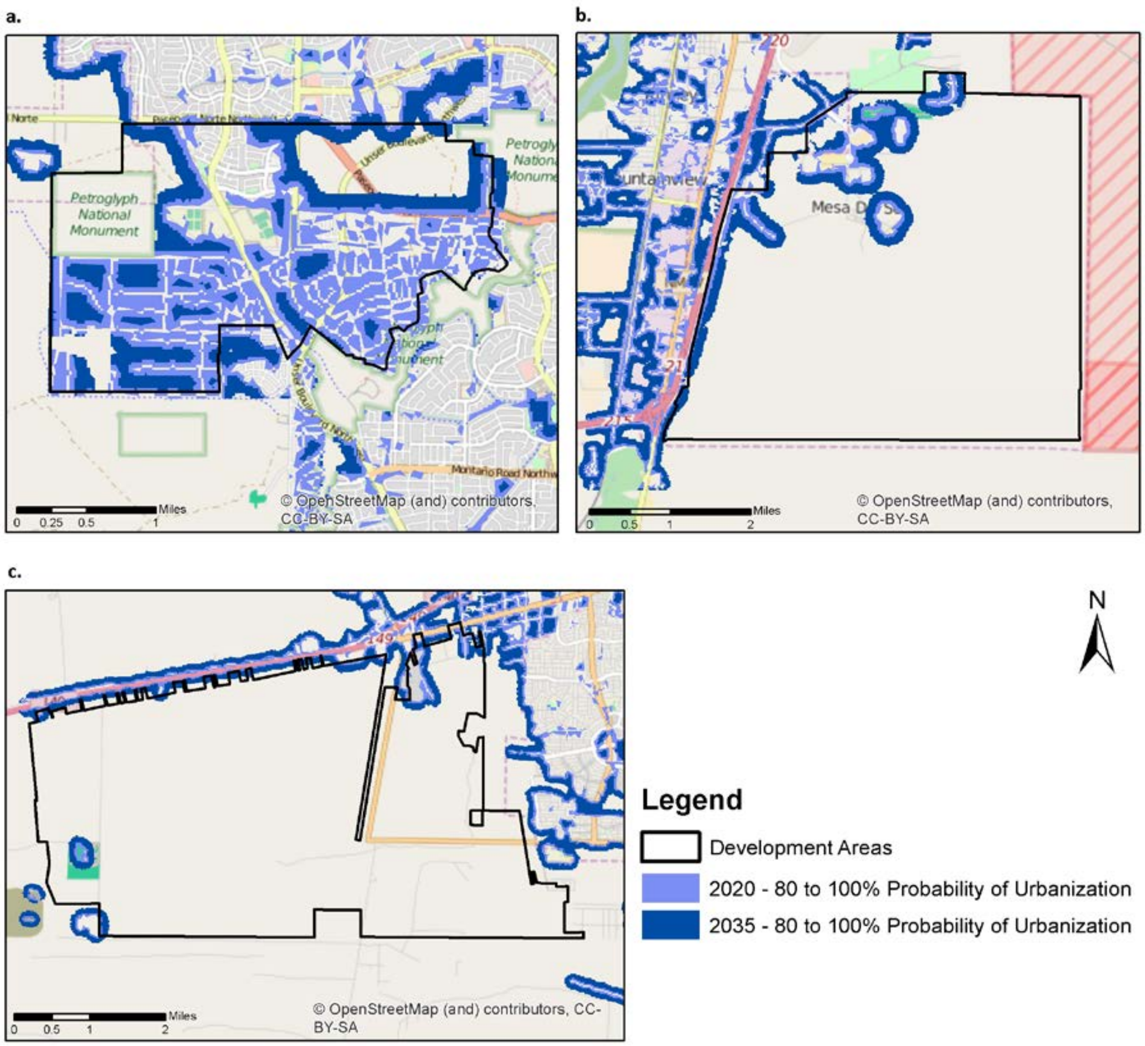


Fig. 4.9 Areas with 80 to 100% Probability of Urbanization for Expansion Scenario during Low Growth Rate for a. Volcano Mesa; b. Mesa del Sol and c. Santolina



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