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Quantifying Spatiotemporal Patterns of Past and Future Urban Trends in El Paso, TX and Their Impact on Electricity Consumption Using NLCD Data and the CA-Markov Model

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QUANTIFYING SPATIOTEMPORAL PATTERNS OF PAST AND FUTURE URBAN TRENDS IN EL PASO, TX AND THEIR IMPACT ON ELECTRICITY CONSUMPTION USING NLCD DATA AND THE CA-MARKOV MODEL

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Dedication

This dissertation is dedicated to my Lord and Savior, Jesus Christ, for all his blessings; and my family. I want to thank my grandfather, Wilbur, for his example of hard work and love. I want to especially thank my Dad, William, for his prayers, encouragement, and unfailing love. I could not have accomplished this without my Dad. My brother, Jim, for his prayers and love during this process and always. My sister, Donna, for making me promise to continue my education and her love. My sister, Nancy, for being my example as the first in our family to graduate college and her love. I would also like to thank my friends for their encouragement.

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by

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DISSERTATION

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Abstract

As cities continue to grow, their urban form continues to evolve over. Understanding this evolution allows for planners, engineers, and decision makers to plan for a sustainable community. Change analysis was conducted for El Paso, Texas county to determine the areas of growth within the past 15-years (2001-2016). The results indicate that growth has primarily occurred within the city of El Paso, in particular Districts 5 (east side), 1 (west side), and 4 (northeast), with District 5 experiencing substantial growth. Developed sub-categories medium and High intensity experienced the fastest growth, which represents single-family housing and compact/commercial areas. However, landscape metrics indicate that the dominating land-use is single-family housing (low and medium intensity). Landscape metrics suggest as the districts continue to grow, fragmentation and shape irregularity of developed areas decrease. The metrics also indicate a diverse sub-category landscape, which may suggest mixed-use within developed areas.

Using past growth trends, CA-Markov is employed to predict 2031 land-use. The counties' projected growth is evenly contributed to El Paso city and outside city limits. Growth outside city limits is expected within Plan El Paso's potential annexation areas (City of El Paso 2012), with the exception of projected growth adjacent to District 1. Similar trends for city growth are suggested in 2031 land-use, with Districts 1, 4, and 5 dominating the cities' growth. The landscape metrics suggest as Districts 1 and 5 continue to expand, there is a decline in fragmentation. However, District 4 indicates an increase in fragmentation as the districts' developed areas expand. Panel data analysis was performed to investigate the relationship between landscape metrics and electricity consumption. The results indicate that the developed mean patch area is positively correlated with consumption, provided the metric does not remain

constant. The findings suggest that future growth continues to be directed within Districts 1 and 4, with fragmentation discouraged through city policies. The vast growth concentration within single-family housing should be redirected to compact housing within the high-intensity sub-category. Though these categories have experienced the fastest growth, high intensity comprises the smallest area of the districts' landscape. Further research should be conducted to include metrics that describe the interconnection of developed patch areas and an increase in time observations to provide a better understanding of the landscape metrics and electricity consumption relationship.

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Chapter 1: Introduction

1.1 Problem Statement

Urbanization has become an increasing concern to planners, engineers, decision-makers, and the public in recent years. Urban growth is a necessary process to meet the needs of a growing population through housing, roadways, and commercial buildings; which are examples of what encompasses urban growth. The patterns and rate of urban expansion have been studied extensively in various cities of the United States through the use of remote sensing and geographic information system (GIS). However, minimal research has been conducted to understanding the urbanization growth of El Paso, Texas in the past 15 years. Understanding El Paso's past urban growth patterns allows for a basis to predict future trends of urbanization. Understanding future urban growth patterns allows decision-makers and stakeholders to plan accordingly for a sustainable El Paso. According to the El Paso Comprehensive Plan (Plan El Paso), "managing El Paso's outward expansion is perhaps the most complex and difficult strategy…" (City of El Paso 2012). Landscape metrics are a means to understand various aspects of urban growth patterns including fragmentation, sporadic growth, infill, or outward sprawl. Understanding growth patterns allows informed policy creation to plan for smart communities, which consist of dense development to limit transit times, reduce infrastructure costs, and are environmentally conscious. Urban growth has also placed a strain on resources such as energy consumption. Residential and commercial sectors account for 40% of U.S. energy consumption. Relating El Paso's urban growth patterns to electricity consumption allows decision-makers and the public to make informed decisions based on scientific analysis for policies and urban planning strategies.

1.2 Objectives

The following objectives illustrate the focus of this dissertation:

1) Provide an understanding of El Paso's past growth from 2001 – 2016 utilizing change analysis.
2) Utilize landscape metrics to analyze El Paso's urban dynamic growth patterns.
3) Predict future land-use within El Paso County for 2031 utilizing CA-Markov and apply landscape metrics to understand growth patterns.
4) Examine the relationship between El Paso's landscape metrics and electricity consumption.

1.3 Significance of Research

"The proper design and management of the physical environment-both the natural and man-made realms – will determine if we can provide an even better El Paso to our children and grandchildren than the one we know today," from El Paso's City Comprehensive Plan. The purpose of this study was to provide decision-makers and stakeholders with an understanding of El Paso's urban growth patterns within the last 15-years, project and analyze future growth patterns, and its' subsequent impact on electricity consumption in order to make informed decisions. Cities typically consist of an urban center that consists of the cities' nucleus from which employment, entertainment, and government resources are centered. Thus, a cities' growth is centered around the urban centers. The urbanization analysis of such cities' focus on growth trends from the urban center. However, El Paso's growth has dispersed into three main wedges due to El Paso's unique geographical setting consisting of urban growth constrains. The constraints include a countries' border (Mexico), state border (New Mexico), largest urban park in the United States (Franklin Mountains State Park), and military reservations; which dictate El Paso's urban expansion locations. These constraints have forced urban expansion beyond El

Paso's urban center (City of El Paso 2012). This study focused on specific districts within the county that possessed the majority of urban growth within the study period. Minimal research has been conducted on El Paso's urban growth trends and consequential patterns. Therefore, this study adds to the existing research and provided an analysis of El Paso's urban growth trends from 2001-2016, and utilized landscape metrics to quantify the resulting urban dynamic patterns. CA-Markov was incorporated to project 2031 future growth to understand where urban development is projected to occur within El Paso county and analyze its' projected landscape patterns. Urbanization demands an increase in resources, such as electricity, to meet the needs of a growing community. According to Plan El Paso, the sustainable energy goal consists of "promote behavioral changes and consumption pattern that conserve energy…" (City of El Paso 2012). Due to data availability, this study focused on El Paso's urban dynamic patterns impact on electricity consumption, a secondary source of energy, within El Paso's fastest-growing areas within the last 15 years (2001-2016). Lessons learned from this relationship will provide decision-makers, urban planners, and residents a statistical basis for making informed decisions on how to expand El Paso to provide the optimum quality of life for the residents. This study is an example for urban areas, like El Paso, which possess constraints that influence urban growth patterns, and how these areas impact electricity consumption. El Paso is also a case study for cities who exhibit growth within specific regions of the city and wish to have an understanding of the growth characteristics.

1.4 Organization

This dissertation begins with the literature review of topics such as the application of remote sensing in understanding urban development, landscape metrics for dynamic urban growth patterns, predictions of land-use, and the relationship between electricity consumption and urban growth. The methodology adopted and data collection for this study are discussed in Chapter 3. This chapter discusses the location of the study area, land-use change analysis implemented along with the landscape matrices utilized, land-use prediction for 2026, and the role of electricity consumption in urban growth. Chapter 4 discusses the results of the analysis, including the change analysis, the accuracy of the data utilized in the study, landscape matrices and their findings, future prediction of land-use for 2026, and the relationship between urban patterns and electricity consumption. A summary of the study, concluding remarks, limitations, and recommendations are presented in Chapter 5 of this dissertation.

Chapter 2: Literature Review

2.1 Background

The world's population is estimated to grow by approximately one billion people within the next decade, reaching 8.5 billion by 2030 (United Nations 2017). According to the United Nations, 3.5 billion people, half of the world's population, currently reside within cities and is expected to increase to 5 billion by the year 2030 (United Nations 2016). This results in "60% of the world's population will live in cities by 2030 (United Nations n.d.)." The term "cities" is commonly referred to as incorporated areas that have legal jurisdiction to conduct governmental activities, such as collecting taxes, within "legally defined geographic boundaries" (U. C. Bureau 2015). The U.S. Census Bureau defines urban areas as "a cluster of densely settled census blocks that together have a population of at least 2,500 people" (U. C. Bureau 2015). Thus, the term "urbanization" refers to the spatial distribution of former rural areas into urban, built environments (United Nations 2018). In 1990, the U.S. possessed 86 cities with a population of 300,000 or more. The number of cities grew to 144 in 2018 and is projected to contain 158 cities with a population of 300,000 or more in 2030 (United Nations 2018). Within the past eight years (2010 – 2018), the United States has experienced an approximate 6% population increase, with Texas ranked first in population growth at nearly 3.6 million people added (U. C. Bureau 2015). In 2001, 79% of the US population lived in urban areas. The percentage increased to 82% in 2016 and is projected to increase to 85% by 2031 within the US (United Nations 2018). Metropolitan areas are designated by the U.S. Office of Management and Budget, and may consist of one or several counties, an urban center of a minimum of 50,000 people, and may include additional cities that rely on the urban center for their economic and social benefits (U. C. Bureau 2015). Cities are the center of economic prosperity and advancement opportunities. As a result, population growth is considered an indicator of projected city growth to accommodate the needs of residences such as drinking water and wastewater, transportation, and housing. As cities continue to expand, it is vital to plan and manage expansion wisely and not randomly. El Paso County is expected to reach a population of over 1 million by 2030, which has continuously expanded outward since 1873 (City of El Paso 2012). Understanding past and future urban growth and their patterns are vital in planning and designing sustainable and efficient future development. To ensure a sustainable environment, consideration of energy efficiency within new development is a priority under the Energy goal in Plan El Paso. Meeting the energy needs for the present without compromising future El Pasoan's resources, is the goal of understanding the relationship between urban growth and electricity consumption. Providing an analysis of past and future land-use within the region, and how these patterns affect energy consumption will provide decision-makers and stakeholders vital information to make informed and sustainable decisions.

2.2. Understanding Urban Development Utilizing Remote Sensing

As a result of city expansion, land cover is rapidly changing to accommodate the needs of a growing population (Tv, Aithal, and Sanna 2012). Urbanization incorporates land cover and land-use change in and around metropolitan areas. Land cover pertains to the current land features (Sudhira, Ramachandra, and Jagadish 2004; Tv, Aithal, and Sanna 2012), which can include the natural environment (Chen Liping, Sun Yujun, and Saeed 2018), while land-use relates to human dwellings and resulting modification of land cover (Chen Liping, Sun Yujun, and Saeed 2018; Sudhira, Ramachandra, and Jagadish 2004; Tv, Aithal, and Sanna 2012). Land-use and land cover (LULC) change refers to the transformation of one land classification to another. This transformation occurs during urbanization when the native land cover is transformed to built-up urban areas. Urbanization is the fastest growing classification of land-use (United Nations 2016). Synonymous with impervious surface cover, urbanization includes road, residential/commercial buildings, and structures. LULC change of cities exhibits various growth patterns and size over time. This spatial-temporal relationship has played a critical role in monitoring and mapping urbanization trends. The tools used in analyzing and understanding spatial-temporal trends are Remote Sensing (RS) and Geographic Information Systems (GIS). The coupled relationship between RS and GIS application has been well-documented for its effective use in mapping and analyzing urban development. This relationship incorporates satellite imagery to perform LULC changes and ultimately a change detection analysis (Aburas et al. 2017). Change detection analysis provides both, a visual and quantitative analysis, as to the amount of change that has occurred over a specified length of time. It is primarily used to measure, monitor, and evaluate LULC changes that have occurred within a study area (Aburas et al. 2017). The stages of change detection analysis are data acquisition and processing, accuracy assessment, mapping, and identifying occurrences of change (Aburas et al. 2017; Alkan et al. 2013; Suribabu, Bhaskar, and Neelakantan 2012). Data acquisition is dependent upon the desired study and availability of data.

An error matrix and kappa index are popular accuracy assessments conducted for verification of data. Various maps are then created to identify and analyze land-use change. The final product consists of maps and statistical information to provide a visual and quantitative understanding of land-use change (Aburas et al. 2017). Change detection analysis is vital in understanding the characteristics and processes of city growth.

2.2.1 Urban Development Analysis within Arid Regions/El Paso

Earlier research studies have been conducted to understand urban dynamics for metropolitan areas centered within wooded or agricultural rich regions within the United States (US), including Washington, D.C. – Baltimore and Minneapolis-St. Paul (Sexton et al. 2013; Yuan et al. 2005). These studies discuss the effects of urbanization on deforestation and farmlands. On the contrary, for arid urban environments, research has incorporated Phoenix, AZ as a study area , where the region is used for a proposed expert land cover classification system (Stefanov, Ramsey, and Christensen 2001). Phoenix Metropolitan area has also been the study area to examine possible land fragmentation due to rapid urban growth, and examine the accuracy of land cover data by the National Land Cover Database (Shrestha et al. 2012). A comparison of spatiotemporal patterns among Phoenix, AZ and Las Vegas, NV was conducted to compare growth patterns of the vastly growing urban areas (Wu et al. 2011). Urban growth patterns have focused included Tucson, AZ to measure the effects of urbanization (DiBari 2007).

El Paso, Texas is one such city located within an arid environment. Numerous research articles have included a discussion of El Paso's growth using remote sensing. However, these articles focus on a larger study region which includes the entire El Paso Del Norte Region. Few urban dynamic studies focused solely on the City of El Paso to provide an extensive understanding of its' spatiotemporal patterns and drivers. Remote sensing technology has been utilized for analyzing critical areas within El Paso-Juarez for flood control as a result of the extreme weather events (such that occurred in 2006 (Barud-Zubillaga 2011)), evaluating extreme rainfall scenarios and subsequent runoff due to land-use change and studying its' impact on watersheds within El Paso (Neelam 2018). Studies also incorporated remote sensing to analyze air pollutants within the region (Mahmud 2016), nighttime urban heat retention and subsequent health effects within El Paso (Amaya et al. 2016), and land-use change effects on the ecosystem (Miyazono, Patiño, and Taylor 2015). Land-use change analysis was conducted for the Middle Rio Grande Basin along a 16km swath of either side of the Rio Grande River, which includes portions of El Paso-Ciudad Juarez. Ciudad Juarez is located directly adjacent to El Paso, separated only by the Rio Grande River. Mubako et al. discussed the spatiotemporal changes occurring over a period of 25-years (1990 – 2015) for water resource and policy management (Mubako et al. 2018). Everett included portions of El Paso in land-use change analysis and its' impact on the Native American community of Ysleta del Sur Pueblo's culture (Everett 2016).

2.2.2 National Land Cover Database (NLCD)

The National Land Cover Database (NLCD) is a result of a collaboration among federal agencies (Multi-Resolution Land Characteristics Consortium) and was the pioneer in providing consistent land cover information for the conterminous United States utilizing Landsat imagery (Wickham et al. 2014; Shrestha et al. 2012). The most recent version of NLCD is the 2016 product suite, which covers a 15-year period from 2001 – 2016 (2001, 2004, 2006, 2008, 2011, 2013, 2016) for the Continental United States (CONUS) using categorical land cover information. The suite was developed based on four extensive mapping techniques which include: spectral signatures, time-dependent spectral succession and trajectory patterns, spectral patch shape, and ancillary data (Homer et al. 2020). This more comprehensive method updates previous NLCD releases and allows a comparison of land cover data among the time periods provided (Homer et al. 2020).

The NLCD 2016 provides 30m revolution images with eight class categories for CONUS (MRLC 2016). Within each class category, the categories are further divided into classification descriptions. The developed class category consists of four classification descriptions based on varying impervious surface percentages (Table 2.1). The remaining categories pertain to non-impervious areas, such as water, barren land, forest, and shrubland. The NLCD 2016 classes and descriptions allow for the creation of land-use maps, which provide a visual interpretation of land-use for regions of interest.

Table 2.1: NLCD 2016 Land Cover Classification

Class	**Description**
Water	Open Water: < 25% of vegetation or soil
	Perennial Ice/Snow: > 25% of ice and/or snow
Developed	Developed, Open Space: < 20% impervious surface
	Developed, Low Intensity: 20% - 49% impervious surface
	Developed, Medium Intensity: 50% - 70% impervious surface
	Developed, High Intensity: 80% - 100% impervious surface
Barren	Barren Land: < 15% vegetation
Forest	Deciduous Forest: > 20% vegetation, > 75% of trees shed leaves seasonally
	Evergreen Forest: > 20% vegetation, > 75% of trees maintain leaves yearly
	Mixed Forest: > 20% vegetation, neither deciduous/evergreen > 75%
Shrubland	Dwarf Scrub: > 20% shrub, < 20 cm tall shrubs
	Shrub/Scrub: > 20% shrub, < 5 m tall shrub
Herbaceous	Grassland/Herbaceous: gramanoid/herbaceous vegetation > 80%
	Sedge/Herbaceous: sedges/forbs > 80%
	Lichens: fruticose/foliose lichens > 80%
	Moss: > 80% moss
Planted/Cultivated	Pasture/Hay: > 20% pasture/hay vegetation
	Cultivated Crops: > 20% crop vegetation
Wetlands	Woody Wetlands: > 20% forest/shrubland, soil/substrate saturated/covered with water
	Emergent Herbaceous Wetlands: > 80% perennial herbaceous, soil/substrate saturated/covered with water

The NLCD 2016 suite is the most accurate release in NLCD history (Homer et al. 2020) and has been used extensively to study urbanization (Shrestha et al. 2012; Bounoua et al. 2018; Kew and Lee 2013). However, an argument has been posed to question past versions of NLCD reliability in forest areas where satellite imagery does not detect minor development (Irwin and Bockstael 2007). Shrestha, et al. 2012 found that the NLCD, in particular 2001 NLCD, was "very accurate" for assessing developed areas in the treeless desert region of Phoenix, due to the lack of satellite obstruction from the treeless environment (Shrestha et al. 2012). It was recommended that NLCD be used in analyzing urban dynamics in desert environments to save time and resources (Shrestha et al. 2012).

2.2.3 Classification Accuracy Assessment

An imperative step in developing land-use maps is determining the accuracy of the maps. This process begins by creating ground-referenced random points of the subject area and determining the classification of each point using Google Earth images. The ground-referenced points are then matched and compared to the land-use classified image. The amount of "matches" and "mismatches" are utilized in an error matrix (confusion matrix), which includes various probability terms that describe the performance of the classification data (Table 2.2) (Keranen and Kolvoord 2014; Mubako et al. 2018).

Table 2.2: Error Matrix

	Actual Category: Ground Truth		**Total**	**Errors of Commission**	**User's Accuracy**
Classified Category	**(0) Developed**	**(1) Barren**			
(0) Developed	TD	FD	(TD+FD)	FD/(TD+FD)	TD/(TD+FD)
(1) Barren	FB	TB	(FB+TB)	FB/(FB+TB)	TB/(FB+TB)
Total	(TD+FB)	(FD+TB)	Grand Total*	(TD+TB)/Grand Total	Overall Accuracy
Errors of Omission	FB/(TD+FB)	FD/(FD+TB)			
Producer's Accuracy	TD/(TD+FB)	TB/(FD+TB)			

The terms utilized in the error matrix are described as the following:

- True Developed (TD): The classification map states it's developed, and it is a developed area.
- False Developed (FD): The classification map states it's developed, and it is not a developed area.
- True Barren (TB): The classification map states it's barren, and it is a barren area.

- False Barren (FB): The classification map states it's barren, and it is not a barren area.
- Errors of Commission: Probability that the category is identified, actual conditions state it does not exist (the map says “it is, and it isn’t”).
- User's Accuracy: Probability of correct classification in comparison to actual conditions.
- Errors of Omission: Probability that the category is omitted from the correct class (the map says “it isn’t, and it is”).
- Producer's Accuracy: Probability of a correctly assigned classification to the correct class.
- Overall Accuracy: Probability of overall correct classification.

The column information relates to the pixel classification in relation to the ground truth. The rows indicate the pixel classification in relation to their assigned class. The producer’s accuracy provides insight for the creator of the classified map, as it relates to the probability that a land use type is classified correctly. Its’ complement metric is error of omissions. Whereas, the user’s accuracy relates to the probability of the classification to the actual site conditions, and is essential for map users (Rwanga and Ndambuki 2017). Thus, its’ complement is errors of commission. Both producer’s and user’s accuracy are essential in understanding the validity of the data (Congalton 1991). The overall accuracy provides insight into the validation of the entire data set.

In land-use research, the error matrix also includes the Kappa coefficient. The Kappa coefficient (herein Kappa) is used extensively for accuracy assessment in various research subjects, including medical, psychology, and remote sensing to understand data accuracy (Stehman 1996; TANG et al. 2015; Viera and Garrett 2005). Kappa provides an understanding of the classified data compared to the classification by chance. The Kappa coefficient calculates the difference between observed agreement and expected agreement. The observed agreement, or overall agreement; represents the number of instances that are correctly classified. Whereas, expected agreement considers the correctly classified instances based on chance (Foody 2020; Viera and Garrett 2005).

The following provides the general Kappa coefficient equation:

$$Kappa, K = \frac{(p_o - p_e)}{(1 - p_e)} \qquad (2.1)$$

Where the observed agreement, p_o = observed agreement and p_e = expected agreement

A suggested agreement range to assist in interpreting the Kappa coefficient results, is depicted in Table 2.3 (Landis and Koch 1977; Viera and Garrett 2005):

Table 2.3: Kappa coefficient agreement range

Kappa Statistic	**Strength of Agreement**
< 0%	Less than chance
0% – 20%	Slight
21% – 40%	Fair
41% - 60%	Moderate
61% - 80%	Substantial
81% - 100%	Almost Perfect

Although the Kappa coefficient has been used extensively in remote sensing applications, recently a call to abolish the use of Kappa for remote sensing applications has gained momentum. The argument centers around Kappa's focus on agreement beyond chance. Rather than the accuracy of the data. Kappa is also hard to interpret, even with the use of the suggested ranges outlined in Table 1. With highly favorable overall accuracy results, the Kappa can vary significantly. Instead, the assessment of each class should be considered such as the producer's and user's accuracy along with the error matrix is suggested (Foody 2020).

2.3 Landscape Metrics

Landscape metrics enhance the change detection analysis by providing an effective means to quantify spatiotemporal patterns of the urban landscape (Tv, Aithal, and Sanna 2012). Landscape metrics also provide a quantifiable understanding of urban sprawl. Urban sprawl typically occurs on the outskirts of a city, where urban growth is sporadic and not properly planned. Landscape metrics provide an understanding of growth attributes; such as shape, complexity, aggregation, and diversity of growth (Tv, Aithal, and Sanna 2012) through the use of size, shape, and patches as a result of remote sensing (Shrestha et al. 2012). Research suggests that a few selected landscape metrics are capable to successfully explain the spatiotemporal characteristics of urbanization (Wu et al. 2011). Specific metrics utilized include patch density, number of patches, and class area (Shrestha et al. 2012; Wu et al. 2011; Flores 2008). Landscape metrics are typically used for entire city areas. This includes analyzing landscape metrics at differing spatial resolutions (Wu et al. 2011) and concentric circles with an increasing specific distance surrounding the study area ((Tv, Aithal, and Sanna 2012). However, limited research has been conducted on comparing the landscape metrics of the entire city to specific districts within the city that have illustrated the most growth.

Utilizing landscape metrics for the El Paso regions includes past research for Las Cruces, NM and Ciudad Juarez, Mexico, where fragmentation patterns due to urban expansion were investigated (Flores 2008; York et al. 2011). However, limited research has been conducted to understand the urban dynamics of El Paso using landscape metrics.

2.3.1 FRAGSTATS Landscape Metrics Model

FRAGSTATS is a popular computer software program that generates landscape metrics and was developed in 1995 by Dr. Kevin McGarigal and Barbara Marks of Oregon State University (McGarigal and Marks 1995). The program has undertaken several upgrades and currently is compatible with ArcGIS. FRAGSTATS has been used extensively in research as a tool in determining the landscape metrics for various study areas around the world. Past research study areas using FRAGSTATS include India, Canada, and China (Cumming and Vernier, n.d.;

X. Li et al. 2001; Midha and Mathur 2010). A comparison of landscape metrics of Phoenix, AZ and Las Vegas, NV, and spatiotemporal pattern analysis studies have been performed for Austin TX and Phoenix Metropolitan Area using the program (Kim et al. 2018; Shrestha et al. 2012). FRAGSTATS is a preferred tool in measuring urban dynamics.

2.4 Future Land-use

Predicting future land-use cover is an additional but critical aspect in analyzing urbanization in order to make informed decisions today to ensure an optimal future living environment for residents and the environment. Plan El Paso Comprehensive Plan discusses a "Future Land-use Map", Figure 1, which depicts areas that are available for immediate urban expansion and potential annexation areas that are deemed not necessary immediately but are available if needed (City of El Paso 2012). The areas available for immediate growth are designated O-7 Urban Expansion and are Areas 1 – 3 in Figure 2.1. These areas are ideal for immediate expansion as the areas are owned by the City itself, within city limits, and the city can decipher when and how the expansion will occur through the use of municipal services, zoning, and subdivision of land (City of El Paso 2012). Area 1 is located west of the Franklin Mountains, Area 2 is east of the Franklin Mountains, and Area 3 is adjacent to the military and industrial areas.

Potential annexation areas are located far east of El Paso city. The city has limited authority over areas outside the city boundary and would require annexation to have full control. This option is less favorable than encouraging growth within the city limits, due to the expense of providing necessities such as roads and utilizes and competitive interest in the land from other cities, governments, and stakeholders. However, annexed areas would be subject to municipal services, zoning, and subdivision of land along with collecting required city taxes. Providing a statistical basis for predicting future land-use, is critical in providing decision-makers with an understanding of the areas projected urban growth patterns.

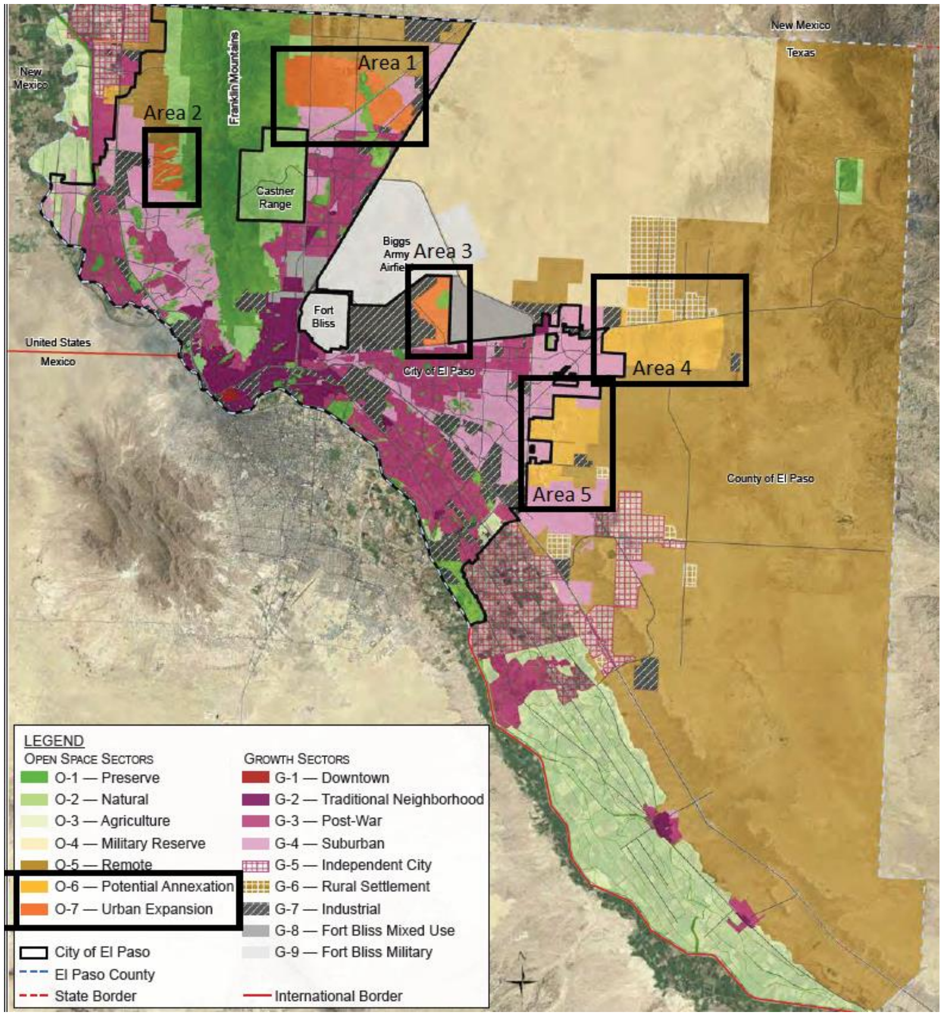

Figure 2.1: Future Land-use Map (City of El Paso 2012)

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2.4.1 CA-Markov Model

Predicting future land-use has been used extensively in the past 15 years (Aburas et al. 2016) for urban development planning and management using the CA-Markov model (Chen Liping, Sun Yujun, and Saeed 2018; Jokar Arsanjani et al. 2013; Tang and Di 2019; Rimal et al. 2017). CA-Markov is a hybrid model that incorporates past spatial and temporal trends to predict future projections. CA (cellular automata) is limited due to its' inability to consider outside factors such as, physical and socioeconomic factors (Aburas et al. 2016). Therefore, a quantitative system must be included such as Markov Chain model. The probability model, Markov Chain model, is used extensively in analyzing land-use change due to its' stochastic process of predicting the probability of change from one state to another using the preceding state conditions (Subedi, Subedi, and Thapa 2013; Chen Liping, Sun Yujun, and Saeed 2018; Taha 2007). The analysis is conducted for a specific time period, with the start time as the baseline and is discrete in time and state. The Markov model is based on transition probability (Fu, Wang, and Yang 2018). Thus, it results in a transition probability matrix, which describes the probability of a state transitioning into another in matrix form. The following illustrates the Markov Chain probability matrix:

$$p_{ij} = \mathbb{P}(\boldsymbol{X_{t+1}} = \boldsymbol{j} \mid \boldsymbol{X_t} = \boldsymbol{i}) \tag{2.2}$$

$$\sum_j p_{ij} = 1, i = 1, 2, \ldots, n$$

$$p_{ij} \geq 0, (i, j) = 1, 2, \ldots, n$$

$$\mathrm{P} = \begin{bmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \vdots & \vdots \\ p_{n1} & \cdots & p_{nn} \end{bmatrix}$$

$n = number\ of\ states$

$t = points\ in\ time$

$i = state\ at\ t - 1$

$j = state\ at\ t$

Along with the Markov probability matrix, suitability maps are also implemented in the CA-Markov model. Suitability maps illustrate the probability of a cells' transition by utilizing transition rules for each land-use class. Transition rules incorporate socio-economic and/or physical factors' influence on land-use change through the use of multi-criteria evaluation (MCE) (Subedi, Subedi, and Thapa 2013). MCE combines transition rules for constraints and factors to form a single index accurately predict land-use change (Chen Liping, Sun Yujun, and Saeed 2018). Constraints do not allow class expansion, while factors provide a probability of class expansion typically based on distance (Chen Liping, Sun Yujun, and Saeed 2018). The result of the MCE analysis is presented as suitability maps.

The Markov transition probability matrix along with suitability maps are then applied in the CA-Markov model where spatial relations among states are analyzed. Cellular Automata (CA) considers discrete spatial and time configurations for complex arrangements. Therefore, the study time period is incorporated, along with the state of neighboring cells. The hybrid model is expressed as follows (Fu, Wang, and Yang 2018):

$$S_{ij}^{t+1} = f(S_{ij}^{t}, \Omega_{ij}^{t}, V) \tag{2.3}$$

$Located\ at\ row\ i\ and\ column\ j$:

$S_{ij}^{t+1} = state\ of\ cell\ at\ time\ t+1$

$S_{ij}^{t} = state\ of\ cell\ at\ time\ t$

$\Omega_{ij}^{t} = state\ of\ neighbors\ at\ time\ t$

$V = suitability\ factors$

$f = transition\ rule$

CA is an iterative process that is composed of cells, each cell changes/maintains a state at each time iteration based on rules provided by the transition probability matrix and area, and can be utilized from the simplest of patterns to complex algorithmic problems (Berto and Tagliabue 2017). As a result, cells within close proximity to existing areas possess an increase in transition probability resulting in land-use changes (Fu, Wang, and Yang 2018). The CA-Markov output provides a projected land cover map of the time period in question.

The advantage of the hybrid CA-Markov model is that the Markov Chain model considers the change of a cell from one point in time to another. However, the influence of the neighboring cells is not considered. Whereas the CA model does consider the state of the surrounding cells. The state of the neighboring cells influences the potential for a cell change in state (Jokar Arsanjani et al. 2013). The disadvantage of the CA-Markov model is the lack of integrating socio-economic influence within the expansion scenario. However, integration of models such as fuzzy logic, logistic regression, and multiple criteria evaluation allows the inclusion of socio-economic factors such as population and income. These methods incorporate weighted factors from historical data, policies, surveys, and literature review (Fu, Wang, and Yang 2018; 2018)

Once the results are provided, a verification of the CA-Markov model output is conducted. This process follows the same procedure outlined in Section 2.2.3 Classification Accuracy Assessment. The CA-Markov model is used to predict the land-use of a time period with reference data. The predicted results are compared to the reference data for validation using the accuracy assessment procedure. If the accuracy assessment is acceptable, the projection of future land-use is predicted (Chen Liping, Sun Yujun, and Saeed 2018; Rimal et al. 2017; Jokar Arsanjani et al. 2013).

2.4.2 TerrSet Geospatial Monitoring and Modeling System

TerrSet is a software package possessing a wide range of monitoring and modeling applications using geospatial data. One of the popular applications is IDRISI GIS Analysis Tools. IDRISI possesses a variety of statistical analysis tools that incorporate raster data, which is the matrix cell formation that results in land-use maps. One of the analytical tools within IDRISI is the CA-Markov tool. The CA-Markov tool has been used extensively in land-use prediction (Subedi, Subedi, and Thapa 2013; Rimal et al. 2017; Chen Liping, Sun Yujun, and Saeed 2018; Wang, Zheng, and Zang 2012; Fu, Wang, and Yang 2018). This analytical tool can and has been used to understand what future landscapes will exhibit to implement policies, environmental constraints, and utilize in urban development planning.

2.5 Electricity Consumption and Urban Development

Globally, cities contribute to 70% of energy use and an average of 45% of greenhouse gas emissions (United Nations 2015). For energy consumption within the U.S., 40% is attributed to residential and commercial sectors (US Energy Information Administration 2019). Thus, as urban growth continues, the demand for energy will increase to meet the communities' needs. Various socio-economical and physical attributes contribute to a society's energy use. Income, education, unemployment percentage are examples of socio-economical attributes (Abbasabadi et al. 2019), while travel distance, building characteristics, and land-use are physical attributes that contribute to energy consumption (Abbasabadi et al. 2019; Zhao, Thinh, and Li 2017). The relationship between urban form and energy consumption, in particular electricity, has been studied at various levels. The levels include neighborhood attributes including street configurations and tree shade (C. Li, Song, and Kaza 2018); to the city level where density and location were factors found to contribute to electricity consumption (Wilson 2013). While these relationships have been extensively studied, minimal research has been conducted to quantify the correlation between spatiotemporal information, utilizing landscape metric results, to energy consumption (Zhao, Thinh, and Li 2017). Zhao et al. (2017). These studies have indicated that urban growth and irregular patterns contribute to energy consumption (Zhao, Thinh, and Li 2017). Therefore, it is imperative to examine the impact of urban dynamics on energy consumption to allow decision-makers and planners make informed decisions and policies for a sustainable community.

Several studies have examined energy consumption, in particular electricity consumption, within El Paso, Texas. Electricity is a secondary source of energy, generated from renewable and nonrenewable sources (US Energy Information Administration 2020). Research for the El Paso area related to energy consumption has focused on building optimization (Moreno and Taboada 2013), electricity consumption and economic factors (Fullerton Jr and Walke 2019; Fullerton and Walke 2018), and implementation of solar technology for water desalination (Delgado, Beach, and Luzzadder-Beach 2020; Lu, C. Walton, and H.P. Swift 2001). Little is known about the relationship among El Paso's landscape patterns and energy consumption, in particular electricity consumption.

2.5.1 Panel Data Analysis

Panel data analysis has been used for analyzing the relationship between landscape metrics and electricity consumption within urban environments (Zhao, Thinh, and Li 2017; Chen et al. 2011). The advantage of panel data is that it considers both time and space, as it analyzes a particular individual (cities, districts, companies) over various points in time. Panel data can be presented in a balanced or unbalanced panel form. The balanced panel indicates the individuals are observed over the same points in time. Whereas, unbalanced panel data possesses individuals with some observations over points in time. This study utilized balanced panel data. Panel analysis consists of three major regression models: pooled regression, variable intercepts and constant coefficients, and variable intercepts and variable coefficients models. An F-test is performed in order to determine which model is best fits the data. The pooled regression indicates that the additional random or fixed effects do not significantly affect the model. If the pool regression model is rejected, then a Hausman test is performed to determine if random or fixed effects should be considered. The selected model is then implemented to determine the metrics that exhibit a significant relationship with electricity consumption.

2.6 Summary

Urban growth has been widely examined using spatiotemporal technology of remote sensing and geographic information systems (GIS). The results obtained through these technologies provide an understanding of where the growth has transpired within a study area and to what extent. Resources, such as the National Land Cover Database (NLCD), provide land-cover and land-use information, for the United States, for use in understanding urban dynamic trends. Patterns exhibited within the change of urban dynamics can be quantified using landscape metrics. FRAGSTATS has been the preferred program to perform the landscape metrics for research studies. Understanding past land-use patterns of growth provide a basis for predicting future land-use. TerrSet Geospatial Monitoring and Modeling System is utilized to incorporate the statistical CA-Markov model which incorporates past spatial and temporal attributes in predicting future land-use for a study area. As urban areas continue to grow, electricity consumption will inevitably increase. This relationship between landscape patterns and electricity consumption will provide decision-makers, planners, and residents with a statistical-based methodology to make informed decisions, policies, and urban planning procedures for a sustainable community.

Chapter 3: Data and Methodology

This research provides a comprehensive analysis of past and future urban growth trends, landscape metrics to quantify growth patterns, and the relationship between urban patterns and electricity consumption. The methodology adopted for this research is depicted in Figure 3.1. The methodology is discussed in detail later in this chapter.

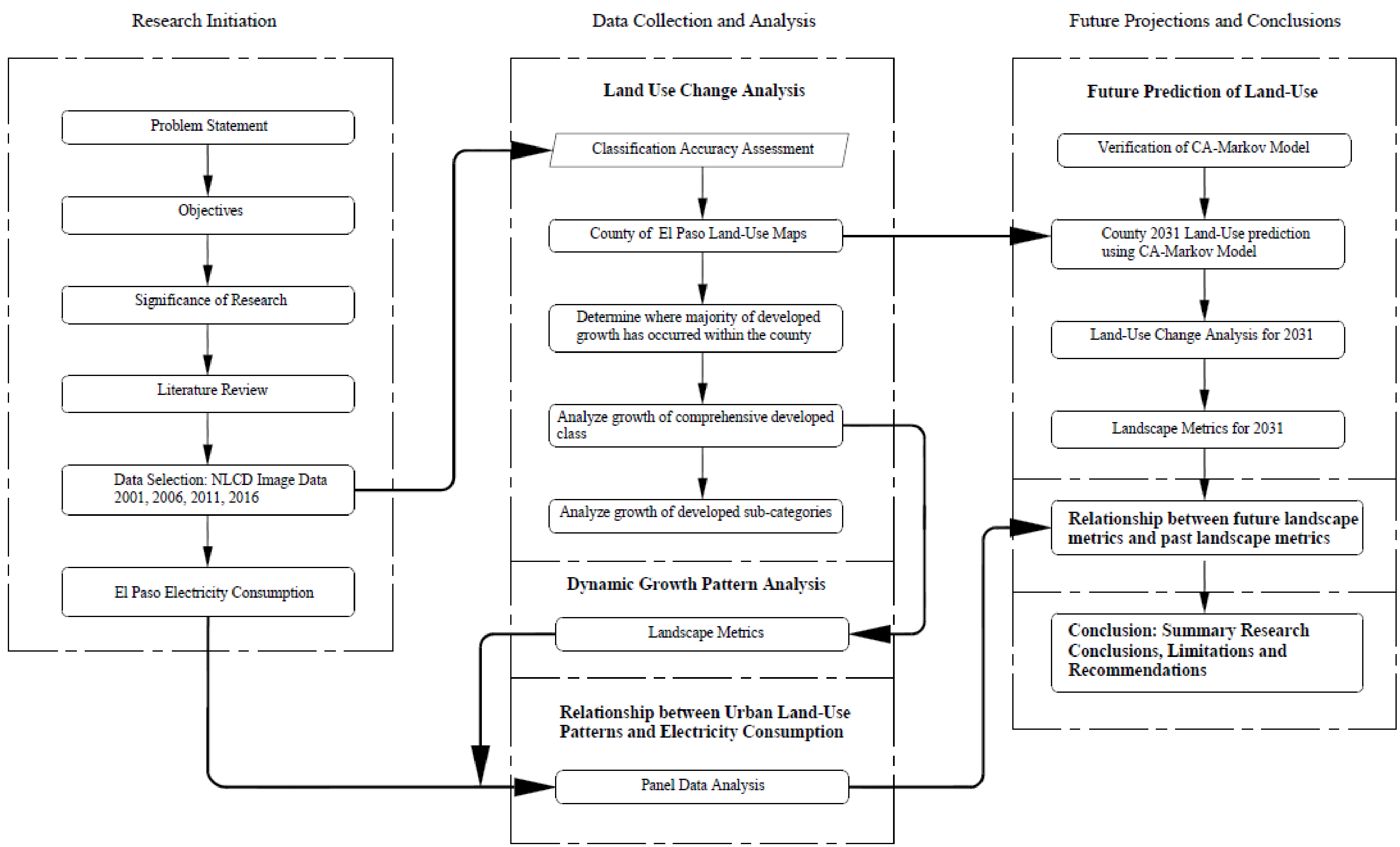


Figure 3.1: Workflow diagram for research methodology

3.1 Geographical Location

El Paso County is located at the westernmost point of Texas and borders the state of New Mexico and the country of Mexico. It lies within the largest desert region in North America, the Chihuahuan Desert. The region is comprised of a variety of features including the Rio Grande River, desert shrublands, and the largest urban national park, Franklin Mountains State Park, at approximately 104 km^2 (Fig 3.2). Though the area resides within the largest desert region in North America, the Chihuahuan Desert, the area includes agricultural farmland of various crops including cotton, pecans, and hay (United States Department of Agriculture 2017), as a result of irrigation from the Rio Grande. Several U.S. military reservations are also located within El Paso County. The reservations include the main post of the countries' second-largest U.S. Army base - Fort Bliss, Castner Range, and Biggs Army Airfield ("Fort Bliss, TX (TEXAS)" 2018). El Paso County was home to more than 840 thousand people in 2018, with the population estimated to increase to over 952,000 by 2020 (Texas Department of State Health Services 2014; U.S. Census Bureau 2019). The county consists of several minor cities and towns including Horizon City, Socorro, Clint, Vinton, and Anthony. City of El Paso (hereafter El Paso) is by far the largest populous city in the county and was ranked 22nd among the most populous cities in the nation by 2018 (U. S. C. Bureau 2019) with an estimated population of over 683 thousand. El Paso accounted for 70% of the county' population in 2018 (U. S. C. Bureau 2019).

Unlike many other cities that are able to expand in various directions around urban centers, such as Phoenix and Las Vegas, El Paso's growth is restricted due to several jurisdiction entities. The jurisdictions include a country (Mexico) and states (New Mexico and Chihuahua, Mexico) that lie adjacent to the study area. This uniqueness adds to the complexity and interest of understanding the growth patterns of not only an urbanized area located within a desert region but the second-largest US-Mexico border city next to San Diego, CA. El Paso wraps around the southern tip of the Franklin Mountains and extends along the west and east side of the mountain. On the eastern side of the mountain, the city can expand northward and eastward. However, new development is limited on the western side as the boundaries to Mexico and New Mexico are in close proximity. The city is comprised of eight representative districts. Each district elects a representative to reside on the City Council for administering/amending the cities legislative duties, including budgets, taxes, policies, and ordinances.

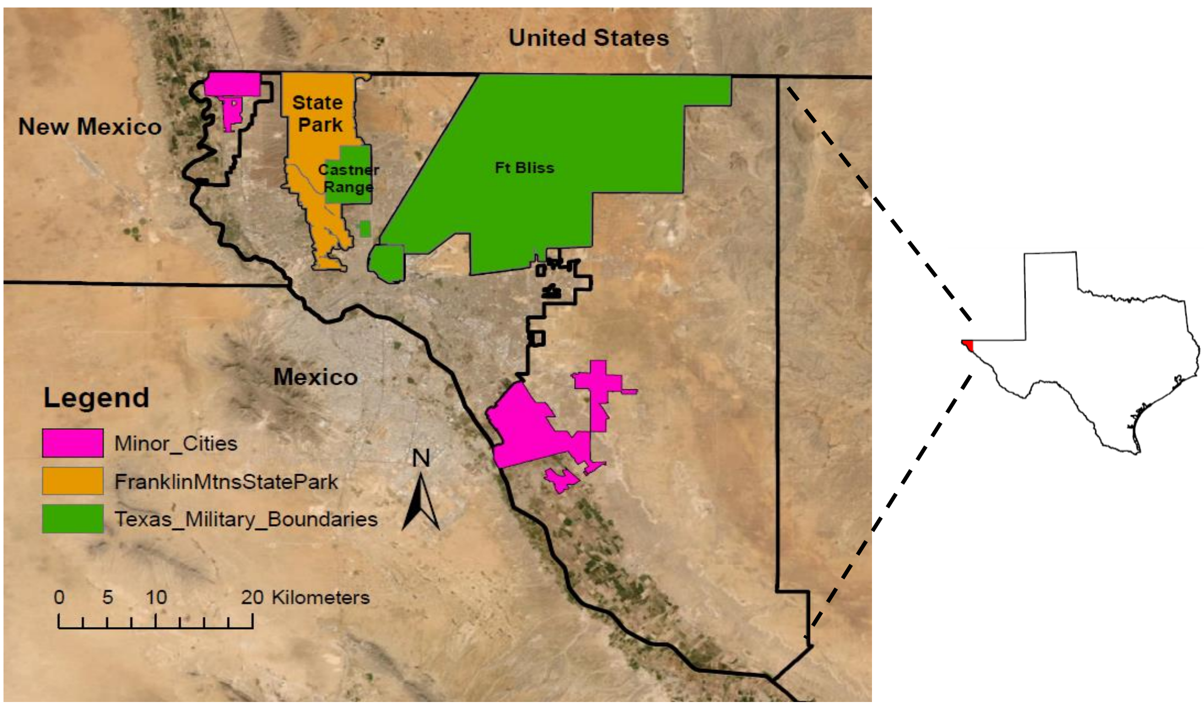


Figure 3.2: El Paso County and surrounding area

3.2 Land-Use Change Analysis

Land-use change analysis provides information on the growth or decline in land-use utilizing a combination of remote sensing and data management (Figure 3.3).

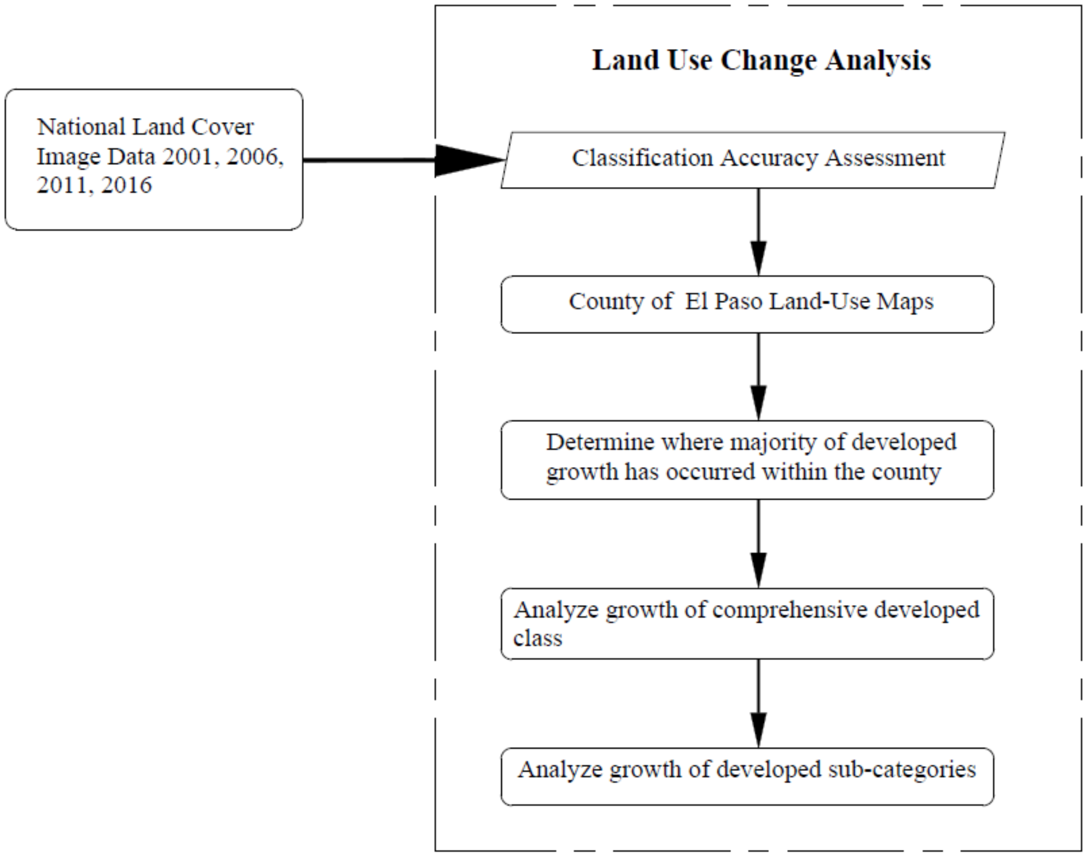


Figure 3.3: Land-use change analysis methodology

Applying georeferenced imagery from remote sensing, land-use maps are created to provide a visual representation of land-use within an area of interest. Viewing land-use maps over a desired time period, changes in land-use can be viewed through visual inspection. The maps also incorporate a database management system, which allows cell count of specified classes or categories, queries, and calculations in order to analyze data. Analyzing land-use maps and its' data over time provides insight into land-use changes. The focus of this study is on urban development changes within the El Paso region. Therefore, the land-use maps generated focus on the urban development that has transpired during 2001 – 2016.

3.2.1 National Land Cover Database

This study focuses on the NLCD developed class as an entirety and as individual sub-categories (Table 3.1) utilizing the NLCD 2016 suite of land cover data. Whereas, the remaining classes are combined into an "undeveloped" class due to their lack of inclusion of impervious surface.

Table 3.1: Land Cover Classification for Study

Class		Descriptions
Developed		Developed, Open Space: < 20% impervious surface
		Developed, Low Intensity: 20% - 49% impervious surface
		Developed, Medium Intensity: 50% - 70% impervious surface
		Developed, High Intensity: 80% - 100% impervious surface
Undeveloped (Barren)	Barren	Barren Land: < 15% vegetation
	Forest	Deciduous Forest: > 20% vegetation, > 75% of trees shed leaves seasonally
		Evergreen Forest: > 20% vegetation, > 75% of trees maintain leaves yearly
		Mixed Forest: > 20% vegetation, neither deciduous/evergreen > 75%
	Shrubland	Dwarf Scrub: > 20% shrub, < 20 cm tall shrubs
		Shrub/Scrub: > 20% shrub, < 5 m tall shrub
	Herbaceous	Grassland/Herbaceous: gramanoid/herbaceous vegetation > 80%
		Sedge/Herbaceous: sedges/forbs > 80%
		Lichens: fruticose/foliose lichens > 80%
		Moss: > 80% moss
	Planted/Cultivated	Pasture/Hay: > 20% pasture/hay vegetation
		Cultivated Crops: > 20% crop vegetation
	Wetlands	Woody Wetlands: > 20% forest/shrubland, soil/substrate saturated/covered with water
		Emergent Herbaceous Wetlands: > 80% perennial herbaceous, soil/substrate saturated/covered with water
	Water	Open Water: < 25% of vegetation or soil
		Perennial Ice/Snow: > 25% of ice and/or snow

3.2.2 Classification Accuracy Assessment

An accuracy assessment of the classified maps is an essential process in change detection. This process incorporates ground-referenced random points of the subject area and comparing them to the classification of each point using Google Earth images. This study utilized 300 random points for the county and 150 random points for the city level assessment (Fig 3.4). Congalton (1991) suggests a minimum of 50 random points per class (Congalton 1991). At the county level, the developed class random points ranged from 53 (2006) to 62 (2016); and 237 (2016) to 246 (2006) for the barren class. The number of random points varied from 73 (2001) to 96 (2016) for the developed class, and 54 (2016) to 77 (2001) for the barren class at the city level. The amount of random points for the developed category at the county and city level reflects the proportion of developed areas at these levels. Between 2001 and 2016, the developed area averages 22% at the county level and roughly 60% at the city level. The comparison of the random points between the ground reference data and the classification images are incorporated into an error matrix to provide an understanding of the accuracy of the data.

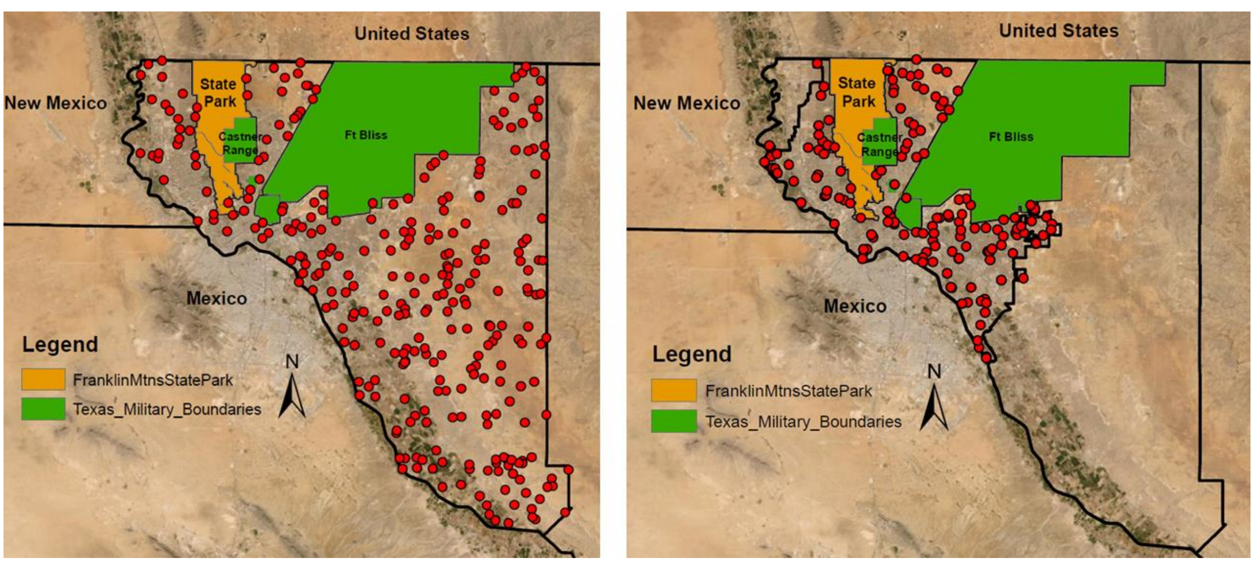


Figure 3.4: 2001 Random Points for County (left) and city of El Paso (right)

3.2.3 El Paso Land-Use Maps

Once the accuracy of land-use maps is assessed and deemed acceptable to utilize, the percentage of development growth was analyzed at the county level. The assessment includes determining where the majority of the developed growth took place within the county during the study period (2001-2016). This area is further analyzed to delineate regions of development at a smaller scale (Fig 3.5). This analysis is conducted through the use of land-use maps generated in ArcGIS utilizing the NLCD data.

Figure 3.5: Analyzing developed areas within the El Paso region.

To measure the developed growth and determine the areas where the majority of the growth occurred, the percentage change in development was utilized.

$$\%\ change\ in\ development = \frac{DA_2 - DA_1}{DA_1} * 100 \qquad (3.1)$$

$DA_1 = Developed\ Area\ (km^2)\ at\ time\ T_1$
$DA_2 = Developed\ Area\ (km^2)\ at\ time\ T_2$

3.3 Dynamic Growth Pattern Analysis

Dynamic growth pattern analysis is conducted by incorporating land-use maps to calculate landscape metrics (Figure 3.6).

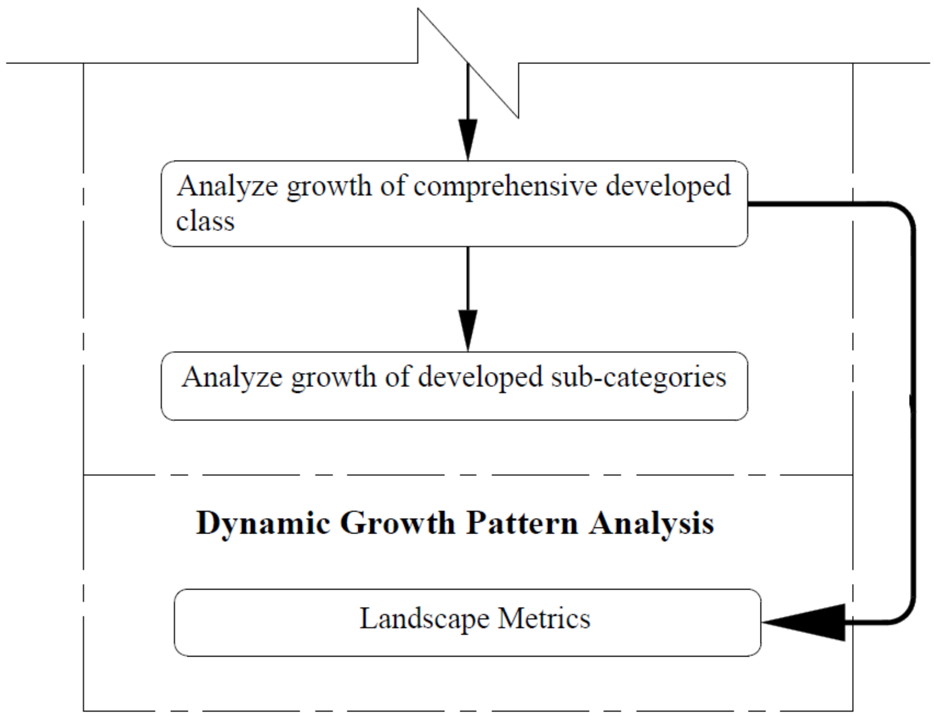


Figure 3.6: Dynamic growth pattern analysis methodology

FRAGSTATS has been used extensively to determine the landscape metrics of urban spatiotemporal dynamics in research (Kim et al. 2018; Megahed et al. 2015; Shrestha et al. 2012; Wu et al. 2011). FRAGSTATS 4.2 software was utilized to analyze class and landscape metrics for the top 3 districts (Districts 5, 1, and 4) with the most urban growth within El Paso during 2001 - 2016. A minimal amount of landscape metrics can demonstrate the urban dynamic behavior within a study area (Wu et al. 2011). Six metrics were utilized for the class level and four metrics for the landscape level to further understand the urban dynamics (Table 3.2). The class metrics (PLAND, AREA_MN, ED, LSI, NP, and PD) focuses on the developed land-use type, as this class is the focus of this study. The comprehensive developed class was first analyzed, followed by the NLCD developed sub-categories. The landscape metrics (LPI, PD, SHDI, and CONT) pertains to the dynamics with respect to the entire landscape within each district. Patch is a term used extensively in landscape metrics and refers to the cluster of joining cells with the same land-use type (Turner and Gardner 2015).

Table 3.2: Description of landscape metrics

Metric Type	Metric	Acronym	Range	Units	Description
Class	Percentage of Landscape	PLAND	$0 < PLAND \leq 100$	%	Percentage of a specific class area within data
Class	Number of Patches	NP	$NP \geq 1$	Dimensionless	Number of patches within the landscape
Class	Mean Patch Area	AREA_MN	$AREA\_MN > 0$	m^2	Sum of all patch areas for specific patch type, divided by the number of patches of the same type.
Class	Edge Density	ED	$ED \geq 0$	m/ha	Total length of edge segments per area for class or landscape
Class, Landscape	Landscape Shape Index	LSI	$LSI \geq 1$	Dimensionless	A standardized measure of edge density which adjusts for the size of the landscape.
Class, Landscape	Patch Density	PD	$PD > 0$	Number per 100 hectares	Indicates the number of patches per unit area of the landscape.
Landscape	Shannon's Diversity Index	SHDI	$SHDI \geq 0$	Dimensionless	Measures diverse landscapes.
Landscape	Contagion	CONT	$0 < CONTAG \leq 100$	%	Indicates the class occupancies within the landscape.

3.4 Future Prediction of Land-use

In this study, spatial and temporal trends of urban development are utilized to predict future land-use changes (Figure 3.7).

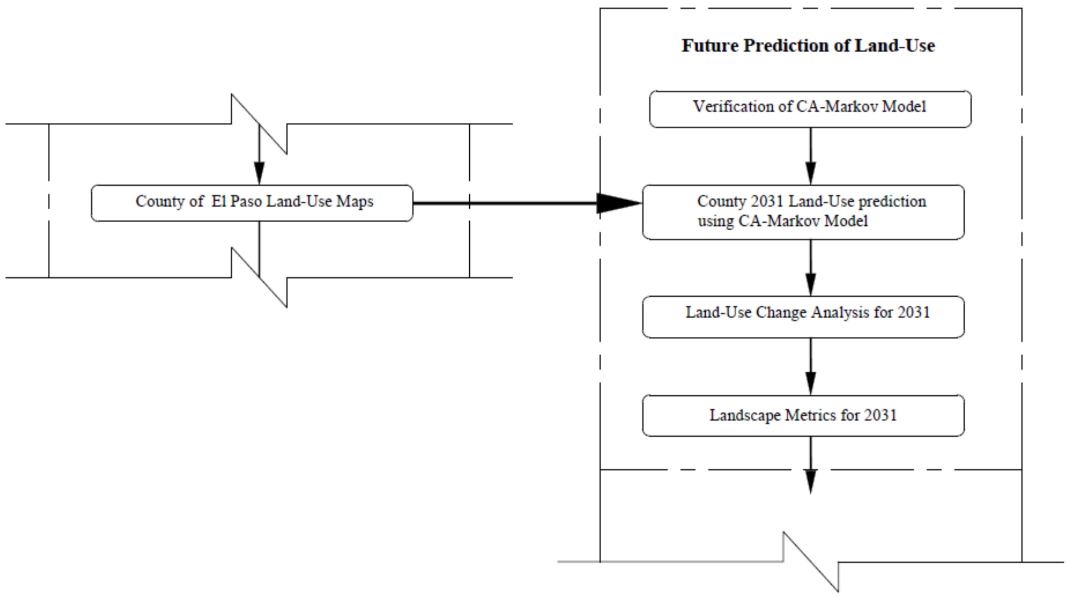


Figure 3.7: Future prediction of land-use methodology

IDRISI analysis package, in TerrSet software, incorporates CA-Markov statistical analysis to predict future land-use. El Paso Counties' land-use classification was predicted for 2031. Utilizing the urban area land-use maps, a Markov Chain model was developed utilizing a base year and a second time period land-use image. The number of time periods between the base and second time period is used as an input, along with the number of time periods beyond the second time period that is required to be projected. The results of the Markov model are presented as a transition matrix, which provides the probability of one state transitioning to another. Utilizing the basic scenario of two states, an example of the transition matrix of the probability of the developed class transitioning into the barren (undeveloped) class is demonstrated in Table 3.3. As the number of states increases, the number of rows and columns also increase within the transition probability matrix dependent upon the data analyzed.

Table 3.3: Transition matrix for developed and barren (undeveloped)

	Developed	**Undeveloped (Barren)**
Developed	Probability that state Developed will remain at state Developed	Probability that state Developed will transition to state Barren
Undeveloped (Barren)	Probability that state Barren will transition to state Developed	Probability that state Barren will remain at state Barren

Along with the Markov transition matrix, suitability maps are created for each land-use class to incorporate socio-economic and/or physical influences on land-use change. Utilizing transition rules, the criteria include constraints and factors of influence. Constraints are criteria that will not be suitable for change, and factors implement the probability of change. This study implemented two physical factors: 1) distance from developed areas and 2) distance from roadways due to the availability of data. While the constraint was the developed area. This implies that the existing developed area will remain developed and will not change from this class. Distance to existing urban areas are considered influencers for future urban growth (Subedi, Subedi, and Thapa 2013; Chen Liping, Sun Yujun, and Saeed 2018), and suggest fuzzy functions (linear and J-shaped) and control points. The weights of each factor were selected from a consensus of research for the multi-criteria evaluation (MCE) model (Rimal et al. 2017; 2017; Chen Liping, Sun Yujun, and Saeed 2018), as demonstrated in Table 3.4.

Table 3.4: Suitability map criteria

Type	Description	Fuzzy Function	Control Points	Weight
Factor	Distance from roads	J-shaped/Monotonically decreasing	1-100m highest suitability 100 – 9500m decreasing suitability	0.42
Factor	Distance from the developed area	Linear/Monotonically decreasing	1-100m highest suitability 100 – 8000m decreasing suitability	0.58
Constraint	Developed area			

The results from the fuzzy function for the physical factors are demonstrated in Figure 3.8. The maps depict the possibility of a cell changing to another class due to the influence of the factor. The closer a cell is to a physical factor, the higher the probability of it changing class.

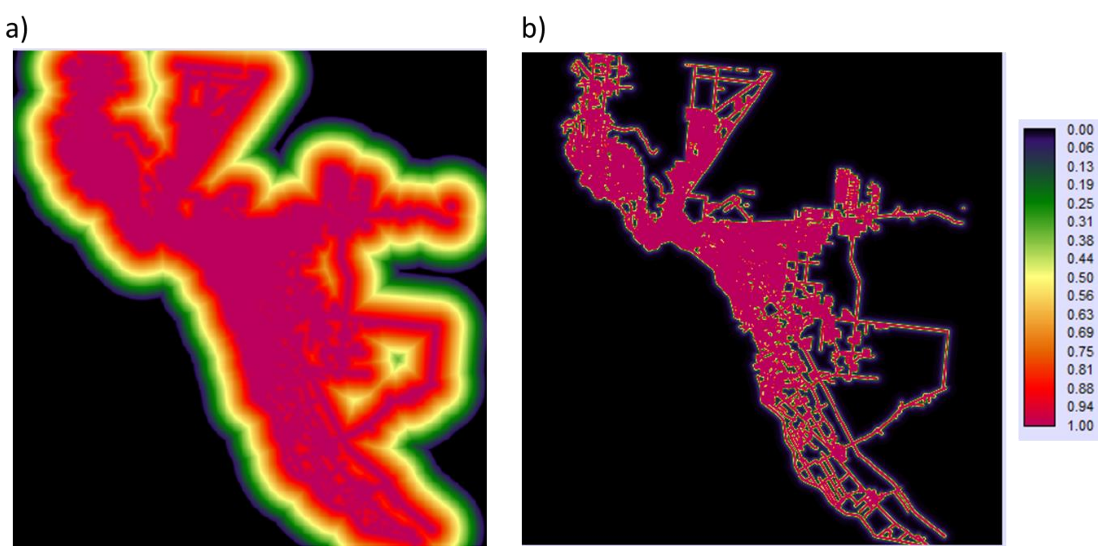


Figure 3.8: Fuzzy function results a) distance from developed areas b) distance from roads

Typically, constraints such as roads, slope, construction, and water areas are considered constraints within the CA-Markov model. In this study, roads are classified as developed or sub-category of developed. There are no existing water areas within the districts studied. The slope was not a factor as the Franklin Mounts State Park area was removed from the original data and the vast majority of the districts are flat open areas. With the removal of constraints from the original data by extracting the military reservations and the Franklin Mountains State Park, development was free to expand into the remaining undeveloped (barren) areas within each district.

The Markov transition probability matrix and suitability maps are then applied in the CA-Markov model where spatial relations are among states that are analyzed. Additional inputs into the CA-Markov model is a base year land cover image and the number of iterations, which is dependent on the number of time periods the future period to be projected is. A 5x5 continuity filter type was also implemented in the model as demonstrated in Figure 3.9.

0	0	1	0	0
0	1	1	1	0
1	1	1	1	1
0	1	1	1	0
0	0	1	0	0

Figure 3.9: 5 x 5 contiguity filter

The continuity filter is a kernel that considers the state of neighboring cells as spatially explicit for weighing factors. This results in cells farther from a land-use class possessing less suitability than closer cells to transition into another state. The CA-Markov model uses the input information to run a series of iterations resulting in each cell assigned to a class based on the highest weighted suitability. The process is verified by analyzing and predicting a time period where data is known.

The verification process follows the classification accuracy assessment procedure. The procedure uses the known NLCD data to compare to the prediction results. 1000 random points for both county and city levels were utilized (Fig 3.10). The developed class possessed 255 random points at the county level and 667 at the city level. The barren (undeveloped) class contained 743 random points at the county level and 331 at the city level. The amounts exceed the recommended 50 random points per class for accuracy assessment (Congalton 1991). The results of the comparison of the random points between the NLCD data and the predicted data are incorporated into an error matrix to understand the CA-Markov models' accuracy.

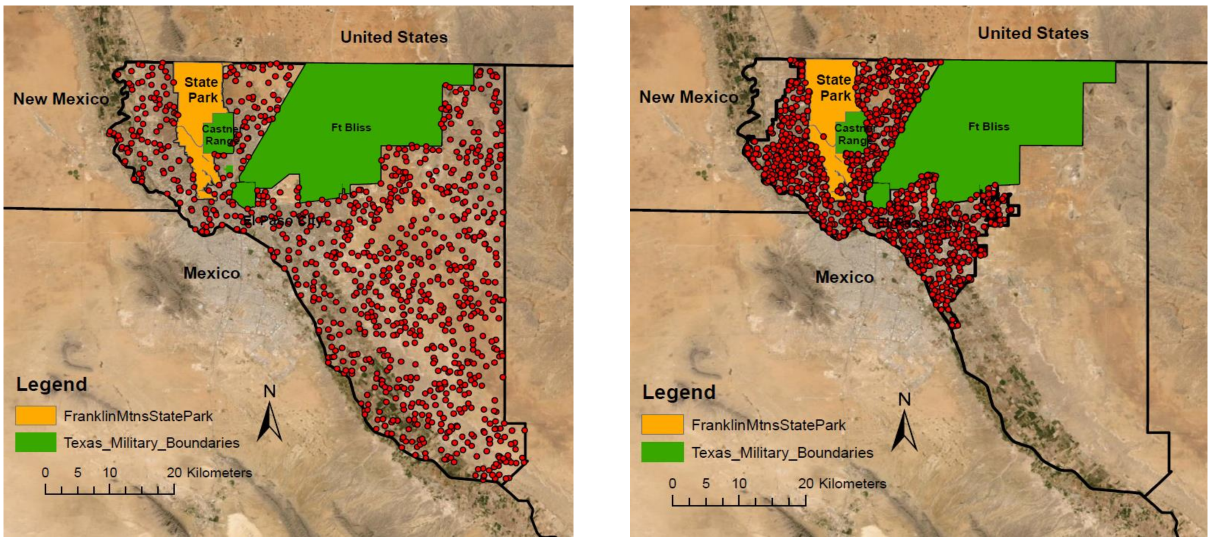


Figure 3.10: Random Points for County (left) and city of El Paso (right)

3.5 Land-use Patterns and Electricity Consumption

Landscape metrics provide a quantitative analysis of the urban landscape within a study area. In order to example the relationship between landscape metrics and their possible impacts on electricity consumptions, a panel data analysis is adopted (Figure 3.11).

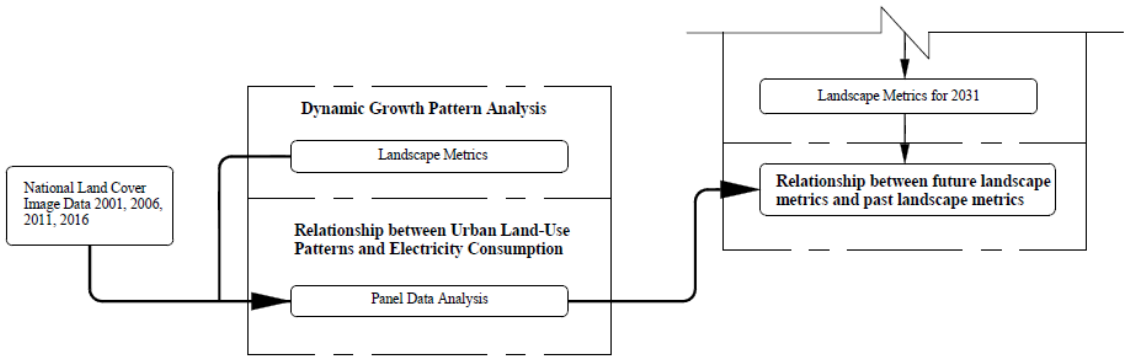


Figure 3.11: Landscape metrics and electricity consumption methodology

Panel data analysis consists of three models: pooled regression, variable intercepts and constant coefficients, and variable intercepts and variable coefficients models. Pooled regression is expressed as the following (Zhao, Thinh, and Li 2017; Brooks 2019):

$$y_{it} = \alpha + \beta x_{it} + \epsilon_{it}$$

Where:

$i = individuals, 1, \dots\dots, N$

$t = time, 1, \dots\dots, T$

$y_{it} = dependent\ variable$

$\alpha = intercept$

$\beta = coefficient\ of\ the\ variables$

$x_{it} = independent\ variable$

$\varepsilon_{it} = error\ term$

The variable intercepts and constant coefficients model pertain to both the fixed and random-effects models. Fixed-effects model applies to non-random sampling/selection panel data (Seddighi 2012), and assumes "the intercept α_i, is uncorrelated with x_{it} and a constant value for i" (Zhao, Thinh, and Li 2017; Hsaiao 2003). Whereas, random-effects model applies to random sampling/selection data (Seddighi 2012) where "α_i is affected by x_{it} [and] α_i involves not only a constant but also a random term caused by x_{it}" (Zhao, Thinh, and Li 2017; Hsaiao 2003). The fixed/random-effects model is expressed as:

$$y_{it} = \alpha_i + \beta x_{it} + \varepsilon_{it}$$

Where:

$i = individiudals, 1, \ldots\ldots, N$

$t = time, 1, \ldots\ldots, T$

$y_{it} = dependent\ variable$

$\alpha_i = fixed\ or\ random\ effects$

$\beta = coefficient\ of\ the\ variables$

$x_{it} = independent\ variable$

$\varepsilon_{it} = error\ term$

The third model indicates coefficients may vary among individuals:

$$y_{it} = \alpha_i + \beta_i x_{it} + \varepsilon_{it}$$

Where:

$i = individiudals, 1, \ldots\ldots, N$

$t = time, 1, \ldots\ldots, T$

$y_{it} = dependent\ variable$

$\alpha_i = fixed\ or\ random\ effects$

$\beta_i = coefficient\ of\ explanatory\ variable\ x_{it}$

$x_{it} = independent\ variable$

$\varepsilon_{it} = error\ term$

An F-test is first conducted in order to verify which model to incorporate. The hypothesis states:

$$H_1 = \beta_1 = \beta_2 = \cdots = \beta_N$$

$$H_2 = \alpha_1 = \alpha_2 = \cdots \alpha_N \ ; \ \beta_1 \neq \beta_2 \neq \cdots \neq \beta_N$$

Where H_1 refers to the pooled regression model, where intercepts and coefficients are constant for individuals and time. H2 states intercepts are variable and coefficients are constant. If H_1 is accepted, then the pooled regression model is incorporated. If H_2 is accepted, intercepts are variable and coefficients are constant (Chen et al. 2011; Hsaiao 2003). The Hausman test is then implemented to indicate whether the fixed or random model is implemented.

The panel data analysis is limited to the number of time series observations, t is at least as large as the total number of independent variables, indicating that $t \geq k + 1$. For this study the number of time periods, $t = 2$ and the number of independent variables, $k = 6$. Therefore, a single independent variable must be analysis at a time for this study.

3.6 Summary

Using the NLCD land-cover data, a land-use change analysis was conducted for El Paso County for the 15-year study period of 2001-2016. The change analysis consisted of verifying the NLCD for the region, and examining land-use maps to understand growth trends. The analysis provided an understanding of the locations of concentrated growth. The land-use maps provided allowed for an urban dynamic analysis through landscape metrics. The metrics provided a quantitative depiction of the urban land-use patterns. Utilizing the previous 15-year land-use maps, allowed for predicting the 2031 future land-use for El Paso. Change analysis was also conducted for the projected land-use, along with the landscape metrics to understand the predicted urban dynamics. Finally, the relationship between the past concentrated growth areas and electricity consumption was analyzed to understand which metrics were possibly correlated with electricity consumption. This study provides a synopsis of past and future growth trends and patterns, and the impact on electricity consumption for the El Paso area.

Chapter 4: Data Analysis

This chapter discusses the data analysis and results conducted for this study. The following sections discuss the findings of the past and future land-use change analysis, consequential urban dynamic patterns, and their relationship to electricity consumption.

4.1 Land-Use Change Analysis

Land-use change analysis incorporates land-use maps generated from remote sensing and corresponding database management techniques to analyze land-use change over time. In order to use analyze the data, a classification accuracy assessment must first be conducted. After the data has been verified and is deemed acceptable for analysis, the generated maps and data are then assessed as to the changes in land-use that have occurred over a study period. The following sections provide the results of the accuracy assessment and land-use change analysis.

4.1.1 Classification Accuracy Assessment

The classification accuracy assessment was conducted for both El Paso County and the city of El Paso. Utilizing 300 random points for the county and 150 random points for the city, the results are illustrated in Table 4.1 – 4.2.

Table 4.1: County/City 2001 – 2006 classification accuracy

	2001										
	Overall Accuracy	**Kappa Coeff.**	**Kappa Coefficient Agreement**	**User's accuracy**		**Error of Commission**		**Producer's accuracy**		**Error of Omission**	
				Dev.	**Barren**	**Dev.**	**Barren**	**Dev.**	**Barren**	**Dev.**	**Barren**
County	94%	81%	Almost Perfect	83%	97%	17%	3%	86%	96%	14%	4%
City	90%	80%	Substantial	92%	88%	8%	12%	88%	92%	12%	8%
	2006										
	Overall Accuracy	**Kappa Coeff.**	**Kappa Coefficient Agreement**	**User's accuracy**		**Error of Commission**		**Producer's accuracy**		**Error of Omission**	
				Dev.	**Barren**	**Dev.**	**Barren**	**Dev.**	**Barren**	**Dev.**	**Barren**
County	98%	92%	Almost Perfect	98%	98%	2%	2%	90%	100%	10%	0%
City	94%	87%	Almost Perfect	97%	90%	3%	10%	94%	95%	6%	5%

Table 4.2: County/City 2011-2016 classification accuracy

	2011										
				User's accuracy		Error of Commission		Producer's accuracy		Error of Omission	
	Overall Accuracy	Kappa Coeff.	Kappa Coefficient Agreement	Dev.	Barren	Dev.	Barren	Dev.	Barren	Dev.	Barren
County	97%	91%	Almost Perfect	95%	98%	5%	3%	90%	99%	10%	1%
City	93%	86%	Almost Perfect	98%	87%	2%	13%	92%	96%	8%	4%

	2016										
				User's accuracy		Error of Commission		Producer's accuracy		Error of Omission	
	Overall Accuracy	Kappa Coeff.	Kappa Coefficient Agreement	Dev.	Barren	Dev.	Barren	Dev.	Barren	Dev.	Barren
County	96%	88%	Almost Perfect	98%	95%	2%	5%	84%	100%	16%	0%
City	95%	88%	Almost Perfect	98%	89%	2%	11%	94%	96%	6%	4%

As the focus of this study is on the expansion of the developed areas, the accuracy assessment results discussed will concentrate on the developed class. As previously discussed, the producer's and user's accuracy is recommended to provide insight into the performance of classification. The user's accuracy, which is vital from the user's perspective as it relates to the probability of correct classification to actual conditions on-site (Rwanga and Ndambuki 2017), ranges from 83% (2001) to 98% (2006 and 2016) for the developed class. The corresponding error of commission ranged from 2% (2006 and 2016) to 17% (2001). The producer's accuracy for the developed class ranged from 84% (2016) to 90% (2006 and 2011). The error of omission ranged from 10% (2006 and 2011) to 16% (2016). The overall accuracy for the developed class ranged from 94% (2001) to 98% (2006). A rigorous method of interpreting accuracy lies with the Anderson classification system. This system recommends the "minimum level of interpretation accuracy in the identification of land-use and land cover categories from remote sensor data should be at least 85 percent (Anderson et al. 1976). The overwhelming majority of the accuracy terms met this stringent classification. The exception includes the counties' user's accuracy in 2001 at 83% and producer's accuracy at 84% in 2016. However, these percentages fall in the upper range of 75-85% region perceived as satisfactory for the overall and categorical accuracy considering a balance between the "ideal and the affordable" (Mubako et al. 2018; Congalton 1991).

The Kappa coefficient was also determined to provide a complete traditional error matrix. The Kappa ranged from 81% (2001) to 92% (2006) and are rated "almost perfect" at the county level. At the city level, Kappa ranged from 80% (2001) to 88% (2016), and was rated "substantial" for 2001; while the years 2006 – 2016 rated "almost perfect". The "substantial" agreement ranges between 61% - 80%, with the cities' 2001 Kappa located at nearly the "almost perfect" agreement.

Due to the vast majority of assessment terms meeting the stringent Anderson classification system requirements of at least 85% accuracy and the remaining assessments reaching the higher end of the acceptable range of 75-85% accuracy, and all Kappa agreements either meeting or border "almost perfect" agreement; the classification data were suitable to proceed with the analysis.

4.1.2 Change Analysis Results

The land-use change analysis for this study incorporated land-use maps (generated from remote sensing) and the corresponding database management techniques to analyze land-use change over time. The land-use maps were generated based on two methods: 1) developed, which combines all sub-categories within the NLCD developed category vs barren (undeveloped) class and 2) the sub-categories within the developed class outlined in NLCD. The goal of this process was to provide a comprehensive and detailed understanding of urban development within the region.

4.1.2.1 Comprehensive Developed Class

The land-use classification process resulted in four land-use maps, which provided a detailed understanding of where the concentration of urban expansion took place within El Paso County from 2001 to 2016 (Fig 4.1), excluding the military reservation areas and Franklin Mountains State Park. The urban expansion analyzed the NLCD developed class comprehensively, as a single class.

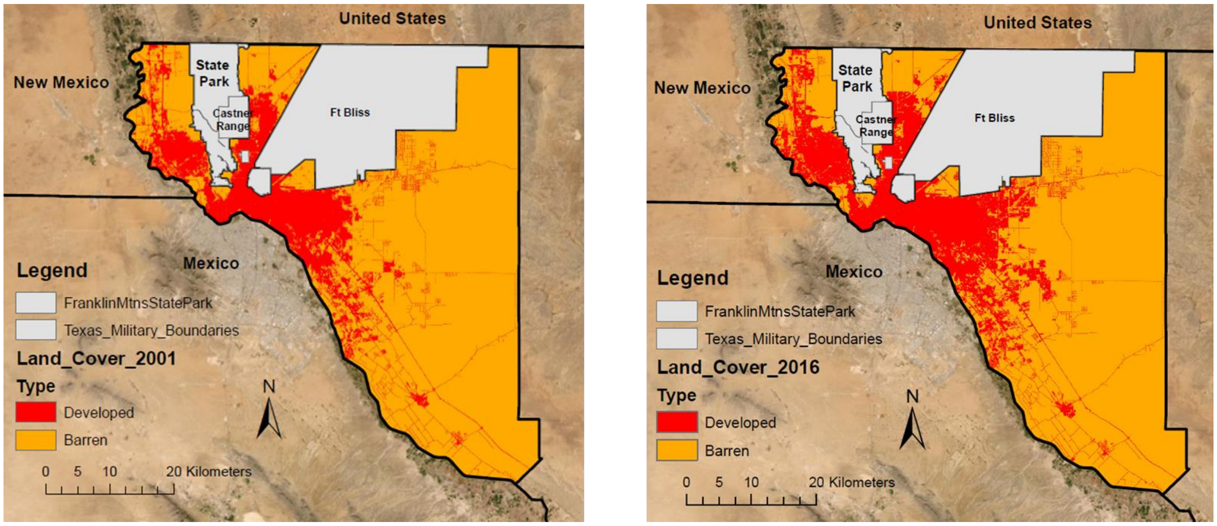


Figure 4.1: 2001 (left) and 2016 (right) county land cover maps.

At the county level, the results demonstrated the developed class increased by 24% from 2001 – 2016 (Table 4.3). The largest development growth occurred from 2001 to 2006 at 12.73%. Urban growth proceeded to decrease in the following 5-year increments, from 5.66% (2006-2011) to 4.15% (2011-2016).

Table 4.3: County land-use area and change in percentage

Land-use type	**2001 Class Area (km^2)**	**2006 Class Area (km^2)**	**2011 Class Area (km^2)**	**2016 Class Area (km^2)**
Developed	382.52	431.21	455.63	474.54
Barren (Undeveloped)	1619.20	1570.50	1546.04	1527.12
	2001 - 2006	2006 - 2011	2011 - 2016	**2001 - 2016**
% Change in Development	12.73%	5.66%	4.15%	**24.06%**

Within the county's growth in development that occurred from 2001 – 2016, 68% of the expansion transpired within the City of El Paso. Figure 4.2 illustrates the counties' urban growth with the expansion concentrated within the city of El Paso.

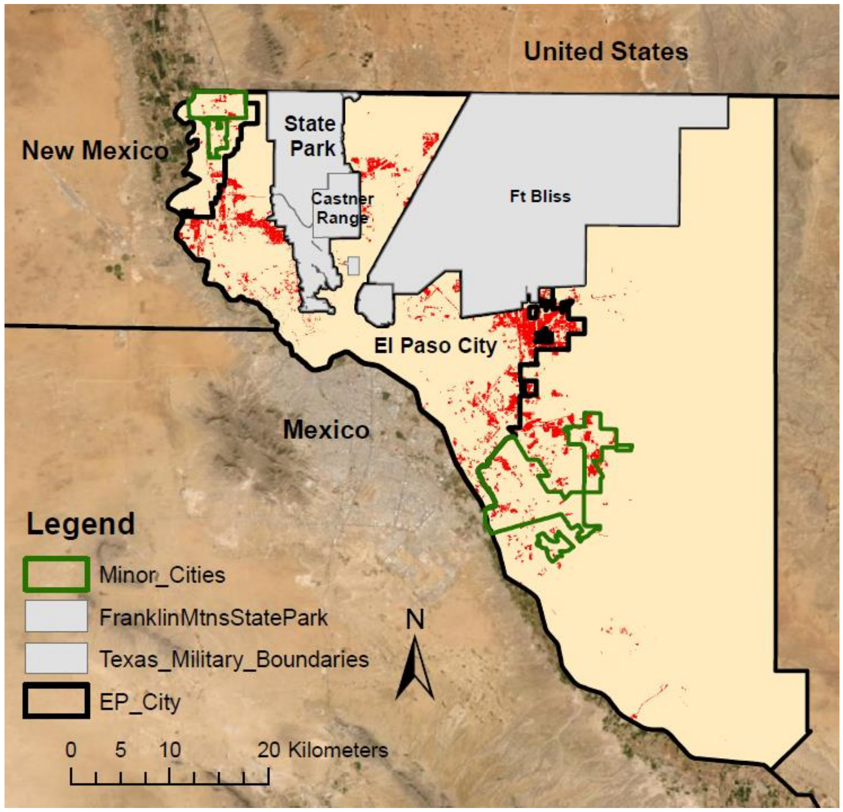


Figure 4.2: 2001 to 2016 County Growth (red).

The counties' urban growth, within the 5-year incremental study period, was also largely contributed to within the City of El Paso (Table 4.4). To measure the percentage of the cities' contribution to the growth of the county, the following formula was utilized.

$$\% \text{ of County change contributed to City of El Paso} = \frac{CityDA_2 - CityDA_1}{CountyDA_2 - CountyDA_1} * 100$$

$$\begin{aligned}
CityDA_1 &= City\ Developed\ Area\ (km^2)\ at\ time\ T_1 \\
CityDA_2 &= City\ Developed\ Area\ (km^2)\ at\ time\ T_2 \\
CountyDA_1 &= City\ Developed\ Area\ (km^2)\ at\ time\ T_1 \\
CountyDA_2 &= City\ Developed\ Area\ (km^2)\ at\ time\ T_2
\end{aligned} \tag{4.1}$$

The city originally contributed 71% of the county's development from 2001 – 2006, and gradually decreased to 68% (2006 – 2011) and 59% (2011 – 2016).

Table 4.4: Contribution of city growth towards county expansion

	2001 - 2006	2006 - 2011	2011 - 2016
% County change occurring within City of El Paso	71.43%	68.23%	59.15%

Due to the majority of development occurring within the city limits of El Paso, the city was further analyzed to determine the amount and location of growth within its' limits. The city of El Paso (herein El Paso) grew by over 21% from 2001 to 2016 (Table 4.5). Similar to the county, El Paso's largest developmental growth occurred from 2001 – 2006 at almost 12%. The urban development continued to decline to 5% (2006-2011) and 3.25% (2011–2016). The growth percentages and patterns of El Paso reciprocate the growth patterns at the county level.

Table 4.5: City land-use area and change in percentage

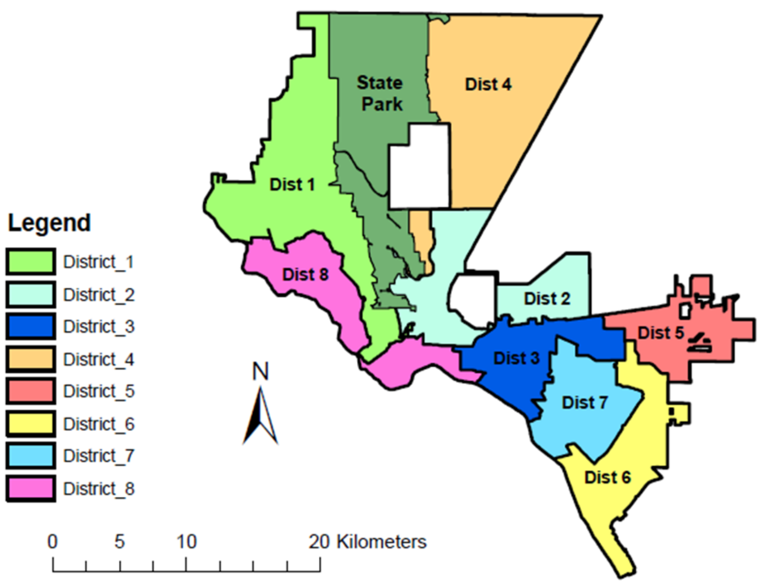
Land-use type	2001 Class Area (km^2)	2006 Class Area (km^2)	2011 Class Area (km^2)	2016 Class Area (km^2)
Developed	292.27	327.06	343.71	354.90
Barren (Undeveloped)	265.90	231.12	214.42	203.23
	2001 - 2006	2006 - 2011	2011 - 2016	**2001 - 2016**
% Change in Development	11.90%	5.09%	3.25%	**21.43%**

To understand the areas experiencing the urban growth within the city, the 8 districts that comprise the city were further analyzed. Each districts' urban growth was determined relative to the total growth within the city. This allowed a comparison between the districts.

$$District\ growth\ (relative\ to\ total\ growth\ in\ City\ of\ El\ Paso) = \frac{DistrictDA_2 - DistrictDA_1}{CityDA_2 - CityDA_1} * 100 \tag{4.2}$$

$DistrictDA_1 = District\ Developed\ Area\ (km^2)\ at\ time\ T_1$
$DistrictDA_2 = District\ Developed\ Area\ (km^2)\ at\ time\ T_2$
$CityDA_1 = City\ Developed\ Area\ (km^2)\ at\ time\ T_1$
$CityDA_2 = City\ Developed\ Area\ (km^2)\ at\ time\ T_2$

From 2001 – 2016, the districts with the highest city contribution of growth were Districts 5 and 1 at approximately 31.5% and 28.00%; respectively (Fig 4.3). Districts 6 and 4 follows at 14.84% and 12.25%, respectively. The remaining districts contributed less than 6% of the cities' urban growth.



District	%age growth (relative to the total growth in the City of El Paso)
1	28.00%
2	5.93%
3	0.29%
4	12.25%
5	31.72%
6	14.84%
7	3.47%
8	3.49%

Figure 4.3: 2001 – 2016 district growth relative to city growth.

District 6 is the third-highest contributor to growth at 14.84% from 2001-2016. However, District 6 growth mainly occurred from 2001 – 2006 (Fig 4.4). After 2006, District 6 seen a drastic decline in its' contribution to growth at 7.54% (2006-2011) and 6.32% (2011-2016). Districts 5, 1, and 4 have the most contribution of growth and have ranked in top contributing districts throughout 2001-2016. The contribution is illustrated among the 2006-2011 and 2011-2016 time series. For 2001-2006, District 1 and 5 were the top 2 districts in growth, followed by district 6 and 4. Due to Districts 5, 1, and 4 consistent top growth relative to the city, these districts were further analyzed for urban dynamic patterns and developed sub-category growth.

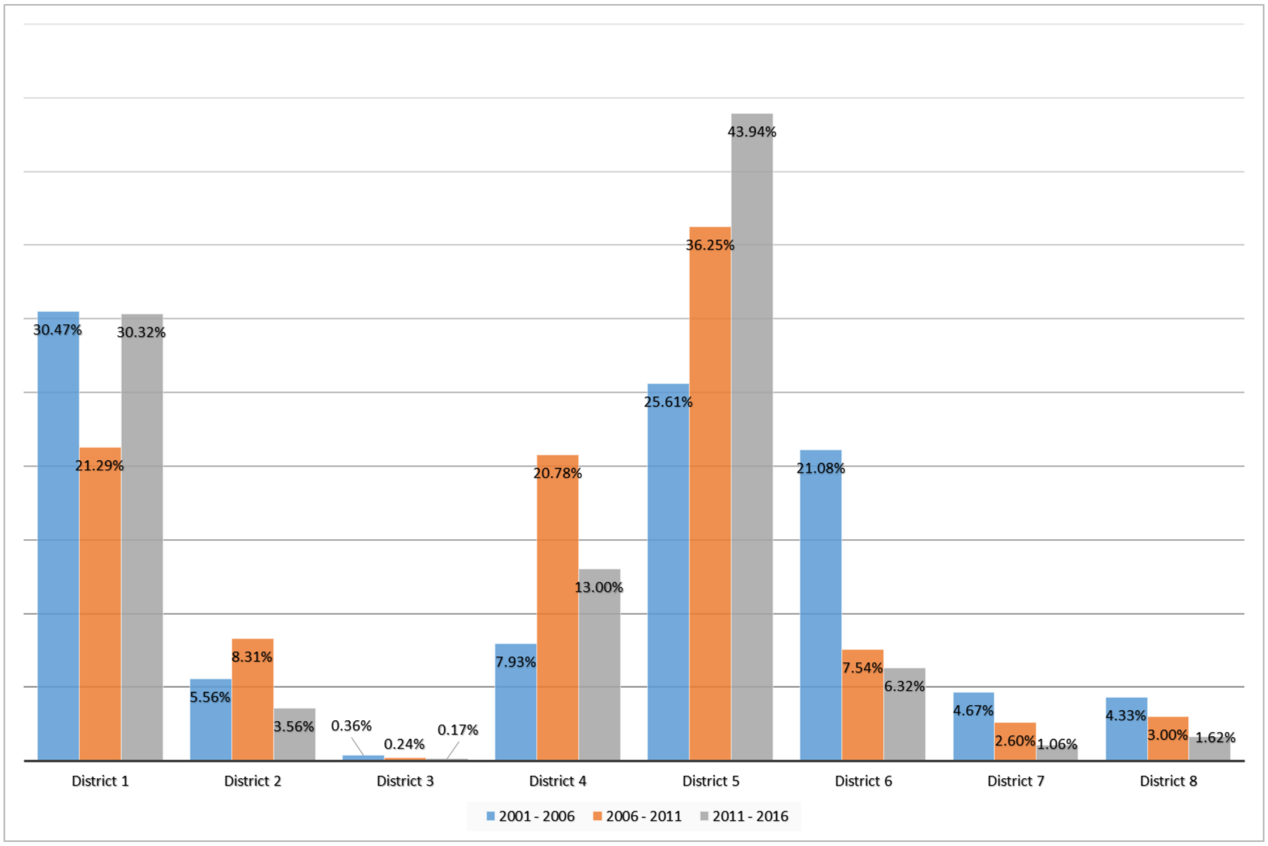


Figure 4.4: 5-year district growth relative to city growth.

El Paso County and the city exhibited similar growth trends. Urban expansion was highest within the 2001-2006 5-year period. The vast majority of the counties' growth transpired within the city of El Paso for both the 15-year and 5-year incremental study period. Within the city, the consistent growth occurring within District 5 (east side), 1 (west side), and 4 (northeast), with District 5 experiencing the fast growth rate. District 6 experienced large growth between

2001 to 2006, but drastically decreased after this time period. Due to consistent and high growth rates within District 5, 1, and 4, these districts landscape patterns were further analyzed.

4.1.2.2 Developed Sub-categories

Districts 5, 1, and 4 exhibited the highest and consistent development growth patterns relative to the city of El Paso. Therefore, the development within these three districts was studied further by analyzing the developed NLCD sub-category growth patterns relative to the districts themselves. The developed sub-categories represent various percentages of impervious surface area as described in Table 4.6.

Table 4.6: Developed class detailed descriptions

Class	Value #	Sub-category	Description	Examples
Developed	21	Developed, Open Space	< 20% impervious surface	large-lot single-family housing, parks, golf courses, recreational areas with vegetation
	22	Developed, Low Intensity	20% - 49% impervious surface	single-family housing
	23	Developed, Medium Intensity	50% - 70% impervious surface	single-family housing
	24	Developed, High Intensity	80% - 100% impervious surface	apartment complexes, row houses, commercial/industrial areas

The change percentage patterns described in this section are relative to the district itself.

$$\% \; change \; in \; sub - category = \frac{SA_2 - SA_1}{SA_1} * 100 \qquad (4.3)$$

$$SA_1 = Developed \; Sub - Category \; Area \; (km^2) \; at \; time \; T_1$$
$$SA_2 = Developed \; Sub - Category \; Area \; (km^2) \; at \; time \; T_2$$

The developed sub-category with the highest percentages of change from 2001 to 2016 within District 5 was medium intensity at 289% (Figure 4.5), which is three-fold its' original area. Closely following was developed, the high intensity at 276%. The highest change percentage for District 1 was 79% in developed, open space; followed by developed, high intensity at 60%. District 4 exhibited a 58% change in developed, high intensity and 42% in developed, medium intensity. The majority of developed sub-categories' change occurred within the medium intensity and high-intensity sub-categories within these districts.

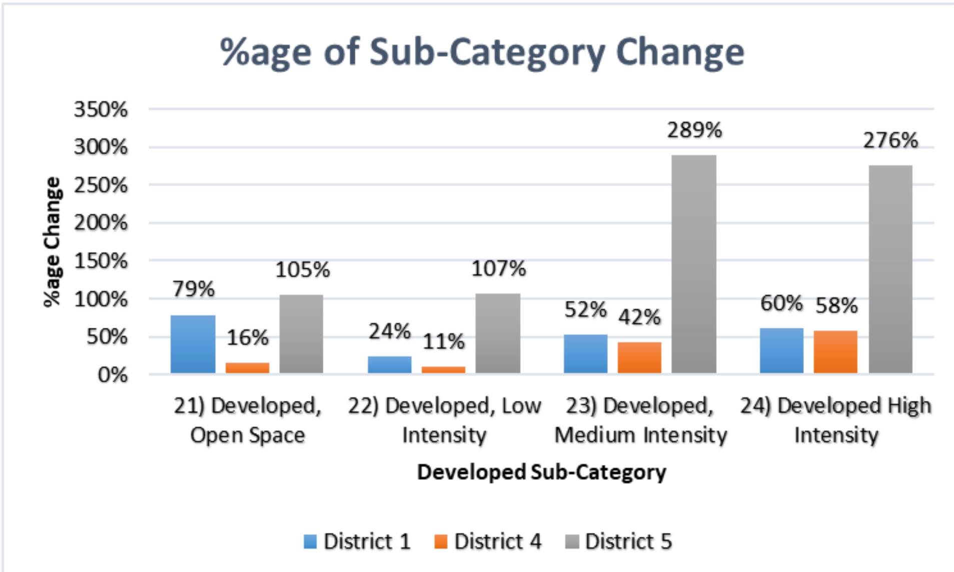


Figure 4.5: 2001-2016 change in developed sub-categories.

The districts' 5-year growth mimics those of the 15-year study period (2001-2016). The developed sub-categories exhibiting the largest change percentage are concentrated in high intensity, followed by medium intensity (Table 4.7). The exception is District 1 from 2001 to 2006, the largest change in growth occurred in the developed, open space sub-category at the rate of over 57%. After 2006, the change in District 1 open space drastically reduced to 8.48% and 4.84% in 2006-2011 and 2011-2016, respectively.

Table 4.7: 5-year sub-category growth relative to growth within the district.

District 5			
Developed Sub-Category	**2001-2006**	**2006-2011**	**2011-2016**
21) Developed, Open Space	55.74%	26.05%	4.60%
22) Developed, Low Intensity	46.95%	24.23%	13.13%
23) Developed, Medium Intensity	**129.26%**	33.52%	27.02%
24) Developed High Intensity	92.78%	**46.34%**	**33.12%**

District 1			
Developed Sub-Category	**2001-2006**	**2006-2011**	**2011-2016**
21) Developed, Open Space	**57.25%**	8.48%	4.84%
22) Developed, Low Intensity	14.31%	3.62%	4.53%
23) Developed, Medium Intensity	28.08%	9.63%	8.30%
24) Developed High Intensity	30.95%	**11.65%**	**9.77%**

District 4			
Developed Sub-Category	**2001-2006**	**2006-2011**	**2011-2016**
21) Developed, Open Space	6.77%	8.51%	0.10%
22) Developed, Low Intensity	2.82%	5.77%	1.67%
23) Developed, Medium Intensity	16.02%	14.55%	7.03%
24) Developed High Intensity	**21.75%**	**16.38%**	**11.57%**

A visual representation of these changes is presented as land-use maps. The concentration of developed high and medium intensity change within District 5 is visually compared in 5-year increments in Figure 4.6. It is observable that the medium intensity, depicted in blue, is the dominant sub-category within District 5. This category had the largest percentage change of all the districts and their sub-categories at 129% from 2001 to 2006. Developed, high intensity (shown in red) possessed the second-largest sub-category change at roughly 93% from 2001 to 2006. The developed, high-intensity category had the largest change percentage from 2006 to 2011 and 2011 to 2016, at 46% and 33%; respectively. The developed medium intensity followed at roughly 33.5% and 27% from 2006 to 2011, and 2011 to 2016; respectively.

District 5 possessed a significant growth within medium intensity from 2001-2006, indicating single-family housing development dominated. In the following years, high intensity (compact housing and commercial areas) dominated with medium intensity following. This indicates compact housing and commercial areas followed the intense single-housing growth.

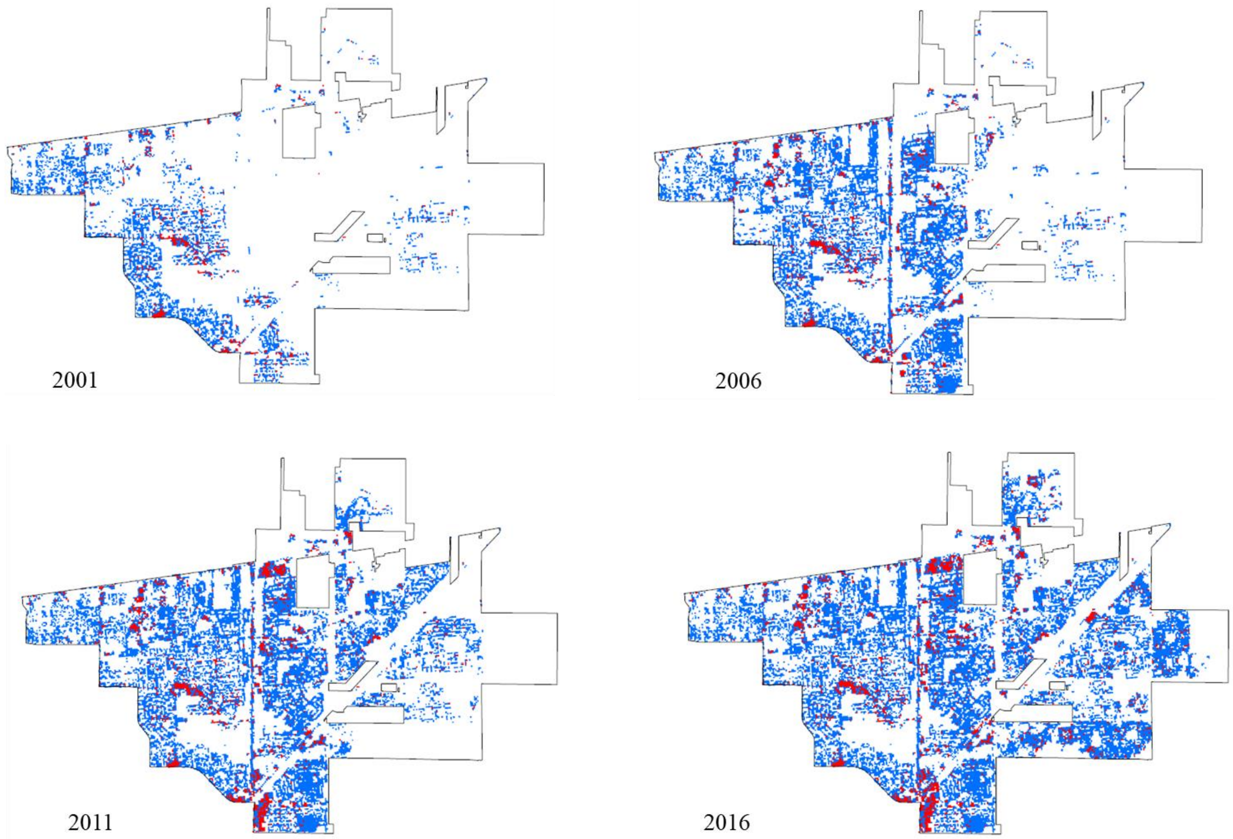


Figure 4.6: District 5 23) Developed, Medium Intensity (blue) and 24) Developed, High Intensity (red).

District 1 urban change was dominated by developed, open space for 2001-2006 at 57% as illustrated in green in Figure 4.7. Followed by developed, high intensity (shown in red) at 31%. However, the developed, open space category drastically reduced to nearly 8.5% and 4.8% change from 2006 to 2011 and 2011 to 2016; respectively. Developed, high intensity is the leader in percent change at approximately 11.5% and 9.5% for 2006-2011 and 2011-2016;

respectively. Developed, medium intensity (shown in blue) followed at roughly 9.5% and 8% for 2006-2011 and 2011-2016 respectively.

District 1 highest growth occurred in open space from 2001-2006, with high intensity and medium intensity following at nearly 31% and 28%; respectively. Medium and high intensity categories maintained a consistent and high growth percentages within District 1 throughout the 5-year increments, indicating the consistent growth for single-family housing (medium intensity) and compacted living and commercial areas (high intensity).

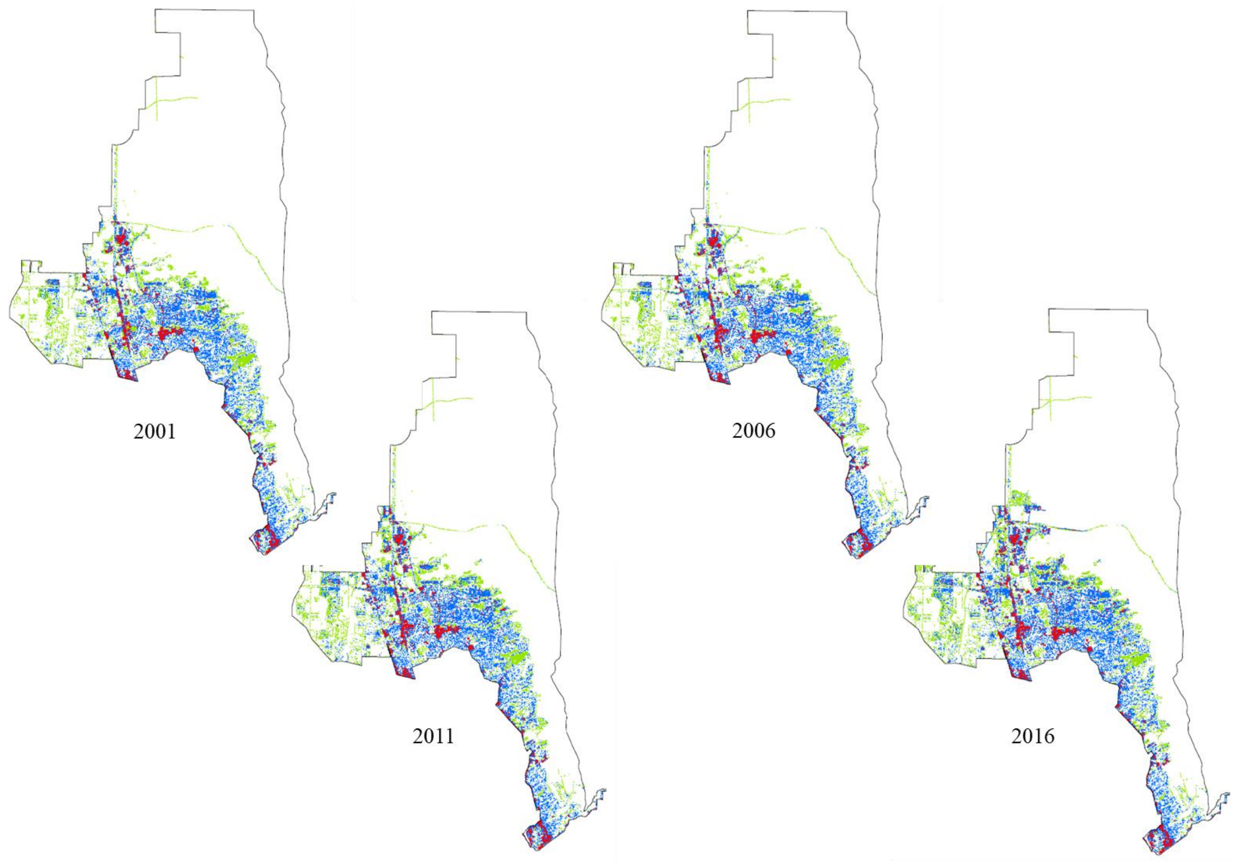


Figure 4.7: District 1 21) Developed, Open Space (green), 23) Developed, Medium Intensity (blue), and 24) Developed, High Intensity (red).

District 4 percent change was concentrated within developed, high (red) and medium (blue) intensity (Fig 4.8). The high-intensity sub-category led the change in percentage for the three 5-year study periods at 21.8% (2001-2006), 16.4% (2006-2011), and 11.6% (2011-2016).

Medium intensity followed at approximately 16% (2001-2006), 14.5% (2006-2011), and 7% (2011-2016).

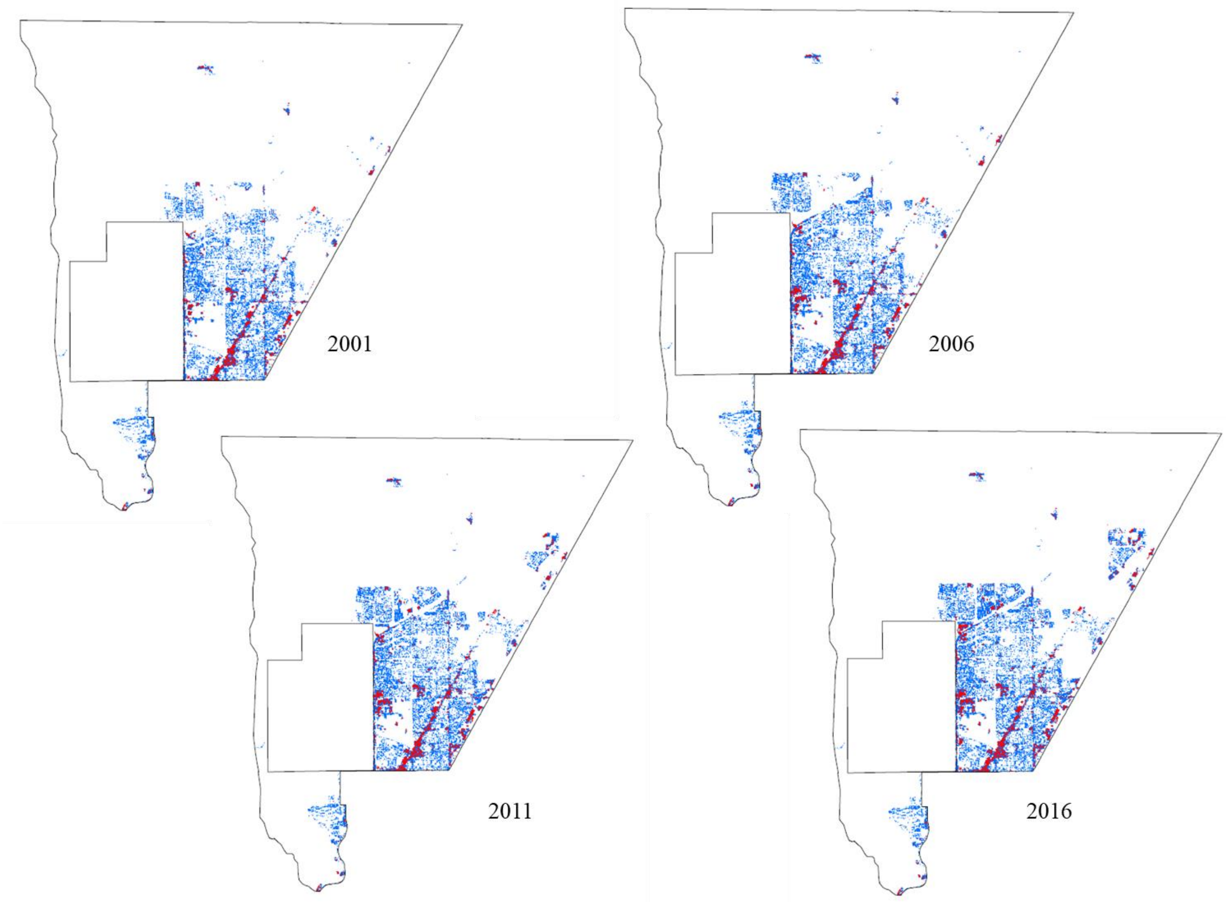


Figure 4.8: District 4 23) Developed, Medium Intensity (blue) and 24) Developed, High Intensity (red).

The NLCD developed sub-categories were examined within Districts 5, 1, and 4 due to their high and consistent growth rates with respect to the district itself. The districts' growth trends for the 5-year increments mimic the trends for the 15-year study period. Medium and high intensity sub-categories are the fastest-growing developed land-use within each district. The exception is District 1, who possessed open space as the largest growth within 2001-2006. By visual inspection, the medium intensity category dominates the growth in all districts. Indicating the vastly growing single-family housing. High intensity categories (compact housing and commercial areas) experienced large percentage growth but encompass a smaller area. These two sub-categories dominate urban growth.

4.2 Landscape Metrics

The landscape metrics were selected to provide an understanding of the urbanization patterns for the developed class comprehensively and as sub-categories as outlined in NLCD. When analyzing the comprehensive developed class, class-level metrics were utilized due to the limited number of classes (developed and undeveloped). Both class-level and the landscape-level metrics were utilized in understanding the urban patterns for the developed sub-categories within the top three developmental growth districts in El Paso (Districts 5, 1, and 4). The class level pertains to the urban dynamics exhibited by a particular class (developed, developed-open space, developed-low intensity, etc.). The landscape-level provides an understanding of land-use in relation to all of the data, including the undeveloped class. Six metrics were selected for class level and four metrics were chosen for the landscape level, which were deemed acceptable to provide an understanding of the landscape (Wu et al. 2011; Zhao, Thinh, and Li 2017; Shrestha et al. 2012). Two of the metrics, including the landscape shape index and patch density, were administered for both the class and landscape levels.

4.2.1 Comprehensive Developed Class

The landscape metrics provided an understanding of the comprehensively developed class growth characteristics within Districts 5, 1, and 4. The results for the class-level metrics were relative to the district itself (Figure 4.9). The developed percentage of landscape increased linearly for District 5 from 27% in 2001 to 74% in 2016. Districts 1 and 4 also exhibited an increase in development from 36% to 51.5% and 27% to 33%, respectively. This reflects the vast urban growth within District 5 and the consistent growth that transpired within Districts 1 and 4 for the 15-year study period.

Urban growth can occur with fragmented patterns of patches. Patches are clusters of cells with the same land-use type. The number of patches significantly decreased for Districts 5 and 1. District 5 decreased by 73% of the number of patches from 2001 to 2016. District 1 had an approximate 63% decrease in the number of patches. District 4 had a smaller decrease in the number of patches at over 16.5%. This indicates that District 5 and 1 had an extensive decrease in fragmentation of the developed land-use. This also illustrates in-fill development to connect the patches of existing urban development. Thus, the significant decrease in patch density for District 5, a relative decrease in District 1, and a slight decrease in District 4. The edge density for District 5 decreased, while remained relatively constant for the remaining districts. This can be attributed to Districts 5 drastic urban growth that encompasses a large amount of the landscape. While the remaining districts saw relatively constant edge density due to the smaller developed area relative to the districts themselves. In other words, the landscape of the districts is not dominated by developed area. Therefore, the length of all edge segments per hectare remained relatively constant. As the developed class increased, the mean patch area also significantly increased for Districts 5 and 1. As the number of patches decreased, the complexity of the shape of the developed class also decreased as illustrated with the landscape shape index (LSI). The decrease in LSI indicates a decrease in the irregularity of the developed class shape.

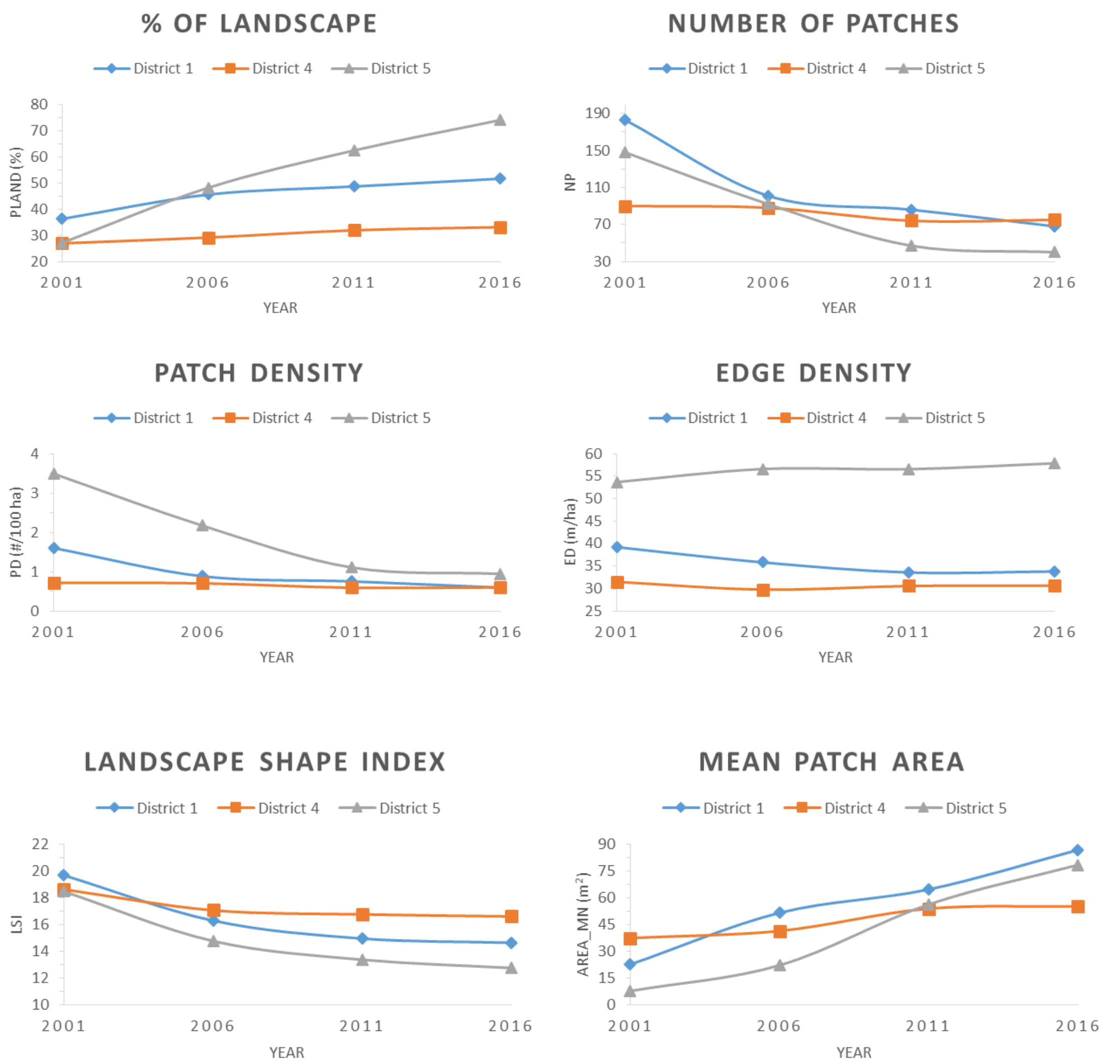


Figure 4.9: Class-level metrics.

The percentage of developed landscape demonstrates that District 5 experienced a linear growth rate from 2001-2016, compared to the remaining districts (Districts 1 and 4) which experienced gradual continued growth. As the districts expanded, fragmentation decreased as illustrated by the decrease in the number of patches and patch density, and the increase in mean patch area. The increase in urban development also decreased the irregularity of the developed shape areas within the districts.

4.2.2 Developed Sub-Categories

The developed class metric results for the sub-categories within the three districts (District 1, 4, and 5) are demonstrated in Figures 4.10 to 4.12. The metric results are relative to the district itself. For Districts 1 and 4, developed, low intensity dominated the landscape; followed by medium intensity in percentage of landscape (PLAND) depicted in Figure 4.10. District 5 was dominated by the developed, low intensity in 2001. However, the medium intensity quickly became the prevailing category after 2006; followed by low intensity. Medium intensity development within Districts 4 and 5 possessed the greatest number of patches; followed by open space. District 1 had the largest number of patches within open space, followed by medium intensity. Intuitively, the open space category would possess a high number of patches due to its' composition of parks, golf courses, and recreational areas. These areas should be fragmented or spread throughout the landscape. Whereas the medium intensity category was comprised of single-family housing and possessed a high number of patches within the three districts. This may be an indication of mixed-use within the urban areas. Patch density (PD) for Districts 1 and 4 followed a similar pattern as the number of patches, with open space dominating District 1 and medium intensity leading District 4, suggesting landscape fragmentation per unit area of landscape within these categories. District 5 demonstrated the dominating patch density occurring within the low intensity and its' vast increase in patch density from 2001 to 2016. The second leading category was open space. Therefore, fragmentation within District 5 was occurring within the low-intensity category per unit area. The three districts' edge density (ED) was similar to the percentage of landscape (PLAND) due to its' depiction of the total length of edge segments for the sub-category per hectare. The dominating sub-category within the district also would possess the majority of edge distance. The landscape shape index (LSI) indicated the complexity of the shape relative to the entire landscape. Within the three districts, low intensity and medium intensity were among the top two categories exhibiting complexity to shape. Within Districts 1 and 4, the mean patch area

(AREA_MN) was led by the low-intensity category. Whereas, District 5 was dominated by medium intensity. The mean patch area followed the percentage of landscape and these were the categories dominating the district areas.

The low and medium intensity domination in each district demonstrates the prevailing single-family housing within the urban landscape. This is verified in Plan El Paso, which states "the detached home on a moderately sized lot has been the predominant pattern since early in El Paso's history, accounting for two-thirds of the City's current housing units" (City of El Paso 2012). While, "El Paso has relatively little multi-family housing" (City of El Paso 2012) as illustrated by high intensity (compact and commercial areas) compromised the least amount of area within each district. Mixed-use areas, consisting of a variety of land-use areas, may suggest a slight increase in the number of patches, edge density, patch density, and landscape shape index within each category. District 5 experienced a linear increase in single-family housing (medium and low intensity) mean patch area, indicating the rapid growth within this land-use type.

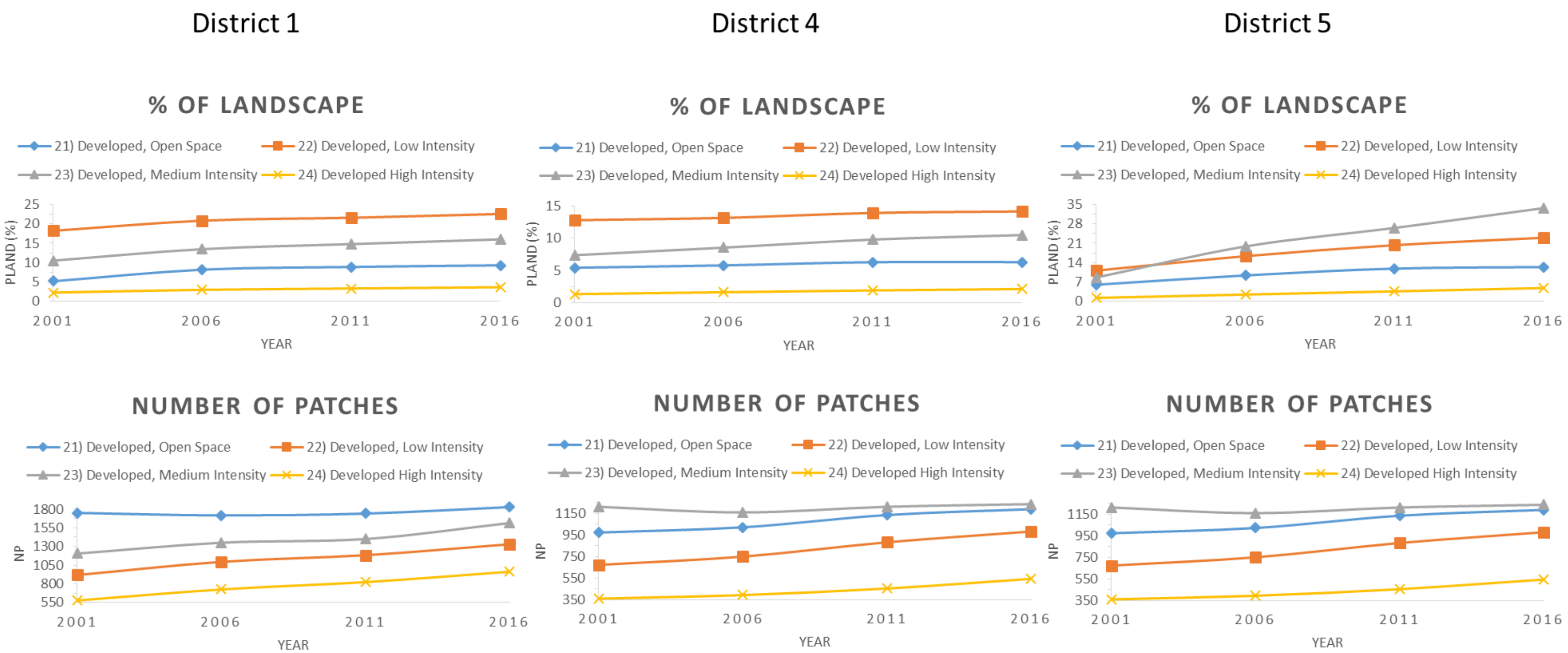


Figure 4.10: % of Landscape and Number of Patches metrics

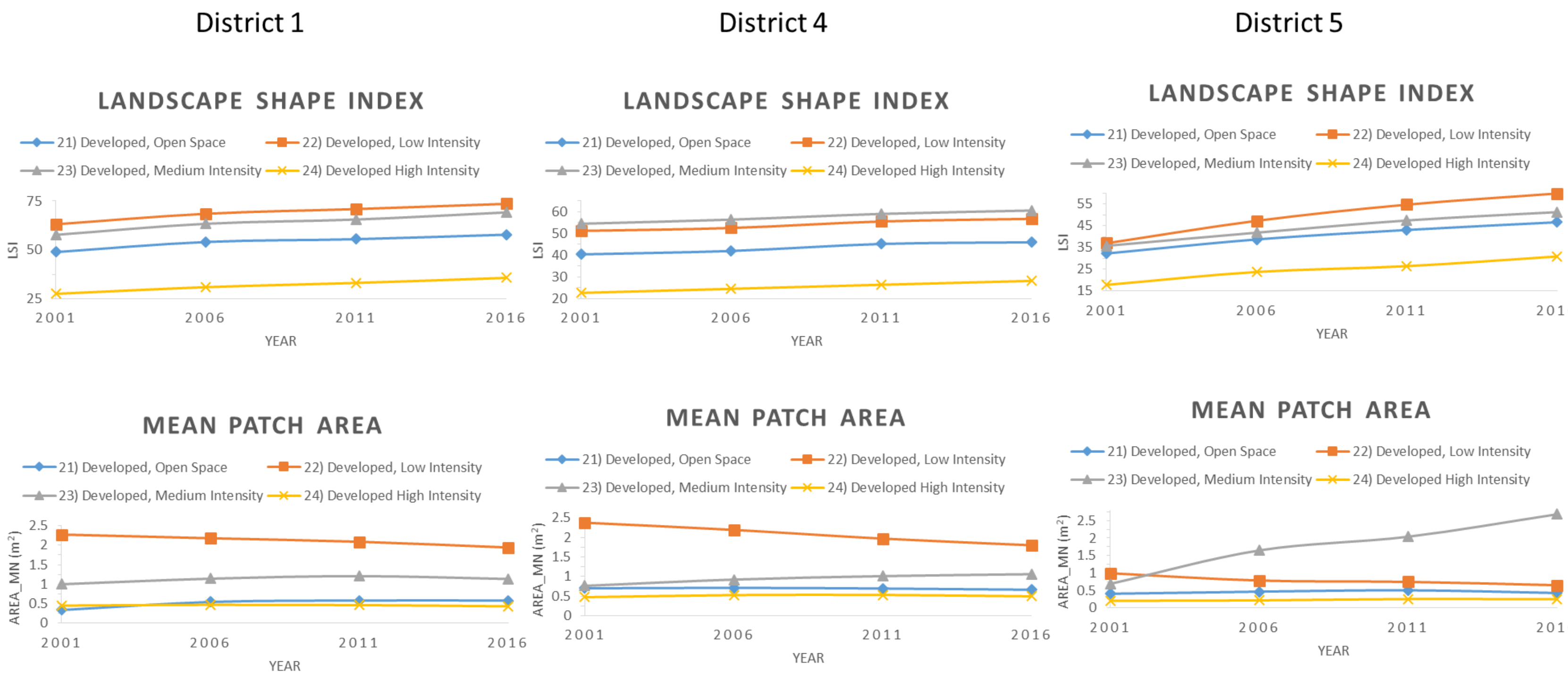


Figure 4.11: Landscape Shape Index and Mean Patch Area metrics

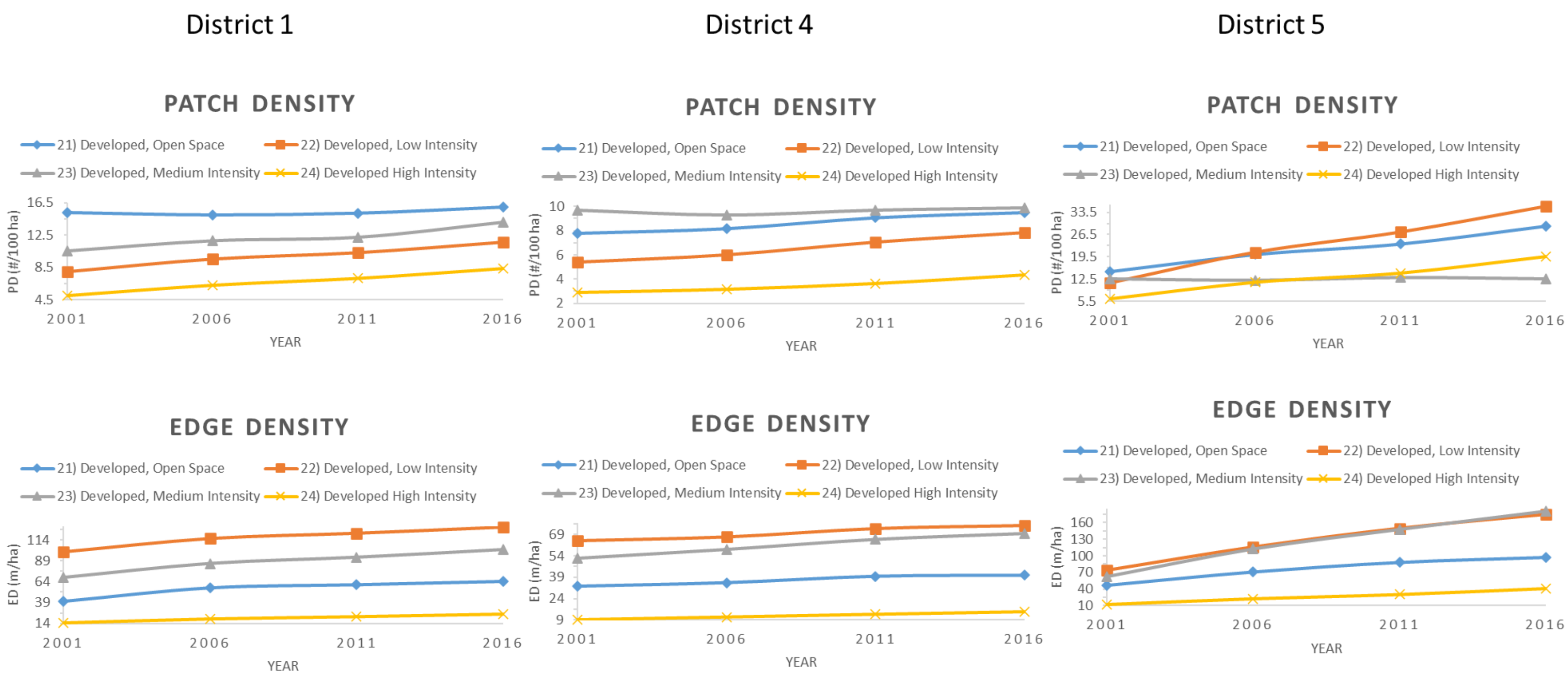


Figure 4.12: Patch Density and Edge Density metrics

Landscape metrics provide a deeper understanding of the entire landscape by considering the landscape as an entirety. The landscape metrics considers all developed sub-categories and barren (undeveloped) areas. The linear increase in landscape shape index (LSI) for District 5 indicated a continuous increase in the shape complexity within this district (Fig 4.13). Districts 1 and 4 also had an increase in complexity, but at a slow rate compared to District 5 due to the changes within the landscape. Patch density is a metric in relation to a unit area of the landscape. District 5 again had a drastic linear increase in patch density, compared to Districts 1 and 4. This was indicative of landscape fragmentation concentrated within District 5. Increasing uneven distribution or diversity of land-use types was evident in District 5 as depicted by Shannon's diversity index. This uneven distribution greatly increased between 2001 to 2006 and began to taper after 2006. Diversity had also gradually increased within Districts 1 and 4. All three districts decreased within the Contagion metric, which measures diversity of classes. Thus, suggesting diversity among class types within the landscape.

Fragmentation within the districts developed areas is suggested from the significant landscape shape index (LSI) for Districts 5 and 1, a significant increase in District 5 patch density (PD), and increases in Shannon's diversity index (SHDI). The decrease in Contagion indicates an increase in a diverse landscape. The fragmentation and diversity in landscape, may suggest an increase in mixed-use due to urban development. Mixed-use is encouraged in Plan El Paso to reduce transit time, accessibility to city transit, and offer local amenities, such as goods and services (City of El Paso 2012).

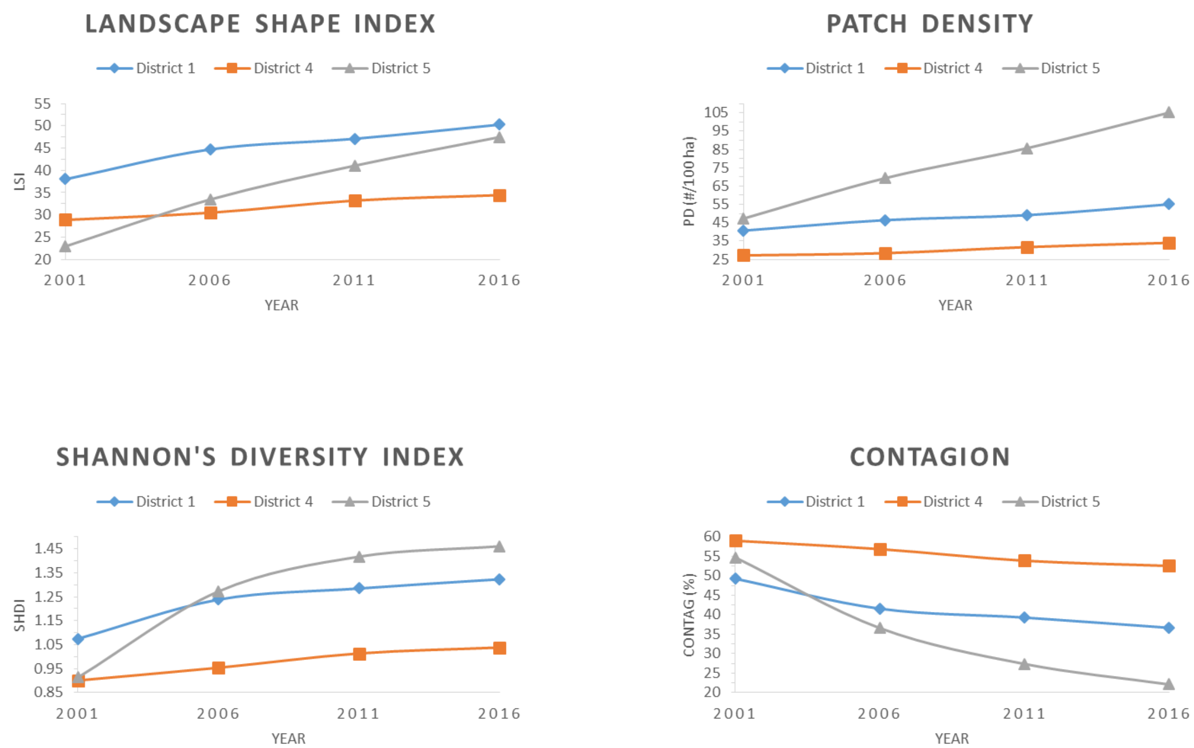


Figure 4.13: Landscape-level metrics

4.3 Future Prediction of Land-Use

Providing a prediction of future land-use in El Paso based on statistical analysis will equip decision-makers, planners, and developers to make informed decisions to prepare for the expansion of the area with the goal to provide an optimal quality of life for the community. To model future expansion, the model itself must first be verified using existing data.

4.3.1 Verification of CA-Markov Model

Verification of the CA-Markov model was conducted using the acquired NLCD data for 2001 and 2011 to predict the land-use for 2016. Using 1,000 random points for both County and City level, the results are provided in Table 4.8.

Table 4.8: CA-Markov accuracy utilizing 2001 and 2011 data to predict 2016

	Using 2001 and 2011 data to Predict 2016										
				User's accuracy		Error of Commission		Producer's accuracy		Error of Omission	
	Overall Accuracy	**Kappa Coeff.**	**Kappa Coefficient Agreement**	**Dev.**	**Barren**	**Dev.**	**Barren**	**Dev.**	**Barren**	**Dev.**	**Barren**
County	96%	89%	Almost Perfect	91%	98%	9%	2%	93%	97%	7%	3%
City	93%	85%	Almost Perfect	94%	91%	6%	9%	95%	89%	5%	11%

Adopting the Anderson classification system, all of the accuracy terms exceed the stringent 85 percent minimum accuracy (Anderson et al. 1976) for both the county and city level. The inclusion of the Kappa to satisfy the traditional error matrix, are rated "almost perfect", above 81% accuracy, for both levels. This is consistent with previous research where the CA-Model accuracy was found to possess Kappa coefficient of 81% and greater (Rimal et al. 2017; Chen Liping, Sun Yujun, and Saeed 2018; Subedi, Subedi, and Thapa 2013; Fu, Wang, and Yang 2018), and overall accuracy of 91% (Fu, Wang, and Yang 2018). The assessment results verify the use of the CA-Markov method for predicting future land-use in the El Paso area.

4.3.2. 2031 Future Land-Use Prediction

Future land-use prediction consists of determining the landscape in 2031 utilizing the CA-Markov model. The resulting land-use maps are analyzed for change analysis to understand the locations of projected urban growth.

4.3.2.1. 2031 CA-Markov Model

Utilizing El Paso County NLCD land cover data for 2001 and 2016, land-use was predicted for 2031 by applying the CA-Markov method. The land-use image for the base year 2001 and second time period of 2016, Markov analysis resulted in a transition matrix providing the probability of the developed state transitioning into a barren (undeveloped) state (Table 4.9). The matrix indicates the developed cells will remain developed, and the developed cells will not transition into barren state. A barren cell has a 0.0568 probability to transition into a developed state, and 0.9432 probability of remaining as a barren cell.

Table 4.9: Transition matrix for developed and barren class

	Developed	Undeveloped (Barren)
Developed	1.0000	0.000
Undeveloped (Barren)	0.0568	0.9432

The Markov transition matrix considers temporal trends to land-use changes, while suitability maps consider spatial trends. The suitability maps were created with physical factors of distance from developed areas and distance from roadways as discussed in Section 3.4 (Fig 4.14). The suitability maps provide the probability of a cells' land-use transition with respect to the spatial aspect.

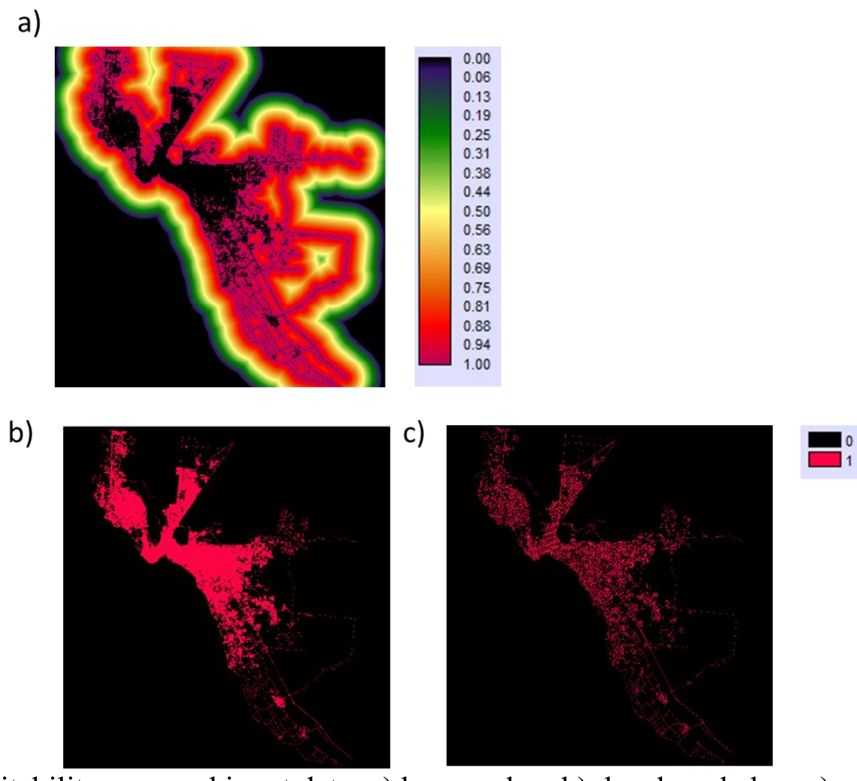


Fig 4.14: Suitability map and input data: a) barren class b) developed class c) roads

The Markov transition probability matrix and suitability maps were utilized in the CA-Markov model, resulting in the predicted land-use for 2031 (Fig 4.15).

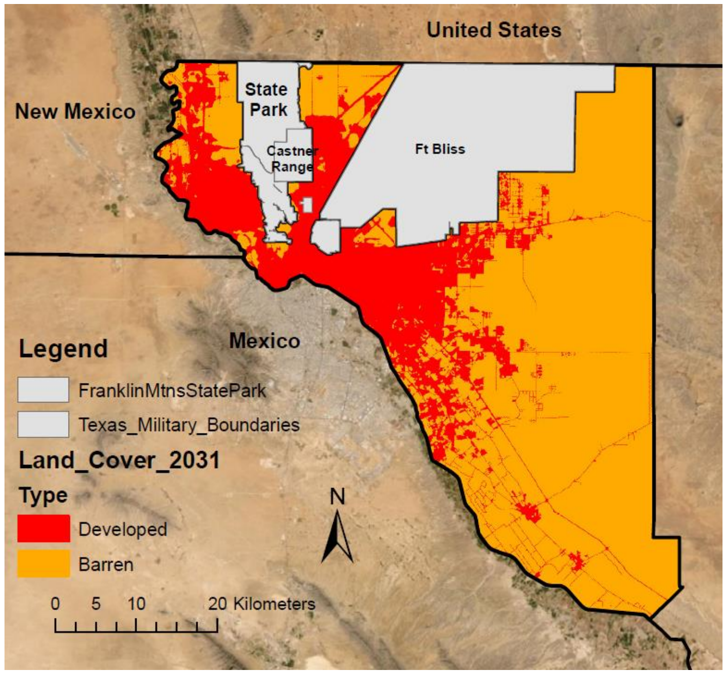


Figure 4.15: 2031 projected county land cover map

4.3.2.2 County 2031 Change Analysis Results

Discussion of the projected growth within the study area, is similar to the format explaining change analysis for known data in Section 4.1.2. Comparing the 15-year incremental time periods (2001-2016 and 2016-2031), the county urban growth from 2016 to 2031 decreased to 18.24% (Table 4.10). This is in comparison to the previous 15-year period (2001-2016) which possessed a 24% change in development. The decline is expected, as previously discussed, the 5-year incremental time periods from 2001-2016, continuously declined as well (Section 4.1.2).

Table 4.10: County land-use area and change in percentage

Land-use type	2001 Class Area (km^2)	2016 Class Area (km^2)	2031 Class Area (km^2)
Developed	382.52	474.54	561.12
Barren (Undeveloped)	1619.20	1527.12	1439.60
	2001 - 2016	2016-2031	
% Change in Development	24.06%	18.24%	

Of the projected expansion that occurred within the county, 51% occurred within the city of El Paso compared to approximately 66% for 2001-2016 (Table 4.11). Therefore, urban growth is projected to be evenly split within the city limits of El Paso and outside the city boundary.

Table 4.11: Contribution of city growth towards county expansion

	2001-2016	2016-2031
% County change occurring within City of El Paso	65.91%	51.03%

The projected development from 2016-2031 is expected to occur 51% within the city of El Paso and 49% outside the city limits as illustrated in Figure 4.16.

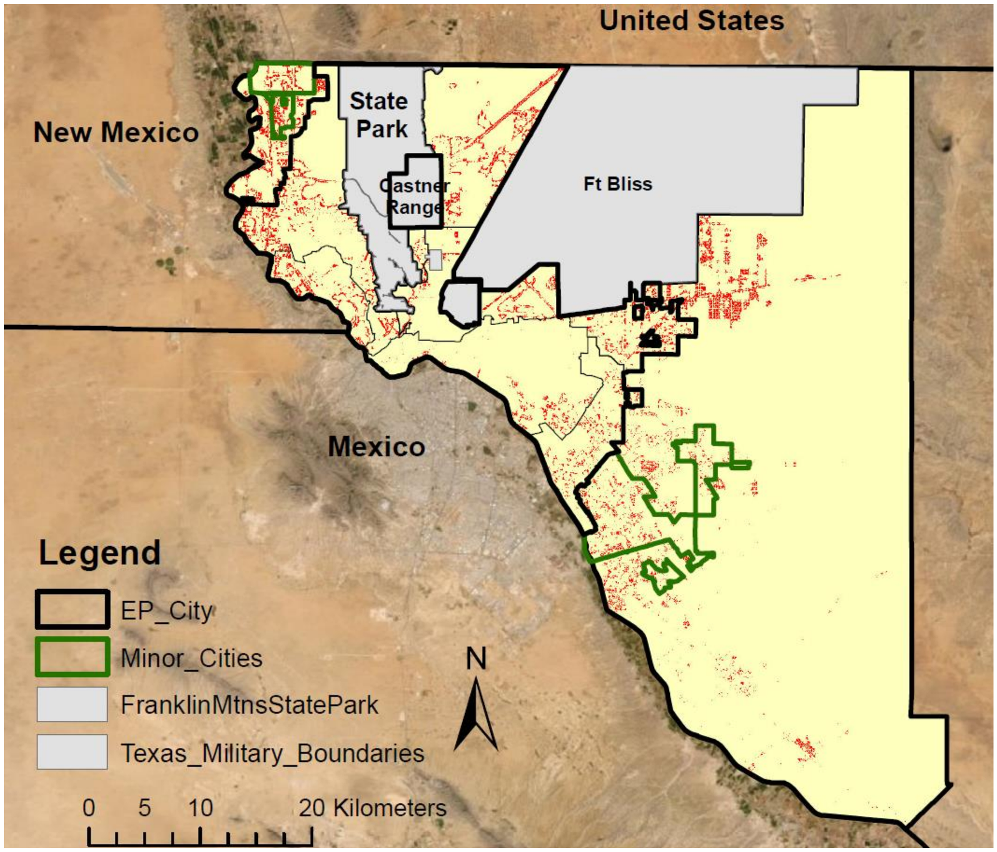


Figure 4.16: 2016 to 2031 county growth (red).

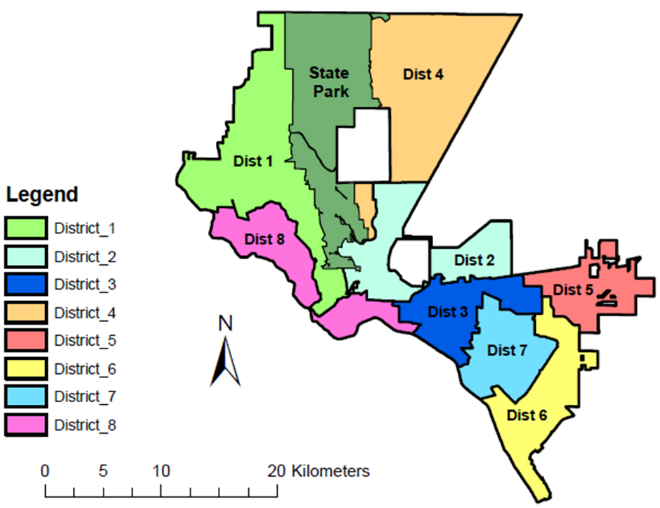
4.3.2.3 City of El Paso 2031 Change Analysis Results

Due to the even projected contribution of growth within the city of El Paso and outside city limits, both areas' expansion patterns will be discussed. First, the projected growth within the city of El Paso is presented. The 8 districts within the city were analyzed to determine the locations of concentrated growth. District 1 is projected to have the largest percentage of growth at roughly 24% (Fig 4.17). Followed by Districts 4 and 5 at 22.66% and 13.76%, respectively. The projected growth is logical, as Districts 1 and 4 possess the largest percentage of the barren area within the city in 2016 at 27.27% and 41.20%, respectively; among the districts (Table 4.12).

Table 4.12: Percentage of district barren area relative to the city.

	2016							
	District 1	**District 2**	**District 3**	**District 4**	**District 5**	**District 6**	**District 7**	**District 8**
Barren (Undev.) Area (km^2)	27.27%	10.87%	0.33%	41.20%	5.43%	7.53%	1.75%	5.61%

Districts 1 and 4 were also leaders in city growth from 2001-2016. Districts 8 and 2 follow with projected percentage growth at 11.91% and 11.43%, respectively. The remaining districts possess less than 9% growth.



District	%age growth (relative to the total growth in the City of El Paso)
1	24.39%
2	11.43%
3	1.16%
4	22.66%
5	13.76%
6	8.88%
7	5.80%
8	11.91%

Figure 4.17: 2016 to 2031 projected district growth relative to the city.

Comparing the districts' 15-year growth percentages between 2001-2016 and 2016-2031, the increase and decrease in growth is visibly evident in Figure 4.18. The districts with the largest increase in growth percentage from 2001-2016 to 2016-2031 are Districts 4, 8 and 2. District 4 projects the highest increase at 10.41% compared to 2001-2016. Districts 8 and 2 have an increase of 8.42% and 5.5%. District 4 contained the cities' majority of barren land for development in 2016 at 41.20%. Therefore, it is logical that District 4 would have an increase in development. District 1 contained the largest amount of the cities barren land in 2016 at 27.27%. However, the projection indicates that District 1 has a decrease in growth percentage by -3.61% compared to 2001-2016. District 5 exhibits the largest difference in growth percentage among the 15-year comparisons, at nearly 18%. The substantial growth that District 5 possessed during 2001-2016 may have an impact on the projected growth.

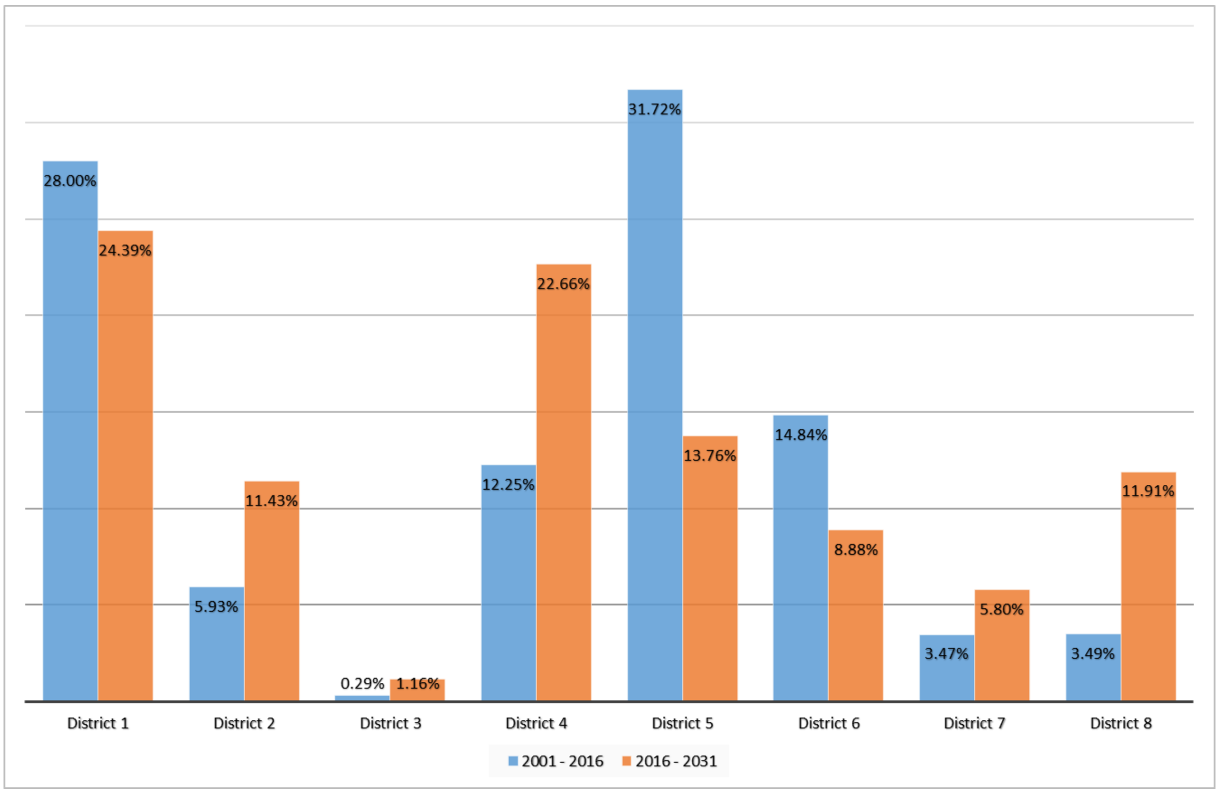


Figure 4.18: 15-year district and projected growth.

The leading districts in projected growth (Districts 1, 4, and 5) mimic the previous 15-year growth. However, District 1 is predicting to experience the highest growth, followed by District 4 and 5. District 1 and 4 growth follows Plan El Paso's Comprehensive Plan designation districts for immediate growth. District 4 experiences growth within the specific area designated for the districts' growth. However, District 1 indicates growth outside of the designated area.

This may suggest possible infill of future growth. District 5 expansion is expected, as the district continues to expand within the plans designated suburban area for this district.

4.3.2.4 Outside El Paso City 2031 Change Analysis Results

Outside the city limits of El Paso, 49% of the projected growth for 2031 occurs. The county of El Paso is comprised of several cities including El Paso, Anthony, Clint, Horizon City, Socorro, Vinton, and Fabens. With the exception of El Paso, the cities' total contribution to the counties projected growth in 2031 is approximately 25% (Figure 4.19). The majority of future growth is to occur outside city limits.

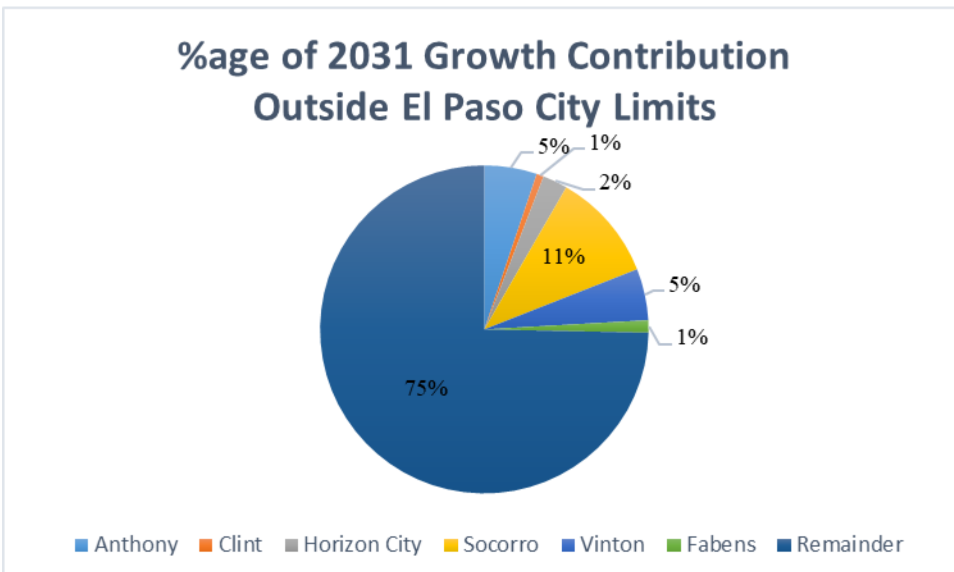


Figure 4.19: City contributions to projected growth outside El Paso city limits.

Figure 4.20 displays where future growth is projected outside of the city limits. The projected growth is concentrated in 3 main areas: Area 1) adjacent to District 5, Area 2) adjacent to District 6, and Area 3) adjacent to District 1 along the New Mexico border. Area 1 and 2 are located within the potential annexation areas proposed by the Plan El Paso Comprehensive Plan. The potential annexation spaces will be utilized for urban growth by 2031. Area 3 is not located within a preferred annexation area. Therefore, the growth in Area 3 should be mitigated through policies.

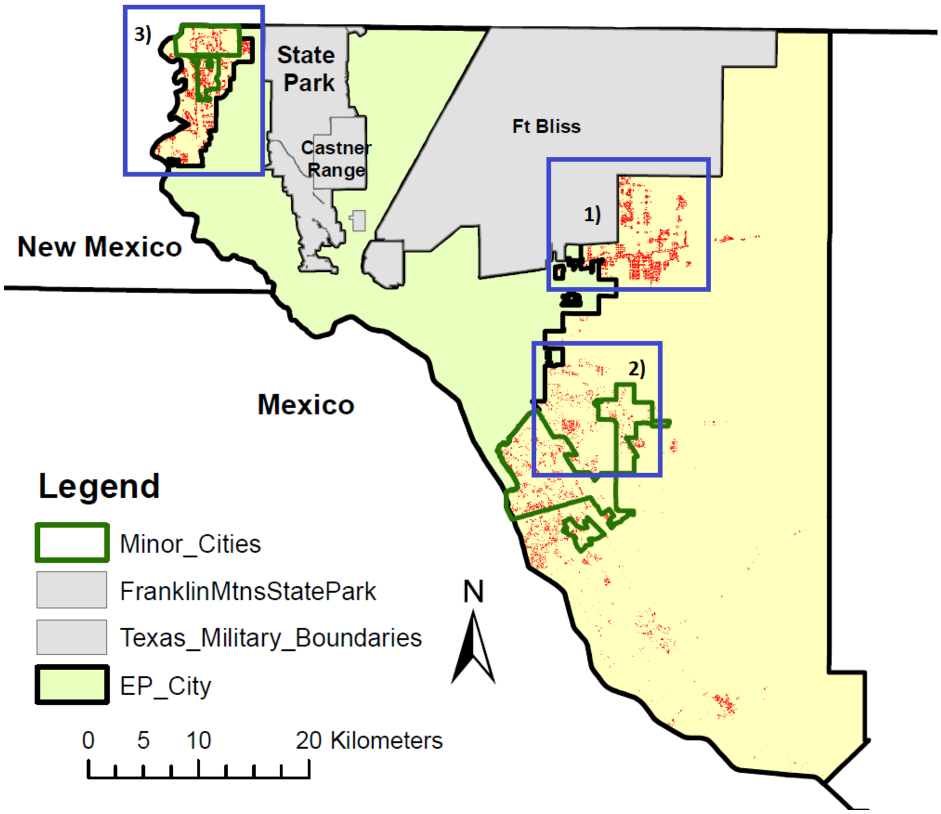
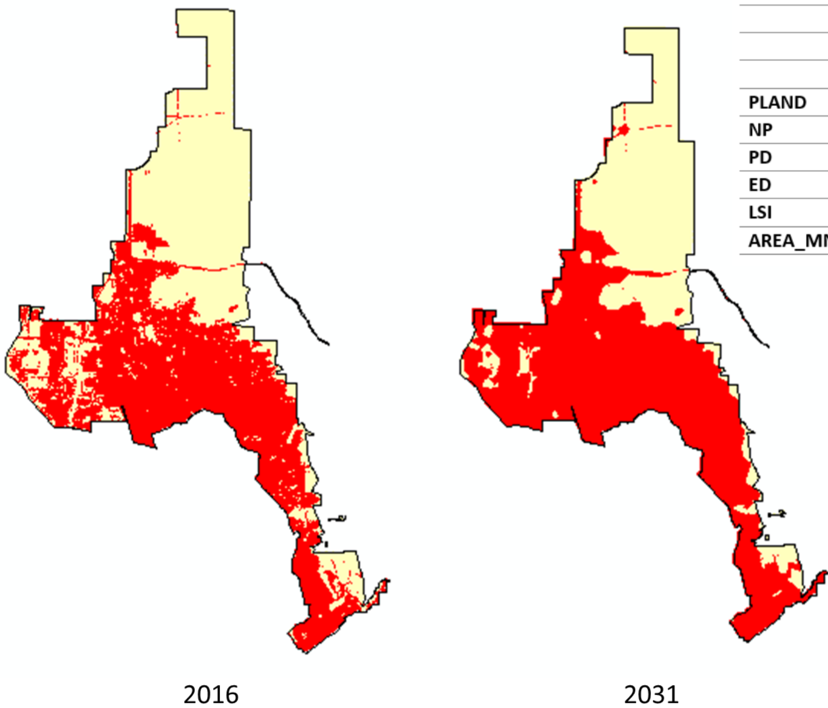


Figure 4.20: Growth clusters outside city limits.

Outside the city limits of El Paso, urban growth adjacent to Districts 5 and 6 (Areas 1 and 2) occur within potential annexation areas according to Plan El Paso Comprehensive Plan. The growth projected adjacent to District 1 (Area 3) does not occur within a potential annexation area. Therefore, actions should be taken to mitigate growth within this area, and encourage growth within the designated immediate or possible annexation areas.

4.4 2031 Landscape Metrics

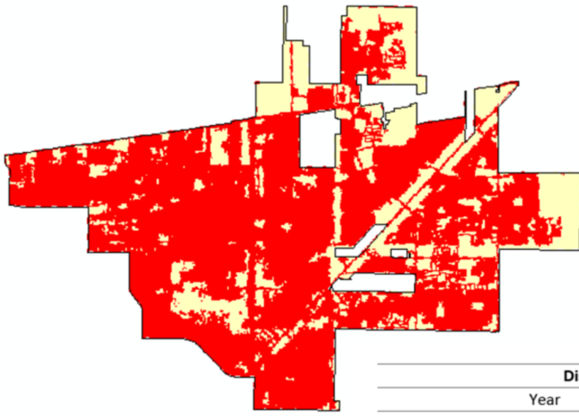
Landscape metrics were analyzed for Districts 1, 4, and 5 to provide an understanding of the projected growth patterns for 2031. The comparison of District 1 in 2016 to the projected 2031 land-use of the developed and undeveloped (barren) area is illustrated in Figure 4.21. The percentage of the developed area (PLAND) increased by 18%. The number of patches (NP) decreased by 24%, indicating infill within the existing developed area. The patch density (PD), measuring the number of patches per 100 hectares of developed area, decreased slightly (23%) compared to 2016; also indicates infill development. Edge density (ED), which measures the total edge distance per developed patch, and the landscape shape index (LSI), indicates shape regularity, decreased. Suggesting as the developed class increased, the edge length of the developed patches decreased, and the irregularity of the developed class decreased. The mean patch area (AREA_MN) also increased, due to the increase in the developed class.



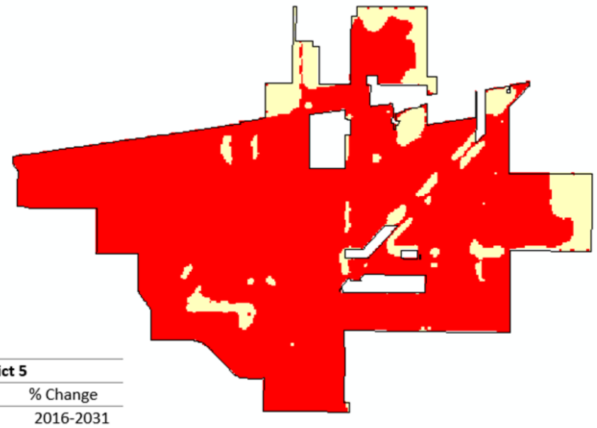
District 1			
	Year		% Change
	2016	2031	2016-2031
PLAND	51.582	61.0926	18%
NP	68	52	-24%
PD	0.5941	0.455	-23%
ED	33.7962	9.4672	-72%
LSI	14.6433	5.4207	-63%
AREA_MN	86.8288	134.2644	55%

Figure 4.21: District 1 landscape metrics for developed class (red) in 2016 (left) and 2031 (right)

District 5 possesses similar results as District 1 (Figure 4.22). The percentage of the developed area (PLAND) increased by 19%. The number of patches (NP), patch density (PD), edge density (ED) decreased indicating infill within District 5. The mean patch area increase of 77% is indicative of the increase in the developed class area.



2016

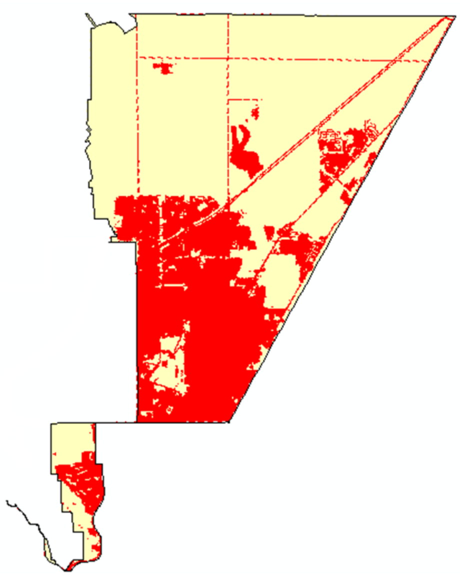


2031

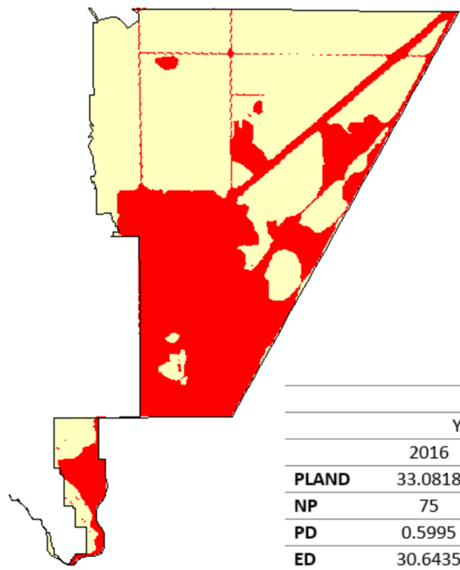
District 5			
	Year		% Change
	2016	2031	2016-2031
PLAND	73.9673	88.3434	19%
NP	40	27	-33%
PD	0.943	0.6368	-32%
ED	57.8576	12.4964	-78%
LSI	12.754	4.1497	-67%
AREA_MN	78.4417	138.7279	77%

Figure 4.22: District 5 landscape metrics for developed class (red) in 2016 (left) and 2031 (right)

District 4 possesses slightly different metric results compared to Districts 1 and 5. The percentage of the developed area (PLAND) also increased in District 5 by 24% (Fig 4.23). The number of patches (NP) and patch density (PD) slight increase at 27% for both metrics, suggests possible slight fragmentation within District 4. The decrease in edge density (ED) suggests the patch areas increased. The decrease in landscape shape index (LSI), indicates a decrease in shape irregularity for the developed class. The mean patch area relatively stayed constant, suggesting the developed growth area relative to the number of patches remained constant



2016



2031

District 4			
	Year		% Change
	2016	2031	2016-2031
PLAND	33.0818	41.1381	24%
NP	75	95	27%
PD	0.5995	0.7604	27%
ED	30.6435	13.5378	-56%
LSI	16.6084	7.4543	-55%
AREA_MN	55.1832	54.1004	-2%

Figure 4.23: District 4 landscape metrics for developed class (red) in 2016 (left) and 2031 (right)

According to the landscape metrics, Districts 1, and 5 experience infill development. However, district 4 experiences slight fragmentation compared to the other districts. The rate of infill for district 4 is slower than the other districts. Infill should be encouraged for District 4.

4.5 Relationship of Urban Form and Electricity Consumption

The panel data analysis to understand the relationship between urban form and electricity consumption was performed using STATA software. To determine which panel regression model to use, the f-test was conducted (Table 4.13). The constant intercepts and coefficients model, contained one metric that was significant. Whereas, the variable intercepts and constant coefficients, indicate three metrics are significant. R-squared (R^2) was also considered when choosing a model, due to its' ability to interpret how well the model fits the data. The variable intercepts and constant coefficients model possess significantly higher R^2 values than the constant intercepts and coefficients model, indicating this model fits the data well. Therefore, the variable intercepts and constant coefficients model was further analyzed.

Table 4.13: F-test results.

	F-test	PLAND	NP	PD	ED	LSI	AREA_MN
Constant intercepts and coefficients	Prob > F	0.5924	0.8614	0.5395	0.9291	0.6756	0.0325**
	R-squared	0.0778	0.0086	0.1009	0.0022	0.0483	0.7206
Variable intercepts and constant coefficients	Prob > F	0.0763*	0.2984	0.1143	0.1051	0.0166**	0.0916*
	R-squared	0.8531	0.4923	0.7844	0.8008	0.9670	0.8252

* Significant at 0.10
** Significant at 0.05

The Hausman test was implemented to determine if fixed or random effects should be implemented in the variable intercepts and constant coefficients model, using the following hypothesis:

H_o = random-effects model selected (null hypothesis)

H_1 = H_o is not true, fixed effect model selected

Using a significance level, α, of 0.10, the Hausman test results (Table 4.14) indicate the null hypothesis cannot be rejected. Therefore, the random-effects model was selected for analysis.

Table 4.14: Hausman test results

	Hausman Test Results					
	PLAND	NP	PD	ED	LSI	AREA_MN
Probability	0.0002***	0.1543	0.0057***	0.0044***	0.0000***	0.2463

* Significant at 0.10
** Significant at 0.05
***Significant at 0.01

The relationship between landscape metrics and electricity consumption is as follows:

$$EC_i = \alpha_i + \beta_i(x_{it}) + \epsilon_{it} \qquad (4.4)$$

$EC_i = electricity\ consumption\ [(10^6)kWh]$
$i = district$
$\alpha_i = district\ random\ effects\ coefficient$
$\beta_1 = coefficient\ of\ landscape\ metric$
$x_{it} = landscape\ metric\ for\ district\ i\ at\ time\ t$
$\varepsilon_{it} = error\ term$

The panel data analysis utilizing the random-effects was performed to understand the impact of a metric on electricity consumption. The random-effects model indicates that one metric is significantly correlated with electricity consumption, mean patch area (AREA_MN), with a 0.01 significant level (Table 4.15). The remaining metrics were not significantly correlated with electricity consumption for this study.

Table 4.15: Random effects panel data analysis results.

	PLAND	**NP**	**PD**	**ED**	**LSI**	**AREA_MN**
Coefficient	2.0280	-0.3468	-138.7726	-0.1452	-46.8625	4.1058*
Constant	183.1866	307.6474	391.2038	290.9861	980.9685	14.5148

* Significant at 0.01

The mean patch area describes the sum of all developed patch areas divided by the number of patches for a class. This metric increased within each district throughout the study period, with the exception of District 4; indicating that as the developed area increased, fragmentation decreased (Table 4.16). Districts 1 and 5 projected a decrease in the number of patches (NP) and an increase in the percentage of developed area. Thus, an increase in mean patch area. However, District 4 projected a relatively constant mean patch area from 2016 to 2031. This is due to the increase in the developed area (24%) and the number of developed patches (27%) increasing from 2016 to 2031.

Table 4.16: Metrics Percentage Change

%age Change from 2016 - 2031			
	AREA_MN	PLAND	NP
District 1	55%	18%	-24%
District 4	-2%	24%	27%
District 5	77%	19%	-33%

Electricity consumption will increase by 4.1058 (10^6 kWh) for every unit increase in the mean patch area. This indicates that District 1 will increase by 209.27 (10^6 kWh), exhibiting a linear increase in electricity consumption (Fig 4.24). District 5 increase of 262.035 (10^6 kWh), indicating a sharp increase within the 5-year period from 2011 to 2016. However, a slight decline in electricity consumption from 2016 to 2031. This is indicative of the decline in urban development within the district. District 4 increases the least at 18.96 (10^6 kWh). This is due to District 4 experiencing a relatively constant mean patch area, AREA_MN, from 55.1832 (2016) to 54.1004 (2031).

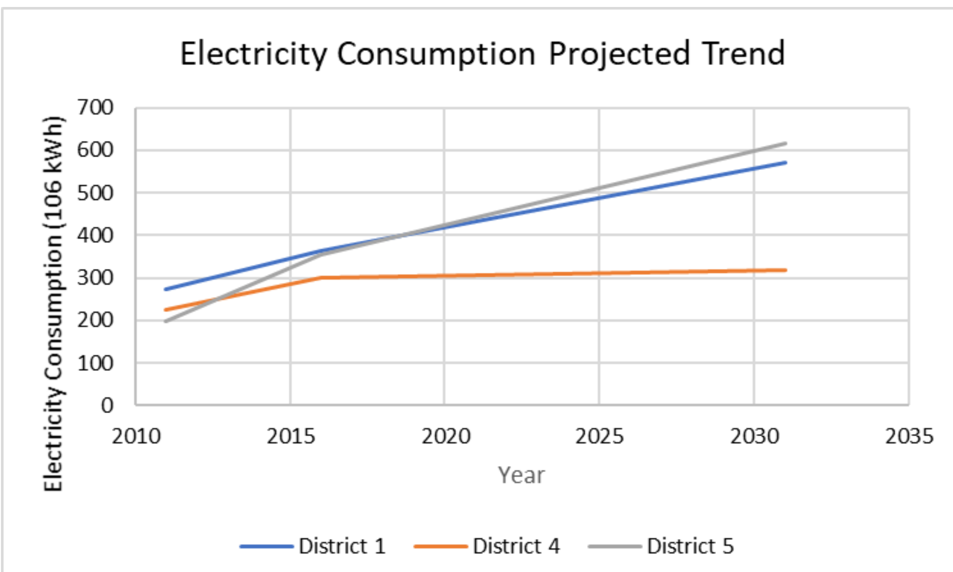


Figure 4.24: Projected electricity consumption trend

District 1 and 5 findings are consistent with recent research, as urban areas expand consequentially electricity consumption increases (Zhao, Thinh, and Li 2017; Chen et al. 2011). However, additional factors of fragmentation, such as the number of patches (NP) and the percentage of developed area, were found to be correlated with energy consumption (Chen et al. 2011). This study did not support this finding. It is suggested to increase the number of time periods analyzed and the number of metrics in order to provide a better understanding of the relation of landscape metrics and electricity consumption over time.

4.6 Summary

From 2001-2016, urban growth within El Paso county concentrated within the city limits of El Paso. The majority of growth occurred within Districts 5 (east side), 1 (west side), and 4 (northeast), with District 5 experiencing a vastly increase in linear growth. The developed growth is concentrated within medium and high intensity sub-categories; which represents single-family housing, and compact housing and commercial use; respectively. However, high intensity does not dominate the districts' landscape. Single-family housing dominates the districts landscape as represented with low and medium intensity categories. The fragmentation and increase in the irregularity of sub-categories indicates possible mixed-use within the developed categories.

Future growth is expected to be evenly distributed within the city of El Paso and outside the city limits. The future city landscape mimics that of the past, with Districts 1, 4, and 5 dominating in the percentage of growth. However, the intensity differs from past growth trends with District 1 leading in percentage growth followed by District 4 and lastly District 5. These districts are expected to experience infill of development, with District 4 experiencing slight fragmentation. Outside the city limits of El Paso, growth is concentrated adjacent to Districts 5, 6, and 1. These areas concentrated within potential annexation areas, with the exception of outside District 1 growth.

Mean patch area is positively correlated with electricity consumption. This metric describes the developed area per number of patches. Contrary to recent research, various metrics describing fragmentation and growth, such as the number of patches (NP) and percentage of landscape (PLAND) were not found to be significantly correlated with electricity consumption

Chapter 5: Conclusion

5.1 Summary of Research Objectives and Findings

Objective 1) Provide an understanding of El Paso's past growth from 2001 – 2016 utilizing change analysis.

Using land-cover data from the U.S. government generated National Land Cover Database (NLCD), a land cover change analysis was performed for El Paso County. The land cover classes examined were developed (all urban growth) vs barren (undeveloped) classes. In addition, the NLCD developed sub-categories vs barren (undeveloped) classes were examined. The results indicate El Paso experienced constant growth from 2001-2016, with 2001-2006 experiencing the largest percentage of growth at 12.73%. The counties' urban growth continued, however at a lower percentage of 5.66% and 4.15%, in 2006-2011 and 2011-2016, respectively. The majority of this growth occurred within the city limits of El Paso. The city accounted for 71.43% of the counties' growth from 2001-2006; and decreased to 68.23% and 59.1% in the following 5-year increments.

The cities' consistent growth primarily occurred within Districts 5 (31.72%), 1 (28%), and 4 (12.25%) from 2001-2016. Examining urban growth in 5-year increments, from 2001-2006, the cities' growth occurred within Districts 1 (30.47%) and 5 (25.61%); followed by District 6 (21.08%). The following years, Districts 5, 1, and 4 were the top districts of city growth, with District 5 exceeding at 36.25% and 43.94% from 2006-2011 and 2011-2016; respectively.

Examining a breakdown of the developed area within each district, the NLCD developed sub-categories growth were examined. High and medium intensity sub-categories were the leading categories of growth within each district. The high intensity represents compact housing (apartments) and commercial areas; while medium intensity consists of single-family housing. District 5 experienced nearly a three-fold increase from 2001-2016 in medium intensity (single-family) and high intensity (compact housing high and commercial area) at 289% and 276%, respectively. District 5 continued to lead in the largest percentage growths within high and medium intensity among the 5-year incremental periods, with 129.26% percent growth within medium intensity from 2001-2006. District 1 experienced the top growth sub-category was open space at 79% from 2001-2016. However, further examination of the 5-year increments indicate this growth mainly occurred from 2001-2006, and changed to high and medium intensity within the following 5-year study periods.

Objective 2) Utilize landscape metrics to analyze El Paso's urban dynamic growth patterns.

Class-level landscape metrics were calculated for both developed and developed sub-categories within Districts 5, 1, and 4. The developed landscape metrics results suggest a decrease in fragmentation within each district. This indicates infill occurred as the developed areas increased within each district. This is in compliance with the overall goal within Plan El Paso's Comprehensive Plan to "encourage infill development within the existing City over peripheral expansion to conserve environmental resources, spur economic investment, repair social fabric, reduce the cost of providing infrastructure and services, and reclaim abandoned areas" (City of El Paso 2012).

Single-family housing dominates the districts landscape as the low and medium intensity sub-categories. Though high intensity was one of the leading growth sub-categories, it comprises the least amount of area within each district. This is verified in Plan El Paso, which states El Paso offers limited multi-family housing, with the majority of housing comprised of single detached homes (City of El Paso 2012). The increase in fragmentation within the sub-categories suggests possible mixed-use neighborhoods.

Landscape-level metrics examine the landscape in its' entirety including barren (undeveloped) areas. The results indicate fragmentation among all districts, suggesting mixed-use neighborhoods with diverse land-use categories.

Objective 3) Predict future land-use within El Paso County for 2031 utilizing CA-Markov and apply landscape metrics to understand growth patterns.

Utilizing CA-Markov, El Paso's future land-use for 2031 was projected. The CA-Markov model was found to be highly accurate with a Kappa Coefficient Agreement of "almost perfect", above 85%, and an overall accuracy of above 93%. Contrary to the previous 15-year period (2001-2016), the projected developed growth percentages are evenly distributed among the city of El Paso and outside city limits at 51% and 49%, respectively. Therefore, both areas were examined further. The city growth patterns mimic those of the previous 15-year period with growth concentrating within Districts 1, 4, and 5. However, District 1 leads in growth, followed by District 4 and 5.

Outside El Paso city limits, growth is concentrated adjacent to Districts 1, 5, and 6. The areas adjacent to Districts 5 and 6 are in potential annexation areas according to Plan El Paso Comprehensive Plan. The growth outside of District 1 does not occur within a potential annexation area.

The landscape metrics were applied to the fastest-growing districts within the city of El Paso, Districts 1, 4, and 5. These districts experienced infill. However, District 1 experiences infill at a slower rate than the remaining district. Infill should be encouraged as discussed in Plan El Paso (City of El Paso 2012).

Objective 4) Examine the relationship between El Paso's landscape metrics and electricity consumption.

Using a random effects panel analysis, mean patch aria (AREA_MN) was positively correlated with electricity consumption. This suggest that as developed areas increased and patch areas decrease, consequently electricity consumption increased. This is due to the increase in developed area. While, the remaining metrics were not found to be significantly correlated. Suggesting that more observations, both time and metrics, should be implemented for further study.

5.2 Significance and Recommendations

"Managing El Paso's outward expansion is perhaps the most complex and difficult strategy…", Plan El Paso Comprehensive Plan (City of El Paso 2012). This study aims to assist decision-makers and stakeholders with lessons learned from El Paso's past and future urban growth trends and subsequent patterns, and their influence on electricity consumption in order to make informed decisions for a better future for El Pasoan's. Knowing where El Paso has experienced growth and the projected growth areas for 2031, allows decision-makers to mitigate unwanted growth patterns and encourage optimal patterns such as infill. The following recommendations are based on the findings of this study:

- Continue to encourage high intensity growth, in particular compact housing such as apartments. Thus, will increase the sub-categories' area and provide compact housing options.
- Plan for annexation adjacent to District 5 due to the extensive growth this district experienced and is projected to experience. The projected growth is to continue adjacent to the district. However, outside the city limits.
- Encourage infill/compact growth within District 1 as apposed to the projected growth adjacent to District 1, which is in agreement with Plan El Paso's goals.
- Continue infill/compact growth to reduce electricity consumption.

These recommendations may be enforced through policies, zoning, subdivision planning, and availability of utilities as the state in Plan El Paso (City of El Paso 2012).

5.3 Limitations and Future Studies

This study consists of the following limitations and recommendations to improve this study for future research:

- The proposed Borderland Expressway project is not included in this study. Construction for the project is slated to begin 2022 and would extend the existing Loop 375 to the New Mexico state line located within District 4 (TxDOT 2020). The Borderland Expressway and its' impact on urban growth is suggested to be included for future studies.
- The CA-Markov presented in this study considered the spatiotemporal aspects of the study area. It is recommended that socio-economic factors such as population change, employment change, highway accessibility, and income be incorporated into the model to provide a more thorough understanding of various factors affecting urban growth.
- This study utilized past urban trends to predict future urban expansion. It is recommended that various growth percentage scenarios be incorporated to provide an understanding of future growth pattens, based on the scenarios along with a sensitivity analysis for each scenario.
- Obtaining electricity consumption data for developed sub-categories is suggested to analyze the relationship of the landscape metrics and consumption among the sub-categories.
- The NLCD data used in the study were limited to 5-year increments from 2001-2016. Obtaining land-use data for current years, is recommended to provide a more current study. This limitation also affected the landscape metrics and electricity consumption analysis to a 2-year study period (2011 and 2016). Additional land-use information would improve the metrics and electricity consumption analysis. In addition, the panel data analysis may support the fixed/random-effects model with the additional time periods.
- Continued projection of growth past 2031 is recommended to understand long-term land-use growth.

- A policy scenario of implementation of El Paso's Smart Code (City of El Paso 2020) and its' impact on urban growth is recommended to be included in the study.

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Vita

Joanne Moyer earned her Bachelor of Engineering degree in Civil Engineering from The University of Texas at El Paso in 2007. While pursuing her Master of Science degree in Civil Engineering, she worked full-time for a structural engineering firm. She obtained her MS in 2010 from The University of Texas at El Paso. She began her doctoral program with the University of Texas at El Paso in 2015.

From 2015 to present, Joanne has worked as a lecturer for El Paso Community College (EPCC) and teaching assistant for The University of Texas at El Paso (UTEP). She has taught Civil Engineering Fundamentals and Engineering Economy at EPCC, and was a teaching assistant for the construction management program at UTEP.

Joanne was awarded the first scholarship from the American Society of Professional Estimators (ASPE) Chapter 40 in 2017. Joanne also served as a fellow for the Hispanic-Alliance for the Graduate Education and the Professoriate in Environment Sciences and Engineering from 2018 to 2019, where she received training in transitioning for STEM faculty in higher education. She presented her doctoral research in poster presentation at the 2019 Natural Capital Symposium at Stanford University, and the Graduate Student Research Expo in 2017 (UTEP).

Joanne looks forward to a career in academia where she can use her experience and education to prepare future generations of civil engineers.

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