Land Use/ Land Cover Change Patterns And Trends In Two Dryland Regions

Omar Sulaiman Belhaj

University of Texas at El Paso

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LAND USE/ LAND COVER CHANGE PATTERNS AND TRENDS IN TWO DRYLAND REGIONS

OMAR SULAIMAN BELHAJ

Doctoral Program in Environmental Science and Engineering

Approved:

______________________________
Craig E. Tweedie, Ph.D., Chair

______________________________
Raed E Aldouri, Ph.D., Co-Chair

______________________________
Musa J. Hussein, Ph.D.

______________________________
William L. Hargrove, Ph.D.

______________________________
Stanley T. Mubako, Ph.D.

______________________________
Stephen L. Crites, Jr., Ph.D.
Dean of the Graduate School
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By

Omar Sulaiman Belhaj
August 2022
DEDICATION

I would like to dedicate this dissertation to my father and my mother

May Allah “God” protect them

To my brothers and sisters,

My wife and children,

For their endless sacrifice, love, hope, and belief show me that greatness comes only through hard work.
LAND USE/ LAND COVER CHANGE PATTERNS AND TRENDS IN TWO DRYLAND REGIONS

by

OMAR SULAIMAN BELHAJ, MSc

DISSERTATION

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of the Requirements
for the Degree of

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ABSTRACT

Development and climate change affect the environment in numerous ways and to varying degrees. This effect appears prominent and more influential in arid regions. Therefore, land use/land cover in these regions experience profound changes such as plant cover decrease and extinction of some plant species. Also, land use/land cover in these regions has critical impacts on the environment and its components, such as shrublands shrinking and losing the habitat of animal species. The degree of changes and effects reaches severe levels that become urgent to figure out the impacts and find solutions to stop or mitigate the negative consequences. This research was implemented in two different areas on two continents to measure land use/land cover changes, analyze them, and predict their future circumstances. This research will identify the actual areas of the different land use/land cover categories in the study areas and clarify the changes in these categories over time that are needed for land management and planning. These two regions are located at the same latitude in the northern hemisphere and face similar climate conditions and challenges. Also, these two regions suffer from water scarcity and quality issues that cause water use limitations and shortages.

The district of Khoms, Libya, is a semiarid-to-arid region located in North Africa. The land use/land cover study revealed a 16% per year long-term historical urban growth rate, leading to an urbanization increase of 658% from just 800 ha in 1976 to 6,067 ha in 2015 over the 40-year analysis period. The growth of urban areas replaced natural and agricultural lands. These results are essential to know the actual land use/land cover areas and their changes in the Khoms district. As well, these results will help to realize the real stress on sustainability in the district and the surrounding areas and push towards better management of the district and the surrounding areas that face the same conditions.
The Middle Rio Grande Region is a semiarid to an arid region in North America on the southwest border between the US and Mexico. The region encompasses the three vibrant and fast-growing metropolitan cities of El Paso, Texas, Las Cruces, New Mexico, and Ciudad Juarez, Mexico. Different land use/land cover patterns and trends prevailed in this area during the 24-year study period from 1994-to 2015. This research focused on understanding recent trends, present circumstances, and likely future development scenarios of the Middle Rio Grande Region. Specifically, I analyzed changes in surface water bodies and land use/land cover and predicted future changes in different land use/land cover categories based on past change trends. The results showed that the area of surface waterbodies decreased by more than 56% in the last 26-year period, 1994-2020. The extent of agricultural lands decreased by ~12%. Urbanization growth dominated documented land use/land cover trends by ~45%, especially around El Paso, Texas, Las Cruces, New Mexico, and Ciudad Juarez, Mexico.

Land use/land cover changes in the region appear to continue in the future years of 2020-2040 with the same patterns and trends. Results indicated that the extent of agricultural land will decrease by ~14% in 2020-2040, mainly around the major metropolitan areas of El Paso, Ciudad Juárez, and Las Cruces to provide land to open space and urban development, which will increase by ~20% and ~29% respectively. The surface water areas across the region, which face growing demands, will decrease ~15% if current change rates continue.

Results from this research are an important resource for stakeholders, authorities, and decision-makers to understand the changes in land use/land cover, work to control the impacts of these changes, and plan for best practices in the future. In addition, the research shows the ability of remote sensing and geographic information system technologies to identify, analyze land use/land cover, and predict their future changes, patterns, and trends.
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CHAPTER 1: INTRODUCTION

Natural resources face significant challenges and changes on all levels and locations around the globe (Belhaj et al., 2020), including the US (Riebsame, 2019). Development and intensive consumption of these resources appear to be driving most environmental changes occurring on earth (Islam et al., 2018). The land is a critical resource for the livelihood and well-being of people. Land use/land cover is one of the most significant features that imply land surface appearance and environmental characteristics. The change in land use/land cover reflects the transformation of natural resources and the trends of this change (Arowolo et al., 2017, Islam et al., 2018). Land use/land cover change has essential impacts on the functioning of socioeconomic and environmental systems and affects sustainability, food security, biodiversity, and people's vulnerability, and global ecosystems (Miheretu et al., 2018). Land use/land cover change is considered an important tool for assessing global change on different spatiotemporal scales (Islam et al., 2018). The sustainable management of the earth's surface, including land use/land cover changes, remains critical environmental challenge humankind must quantify and address (Guzha et al., 2018). Environmental management approaches do not always reflect the full range of benefits attained from natural resources or even the various users that count on these benefits.

The goal of taking an ecosystem-based approach to resource management would be to address the most effective resolutions to make the most of the natural resources available in a wide-ranging and flexible way (Fernandino et al., 2018). Water is also a crucial resource for human existence and development (Li et al., 2013; Acharya et al., 2018; Varis et al., 2019) and animals, plants, and ecosystems. Its change is a significant indicator of environmental, meteorological, and anthropogenic feedback (Zhai et al., 2015; Acharya et al., 2019). The deterioration of water resources can result in increased poverty, insecurity, and the degradation of biological diversity.
(Campos et al., 2012; Gupta, 2019; Abell et al., 2019). Information on surface water amount and distribution is essential for surface water mapping, estimating quantities for drinking and irrigation purposes, land use/land cover assessment, and monitoring environmental change (Acharya et al., 2019; Qin et al., 2020). Documentation of surface water dynamics also provides an important metric for protecting the environment and its components (Campos et al., 2012; Gupta, 2019; Abell et al., 2019). The rise in water uses throughout the twentieth century and through the first decades of this century have led to severe water scarcity in many regions around the world and changes in mean hydro-climatological circumstances under climate change that potentially increase water scarcity in those regions (Greve et al., 2018; Abell et al., 2019). Many researchers have studied waterbodies, and academics and a range of approaches have been designated to delineate and study these landscape components and change (Yang et al., 2017). Weather variability and climate change can potentially affect the availability of resources, possibly negatively, resulting in decreased environmental sustainability (Gutzler, 2013; Mu et al., 2018). However, population growth and increasing demand for food, energy, and water could result from climate change in the long term (Gutzler, 2013; Mu et al., 2018; Bohn et al., 2018).

Remote sensing imagery is an important data source for assessing land cover change and surface water dynamics (Huang et al., 2018; Halefom et al., 2018; Pandey et al., 2019). The wide range of remote sensing data amounts to massive data sets with different spatial and temporal cover and resolutions (Huang et al., 2018; Halefom et al., 2018; Wang, 2019; Pandey et al., 2019; Kadhim et al., 2020; Belhaj et al., 2020; Dagnachew et al., 2020). These data allow a large number of researchers and professionals to identify and analyze many issues in various fields and scales with high precision, and provide confident results to understand these issues, find adequate solutions, and make the right decisions (Liping et al., 2018; Wang et al., 2020). Remote sensing
data and geographic information systems technologies can help stakeholders map where changes are occurring, understand development patterns and seasonal land changes, and assess current management activities and policies (Butt et al., 2015; Halefom et al., 2018; Kadhim et al., 2020; Belhaj et al., 2020). Remote sensing approaches are particularly useful for cross-border studies where access and other logistic constraints can prevail and for studies focused on forecasting future changes (Chang et al., 2018; Mubako et al., 2018). In addition, remote sensing data sources provide cost-effective, readily available data from which land use maps can be made (Mahdavi et al., 2018; Foo et al., 2019; Kpienbaareh et al., 2019). Land use maps can be used to calculate water use and urbanization trends to better manage resources in the targeted area and plan sustainable growth and economic development (Perez, 2001; Shao et al., 2020; Mondal et al., 2020). The transition from a dispersed population to one that increasingly resides in densely populated communities where non-agricultural economic activities predominate is known as urbanization (Wineman et al., 2020). Furthermore, satellite imagery allows for multiple temporal change assessments that can utilize plant phenological characteristics to differentiate between vegetation types (Petrakis, 2015; Khaliq et al., 2019).

Using remote sensing and geographic information system technologies' characteristics, globalization, and capabilities to address environmental problems, reflect their actual image, and reach the right decisions to deal with them, this research was implemented in two study areas with two different extents on two different continents. The research applies various techniques and temporal resolutions to selected data collected by Landsat satellites. The two regions are drylands with several similar characteristics: First, these two areas are located at the same latitude in the northern hemisphere. Second, they are semiarid to arid regions facing identical climate conditions and challenges despite having different surface features and water resources. Third, they are
experiencing intensive urbanization growth that affects land use/land cover features with similar change trends that affect the cities’ surrounding areas, applicable agricultural lands, and disruption to ecosystem goods and services. Urban growth is considered more horizontal generally in the two regions with three floors and fewer buildings, as Zambon et al., 2018 demonstrated. Fourth, these two regions face severe water scarcity with increasing water demands for human and environmental sectors. For example, horizontal expansion can lead to increases in per capita rates of outdoor water use, while the high-density development pattern can lead to lower outdoor water use (Heidari et al., 2021). Also, climate change affects urban water demand; therefore, water demand will increase under rising temperatures (Sanchez et al., 2020). The water crisis is exacerbated by fast urbanization and a changing climate (Msongaleli et al., 2022). In addition, water quality degradation is another significant issue and increasingly limits water use. The following sections detail the two primary study regions and include information about their location, water, climate, population, vegetation, and land use/land cover addressed and explained.

1.1: The Khoms District

The first study area is the district of Khoms, Libya, which is semiarid to an arid region located in North Africa. Khoms is one of the largest districts in Libya, and its location is between the capital Tripoli in the west and Misurata, the second largest district in the east. It is 1,000 km$^2$ about 100 km east of the capital Tripoli. It is bounded by the Besis Island in the northwest, Kaam spring in the northeast, the Mediterranean Sea in the north, and the districts of Amamera, Mesalata, and Alos in the south between longitudes 130 59' 00" E and 140 27' 38" E and latitudes 32° 36' 18" N and 32° 54' 17" N (Figure 1.1). The location gives the district special economic and geographical significance. With one of the largest and deepest ports in the country situated in the City of Khoms, the district is the country’s gateway to the world in terms of trade, handling
commodities that include various species of fish such as tuna, salmon, and sardines. Other important economic activities include tourism, especially to the UNESCO World Heritage site of Leptis Magana, once the largest city of the ancient Roman Empire; irrigated and non-irrigated agriculture; and an industrial hub that includes two concrete factories and the 1,080-Megawatt Khoms electricity generation power plant (Nassar et al., 2017), one of the largest in Libya. Given the high socio-economic profile of the Khoms District, it is of paramount importance to gain a deep understanding of urban growth patterns, trends, and associated environmental issues and to plan and implement sustainable growth programs. In particular, there is a paucity of quantitative land conversion studies focusing on this environmentally fragile yet economically important coastal region of a developing country that has been experiencing significant political upheaval in recent years.

Figure 1.1: Location of the Khoms District study area.
1.1.1: Water Availability and Sustainability

Water availability and sustainability in the Khoms district are very critical. The water in this district comes from rains and groundwater to provide different sectors with their demands. Groundwater extraction increased during the last decades due to the expansion of irrigated agriculture and tillage machinery. Increasing salinization of coastal aquifers due to saltwater intrusion from the Mediterranean Sea is a major water management issue in the area. Groundwater salinity has risen from 889 parts per million (ppm) in 1994 to 1036 ppm in 2004, to 1045 ppm in 2009 in the northwestern part of the study area, and from 2750 ppm in 1970 to 3616 ppm in 2008 in the northeast. The natural Kaam Spring, an economically important water source that flows in the northeast part of the study area, has not been spared from the salinity increase, rising from 2380 ppm in 1970 to 2704 ppm in 2007. In contrast, groundwater salinity has generally decreased from the coast going inland southwards, 1080 ppm in the southwest and 1750 ppm in the southeast (Libyan General Water Authority, 2006).

1.1.2: Climate and Climate Change

Libya’s climate is affected by the Mediterranean Sea to the north and the Sahara Desert to the south. As a result, abrupt transitions in weather conditions are experienced across the country. The Khoms district falls in the Mediterranean climate zone with cold, rainy winters and dry, hot summers. An annual rainfall of 200–300 mm. Temperature varies by month and season, with a minimum average of 14°C in December, a maximum average of 28°C in July and August, and an annual average of 20°C. Climate change has affected the area through a decrease in rainfall by ~20.92 mm per month per century since the 1950s and a rise in temperature, which has increased by 0.89°C per century, from 1901-2000 (Libyan Weather Center, 2008).
1.1.3: Vegetation

The Khoms district is characterized by olive plantations, palm trees, vineyards, citrus, and almonds in both irrigated and non-irrigated lands. However, forest and windbreak trees such as pine, cypress, and carobs cover many parts in the north. Also, the Khoms district has some other vegetation such as thyme, rosemary, wormwood grasses, and castor. The district is considered an agricultural area where many crops are planted, such as barley, wheat, alfalfa, and many seasonal fruits. In some areas, vegetables such as tomatoes, pepper, cucumber, watermelon, onion, and lettuce are also planted in irrigated croplands. Pasture areas dominate many parts of the district, especially in the south (Belhaj et al., 2020; Hadia et al., 2020; Ageel, 2020).

1.1.4: Land Use and Land Cover

The Khoms district contains several land use/land cover categories. These categories depend on water availability, soil properties, and land use. Irrigated agriculture with a diversity of trees and crops covers some portions with a sufficient and appropriate amount of water and fertile soil. Various types of buildings and construction persist in Khoms City and intensive other urbanized regions. Native plants and shrublands are widespread around the district on mountains, hills, and the southern areas, especially those with little anthropogenic disturbance. However, barlands cover some places, especially those influenced by human activities and the southern parts (Belhaj et al., 2020).

1.1.5: Population

With the world’s highest population growth rates and urbanization in coastal zones expected to occur in Africa (Neumann et al., 2015), this case study epitomizes urban development challenges faced by many fast-growing, densely populated coastal cities on the African continent and in other coastal regions experiencing similar global change pressures. According to the Libyan
Bureau of Statistics and Census (2007), the total population in the Khoms district at the 2006 census was 146,349, increasing from just over 72,000 people in 1965, as shown in figure 1.2. Despite a relatively low national population density of four people per square km, 75% of Libya’s population is concentrated in coastal cities that make up only 1.5% of the country’s total land area (UNEP, 2010; Belhaj et al., 2020).


Figure 1.2: the Khoms District Population Growth, 1965-2006.

1.2: The Middle Rio Grande Region

The second study area is the Middle Rio Grande Region an arid to a semi-arid region in the southwestern US-Mexico borderlands (Ward et al., 2006; Sheng, 2013; Wilder et al., 2016; Bohn et al., 2018; Wang, 2019). It lies along the US–Mexico border and includes the Middle Rio Grande basin from Magdalena and San Antonio, New Mexico, in the north to the entrance of the Rio Conchos from Mexico in the south. The area of interest is located between north latitudes 34.06000000 and 29.38166667 and west longitudes 107.85694444 and 104.21555556 (Figure 1.3). The total study area is ~36,988 km² (14,280 sq. miles) and includes six water sub-basins. This region covers the area from southern New Mexico to far west Texas in the US and the northern Mexican state of Chihuahua. The region encompasses the three fast-growing cities of Las Cruces,
New Mexico, El Paso, Texas, and Ciudad Juarez, Chihuahua, and has a population of more than two million people (Mubako et al., 2018). The Middle Rio Grande Region faces enormous challenges to its resources because of competition between different stakeholder sectors such as agriculture, livestock raising, municipalities, industry, and wildlife (Nava et al., 2016; Mu et al., 2018; Mubako et al., 2018). The Rio Grande River is the fourth largest river in North America, running through the region from north to south. It starts as a snow-fed stream high in the San Juan Luis Valley in southern Colorado and ends in the Gulf of Mexico (Pascolini-Campbell et al., 2017; Blythe et al., 2018; Chavarria et al., 2018). The Middle Rio Grande includes the main surface water reservoirs in southern New Mexico, the Elephant Butte Reservoir, and the Caballo Lake Reservoir. The river is one of the major sources of water in southern New Mexico and far west Texas in the US, as well as the northern Chihuahua in Mexico. It provides irrigation water for the intensive agriculture practiced throughout the region. It also supplies some drinking water to municipalities and ecosystems throughout the basin (Sheng, 2013; Szynkiewicz et al., 2015; Sanchez, 2017; Chavarria et al., 2018; Randklev et al., 2018; Cox et al., 2018).

This region contains various land use/land cover features and practices and has experienced massive changes in natural vegetation and agricultural lands due to disruptive human activities and natural circumstances (Randklev et al., 2018). Urbanization is one of the region's leading causes of land use/land cover change, with high growth rates reported for Las Cruces, New Mexico, El Paso, Texas, and Juarez, Mexico (Szynkiewicz et al., 2015). Mubako et al. (2018) demonstrated that the urban areas of the three main cities in the Middle Rio Grande Region (Las Cruces, El Paso, and Ciudad Juarez) grew about 8% in this area of interest in the 25 years 1990-2015 by taking important areas from agriculture lands and other vegetation which decreased by about 11% in the same period.
Following the Second World War, the border cities between Mexico and the United States entered an era of rapid population growth and industrialization (Sanchez, 2019). Through the Border Industrialization Program, it formed the long-term foundation for economic expansion in that part of Mexico, as well as a more decisive factor of attraction for demographic and urban growth in key border cities (Sanchez, 2019). The pollution of surface water bodies, including cross-border flows, became apparent due to a lack of services infrastructure, particularly piped water, drainage, and treatment, as well as a lack of control over water discharges from industrial
units (Kelly, 2002). Presidents Reagan and De la Madrid signed the La Paz Agreement in 1983, which included a series of annexes dealing with environmental issues on the border between the two countries. This agreement created commitments linked to binational cooperation to address environmental concerns caused by rapid, disorderly, and uncontrolled expansion resulting from urban and industrial growth dynamics at the border (Sanchez, 2019).

The Rio Grande/ Rio Bravo is a critical lifeline that connects nature, history, culture, and communities through generations. It connects cultures, people, ecosystems, and economies by crossing landscape and political boundaries, resulting in a complex socio-ecological system (Gossett et al., 2012). These features create a complex habitat with climatic and hydrologic extremes, ranging from high mountain terrain to desert landscapes, a river canyon, and a large deltaic floodplain, resulting in an extraordinarily high diversity of plant and animal species. Abundant national parks and conservation areas are located throughout the region to acknowledge, maintain, and enhance the region's river, as well as give opportunity for Americans to connect with their natural resources and heritage (Solis et al., 2022).

Many transportation networks have been located along with river courses for over a century, with the earliest rail lines dating to the 1830s in the eastern U.S. and the mid-to late-nineteenth century in the western U.S. Road construction, particularly paved roads, generally came later, with paved roads accounting for only 4% of the U.S. Road network in 1900 (Blanton, 2009).

1.2.1: Water Availability and Sustainability

Water scarcity in arid and semiarid environments has become an increasing challenge to human communities and their existence, activities, and development. Population increases, intense nonrenewable resources use, evaporation, and other water losses all contribute to water resource depletion (Gude, 2017; Bierkens et al., 2019). Water directly affects land use/land cover change
(Calijuri et al., 2015; REF). For example, water reduction causes a decrease in vegetation cover, and water abundance protects and flourishes vegetation cover (Khan et al., 2018). Three main sources of water available for use in the Middle Rio Grande Region are the surface flow of the Rio Grande River into Elephant Butte and Caballo Reservoirs, local runoff, and infiltration originating from precipitation and local groundwater reserves (Perez, 2001; Collado, 2018; Alger, 2019; Senay et al., 2019; Plassin et al., 2020).

The Rio Grande River is one of few large rivers in the American Southwest, and it supports a diverse set of ecosystems, urban, industrial, interstate, and agricultural demands. Available snowmelt runoff water is fully allocated among users (Burson, 2000; Tsinnajinnie et al., 2018; Bhandari et al., 2019; Senay et al., 2019; VanNijnatten et al., 2020). Water allocations for the United States and Mexico are derived from the shared rivers. They are regulated under a 1906 convention that ensures the equitable distribution of the water of the Rio Grande/Rio Bravo River and the 1944 Water Treaty for the utilization of the Colorado waters and Tijuana Rivers and of the Rio Grande/ Rio Bravo. Under these treaties, the waters of the Rio Grande/ Rio Bravo River are 100% allocated, either to the U.S. or to Mexico, for human use and consumption, leaving stretches of the river completely dry for extended periods (Pascolini-Campbell et al., 2017; Partida, 2018; Blythe et al., 2018; Chavarria et al., 2018; VanNijnatten et al., 2020; Hargrove et al., 2020). Demands for the limited water supplies continue to grow (Gensler et al., 2009; Oad et al., 2009; Oad and Kinzli, 2006; Oad and Kullman, 2006; Kinzli, 2010; Bhandari et al., 2019). As the population increases and drought conditions persist in the Southwest, the Rio Grande River's natural flow has become limited. It cannot meet the urban, industrial, interstate, ecological, and agricultural demands during severe drought conditions (Plassin et al., 2021). Competition for this limited water resource has dramatically increased during the last decade, and many complex issues
have arisen as environmental concerns require a larger portion of total available water (Kinzli and Myrick, 2009; Oad et al., 2009; Oad and Kinzli, 2006; Kinzli, 2010; Senay et al., 2019).

Groundwater withdrawal in this region is increasing (De Stefano et al., 2018; VanNijnatten, 2020; Hargrove et al., 2020). Communities on both sides of the border are highly dependent on this resource for domestic and agricultural use (Sanchez et al., 2020; Hargrove et al., 2020). This resource faces specific challenges such as increased drawdown levels and the deterioration of its quality. The change reflects serious environmental problems and stimulates the different sectors to take the right actions to sustain the resource and rescue the targeted communities (Isaac, 2021).

Water scarcity in the basin persists and reflects the confluence of water supply, both physically and institutionally, and the pressures of expanding water demand (Senay et al., 2019). The problem of water scarcity in the region is serious because of the region's approaching full development conditions and decreasing available water resources supply. Development throughout the region mostly depends on the efficient use of the scarce water supply (Lansford, 1977; Partida, 2018).

The use of water for irrigation and domestic consumption and the use of land for agriculture, urban centers, livestock grazing, and recreation have changed Rio Grande ecosystems by altering flood cycles, channel geomorphology, upslope processes, and water quality and quantity (U.S. Department of the Interior Bureau of Reclamation, 2016). Such abiotic changes have influenced the Middle Rio Grande Basin's biological diversity and ecological functions, altering riparian plant and animal communities' distribution, structure, and composition. From Elephant Butte Reservoir to Amistad Reservoir, the Rio Grande Region faces several change stressors that can affect the sustainable management of this surface water resource (U.S. Department of the Interior Bureau of Reclamation, 2016). Also, change in the surface water system results from stressors. The institutional structures regulating the resource often cannot recognize
or manage the system for feedback of the hydrologic system between surface and groundwater and between agriculture and natural riparian systems (Hogan, 2013). These limit the options to improve the sustainability of water resources (Hogan, 2013). In addition, water resource allocation today faces many quantities and quality challenges in this region and needs improved management (Walsh, 2012). One of the essential elements in the management is the infrastructure on which water sustainability depends. The infrastructure includes the systems that transport and distribute water. It also includes infrastructure that stores and distributes water, such as dams and diversions. In addition, the water system consists of the institutions that store, conserve, and distribute the water (Walsh, 2012). The water management infrastructure in the borderlands, which has persisted for hundreds of years, is in crisis and the water use exceeds the availability (Hogan, 2013; Hargrove et al., 2013; Hargrove et al., 2020). This has had severe negative impacts on ecosystems from California's central valley to the delta of the Rio Grande/ Rio Bravo and has left the human population vulnerable (Walsh, 2012). The Middle Rio Grande Region faces many challenges, such as water coming from different resources. The sustainability of water in the section that stretches from Elephant Butte Dam to Amistad Dam in the face of climate change and increasing human demands faces many challenges in quantity, such as the decrease of Hueco Bolson water level by about 30cm a year in the last 50 years and quality that faces an increase of salinity caused by and connected to human and natural stressors (Hargrove et al., 2013; Hargrove et al., 2020).

1.2.2: Climate and Climate Change

People change the Earth’s environment through fossil fuel burning, urbanization, deforestation, agriculture, and industrial expansion (Ezimah, 2021). Since the Industrial Revolution, atmospheric concentrations of greenhouse gases have increased by 411 ppm, mainly over the past five decades (Tong et al., 2019; Anderson et al., 2019). The worldwide surface
temperature is now about 1.0 °C above pre-industrial levels, with serious negative consequences for humans and natural resources for health and livelihoods (Ebi et al., 2018; Allen et al., 2018; Tong et al., 2019). With continual greenhouse gas emissions, global warming is expected to reach 1.5 °C above pre-industrial levels between 2030 and 2052 (Allen et al., 2018; Shukla et al., 2019; Tong et al., 2019; Craig et al., 2019). Climate change is predicted to raise temperatures across the southwest U.S. and affect regional water availability controlled by precipitation differences (Petrie et al., 2019). Climate change and climate variability are expected to accelerate and increase the duration of drought, food insecurity, an irretrievable decline in livestock numbers, and catalyze decreased economic productivity. (Anderson et al., 2019) Extreme climate events such as heavy rains, increasing temperatures, and intensifying evapotranspiration influence environments and crop yields under rain-fed circumstances in many parts of the world (Omoyo et al., 2015; Anderson et al., 2019; Ward et al., 2019). Land use/land cover change can affect the energy balance at the ground surface and play an essential role in an area's microclimate (Buyadi et al., 2013; Kandel, 2015; Li et al., 2020). A recent change in land use/land cover due to urban encroachment in the Middle Rio Grande Conservancy District, New Mexico, has been considered one aspect that can cause climate change (Griggs, 2011). The Middle Rio Grande Region climate is arid except for small semiarid regions at higher elevations where the precipitation is greater and temperatures cooler (Perez, 2001). In general, there is an excess of evaporation over precipitation, typical of the U.S. Southwest (Perez, 2001, Schmandt, 2002; Collado, 2018; Hargrove et al., 2020). (Gutzler, 2013) argued that the Middle Rio Grande region is a semiarid border region between the U.S. and Mexico in southwestern-North America located in a vulnerable climate area that faces severe challenges to the sustainability of ecosystems and human habitability. These ecosystems and human societies are adapted to the region's desert climate and often experience harsh and
prolonged drought periods (Gutzler, 2013). Over time and with the increased anthropogenic activities, greenhouse gas emissions have increased and negatively affect the climate (Gutzler, 2016; Smith et al., 2018).

Episodic, severe long-term drought has been a ubiquitous feature of the study area's climate. Many studies of old trees in this area have been understood the last centuries' droughts (Gutzler, 2013). For example, in the mid-15th century AD, drought and the late 16th-century drought. Frequency analysis of time series suggested a fluctuation in drought periods, which occurred at least once per century (Gutzler, 2013). For establishing policies to promote sustainability, these observations lead to sobering considerations. The 1950s drought is well-documented, well-remembered, and considered the ‘drought of record (Gutzler, 2013; Jones et al., 2016). Other climate modeling studies have suggested that prolonged anomalies in the Atlantic Ocean or the Indian Ocean could also affect atmospheric circulation in this region and suppress precipitation (Gutzler et al., 2011; Jones et al., 2016). The trend toward warmer temperatures has been ongoing across the area during the late 20th century and continues to the present day (Petrie et al., 2014; Jones et al., 2016). In addition, the streamflow faced reducing situations according to these trends and the increased evaporation rates (Gutzler, 2013; Jones et al., 2016).

Depending on these conditions and model output, the projections of future change suggest that anthropogenic climate change is caused by a steady increase in greenhouse gases (Gutzler, 2013). The temperature is projected to increase. The global Hadley circulation is projected to expand poleward associated with global warming, so the zone of precipitation-suppressing subsidence also extends poleward (Gutzler, 2013). The winter precipitation in the region will be reduced. The surface water budget goes toward drier conditions (Sanchez et al., 2017). Infrequent but increasingly intense storm events that could punctuate these conditions are a trend toward more
severe droughts together with the potential for more severe floods. Furthermore, the total annual streamflow is reduced by between 8% and 29% by the late 21st century in the various scenarios, which could severely impact irrigated agriculture (Gutzler, 2013; Triepke et al., 2019).

1.2.3: Vegetation

The Middle Rio Grande region is a fragile vegetation area responsive to water availability (Hargrove et al., 2013; Wilder et al., 2013). The vegetation condition is directly correlated to local circumstances such as water, climate, and human activities (Wang, 2019; Nguyen et al., 2019). These influence its appearance, productivity, and cover. The lower the effects of local circumstances, the higher the density of vegetation, and the higher effects of local circumstances, the lower the vegetation density. Studies on local vegetation types and variations in this region have provided substantial empirical support for this relationship (Perez, 2001; Wang, 2019; Nguyen et al., 2019).

The flora of the Rio Grande Valley is diverse, and the vegetation patterns are intricate. Natural vegetation is zoned; its distribution is closely related to elevation, latitude, moisture, and soil condition. Native vegetation is restricted to three major environments, overlapping some areas. Tables 1.1 show hillside vegetation, 1.2 shows intermediate zone plants, and 1.3 shows river valley zone plants (Perez, 2001; Kinzli, 2010; National Park Service, 2011; Hamilton et al., 2019; Steinberg, 2019).

<table>
<thead>
<tr>
<th>NO.</th>
<th>Common name</th>
<th>Scientific name</th>
<th>Plant type</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Creosote bush</td>
<td><em>Larrea Tridentata</em></td>
<td>Evergreen</td>
<td>Dominant spring and fall</td>
</tr>
<tr>
<td>2</td>
<td>Big-leaf yucca</td>
<td><em>Yucca Pallida Mckelvey</em></td>
<td>Evergreen</td>
<td>Shrub</td>
</tr>
<tr>
<td>3</td>
<td>Ocotillo</td>
<td><em>Fouquieria Splendens</em></td>
<td>Deciduous</td>
<td>Shrub</td>
</tr>
<tr>
<td>4</td>
<td>Lechuguilla Verde</td>
<td><em>Agave Bovicornuta</em></td>
<td>Evergreen</td>
<td>Shrub</td>
</tr>
</tbody>
</table>
Deep deposits of fertile soil have developed in the Rio Grande Valley throughout its geologic history and have supported agricultural production (Perez, 2001). The region’s farming activities are restricted to this area, where the land surface is somewhat leveled, and the mean depth to the water table is about 180 cm (Perez, 2001). Table 1.4 shows irrigated soils sustain plants principally.

Table 1.2: Intermediate zone plants

<table>
<thead>
<tr>
<th>NO.</th>
<th>Common name</th>
<th>Scientific name</th>
<th>Plant type</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Prickly pear</td>
<td><em>Opuntia Engelmannii</em></td>
<td>Evergreen</td>
<td>Shrub like</td>
</tr>
<tr>
<td>2</td>
<td>Grey-thorn Mesquite</td>
<td><em>Halaria. Sp</em></td>
<td>Evergreen</td>
<td>Shrub</td>
</tr>
<tr>
<td>3</td>
<td>Tumbleweeds</td>
<td><em>Sisymbrium Loeselii L</em></td>
<td>Annual</td>
<td>Herb</td>
</tr>
</tbody>
</table>

Table 1.3: River valley zone plants

<table>
<thead>
<tr>
<th>NO.</th>
<th>Common name</th>
<th>Scientific name</th>
<th>Plant type</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>cottonwood trees</td>
<td><em>Populus fremontii</em></td>
<td>Evergreen</td>
<td>Tree</td>
</tr>
<tr>
<td>2</td>
<td>saltbush</td>
<td><em>Atriplex Acantho Carpa</em></td>
<td>Evergreen</td>
<td>Shrub</td>
</tr>
<tr>
<td>3</td>
<td>crown thorns</td>
<td><em>Koeberlinia Spinoza Zucc</em></td>
<td>Deciduous</td>
<td>Shrub</td>
</tr>
</tbody>
</table>

Table 1.4: Irrigated soils sustain these plants principally

<table>
<thead>
<tr>
<th>NO.</th>
<th>Common name</th>
<th>Scientific name</th>
<th>Plant type</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Non-native salt cedar</td>
<td><em>Tamarix ramosissima</em></td>
<td>Evergreen</td>
<td>Tree</td>
</tr>
<tr>
<td>2</td>
<td>Pecan</td>
<td><em>Carya Illinoinensis</em></td>
<td>Deciduous</td>
<td>Tree</td>
</tr>
<tr>
<td>3</td>
<td>Cattails</td>
<td><em>Typha L</em></td>
<td>Perennial</td>
<td>Shrub</td>
</tr>
<tr>
<td>4</td>
<td>Sunflowers</td>
<td><em>Helianthus L</em></td>
<td>Annual</td>
<td>Crop</td>
</tr>
<tr>
<td>5</td>
<td>Alfalfa</td>
<td><em>Medicago sativa L</em></td>
<td>Perennial</td>
<td>Crop</td>
</tr>
<tr>
<td>6</td>
<td>Cotton</td>
<td><em>Gossypium hirsutum L</em></td>
<td>Annual</td>
<td>Crop</td>
</tr>
<tr>
<td>7</td>
<td>Jonhson Grass</td>
<td><em>Sorghum Halepense</em></td>
<td>Annual</td>
<td>Crop</td>
</tr>
<tr>
<td>8</td>
<td>Corn</td>
<td><em>Zea mays</em></td>
<td>Annual</td>
<td>Crop</td>
</tr>
<tr>
<td></td>
<td></td>
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<td>------</td>
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</tr>
<tr>
<td>9</td>
<td>Tomato</td>
<td><em>Solanum lycopersicum</em> L</td>
<td>Annual</td>
<td>Crop</td>
</tr>
<tr>
<td>10</td>
<td>Long green chili</td>
<td><em>Capsicum annuum</em></td>
<td>Perennial</td>
<td>Crop</td>
</tr>
<tr>
<td>11</td>
<td>Jalapeno Pepper</td>
<td><em>Capsicum annuum</em> L</td>
<td>Perennial</td>
<td>Crop</td>
</tr>
<tr>
<td>12</td>
<td>Onion</td>
<td><em>Allium cepa</em> L</td>
<td>Annual</td>
<td>Crop</td>
</tr>
</tbody>
</table>

In addition, small grains and fruit trees suited for this climate grow well and spread in many sites in the region (Perez, 2001; Kinzli, 2010; Lee et al., 2018).

### 1.2.4: Land Use and Land Cover

The Middle Rio Grande Region encompasses various land use/land cover features (Wang, 2019). This variation depends on water availability, soil conditions and properties, and demographic distribution and activities (Sullivan, 2010; Wang, 2019). In areas with enough water and good soil, large areas of irrigated agriculture with various trees and crops typically prevail. In densely populated parts of the region, there is an apparent influence on land use/land cover change due to differences in land use. There is an expansion of different types of constructions, such as housing and economic and industrial facilities, especially in the metropolitan areas (Sullivan, 2010; Mubako et al., 2018).

Different types of plants naturally cover large parts of the region. These plants depend on environmental factors such as periodic floods, droughts, temperature, humidity, elevation, and soil nutrients. Climate change is affecting vegetation and the hydrological cycle in the region. Human activities have a disruptive effect on this vegetation. These activities damage the plants and their environment. They also destroy large parts of the vegetation in the region. The more the activities, the less the vegetation, and the less the activities, the more the vegetation (Burson, 2000; Perez, 2001; Lonard et al., 2002; Nguyen et al., 2019).
1.2.5: Population

The human population of the Middle Rio Grande Region has increased dramatically since European settlement (Finch, 1995). Population density is measured as the number of people per unit of area, usually per square kilometer or square mile. Empirical studies conducted throughout the world (e.g., in San Francisco, Phoenix, and large Western European cities) have shown population density to be positively correlated with urbanization in towns; the greater the population density, the higher the urbanization changes (Jenerette et al., 2007; Dousset et al., 2011). The twin border urban areas of El Paso County, Texas, and Ciudad Juárez, Chihuahua, and Las Cruces were known in the 17th century as a single city (Bath et al., 1998; Liverman et al., 1999). Since those days, El Paso del Norte has changed in every aspect: geographically, demographically, politically, culturally, and economically. As a result, today, the two cities are characterized by different but linked economies, and they clearly represent economic differences along the entire US–Mexico border (Orrenius, 2001). The US-Mexico border region is unique because it is characterized by a large number of people who migrate to the border, including many from central Mexico coming to the northern border (Mondragon and Brandon, 2004). Ciudad Juárez is the most populated city in the north Mexican state of Chihuahua, and it is the fifth-largest city in México, with more than 1,600,000 residents. This city rapidly grew, with an economy dominated by industrial production (Blackman, 2004). Narco-violence and the global recession slowed immigration and commerce beginning in 2008 (Correa-Cabrera, 2013). Ciudad Juárez is bordered to the north by the City of El Paso, Texas. Together, Ciudad Juárez and El Paso form one of the largest bi-national metropolitan areas in the world. El Paso County is 82% Hispanic (US Census Bureau, 2014). The population on the US side of the border in El Paso grew about 4.7% from 2010 to 2016. In addition, Las Cruces’ population increased by approximately 4.2% from 2010 to 2016 (US Census Bureau,
The three cities are now home to more than 2.4 million people (Mubako et al., 2018).

Urban growth is highly correlated to population increase. Rural areas undergo rapid and widespread land-use changes that impact water management, riparian ecosystems, and traditional cultures throughout the western United States. Areas that have historically been focused on agricultural activities are converted to various residential and urban land use configurations to change land use/land cover (Ortiz et al., 2007).

1.3: Motivation and Rationale for This Study

Identifying problems and finding evidence is the first and base step of finding solutions and solving matters. During my life in Libya, I saw the changes in land use/land cover in many places in the country, especially in my hometown Khoms District. The most notable change is the urban sprawl, which refers to an unplanned urban expansion in which major and medium-sized cities extend into rural areas with low-density discontinuous communities, resulting in mixed peri-urban landscapes (Egidi et al., 2020), particularly on agricultural lands. Also, when I came to the US, I noticed changes in land use/land cover, especially in the Middle Rio Grande Region. This situation in the Khoms district and the Middle Rio Grande Region motivated me to find the actual changes in land use/land cover. Also, put the results before decision-makers, interested researchers, and stakeholders for better management and future planning of resources. As mentioned above in the introduction, the Khoms District and the Middle Rio Grande Region are semiarid to arid regions facing similar global change pressures. Both regions are located on the same latitude in the northern hemisphere and face identical weather conditions. Development and urbanization growth are prominent characteristics in these regions. Construction expansion illustrates a huge problem that takes significant spaces from the agricultural lands and adds new
amounts to water demand. Water scarcity and quality are other substantial features in these two regions. The shortage of water supplies is increasing over time. Mounting water salinity is an immense challenge that puts more pressure on water availability and limits its uses in both areas. Urbanization trends show apparent changes in land use/land cover in these regions, especially around the metropolitan lands. The change in land use/land cover leads to identifying, quantifying, and measuring the change and its trends using remote sensing and geographic information system technologies. The remote sensing and geographic information system technologies are applicable to implementation in a large area worldwide and provide the ability to know the different types of land use/land cover features. They can separate amongst vegetation, constructions, water bodies, and bare land. Besides, remote sensing and geographic information system technologies offer the ability to predict future land use/land cover changes. The results of this research will be a good data source for managing urban growth and land use. The results also will be a good database and help authorities and stakeholders in future planning.

1.4: Problem Statement

Urban sprawl in many parts of the Khoms district is a significant concern. In the second decade of the twenty-first century, urban sprawl is consistently defined as a chaotic shift in the spatial structure of suburban communes that occurred because of the deepening of suburbanization, with little control over these processes by spatial policy (Litynski, 2021). This sprawl takes crucial areas from the agricultural lands around the district. The urban sprawl also takes important areas from the native ecosystems. The urban sprawl also encroached into the Mediterranean Sea when the present-day port at Khoms City was constructed, with possible devastating environmental impacts on marine resources (Belhaj et al., 2020). The native ecosystems lost substantial areas during agricultural lands expansion. These changes in the district cause great destruction to the
fragile environment of the district and the surrounding areas and exacerbate desertification indications (Belhaj et al., 2020).

Urban sprawl is also a real problem in the Middle Rio Grande Region (Oad et al., 2009). The urban sprawl appears to be most significant in areas around the three-fastest growing metropolitan areas of El Paso (Texas, USA), Las Cruces (New Mexico, USA), and Ciudad Juárez (Chihuahua, Mexico). Rapid urban growth and climate change in the Rio Grande Basin have increased water resource demand (Douglas, 2009). The predominant upland mixed vegetation land cover category has steadily declined, giving up land to urban and agricultural development (Mubako et al., 2018). The urban sprawl negatively affects the area by losing native vegetation and agricultural lands. It also causes environmental deterioration.

1.5: Research Questions and Hypotheses

1.5.1: Research Questions

The following research questions (RQs) will be addressed to identify, quantify, and measure the urban growth and the land use/land cover change in the Khoms District and the Middle Rio Grande Region study areas. Also, predict the urban growth and the land use/land cover change in the Middle Rio Grande Region.

RQ1: What principal land uses and the different land cover types in the Khoms district 1976-2015? Were there significant changes in land use/land cover?

RQ2: What principal land uses, and the different land cover types dominated the Middle Rio Grande Region 1994-2015? Were there significant changes in land use/land cover?

RQ3: How will land use/land cover types likely change in the future in the Middle Rio Grande Region in 2020-2040?
RQ4: Can remotely sensed data analysis identifies the changes and clarify the trends? And is it practical and feasible to depend on for implementing change assessment and decision making for planning purposes?

RQ5: Are there any similarities or differences in urban growth under the different administrations across the US-Mexico border?

1.5.2: Hypotheses

Based on results from prior research covered in the literature review presented in chapter one that covers the introduction of this research, I am proposing the following hypotheses (Hs), which correspond with each of the research questions outlined immediately above:

H1: There have been significant increases in urbanization and land use/land cover change in the Khoms District over the last 40 years and in the Middle Rio Grande Region over the last 20 years.

H2: The changes in urbanization growth and trends, climate change, and water deficiency have affected land use/land cover features and caused the shrinking of the agricultural and native plant lands.

H3: Continuing urbanization growth, climate change, and water deficiency have a negative impact on land use/land cover features such as agriculture and native plants.

H4: There are differences in land classification results depending on the spatial resolution of the images and the methods used in the classification. Combined classification analyses of remotely sensed data are a reliable way to identify the changes and clarify the trends.

H5: Different government policies in different countries can lead to different urban trends.
1.6: The Objectives

1- Identify and measure the primary land uses and the different land cover types that dominate the Khoms district and how they have changed from 1976-2015.

2- Identify and measure the major land uses and the different land cover types that dominate the Middle Rio Grande Region and how they have changed between 1994-2015.

3- Extract and measure surface waterbodies as a land cover category in the Middle Rio Grande Region by calculating the modified normalized difference water index.

4- Perform land use/land cover change detection analysis in the Middle Rio Grande Region 1994-2015.

5- Predict a likely future change scenario in land use and the different land cover types in the Middle Rio Grande Region 2020-2040.

ABSTRACT

Fast and unplanned urbanization presents a formidable challenge to sustainable urban growth in most developing countries. This study applies Geographic Information System (GIS) and remote sensing (RS) technologies to quantify land use/land cover change in the coastal, economically important district of Khoms, Libya. The study revealed a 16% per year long-term historical urban growth rate, leading to an urbanization increase of 658% from just 800 ha in 1976 to 6,067 ha in 2015 over the 40-year analysis period. Qualitative evaluation of satellite images showed devastating impacts on both terrestrial and marine ecosystems through broad scale clearing of forests and other native areas for agriculture and urban development and through reclamation of the Mediterranean Sea during the construction of a naval base and port at Khoms City. An integrated approach is recommended to explore a range of innovative approaches to address sustainable development issues the Khoms District faces and other similar fast-growing but environmentally fragile developing country locations.

Keywords: Urbanization, Image Classification, GIS, Remote Sensing, Libya, Land Use, Land Cover, Environmental Impacts.

2.1: INTRODUCTION

Urban sprawl is one of the most critical land conversion processes around the world (Haase et al., 2018). Conventional wisdom has it that the high population growth rate is the major underlying driver behind the rapid growth of cities (Jat et al., 2008; UNEP, 2010). The standard way of thinking about urbanization is that people will drift from rural to urban areas searching for better economic opportunities, access to infrastructure, and improved social services (Adepoju,
As this drift occurs, the consumption of resources in cities is expected to more than double from 40 billion tons in 2010 to an unsustainable level of 90 billion tons in 2050, according to a recent study by the IRP (2018). Today, urban areas are home to 55% of the world’s total population, with Africa contributing 13% of the 4.2 billion global urban population (UN-DESA, 2018).

There is an undeniable close correlation between urbanization and the three dimensions of sustainable development: economic, social, and environmental (Cobbinah and Erdiaw-Kwasie, 2018; UN-DESA, 2018; Yan et al., 2018; Lawrence, 2019). On the one hand, well-planned urbanization can improve city dwellers' living conditions, create an enabling environment for socio-economic development, and enable the growth of the middle class (Kayizzi-Mugerwa, 2014; Zhou et al., 2015). Numerous case studies exist where cities have improved sustainability and enhanced the positive impacts of urban development through strategic planning tools and green plans that focus on key sustainability target areas such as climate change and energy, land and water conservation, public spaces, air quality management, waste management, and mobility (see, for example, Yigitcanlar, 2008; Shen et al., 2011). On the other hand, negative consequences of rapid and unplanned urbanization are widespread and well documented in both developed and developing countries. For example, early urbanization experiences in the 1930s and 1940s in developed countries such as the United Kingdom and the United States saw the widespread destruction and conversion of farmlands to urban areas (Firman, 1997). Similarly, recent studies have documented unplanned land conversion and urban development challenges experienced in many developing country cities, including the deterioration of public services, propagation of slums and the informal sector, saltwater intrusion of coastal aquifers, environmental impacts on
riparian and coastal habitats, and widespread urban poverty (UNEP, 2010; Kayizzi-Mugerwa, 2014).

Other widely cited problems resulting from uncontrolled urbanization and unsustainable land-use change practices include the decaying of urban infrastructure, uncontrollable growth of informal settlements, climate change, loss of agricultural land, air pollution, traffic congestion, and the destruction of ecosystems (Huang et al., 2009; Youssef et al., 2011; Zhou et al., 2015; Shen et al., 2017). In fact, the study by Verburg et al. (2006) identifies urbanization as one of the leading threats to the elimination and eventual extinction of large numbers of native species of living organisms. In Steyl and Dennis (2010), a significant drop in the water table and consequent seawater intrusion experienced in the North African coastal countries of Libya, Tunisia, Algeria, Morocco, and Egypt has been attributed to land conversion factors that include rapid urbanization, agricultural water consumption, and periodic droughts. Given this multiplicity of impacts, there is growing interest in using geospatial technologies in research to help map and monitor both spatial and temporal land conversion trends, especially in urban areas.

Geographic Information systems (GIS) and remote sensing technologies have been widely used to map and monitor land use/land cover change and analyze urban growth (Epstein et al., 2002; Yang and Liu, 2005; Haack and Rafter, 2006; Mallupattu and Reddy, 2013; Rawat and Kumar, 2015; Lv et al., 2018). The National Aeronautics and Space Administration (NASA) Landsat satellite data series is a popular choice for such land use/land cover change studies because of its efficiency in providing a synoptic view of an area of interest, repeated coverage over large areas, lower costs in comparison to higher resolution multispectral sensors, and public availability of historical archive imagery (Zhang et al., 2014: Atwah, 2021). There is a need for a comprehensive understanding of both temporal and spatial dynamics of land use change and
human activities, in addition to land use change drivers (Zhao and Murayama, 2011; Dadras et al., 2014). Well-established techniques that have been applied to analyze urban change include image-to-image, map-to-map, and post-classification comparison (Green et al., 1994; Yang and Lo, 2003; Haack and Rafter, 2006; Zhang et al., 2014; Mahboob et al., 2015; Joshi et al., 2016). Built-up area indices have also been estimated using time-consuming, expensive, but accurate techniques such as heads-up digitizing, point sampling, and pattern recognition approaches such as supervised and unsupervised classification and knowledge-based expert system approaches (Epstein et al., 2002; Sugumaran et al., 2003; Lu and Weng, 2005; Mundia and Aniya, 2005).

Controlling urbanization and land use/land cover change to achieve sustainable development requires accurate and reliable information about urban growth patterns and trends; however, attaining this goal is still a formidable challenge in most developing countries (Jiang and Yao, 2010; Arsanjani, 2011). Urban expansion in developing countries tends to follow growth patterns different from developed countries (Gillham, 2002; Helbich and Leitner, 2010). Subsequently, the location and quantification of land use change is the main issue that needs addressing to understand better urban growth in developing and rapidly changing environments (Alsharif and Pradhan, 2014). This is especially true for the North African nation of Libya, where the myriad of issues associated with rapidly urbanizing coastal areas include: overexploitation of natural resources, unplanned housing developments, conversion of agricultural land to urban development, and inadequate legal and institutional mechanisms emanating from political instability.

The main purpose of this study is to assess spatiotemporal patterns and implications of urbanization in the coastal district of Khoms in Libya (Figure 1.1) for the 40 years running from 1976 to 2015. Although urban change is the main category of interest in this study, changes in land
use and land cover are often considered together for practical purposes (Campbell and Wynne, 2011). Therefore, both natural cover and human modifications of the earth’s surface were analyzed by including other land cover categories. Khoms is one of the largest districts in north Libya (Figure 1.1). Its location between the capital Tripoli in the west and Misurata, the second largest district in the east, gives it special economic and geographical significance. With one of the largest and deepest ports in the country situated in the City of Khoms, the district is the country’s gateway to the world in terms of trade, handling commodities that include various species of fish such as tuna, salmon, and sardine. Other important economic activities include tourism, especially to the UNESCO World Heritage site of Leptis Magana, once the largest city of the ancient Roman Empire; irrigated and non-irrigated agriculture; and an industrial hub that includes two concrete factories and the 1,080-Megawatt Khoms electricity generation power plant (Nassar et al., 2017), one of the largest in Libya. Given the high socio-economic profile of Khoms District, it is of paramount importance to gain a deep understanding of urban growth patterns, trends, and associated environmental issues in order to plan and implement sustainable growth programs. In particular, there is a paucity of quantitative land conversion studies focusing on this environmentally fragile yet economically crucial coastal region of a developing country that has been experiencing significant political upheaval in recent years with the world’s highest population growth rates and urbanization in coastal zones expected to occur in Africa (Neumann et al., 2015), this case study epitomizes urban development challenges faced by many fast-growing, densely populated coastal cities on the continent and in other equally troubling world coastal regions. The key question is: What are the urbanization patterns, trends, and possible implications of the observed patterns in this coastal district, and how do the impacts contribute to a fundamental understanding of land use change-related socio-economic, institutional, and policy-making
challenges at the local scale in Libya, and in rapidly urbanizing coastal locations in other developing countries?

This chapter is organized as follows. The following sub-section provides an overview of the study area, including climatic and location characteristics. The methodology follows this, including an overview of satellite imagery data used for the 40-year analysis time frame and the well-established geospatial methods and tools applied. Next, the focus is on both quantitative and qualitative assessments of the results, including discussing the implications of the study findings. Finally, the research article ends with the conclusion.

2.2: METHODOLOGY

2.2.1: Data

Landsat imagery used for this study was acquired from the United States Geological Survey (USGS) for 1976, 1984, 1990, 2000, and 2015 (U.S. Geological Survey, 2018). Two scenes cover this northwestern region of Libya: Path 188 and Row 37 for the northern part and Path 188 and Row 38 for the southern part (Path 202 and Rows 37/38 for the 1976 images). The following sensors cover the Landsat imagery data used: Landsat 2 Multispectral Scanner (MSS); Landsat 4 Thematic Mapper (TM); Landsat 5 TM; Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). Availability and cloud cover of Landsat images were the main considerations in selecting the study timeframe and analysis years. All images used in this study had 10 % or less cloud cover, and seasonality was a less important criterion than irrigation in selecting the images. This is a reasonable assumption because irrigation occurs all year round and is more influential for the overall agricultural-related greenness observed in this arid area of interest compared to scarce rainfall. Table 3.1 provides key metadata details for the satellite images used in the study.
Table 2.1: Details of satellite data used in this study.

<table>
<thead>
<tr>
<th>Landsat Scene ID</th>
<th>Data Source</th>
<th>Date image taken</th>
<th>Spatial reference system</th>
<th>Path/Row</th>
<th>Spacecraft/ Sensor</th>
</tr>
</thead>
<tbody>
<tr>
<td>LM22020371976046AAA05</td>
<td>USGS</td>
<td>1976-02-15</td>
<td>WGS_UTM_Zone_13N</td>
<td>202/037</td>
<td>Landsat 2 MSS</td>
</tr>
<tr>
<td>LM22020381976046AAA05</td>
<td>USGS</td>
<td>1976-02-15</td>
<td>WGS_UTM_Zone_13N</td>
<td>202/038</td>
<td>Landsat 2 MSS</td>
</tr>
<tr>
<td>LT51880371984268XXX02</td>
<td>USGS</td>
<td>1984-09-24</td>
<td>WGS_UTM_Zone_13N</td>
<td>188/037</td>
<td>Landsat 5 TM</td>
</tr>
<tr>
<td>LT51880381984268XXX02</td>
<td>USGS</td>
<td>1984-09-24</td>
<td>WGS_UTM_Zone_13N</td>
<td>188/038</td>
<td>Landsat 5 TM</td>
</tr>
<tr>
<td>LT41880371990212AAA03</td>
<td>USGS</td>
<td>1990-07-31</td>
<td>WGS_UTM_Zone_13N</td>
<td>188/037</td>
<td>Landsat 4 TM</td>
</tr>
<tr>
<td>LT41880381990212AAA03</td>
<td>USGS</td>
<td>1990-07-31</td>
<td>WGS_UTM_Zone_13N</td>
<td>188/038</td>
<td>Landsat 4 TM</td>
</tr>
<tr>
<td>LE71880372000176EDC00</td>
<td>USGS</td>
<td>2000-06-24</td>
<td>WGS_UTM_Zone_13N</td>
<td>188/037</td>
<td>Landsat 7 ETM</td>
</tr>
<tr>
<td>LE71880382000176EDC00</td>
<td>USGS</td>
<td>2000-06-24</td>
<td>WGS_UTM_Zone_13N</td>
<td>188/038</td>
<td>Landsat 7 ETM</td>
</tr>
<tr>
<td>LC81880372015257LGN00</td>
<td>USGS</td>
<td>2015-09-14</td>
<td>WGS_UTM_Zone_13N</td>
<td>188/037</td>
<td>Landsat 8 OLI &amp; TIRS</td>
</tr>
<tr>
<td>LC81880382015257LGN00</td>
<td>USGS</td>
<td>2015-09-14</td>
<td>WGS_UTM_Zone_13N</td>
<td>188/038</td>
<td>Landsat 8 OLI &amp; TIRS</td>
</tr>
</tbody>
</table>

2.2.2: Methods and tools

All tasks were performed using standard, widely applied tools, and modules in ArcGIS 10.5 software. Figure 2.1 provides an overview of the methodology workflow applied. The following four land use classes were defined for the study area:

- Developed;
- Native plants, trees, and bare land;
- Agriculture; and
- Water.

![Methodology workflow using ArcGIS software tools applied in this study](image)
The maximum likelihood supervised classification method was applied. Classification iterations were performed on the minimum noise images for each classification year by repeatedly running the maximum likelihood classification tool while adjusting the number of training samples until consistent classification results were achieved. Post-classification tasks included merging classes, correcting misclassification, and coding the different land use classes. It was not practical to do a field check for this study, so an accuracy assessment was done through comparing the latest classified year maps to images from Google Earth. Random ground reference points were generated across the study area, and sampling areas were defined by creating 30 m buffers around each random point. A Google Earth imagery base map was then added, and ground referencing was conducted by identifying the land cover type around each random point. An error matrix for accuracy assessment was then constructed by comparing the land cover types specified in Google Earth to the corresponding locations of the random ground reference points on the classified image. This proven technique has been successfully applied in other land change studies (Keranen and Kolvoord, 2014).

2.3: RESULTS AND DISCUSSION

2.3.1: Accuracy assessment

A total of 132 randomly generated ground reference points were used for accuracy assessment focusing on 2015, the latest analysis year. The overall accuracy of this classification scheme from the error matrix of omission and commission (Congalton, 1991; Keranen and Kolvoord, 2014) was 95 percent. These classification results were statistically supported by an overall Kappa coefficient of 90 percent (Table 2.2).

<table>
<thead>
<tr>
<th>Classified category: Ground reference</th>
<th>Native plants, Agriculture</th>
<th>Developed</th>
<th>Water</th>
<th>Total number of points</th>
<th>User accuracy (%)</th>
<th>The error of commission (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual category: Ground reference</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Native plants,</td>
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<td></td>
</tr>
<tr>
<td>Agriculture</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Developed</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Water</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

Table 2.2: Error matrix of omission and commission for 2015.
### 2.3.2: Classification results

Table 2.3: Land use classification results summary for the Khoms District, 1976-2015

<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Developed</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Native plants, trees, and bare land</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agriculture</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Water</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total area</td>
<td></td>
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</tr>
</tbody>
</table>

Table 2.3 presents the quantified spectral classification results. The total area of Khoms District in the base analysis year of 1976 was 106,576 ha, with no surface water bodies. This is an unsurprising observation using the 30 m spatial resolution Landsat data in this highly arid area. Similar to the entire country, perennial surface water resources are severely limited, and the region depends almost entirely on non-renewable, fossil groundwater resources (Libya MWR et al., 2014). The proportions covered by the developed and native plants, trees, and bare land categories were at their lowest and highest, respectively, in 1976, prior to the government's inception of a major regional development program.
Figure 2.2: % change of developed in the Khoms District 1976-2015.

Figure 2.3: % change of native plants, trees, and bare land the Khoms District 1976-2015.
The developed category expanded substantially to 2,447 ha in 1984, increasing more than 200% over the base year, as shown in figure 2.2. This was a consequence of an urban development program implemented by the government from the early 1970s to the early 1980s. The total study area increased by 20 ha to 106,596 ha in 2015 (Table 2.2), resulting from a partial reclamation of the Mediterranean Sea during the construction of the port at Khoms City in 1979 (Figure 2.6). The port is clearly discernible in the classified images from 1984 onwards in Figure 2.8. Groundwater well drilling and the establishment of new irrigation projects were part of the development program.
that the government embarked on in the early 1970s. This largely accounts for the expansion of agricultural area by more than 70% relative to the base analysis year, as shown in figure 2.4. Agricultural operations also expanded to the central and southern parts of the Khoms District, producing commodities highlighted in Figure 2.7. It should be noted that the Landsat images used for classification are from different months of the year. Therefore, seasonal variations could have affected the agricultural land cover category results. However, irrigated agriculture occurs all year round in this region, so seasonal variation impacts on the agriculture category were assumed to be minimum. Urban development was the main target category of interest for this analysis, so it was less critical to select Landsat images with close dates compared to, for example, usable images containing minimum cloud cover. The native plants, trees, and bare land category decreased to 72,457 ha, or just over 17% of the base analysis year level, as shown in figure 2.3. This category was the major contributor of land for urban development and agricultural expansion. A prominent feature of this analysis year was the water body in the southeastern part of the study area (Figure 2.8). Construction of the 111 million cubic meter Kaam Valley Dam was completed as part of the government development program to store and provide water for domestic, industrial, and irrigation purposes, as well as for groundwater recharge as shown in figure 2.5.
For the 1990 analysis year, urban development increased by another 20% over the 1984 level to reach 2,937 ha as the population increased, as shown in figure 2.2. However, the native plants, trees, and bare land category also increased slightly to just below 5% of the 1984 level, as shown in figure 2.3, and this happened at the expense of the agricultural category, where a decrease of more than 10% of the 1984 level was experienced as shown in figure 2.4. Excessive abstraction of irrigation water from coastal aquifers resulted in a saltwater intrusion from the Mediterranean Sea as seawater replaced the extracted freshwater, leading to a consequent decrease in the area under agricultural production. Groundwater abstraction from coastal aquifers requires careful management to minimize the impacts of saltwater intrusion, especially in this arid environment where aquifer recharge from precipitation is very low. The Kaam Valley Dam shrank because of water use and the low annual rainfall amount received in the region as shown in figure 2.5. With
no permanent rivers and more than 90% of the land surface receiving below 100 mm of annual rainfall, Libya ranks the most water-scarce country in Africa (UNEP 2010).

Figure 2.7: Selected major crops in Khoms District: Date palm trees in the Lebda area (top left); olive trees at Al Tahrir Farm (top right); alfalfa in the Seleen area (bottom left); and watermelon in the Al Saiah area (bottom right). Tomatoes, pepper, cucumber, goats, and sheep are among other major economically important agricultural commodities produced.

In 2000, the proportions under agriculture and native plants, trees, and bare land categories were generally comparable in magnitude to the historic 1984 and 1990 levels, but there was further shrinkage of the Kaam Valley Dam due to low annual rainfall in the region. The upward trajectory for urban development continued, with an increase of nearly 24% over the 1990 levels, as shown in figure 2.2. By 2015, the developed category had expanded to 6,067 ha, or 658% of the 1976
base year level, as shown in figure 2.2. The main driver behind this positive urbanization trend was an influx of people into the region, as illustrated by the historic population growth curve in Figure 2.2. This rapid urbanization and population growth occurred during a period of political instability in the country characterized by very weak or the absence of legal and institutional mechanisms to regulate haphazard urban construction activities and the wanton conversion of agricultural land to informal urban settlements. The increase in the proportion of native plants, trees, and bare land category in 2015 resulted from reduced agricultural activity attributed to the increased salinity of irrigation groundwater. In addition, widespread political unrest in the country also affected agricultural operations. Surface water contributed less than 0.2 % of the total land cover area for the 2015 analysis year. A cross-tabulation matrix for the years 1976 and 2015 (Table 2.4) confirmed the loss of land from the native category towards the expansion of agricultural land from 18,409 ha in 1976 to 21,536 ha in 2015. The native category also contributed more than half (3,187 ha) of the land as the developed category expanded from 2,382 ha in 1976 to 6,047 ha in 2015 (Table 2.4).

Table 2.4: Cross-tabulation matrix of land use land cover for 1976 and 2015 in hectares (ha).

<table>
<thead>
<tr>
<th></th>
<th>Agriculture</th>
<th>Native plants, trees, and bare land</th>
<th>Developed</th>
<th>2015 Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>7,396</td>
<td>14,081</td>
<td>59</td>
<td>21,536</td>
</tr>
<tr>
<td>Native plants, trees, and bare land</td>
<td>8,630</td>
<td>69,938</td>
<td>263</td>
<td>78,831</td>
</tr>
<tr>
<td>Developed</td>
<td>2,382</td>
<td>3,187</td>
<td>478</td>
<td>6,047</td>
</tr>
<tr>
<td>Water</td>
<td>-</td>
<td>162</td>
<td>-</td>
<td>162</td>
</tr>
<tr>
<td>1976 Total</td>
<td>18,409</td>
<td>87,367</td>
<td>800</td>
<td>106,576</td>
</tr>
</tbody>
</table>

Figure 2.9 provides the overall visual trends for the four analyzed land use categories. This bar graph clearly shows the general decreasing trend for the native plants, trees, and the bare land category, an increasing trend for the developed category, and fluctuations for the water and agriculture categories over the analysis period. The impacts of converting native ecosystems to
agriculture and urban development are visually illustrated at the regional scale in the Google Earth change pairs from the years 2004 and 2015 (Figure 2.10, A, B). The native category was the major contributor of land for agriculture and urban development, categories that both experienced overall increasing trends visually illustrated in Figure 2.9. Bringing more land into agricultural production by clearing natural ecosystems (Figure 2.10, A, B) is a practice that can have far-reaching unintended consequences through desertification and the loss of biodiversity. The urban development pattern in Figure 2.8 reveals an average long-term historic urban growth rate of 16 % per year in the Khoms District. In other words, urban development increased by 658 % when the initial urbanization level in the base analysis year of 1976 is compared to the level in 2015 level. The urban sprawl not only occurred inland through the destruction of inland natural ecosystems and agricultural lands, but it also encroached into the Mediterranean Sea when the present-day port at Khoms City was constructed, with possible devastating environmental impacts on marine resources. Although data on the environmental effects of maritime shipping through the port of Khoms is very scarce, this economically important city might be expected to significantly contribute to adverse environmental impact through water pollution. Indeed, the Mediterranean Sea is regarded as the most oil-polluted among the world’s major seas, with momentous effects on the health of marine ecosystems (Galdies, 2008). The proportion covered by water was trivial for all analysis years, an observation that is consistent with a rainfall-scarce desert environment where the tiny amount of precipitation received varies widely over time and space.

In interpreting the results from this study, it is important to bear in mind the limitations of remote sensing work analyzing surface changes using satellite imagery over time. Possible sources of unquantified uncertainty in the results include differences in spatial resolution of spectral bands from satellite image sources ranging from Landsat 2 to Landsat 8; different availability dates and
seasonality effects; and image cloud cover variations over time. Lastly, no reference field data were collected from the actual ground in Khoms District for accuracy assessment purposes.

Figure 2.9: Land use change trends in Khoms District, 1976-2015.

Figure 2.10.A: Conversion of native land to agriculture and urban settlements has long-term consequences on natural ecosystems. The forests marked in 2004.
Conversion of native land to agriculture and urban settlements has long-term consequences on natural ecosystems. The forests marked in the 2004 image have almost disappeared in the 2015 image.

2.4: CONCLUSION

Standard GIS and remote sensing tools were applied to assess three aspects of land use land cover change. First, the spatial extent of land use/land cover changes in the Khoms District, one of Libya's most economically important districts undergoing rapid urbanization, was quantified. The analysis focused on four land use land cover categories: developed, native, agriculture, and water. Second, temporal trends of the four classes over a 40-year timeframe from 1976 to 2015 were assessed. Finally, yet importantly, possible implications of the observed patterns and trends for Khoms District and other similar coastal regions in the context of sustainable urban development were highlighted.
The study revealed a 16 % per year long-term historic urban growth rate that expanded urban land use in Khoms District from just 800 ha in 1976 to 6,067 ha in 2015, an increase of 658 % over the 40-year period. The area under agriculture increased only slightly, but the native category experienced an expected decrease that was consistent with the conversion of terrestrial ecosystems to agriculture and urban development. Indeed, a qualitative examination of satellite images from the district showed broad scale clearing of forests and other native areas for agriculture and urban development. Urban development in the district also affected the marine environment through the reclamation of the Mediterranean Sea during the construction of a port at Khoms City. Consider the well-intended government development program implemented in the early 1970s to early 1980s in Khoms District. The initiative was earmarked to boost socio-economic development through agriculture and infrastructure development, but challenges that include lack of planning, political unrest, a growing population, and over abstraction of groundwater from coastal aquifers have all conspired to reveal an unsustainable interaction between the rapidly urbanizing society and the physical environment in Khoms District.

This study furnished the overall spatial patterns and temporal trends of land use and land cover across Khoms District using only five snapshot years over a 40-year period. However, such a rapidly urbanizing region requires planned urbanization that will improve the quality of life through planned development that will require frequent and updated information about the district and its infrastructure. Therefore, future studies need to focus on urban monitoring using higher temporal, spectral, and spatial resolution remote sensing data. For example, important urban attributes such as weather data, disaster response operations, and utility and transportation infrastructure, to name a few, may require temporal remote sensing data in the order of less than five years or even a few minutes. Detailed urban plans may also need high spectral resolution
images that provide sufficient distinction between urban structures and their background. Similarly, city planners and decision-makers who are trying to distinguish between individual buildings will require remote sensing data with much higher spatial resolution than the 30 m Landsat data used for this study.

Finally, exploring a wide range of innovative approaches to implement sustainable solutions and address the challenges highlighted for Khoms District and other similar locations in an integrated manner is recommended. These approaches can range from better management of coastal aquifers and pollution monitoring to reinforcing existing legal and institutional mechanisms for better environmental protection. Even a rethink of what and how agricultural commodities are being produced in the region may be welcome to achieve a sustainable balance between this fragile desert environment and food requirements for a rapidly growing urban population.
CHAPTER 3: SPACE-BASED MEASUREMENT OF LAND USE/LAND COVER CHANGE IN THE MIDDLE RIO GRANDE REGION: AN OPPORTUNITY FOR UNDERSTANDING GLOBAL CHANGE IN A WATER-SCARCE TRANSBOUNDARY RIVER BASIN

ABSTRACT

Development and its expansion in dryland environments and experiencing climate warming and land-use/land-cover, impacting ecosystems and their sustainability and resiliency. Remote sensing and Geographic Information Systems (GIS) technologies provide opportunities to analyze land use/landcover change trends at local to regional scales over the past few decades. This study applied remote sensing and GIS techniques to identify and measure land-use/land-cover change in the Middle Rio Grande River Basin. A novel classification process is applied to assess land use and land-cover change between 1994 to 2015 in the Middle Rio Grande Region on the US-Mexico border, between San Antonio, New Mexico and Presidio, Texas, and Ojinaga, Chihuahua, which includes the cities of El Paso, Texas, Ciudad Juárez, Chihuahua, and Las Cruces, New Mexico. Results show that the native land cover has been declining and is being replaced by urban development and agricultural expansion. Metropolitan areas across the region increased by 45%, from ~1.59 percent of the total study area in 1994 to more than 2.9 percent in 2015. The majority of expansion occurred around the major metropolitan areas of El Paso, Ciudad Juárez, and Las Cruces. Other land-use changes included a decrease in agricultural land cover and a loss of wetlands, possibly due to a reduction in streamflow. Possible impacts of these land-use/land-cover changes on water resources include a shortage of water allocations for agriculture and ecosystems and the transfer of some water allocations to land developers in cities, as Hargrove et al. 2020 demonstrated. Metropolitan planners, farmers, and other stakeholders are likely to find
the study valuable for planning water conservation measures, preparing for future water supply and treatment infrastructure growth, and monitoring groundwater availability and quality as urban populations grow.

Keywords: Environment, Development, sustainability, metropolitan areas, ecosystems, climate, infrastructure, land use; and land cover change.

3.1. INTRODUCTION

Land resources encounter severe challenges worldwide, especially in arid and semi-arid regions, which occupy about one-third of the global land. Landcover degradation, soil erosion, water depletion, and ecosystem deterioration are some land resource changes (Verburg et al., 2011; Biro et al., 2013; Omoyo et al., 2015; Heo et al., 2015; Zhu et al., 2015; Zhang et al., 2015; Yin et al., 2017; Randklev et al., 2018)). A range of change drivers influences land resource changes at different space and time scales, such as population growth, human activities, and climate change. These drivers put massive pressure on land resources and create uncertainty in these resources ‘availability, long-term sustainability, and resiliency (Arowolo et al., 2017; Halefom et al., 2018; Boggie et al., 2018; Shen et al., 2020).

Land use and land cover are two terms used separately to describe the earth’s surface features and human interactions with these (Liping et al., 2018; Stromann et al., 2019; Merdas et al., 2019; Rajeswari et al., 2019; Sun et al., 2020; Dagnachew et al., 2020). While land-use states how humans have used the land, land cover indicates the biophysical characteristics of the earth’s surface (Verburg et al., 2011; Liping et al., 2018; Merdas et al., 2019; Rajeswari et al., 2019; Sun et al., 2020; Dagnachew et al., 2020). Land use/land cover change is possibly the most significant challenge to land resources and sometimes the most rapid in many places (Guzha et al., 2018; Islam et al., 2018; Belhaj et al., 2020). Land use/land cover change carried various consequences
on local, regional, and global scales. Amongst the intensive consequences of land use/land cover change is the extinction of native species when land use is changed from a comparatively undisturbed state to more intensive uses such as farming, livestock grazing, and selective tree harvesting (Arowolo et al., 2017; Guzha et al., 2018; Islam et al., 2018; Langat et al., 2019). Land use/land cover changes are the results of the interaction of a wide variety of factors like human activities, agriculture, deforestation, animal grazing, and urbanization (Mihretu et al., 2018; Arowolo et al., 2017; Tesfaw et al., 2018; Khan et al., 2020). Also, many indirect factors, such as technological, political, economic, cultural, demographic, and social factors, cause land use/land cover change (Mihretu et al., 2018; Arowolo et al., 2017; Tesfaw et al., 2018). Extensive data on the Earth’s surface is required to monitor and analyze land use/land cover changes. Earlier, this information was created worldwide, mostly by conventional land recognition methods such as field surveys and on-site human-made observations, which required time, cost, and effort (Pandey et al., 2019).

Modern Land use/land cover change studies typically use remotely sensed imagery, which provides excellent data sources from which information about land use/land cover can be extracted and analyzed with various techniques and data sets (Butt et al., 2015; Halefom et al., 2018; Kadhim et al., 2020; Belhaj et al., 2020). Chang et al. (2018) and Mubako et al. (2018) demonstrated that remote sensing data and geographic information systems are valuable transboundary information sources and can be used to implement proficient cross-border studies. Remote sensing and geographic information technologies can help stakeholders map where changes occur, understand development patterns and seasonal land changes over time, and assess current activities and policies. They can also help expect and plan for future changes. Zhang et al. (2015) suggest that medium spatial resolution imagery such as Landsat images are still the most significant data
sources for urban land-cover classification, especially considering the free availability of this imagery, suitable spectral resolutions, and swath extent.

The Middle Rio Grande Region is a dryland ecosystem situated in the southwestern US-Mexico borderlands (Ward et al., 2006; Sheng, 2013). This region covers the area from southern New Mexico to far west Texas in the US and northern Chihuahua in Mexico. This region encompasses the three fast-growing cities of Las Cruces, New Mexico, El Paso, Texas, and Ciudad Juarez, Chihuahua, and is populated by more than two million people (Mubako et al., 2018). The Rio Grande region faces enormous challenges on its resources that encounter significant pressures on these resources uses because of the competition between different stakeholders such as agriculture, livestock raising, municipalities, industry, and wildlife (Nava et al., 2016; Mubako et al., 2018). The Rio Grande River is the fourth largest river in North America and runs through the region from north to south. This river starts as a snow-fed stream high in the San Juan Luis Valley in southern Colorado and ends in the Gulf of Mexico. The Rio Grande River comprises the main surface water reservoirs in southern New Mexico, the Elephant Butte Reservoir and Caballo reservoir. The Rio Grande River is one of the most significant sources of water in southern New Mexico and far west Texas in the US, as well as the northern Chihuahua in Mexico. It provides intensive agriculture practices for their irrigation needs. It also supplies the human communities and the ecosystems throughout the basin with their water needs (Sheng, 2013; Szynkiewicz et al., 2015; Sanchez, 2017; Randklev et al., 2018; Cox et al., 2018).

This Middle Rio Grande Region contains various land use/land cover features and practices and experiences massive changes overtime due to disruptive human activities and natural conditions (Randklev et al., 2018). Urbanization is one of the most influential contributors to land use/land cover change in the region. It continues to grow, especially near the urban centers of Las
Cruces, New Mexico, El Paso, Texas, and Juárez, Mexico (Szynkiewicz et al., 2015). A study conducted by Mubako et al. (2018) on 4288 km$^2$ (1655 sq. miles) in the Middle Rio Grande Region that included the most areas of the three main cities in the region (Las Cruces, El Paso, and Ciudad Juarez) stated that the urban areas grew about 8% in this area of interest in the 25 years 1990-2015 by taking important areas from agricultural lands and other vegetation. The agricultural lands and other vegetation areas decreased by about 11% in this period.

The central aim of this study is to identify and measure land use/land cover change in the Middle Rio Grande Region. The study uses Landsat-based remote sensing and land cover classification to measure changes in the land use practices and land cover features in this region for 21 years from 1994 to 2015 (Figure 1.3).

3.2. METHODS

3.2.1: Materials and methods

The workflow shown in Figure (3.1) reflects the remote sensing and geographic information system procedures applied in this study. The processes start with Landsat data downloading and preparing. Following, atmospheric data correction is applied, imagery is clipped to the extent of the study area, and minimum noise fraction transforming was completed to reduce the inherent spectral dimensionality and noise within multispectral data. After data preparation, image classification was performed. The classification was performed using ArcGIS 10.7.1, ArcGIS Online, ENVI 5.4, Microsoft Excel, and Google Earth professional.
3.2.2: Landsat data preparation

Eight multispectral Landsat scenes cover the study area shown in Figure (1.3) (Path/Row): 031/039, 031/040, 032/038, 032/039, 033/037, 033/038, 034/036, and 034/037. As shown in Figure (3.1), these images were downloaded from the U.S. Geological Survey (USGS) GloVis website (http://GloVis.usgs.gov/) for the years 1994, 2000, 2005, 2010, and 2015. Each scene had less than 10 percent cloud cover. The scenes used for the study area were chosen from Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI), as shown in Appendix (3.1). In fact, Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) collect data with a spatial resolution of 30 meters in the visible, near-IR, and SWIR wavelength regions (U.S. Geological Survey, 2016). The scenes were acquired between the second half of May and the first week of July, which is considered the “leaf-on” season in this area (Dye et al., 2016; Mubako et al., 2018). Substantial procedures were performed on the scenes to prepare them for
classification, including mosaicking the eight scenes in one image and clipping a final image to the study area boundaries.

3.2.3: Atmospheric correction

Kumar and Yarrakula 2017, tested log residuals, flat field correction, IARR (Internal average relative reflectance), QUAC (Quick atmospheric correction), and FLAASH (Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes) atmospheric correction methods. The results showed that FLAASH is the most efficient atmospheric correction method compared to the other methods. Chakouri et al., 2020 tested two physical atmospheric corrections, FLAASH and ATCOR (Atmospheric & Topographic Correction) were compared to the DOS1 (Dark Object Subtraction) image-based method. The FLAASH provided the most accurate Bottom of Atmosphere BOA reflectance estimation. Therefore, I have chosen the FLAASH method to perform the atmospheric corrections. Specific steps implemented in ENVI 5.4 application for the five years that have been selected for the study. These steps included radiometric calibration in determining reflectance at the top of the atmosphere, fast line-of-sight atmospheric analysis of spectral hypercubes (FLAASH) for vapor, and moisture correction in determining surface reflectance.

3.2.4: Minimum noise fraction transform

To reduce the number of bands for processing hyperspectral remote sensing data and improve processing efficiency, a minimum noise fraction (MNF) linear transformation process was used to transform the study area images for all analysis years. This technique, widely applied in remote sensing, is implemented in ENVI 5.4 software (Liu et al., 2016) and reduces the inherent spectral dimensionality and noise within multispectral data. The final minimum noise fraction
Landsat images were approved for classification based on both eigenvalue plots of the ground objects and visual inspection of the images.

3.2.5: Combined Classification

A newly developed object-based classification method was tested in combination with the pixel-based classification method (Aguirre-Gutiérrez et al., 2012). The object-based method produces has been shown to have greater accuracy and create a more robust classification than the pixel-based method when using high-resolution imagery (Cleve et al., 2008; Corcoran and Winstanley, 2008; Hájek, 2008; Costa et al., 2018; Lu et al., 2019). Object-based techniques create an image object via image segmentation and classify the images according to objects rather than pixels (Shivakanth et al., 2018). However, it has been shown that pixel-based land cover classification may sometimes outperform the classification accuracy results for specific land cover categories (Flanders et al., 2003; Shivakanth et al., 2018). In such cases, a combination of both methods' produces optimal results (Aguirre-Gutiérrez et al., 2012).

The combined classification method comprises many steps that start with supervised or unsupervised classification and infiltrate the results based on the homogeneity of surface features to segment and attain the boundaries of surface features to more authentic products (Shivakanth et al., 2018; Lu et al., 2020). This study adopted such a generalized approach and started by implementing a supervised classification utilizing a maximum likelihood format (Gutierrez and Johnson, 2010; Rawat et al., 2013; Mallupattu and Sreenivasula, 2013; Churches et al., 2014; Boori et al., 2015; Rawat and Kumar 2015). Supervised classification uses the spectral information contained in individual pixels to generate land cover classes. The method requires the collection of training samples that are created in the study area and then used to derive spectral signatures of pixels in an image. It requires, therefore, prior knowledge of land use/land cover types in the study area.
area. Pixel signatures are generated and stored in signature files, and digital numbers (DN) of each pixel are then converted to radiance values (Jensen, 2005; Campbell and Wynne, 2011; Mubako et al., 2018). The interactive supervised classification module used to classify the minimum noise images is found in ArcGIS 10.7.1 software. The module was applied for the five analysis years of 1994, 2000, 2005, 2010, and 2015 using the six broad land use categories defined in (Table 3.1). Spectral signatures of the training samples were first analyzed using statistical methods. According to Gao and Liu (2010), a satisfactory spectral signature minimizes confusion between different land-use categories to be mapped. The whole region of interest was classified by assigning each image pixels to the training sample category of the match's highest probability. On average, 150 training samples were created for each land use category using the Landsat 1994_TM imagery since this was the year with the least developed land. A minimum of 500 pixels for each training sample category was used.

After producing the preliminary classified maps, field visits were made to designated features and places in the study area to find similarities and differences between the classified features on maps and their actual appearance and locations on the ground. Coordinates and information about the visited locations were collected. Other inquiry points were assigned to familiar places, checked through high-resolution images downloaded for New Mexico and Texas states' websites, and used historical image visualization in Google Earth Professional. The chosen points were matched with the classified maps, and the misclasses were assigned to be recognized at the ultimate step of classification. Reclassification procedures were processed to correct the misclassified sites depending on the object-based features of these sites shown on the high-resolution images. Therefore, final classified maps that carried more accurate results have been
created. These procedures were applied to the five maps created in the study in 1994, 2000, 2005, 2010, and 2015.

Table 3.1: Description of Land use/ Land cover classification categories used in the study.

<table>
<thead>
<tr>
<th>Land use/ Land cover</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>Cultivated crops, trees, plants, and pastures</td>
</tr>
<tr>
<td>Developed Open space</td>
<td>Sport fields and courts, park, and picnic areas, building yards</td>
</tr>
<tr>
<td>Developed area</td>
<td>Urban development constructions, buildings, concrete, and roads</td>
</tr>
<tr>
<td>Water</td>
<td>Open waterbodies in natural and human-made surface waterbodies</td>
</tr>
<tr>
<td>Evergreen Forest</td>
<td>Green trees on mountains and hills in the study area</td>
</tr>
<tr>
<td>Shrubs</td>
<td>Mountains, scrub/shrub, grass, and barren land features in the area</td>
</tr>
</tbody>
</table>

3.2.6: Finalizing Classification Mapping

Finalizing classifications of remotely sensed imagery is a balance between achieving outstanding quality classified final maps and the potential loss of essential map details through the unnecessary use of generalization tools (Keranen et al., 2014; Mubako et al., 2018). Therefore, the majority filter procedure was not applied to protect the isolated and small regions in the reclassified maps, which are real features in the study area. In addition, a boundary cleaning filter was applied to these maps to smooth the boundaries and improve their layout. These steps were done through a series of geoprocessing tools in the Spatial Analyst Extension of ArcGIS 10.7.1.

3.2.7: Accuracy Assessment

The validity of classifications was confirmed by calculating multiple metrics indicative of the mapped accuracy of the classification. Classification accuracy was performed for individual land use categories and the total classification by creating a confusion matrix (Butt et al., 2015; Islam et al., 2018; Mubako et al., 2018). Six statistics were calculated: (1) overall accuracy, which represents the proportion of all correct classifications; (2) Kappa coefficient, a measure of the agreement of accuracy in classification assessment; (3) user accuracy, which calculates the probability that a classified pixel is correct on the ground; (4) producer accuracy, which is the probability that a pixel of a particular land-use type is assigned the correct land use category; (5)
omission error, which represents specific categories that were omitted when they exist on the ground; and (6) commission error, which represents categories that were identified as existing on the ground when in fact they do not (Butt et al., 2015; Mubako et al., 2018).

3.3: RESULTS AND DISCUSSION

3.3.1: Land use/land cover measurement and change trends

After producing the final classified maps, the areas of individual classes were calculated for the study area. This process was executed through the feature attributes related module in ArcGIS 10.7.1 for the five sample years. The final results are given in Table (3.2) and Figure (3.3).

Table 3.2: The Middle Rio Grande land use/land cover results 1994-2015.

<table>
<thead>
<tr>
<th>Year</th>
<th>Agriculture</th>
<th>Developed open space</th>
<th>Developed area</th>
<th>Water</th>
<th>Evergreen forest</th>
<th>Shrubs</th>
<th>Total Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>1994</td>
<td>1245</td>
<td>29</td>
<td>589</td>
<td>241</td>
<td>1663</td>
<td>33221</td>
<td>36988</td>
</tr>
<tr>
<td>2000</td>
<td>1190</td>
<td>33</td>
<td>768</td>
<td>185</td>
<td>1749</td>
<td>33063</td>
<td>36988</td>
</tr>
<tr>
<td>2005</td>
<td>1125</td>
<td>36</td>
<td>933</td>
<td>122</td>
<td>2126</td>
<td>32646</td>
<td>36988</td>
</tr>
<tr>
<td>2010</td>
<td>1111</td>
<td>40</td>
<td>1022</td>
<td>135</td>
<td>2155</td>
<td>32525</td>
<td>36988</td>
</tr>
<tr>
<td>2015</td>
<td>1091</td>
<td>40</td>
<td>1078</td>
<td>106</td>
<td>1148</td>
<td>33825</td>
<td>36988</td>
</tr>
</tbody>
</table>

Figure 3.2: The Middle Rio Grande land use/land cover classes change 1994-2015.
The results showed many changes in the study area's land use/land cover classes. Agriculture lands decreased from 1245 km$^2$ (3.37 percent) of the total study area in 1994 to 1091 km$^2$ (2.97 percent) in 2015. This is attributed mainly to the intensification of developing activities and the reduction of cultivation practices related to water use, and a shift from cotton and alfalfa production with some production of chili peppers, vegetables, vineyards, and orchard crops to more profitable crops such as pecans for the analysis period (Hargrove et al., 2020). The open space areas, including parks, sports fields and courses, and green areas, in cities and considered human-friendly development increased following the urban growth from 29 km$^2$ (0.08 percent) in 1994 to 40 km$^2$ (0.11 percent) in 2015. Truth or Consequences City Golf Course and some other sports fields around in this county, as shown in Figure (3.15), reflect a sample of the open space category and indicate the importance of this land feature. The proportion of developed areas, including urban areas and other types of construction within the study area, increased over time from 589 km$^2$ (1.59 percent) in 1994 to 1078 km$^2$ (2.94 percent) in 2015. The increase happened primarily around the central three urban cities of cities El Paso (Texas, USA), Las Cruces (New Mexico, USA), and Ciudad Juárez (Chihuahua, Mexico). A part of the urban growth between 1994-2015 in northeastern Las Cruces is shown in Figures 3.9 and 3.10 by space image and the area’s classification. However, many along the Middle Rio Grande Region scattered minor cities, towns, communities, and neighborhoods contributed to the urban expansion through the growth of urbanization in these cities, towns, communities, and neighborhoods.

The areal extent of surface water decreased from 241 km$^2$ (0.65 percent) in 1994 to 122 km$^2$ (0.33 percent) in 2005. Surface water increased in 2010 to 135 km$^2$ (0.36 percent). In contrast, surface water decreased to 106 km$^2$ (0.29 percent) in 2015, by a total decrease of the surface water area by over 56 percent for the 21 years 1994-2015. Elephant Butte and Caballo's large reservoirs
comprised the majority of the surface water extent and were located in the northern part of the study area. They are also considered the primary source of surface water in the southern part of the region. The decrease in water in the Elephant Butte reservoir between 1994-2015 was shown in Figures 3.13 and 3.14.

Evergreen forest cover is restricted to some marginal zones in the region and almost in the northern part of the Magdalena Mountains, San Mateo Mountains, and Black Range. The areas of evergreen forests increased from 1663 km² (4.5 percent) in 1994 to 2155 km² (5.83 percent) of the total area in 2010. However, these areas decreased to 1148 km² (3.1 percent) in 2015 due to fires that burned significant parts of these forests. Records indicated several fires, the largest silver fire in 2013, which burned about 138,705 acres in the black Range, New Mexico. Also, San Mateo Mountains fire in 2015 burned 17,843 acres (US Forest Service, 2020; New Mexico fire information, 2020). Figures 3.11 and 3.12 show the change in the Black Range mountains in the north part of the study area before and after June 2013 Forest fires and as 2010 and 2015 classification. Shrublands covers were the most dominant land cover in the study area for each of the time periods studied. The shrublands class lost important lands in many parts across the region. The results showed that shrublands covered 33221 km² (89.82 percent) in 1994 and shrunk to 32525 km² (78.93 percent) in 2010. This component gained some areas to be 33225 km² (90.56 percent) in 2015 due to forest fires and surface water area reduction. The changes in land use/land cover 1994-2015 are shown in Figures 3.4-3.8.
Figure 3.3: The Middle Rio Grande land use/land cover classes change 1994-2015.
Figure 3.4: The Middle Rio Grande Land use/ Land cover 1994
Figure 3.5: The Middle Rio Grande Land use/ Land cover 2000
Figure 3.6: The Middle Rio Grande Land use/ Land cover 2005
Figure 3.7: The Middle Rio Grande Land use/ Land cover 2010
Figure 3.8: The Middle Rio Grande Land use/Land cover 2015.
Figure 3.9: urban growth in Las Cruces, NM. 1994
Figure 3.10: urban growth in Las Cruces, NM. 2015
Figure 3.11: Black Range Forest fires (January 2013 before the fire).
Figure 3.12: Black Range Forest fires (June 2013 after the fire).
Figure 3.13: the Elephant Butte Reservoir, NM. 1994
Figure 3.14: the Elephant Butte Reservoir, NM. 2015.
Figure 3.15: Truth or Consequences, NM Golf Course, and some other sport fields. 2015
3.3.2: Results Validation

3.3.2.1: Accuracy assessment

For the study area, five maps were classified for 1994, 2000, 2005, 2010, and 2015. To validate the classification results, an accuracy assessment was applied using several extension tools in ArcGIS 10.7.1, focusing on analysis years 2005, 2010, and 2015. These three years, I got their high-resolution images from Texas and New Mexico states. 2005, 2010, and 2015 images are very supportive in-ground checks of classification results. Also, field visits were made to the areas in New Mexico and Texas to support the ground check of classification results. However, Google Earth was used in the ground check in Mexico part that I could not check in the field because of the restrictions on border movement. The classification quality is oriented in a confusion matrix that is widely used to present accuracy assessment information in remote sensing (Tilahun et al., 2015; Mubako et al., 2018). About 520 points were used for each classified map (year). A stratified random sampling method was applied for the validation. The method assigned sampling points according to the proportion area of each class in the study area. The overall accuracy of 99 percent was obtained in 2005, 2010, and 2015. Subjectivity in interpreting classification results, fuzzy boundaries between land use categories, and uncertainty in the supervised classification algorithm in assigning land use categories to mixed pixels are all possible sources of intrinsic uncertainty and error that could have been propagated in this type of study. Calculating the Kappa statistics, which account for classification agreements owing to chance, is an alternative approach to measuring classification accuracy. The Kappa coefficient was 0.96 for three years, statistically supporting the classification's overall accuracy. For all land use/land cover categories, the producer accuracy ranged from 88.2 percent to 100 percent for the three years and user accuracy from 90 to 100 percent. Detailed assessment results are presented in Tables 3.3, 3.4, and 3.5.
As Mubako et al. (2018) mentioned, overall classification accuracy and the accuracy for all classes greater than 75-85 percent is acceptable. That accuracy assessment compromises the ideal and the affordable (Mubako et al., 2018). Wickham et al. (2013) recommended an acceptable overall classification accuracy between 84-85 percent for most satellite data classification studies to evaluate the National Standard Land Cover Database (NLCD) classification system. The coarse 30 m spatial resolution of the Landsat images utilized in the study also contributed to classification errors. Two or even more spectral classes were frequently recorded inside one pixel using this low-resolution data, which obviously influenced classification accuracy. Errors were experienced when performing the accuracy assessment with some pixels for some classes. Therefore, our results' classification errors are partly due to impure training samples that captured mixed land use categories. Accurate reference data is essential for testing classification accuracy (Martin et al., 2014). Therefore, accuracy errors were calculated as part of the assessment. The results showed that commissions' errors were not over 10% for some classes and the errors of omissions were not over 12% for some individual classes.

Table 3.3: Confusion matrix showing classification accuracy for 2005 map.

<table>
<thead>
<tr>
<th>Classified</th>
<th>Ground truth</th>
<th>Agriculture</th>
<th>Open space</th>
<th>Developed area</th>
<th>Water</th>
<th>Evergreen Forest</th>
<th>Shrubs</th>
<th>Total ground</th>
<th>User's accuracy %</th>
<th>The error of commission %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>Agriculture</td>
<td>14</td>
<td>0</td>
<td>0</td>
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<td>0</td>
<td>0</td>
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<td>Developed area</td>
<td>Developed area</td>
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<td>0</td>
<td>12</td>
<td>0</td>
<td>0</td>
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<td>0</td>
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<td>10</td>
<td>100</td>
<td>0</td>
</tr>
<tr>
<td>Evergreen Forest</td>
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<td>0</td>
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<td>26</td>
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<td>10</td>
<td>27</td>
<td>444</td>
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</tr>
</tbody>
</table>

Producer accuracy % 93.33
The error of omission % 6.67
overall accuracy % 98.84
Kappa coefficient 0.96

Table 3.4: Confusion matrix showing classification accuracy for 2010 map.
### Table 3.5: Confusion matrix showing classification accuracy for 2015 map.

<table>
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<tr>
<th>Classified</th>
<th>Ground truth</th>
<th>Ground truth</th>
<th>Ground truth</th>
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<th>Ground truth</th>
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</thead>
<tbody>
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<td></td>
<td>Agriculture</td>
<td>Open space</td>
<td>Developed area</td>
<td>Water</td>
<td>Evergreen Forest</td>
<td>Shrubs</td>
<td>Total ground</td>
<td>User's accuracy %</td>
<td>The error of commission %</td>
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<tr>
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<td>99.09</td>
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### 3.4 Discussion

The US-Mexico border Middle Rio Grande Region is dryland covering ~36988 km² (14281 sq miles). I studied this region to measure land use/land cover and find their changes for 21 years (1994–2015) by using remote sensing and geographic information systems. The study divided the period into five years which are 1994, 2000, 2005, 2010, and 2015.
The results showed significant changes in land use/land cover features during the study period 1994-2015. The open space areas increased about 27 percent. The developed area across the area of interest increased 45 percent in 21 years between 1994-2015 by winning important extents from agricultural and shrublands, and the most growth occurred around the metropolitan areas of El Paso (Texas, USA), Las Cruces (New Mexico, USA), and Ciudad Juárez (Chihuahua, Mexico). The shrublands increased about 1 percent. On the other hand, the agricultural lands decreased by about 12 percent. Surface water decreased more than 55 percent in this period. The evergreen forests decreased by about 30 percent.

The study results presented that the Middle Rio Grande Region, like other drylands, faces serious challenges, such as water reduction and competitive demand growth amongst sectors such as agriculture and domestic uses. Shrubs and native plants disturb naturally during climate change, like temperature increase and human activities such as urbanization growth and construction expansion.

However, there are similarities and differences in changes between the Middle Rio Grande Region and the other drylands. The effect of the change on the area depends on the location and management of this area. A study in the Kathmandu Valley, Nepal, for the period 1989-2016 showed similarities in land use/land cover changes with the Middle Rio Grande Region. The results showed that urban areas expanded up to 412% in the last three decades, and most of this expansion occurred with the conversions of 31% of agricultural land. The majority of the urban expansion happened during 1989–2009, and it is still growing along the major roads in a concentric pattern, significantly altering the cityscape of the valley (Ishtiaque et al., 2017). Another study in the Zayandehrood ecologic sub-basins of Central Iran, Asia, and also showed similarities in land use/land cover changes with the Middle Rio Grande Region. The results revealed that from 1985
to 2016, residential areas doubled, and industrial areas increased at the expense of rangelands. The study also revealed cropland expansion at the expense of rangelands, cropland abandonment, and contraction of croplands due to residential and industrial development (Mazloum et al., 2021). Also, a study focused on Palapye, a predominantly dryland agricultural region in eastern Botswana, Africa, aimed to analyze land use/land cover change and divided the period into two intervals (1986-2000, 2000-2014). This study showed similarities in land use/land cover changes with the Middle Rio Grande Region. The results showed that cropland was a vibrant losing category in the first-time interval, while it was a clear gaining category during the second time interval. Cropland expanded into shrublands in the southwestern part of the study area. The built-up category was active in gains during the second time interval as it targeted grasslands and shrublands (Akinyemi et al., 2018). On the other hand, and through good management, a study in Karoo drylands, South Africa, Africa, revealed that more than 95% of the Karoo is comprised of land classified as Natural, which has been relatively stable since 1990. An analysis of repeat photographs shows that vegetation cover has either remained unchanged or has increased at most locations. However, the Karoo drylands appear less degraded than they were in the mid-twentieth century (Timm Hoffman et al., 2018).

Land use/land cover changes in the Middle Rio Grande Region have many implications on the region. Reducing snowpack in the headwaters of the Rio Grande River causes a growing water supply deficit and failure to sustain the competing demands of different sectors even though these demands for surface water stay the same in aggregate (Hargrove et al., 2020). Increasing the pressure on the reservoirs of surface water used as a water source for various uses. For example, this appears clearly in the Elephant Butte Reservoir, the primary surface water source in the Middle Rio Grande Region. Its capacity since 2011 fluctuated between 3-25% of the total capacity.
(Vaisvil, 2019; Townsend, 2019). Rising soil and water salinity and growing constraints on using of these resources for agricultural production, drinking, and various environmental needs. Relying on the growth of groundwater to provide the necessary water supplies for various uses and the pressure and negative impacts on this limited to nonrenewable water resource also face many serious problems such as depletion and quality deterioration (Hargrove et al., 2020). The loss of grasslands, shrublands, and forests to urban development can lead to loss of natural habitats and ecological diversity, higher risk of flooding due to increased surface runoff in paved urban areas, and increased water pollution from point and non-point sources, such as new industries waste facilities. When considering outdoor recreation, the loss of natural landscapes may decrease income from tourism that is associated with water-dependent natural ecosystems (Mubako et al., 2018).

This change in land use / land cover raises some critical questions that need an answer, such as what is the extent of land use/ land cover change in this region? What is the change limit of the cities such as El Paso and Ciudad Juarez? What is the effect of this change on sustainability and the region's future? Do we need to stop this change, control it, or adapt to the new situation? What are the implications of the change?

3.5: Conclusion

Remote sensing and geographic information systems technologies across boundary tools for cooperation and research were used to visualize, measure, and assess land use/ land cover change in the Middle Rio Grande Region, a dryland environment in the USA and Mexico borderlands. This region faces significant natural consequences associated with land use/ land cover change from one type to another, especially in relation to sustainable water management.
The results from the study showed many changes in land use/land cover. For instance, the developed area across the area of interest increased 45 percent in 21 years between 1994-2015, and the most growth occurred around the metropolitan areas of cities El Paso (Texas, USA), Las Cruces (New Mexico, USA), and Ciudad Juárez (Chihuahua, Mexico). Surface water decreased by more than 55 percent in the period 1994-2015. The dominant shrublands in the area of interest have changed and have lost areas and parts to the urban and agriculture and gained others from forests and a reduction in surface water cover.

This study’s findings stand as an excellent view for visualizing and understanding spatial and temporal environmental change in this region and helping stakeholders on different levels and responsibilities to balance development requirements and protect dynamic ecosystems.

Future research is recommended on monitoring land use/land cover change in the region on a macroscale that can cover the cities and the local areas to understand the effect of development on natural resources such as shrublands and forests. Conservation of environmental flows by controlling human actions that disrupt the resources. A detailed assessment of the driving forces behind the trends and patterns of land use/land cover change is revealed in this study.

The study's results reveal the requirement to change land use policies to include guidelines and regulations that can help maintain the resources, such as putting restrictions on water consumption and changing agriculture practices towards less water use produce.
CHAPTER 4: MODIFIED NORMALIZED DIFFERENCE WATER INDEX (MNDWI) AS A VISUALIZATION INDICATOR FOR CHANGE IN SURFACE WATERBODIES IN THE MIDDLE RIO GRANDE BASIN

ABSTRACT

Surface water from the Rio Grande River is one of the primary water sources for southern New Mexico and Far West Texas in the United States (U.S.) and northern Chihuahua in Mexico. The river supplies several users, including agriculture, municipalities, industry, and wildlife. Surface water from precipitation, lakes, ponds, and swamps plays a significant role in the region's water supplies. However, climate change and the fast growth of the major metropolitan areas of El Paso, Ciudad Juárez, and Las Cruces have resulted in changes in land-use practices and increased water demand in response to growing competition between urban water needs and other uses. This study applies the Modified Normalized Difference Water Index (MNDWI) to visualize, monitor, and identify changes in surface water bodies in the Middle Rio Grande River Basin for a 26-year 1994-2020 study period. The area spans from San Antonio, New Mexico to Presidio, Texas and to Ojinaga, Chihuahua, including the cities of El Paso, Texas, Ciudad Juárez, Chihuahua, and Las Cruces, New Mexico, all metropolitan areas on the U.S.-Mexico border. Results show that surface water bodies have experienced an overall decrease in surface area during the last twenty-six years by more than 66 percent. This decrease is especially evident for the Elephant Butte and Caballo reservoirs, which decreased by about 83 percent and 72 percent, respectively. In 2020, surface water bodies increased by approximately 31.9 % compared to 2018 storage and reduced the surface water area decrease to 46.9 percent. Geographic information systems (GIS) and remote sensing (RS) proved useful tools for analyzing surface water change.
over time and monitoring mesoscale regions experiencing climate change, rapid urban growth, and water scarcity.

**Keywords:** Waterbodies, Modified Normalized Difference Water Index (MNDWI), environment, sustainability, ecosystems, climate, agriculture.

**4.1: INTRODUCTION**

Surface water is a crucial water resource for human existence and development (Li et al., 2013; Acharya et al., 2018; Varis et al., 2019), as well as for animals, plants, and ecosystems (Huang et al., 2018; Qin et al., 2020). Its change is a significant indicator of environmental, meteorological, and anthropogenic actions (Zhai et al., 2015; Acharya et al., 2019). The deterioration of this resource increases poverty, insecurity, and biological diversity degradation (Campos et al., 2012; Gupta, 2019; Abell et al., 2019). Information on surface water amount and distribution is essential for surface water mapping, estimating quantities for drinking and irrigation purposes, land use/land cover, and monitoring change (Acharya et al., 2019; Qin et al., 2020). It also provides the capability to protect the environment and its components (Campos et al., 2012; Gupta, 2019; Abell et al., 2019). A vital rise in water uses throughout the twentieth century and through the first decades of this century has led to severe water scarcity in many regions around the world, and changes in mean hydro-climatological conditions under climate change potentially increase water scarcity in those regions (Greve et al., 2018; Abell et al., 2019). Many scientists and scholars have studied surface water bodies, and numerous methods have been established to delineate and study this landscape component (Yang et al., 2017). Weather variability and climate change can potentially affect water availability, possibly negatively, resulting in a change in environmental sustainability (Gutzler, 2013; Mu et al., 2018). However, population growth and
increasing their demand for food, energy, and water could result from climate change in the long
term (Gutzler, 2013; Mu et al., 2018; Bohn et al., 2018).

Remote sensing and geographic information system technologies have been extensively
used in various studies that include land use/cover change, urban growth, and aquatic resources
(Rokni et al., 2014; Li et al., 2013; McFeeters, 2013; Butt et al., 2015; Zhang et al., 2016; Mubako
et al., 2018; Acharya et al., 2018; Islam et al., 2018). Remote sensing tools at different spatial,
spectral, radiometric, and temporal resolutions offer a vast amount of data that have become
significant sources for distinguishing, extracting, measuring, and reserving surface water bodies
and their changes in recent times (Rokni et al., 2014; Qiandong Guo et al., 2017; Jason Yang &
Xianrong Du, 2017; Tena et al., 2019). Remote sensing has become a relatively low-cost source
for feature detection and understanding of hydrogeological systems (Acharya et al., 2019).
Methods that have been developed and applied to identify, extract and measure waterbodies
include (1) thematic classification (Zhai et al., 2015; Acharya et al., 2018; Huang et al., 2018), (2)
linear unmixing models (Burazerovic et al., 2014; Huang et al., 2018; Jarchow et al., 2019), (3)
single-band thresholding (Huang et al., 2018; Mondejar et al., 2019), and (4) applications of
spectral water indices (Acharya et al., 2018; Wang et al., 2018; Huang et al., 2018; Babaei et al.,
2019; Herndon et al., 2020). Spectral water index methods, such as the normalized difference water
index (NDWI) and modified normalized difference water index (MNDWI), which are calculated
from one green-band image and one near-infrared (NIR) or shortwave infrared (SWIR) band
image, can extract water body information more accurately, rapidly, and thoroughly than general
feature classification methods (Li et al., 2013; Babaei et al., 2019). Water's important spectral
characteristics are that it absorbs (NIR) radiation, transmits green and red lights, and allows for
light reflection by features such as benthic sediments, aquatic plants, and other features (McFeeters
On the other hand, vegetation and dry soil reflect NIR strongly. Based on these characteristics, either a single band or a ratio of two bands is typically used for water extraction (McFeeters 1996). For instance, density slicing to Landsat TM band 4 proved to be an efficient method for extracting water bodies from rivers and lakes (Qiandong Guo et al., 2017). The two band-method ratios usually use a visible band, such as green or red, divided by a NIR band. Therefore, water features are boosted while this process represses terrestrial vegetation and soil features. Using green and NIR bands, McFeeters (1996) proposed a normalized difference water index (NDWI) to extract open waterbodies. However, Xu (2006) used the modified normalized difference water index (MNDWI) algorithm to extract open water structures by replacing a NIR band with the SWIR band because the SWIR band spectral value of most land features is larger than that of the green band, but water feature is the opposite (Qiandong Guo et al., 2017).

McFeeters (1996) developed the normalized difference water index (NDWI) in this equation:

\[ \text{NDWI} = \frac{\rho_{\text{Green}} - \rho_{\text{NIR}}}{\rho_{\text{Green}} + \rho_{\text{NIR}}} \]

Where:

- \( \rho_{\text{green}} \) is the reflectance of the green band, and \( \rho_{\text{NIR}} \) is the reflectance of the NIR band.

The NDWI value ranges from -1 to 1, and McFeeters (1996) set zero as the threshold. That means the feature is water if NDWI > 0, and it is non-water if NDWI ≤ 0.

To recompense the weaknesses of McFeeters’ NDWI, Xu (2006) proposed the modified NDWI (MNDWI), in which the SWIR band (Landsat TM band 5) was used to replace the NIR band.

\[ \text{NDWI} = \frac{\rho_{\text{Green}} - \rho_{\text{SWIR}}}{\rho_{\text{Green}} + \rho_{\text{SWIR}}} \]

Where:
\( p_{\text{green}} \) is the reflectance of the green band, and \( p_{\text{SWIR}} \) is the reflectance of the SWIR band.

Like McFeeters’ NDWI, the threshold value for MNDWI was set to zero (Xu, 2006). However, Xu (2006) found a manual adjustment of the threshold could achieve more accurate results in the extraction of water bodies (Haibo et al., 2011; Xie et al., 2016; Zhang et al., 2018; Atwah, 2021).

The Rio Grande River is the most crucial water source in the Rio Grande region and flows from north to south, providing essential water requirements to many sectors. It begins as a snow-fed stream high in the San Juan Luis Valley in southern Colorado. Otherwise, it makes the main surface water reservoirs in southern New Mexico, the Elephant Butte reservoir and the Caballo reservoir. By the time it reaches the border between New Mexico and Texas, it has taken on the color and composition of the farmlands watered on the south's route (Perez, 2001; Pascolini-Campbell et al., 2017; Blythe et al., 2018).

The Rio Grande River is the fourth largest on the North American continent. It supports extensive irrigated agriculture as well as rapidly growing cities in three U.S. and five Mexican states. From El Paso, Texas, to the Gulf of Mexico, the river marks the international border between the U.S. and Mexico. Treaties for sharing the Rio Grande's water between the two countries and arrangements for joint management were concluded in 1906 and 1944 (Schmandt, 2002; Pascolini-Campbell et al., 2017; Blythe et al., 2018; Chavarria et al., 2018). Furthermore, surface water from precipitation along the region and several unconventional water sources such as wastewater treatment facilities form some water lakes, ponds, and swamps in many places in the region, playing a significant role in water supplies. Changes in surface water due to climate change and the competing demands observed in the region, and a declining flow in the Rio Grande
River make it imperative to monitor water resources and identify more management options (Pascolini-Campbell et al., 2017; Chavarria et al., 2018; Mu et al., 2018; Overpeck et al., 2020).

In this study, Modified Normalized Difference Water Index (MNDWI) was applied to Landsat images in order to attain these objectives:

1. Extract the surface water bodies in the Middle Rio Grande Region.
2. Measure the surface area of surface water bodies in this region.
3. Find the changes in surface area of water bodies in the 26 years 1994-2020.

4.2: MATERIALS AND METHODS

The flowchart presented in Figure 4.1 below visualizes the RS and GIS techniques applied in this study. Key steps accomplished include data downloading and preparing, atmospheric correction, data clipping, minimum noise fraction transform (McFeeters, 2013; Rokni et al., 2014; Liu et al., 2016), and determination of MNDWI (Xu, 2006). This work was performed using the software ArcGIS 10.7.1 map, ArcGIS Online, ENVI 5.4, Microsoft Excel, and Google Earth.

![Flowchart showing RS and GIS technologies used in the study.](image-url)
4.2.1: Data collection

Landsat images were downloaded from the U.S. Geological Survey (USGS) Earth Explorer and Global Visualization Viewer (GloVis) websites (http://earthexplorer.usgs.gov/, http://glovis.usgs.gov/) for the years 1994, 2000, 2005, 2010, 2015, 2018, and 2020 as shown in figure 4.1. The following eight multispectral Landsat scenes cover the area of interest shown in Fig. 1.3 (Path/Row): 031/039, 031/040, 032/038, 032/039, 033/037, 033/038, 034/036, and 034/037. Each scene had less than 10 percent cloud cover. Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) provided the chosen area images. The dates for images ranged between the end of May and the first half of July; a period considered "leaf-on" in this study region. Dates for the Landsat 2020 images used in this study ranged between the end of March and the second half of April. Preparatory steps were performed, including extracting the images to the study area boundaries, creating mosaics, and color correction. Also, atmospheric corrections and minimum noise fraction transform were made. Appendix 4.1. shows Satellite data used in the study.

4.2.2: Modified Normalized Difference Water Index (MNDWI) Calculation

In this study, MNDWI was calculated according to the procedure in Xu (2006). This index was developed to overcome the limits of NDWI (Gautam et al., 2015; Acharya et al., 2019). In MNDWI, the SWIR band (Landsat TM and ETM band 5, Landsat OLI band 6) was replaced the NIR band in McFeeters’ NDWI equation to be the equation for calculating MNDWI is:

$$\text{MNDWI} = \frac{(\rho_{\text{Green}} - \rho_{\text{SWIR}})}{(\rho_{\text{Green}} + \rho_{\text{SWIR}})}$$

Like McFeeters’ NDWI, the threshold value for MNDWI was set to zero (Xu, 2006). However, Xu (2006) found a manual adjustment of the threshold could achieve more accurate results in the extraction of waterbodies (Ji et al., 2009). ArcGIS software was used to calculate the
MNDWI index using the Spatial Analyst Tool. The index was applied to all imagery in the seven analysis years.

4.2.3: Field survey

Field visits were undertaken to Elephant Butte and Caballo Reservoirs and other places along the Rio Grande River to check for similarities and differences between the classified features and their real locations using portable Global Positioning System (GPS) units. Coordinates and attributes of these places were also collected and assigned to familiar places through image visualization on Google Earth.

4.2.4: Accuracy Assessment

To assess the accuracy of surface waterbodies extracted by MNDWI for the years 1994, 2000, 2005, 2010, 2015, 2018, and 2020 in the area of interest, and accuracy assessment of waterbodies extracted was conducted using the software ArcGIS 10.7.1. The study area was divided into two categories: waterbodies and non-waterbodies, and 500 sampling points were randomly generated in the study area with 250 points for each category. Each point was evaluated using high-resolution images (the US only) and/or Google Earth historical imagery.

Accuracy assessment was performed by building a confusion matrix for each interest region (Acharya et al., 2019). The following five statistics were calculated: (1) Overall accuracy, which represents the proportion of all correct classifications (2) Kappa coefficient, which measures the accuracy agreement in classification assessment. (3) User accuracy, which calculates the probability that a pixel classification is correct on the ground. (4) Producer accuracy, which is the probability that a pixel of a particular land-use type is assigned the correct land use category (5) Omission error, which represents specific categories that were omitted when they exist on the
ground and (6) Commission error, that represents categories that were identified as existing on the ground when in fact they do not (Feyisa et al., 2014; Mubako et al., 2018; Acharya et al., 2019).

4.3: RESULTS AND DISCUSSION

4.3.1: Surface waterbodies areas, change, and trends

MNDWI calculation results shown in Table 4.1, Figure 4.2, and figure 4.3 generally show that surface water bodies experienced a reduction in surface area during the 26 years 1994-2020 due to the increase in temperature trends and decrease in winter rains (Gutzler, 2013) and the reduction of snowpacks in the Rio Grande headwaters (Gutzler, 2013; Hargrove et al., 2020). The total surface area decreased from 230.86 km² (89.14 sq. miles) in 1994 to 177.93 km² (68.70 sq. miles) in 2000, a 22.9 % decrease. It continued decreasing to 107.60 km² (41.54 sq. miles) in 2005, a 39.5 % decrease. It increased to 113.31 Km² (43.75 sq. miles) in 2010, a 5 % increase. However, it decreased to 86.52 km² (33.41 sq. miles) in 2015, 23.7 % for an overall decrease of 62.5 %. It also reduced from 86.52 km² (33.41 sq. miles) in 2015 to 76.63 km² (29.59 sq. miles) in 2018, an 11.4 % decrease during this time step and an overall reduction of 66.8 % for the time series. In the first half of 2020, it was found that surface water bodies increased to 112.5 km² (43.44 sq. miles), an increase of 31.9 % compared to 2018 storage. 2020 was an unusual year because after the melt of the high snowpack in river headwaters in 2018-2019, a significant irrigation user of water in Elephant Butte, the El Paso Water Improvement District #1, stored some of this good year in the reservoir rather than taking it all at once (Udall, 2020). In addition, and from the results, it was found that the surface water bodies experienced an overall decrease of 51.3 % for the 26 years of analysis.

Table 4.1: MNDWI results for the study area.

<table>
<thead>
<tr>
<th>Year</th>
<th>Land use category area (km²)</th>
<th>Waterbodies</th>
<th>Non waterbodies</th>
<th>Total Area</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The Middle Rio Grande surface waterbodies change 1994-2020

<table>
<thead>
<tr>
<th>Year</th>
<th>Surface Area (km²)</th>
<th>Total Volume (km³)</th>
<th>Perimeter (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1994</td>
<td>230.86</td>
<td>36757.14</td>
<td>36988</td>
</tr>
<tr>
<td>2000</td>
<td>177.93</td>
<td>36810.07</td>
<td>36988</td>
</tr>
<tr>
<td>2005</td>
<td>107.60</td>
<td>36880.40</td>
<td>36988</td>
</tr>
<tr>
<td>2010</td>
<td>113.31</td>
<td>36874.69</td>
<td>36988</td>
</tr>
<tr>
<td>2015</td>
<td>86.52</td>
<td>36901.48</td>
<td>36988</td>
</tr>
<tr>
<td>2018</td>
<td>76.63</td>
<td>36911.37</td>
<td>36988</td>
</tr>
<tr>
<td>2020</td>
<td>112.50</td>
<td>36875.5</td>
<td>36988</td>
</tr>
</tbody>
</table>

Figure 4.2: Middle Rio Grande Surface Waterbody change 1994-2020.
Figure 4.3: Middle Rio Grande Surface Waterbody change 1994-2020.
Change of surface water bodies storage in the region is evident in the main surface water reservoirs of Elephant Butte and Caballo Lakes, where water is accumulated and then allocated flow for the Rio Grande River water along the region. Changes in these reservoirs’ storage are one of the most critical factors impacting water supplies downstream. While the rising storage of these water bodies justifies more allocations downstream to demanded sectors such as agriculture, the reducing storage causes meaningful cuts to allocations and shortages in meeting water demands.

Moreover, as in Table (4.2), the surface area of the Elephant Butte reservoir decreased from 141 km² (54.4 sq. miles) in 1994 to 120.26 km² (46.43 sq. miles) in 2000, a decrease of 16.5 %. While it shrunk to 54 km² (20.8 sq. miles) in 2005, a 55 %, Elephant Butte reservoir increased to 60.06 km² (23.19 sq. miles) in 2010 (11 % increase). However, it decreased to 45 km² (17.4 sq. miles) in 2015, 16.7 %, for an overall decrease of 68 %. The surface area of this reservoir decreased from 45.17 km² (17.44 sq. miles) in 2015 to 24 km² (9.3 sq. miles) in 2018, a decrease of 45.9 % and an overall decrease of 83 % for the 26-year period. In 2020 and due to the reduction of water release, the Elephant Butte Reservoir’s surface area increased to 50.03 km² (19.32 sq. miles), an increase of 51.4 % from what it was in 2018 to reduce the overall decrease to 65.3 %.

Figures 4.4, 4.6, and 4.8 show changes in surface area in the Elephant Butte reservoir. Caballo reservoir water storage decreased from 43 km² (16.6 sq. miles) surface area in 1994 to 26.78 km² (10.34 sq. miles) in 2000, a drop of 39.1 % to 16 km² (6.2 sq. miles) in 2005, a decline of 37.8 %. It increased to 21.15 km² (8.17 sq. miles) in 2010. However, Caballo's surface water area decreased to 14 km² (5.4 sq. miles) in 2015, 34.1 %, for an overall decrease of 68.3 % in the 26 years. Besides, it decreased from 14 km² (5.4 sq. miles) in 2015 to 12.32 km² (4.76 sq. miles) in 2018, an 11.3 % for an overall decrease of 72 % 26-year period. In 2020 and due to the reduction of water release, the Caballo Reservoir’s surface area increased to 20.07 km² (7.75 sq. miles) by 37.5% from what
it was in 2018 to reduce the overall decrease water in this reservoir to 54.3 % in 26 years. Figures 4.5, 4.7, and 4.9 show the change in surface area in Caballo reservoir.

Table 4.2: Elephant Butte and Caballo reservoirs surface water areas results.

<table>
<thead>
<tr>
<th>Year</th>
<th>Surface area (km²)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Elephant Butte</td>
</tr>
<tr>
<td>1994</td>
<td>144.10</td>
</tr>
<tr>
<td>2000</td>
<td>120.26</td>
</tr>
<tr>
<td>2005</td>
<td>54.09</td>
</tr>
<tr>
<td>2010</td>
<td>60.06</td>
</tr>
<tr>
<td>2015</td>
<td>45.18</td>
</tr>
<tr>
<td>2018</td>
<td>24.43</td>
</tr>
<tr>
<td>2020</td>
<td>50.03</td>
</tr>
</tbody>
</table>

Figure 4.4: Elephant Butte Reservoir surface water change 1994-2020.

Figure 4.5: Caballo Reservoir surface water change 1994-2020.
Figure 4.6: the Elephant Butte reservoir change 1994-2020
Figure 4.7: the Caballo reservoir change 1994-2020.
Figure 4.8: Elephant Butte Reservoir November 2018.

Figure 4.9: Caballo Reservoir July 2018. (pinterest.com)
4.3.2: Accuracy assessment

4.3.2.1: Confusion matrix

The results showed that MNDWI proposed in this study achieved the highest accuracy with the best visual effect in water extraction. We detail accuracy assessment results for the area of interest, focusing on analysis years 2010, 2015, and 2018. The MNDWI method's quality is provided in a confusion matrix, a widely used tool to present accuracy assessment information in remote sensing (Tilahun et al., 2015; Mubako et al., 2018). The overall accuracy was 98 percent in 2010. The Kappa coefficient was 0.96, the producer accuracy ranged from 96 percent to 100 percent for 2010, and the user accuracy also ranged from 96 to 100 percent (Table 4.3).

Table 4.3: Confusion matrix for 2010 image showing classification accuracy and errors.

<table>
<thead>
<tr>
<th>Classified category</th>
<th>Waterbodies</th>
<th>Nonwaterbodies</th>
<th>Total number of samples</th>
<th>User accuracy %</th>
<th>The error of commission %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>250</td>
<td>0</td>
<td>250</td>
<td>100</td>
<td>0</td>
</tr>
<tr>
<td>Nonwaterbodies</td>
<td>10</td>
<td>240</td>
<td>250</td>
<td>96</td>
<td>4</td>
</tr>
<tr>
<td>Total</td>
<td>260</td>
<td>240</td>
<td>500</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Producer accuracy %</td>
<td>96</td>
<td>100</td>
<td>Overall accuracy % 98</td>
<td></td>
<td></td>
</tr>
<tr>
<td>The error of omission %</td>
<td>4</td>
<td>0</td>
<td>Kappa coefficient 0.96</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The overall accuracy was 96 percent in 2015. The Kappa coefficient was 0.92, the producer accuracy ranged from 92 percent to 100 percent for 2015, and user accuracy from 92 to 100 percent (Table 4.4).

Table 4.4: Confusion matrix for 2015 image showing classification accuracy and error.

<table>
<thead>
<tr>
<th>Classified category</th>
<th>Waterbodies</th>
<th>Nonwaterbodies</th>
<th>Total number of samples</th>
<th>User accuracy %</th>
<th>The error of commission %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>250</td>
<td>0</td>
<td>250</td>
<td>100</td>
<td>0</td>
</tr>
<tr>
<td>Nonwaterbodies</td>
<td>21</td>
<td>229</td>
<td>250</td>
<td>92</td>
<td>4</td>
</tr>
<tr>
<td>Total</td>
<td>271</td>
<td>229</td>
<td>500</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The overall accuracy was 97 percent in 2018. The Kappa coefficient was 0.95, the producer accuracy ranged from 95 percent to 100 percent for 2018, and user accuracy also ranged from 95 to 100 percent (Table 4.5).

Table 4.5: Confusion matrix for 2018 image showing classification accuracy and error.

<table>
<thead>
<tr>
<th>Classified category</th>
<th>Actual category: Ground truth</th>
<th>Waterbodies</th>
<th>Nonwaterbodies</th>
<th>Total number of samples</th>
<th>User accuracy %</th>
<th>The error of commission %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td></td>
<td>250</td>
<td>0</td>
<td>250</td>
<td>100</td>
<td>0</td>
</tr>
<tr>
<td>Nonwaterbodies</td>
<td></td>
<td>13</td>
<td>237</td>
<td>250</td>
<td>95</td>
<td>5</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>263</td>
<td>237</td>
<td>500</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Producer accuracy %</td>
<td></td>
<td>95</td>
<td>100</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>The error of omission %</td>
<td></td>
<td>5</td>
<td>0</td>
<td></td>
<td></td>
<td>Kappa coefficient 0.95</td>
</tr>
</tbody>
</table>

The overall classification accuracy for both classes of the study is more than the 75-85 percent, which is acceptable as stated in GIS studies, and supports that accuracy assessment is a compromise between perfect and confident (Keranen and Kolvoord, 2014; Wondrade et al., 2014, Mubako et al., 2018). The overall classification accuracy should be in the range of 84-85 percent for most satellite data classification studies (Wickham, 2013). User and producer accuracy results were thus reasonable. Another method of confirming classification accuracy is calculating the Kappa coefficient. Kappa coefficient commonly underestimates overall accuracy and is recommended for vegetation mapping (Congalton and Green, 1999; Akasheh et al., 2008). Accurate reference data are essential for testing classification accuracy (Martin et al., 2014). Therefore, our results' classification errors are partly due to the uncertainty of some water features along the river, especially in flatter areas and locations where shallow waterbodies or wetlands
exist. These areas are covered by shrublands, grown vegetation, or suspended materials whose features overlap with water features. This overtopping was observed mostly in areas where features are smaller than the spatial resolution and were reimaged in the wrong pixel of the raster data. Errors of results were calculated using omissions and commissions, which were found from 0 to 5%.

4.3.2.2: Field survey

The collected coordinates and the assigned points were checked and matched with the produced maps. These points did not cover the whole study area because that was not practical, but the results gave more confidence to MNDWI calculations.

4.3.2.3: HydroData comparison

As an additional process to confirm the accuracy of the MNDWI results, I compared the results of the surface areas for Elephant Butte and Caballo reservoirs with HydroData, which is the U.S. Bureau of Reclamation’s hydrologic database access portal that provides Reservoir data (including storage, inflow, releases, elevation, and more), Gage data (flow, flow volume, and side inflows), and Basin maps (including current reservoir capacity and current and historical snow and precipitation charts) (https://www.usbr.gov/uc/water/hydrodata/nav.html). Table 4.6 expresses the comparative results of MNDWI and HydroData of Elephant Butte reservoir at the exact date of the requisitioned Land sat data used in this study as in Appendix 4.1. The results indicate that the Elephant Butte reservoir’s surface area matched 87.41% of the HydroData results.

<table>
<thead>
<tr>
<th>Class Year</th>
<th>Waterbodies measured km²</th>
<th>% Period change</th>
<th>% Total change</th>
<th>Waterbodies estimated (HydroData) km²</th>
<th>Difference</th>
<th>% Difference</th>
<th>% Accuracy of MNDWI</th>
</tr>
</thead>
<tbody>
<tr>
<td>1994</td>
<td>144.10</td>
<td></td>
<td></td>
<td>140.24</td>
<td>3.86</td>
<td>2.68</td>
<td>97.32</td>
</tr>
<tr>
<td>2000</td>
<td>120.26</td>
<td>-16.50</td>
<td>-16.50</td>
<td>115.48</td>
<td>4.78</td>
<td>3.97</td>
<td>96.03</td>
</tr>
<tr>
<td>2005</td>
<td>54.09</td>
<td>-55.00</td>
<td>-62.50</td>
<td>51.94</td>
<td>2.15</td>
<td>3.97</td>
<td>96.03</td>
</tr>
</tbody>
</table>
Table 4.1: Comparison between MNDWI and HydroData of Caballo reservoir.

<table>
<thead>
<tr>
<th>Class</th>
<th>Year</th>
<th>Waterbodies measured km²</th>
<th>% Period change</th>
<th>% Total change</th>
<th>Waterbodies estimated (HydroData) km²</th>
<th>Difference</th>
<th>% Difference</th>
<th>% Accuracy of MNDWI</th>
</tr>
</thead>
<tbody>
<tr>
<td>1994</td>
<td>43.98</td>
<td>43.91</td>
<td>0.07</td>
<td>0.16</td>
<td>99.84</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2005</td>
<td>16.65</td>
<td>-37.80</td>
<td>-62.10</td>
<td>15.63</td>
<td>6.15</td>
<td>93.85</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2010</td>
<td>21.15</td>
<td>27.00</td>
<td>-51.90</td>
<td>17.39</td>
<td>3.76</td>
<td>82.21</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2015</td>
<td>13.94</td>
<td>-34.10</td>
<td>-68.30</td>
<td>13.54</td>
<td>2.89</td>
<td>97.11</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2018</td>
<td>12.32</td>
<td>-11.30</td>
<td>-72.00</td>
<td>12.52</td>
<td>-1.69</td>
<td>98.31</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2020</td>
<td>20.07</td>
<td>40.31</td>
<td>-53.08</td>
<td>21.91</td>
<td>-1.84</td>
<td>90.84</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The average accuracy 91.76

Table 4.7 expresses the comparative results of MNDWI and HydroData for Caballo reservoir at the exact date of the requisitioned Land sat data used in this study as in Appendix 4.1. The results indicate that the surface area of the Caballo reservoir matched 91.76% of the HydroData results.

The average accuracy 87.41

4.4. CONCLUSION

This study applied modified normalized difference water index MNDWI as remote sensing and geographic information systems techniques to visualize, extract, measure, and assess surface water feature alteration in the Middle Rio Grande region in the 26 years 1994-2020.

Results show that surface aquatic features have decreased more than 66 percent from 1994 until 2018. The main water reservoirs of the Elephant Butte reservoir decreased 83 percent, and the Caballo reservoir decreased 72 percent. Moreover, in 2020, the surface water area ended with a reduction of 46.9 percent after saving reasonable amounts of water in the 2018 and 2019 seasons. The storage of the two reservoirs ended with a decrease of 59 percent in the Elephant Butte
reservoir and 53 in the Caballo reservoir. The study results are valuable outcomes that will help understand the spatial and temporal aspects of surface water and its change in this region and support stakeholders and decision-makers manage this precious component better.

These results bring up some important questions that need to be answered, like what will the future of surface water extent in the region? What are the implications of surface water reduction on future settlement in the region? What are the consequences of surface water reduction on biodiversity and sustainability in the region? What are the impacts of surface water reduction on the ecological systems in and around the Elephant Butte and Caballo reservoirs? Is there any way to mitigate the change of waterbodies areas?

This study recommended some changes and improvements in water uses and conservation. Because of the large surface area of the Elephant Butte and the Caballo reservoirs, there is a need to work toward reducing evaporation rates by covering their surface. Since most farming lands use flood irrigation methods that consume vast amounts of water, shifting to more efficient and less water consumption methods such as sprinkler and drip methods is better. Because agriculture consumes an immense amount of water, change agriculture practices to less using water crops. Policy changes to better water use practices that sustain this resource and extend its existence. Implementing more scientific research on the driving forces behind surface water change and the deficit of its needs that Hargrove et al. demonstrated in 2020 be conducted, which are: decreased snowpack and changed flows times in the headwaters of the Rio Grande/Rio Bravo, increasing temperatures and evapotranspiration rates, change of agricultural practices toward high water demand crops, increasing salinity in water sources and soils, and urban growth in the river area.

ABSTRACT

Change detection of land-use/land-cover is one of the important analysis measures applied to land use/land cover classifications to find where and when the changes happened, their areas, patterns, and trends. Remote sensing (RS) and Geographic Information System (GIS) technologies provide opportunities and abundant applications to implement change detection at different scales, such as regional scales that were not available earlier. This study applied remote sensing and GIS technologies to perform land-use/land-cover change detection in the Middle Rio Grande Region. Change detection analysis applied to land use/land cover classifications for the 21-year period 1994-2015 in the Middle Rio Grande Region on the US-Mexico border, the area from near San Antonio, New Mexico to Presidio, Texas and Ojinaga, Chihuahua, including cities of El Paso, Texas, Ciudad Juárez, Chihuahua, and Las Cruces, New Mexico. Results show that the agricultural land decreased by about 12%, mainly around the major metropolitan areas of El Paso, Ciudad Juárez, and Las Cruces, to provide land for developed open space and developed urban areas, which increased by about 27% and 45% respectively. The surface water areas across the region decreased by about 56% due to precipitation and snowpack reduction. Other identified land use changes include a decrease in Evergreen forests which decreased by about 30%, and loss of wetlands during fires and precipitation reduction. Shrubland areas increased and decreased to end with about a 1% increase at the end of the analysis period in 2015 by gaining some significant areas from agriculture, evergreen forests, and surface water. Possible impacts of these changes include a shortage of water allocations for the competitive demands of agriculture and the transfer of some of these allocations to land developers in cities. Official developers, decision makers,
ranchers, sponsors, and other stakeholders might find the study valuable and helpful in resource management, water conservation measures, environment protection, and forecasting future growth.

**Keywords:** Change detection, change patterns, Change trends, Environment, ecosystems, climate, land use, land cover.

### 5.A.1. Introduction

Change detection is an approach for analyzing data of an area at different times and distinguishes the information of change (Almutairi et al., 2010; Hussain et al., 2013; Wan et al., 2018; Silveira et al., 2018; Xu et al., 2019). The objectives of change detection include identifying the geographical location and type of changes, quantifying the changes, and assessing the accuracy of change detection results (Longbotham et al., 2012; Hussain et al., 2013; Kotkar et al., 2015; Devi et al., 2015; Dalmiya et al., 2019; Asokan et al., 2019). It has been widely used in monitoring natural resources, disasters, ecosystems, and urban development (Longbotham et al., 2012; Wan et al., 2018; Xu et al., 2019). Change detection bases use multi-temporal data to analyze the temporal effects of phenomena and quantify the changes (Hussain et al., 2013; Devi et al., 2015; Asokan et al., 2019; Xu et al., 2019). Monitoring changes provide visions for scientists and guidance for planning authorities, decision-makers, resource management, and sustainable environmental management. Monitoring changes requires measuring and understanding patterns and trends of change (Homer et al., 2020; Kaya et al., 2020; Chamling et al., 2020). Driving forces contributing to land use change. Comprise demographic, commercial, technological, institutional, and socio-cultural forces (Zhu et al., 2010; Van Vliet et al., 2015; Kale et al., 2016; Kaya et al., 2020; Dagnachew et al., 2020), biophysical circumstances, spatial communications, spatial strategies (Van Vliet et al., 2015; Kaya et al., 2020), slope, elevation, distance to roads, distance
to rivers, distance to community centers, an average of annual precipitation, people density, soil types (Zhu et al., 2010; Kale et al., 2016; Andualem et al., 2018; Hishe et al., 2020), and industrial development (Boori et al., 2015; Kaya et al., 2020). These forces put pressure on land resources and create uncertainty in their availability, long-term sustainability, and resiliency (Arowolo et al., 2017; Halefom et al., 2018; Boggie et al., 2018; Shen et al., 2020). Considering and understanding these forces is important for framing and implementing effective and environmental land use policy (Kaya et al., 2020; Chamling et al., 2020).

Land-use/land-cover change detection has been a major driver of the advances in remote sensing data analysis (Chen et al., 2012; Andualem et al., 2018; Tewabe et al., 2020). Change detection can be divided into pixel-based and object-based change detection (Tan et al., 2019; Wan et al., 2019). Change detection techniques have used individual pixels (pixel-based) as basic units of analysis for a long time. Recently, and after the availability of high-performance computing systems and effective software algorithms, more opportunities have been augmented for feature segmentation and extraction from multispectral and multiscale remote sensing imagery and the implementation of a recent change detection approach that has become known as object-based change detection (Chen et al., 2012; Bueno et al., 2019; Wan et al., 2019).

In this study, I applied change detection analysis to the Middle Rio Grande Region. The objectives of this study are to identify the types of changes and their geographical locations, quantify the changes, detect the trends of these changes, and assess the accuracy of change detection results by using remote sensing and geographic information systems technologies in this region for 21 years from 1994 to 2015 (Figure 1.3).

5.A.2: DATA AND METHODOLOGY
**5.A.2.2: Materials and methods**

**5.A.2.2.1: Data Preprocessing**

The flowchart shown in Figure (5.A.1) reflects the RS and GIS procedures applied in this study. Eight multispectral Landsat scenes cover the study area shown in Figure (1.3) (Path/Row): 031/039, 031/040, 032/038, 032/039, 033/037, 033/038, 034/036, and 034/037. These images were downloaded from the U.S. Geological Survey (USGS) GloVis website (http://GloVis.usgs.gov/) for the years 1994, 2000, 2005, 2010, and 2015. Each scene had less than 10 percent cloud cover.

The scenes used for the study area were chosen from Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI). The dates of the scenes were between the second half of May and the first week of July, which is considered the “leaf-on” season in this area. Substantial procedures were performed on the scenes to prepare them for the study, including mosaicking the eight scenes into one image, correcting the color differences, and clipping a final image to the study area boundaries.

Atmospheric correction was performed to remove water vapor and aerosol effects and is considered the optimal atmospheric correction method that can be used (Nguyen et al., 2015; Wang et al., 2018). Specific steps implemented in the software ENVI 5.4 were applied to the five years that have been chosen for the study. These steps included radiometric calibration to determine reflectance at the top of the atmosphere and fast line-of-sight atmospheric analysis of spectral hypercubes (FLAASH) for vapor and moisture correction to determine surface reflectance. The minimum noise fraction (MNF) linear transformation process was used to transform the study area
imagery for all analysis years. This technique, widely applied in remote sensing, was implemented in ENVI 5.4 software (Liu et al., 2016) and reduces inherent spectral dimensionality and data noise.

Figure: 5.A.1: flowchart showing RS and GIS proposed methods used in the study.
5.A.2.2.2: Image Class detection

An object-based classification method was tested alongside pixel-based classification methods using Landsat data. Supervised classification with maximum likelihood was performed by ArcGIS 10.7.1 for the five analysis years of 1994, 2000, 2005, 2010, and 2015 using the six broad land use categories defined in (Table 3.1).

5.A.2.2.3: Change detection analysis

The significance of change detection analysis is to determine which land use/land cover class changed to which (Tewabe et al., 2020). There are several used land change detection methods that include image overlay, classification comparisons, change vector analysis, principal component analysis, image rationing, and the differencing of normalized difference vegetation index (NDVI) (Silviera et al., 2018; Huang et al., 2018; Tewabe et al., 2020). Also, some modeling tools are used for change detection analysis, such as the CA-Markov model (Huang et al., 2018; Wang et al., 2020). After making land use/land cover maps for the five years 1994, 2000, 2005, 2010, and 2015, change detection analysis was performed by using classification comparisons and the CA-Markov model to identify the types of changes, their geographical locations, quantify the changes, detect the patterns and the trends of these changes, and assess the accuracy of change detection. Percentile changes in total areas and class area changes were calculated for the five years 1994, 2000, 2005, 2010, and 2015. In addition, the annual rate of change for the analysis years was calculated. Furthermore, four differences change maps were created in 1994-2000, 2000-2005, 2005-2010, and 2010-2015 to detect the change in land use/land cover categories, their patterns, and trends during the analysis period. Finally, create change trend maps for some categories such as urbanization during the analysis years 1994-2015.
5.A.2.2.4: Accuracy assessment

Accuracy assessment or validation is an essential phase in processing remote sensing data. It presents the outcome data's information value to a user and utilizes its quality for use (Tilahun et al., 2015; Rwanga et al., 2017). Classification accuracy was performed for individual land use categories and the total classification by creating a confusion matrix (Butt et al., 2015; Arulbalaji et al., 2016; Islam et al., 2018; Mubako et al., 2018). Five statistics were calculated: (A) overall accuracy, representing the proportion of all correct classifications. (B) Kappa coefficient measures the agreement of accuracy in classification assessment. (C) User accuracy calculates the probability that a pixel classification is correct on the ground. (D) Producer accuracy is the probability that a pixel of a particular land use type is assigned the correct land use category. (E) Omission error, that represents certain categories that were omitted when they existed on the ground. (F) Commission error, that represents categories that were identified as existing on the ground when in fact, they do not (Butt et al., 2015; Mubako et al., 2018).

5.A.3: Results and Discussion

5.A.3.1: Land-use/ land-cover class measurement

Class measurements were performed to find the areas of the individual classes of the study area. The processes were accomplished through a feature attributes related module in ArcGIS 10.7.1 for the five years. The final results were arranged in the table (5.A.1) and shown in figure 5.A.2.


<table>
<thead>
<tr>
<th>Year</th>
<th>Agriculture</th>
<th>Developed open space</th>
<th>Developed area</th>
<th>Water</th>
<th>Evergreen forest</th>
<th>Shrubs</th>
<th>Total Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>1994</td>
<td>1245</td>
<td>29</td>
<td>589</td>
<td>241</td>
<td>1663</td>
<td>33221</td>
<td>36988</td>
</tr>
<tr>
<td>2000</td>
<td>1190</td>
<td>33</td>
<td>768</td>
<td>185</td>
<td>1749</td>
<td>33063</td>
<td>36988</td>
</tr>
<tr>
<td>2005</td>
<td>1125</td>
<td>36</td>
<td>933</td>
<td>122</td>
<td>2126</td>
<td>32646</td>
<td>36988</td>
</tr>
</tbody>
</table>
5.A.3.2: Change Detection Analysis

5.A.3.2.1: Land use/land cover percentile change of total areas

Land use/land cover class areas changed during the analysis period 1994-2015, as shown in Table 5.A.2. The table designates the percentile of each category at the beginning of the study in 1994. It also shows each class’s change percentile from the total area of interest during the study period. The results show that agriculture and surface water areas experienced a continuous decrease during the analysis period to reach 2.95 percent of the total area in 2015. However, developed open space and developed areas increased repeatedly during the analysis period to cover 0.11 percent of the entire area in 2015. Evergreen forest areas increased during 1994-2010 to be

<table>
<thead>
<tr>
<th>2010</th>
<th>1111</th>
<th>40</th>
<th>1022</th>
<th>135</th>
<th>2155</th>
<th>32525</th>
<th>36988</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015</td>
<td>1091</td>
<td>40</td>
<td>1078</td>
<td>106</td>
<td>1148</td>
<td>33525</td>
<td>36988</td>
</tr>
</tbody>
</table>

Figure 5.A.2: The Middle Rio Grande land use/land cover classes 1994-2015.
5.83 percent of the total area. Those areas decreased after 2010 to be 3.10 percent in 2015. Shrubland areas decreased during 1994-2010 to be 87.93 percent of the entire area, and then it increased by gaining areas from the decreased areas, such as evergreen forests, to be 90.64 percent in 2015.


<table>
<thead>
<tr>
<th>% Change in total area</th>
<th>1994</th>
<th>2000</th>
<th>2005</th>
<th>2010</th>
<th>2015</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>3.37</td>
<td>3.22</td>
<td>3.04</td>
<td>3.00</td>
<td>2.95</td>
</tr>
<tr>
<td>Open space</td>
<td>0.08</td>
<td>0.09</td>
<td>0.10</td>
<td>0.11</td>
<td>0.11</td>
</tr>
<tr>
<td>Developed area</td>
<td>1.59</td>
<td>2.08</td>
<td>2.52</td>
<td>2.76</td>
<td>2.91</td>
</tr>
<tr>
<td>Water</td>
<td>0.65</td>
<td>0.50</td>
<td>0.33</td>
<td>0.36</td>
<td>0.29</td>
</tr>
<tr>
<td>Evergreen forest</td>
<td>4.50</td>
<td>4.73</td>
<td>5.75</td>
<td>5.83</td>
<td>3.10</td>
</tr>
<tr>
<td>Shrubs</td>
<td>89.82</td>
<td>89.39</td>
<td>88.26</td>
<td>87.93</td>
<td>90.64</td>
</tr>
</tbody>
</table>

5.A.3.2.2: land use/land cover percentile changes of class areas

The areas of land-use/land-cover categories changed during the analysis period 1994-2015, as shown in table 5.A.3, which explains the percentile change of each of these categories for four different periods; 1994-2000, 2000-2005, 2005-2010, and 2010-2015. It also shows the total change percentile for the 21 years of the analysis. For example, the agriculture category decreased by 4.42 percent in the first analysis period 1994-2000, 5.46 in the second period 2000-2005, 1.24 percent in the third period 2005-2010, and decreased by 1.8 percent in the fourth period 2010-2015. However, this category decreased during the 21 years, about 12 percent of its area to allow the developed areas to expand and cover new parts in the region.


<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>-4.42</td>
<td>-5.46</td>
<td>-1.24</td>
<td>-1.80</td>
<td>-12.37</td>
</tr>
<tr>
<td>Open space</td>
<td>12.12</td>
<td>8.33</td>
<td>10.00</td>
<td>0.00</td>
<td>27.50</td>
</tr>
<tr>
<td>Developed area</td>
<td>23.31</td>
<td>17.68</td>
<td>8.71</td>
<td>5.19</td>
<td>45.36</td>
</tr>
<tr>
<td>Water</td>
<td>-23.24</td>
<td>-34.05</td>
<td>9.63</td>
<td>-21.48</td>
<td>-56.02</td>
</tr>
<tr>
<td>Evergreen forest</td>
<td>4.92</td>
<td>17.73</td>
<td>1.35</td>
<td>-46.73</td>
<td>-30.97</td>
</tr>
</tbody>
</table>
The areas of land-use/land-cover categories changed during the analysis period 1994-2015 at different annual rates, as shown in Table 5.A.4. The change rates are different from one category to another and from period to another. These rates indicate a decrease in some classes, such as agriculture, which reflects the reduction of agricultural lands, which were lost in 1994-2000 period 9.17 km² annually, lost in 2000-2005 period 13 km² annually, lost in 2005-2010 2.8 km² annually, and lost in 2010-2015 period 4 km² annually. Some other rates indicate an increase in class areas such as developed open space, which increased by 0.67 km² annually in the 1994-2000 period, 0.6 km² annually in 2000-2005 period, and 0.8 km² annually in the 2005-2010 period. Developed areas increased overtime by 29.83 km² annually in 1994-2000, 33 km² annually in 2000-2005, 17.8 km² annually in 2005-2010, and 11.2 km² annually in 2010-2015. Evergreen forests and shrublands appeared to fluctuate according to precipitation and forest fires.

Table 5.A.4: The Middle Rio Grande land use/land cover annual rate of change (km²/y) 1994-2015

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>-9.17</td>
<td>-13.00</td>
<td>-2.80</td>
<td>-4.00</td>
</tr>
<tr>
<td>Open space</td>
<td>0.67</td>
<td>0.60</td>
<td>0.80</td>
<td>0.00</td>
</tr>
<tr>
<td>Developed area</td>
<td>29.83</td>
<td>33.00</td>
<td>17.80</td>
<td>11.20</td>
</tr>
<tr>
<td>Water</td>
<td>-9.33</td>
<td>-12.60</td>
<td>2.60</td>
<td>-5.80</td>
</tr>
<tr>
<td>Evergreen forest</td>
<td>14.33</td>
<td>75.40</td>
<td>5.80</td>
<td>-201.40</td>
</tr>
<tr>
<td>Shrubs</td>
<td>-26.33</td>
<td>-83.40</td>
<td>-24.20</td>
<td>200.00</td>
</tr>
</tbody>
</table>

To understand how land use/land cover changes happened, their trends, patterns, and changes in land use/land cover categories were analyzed during the 1994-2000, 2000-2005, 2005-2010, and 201-2015 periods. Results showed complex dynamics of change in the region among land use/land cover categories where certain land uses lost their areas to other land uses and gained from them other areas in other sites.
5.A.3.2.4: 1994-2000 change detection

1994-2000 changes in land use/land cover areas are shown in table 5.A.5. Figures 5.A.3 and 5.A.4 indicate the changes in different categories. The decrease in agricultural areas largely offset developed growth. For example, about 51 km² of the agricultural lands were converted into developed areas. The changes in surface water areas noted in agriculture settings are not changes but reflect water management strategies that are dependent on allocations and other factors. The shrublands areas also decreased following the expansion of agriculture, developed, and evergreen forests categories. Change detection results reflected the trend to produce high water consumption crops such as alfalfa or pecans instead of managing the decreased water resources towards less water consumption crops. Agricultural lands added about 12 km² from shrublands to increase water deficit complications and environmental problems such as losing native vegetation. In addition, the surface water bodies areas decreased. Developed open space, developed areas, and evergreen increased by taking areas from the shrublands and the agricultural areas. For instance, about 332 km² of shrublands were converted to forests. Also, significant areas of all categories resist the change, as shown in figures 5.A.5 and 5.A.6.

Table 5.A.5: The Middle Rio Grande cross tabulation matrix 1994-2000 (areas in km²).

<table>
<thead>
<tr>
<th>Category</th>
<th>Agriculture</th>
<th>Open space</th>
<th>Developed area</th>
<th>Water</th>
<th>Evergreen forest</th>
<th>Shrubs</th>
<th>2000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>1173.78</td>
<td>0.00</td>
<td>1.26</td>
<td>3.07</td>
<td>0.02</td>
<td>11.91</td>
<td>1190.04</td>
</tr>
<tr>
<td>Open space</td>
<td>1.73</td>
<td>28.49</td>
<td>0.71</td>
<td>0.05</td>
<td>0.00</td>
<td>2.40</td>
<td>33.38</td>
</tr>
<tr>
<td>Developed area</td>
<td>50.60</td>
<td>0.79</td>
<td>584.10</td>
<td>0.22</td>
<td>0.02</td>
<td>132.02</td>
<td>767.75</td>
</tr>
<tr>
<td>Water</td>
<td>5.95</td>
<td>0.11</td>
<td>0.10</td>
<td>172.21</td>
<td>0.02</td>
<td>6.97</td>
<td>185.35</td>
</tr>
<tr>
<td>Evergreen forest</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>1417.70</td>
<td>331.60</td>
<td>1749.30</td>
</tr>
<tr>
<td>Shrubs</td>
<td>13.15</td>
<td>0.02</td>
<td>2.36</td>
<td>65.03</td>
<td>245.71</td>
<td>32736.10</td>
<td>33062.38</td>
</tr>
<tr>
<td>1994</td>
<td>1245.21</td>
<td>29.42</td>
<td>588.54</td>
<td>240.57</td>
<td>1663.47</td>
<td>33220.99</td>
<td>36988.19</td>
</tr>
</tbody>
</table>
Figure 5.A.3: The Middle Rio Grande change detection 1994-2000.
Figure 5.A.4: El Paso County change detection 1994-2000.
Figure 5.A.5: The Middle Rio Grande persistence areas of change 1994-2000.
Figure 5.A.6: El Paso County persistence areas of change 1994-2000.
As shown in Table 5.A.6 and figure 5.A.19, the different land-use/land-cover categories experienced gains and losses in their areas during the 1994-2000 period. These uses ended with net change indicating a decrease of some land-use/land-cover areas such as agriculture which gained about 16 km² most of these areas from shrublands and lost about 71 km² most of them to developed areas to end up with a decrease of about 55 km² as shown in figures 5.A.7 and 5.A.8. Surface waterbodies gained about 13 km² by covering some areas during the increase of streamflow and water allocations to the agricultural lands. These areas lost about 68 km², most from the Elephant Butte and Caballo reservoirs, due to snowpack and streamflow reduction to a decrease of about 55 km² as shown in figures 5.A.13 and 5.A.14. shrublands gained about 326 km², most of them from surface waterbodies areas that were shrinking along the region and allowing shrublands to grow instead, and evergreen forests that lost significant areas due to wildfires. However, shrublands lost about 485 km², most of them to evergreen forests and urban expansion areas, to decrease by about 158 km² at the end of the period as shown in figures 5.A.17 and 5.A.18. Developed open space area gained about five km² whereas it lost about one km² area to end up with an increase of about four km² as shown in figures 5.A.9 and 5.A.10. The developed area gained about 183 km² and lost about four km² areas to increase by about 179 km², as shown in figures 5.A.11 and 5.A.12. The evergreen forest areas gained about 332 km² and lost about 246 km² to end up with an increase of about 86 km² during their recovery, as shown in figures 5.A.15 and 5.A.16.

<table>
<thead>
<tr>
<th>1994-2000 change detection</th>
<th>Gains at the end of the period</th>
<th>Losses at the end of the period</th>
<th>Net change at the end of the period</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sq.km</td>
<td>% Change</td>
<td>Sq.km</td>
</tr>
<tr>
<td>Agriculture</td>
<td>16.26</td>
<td>1.37</td>
<td>-71.46</td>
</tr>
<tr>
<td>Open space</td>
<td>4.89</td>
<td>14.65</td>
<td>-0.92</td>
</tr>
<tr>
<td>Developed area</td>
<td>183.68</td>
<td>23.92</td>
<td>-4.44</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Vegetation Type</th>
<th>Gains</th>
<th>Losses</th>
<th>Net Change</th>
<th>1994-2000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evergreen forest</td>
<td>331.6</td>
<td>18.96</td>
<td>-245.76</td>
<td>-14.77</td>
</tr>
<tr>
<td>Shrubs</td>
<td>326.28</td>
<td>0.99</td>
<td>-484.89</td>
<td>-1.46</td>
</tr>
</tbody>
</table>

Figure 5.A.7: El Paso County gains, losses, and net change of agriculture areas 1994-2000.
Figure 5.A.8: The Middle Rio Grande gains, losses, net change of agriculture areas 1994-2000.
Figure 5.A.9: The Middle Rio Grande gains, losses, and net change of developed open space areas 1994-2000
Figure 5.A.10: El Paso County gains, losses, and net change of developed open space areas 1994-2000.
Figure 5.A.11: The Middle Rio Grande gains, losses, and net change of developed areas 1994-2000.
Figure 5.A.12: El Paso County gains, losses, and net change of developed areas 1994-2000.
Figure 5.A.13: The Middle Rio Grande gains, losses, and net change of water areas 1994-2000.
Figure 5.A.14: Sierra County gains, losses, and net change of water areas 1994-2000.
Figure 5.A.15: The Middle Rio Grande gains, losses, and net change of evergreen forest areas 1994-2000.
Figure 5.A.16: Socorro County gains, losses, and net change of evergreen forest areas 1994-2000.
Figure 5.A.17: The Middle Rio Grande gains, losses, and net change of shrublands areas 1994-2000.
Figure 5.A.18: El Paso County gains, losses, and net change of shrublands areas 1994-2000.
The Middle Rio Grande gains, losses, and net change of class areas 1994-2000

<table>
<thead>
<tr>
<th></th>
<th>Agriculture</th>
<th>Open space</th>
<th>Developed area</th>
<th>Water</th>
<th>Evergreen forest</th>
<th>Shrubs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gains</td>
<td>16.26</td>
<td>4.89</td>
<td>183.68</td>
<td>13.14</td>
<td>331.6</td>
<td>326.28</td>
</tr>
<tr>
<td>Losses</td>
<td>-71.46</td>
<td>-0.92</td>
<td>-4.44</td>
<td>-68.37</td>
<td>-245.76</td>
<td>-484.89</td>
</tr>
<tr>
<td>Net change</td>
<td>-55.21</td>
<td>3.97</td>
<td>179.24</td>
<td>-55.23</td>
<td>85.84</td>
<td>-158.61</td>
</tr>
</tbody>
</table>

Figure 5.A.19: The Middle Rio Grande gains, losses, and net change of class areas 1994-2000.

5.A.3.2.5: 2000-2005 change detection

2000-2005 changes of land use/land cover as shown in table 5.A.7. Figures 5.A.20. and 5.A.21 indicate the changes of different categories. Also, significant areas of all categories persist in the change and continue with the same characteristics as shown in figures 5.A.22 and 5.A.23. The results show that about 35 km² of the agricultural lands were converted into developed areas following urban growth in the region. As well, agricultural lands lost about 52 km² that was converted to the shrublands in the same period. The result illustrated another severe problem: the trend to produce high water consumption crops such as alfalfa or pecans instead of managing the decreased water resources towards more water efficient crops. However, agricultural lands gained about 22 km² from shrublands to raise water deficit complications and environmental problems such as losing native vegetation. In addition, the extent of surface water areas decreased.
Developed open space, developed areas, and evergreen forests increased by taking essential areas from the shrublands and the agriculture areas. For example, about 523 km² of shrublands were converted to forests. The changes in surface water areas noted in agriculture settings are not changes but reflect water management strategies that are dependent on allocations and other factors. The shrublands’ areas also decreased to give about 22 km² of its areas to agriculture and 130 km² to the developed area. Moreover, the surface waterbodies decreased to provide about 77 km² to shrublands. Developed open space increased by taking about one km² from agricultural lands, two km² from the developed area, and two km² from shrublands. Developed areas increased by taking 35 km² from agricultural lands and 130 km² from shrublands.

Table 5.A.7: The Middle Rio Grande cross tabulation matrix 2000-2005 (areas in sq.km).

<table>
<thead>
<tr>
<th>Category</th>
<th>Agriculture</th>
<th>Open space</th>
<th>Developed area</th>
<th>Water</th>
<th>Evergreen forest</th>
<th>Shrubs</th>
<th>2005</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>1097.00</td>
<td>0.14</td>
<td>0.00</td>
<td>6.07</td>
<td>0.01</td>
<td>21.97</td>
<td>1125.19</td>
</tr>
<tr>
<td>Open space</td>
<td>0.86</td>
<td>30.78</td>
<td>2.18</td>
<td>0.10</td>
<td>0.00</td>
<td>2.34</td>
<td>36.25</td>
</tr>
<tr>
<td>Developed area</td>
<td>35.00</td>
<td>2.04</td>
<td>765.11</td>
<td>0.66</td>
<td>0.06</td>
<td>129.70</td>
<td>932.57</td>
</tr>
<tr>
<td>Water</td>
<td>5.27</td>
<td>0.14</td>
<td>0.47</td>
<td>101.47</td>
<td>0.00</td>
<td>14.25</td>
<td>121.60</td>
</tr>
<tr>
<td>Evergreen forest</td>
<td>0.02</td>
<td>0.00</td>
<td>0.02</td>
<td>0.01</td>
<td>1601.44</td>
<td>523.23</td>
<td>2124.72</td>
</tr>
<tr>
<td>Shrubs</td>
<td>51.85</td>
<td>0.29</td>
<td>0.00</td>
<td>77.03</td>
<td>147.45</td>
<td>32371.00</td>
<td>32647.62</td>
</tr>
<tr>
<td>2000</td>
<td>1189.99</td>
<td>33.38</td>
<td>767.78</td>
<td>185.35</td>
<td>1748.96</td>
<td>33062.48</td>
<td>36988</td>
</tr>
</tbody>
</table>
Figure 5.A.20: The Middle Rio Grande change detection 2000-2005.
Figure 5.A.21: El Paso County change detection 2000-2005.
Figure 5.A.22: The Middle Rio Grande change persistence areas 2000-2005.
Figure 5.A.23: El Paso change persistence areas 2000-2005.
As shown in Table 5.A.8 and figure 5.A.36, the different land-use/land-cover categories their gains and losses of their areas and net change during the 2000-2005 period. Agricultural lands gained about 28 km² most of these areas from shrublands and lost about 93 km², most of them to shrublands due to decreasing agricultural activities in some parts. Also, some other agricultural lands were converted to developed areas as part of the urban growth to decrease by about 65 km², as shown in figures 5.A.24 and 5.A.25. Surface waterbodies gained about 20 km² by covering some areas during the increase of streamflow and water allocations to the agricultural lands. These areas lost about 84 km², most from the Elephant Butte and the Caballo reservoirs due to snowpack and streamflow reduction to decrease by about 64 km² as shown in figures 5.A.30 and 5.A.31. Shrublands gained about 267 km², most of them from evergreen forests, and surface waterbodies decrease. However, shrublands lost about 691 km², most of them to evergreen forests and urban expansion areas, ending with about 415 km² decrease as shown in figures 5.A.34 and 5.A.35. Developed open space areas gained about five km² whereas it lost about three km² areas to end up with an increase of nearly three km² as shown in figures 5.A.26 and 5.A.27. The developed area gained about 167 km² and lost about three km² areas to increase by approximately 165 km², as shown in figures 5.A.28 and 5.A.29. The evergreen forest area gained about 523 km² and lost about 148 km² areas to increase by about 376 km² during their recovery, as shown in figures 5.A.32 and 5.A.33.


<table>
<thead>
<tr>
<th>2000-2005 change detection</th>
<th>Gains at the end of the period</th>
<th>Losses at the end of the period</th>
<th>Net change at the end of the period</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sq. km</td>
<td>% Change</td>
<td>Sq. km</td>
</tr>
<tr>
<td>Agriculture</td>
<td>28.19</td>
<td>2.51</td>
<td>-92.99</td>
</tr>
<tr>
<td>Open space</td>
<td>5.48</td>
<td>15.11</td>
<td>-2.61</td>
</tr>
<tr>
<td>Developed area</td>
<td>167.46</td>
<td>17.96</td>
<td>-2.67</td>
</tr>
<tr>
<td>Water</td>
<td>20.13</td>
<td>16.55</td>
<td>-83.88</td>
</tr>
<tr>
<td>Evergreen forest</td>
<td>523.28</td>
<td>24.63</td>
<td>-147.52</td>
</tr>
</tbody>
</table>
Figure 5.A.24: The Middle Rio Grande gains, losses, and net change of agriculture areas 2000-2005.
Figure 5.A.25: El Paso gains, losses, and net change of agriculture areas 2000-2005.
Figure 5.A.26: The Middle Rio Grande gains, losses, and net change of developed open space areas 2000-2005.
Figure 5.A.27: El Paso gains, losses, and net change of developed open space areas 2000-2005.
Figure 5.A.28: The Middle Rio Grande gains, losses, and net change of developed areas 2000-2005.
Figure 5.A.29: El Paso gains, losses, and net change of developed areas 2000-2005.
Figure 5.A.30: The Middle Rio Grande gains, losses, and change net change of water areas 2000-2005.
Figure 5.A.31: Sierra County gains, losses, and net of water areas 2000-2005.
Figure 5.A.32: The Middle Rio Grande gains, losses, and net change of evergreen forest areas 2000-2005.
Figure 5.A.33: Socorro gains, losses, and net change of evergreen forest areas 2000-2005.
Figure 5.A.34: The Middle Rio Grande gains, losses, and net change of shrublands areas 2000-2005.
Figure 5.A.35: Dona Ana gains, losses, and net change of shrublands areas 2000-2005.
Figure 5.A.36: The Middle Rio Grande gains, losses, and net change of class areas 2000-2005.

5.A.3.2.6: 2005-2010 change detection

Changes in land use/land cover 2005-2010 are shown in table 5.A.9. Also, figures 5.A.37 and 5.A.38 indicate the changes in different categories. The results showed that about 13 km² of the agricultural lands were converted into developed areas following urban growth in the region. Also, agricultural lands lost about three km² that were converted to the shrublands in the same period. The results show the areas that resist change as shown in figures 5.A.39 and 5.A.40.

Agricultural lands gained about three km² from shrublands to raise water deficit complications and environmental problems such as losing native vegetation. In addition, the surface waterbodies areas increased to expand by about 15 km² on shrublands. Developed open space, developed areas, and evergreen forests increased by taking important areas from the shrublands and the agriculture areas. Evergreen forests grew about 30 km² to expand on shrublands. The changes in surface waterbodies areas noted in agriculture settings are not changes but reflect water management.
strategies that are dependent on allocations and other factors. The shrublands' areas also decreased to give about three km$^2$ of its areas to agriculture and 78 km$^2$ to the developed area. Developed open space areas increased by taking about four km$^2$ from agricultural lands, two km$^2$ from the developed area, and two km$^2$ from shrublands. Developed areas increased by taking about 13 km$^2$ from agricultural lands and 78 km$^2$ from shrublands.

Table 5.A.9: The Middle Rio Grande cross tabulation matrix 2005-2010 (areas in sq.km).

<table>
<thead>
<tr>
<th>Category</th>
<th>Agriculture</th>
<th>Open space</th>
<th>Developed area</th>
<th>Water</th>
<th>Evergreen forest</th>
<th>Shrubs</th>
<th>2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>1106.52</td>
<td>0.00</td>
<td>1.04</td>
<td>0.44</td>
<td>0.00</td>
<td>2.70</td>
<td>1110.70</td>
</tr>
<tr>
<td>Open space</td>
<td>0.26</td>
<td>35.49</td>
<td>0.15</td>
<td>0.04</td>
<td>0.00</td>
<td>3.92</td>
<td>39.86</td>
</tr>
<tr>
<td>Developed area</td>
<td>13.07</td>
<td>0.68</td>
<td>930.07</td>
<td>0.03</td>
<td>0.00</td>
<td>78.16</td>
<td>1021.99</td>
</tr>
<tr>
<td>Water</td>
<td>2.34</td>
<td>0.04</td>
<td>0.51</td>
<td>116.83</td>
<td>0.00</td>
<td>15.20</td>
<td>134.92</td>
</tr>
<tr>
<td>Evergreen forest</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>2125.71</td>
<td>29.99</td>
<td>2155.70</td>
<td></td>
</tr>
<tr>
<td>Shrubs</td>
<td>2.90</td>
<td>0.05</td>
<td>1.29</td>
<td>4.26</td>
<td>0.00</td>
<td>32516.54</td>
<td>32525.04</td>
</tr>
<tr>
<td>2005</td>
<td>1125.09</td>
<td>36.25</td>
<td>933.05</td>
<td>121.60</td>
<td>2125.71</td>
<td>32646.51</td>
<td>36988</td>
</tr>
</tbody>
</table>
Figure 5.A.37: The Middle Rio Grande change detection 2005-2010.
Figure 5.A.38: El Paso County change detection 2005-2010.
Figure 5.A.39: The Middle Rio Grande change persistence areas 2005-2010.
Table 5.A.40: El Paso County change persist of class areas 2005-2010.
As shown in Table 5.A.10 and figure 5.A.53, the different land-use/land-cover categories their gains and losses of their areas and net change during the 2005-2010 period. Agricultural lands gained about four km$^2$ most of these areas from shrublands and lost about 18 km$^2$, most of them to shrublands due to decreasing agricultural activities areas in some parts. Also, some other agricultural lands were converted into developed areas to cover the urban growth to end up with a decrease of about 14 km$^2$ as shown in figures 5.A.41 and 5.A.42. Surface waterbodies gained about 18 km$^2$ by covering some areas during the increase of streamflow and water allocations to the agricultural lands. These areas lost about five km$^2$ to increase about 13 km$^2$ due to the increase of streamflow as shown in figures 5.A.47 and 5.A.48. Shrublands gained about eight km$^2$, most of them from agricultural lands and surface waterbodies. However, shrublands lost about 130 km$^2$, most of them to the developed areas and evergreen forests to decrease by about 121 km$^2$ as shown in figures 5.A.51 and 5.A.52. Developed open space areas gained about four km$^2$ whereas it lost about one km$^2$ areas to end up with an increase of about four km$^2$ as shown in figures 5.A.43 and 5.A.44. The developed area gained about 92 km$^2$ and lost about three km$^2$ areas to increase by about 89 km$^2$, as shown in figures 5.A.45 and 5.A.46. The evergreen forest area gained about 30 km$^2$, as shown in figures 5.A.49 and 5.A.50.

Table 5.A.10: The Middle Rio Grande gains, losses, and net change of class areas 2005-2010.

<table>
<thead>
<tr>
<th>2005-2010 change detection</th>
<th>Gains at the end of the period</th>
<th>Losses at the end of the period</th>
<th>Net change at the end of the period</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sq. km</td>
<td>% Change</td>
<td>Sq. km</td>
</tr>
<tr>
<td>Agriculture</td>
<td>4.18</td>
<td>0.38</td>
<td>-18.57</td>
</tr>
<tr>
<td>Open space</td>
<td>4.37</td>
<td>10.96</td>
<td>-0.76</td>
</tr>
<tr>
<td>Developed area</td>
<td>91.92</td>
<td>8.99</td>
<td>-2.98</td>
</tr>
<tr>
<td>Water</td>
<td>18.09</td>
<td>13.41</td>
<td>-4.77</td>
</tr>
<tr>
<td>Evergreen forest</td>
<td>29.99</td>
<td>1.39</td>
<td>0.00</td>
</tr>
<tr>
<td>Shrubs</td>
<td>8.50</td>
<td>0.03</td>
<td>-130.00</td>
</tr>
</tbody>
</table>
Figure 5.A.41: The Middle Rio Grande gains, losses, and net change of agriculture areas 2005-2010.
Figure 5.A.42: Dona Ana County gains, losses, and net change of agriculture areas 2005-2010.
Figure 5.A.43: The Middle Rio Grande gains, losses, and net change of developed open space areas 2005-2010.
Figure 5.A.44: Dona Ana County gains, losses, and net change of developed open areas 2005-2010.
Figure 5.A.45: The Middle Rio Grande gains, losses, and net change of developed areas 2005-2010.
Figure 5.A.46: El Paso County gains, losses, and net change of developed areas 2005-2010.
Figure 5.A.47: The Middle Rio Grande gains, losses, and net change of surface water areas 2005-2010.
Figure 5.A.48: Sierra County gains, losses, and net change of water areas 2005-2010.
Figure 5.A.49: The Middle Rio Grande gains, losses, and net change of evergreen forest areas 2005-2010.
Figure 5.A.50: Socorro County gains, losses, and net change of evergreen forest areas 2005-2010.
Figure 5.A.51: The Middle Rio Grande gains, losses, and net change of shrublands areas 2005-2010.
Figure 5.A.52: Dona Ana County gains, losses, and net change of shrublands areas 2005-2010.
2010-2015 changes in land use/land cover are shown in table 5.A.11. Also, figures 5.A.54 and 5.A.55 indicate the changes in different categories. The results showed the areas as well that persisted in the change and kept their characteristics shown in figures 5.A.56 and 5.A.57. According to the results, agricultural areas continued decreasing with a similar change trend during this period despite less gains and losses. About eight km² of the agricultural lands were converted into developed areas to reflect urban growth in the region. Also, agricultural lands lost about 29 km² that converted to the shrublands in the same period as a decrease in agricultural activities areas. Change detection results reflected another severe problem: the trend to produce high water consumption crops such as alfalfa or pecans instead of managing the decreased water resources towards more water efficient crops. Agricultural lands gained about 17 km² from shrublands to raise water deficit complications and environmental problems such as losing native vegetation. In
addition, the surface water bodies areas decreased to give about 43 km$^2$ to shrublands. Evergreen forests also decreased and lost about 1062 km$^2$ to shrublands due to the wildfires that burned crucial areas of these forests. Developed open space, developed areas, and evergreen forests increased by taking areas from the shrublands and the agricultural areas. The changes in surface water bodies areas noted in agriculture settings are not changes but reflect water management strategies that are dependent on allocations and other factors. The shrublands' areas also decreased to give about 17 km$^2$ of its agricultural areas and 47 km$^2$ to the developed area. Developed open space increased by about one km$^2$ by taking from shrublands and about two km$^2$ from the developed areas. Developed areas increased by taking eight km$^2$ from agricultural lands and 47 km$^2$ from shrublands.

Table 5.A.11: The Middle Rio Grande cross tabulation matrix 2010-2015 (areas in sq.km).

<table>
<thead>
<tr>
<th>Category</th>
<th>Agriculture</th>
<th>Open space</th>
<th>Developed area</th>
<th>Water</th>
<th>Evergreen forest</th>
<th>Shrubs</th>
<th>2015</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>1069.64</td>
<td>0.00</td>
<td>0.00</td>
<td>3.61</td>
<td>0.01</td>
<td>17.40</td>
<td>1090.66</td>
</tr>
<tr>
<td>Open space</td>
<td>0.36</td>
<td>37.08</td>
<td>1.69</td>
<td>0.09</td>
<td>0.01</td>
<td>1.42</td>
<td>40.65</td>
</tr>
<tr>
<td>Developed area</td>
<td>7.69</td>
<td>2.53</td>
<td>1019.81</td>
<td>0.86</td>
<td>0.07</td>
<td>47.24</td>
<td>1078.20</td>
</tr>
<tr>
<td>Water</td>
<td>3.59</td>
<td>0.05</td>
<td>0.48</td>
<td>87.04</td>
<td>0.00</td>
<td>15.28</td>
<td>106.44</td>
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<tr>
<td>Evergreen forest</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
<td>0.02</td>
<td>1093.05</td>
<td>54.57</td>
<td>1147.64</td>
</tr>
<tr>
<td>Shrub</td>
<td>29.42</td>
<td>0.13</td>
<td>0.00</td>
<td>43.29</td>
<td>1062.13</td>
<td>32389.48</td>
<td>33525.45</td>
</tr>
<tr>
<td>2010</td>
<td>1110.70</td>
<td>39.79</td>
<td>1021.98</td>
<td>134.92</td>
<td>2155.27</td>
<td>32525.39</td>
<td>36988.04</td>
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</table>
Figure 5.A.54: The Middle Rio Grande change detection 2010-2015.
Figure 5.A.55: El Paso County change detection 2010-2015.
Figure 5.A.56: The Middle Rio Grande change Persistence areas 2010-2015.
Figure 5.A.57: El Paso County change persistence areas 2010-2015.
As shown in Table 5.A.12 and figure 5.A.70, the different land-use/land-cover categories their gains and losses of their areas and net change during the 2010-2015 period. Agricultural lands gained about 21 km² most of these areas from shrublands and lost about 41 km², most of them to shrublands due to decreasing agricultural activities areas in some parts. Also, some other agricultural lands were converted to developed areas as part of the urban growth to decrease in total by about 20 km², as shown in figures 5.A.58 and 5.A.59. Surface waterbodies gained about 19 km² by covering some areas during the increase of streamflow and water allocations to the agricultural lands. Surface waterbodies areas lost about 48 km², to decrease about 28 km² at the end of this period as shown in figures 5.A.64 and 5.A.65. Shrublands gained about 1136 km², most of them from the decrease of surface waterbodies areas and evergreen forests due to wildfires. However, shrublands lost about 136 km², most of them to the evergreen forests and developed areas to increase by about 1000 km² at the end of this period, as shown in figures 5.A.68 and 5.A.69. Developed open space areas gained about four km² whereas it lost about four km² areas to end up with the same areas as shown in figures 5.A.60 and 5.A.61. Developed areas gained about 58 km² and lost about two km² to increase by about 56 km² at the end of the period as shown in figures 5.A.62 and 5.A.63. The evergreen forest areas gained about 55 km² and lost about 1062 km² to end up with a total decrease of about 1008 km² at the end of the analysis period, as shown in figures 5.A.66 and 5.A.67.

Table 5.A.12: The Middle Rio Grande gains, losses, and net change of class areas 2010-2015.

<table>
<thead>
<tr>
<th>2010-2015 change detection</th>
<th>Gains at the end of the period</th>
<th>Losses at the end of the period</th>
<th>Net change at the end of the period</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sq. km</td>
<td>% Change</td>
<td>Sq. km</td>
</tr>
<tr>
<td>Agriculture</td>
<td>21.09</td>
<td>1.93</td>
<td>41.06</td>
</tr>
<tr>
<td>Open space</td>
<td>3.57</td>
<td>9.01</td>
<td>3.78</td>
</tr>
<tr>
<td>Developed area</td>
<td>58.40</td>
<td>5.42</td>
<td>2.17</td>
</tr>
<tr>
<td>Water</td>
<td>19.40</td>
<td>18.22</td>
<td>47.88</td>
</tr>
<tr>
<td>Evergreen forest</td>
<td>54.59</td>
<td>4.76</td>
<td>1062.22</td>
</tr>
<tr>
<td>Shrubs</td>
<td>1135.97</td>
<td>3.39</td>
<td>135.91</td>
</tr>
</tbody>
</table>

Figure 5.A.58: The Middle Rio Grande gains, losses, and net change of agriculture areas 2010-2015.
Figure 5.A.59: El Paso County gains, losses, and net change of agriculture areas 2010-2015.
Figure 5.A.60: The Middle Rio Grande gains, losses, and net change of developed open space areas 2010-2015.
Figure 5.A.61: El Paso County gains, losses, and net change of developed open space areas 2010-2015.
Figure 5.A.62: The Middle Rio Grande gains, losses, and net change of developed areas 2010-2015.
Figure 5.A.63: El Paso County gains, losses, and net change of developed areas 2010-2015.
Figure 5.A.64: The Middle Rio Grande gains, losses, and net change of surface water areas 2010-2015.
Figure 5.A.65: Sierra County gains, losses, and net change of surface water areas 2010-2015.
Figure 5.A.66: The Middle Rio Grande gains, losses, and net change of evergreen forest areas 2010-2015.
Figure 5.A.67: Socorro County gains, losses, and net change of evergreen forest areas 2010-2015.
Figure 5.A.68: The Middle Rio Grande gains, losses, and net change of shrublands areas 2010-2015.
Figure 5.A.69: Dona Ana County gains, losses, and net change of shrub areas 2010-2015.
5.A.3.3: Change Detection trends

Land use/land cover appears to have trends of change overtime. Figures 5.A.71-5. A.75 show the change trends of the developed area expansion during the analysis period 1994-2015. Trends of this category centered on the urban areas of the three cities of El Paso, Juarez, and Las Cruces. These trends went in almost circular growth around these cities. The trends appeared to go more north in 1994-2000 during Las Cruces, El Paso, and Juarez north expansion while trends went more south in 2000-2005, 2005-2010, and 2010-2015 because El Paso and Juarez cities grew south, and Las Cruces grow east after 2000, as shown in figures 5.A.75 and 5.A.76.
Figure 5.A.71: The Middle Rio Grande Region_1994-2000 spatial trend of developed areas.
Figure 5.A.72: The Middle Rio Grande Region 2000-2005 spatial trend of developed areas.
Figure 5.A.73: The Middle Rio Grande Region_2005-2010 spatial trend of developed areas.
Figure 5.A.74: The Middle Rio Grande Region 2010-2015 spatial trend of developed areas.
Figure 5.A.75: El Paso County 2010-2015 spatial trend of developed areas.
Figure 5.A.76: Ciudad Juarez City 2010-2015 spatial trend of developed areas.
5.A.3.4: accuracy assessment

Five classifications were generated for the years 1994, 2000, 2005, 2010, and 2015 of the study area. To validate the classification results, an accuracy assessment was applied to the study's results by using several extension tools in ArcGIS 10.7.1. Accuracy assessment focused on analysis years 2005, 2010, and 2015 as stated in chapter 3 (3.3.2.1) and had an overall accuracy of 99% for the three years.

5.A.4: CONCLUSION

Change detection analysis processes that use remote sensing and geological information system technologies are adequate procedures to understand how, when, and where land use/land cover changes happen and their patterns and trends. Many applications were applied for these analysis measures, such as ArcGIS and TerrSet, that were used to accomplish this study.

The sustainability of natural resources in the Middle Rio Grande Region as a dry region and other similar locations continue to face challenges such as water supply shortage, groundwater depletion (Hargrove et al., 2020), loss of biodiversity (Fowler et al., 2018), soil pollution (Hargrove et al., 2020) and air pollution (Regier et al., 2020). Therefore, looking for solutions that promote sustainability and resiliency has become more important for sustaining resources and managing change.

The study results explained how, when, and where land use/land cover changes happened in the 21 years 1994-2015 in the Middle Rio Grande Region on the USA and Mexico border. The most dramatic change was the expansion of developed land cover classes across the study area, which grew 45 percent, and most around the metropolitan areas of El Paso, Ciudad Juarez, Las Cruces, and many other small cities and towns. Most of this expansion came at a loss to agricultural areas and shrublands. Surface waterbodies area decreased by more than 55 percent during the study
period and were replaced mainly by shrublands. However, shrublands were lost to agriculture. Shrublands also expanded in some areas due to forest fires and a reduction in surface water.

This study provides some of the first observations focused on the region's spatial and temporal environmental change and a red flag to realize the real land use/land cover change situation. Results may provide stakeholders and decision-makers with a valuable dataset for managing and forecasting development requirements, protecting ecosystems' goods and services, and estimating future demand.

The study raises some serious questions that need to be answered. The analysis applied to the classification maps revealed changes in different classes. Is the difference reasonable, acceptable, or needs to be modified, altered, or stopped? Since the developed areas expand on shrublands and agricultural areas covered with different plants, what is the future of heat island in the changed areas? Because the decrease in surface water continues over time and water demand increases, what will replace the surface water shortage?

Research on monitoring land use/land cover change and analyzing the change is an important subject that can help us understand our resources, assist in managing them, extend their lives for our needs, and provide the supplies for future generations. Further research studies with more details on the resources, their changes, their change trends, and their driving forces in this region using high resolution remote sensing data are significant and recommended.
CHAPTER 5.B: LAND USE/ LAND COVER FUTURE CHANGE PREDICTION USING CA-MARKOV MODEL AND REMOTE SENSING IN THE MIDDLE RIO GRANDE REGION 2020-2040

ABSTRACT

Future impacts on ecosystems, predict change locations, when these changes will likely happen, and their estimated extents, patterns, and trends have become important to these systems' protection and sustainable development. In the latest years, some prediction models have been used within Geographic Information System (GIS) to estimate future change locations, trends, and patterns. This study used the TerrSet model to predict land-use/land-cover change in the Middle Rio Grande Region and find their patterns and trends. The TerrSet model was applied to 2010 and 2015 land-use/land-cover classification data to predict the future change in the 20 years 2020-2040 in the Middle Rio Grande Region. This region located on the US-Mexico border, the area from near San Antonio, New Mexico to Presidio, Texas and Ojinaga, Chihuahua, including cities of El Paso, Texas, Ciudad Juárez, Chihuahua, and Las Cruces, New Mexico. Results indicated that agricultural lands are likely to decrease by about 14% in the 20 years 2020-2040, and mainly around the major metropolitan areas of El Paso, Ciudad Juárez, and Las Cruces are likely to continue to undergo urban expansion. Developed open space areas and developed areas will likely increase by about 20% and 29%, respectively, in this period. The surface waterbodies areas across the region will likely decrease by about 15%. Evergreen forests are estimated to decrease by about 1%. Shrublands areas will decrease by about 1%. Developers, decision-makers, ranchers, sponsors, and other stakeholders might find the study valuable and helpful in resource management, water conservation measures, environment protection, future growth preparation in water supply, treatment, and monitoring.
Keywords: Future prediction, change patterns, Change tendencies, Environment, ecosystems, climate, land use, land cover.

5.B.1: INTRODUCTION

Human activities made an enormous change in resources in many locations overtime (Mishra et al., 2014; Hansen et al., 2015; Kucsicsa et al., 2019). Land-use/land-cover changes are expanded, and exacerbated processes are deemed to be one of the most significant environmental concerns worldwide (Kucsicsa et al., 2019). It also has a significant impact on ecosystem processes, biological systems, and biodiversity (Sohl et al., 2013; Yuan et al., 2015; Liping et al., 2018; Kucsicsa et al., 2019). Monitoring changes provides clear insight for scientists and guidance for planning authorities, decision-makers, resource management, and sustainable environmental management. Monitoring changes requires measuring and understanding patterns and trends of change (Homer et al., 2020; Kaya et al., 2020; Chamling et al., 2020). Numerous land use/land cover change research projects focused on environmental changes use multi-temporal remote sensing data frameworks. These research projects constantly revealed how human activities, in combination with natural resources, are crucial drivers of land use/land cover dynamics at all spatial and temporal scales (Munthali et al., 2020). In addition, future land-use/land-cover change is another characteristic considered to play an important role in decision-making processes and future planning (Mishra et al., 2014; Hansen et al., 2015; Rimal et al., 2017; Moyer et al., 2020; Munthali et al., 2020).

For land use/cover change research, remote sensing data has become a valuable resource because of its chronological frequency, a digital format appropriate for computer systems, comprehensive view, and wide range of spatial and spectral resolutions (Chen et al., 2012; Hussain et al., 2013; Butt et al., 2015; Huang et al., 2018; Halefom et al., 2018; Wang, 2019; Pandey et al.,
It has also been widely used in observing natural resources, catastrophes, ecosystems, and urban expansion (Longbotham et al., 2012; Wan et al., 2018; Xu et al., 2019). The free access to the USGS Landsat archive and development of remote sensing techniques, land use/land cover change dynamics with temporally high frequent datasets become possible. Since Landsat 1 was launched in 1972 as the first land-surface image satellite, satellite data have been widely used for urban area analysis (Khawaldah, 2016). Intermediate spatial resolution imagery such as Landsat images are still the most substantial data resources for urban land-cover classification, especially considering their cost, suitable spectral resolutions, and swath extent (Zhang et al., 2015).

Recently, and after the availability of high-performance computer systems and operative application algorithms, more possibilities have been amplified for feature segmentation and extraction from multispectral and multiscale remote sensing imagery and the implementation of a recent land use/land cover change approach (Chen et al., 2012; Bueno et al., 2019; Wan et al., 2019). Remote sensing and geographic information system technologies are cross-border resources and suitable for implementing proficient transboundary research (Chang et al., 2018; Mubako et al., 2018). These technologies can help stakeholders map where changes occur, understand development patterns and seasonal land changes over time, and assess current activities and policies. They can also help expect and plan for future changes (Liping et al., 2018; Wang et al., 2020).

Land use/land cover future change prediction requires effective models that have the ability to project future features, their patterns, and trends (Hamad et al., 2018; Kucsicsca et al., 2019). Land-use/land cover change modeling implies time interpolation or extrapolation when the modeling surpasses the recognized period (Di Marco et al., 2019; Ren et al., 2019; Chini et al.,
Land use/land cover models can offer a basis to address and segregate the complex cluster of biophysical and socioeconomic factors that affect the rate, quantity, extent, and location of land use/land cover changes. Moreover, these models can be used to estimate multiple land use/land cover alterations' impacts on climate change, carbon cycling, biodiversity, water budgets, and the provision of further crucial ecosystem amenities (Ren et al., 2019). Understanding the model components, data requirements, and functions of the model is imperative to ensure their applicability for several research and policymaking purposes (Ren et al., 2019). Land use/land cover change models can be characterized into two categories—spatial description models and spatial transition models (Tang et al., 2019). The spatial description models describe the dynamics of landscape structure through a variety of regression or statistical methods, whereas the spatial transition models include more spatial information, such as the location or state arrangement of the place (Tang et al., 2019).

Mainly used models for predicting land use/land cover changes are analytical equation-based models, statistical models, evolutionary models, cellular models, Markov models, hybrid models, expert system models, and multiagent models (Sohl et al., 2013; Liping et al., 2018; Tang et al., 2019). The most widely used models in land use change monitoring and predicting are cellular and agent-based models or a mixed model based on these two types of models (Sohl et al., 2013; Aburas et al., 2016). The Markov chain and Cellular Automata (CA-Markov) model is a hybrid of the Cellular Automata and Markov models. This model efficiently combines the advantages of the long-term predictions of the Markov model and the ability of the Cellular Automata (CA) model to simulate the spatial difference in a complex structure and has been shown to efficiently simulate land use/land cover change in other studies (He et al., 2014; Liping et al., 2018; Fu et al., 2018; Tang et al., 2019; Moyer, 2020). Combining the Markov-chain model and
cellular automata (CA) is considered by some researchers to be one of the best options for land use/land cover analysis over different spatial scales and is recognized as a more powerful and effective modeling technique for the change simulation (Rimal et al., 2017; Rimal et al., 2018). This model surpassed other regression-based models in predicting land use change and abundant researchers used the CA-Markov model to visualize and observe land use/land cover changes and their future predictions (Liping et al., 2018; Tang et al., 2019).

The Middle Rio Grande Region is a dryland ecosystem situated in the southwestern US-Mexico borderlands (Ward et al., 2006; Sheng, 2013). This region covers the area from southern New Mexico to far west Texas in the US and northern Chihuahua in Mexico. This region encompasses the three fast-growing cities of Las Cruces, New Mexico, El Paso, Texas, and Ciudad Juarez, Chihuahua, and is populated by more than two million people (Mubako et al., 2018). The Rio Grande region faces enormous challenges on its resources that encounter significant pressures on these resources uses because of the competition between different stakeholders such as agriculture, livestock raising, municipalities, industry, and wildlife (Nava et al., 2016; Mubako et al., 2018). The Rio Grande River is the fourth largest river in North America and runs through the region from north to south. This river starts as a snow-fed stream high in the San Juan Luis Valley in southern Colorado and ends in the Gulf of Mexico. The Rio Grande River comprises the main surface water reservoirs in southern New Mexico, which are the Elephant Butte Reservoir and Caballo reservoir. The Rio Grande River is one of the most significant sources of water in southern New Mexico and far west Texas in the US, as well as the northern Chihuahua in Mexico. It provides intensive agriculture practices for their irrigation needs. It also supplies the human communities and the ecosystems throughout the basin with their water needs (Sheng, 2013; Szynkiewicz et al., 2015; Sanchez, 2017; Randklev et al., 2018; Cox et al., 2018).
This Middle Rio Grande Region contains various land use/land cover features and practices and experiences massive changes over time due to disruptive human activities and natural conditions (Randklev et al., 2018). Urbanization is one of the most pervasive contributors to land use/land cover change in the region and continues to grow, especially near the urban centers of Las Cruces, New Mexico, El Paso, Texas, and Juárez, Mexico (Szyrkiewicz et al., 2015). In a study conducted by Mubako et al. (2018) on 4288 km² (1655 sq. miles) in the Middle Rio Grande Region, that included the most areas of the three main cities in the region (Las Cruces, El Paso, and Ciudad Juarez) stated that the urban areas grew about 8% in this area of interest in the 25 years 1990-2015 by taking important areas from agricultural lands and other vegetation. The agricultural lands and other vegetation areas decreased by about 11% in this period.

Following the Second World War, the border cities between Mexico and the United States entered an era of rapid population growth and industrialization (Sanchez, 2019). Through the Border Industrialization Program, it formed the long-term foundation for economic expansion in that part of Mexico, as well as a stronger factor of attraction for demographic and urban growth in key border cities (Sanchez, 2019). The pollution of surface water bodies, including cross-border flows, became apparent due to a lack of services infrastructure, particularly piped water, drainage, and treatment, as well as a lack of control over water discharges from industrial units (Kelly, 2002). Presidents Reagan and De la Madrid signed the La Paz Agreement in 1983, which included a series of annexes dealing with environmental issues on the border between the two countries. This agreement created commitments linked to binational cooperation to address environmental concerns caused by rapid, disorderly, and uncontrolled expansion resulting from urban and industrial growth dynamics at the border (Sanchez, 2019).
Many transportation networks have been located along with river courses for over a century, with the earliest rail lines dating to the 1830s in the eastern U.S. and the mid-to late-nineteenth century in the western U.S. Road construction, particularly paved roads, generally came later, with paved roads accounting for only 4% of the U.S. Road network in 1900 (Blanton, 2009).

This study applied future prediction analysis of land use/land cover to Landsat images of the Middle Rio Grande Region. Using land change modeler in TerrSet model. TerrSet is a software package of monitoring and modeling applications using geospatial data in 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 (Wang et al., 2012; Rimal et al., 2017; Moyer, 2020). 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 (Moyer, 2020).

The goals of this study are 1) Analyze the spatiotemporal dynamics of land use/land cover features and practices 2005-2015. 2) Explore future land use/land cover change trajectories 2020-2040. 3) Assess the accuracy of land use/land cover change and land use/land cover future prediction change results by using remote sensing and geographic information systems technologies in this region (Figure 1.3).

5.B.2: DATA AND METHODOLOGY

5.B.2.1: Materials and methods

The flow diagram is given in Figure (5.B.1) describes how remote sensing and geographic information system measures were applied in this study. Eight multispectral Landsat scenes cover the study area that is shown in Figure (1.3) (Path/Row): 031/039, 031/040, 032/038, 032/039,
033/037, 033/038, 034/036, and 034/037. These images were downloaded from the U.S. Geological Survey (USGS) GloVis website (http://GloVis.usgs.gov/) for the years 2005, 2010, and 2015. Each scene had less than 10 percent cloud cover. The scenes that were used for the study area were chosen from Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI). The dates of the scenes were between the second half of May and the first week of July, which is considered the “leaf-on” season in this area. Substantial procedures were performed on the scenes to prepare them for the study, including mosaicking the eight scenes in one image, correcting the color differences, and clipping a final image to the study area boundaries. Data atmospheric correction was performed for Landsat imagery to remove water vapor and aerosol effect, which is considered the optimal atmospheric correction method that can be used (Nguyen et al., 2015; Wang et al., 2018). Nguyen et al., 2015 used some modules based on relevant equations and rescaling factors to improve image quality and appearance. Specific steps implemented in ENVI 5.4 application for the five years that have been chosen for the study. These steps included radiometric calibration to determine reflectance at the top of the atmosphere, fast line-of-sight atmospheric analysis of spectral hypercubes (FLAASH) for vapor, and moisture correction to determine surface reflectance. The minimum noise fraction (MNF) linear transformation process was used to transform the study area images for all analysis years. This technique is widely applied in remote sensing, is implemented in ENVI 5.4 software (Liu et al., 2016), and reduces inherent spectral dimensionality and data noise. The final minimum noise fraction Landsat images were approved to be used for change detection based on both eigenvalue plots and visual inspection of the images.
5.B.2.1.2: Land Use/ Land Cover Future Prediction Analysis

After land use/land cover maps for the three years 2005, 2010, and 2015 were created, a land use/land cover future change prediction analysis was performed. The process was accomplished by using the Land Change Modeler (LCM) in the TerrSet CA-Markov model to
predict the types of changes, their physical locations, measure the changes, find the patterns and the trends of these changes for the period 2020–2040, and assess the prediction accuracy for 2015 because this year has real classification map and predicted map. The goal of the Land Change Modeler (LCM) in TerrSet is to visualize change and produce models (Hamad et al., 2018), particularly in the case of stable land cover rather than rapid change situations (Megahed et al., 2015). Three segments of results can be accredited in LCM: the quantitative assessment of different land use/land cover categories, a net change of each land use/land cover class, and the contributors to the net change experienced by each land use/land cover category. The LCM in TerrSet is easy to use and has fairly low-level data requirements (Mishra et al., 2014). Moreover, land use/land cover change analysis, transition potential modeling, and land use/land cover change prediction have three main steps, which predict future land use/land cover based on the historical change of time series land use/land cover maps. Models of land use change in LCM can also be created (Krishna, 2010). The location and magnitude of land use/land cover change are two crucial issues that are addressed in modeling. Furthermore, land use/land cover change models should represent part of the complexity of land use/land cover systems. Therefore, temporal and spatial changes in a specific area can be evaluated by future land use/land cover change simulation (Veldkamp et al., 2001). A significant stage in the modeling process is the model calibration and validation process for predicting future changes (Singh et al., 2015). The simulation of past and future change within the land use/land cover change model aims to understand and quantify the processes that affect land use/land cover change (Moudls et al., 2015). As well, the key goal of model validation is the accuracy assessment of the predictions. In the validation process, a comparison is made between predicted land cover and an observed land cover map derived from satellite images (Hamad et al., 2018). The prediction changes of total areas and class area changes
are calculated in this study for the following five-year time steps 2020, 2025, 2030, 2035, and 2040. In addition, the annual rate of future change for the analysis years was calculated. Furthermore, four differenced change maps were created (2020-2025, 2025-2030, 2030-2035, and 2035-2040) to predict the change of land use/land cover categories, their patterns, and trends during the analysis period.

5.B.2.1.3: Model validation

Validation is an essential phase in the processing of remote sensing data. It presents the outcome data's information value to a user and utilizes the data's quality for use (Tilahun et al., 2015; Rwanga et al., 2017).

A) Classification of images was confirmed by assessing the accuracy of the created images of 2005, 2010, and 2015. Classification accuracy is accomplished for individual land use categories and the total classification through creating a confusion matrix (Butt et al., 2015; Arulbalaji et al., 2016; Islam et al., 2018; Mubako et al., 2018). Six statistics were calculated: (1) Overall accuracy, which represents the proportion of all correct classifications. (2) Kappa coefficient measures the agreement of accuracy in classification assessment. (3) User accuracy, which calculates the probability that a pixel classification is correct on the ground. (4) Producer accuracy, which is the probability that a pixel of a particular land use type is assigned the correct land use category. (5) Omission error, which represents certain categories that were omitted when they existed on the ground. (6) Commission error, which represents categories that were identified as existing on the ground when in fact they do not (Butt et al., 2015; Mubako et al., 2018).

B) Land change Modeler validation by creating a prediction map and comparing it with a real classification map to find the similarities and differences between both maps.
C) Land use/ land cover future prediction change validation was performed by comparing
the results of the 2015 actual classification image with a 2015 predicted image by the TerrSet
model.

There are always uncertainties in the acceptability of results to predict land use/ land cover change,
particularly when results predict future situations based on disturbed variables. But there are again
some scopes of checking the results in GIS techniques performed on neural network built-in
module in the TerrSet version of IDRISI. Iterations of prediction, which were 10000, were
considered sufficient for running the data. The accuracy was obtained as 81 % for all the
conversion types.

5.B.3: RESULTS AND DISCUSSION

5.B.3.1: Land-use/ land-cover class measurement

As stated in chapter 3, the final classification maps, and class measurements were created
to find the areas of the individual classes of the study area. The processes were accomplished
through a feature attributes related module in ArcGIS 10.7.1 for the three years. The final results
for the three years 2005, 2010, and 2015 were made and arranged in Table (5.B.1) and shown in
figure 5.B.2. These results will be used for land use/ land cover future prediction change.

<table>
<thead>
<tr>
<th>Year</th>
<th>Agriculture</th>
<th>Developed open space</th>
<th>Developed area</th>
<th>Water</th>
<th>Evergreen forest</th>
<th>Shrubs</th>
<th>Total Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>1125</td>
<td>36</td>
<td>933</td>
<td>122</td>
<td>2126</td>
<td>32646</td>
<td>36988</td>
</tr>
<tr>
<td>2010</td>
<td>1111</td>
<td>40</td>
<td>1022</td>
<td>135</td>
<td>2155</td>
<td>32525</td>
<td>36988</td>
</tr>
<tr>
<td>2015</td>
<td>1091</td>
<td>40</td>
<td>1078</td>
<td>106</td>
<td>1148</td>
<td>33525</td>
<td>36988</td>
</tr>
</tbody>
</table>
Figure 5.B.2: The Middle Rio Grande land use/land cover classes 2005-2015.

5.B.3.2: Land Use/ Land Cover Change Future Prediction Analysis

Land use/land cover future change prediction analysis was performed by using the Land Change Modeler (LCM) in the TerrSet CA-Markov model to predict the types of changes, their physical locations, measure the changes, find the patterns and the trends of these changes for the period 2020-2040 as shown in Table 5.B.2.

Table 5.B.2: The Middle Rio Grande land use/land cover change future prediction results 2020-2040.

<table>
<thead>
<tr>
<th>Year</th>
<th>Agriculture</th>
<th>Developed open space</th>
<th>Developed area</th>
<th>Water</th>
<th>Evergreen forest</th>
<th>Shrubs</th>
<th>Total Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>2020</td>
<td>1052</td>
<td>40</td>
<td>1247</td>
<td>98</td>
<td>1137</td>
<td>33414</td>
<td>36988</td>
</tr>
<tr>
<td>2025</td>
<td>1038</td>
<td>40</td>
<td>1392</td>
<td>90</td>
<td>1135</td>
<td>33293</td>
<td>36988</td>
</tr>
<tr>
<td>2030</td>
<td>1020</td>
<td>40</td>
<td>1441</td>
<td>88</td>
<td>1267</td>
<td>33132</td>
<td>36988</td>
</tr>
<tr>
<td>2035</td>
<td>992</td>
<td>41</td>
<td>1541</td>
<td>82</td>
<td>1122</td>
<td>33210</td>
<td>36988</td>
</tr>
<tr>
<td>2040</td>
<td>971</td>
<td>42</td>
<td>1617</td>
<td>79</td>
<td>1130</td>
<td>33149</td>
<td>36988</td>
</tr>
</tbody>
</table>
5.B.3.2.1: Land use/land cover percentile predicted change of total areas

Land-use/land-cover categories cover portions of the total study area. These categories' areas are predicted to change during the analysis period 2020-2040, as shown in Table 5.B.4. The table designates the percentile of each category at the begging of the study in 2020. It also shows each class's change percentile from the total area of interest during the study period. The results show that agriculture and surface water areas will experience a continuous decrease during the analysis period. However, developed areas will repeatedly increase during the analysis period. Developed open space will not have apparent change at the beginning of the analysis, while it will increase slightly in the last ten years of prediction analysis. Evergreen forest areas will fluctuate during the prediction analysis period 2020-2040. On the other hand, the shrublands areas will decrease during 2020-2040 by cutting some areas for development.

Table 5.B.3: The Middle Rio Grande land use/land cover percentile predicted change of total areas 2020-2040.

<table>
<thead>
<tr>
<th>% Change in total area</th>
<th>Year 2020</th>
<th>Year 2025</th>
<th>Year 2030</th>
<th>Year 2035</th>
<th>Year 2040</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>2.84</td>
<td>2.81</td>
<td>2.76</td>
<td>2.68</td>
<td>2.63</td>
</tr>
<tr>
<td>Open space</td>
<td>0.11</td>
<td>0.11</td>
<td>0.11</td>
<td>0.11</td>
<td>0.11</td>
</tr>
<tr>
<td>Developed area</td>
<td>3.37</td>
<td>3.76</td>
<td>3.90</td>
<td>4.17</td>
<td>4.37</td>
</tr>
<tr>
<td>Water</td>
<td>0.26</td>
<td>0.24</td>
<td>0.24</td>
<td>0.22</td>
<td>0.21</td>
</tr>
<tr>
<td>Evergreen forest</td>
<td>3.07</td>
<td>3.07</td>
<td>3.43</td>
<td>3.03</td>
<td>3.06</td>
</tr>
<tr>
<td>Shrubs</td>
<td>90.34</td>
<td>90.01</td>
<td>89.58</td>
<td>89.78</td>
<td>89.60</td>
</tr>
</tbody>
</table>

5.B.3.2.2: land use/land cover percentile predicted change of class areas

The areas of land-use/land-cover categories changed during the analysis period 2020-2040 as shown in Table 5.B.4, which explains the percentile change of each of these categories for different periods of time starting from 1994 to 2000, 2005, 2010, and 2015. It also shows the total change percentile of the 21-year period of the analysis.

Table 5.B.4: The Middle Rio Grande land use/land cover percentile predicted change of class areas 2020-2040.

<table>
<thead>
<tr>
<th>Year</th>
<th>2020</th>
<th>2025</th>
<th>2030</th>
<th>2035</th>
<th>2040</th>
<th>Total change</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
% Change of class

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>-3.57</td>
<td>-1.33</td>
<td>-1.73</td>
<td>-2.75</td>
<td>-2.12</td>
</tr>
<tr>
<td>Open space</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>2.50</td>
<td>2.44</td>
</tr>
<tr>
<td>Developed area</td>
<td>15.68</td>
<td>11.63</td>
<td>3.52</td>
<td>6.94</td>
<td>4.93</td>
</tr>
<tr>
<td>Water</td>
<td>-7.55</td>
<td>-8.16</td>
<td>-2.22</td>
<td>-6.82</td>
<td>-3.66</td>
</tr>
<tr>
<td>Evergreen forest</td>
<td>-0.96</td>
<td>-0.18</td>
<td>11.63</td>
<td>-11.44</td>
<td>0.71</td>
</tr>
<tr>
<td>Shrubs</td>
<td>-0.33</td>
<td>-0.36</td>
<td>-0.48</td>
<td>0.24</td>
<td>-0.18</td>
</tr>
</tbody>
</table>

5.B.3.2.3: land use/land cover predicted annual rate of change

The areas of land-use/land-cover categories changed during the analysis period 2020-2040 at different annual rates, as shown in Table 5.B.5. The change rates are different from one category to another and from one period to another. Some of these rates indicate decreasing, such as agriculture change rates, which reflect the reduction of agricultural lands. Some others indicate increasing such as developed open space and developed areas, which increase overtime. Evergreen forests and shrublands have fluctuated rates according to precipitation reduction and forest fires that gave important areas to these categories.

Table 5.B.5: The Middle Rio Grande land use/land cover annual rate of predicted change of class areas 2020-2040 (km²).

<table>
<thead>
<tr>
<th>The annual rate of predicted change</th>
<th>Period</th>
<th>2015-2020</th>
<th>2020-2025</th>
<th>2025-2030</th>
<th>2030-2035</th>
<th>2035-2040</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>-0.71</td>
<td>-0.27</td>
<td>-0.35</td>
<td>-0.55</td>
<td>-0.42</td>
<td></td>
</tr>
<tr>
<td>Open space</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.50</td>
<td>0.49</td>
<td></td>
</tr>
<tr>
<td>Developed area</td>
<td>3.14</td>
<td>2.33</td>
<td>0.70</td>
<td>1.39</td>
<td>0.99</td>
<td></td>
</tr>
<tr>
<td>Water</td>
<td>-1.51</td>
<td>-1.63</td>
<td>-0.44</td>
<td>-1.36</td>
<td>-0.73</td>
<td></td>
</tr>
<tr>
<td>Evergreen forest</td>
<td>-0.19</td>
<td>-0.04</td>
<td>2.33</td>
<td>-2.29</td>
<td>0.14</td>
<td></td>
</tr>
<tr>
<td>Shrubs</td>
<td>-0.07</td>
<td>-0.07</td>
<td>-0.10</td>
<td>0.05</td>
<td>-0.04</td>
<td></td>
</tr>
</tbody>
</table>

5.B.3.2.4: Land use/land cover classes future change prediction 2020-2040

Land use/land cover areas are predicted to change from 2015 to 2040 in the study area as shown in tables 5.B.2, 5.B.4, and figures 5.B.3-5.B.12 show the estimated continually decrease of the agricultural areas by 3.57% by 2020, 1.33% by 2025, 1.73% by 2030, 2.75% by 2035, and 2.12% by 2040 with an overall decrease of 11% to give those areas to urbanization growth and the
shrublands as a decrease in agriculture activities. The shrublands areas are also likely will decrease by about 0.33 % by 2020, 0.36 % by 2025, 0.48 % by 2030, 0.24 % by 2035, and 0.18% by 2040 and with an estimated total decrease of 1.12% in 2040 to give some of its areas to agriculture, developed, and evergreen forests. The surface water areas will likely decrease by 7.55% by 2020, 8.16% by 2025, 2.22% by 2030, 6.82% by 2035, and 3.66% by 2040, with an estimated total decrease of 25.47% due to the continuous reduction of snowpack and streamflow. Evergreen forests are expected to decrease 0.96% by 2020, 0.18% by 2025, and 11.77% by 2035 due to the continuing water reduction and some occasions such as human actions or fires. However, evergreen forests are expected to increase by 11.63% in 2030 and 0.71% in 2040, ending with an estimated decrease of 1.57% at the end of the prediction period in 2040. Developed open space will likely experience an increase of 2.5% by 2035 and 2.44% by 2040, by an estimated total increase of 5% by 2040. Developed open space will not experience apparent change due to no new developed area in new parts of the region, but the increase will be in the same existing places. Developed areas are expected to increase by about 15.68% by 2020, 11.63% by 2025, 3.52% by 2030, 6.94% by 2035, and 4.93% by 2040, with a total increase of 50% for the 20-year prediction period by replacing primarily shrublands and agriculture areas.
Figure 5.B.3: The Middle Rio Grande land use/land cover classes prediction 2020.
Figure 5.B.4: Las Cruces, El Paso, and Juarez Land use/land cover classes prediction 2020.
Figure 5.B.5: The Middle Rio Grande land use/ land cover classes prediction 2025.
Figure 5.B.6: Las Cruces, El Paso, and Juarez land use/land cover classes prediction 2025.
Figure 5.B.7: The Middle Rio Grande land use/land cover classes prediction 2030.
Figure 5.B.8: Las Cruces, El Paso, and Juarez Land use/land cover classes prediction 2030.
Figure 5.B.9: The Middle Rio Grande land use/land cover classes prediction 2035.
Figure 5.B.10: Las Cruces, El Paso, and Juarez land use/land cover classes prediction 2035.
Figure 5.B.11: The Middle Rio Grande land use/land cover classes prediction 2040.
Figure 5.B.12: Las Cruces, El Paso, and Juarez land use/land cover classes prediction 2040.
5.B.3.2.5: accuracy assessment of classified maps

Three maps were classified for the years 2005, 2010, and 2015 in the study area. To validate the classification results, an accuracy assessment was applied to the study’s results by using several extension tools in ArcGIS 10.7.1. The classification quality is oriented in a confusion matrix that is widely used to present accuracy assessment information in remote sensing (Tilahun et al., 2015; Mubako et al., 2018). The overall accuracy of 99 percent was obtained in 2005, 2010, and 2015. The Kappa coefficient was 0.96 for three years, which statistically supported the classification's overall accuracy.

5.B.3.2.6: Validation of Land Change Modeler

To ensure that the TerrSet model can predict land use/land cover in the Middle Rio Grande Region, a validation procedure applies to three selected classification maps. The validation panel in the land change modeler allows to assess the quality of the predicted land use/land cover map compared to a real map. The validation process applies a three-way crosstabulation among the later land use/land cover map, the predicted land use/land cover map, and a real land use/land cover map.

In this study, the process was accomplished using the 2010 land use/land cover classification map, 2015 land use/land cover predicted map, and 2015 land use/land cover classification map. The results from the validation process became reasonable. First, the 2015 prediction of the same change trend classes 2005-2015, shown in table 5.B.2, matches the 2015 actual classes, such as the increase of developed areas from 2005 to 2015 which increased 89 Km² in 2010 and 56 Km² in 2015 in actual classification maps as well as predicted to increase 76 Km² in 2015. Second, the 2015 prediction of the different change trend classes 2005-2015, which is shown in table 5.B.2, did not match the 2015 actual classes, such as the increase in surface water areas of 13 Km² and
the evergreen forests of 29 Km² from 2005 to 2010 however the decrease in surface water areas 29 Km² and the evergreen forests 1007 Km² from 2010 to 2015. The predicted 2015 map indicated that surface water increased by 41 Km² and evergreen forest increased by 1062 Km². These results meet the technical bases of the land change modeler, which uses the Markov chain in its predictions that consider the previous events to estimate future ones. Also, these results allow using Land Change Modeler to produce satisfactory land use/land cover future change prediction results.

5.B.3.2.7: Validation of predicted land use/land cover change maps

To validate future prediction, land use/land cover change, 2015 land use/land cover change prediction was performed using the TerrSet Model. The results are stated in table 5.B.6. The 2015 future prediction land use/land cover change results were compared to the actual 2015 land use/land cover change classification that was performed earlier. From the results, differences between the actual classification and prediction were calculated. Future prediction land use/land cover change accuracy was calculated. Therefore, the predicted accuracy of agriculture was found at 99.43%. Developed open space predicted accuracy was found to be 100%. Developed area predicted accuracy was found at 95.45%. Also, the predicted accuracy of shrublands was found at 96.79%.

On the other hand, the predicted accuracy of the evergreen forest was found at 12.83%. This is very low accuracy, but this result is reasonable because the evergreen forests were 2126 km² in 2005 and increased to 2155 km² in 2010, while they decreased in 2015 to 1148 km² by about 47%. Also, the predicted accuracy of water was found to be 79.76%, which is slightly low accuracy, but this result is reasonable because the water was 122 km² in 2005 and increased to 135 km² in 2010 while it decreased in 2015 to 106 km² by about 21%.
Table 5.B.6: 2015 future prediction land use/ land cover change accuracy

<table>
<thead>
<tr>
<th>Category</th>
<th>2015 actual classes km²</th>
<th>2015 predicted classes km²</th>
<th>Difference km²</th>
<th>difference %</th>
<th>Predicted accuracy %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>1091</td>
<td>1097</td>
<td>6</td>
<td>0.57</td>
<td>99.43</td>
</tr>
<tr>
<td>Open space</td>
<td>40</td>
<td>40</td>
<td>0</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Developed area</td>
<td>1078</td>
<td>1127</td>
<td>49</td>
<td>4.55</td>
<td>95.45</td>
</tr>
<tr>
<td>Water</td>
<td>106</td>
<td>128</td>
<td>22</td>
<td>20.24</td>
<td>79.76</td>
</tr>
<tr>
<td>Evergreen forest</td>
<td>1148</td>
<td>2148</td>
<td>1000</td>
<td>87.17</td>
<td>12.83</td>
</tr>
<tr>
<td>Shrubs</td>
<td>33525</td>
<td>32448</td>
<td>-1077</td>
<td>-3.21</td>
<td>96.79</td>
</tr>
<tr>
<td>Overall predicted accuracy</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>80.71</td>
</tr>
</tbody>
</table>

5.B.4. DISCUSSION

Many models in remote sensing and geographic information applications with different methods are used on various levels and places to accomplish land use/ land cover future change prediction processes and forecast how land use/ land cover features will be and their patterns and change trends. TerrSet model, which is used in this study, is one of these models with reliable results built on the Markov chain of action changes that estimate new changes depending on the previous actions.

Land use/ land cover future change prediction in the Middle Rio Grande Region was created in this study to estimate the likely future change scenario for the next 20 years, 2020-2040. The estimation period is divided into five equal intervals continuing the same 1994-2015 period classification approach. It is also performed for the next 20 years and not more to be acceptable for a prediction built on past actions and events that happened in the region in 2005, 2010, and 2015.

The estimated results derived from the TerrSet model showed that land use/ land cover change in the Middle Rio Grande Region would likely continue the same trends and patterns for the next 20 years. These estimations are built in this way because the model, which uses the Markov chain, made its predictions depending on the actual trends and patterns revealed from the classification of 2005, 2010, and 2015 images. The model also uses some disturbance variables.
such as developed areas, existing roads, and the digital elevation of the region that prevent expansion on roads, the previously developed areas, or the high elevated areas in the region.

The estimations covered the whole region with the main three cities of El Paso, Texas, Ciudad Juárez, Chihuahua, and Las Cruces, New Mexico, as well as the other small cities and villages that cover essential areas in this region. The estimations were general predictions without considering any plans of the cities that are difficult to consider because these cities are in two different countries and three different states with different policies, regulations, and plans. However, the uncertainty of the estimations could play a role in perfect results because the change will not be the same for a long time, especially with more extreme and prolonged droughts due to climate change and its impacts that could exacerbate these changes. These changes are more likely a sigmoidal curve in the long run, not just linear forever. Moreover, the region's development would settle down in the long run.

Although the results were general estimations, they implied a likely continuous horizontal expansion of undesirable actions such as expanding developed areas by about 50% on planted areas like shrublands, which will likely decrease about 1%, and agricultural areas, which will likely decrease 11%. The results also reveal a worrying prediction that showed a continual decrease in the surface water. The results predicted that the surface water would decrease by 25% by 2040, increasing water deficit and competitive water demands for different sectors from which agriculture is the highest water user.

5.B.5. CONCLUSION

Land use/land cover future change prediction is one of the significant analysis challenges that can be accomplished to estimate the imminent changes of land use/land cover features. This analysis helps plan better strategies, control different alterations of appearing landscapes and
protect the environment. The study results showed that agricultural lands are likely to remain decreasing. The developed will increase almost around the metropolitan areas of El Paso, Ciudad Juarez, and Las Cruces. The surface water areas and shrublands also will probably continue decreasing in the next 20 years, 2020-2040. The study's outcomes are outstanding interpretations for understanding a likely future spatiotemporal environmental change scenario in the region that can help stakeholders and decision-makers balance development requirements, protect dynamic ecosystems, and estimate future demand.

Prediction findings mean overexploiting the region's sensitive resources that can lead to loss of biodiversity, natural habitats, increased pollution, and a higher risk of flooding, erosion, and siltation of the river and water reservoirs. Therefore, it is essential to highlight the need for policy changes toward sustainable water resources for acceptable use, including restricting water-consuming plants and limiting residential water uses. Reducing evaporation rates from waterbodies such as the Elephant Butte and Caballo reservoirs decreases the exposed surface water area. Changing the irrigation methods towards less and more efficient irrigation systems such as sprinkler or drip irrigation that save more water. Searching for new clean water resources such as desalination or wastewater treatment. Change agriculture practices toward less water consumption crops.

The results brought some serious questions related to the future of the resources and the region that need to be answered like, what will the land use/land cover future of the region look like? What land use/land cover changes will take place in the region in the future that can negatively affect the region? What are the possible steps that can be taken to mitigate the undesirable change? Are there alternative resources that can substitute the loss or the reduction in available resources to support and sustain the region’s life?
Finally, further potential research studies on resource changes, trends, and driving forces in this region are significant and recommended. First, continue attempting land use/land cover future estimations with different approaches and models that can predict reliable future scenarios. Second, focus on a local scale with higher resolution data that can consider plans and provide more information to understand the change, facilitate planning, and deal with the expected situation. Third, understand the driving forces of change in the region during climate change and its impacts.
CHAPTER 6: DISCUSSION

Drylands arise on all continents, cover about 41% of the earth’s landmass, and are projected to expand, partly due to climate change (Echchelh et al., 2018; Antle et al., 2019; Metternicht et al., 2020). About 2.1 billion people inhabit these regions, many of them in developing countries, and are directly dependent on the land’s natural resources (UN, 2010, Huang et al., 2017). An estimated half of the global population will live in regions with high water scarcity by 2030 (UN, 2012). Drylands are an essential component of all agricultural lands, with about 50% of the arid and semi-arid area land on Earth being used for agriculture. Drylands grow 44% of the world’s food and support 50% of the world’s livestock. Dryland agriculture represents a significant economic activity, and about a third of the population living in these regions depend on agriculture, particularly in Africa and Asia. In developed countries, agriculture in drylands also has significant economic importance, including the USA, where only 7% of wheat is irrigated. (Echchelh et al., 2018; Antle et al., 2019). Research on drylands is a substantial concern, especially their sensitivity to climate and water availability changes. However, human activities have a considerable influence on these lands. Consequently, this research was implemented in two dryland regions located in different countries on two different continents to show what these two regions face and their connection according to water availability, development, human activities, and climate change, namely the Khoms district, Libya, in North Africa and the Middle Rio Grande Region on the US-Mexico border in North America. These two regions located in the northern hemisphere face similar climate conditions, water scarcity, water quality degradation, and intensive urban sprawl even though the Khoms District is smaller than the Middle Rio Grande Region. The research focused on the spatiotemporal patterns of land use/land cover change using remote sensing and geographic information system technologies. These technologies are adequate to be applied in
various places worldwide, and they are transboundary tools that can be applied across administrative borders and barriers. Consequently, they are useful for promoting cross-border collaboration through data harmonization and sharing arrangements at many levels (Mubako et al., 2018).

Results from studies applied in this research showed that the agricultural land areas decreased following significant urban development. In the Khoms district, Libya, even though there were increased agricultural lands in some southern parts after development in the 1970s and improved socioeconomic conditions, about 2,382 hectares of the old agricultural fertile lands were converted to buildings through city sprawl or housing expansion in areas around Khoms city or far from it because of the absence of government development planning or protecting the native or agricultural lands (Belhaj et al., 2020).

In the Middle Rio Grande Region, the agricultural lands decreased by more than 12% and were replaced by buildings, mainly around the three cities of Juarez, El Paso, and Las Cruces. These developed areas are considered one of the most influential drivers of change (Hargrove et al., 2020). In both regions, urban lands continually grew. The Khoms district developed areas increased by about 658% during the last 40 years, 1976-2015, with about 16% annual growth rate (Belhaj et al., 2020), and developed areas increased by 45% in 21 years 1994-2015 in the Middle Rio Grande Region. Different types of construction, including residential, commercial, and industrial, expanded on native landscapes and agricultural areas, causing a shrinking of these areas. It also intensified various human demands for food and water supplies (Hargrove et al., 2020). From the results, most surface water bodies also reduced in area. For example, the Khoms district surface water area in the Kaam reservoir decreased from 74 hectares in 1984 to 21 hectares in 2000, despite increasing to 162 hectares in 2015 (Belhaj et al., 2020). The domestic daily
consumption in north Libya, where Khoms district is located, is 150-250 liters/day. The irrigated agricultural water uses 3,100 m³/ha and 15,000 m³/ha for animal food irrigated crops such as alfalfa (Wheida et al., 2006). As well, in the Middle Rio Grande, surface water bodies decreased from 241 km² in 1994 to 185 km² in 2000, reaching 106 km² in 2015. These results indicate a water deficit in the two regions and stress increasing on this resource over time to provide the different sectors' water demands. For example, in Texas, U. S urban uses are approximately 3,000 m³/ha, while irrigated agriculture uses 6,000–9,000 m³/ha for row crops and 12,000–18,000 m³/ha for perennial crops like pecans and alfalfa. However, in New Mexico, U.S surface water irrigated agriculture uses about 4.5 a-ft/a, and irrigated agriculture uses about 6000 m³/ha in Chihuahua, Mexico (Hargrove et al., 2021). These results support Bohn et al. (2018). They found that regional changes in land and water use along the US–Mexico border resulted in divergent trends in the US and Mexico and that, in aggregate, have led to a substantial reduction of natural resources and ecosystems and an unsustainable trajectory in land and water resources. Results also support Hargrove et al., 2020 who demonstrated that surface water from the Rio Grande River no longer meets agricultural water needs and is increasingly scarce due to many change drivers, including a) Decreasing snowpack and changing flows time in the headwaters of the Rio Grande/Rio Bravo; b) Rising temperatures and increasing of evapotranspiration rates; c) Change of agricultural practices and trends towards higher water demand crops and the increasing salinity in water sources and soils; d) Urbanization growth and construction expansion in the region, and e) Growing demand for environmental services, such as riparian habitat and environmental flows.

Reduction in water quantities and change in water use patterns have many implications on water use in the two regions. Firstly, climate change affects surface water supply due to increasing temperatures and reducing snowpack in the headwaters of the Rio Grande River, which causes a
growing water supply deficit and failure to sustain competing demands from different sectors, even though these demands for surface water stay the same in aggregate (Hargrove et al., 2020). This was also noted in the Khoms District, in which rain agriculture is considered an essential contributor to irrigated agriculture in agricultural production. Secondly, the pressure on the reservoirs of surface water used as a water source for various uses is increasing. For instance, the Elephant Butte Reservoir, the main surface water source in the Middle Rio Grande Region, has a capacity since 2011 that fluctuates between 3-25% of the total capacity. This scenario was also similar to the Kaam Reservoir in Khoms, Libya, which stored only 12% of its capacity in 2015 (Vaisvil, 2019; Townsend, 2019; Belhaj et al., 2020). Thirdly, the increase in soil and water salinity and growing constraints to the use of these resources for agricultural production, drinking, and various environmental needs. Lastly, the tendency to rely on groundwater to provide the necessary water supplies for various uses and the pressure and negative impacts on this limited to nonrenewable water resource which also faces many serious problems such as depletion and quality deterioration (Belhaj et al., 2020; Hargrove et al., 2021).

Evergreen forests cover the northern Middle Rio Grande Region study area known as Magdalena Mountains, San Mateo Mountains, and Black Range. Trees in this area have persisted since 1426 (Schneider, 2014). These forest areas fluctuated during the study period from 1994-2015. While they increased from 1663 km² in 1994 to 2155 km² in 2010, these areas decreased to 1148 km² in 2015 due to wildfires. The largest of these fires was the Silver Fire in 2013, which burned about 138,705 acres (561.32 km²) in the black Range of New Mexico. Also, the San Mateo Mountains fire of 2015 burned 17,843 acres (72.21 km²) (US Forest Service, 2020; New Mexico fire information, 2020). The American Southwest is characterized by low annual rainfall, clear skies, and a warm climate (Schneider, 2014). Research has shown that huge fire years are
significantly drier on an annual to interannual scale, whereas smaller fires, on average, occur in wetter years. More fuel build-up in wet years leads to larger fires in drought years because the vegetation that grew in the wet years serves as a fuel. Conditions usually one year before and during the fire year are, on average drier. For large-scale fires, drought several years before a fire is usually more severe because fuel accumulates in the few years of wet conditions prior to the fire (Grissino-Mayer et al., 2004; Kitzberger et al., 2007; Schneider, 2014). The early growing season (late spring to early summer) had the highest percentage (63%) of fire occurrence, while 37% of fire events occurred in the middle portion of the growing season (Schneider, 2014). Fire frequency ranged from 7 to 8 years, from 1630 to 1890. Fires ceased after 1890, with only two recorded fire events in 1906 and 1953 (Schneider, 2014). Fire is more likely to occur in the Southwest when La Niña events and drought conditions follow warm (El Niño) phases. When different climate phases are in synchrony, associated changes in precipitation and storm tracks influence fire occurrence. Short intervals for fire occurrence ranged from 3.1 to 3.7 years, while the Upper Exceedance Interval, which delimits unusually long intervals, ranged from 12.2 to 13 years across both percent-scarred classes. The Maximum Hazard Interval, the fire interval associated with the most prolonged period the study site can go without burning, ranged from 17.2 to 18.1 years for both scarred classes (Schneider, 2014).

Native vegetation that includes shrublands and grasslands dominates both study areas and covers large parts of these regions. In the Khoms district, 87,367 hectares were covered with native plants at the beginning of the study period in 1976, while these areas reduced overtime to 78,831 hectares in 2015. Therefore, 3,187 hectares were transformed by construction, and 14,081 hectares were converted to agriculture by 2015 (Belhaj et al., 2020). Shrublands in the Middle Rio Grande Region covered 33221 km² in 1994 and shrunk to 32525 km² in 2010. Native vegetation increased to 33225 km² in 2015 due to forest fires and surface water area reduction.
Results showed complex dynamics of change in the region among land use/land cover categories where certain land uses were reduced in area, and other land uses gained in area. The Middle Rio Grande Region faced severe challenges and changes that affected its sustainability and made this region more sensitive and vulnerable to any subsequent events or actions.

The future situation in the Middle Rio Grande Region is another critical issue that deserves attention and research after understanding the present conditions, changing trends, and patterns. As Andrey Andreyevich Markov proposed in his stochastic processes, a sequence of possible events in which each event's probability depends only on the state attained in the previous event (Dhillon, 2013; Hayes, 2013), I applied land use/land cover future change predictions to the Middle Rio Grande Region 2020-2040. This research has offered a future vision for the region's land cover and the probability of these changes. Results suggest that agricultural land will continue decreasing over the next 20 years, with an estimated 11 percent due to urban growth. Developed areas will likely continue to expand and have an estimated ~50 percent expansion over the next 20 years. Surface waterbodies will likely continue to decrease over the next 20 years by 50 percent due to the snowpack and rain reduction. This change will influence the region and may determine future urban and industrial development. Evergreen forests will likely continue decreasing in the next 20 years due to climate conditions and wildfires. Pressure on shrublands also will remain due to climate change conditions and urban sprawl. These areas will likely reduce in the area through the expansion of urban environments. Future land use/land cover change estimation results in the Middle Rio Grande 2020-2040 should encourage stakeholders and authorities to take the necessary measures to promote sustainable development in the region.

While the results of all the studies in this research project were reasonable, classifying pixels of several classes has been difficult. For instance, spectral mixing for water, agriculture, and other
vegetation was seen in some places where wetlands have existed. There were reasons beyond these results related to the technology used in the classification, such as the resolution of the data used from Landsat with coarse 30 m spatial resolution and the classification processes from data calibration to atmospheric corrections of these data (Mubako et al., 2018). Also, there were other reasons related to the locations of the studies and the circumstances related to these locations, such as climate change in these drylands. Climate change is anticipated the increase in the temperatures causes urban heat island in the urbanization areas, which have severe negative consequences for the city's environment, people's health, and economic development, and triggers rising evapotranspiration rates and increasing water use and demand (Zhang et al., 2020; Liang et al., 2020).


6.1. Conclusions

Studying land use/land cover from several directions, with different methods, in altered times, and in various places is a huge challenge and, at the same time, an information source that is needed for dryland regions. This research applied remote sensing and geographic information system technologies to two regions in two different places located in the same hemisphere with similar climate change conditions and has strong connections in the similarity of water resource forms, availability, quality, and growing competitive demands. They also face intensive urban growth around the main cities, adjacent counties, and agricultural and shrublands.

As stated, and discussed in the previous chapters, the results from this research confirmed the intensive expansion of the developed areas. These areas increased by more than 658% in the Khoms District, Libya, over 41 years 1976-2015 and 45% in the Middle Rio Grande Region over 21 years 1994-2015, considering the variation of the areas of each region which is too small in the Khoms District case than the Middle Rio Grande and the study period which doubled in the Khoms District case. In both regions, the developed areas' expansion came from losing agricultural lands, which were replaced in the Khoms District case to new areas and decreased in the Middle Rio Grande by about 12%. Shrublands or native plant areas lost significant areas in the two regions to developed and agricultural areas.

Surface water resources face critical circumstances related to quantity, quality, and deficiency in meeting different sectors' needs. For example, surface water areas in the Middle Rio Grande decreased by about 56% due to snowpack reduction, temperature increasing trends, and growth of evapotranspiration rates.

Future eras and human life will become more difficult with more challenges and concerns about environmental sustainability and resiliency because of the excessive exploitation of natural
resources such as water and native vegetation. Nevertheless, urbanization sprawl is still going and challenging life in the region. Land use / land cover future prediction change in the Middle Rio Grande Region results performed by the TerrSet model revealed that these features will likely keep the same patterns and trends in the coming years 2020-2040. Results indicated that the agricultural lands are expected to continue decreasing by about 11%, mainly around the major metropolitan areas of El Paso, Ciudad Juárez, and Las Cruces, to provide land for developed open space, which will likely increase by about 5% and developed areas which will increase about 50%. The surface water areas across the region will decrease by about 25% due to climate change, snowpack reduction, and growing demands. Therefore, we have to manage the available natural resources in a proper manner that will support and facilitate our lives.

Finally, to such an extent and concluding the research work that was accomplished, drylands anywhere are subjects of considerations, studies, and solutions.
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APPENDIX

Appendix 3.1. shows Satellite data used in Space-based Measuring of Land use/Land cover Change in the Middle Rio Grande Region: An Opportunity for Understanding Change Trends in a Water-scarce Transboundary River Basin

<table>
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Spacecraft/Sensor:
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Appendix 4.1. shows Satellite data used in Modified Normalized Difference Water Index (MNDWI) as a visualization indicator for change in surface waterbodies in the Middle Rio Grande Basin

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CURRICULUM VITA


He worked for the agriculture ministry, Libya, since 1988 in water and soil management in many regions of the country. Also, worked in agricultural land protection and agricultural Project monitoring. He joined Elmergib University as an assistant lecturer in the Department of Geology and Environmental Science at the College of Science, Khoms, Libya (2009-2014). When he joined the University of Texas at El Paso, he worked as Research Associate at the Center of Environmental Research Management (2015-2020). He worked as a Teaching Assistant in the Geology Department at the University of Texas at El Paso (2020-2022).

He focuses his research on water and soil, plant, environment, geographic information systems, and remote sensing technologies and applications. He attended many research conferences and published research papers, the latest (Land Use Land Cover Change and Urban Growth in Khoms District, Libya, 1976–2015 (2020). Monitoring of land use/land-cover changes in the arid transboundary middle Rio Grande Basin using remote sensing (2018)).

He attended many professional training courses in environmental management, remote sensing, geographic information systems, and computer applications. He uses several applications and software such as ArcGIS, ERDAS, ENVI, ERMAPPER, and TERREST.

Contact information: Email address: obelhaj@miners.utep.edu

: omarsolliman@gmail.com