2013-01-01

Assessing The Equity Implications Of Greenspace Distribution In An Arid Region

Abdelatif Eldeb
University of Texas at El Paso, abeldeb@miners.utep.edu

ASSESSING THE EQUITY IMPLICATIONS OF GREENSPACE DISTRIBUTION IN AN ARID REGION

ABDELATIF B ELDEB

ENVIRONMENTAL SCIENCE AND ENGINEERING

APPROVED:

Sara E Grineski, PhD, Chair

Timothy W Collins, PhD

Raed Aldouri, Ph.D.

Barry Benedict, Ph.D.

Benjamin C. Flores, Ph.D.
Dean of the Graduate School

Dedication

This research is dedicated to the souls of my parents, may Allah mercy them, without whose help and support my education would not have been possible. It is also dedicated to my wonderful wife, and my four beautiful kids, Abubakr, Basma, Maki, and Tasnem who came into this world during my journey through this work. Finally, it is dedicated to my siblings as thanks for their support and encouragement in completing this project.

ASSESSING THE EQUITY IMPLICATIONS OF GREENSPACE DISTRIBUTION IN AN ARID REGION

By

Abdelatif B Eldeb

DISSERTATION

Presented to the Faculty of the Graduate School of

The University of Texas at El Paso

in Partial Fulfillment

of the Requirements

for the Degree of

Doctor of Philosophy

Department of Environmental Science & Engineering

THE UNIVERSITY OF TEXAS AT EL PASO

December 2013

Acknowledgements

I would like to thank everyone who helped me successfully fulfill this research project and contributed to its development. Without many of their special contributions, it would have been impossible to get this work accomplished.

I owe the deepest appreciation to my Ph.D. advisor, Dr. Sara Grineski for her supervision, advice and guidance from the very early stages of this research. She created an atmosphere that encouraged innovation and shared her extraordinary experiences throughout the work. Without her unflinching encouragement, it would have been impossible for me to finish this dissertation.

I am heartily thankful to my committee members, Dr. Raed Aldouri, Dr. Timothy W Collins and Dr. Barry Benedict who provided immeasurable help, constructive guidance, and feedback since the beginning of my work on this research project. Special thanks go also to Yolanda McDonald for assisting with the assembly of the census data that were the basis of my geographical analysis. I am also appreciative to the Ministry of Higher Education and Scientific, Libya for provided funding during the period of my study.

My research was supported in part by the Southwest Consortium for Environmental Research and Policy (SCERP) Environmental Protection Agency (EPA) Cooperative Agreement EM 83486101-01.

Abstract

In the last few decades, vegetation deterioration is receiving increased attention because of its adverse impacts on societal and human health, environmental sustainability, and quality of life. I have selected two cities in Chihuahua Desert region (El Paso and Juarez) as case study sites to develop a novel and applicable methodology for integrating remotely sensed data of different spectral and spatial resolutions into an analysis of the spatial distribution of an urban amenity. The primary objective of this research is to determine if the spatial distribution of greenspace in 2010 is equitable with respect to socio-demographics in El Paso and in Juarez and to understand why the results for the two studied cities may be similar or different. To provide contextual background for this objective, the following two sub-objectives have been identified to characterize greenspace in the study area: assess vegetation change over a thirty year period from 1984 to 2010 to provide insight into how the distribution of vegetation may change in the future, and examine the relationship between Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) in the study area during the year 2010. Geographic Information System (GIS), remote sensing (RS), and spatial regression methods were used as tools to achieve objectives of this study. The results for the main objective indicates that in El Paso there are not serious inequities related to socially vulnerable groups having less access to green space; the only serious inequity is the lack of greenspace in high density urban neighborhoods. In Juarez, the association between neighborhoods with more renters and less greenspace conforms to a traditional pattern of inequity. Results also show El Paso recorded larger increases in vegetation between the years 1984 and 2010, while Juarez witnessed a small increase in vegetation between 1984 and 2000, and it underwent a decline in vegetation from the

period of 2000 to 2010. Lower levels of vegetation coverage in the study area were also associated with higher land surface temperatures, and vice versa.

Generally, this dissertation cast lights on an important issue in understanding the inequity distribution of greenspace between socio-demographic groups. Mixed quantitative methodologies (correlation, descriptive, and regression) were used in order to address this issue. The outcomes and methods used in this dissertation will be a beneficial reference for close investigation of the distribution of greenspace in El Paso and Juarez in the future.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

1.1 Background:

Urbanization is one of the most important aspects of global change. Population growth and migration from rural to urban areas have been recognized as two main factors contributing to rapid urban growth. Urban growth is occurring at an unprecedented rate worldwide with 65% of the population expected to reside in urban areas by 2025 (Zhou et al. 2011). Over 30% of the world's populations live in arid and semiarid regions and it is expected that the percentage and total numbers of individuals in these dry areas will increase (Koerner et al. 2002). Urbanization may improve our lives, but it also introduces many other problems, such as global warming, industrial waste, air pollution and loss of native vegetation.

In terms of vegetation, urbanization transforms vegetation patterns and ecosystem processes. The presence of buildings, roads, parking lots, and other paved surfaces, in place of vegetation, can affect local weather and climate significantly. Most of the environmental impacts of urbanization studied to date are associated with the loss of greenspace. The loss or degradation of greenspace may deprive creatures of their habitats, reduce biodiversity, and disrupt the structure and process of the urban ecosystem (Tzoulas and James 2004). In semi-arid and arid regions, several studies showed that the urbanization process often increases vegetation (UGEC 2010; Nowak et al. 2012; Kim 2010; Al-Gaadi 2011).

Urban green spaces (UGS) are an integral part of any urban area and their importance is very well known for maintaining environmental quality and sustainability. At the neighborhood level, the availability of greenspaces improves environmental quality, reduces stress, enhances feeling of social safety (Groenewegen et al. 2006; Maas et al. 2009; Troy and Grove 2008), improves physical and mental health (Massa et al. 2006; Mitchell et al. 2008; Baker et al. 2002, Patz

et al. 2005, Grimmond 2007), and reduces the health risks from extreme heat (Jenerette et al., 2011). Because of increasing urbanization, more people face the prospect of living in residential environments with fewer green resources, especially people from low socioeconomic groups. Maas et al. (2006) investigated the strength of the relation between the amount of greenspace in people's living environments and their perceived general health. The relation was analyzed separately for different socioeconomic groups and different age groups. The result showed that the health of people in all age groups benefits significantly from greenspace.

Vegetation also has a strong cooling influence on land surface temperature. This makes it an important amenity in arid environments. The use of greening as a strategy to moderate the urban heat island (UHI) and improve the urban microclimate has been widely emphasized (Taha et al. 1997; Ng 2009). For the arid and semi-arid regions, the best uses of vegetation should take advantage of its shading aspect to reduce the intense solar radiation in the summer as the overheating is mainly due to the heat storage by the sunlit surfaces. Unless regular irrigation is supplied, the evapotranspiration is often weak owing to the lack of water in the soil. Therefore, sparse vegetation, well mixed within the urban structure to produce sufficient shade, is recommended in hot and dry climates (Fahmy et al. 2010). While the benefits of greenspace are clear, to date, it is unknown if green environments are equitably distributed in arid cities like El Paso and Juarez.

Previous studies would suggest that inequitable distribution of greenspace is likely to result in an uneven geography of environmental advantage (e.g., parks) and disadvantage (e.g., hazardous waste disposal sites), leading to an unequal distribution of social benefits and burdens across people and places (Landry and Chakraborty 2009). In order to determine if principles of environmental equity have been violated, quantitative case studies have typically focused on

testing the environmental equity hypothesis, that is, whether all demographic or socioeconomic groups in a particular study area are equally affected by the existing spatial distribution of environmental amenities (Cutter 1995). In my research, I investigated socio-demographic inequalities in greenspace distribution between and among two cities: El Paso and Juarez.

Urban environment research in arid and semi-arid cities, as I conducted here, is essential because the population growth in desert cities continues to explode. Urban planners and government officers need to consider how to manage the urban environment in desert cities to advance sustainable cities and improve the quality of life for people. Extensive research on urban open spaces shows that there are environmental, social, and economic benefits of greenspaces (Tyrväinen 1997, Groenewegen et al. 2006, James et al. 2009). Nevertheless, most of these studies are based in humid cities where greenspaces are dense vegetation. With its focus on an arid study area, results of this study will be relevant to arid regions where vegetation is sparse and limited. The main goal of my dissertation is to build a comprehensive framework for analyzing urban greenspace inequities in an arid region, taking the urbanized region of El Paso and Juarez as a case study.

1.2 Contribution

While the uneven geography of environmental disamenities has received considerable attention in environmental justice research, few studies have examined the concern of equity within the context of urban greenspaces (Heynen 2006; Heynen et al. 2006; Pedlowski et al. 2002; Perkins et al. 2004) and no published study has specifically focused on assessing distributional equity for greenspace in arid and semi-arid regions. The study addressed this gap

in the literature by evaluating the environmental equity implications of greenspace in two cities: El Paso and Juarez.

1.3 Research questions

The following are the three sets of research questions that I have addressed in this dissertation. The first set of questions provided contextual background to my focus on equity by providing insight into how the distribution of vegetation has changed through time and by quantifying the relationship between land surface temperature and vegetation. The second set of questions (the main focus of this dissertation) focused specifically on the equity dimensions in the distribution of greenspace.

1.3.1 Characterizing greenspace in the study area through time

- How has the quantity of vegetation changed between 1984-2010 in El Paso and Juarez?
- What is the relationship between land surface temperature and vegetation in the study area during the year 2010?

1.3.2 Assessing the equity implications of greenspace distribution

- What is the relative significance of socio-demographic characteristics in predicting the distribution of greenspace in El Paso and Juarez in 2010?

1.4 Literature Review

1.4.1 Distribution of greenspace in urbanizing regions

This section focuses on providing context for my analysis of greenspace change (Research Question 1-a). Increasing population and the migration of people from rural to urban areas are considered two main factors that contribute to rapid urban growth. This phenomenon

has caused many impacts on the environment and become a critical issue in global change research (NRC 2001). In most non-arid regions, urbanization has decreased vegetation cover and transformed the natural landscape to built up areas, resulting in a decrease in greenspace in cities and thus fewer benefits for their residents (Kim 2011). In contrast, a few studies have shown that tree cover and grassland in some arid environments have increased due to urbanization process (Al-Gaadi 2011; John et al. 2009; Nowak et al. 2012; Kim 2010). Al-Gaadi (2011) assessed the temporal land cover and vegetation changes from 1990 to 2006 in a desert region of Saudi Arabia. Landsat TM and ETM+ images were used for generating NDVI, and GIS was employed to detect the land cover and vegetation changes. He concluded that the mean NDVI values of the study area increased from 0.09 in 1990 to 0.46 in 2006. John et al. (2009) investigated changes in vegetation cover between 1992 and 2004 in semi-arid Inner Mongolia. The results demonstrated that grassland and cropland (greenspaces) have increased proportionally during the study period.

In recent decades, major efforts have been made to study and monitor land cover change based on remotely sensed Landsat images (Han et al. 2004; Wang et al. 2004; Coop et al. 2009; Avelar et al. 2009; Chen et al. 2009; Bagan et al. 2010; Mustapha et al. 2010; Peijun et al. 2010). Most of these methods involve the use of modern techniques such as remote sensing (RS), geographic information systems (GIS), and change detection to determine the changes in green space between two or more time periods. Peijun et al. (2010) investigated changes in land cover in non-arid environment, and they concluded that built-up land areas in Xuzhou, China between 1987 to 2007 have increased, while farmland has seen a continuous loss due to urbanization. By using NDVI to measure changes in vegetation, the study demonstrated that the areas of vegetation cover have been in a continuous decline over time. Zadeh (2006) compared three

change detection techniques for green space with Landsat TM and ETM+ imageries of Tabriz, Iran. He concluded that 866 hectares of greenspace had been lost during the period 1989 to 2001. In addition, Digirolamo (2006) used Landsat 5 Thematic Mapper (1991) and Landsat 7 ETM+ (2000) imagery of Gwinnett County, Georgia to detect land cover change using the NDVI. After conducting an analysis of vegetation changes from 1991- 2000, they found that the change detection technique was useful and worked well for detecting changes in vegetation and/or vegetative characteristics but it did not always work as well for assessing changes in land use. The study area lost approximately 13,500 hectares of vegetation cover during the study period to urban sprawl, with the majority of the loss coming from forested areas.

A few studies have also conducted the statistical test by Analysis Of Variance (ANOVA) to statistically quantify changes in vegetation, as measured using NDVI. For example, Kadmon et al. (1999) analyzed the mean difference in tree cover between two time periods 1960 and 1992 in Israel using repeated measures ANOVA. They concluded that the mean tree cover of the study area increased from 13% in 1960 to 35% in 1992. Their results point to a significant increase in the percentage cover of trees in the study area between two time periods ($P< 0.001$). However, with rapid changes in land-cover occurring over many arid regions, remote sensing and change detection techniques are essential tools in monitoring changes in vegetation.

1.4.2 The link between vegetation cover and land surface temperature (LST)

This section focuses on providing context for my descriptive analysis of the relationship between NDVI and LST (Research Question 1-b). It is well known that vegetation has cooling effects on urban land surface temperature. Greenspace provides a natural environment for urban residents (Taylor et al. 1995) and contributes to the stabilization of the urban climate (DTLR

2002; DCAUL 2003). It also enhances the urban biodiversity, reduces air pollution, and decreases urban air and land surface temperature (Miller 1997). The cooling effect of greenspace on land surface temperature helps make cities more comfortable places for people. Daytime air temperatures have been found to be approximately two to three degrees lower in urban green spaces than in the adjacent areas (DTLR 2002). In addition, greenspaces block solar radiation directly by providing shade and indirectly by covering surfaces that absorb solar energy (Dong et al. 2005). Thus, greenspace represents an important amenity in urban environments, making an analysis of environmental equity particularly relevant.

Many studies have focused on how urban temperatures are affected by vegetation and impervious surface cover using GIS and Remote Sensing techniques. Most of these studies have found that vegetated areas tend to have lower surface temperatures. For instance, Yuan et al. (2007) investigated the relationships between the land surface temperature (LST), percent impervious surface area, and NDVI. They used satellite data from Landsat 5 TM and Landsat 7 ETM+ to estimate the LST from four different seasons for the Twin Cities, Minnesota in 2002. The results showed there is a strong linear relationship between LST and percent impervious surface for all seasons, whereas the relationship between LST and NDVI is weaker and varies by season.

Several studies have conducted correlational analysis relating LST to NDVI, as I plan to do here. For instance, Sun and Kafatos (2007) presented a comprehensive evaluation of the relationship between vegetation and Land Surface Temperature (LST) over North America. They found that the season-of-year plays important role in the correlation between LST and NDVI. The correlation between NDVI and LST during winter is positive. For warm seasons, the correlation between LST and NDVI is strongly negative. Kim et al. (2005) analyzed the

relationship between LST and NDVI for the Kunsan city, South Korea using a correlation analysis model. The result corresponds to the conventional relationship that there is negative correlation between LST and NDVI. Ping et al. (2006) used the TM images of Hangzhou to study the land surface temperature (LST), the results reveal that there was a clear correlation (corr. = -0.88_ between the LST and vegetation cover (measured using NDVI). Zhangyan et al. (2006) used TM data from Beijing to study the relationship between NDVI and LST, the results show a similar correlation coefficient (-0.82). Furthermore, Ozelkan et al. (2011) measured the relationship between LST and NDVI by using correlation analysis in semi-arid areas of Muğla, Turkey, and they found a negative correlation observed between LST and NDVI during a twenty six-year period.

Vegetation can significantly influence the urban environment through reducing temperature, improving air pollution, and preserving biodiversity in cities. Several studies showed that more greenspace in urban areas is positively related to mitigating the urban heat island effect (e.g., Ca, Asaeda, and Abu 1998; Oh and Hong 2005), which improves the quality of life for urban residents. This makes it an important consideration from an equity perspective.

1.4.3 Equity implications of greenspace distribution

This section focuses on reviewing the literature on environmental equity and greenspace, the primary focus of my dissertation (Research Question 2). In many studies, the terms of environmental justice and environmental equity have been used to convey the same general concept, which refers to the equal distribution of environmental hazards, such as pollution and contamination, across all social groups, as well as equitable policies and processes to reduce differences in those who endure environmental problems (ESA 2012). Environmental justice and

environmental equity are also defined by the fact that all people, regardless of race or socioeconomic status, are entitled to equal protection under environmental laws and to participate in environmental decision making in their community (Bullard 1996; EPA 2003).

While some scholars use the terms environmental equity and environmental justice interchangeably, there is a distinction between the two terms. Environmental equity refers to an equal amount of sharing of risk burdens, and not necessarily a reduction in the burdens themselves (Lavelle, 1994).In addition, Cutter (1995) defined Environmental Justice as "equal access to a clean environment and equal protection from possible environmental harm irrespective of race, income, class or any other differentiating feature of socio-economic status" (p. 111-122). Thus EJ is concerned not only with the distribution of environmental advantages and disadvantages amongst minority groups, but also how those distributions have been developed, and what the best approach is to address them (Greenberg 1993; Kasperson 1994). Such issues are the difference between environmental equity and environmental justice.

Generally, all of these terms help define the interrelationships between local demographic groups and the factors which have, or potentially could, influence the environment they live in like the quality of their air, greenspace, water, and land. McDermott et al. (2011) has identified three major types of equity related to environmental inequity/injustice:

1. Distributional equity studies the results of the allocation of costs, risks and benefits among affected groups of people because of environmental policy or resource management decisions.
2. Procedural equity refers to equality in the political processes that allocate resources and resolve problems. This involves representation, recognition and inclusion, and participation in decision-making. Procedural justice affects behavior; specifically it may

affect dispute behavior, decision compliance, task performance, and other aspects of behavior.

3. Contextual equity looks at the pre-existing conditions under which people engage in procedures and benefit distributions. This source links together the other two dimensions discussed above.

This study focuses primarily on distributional equities with regards to greenspace and socio-demographic characteristics. The majority of studies have found statistical evidence of environmental inequity with regards to race, ethnicity and class but some have not (Landry and Chakraborty 2009; Mohai and Bryant 1992; Anderton et al. 1994; Bowen et al. 1995; Fuller and Gatrell 2009; Atlas 2002). The majority of these studies have focused on the locations of hazardous facilities as a proxy for environmental risks. However, there is increasing recognition that enhancing green, public open spaces in cities provides a strategy to make those cities more sustainable, more livable, and more equitable. Urban greenspaces have important amenity values that are often spatially heterogeneous within urban areas (Cadenasso et al. 2007; Goetz et al. 2003; Grove et al. 2006). Although few studies have examined the spatial distribution of greenspaces from the theoretical perspective of environmental equity (see Heynen et al. 2006; Jensen et al. 2004; Pedlowski et al. 2002; Perkins et al. 2004), some studies have demonstrated that there is an uneven geographical relationship between the existing distribution of greenspace and socio-demographic characteristics.

Shifting focus to urban greenspace, a number of scholars found a positive relationship between higher median household income and more vegetation cover (Grove 1996; Heynen 2006; Heynen and Lindsey 2003; Pedlowski et al. 2002; Talarchek 1990), and vegetation diversity (Martin et al. 2004). These results seem to support the inequity hypothesis by

suggesting that low-income neighborhoods have less access from the existing distribution of this amenity. From the perspective of political ecology studies, some have argued that the unequal distribution of urban greenspace is associated with income levels and unequal power relations (Heynen 2006; Heynen et al. 2006; Pedlowski et al. 2002; Perkins et al. 2004).

Several studies have shown inequalities in the spatial distribution of greenspace for racial/ethnic minorities and low-income groups (Boone et al. 2009; Talen 1997; Wolch et al. 2005; Matthew et al. 2010; Comber et al. 2008; Lindsey et al. 2001). Dajun (2011) evaluated the socioeconomic disparities in greenspace access in Atlanta, Georgia, and concluded that the spatial accessibility to greenspaces was not evenly distributed. Neighborhoods with a higher concentration of African Americans had significantly poorer access to greenspaces. Welch et al. (2005) found that low-income and concentrated poverty areas, as well as neighborhoods of color, lacked access to parks as compared to white-dominated areas in the city of Los Angeles. Kerns and Watters (2012) found that percent of trees in Minnesota decreased with the rising of percent with no high school degree. Talen (1997) found low access to parks corresponding with low housing values and high percentages of Hispanics in Pueblo, Colorado. Other work by Comber et al. (2008) used network analysis in GIS to analyze greenspace accessibility for different ethnic and religious groups in Leicester City, UK. They concluded that Indian, Hindu and Sikh groups have limited access to greenspace in the city.

Previous studies have indicated a larger extent of tree cover in neighborhoods with a higher percentage of owner-occupied housing (Heynen et al, 2006; Perkins et al, 2004). These authors argue that home owners have a greater financial incentive to invest in environmental amenities on their property than renters. First, renters may also be less willing to invest in tree planting adjacent to their residence. Second, the greater financial incentives may drive

homeowners to exert more political pressure than renters to promote public sector investment within their neighborhoods (Heynen et al, 2006; Perkins et al, 2004).

Other studies have found the opposite, with socially advantaged residents lacking access to greenspace (e.g., Tarrant and Cordell 1999). For example, lower park access was found in areas with high-income white residents in Macon, Georgia (Talen 1997). In addition, Nicholls (2001) examined access to public parks in Bryan, Texas and Lindsey et al. (2001) examined urban greenways in Indianapolis, Indiana; the results of both studies show that minorities and low-income groups were not systematically disadvantaged in terms of access to these features. Heather (2011) used Geographic Information System (GIS) and census data to examine access to urban amenities in east Tampa, Florida. The results indicate that low income and elderly groups were found to have greater inequalities in the distribution of greenspace, while owner occupied groups have more greenspace.

Spatial statistical analysis can be used to test the inequity hypothesis related to environmental injustice using data that were created with remote sensing and GIS. For example, McDonald and Grineski (2011) ran spatial regression models using the open source software GeoDa to predict lack of plumbing in El Paso and Juarez. Landry and Chakraborty (2009) used multi-variate spatial regression models to analyze the percentage of tree cover on residential public areas in the city of Tampa, Florida as a function of the explanatory variables at the block group level. They calculated two separate dependent variables for each block group: the percentage of tree cover within all public right-of-way (AROWs); and the percentage of tree cover within public right-of-way ROWs bordering residential parcels (RROWs). The results show that higher median household income was the strongest predictor of higher tree cover on both residential public right-of-way (RROWs) and all public right-of-way (AROWs), while

lower proportion of tree cover on public right-of-way in neighborhoods containing a higher proportion of low-income residents and renters.

While Landry and Chakraborty (2009) used street tree cover as their greenspace variable, others have used NDVI, as I plan to do here. Fuller and Gatrell (2009) also used NDVI and a GIS approach to assess the relationship between environmental risk, environmental amenities and socioeconomic variables in Vigo County, Indiana. They examined the relationship between socioeconomic conditions and environmental data using weighted least squares regression. The results indicated a very weak relationship between median household income and environmental disamenities. Thus, the limitation of this work was that they did not use spatial regression as Landry and Chakraborty (2009) did; therefore, my contribution through this study will use NDVI and spatial regression to analyze the equity distribution of greenspace in the study area. In addition, the majority of studies presented here have focused on race and income, while such variables are not available in Juarez. Therefore, this study will focus on other variables such as age and home ownership, population density, female-headed households and mean level of education.

Most equity studies in urban greenspace have been conducted in humid cities where open spaces are green with dense vegetation (Talen 1997; Tarrant and Cordell 1999; Lindsey et al. 2001; Comber et al. 2008). However, greenspaces in arid and semi-arid cities are different from humid city spaces. In arid and semi-arid regions, the main difference is arid city open spaces have a wide range of greenness which range from native desert with sparse vegetation to irrigated landscapes with dense vegetation (Kim and Wentz 2010). The majority of natural arid open spaces are composed of shrubs with a small number of trees and little or no turf. This study is mainly relevant in an arid region where vegetation is rare and limited. This kind of study is

important because there has been relatively little work published on urban green space inequities in arid regions within the broader urban studies literature. Because existing research is limited, there is a need to examine urban greenspace-inequity critically in the arid region of El Paso and Juarez.

1.5 Study context: El Paso and Juarez

This section focuses on providing background information on the study area, which relates to the comparative aspect of my research design (Research Question 3). The sister cities of El Paso and Ciudad Juarez are located in the Rio Grande/Bravo basin in the Chihuahua Desert, and are known as a bi-national metropolitan area on the border between Mexico and the United States (Fig. 1 provides a contextual perspective on the study area). Both share a common geographical location, natural resources, and a host of environmental problems, including drought, groundwater depletion, water pollution and air pollution (Liverman, Varady, Chavez, & Sanchez, 1999). These twin cities share air- and water-sheds and other biophysical features that unite them environmentally (Heyman, 2007). In 2010, El Paso County had an estimated population of 800,647 while Juarez has about 1,332,131 inhabitants (McDonald and Grineski 2011). Between 1970 and 2009, the population of El Paso County grew by about 108 percent from just over 360,000 to 751,500. During this time Texas experienced a population increase of over 117 percent, while the U.S. population grew by about 48 percent. Juarez's population growth has been more pointed, growing over 230 percent between 1970 and 2009, and also outpacing the growth of Mexico (109 percent) by double (Cambridge Systematics, Inc, 2010).

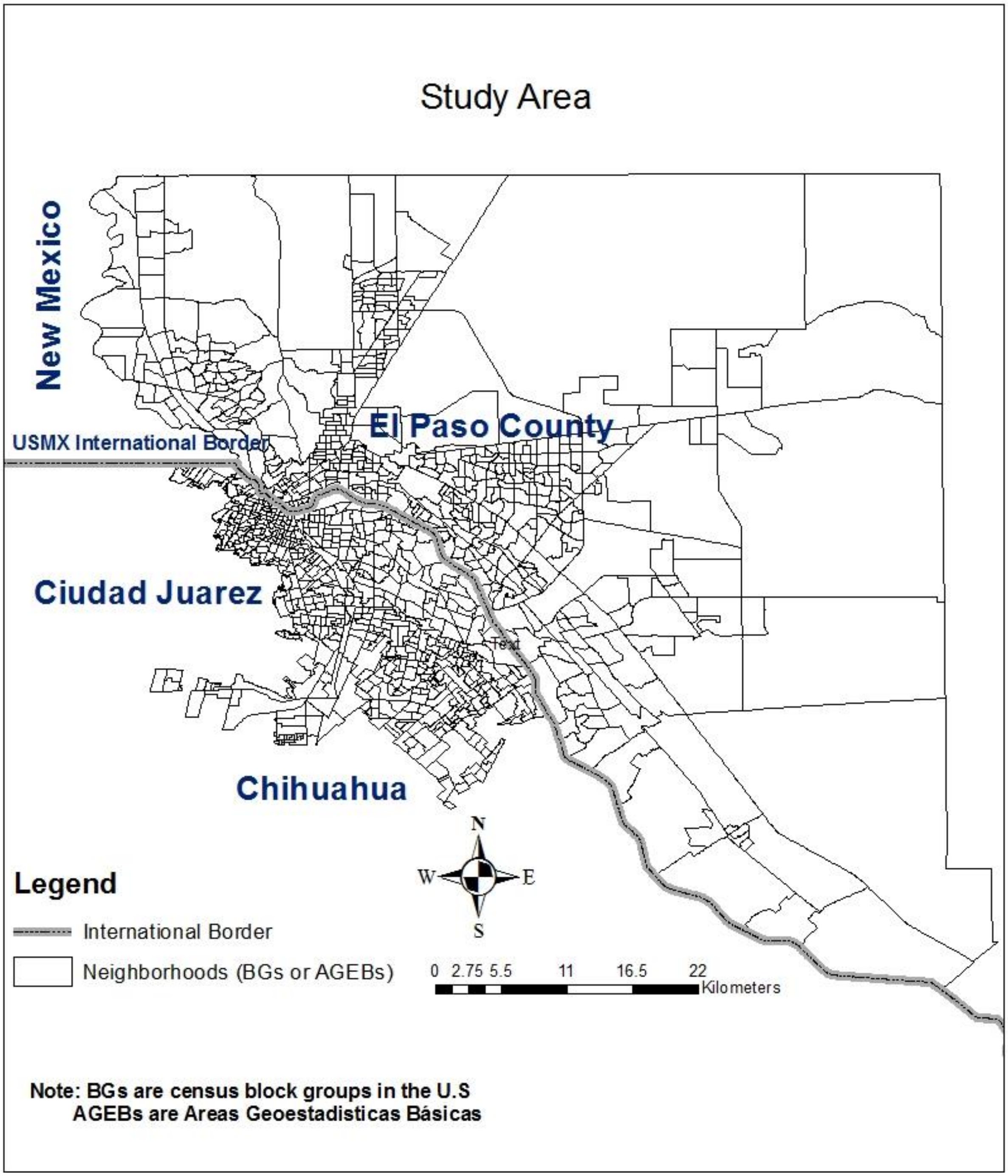


Figure 1.1 The Ciudad Juarez and El Paso County study area at the U.S.-Mexico border

Juarez has a reputation for being a relatively high-wage Mexican city, but an unpublished study conducted by El Colegio de la Frontera Norte in 2006 found that the median annual household income for Juarez was $9,890, while the statistic for Mexico was $11,460 (pesos

converted to 2007 US $) (Grineski and Collins 2010). El Paso County is a majority-minority context, with 82% of residents being Hispanic, and it has a median income of $36,333 (based on 2006-2010 estimates), which is well below the U.S. national average (US Census Bureau 2012). El Paso, although relatively poor in comparison with other cities in the United States, is significantly better off by any standard used to measure levels of socioeconomic development than its neighbor to the south (Bath 1982). Within Juarez, more wealthy residents concentrate in the city center where access to urban infrastructure (e.g., sewage, paved roads) is better, while the poor tend to inhabit self-constructed residences on the urban fringe. In El Paso, lower-income residents typically dwell in the core and the wealthier are able to live away from the city center due to well-developed transportation infrastructure (Grineski and Collins 2010). Thus, such concentrations of people in two cities will likely shape differences in the distribution of greenspace between the two cities.

Several recent environmental justice (EJ) studies have been comparative between the twin cities of El Paso and Ciudad Juarez (Grineski et al. 2012; Grineski and Collins 2010; Collins et al. 2009; McDonald and Grineski 2011; Bath 1982). According to Grineski et al. (2012), who compared climate change-related variables in the two cities of El Paso and Ciudad Juarez, Juarez will likely face increased hazard exposure and increasing social marginality as compared to El Paso because it is a more densely settled city, which shapes the urban heat island, than is El Paso. Juarez has recently been experiencing the effects of a worldwide economic recession and a wave of drug-related violence, making it less stable than El Paso (Grineski et al. 2011). McDonald and Grineski (2011) have compared the relative risk between El Paso and Juarez for living in a neighborhood that lacked plumbing. In terms of similarities, there were two social variables that demonstrated similar patterns across the cities: (1) mean level of education

and (2) proportion under 5 years of age. In terms of differences, there were three variables that demonstrated divergent patterns between the two cities: (1) population density, (2) female-headed households, and (3) proportion renter. Furthermore, Grineski and Collins (2010) explored residential patterns of environmental injustice related to industrial hazards in the El Paso and Juarez metropolis, taking a comparative approach. The results indicated that the patterns of exposure to industrial hazards diverged between the two cities.

Chapter 2: Data and Methods

2.1 Data Sources

The data for this study were collected from various governmental agency databases (USGS and the 2010 US and Mexican Census). The types of data used in this study are listed below:

1. Landsat Thematic Mapper (TM) images every 10 years from 1984 to 2010 were used to generate NDVI values (for evaluating greenspace). For 2010, Landsat images were used to generate NDVI values (for evaluating the environmental equity and greenspace), and generate land surface temperature data (for evaluate the relationship between land surface temperature and NDVI).
2. 2010 Census and American Community Survey (ACS) (2006-2010) data for El Paso neighborhoods and 2010 Mexican census data from the Instituto Nacional de Estadística y Geografia (INEGI) for Juarez neighborhoods were used to characterize the socio-demographics of study area neighborhoods for use in the equity analysis. The six independent variables utilized, to be described below, were: (1) total population density; (2) proportion owner-occupied; (3) proportion 0-4 years old; (4) proportion 65 years old and older; (5) proportion female-headed households; and (6) mean level of education. In El Paso, all variables came from the 2010 census except for mean level of education which came from the ACS.

Table 2.1. Information about data used

Variable	Year	Original Scale/ Resolution	Source	Research question (Q) data was used in
1. NDVI				
	1984	30 m	USGS Landsat TM	Related to research Q1-a
	1990	30 m	USGS Landsat TM	Related to research Q1-a
	2000	30 m	USGS Landsat TM	Relate to research Q1-a
	2010	30 m	USGS Landsat TM	Relate to research Q1-a, Q1-b, and Q2
2. Land surface temperature	2010	30 m	Landsat TM And ETM+	Related to research Q1-b
3. Socio-demographics	2010	Block groups (US) and Areas Geoestadisticas Básicas (Mexico)	2010 Census (US and Mexico); ACS 2006-2010 (US)	Related to research Q2

2.2 Data Details

Several types of software were employed in the present study. ENVI (Environmental Visualization) version 4.8 was used for image processing, and ArcGIS was employed for producing vegetation change maps. GeoDa, Microsoft Excel and SPSS were also used for statistical analysis.

2.2.1 Unit of Analysis

In order to match geographic units across country boundaries, the most equivalent geographic units in areal/population size have been selected for analysis between the U.S. and Mexican censuses (as per Collins et al. 2009; Collins et al. 2012). These units are census block groups (BGs) in the U.S. and Areas Geoestadisticas Básicas (AGEBs) in Mexico. Following Grineski and Collins (2008), neighborhoods with less than 500 people were deleted from the study to establish more stable independent variables. This resulted in 515 neighborhoods for Juarez and 507 neighborhoods for El Paso.

2.2.2 Normalized Difference Vegetation Index (NDVI)

For my analysis, Landsat Thematic Mapper and Landsat Enhanced Thematic Mapper (TM, ETM+) multispectral satellite imagery were used from summer 1984, 1990, 2000, and 2010. Summer scenes were selected since they are subject to the least variability due to changing meteorological conditions, as well as because the trees and plants have leaves during the summer. TM imagery, which has a 30 m pixel size, provides adequate spatial resolution to analyze trends within the urban environment without the excessive processing time that data of finer spatial resolution would require. The work was at the level of the pixel for research question 1, and at the level of the neighborhood for research question 2. In order to quantify the abundance of vegetation for the El Paso and Juarez area (Fig 2.1), the NDVI was created for four selected images (with zero cloud cover and of high quality), which can be acquired from USGS websites (to take the average vegetation in summer) centered on June, July, August, and September in the years 1984, 1990, 2000, and 2010 (for a total of 16 images). NDVI values were derived using the following formula where NIR and RED represent the near infrared and visible red reflectance respectively:

$$NDVI = \frac{NIR - RED}{NIR + RED}.$$

Early applications using Landsat images found that NDVI had significant correlation with the amount of green leaf biomass (Tucker 1979). Lyon et al. (1997) found that NDVI could provide better change detection results compared with other vegetation indices using Landsat images. Valid NDVI values range between 0 and 1, and the common range for green vegetation is 0.2 – 0.8: non-vegetated is 0.0, moderately vegetated ranges from 0.01- 0.29, and highly vegetated ranges from 0.3- 0.8 (Fuller and Gatrell 2009). For the neighborhood-level analysis, the NDVI pixel data were transformed to the neighborhood level by converting census tract vector data to a region of interest (ROI) and then calculating the statistical mean NDVI for each neighborhood. Once the mean NDVI was completed, a text file was exported and then uploaded into ArcGIS to visualize the vegetation distribution in the study area. The NDVI variable used in this equity analysis is mean NDVI.

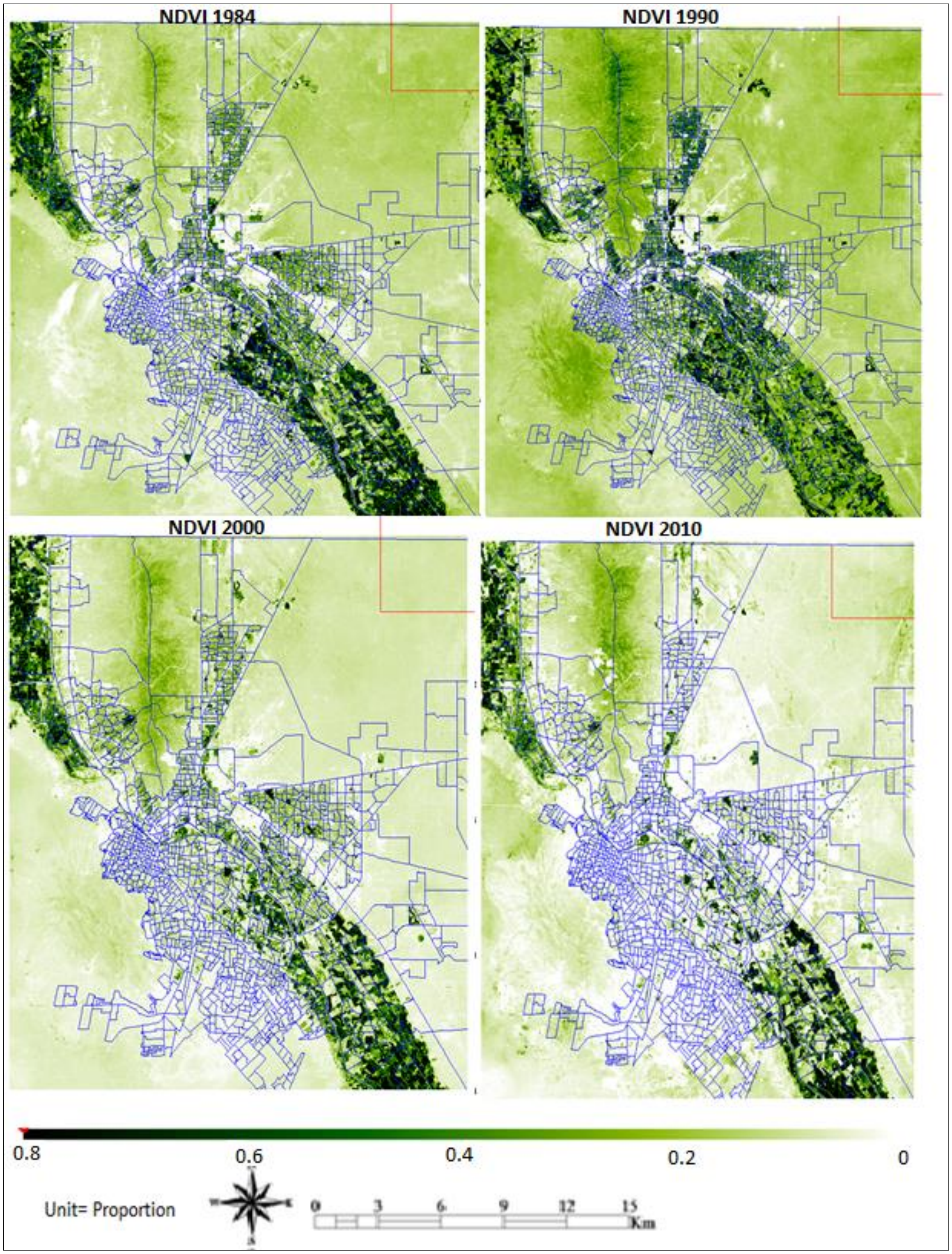


Figure 2.1: NDVI images in El Paso and Juarez per pixel

2.2.3 Vegetation Change Detection

The vegetation delineation tool was conducted using Landsat images per pixel and mile centered on June, July, August, and September in the years 1984, 1990, 2000, and 2010 for monitoring the past and present vegetation status. To identify the presence of vegetation and visualize its level of vigor, four classes, based on the presence of vegetation, were categorized into dense (more 0.70%), moderate (0.70%-0.5%), sparse (0.50%-0.25%), and no vegetation (0.25%--1.0%). These classes were transformed to shapefiles, and then uploaded to GIS ArcMap to generate different distributed vegetation maps for both cities El Paso and Juarez. The NDVI images were detected using change detection analysis for the years 1984, 1990, 2000, and 2010, and then the map was created to visualize the changes over 26 years as five classes: 0.3- 0.7 corresponded to a high increase, 0 - 0.3 to a low increase, 0 to no change, 0 - -3 to a low decrease, and less than -5 to a high decrease (see Zadeh, 2006; Daniel, 2001; Chambers, 2002).

2.2.4 Heat

In order to determine land surface temperature (LST) in the study area, four Landsat TM and ETM+ images acquired on 6 July, 14 Jun, 17 August, and 2 September for 2010 were selected (with zero cloud cover and of high quality) to identify the spatial distribution characteristics of vegetation cover and surface temperatures. Band 6 and Band 61 of TM and ETM+, respectively, were analyzed with respect to the surface temperatures. The processing of the heat data was conducted at the level of the pixel using the same technique as with vegetation and shown in Figure 2.2.

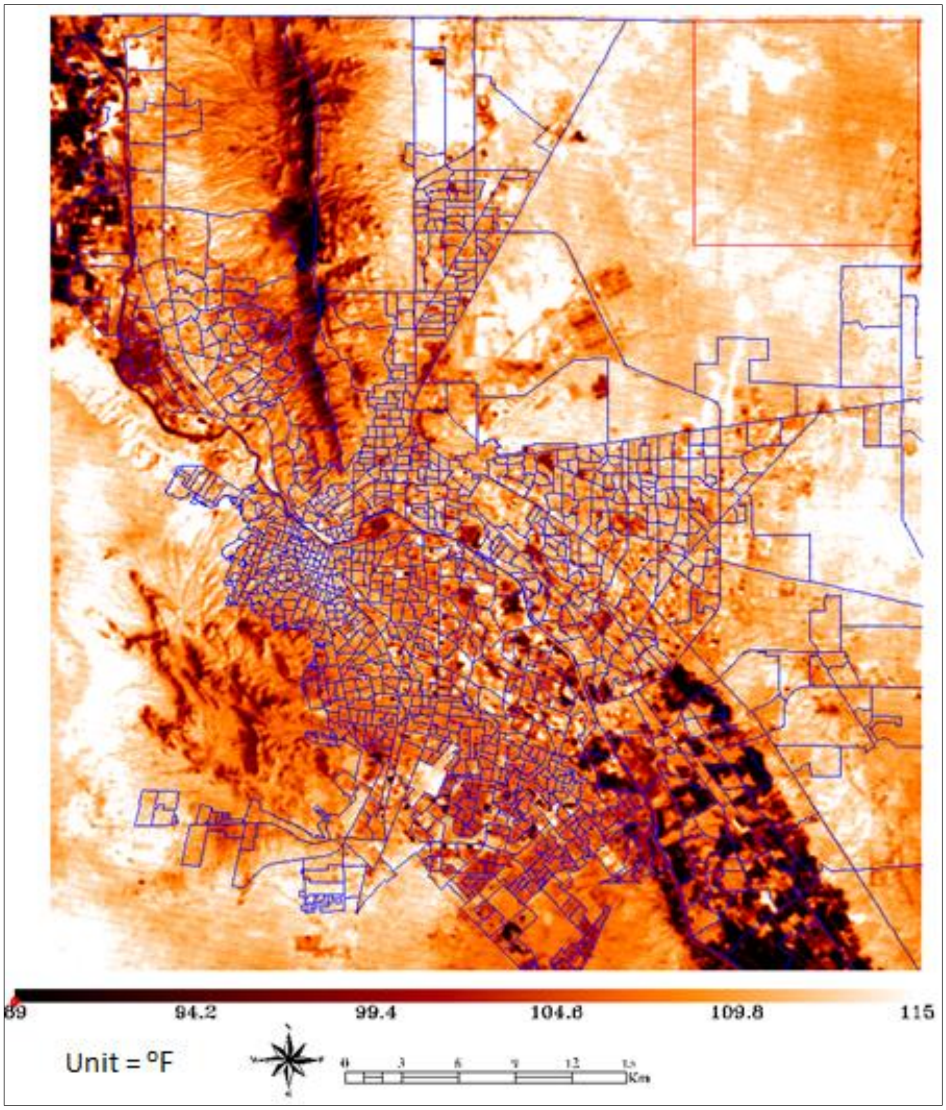


Figure 2.2: Heat 2010 in El Paso and Juarez per pixel

2.3 Independent variables (socio-demographics)

I have chosen the explanatory variables for socio-demographics based on their use in previous environmental justice studies in the region (McDonald and Grineski, 2011; Grineski and Collins, 2010; Grineski and Collins, 2008; Grineski et al. 2010) and because they have been found to have a relationship with tree cover, especially on a neighborhood scale (Heynen 2006,

Heynen and Lindsey 2003, Heynen et al. 2006, Landry and Chakraborty 2009). The analysis included six socio-demographic variables, to be described in what follows.

2.4.1 Population density:

Population density is presumed to drive vegetative change directly. As an area is settled with more people, trees and grasses are displaced by roads and buildings, and indirectly by pollution as the by-product of human activities (Troy et al, 2007). In most of an arid environment, people are aware of the need to have more greenspace and they have invested in their yard and planted grass and trees. As shown in Fig 2.3, the study included population density due to its influence on the distribution of urban greenspace and related inequities. Population density is a measure of the total population divided by the area of the neighborhood in people per km^2. F

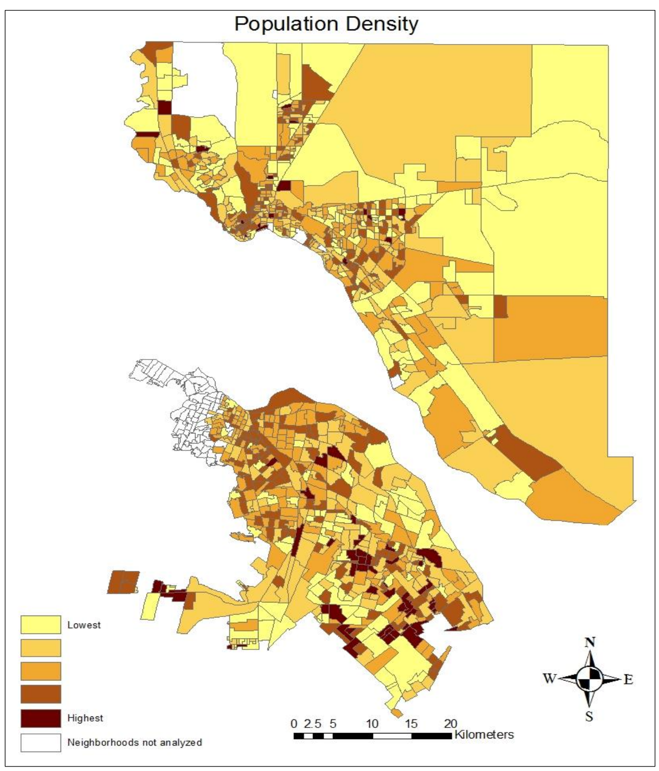


Figure 2.3: Population density for El Paso and Juarez

2.4.2 Proportion owner-occupied

Recent EJ studies show that the percentage of owner occupied housing units in a neighborhood was a significant predictor of greenspace, especially having more grass. This variable is associated with home ownership in part because grass needs frequent maintenance. (Troy et al 2007). Therefore, I include the proportion owner-occupied variable with the assumption that the rates of owner occupancy will be associated with having more vegetation as a result of the ability of people to care for their yard and vegetation. The proportion of owner-occupied housing units was calculated by dividing the total number of owner-occupied housing units by the total number of occupied units in that neighborhood (see Fig 2.4).

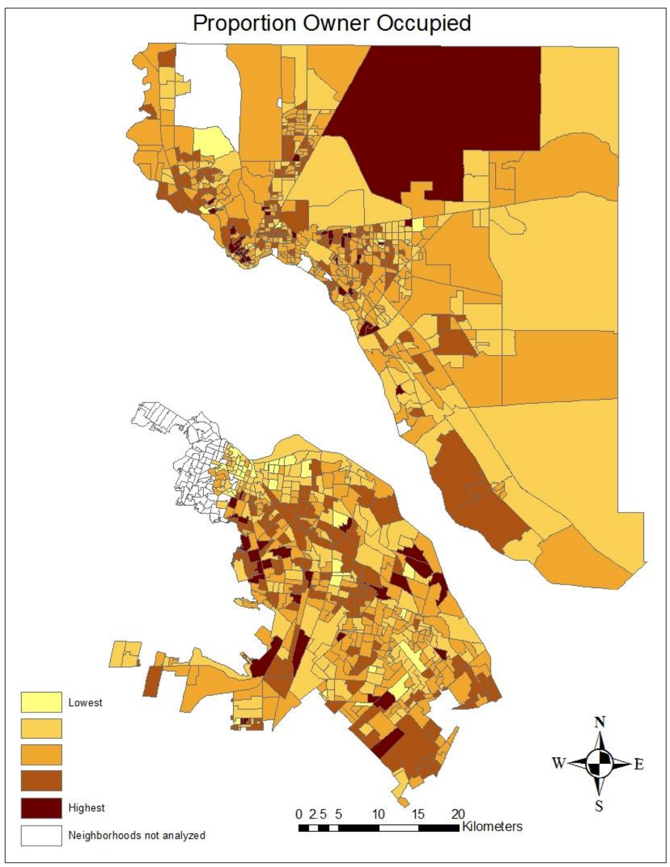


Figure 2.4: Proportion owner occupied for El Paso and Juarez

2.4.3 Proportion 0-4 years old and proportion 65 and older

Literature has shown age to have a relationship with greenspace, which is associated with health implications. The very young and older people have been a focus in the EJ literature due to their increased vulnerability to negative environmental conditions, many of which, such as pollution, heat, noise, and crowdedness, can be ameliorated by the presence of trees (Nowak 1994, 2010; Kinney et al. 2008). The research included these two groups because children and the elderly have greater potential to be positively influenced by the environmental benefits associated with green space(Dwyer et al. 1992, Hull 1992; Kerns and Watters, 2012). In order to construct these two variables, the number of people aged 0–4 and 65 and older divided by the total population in each neighborhood (see Fig 2.5).

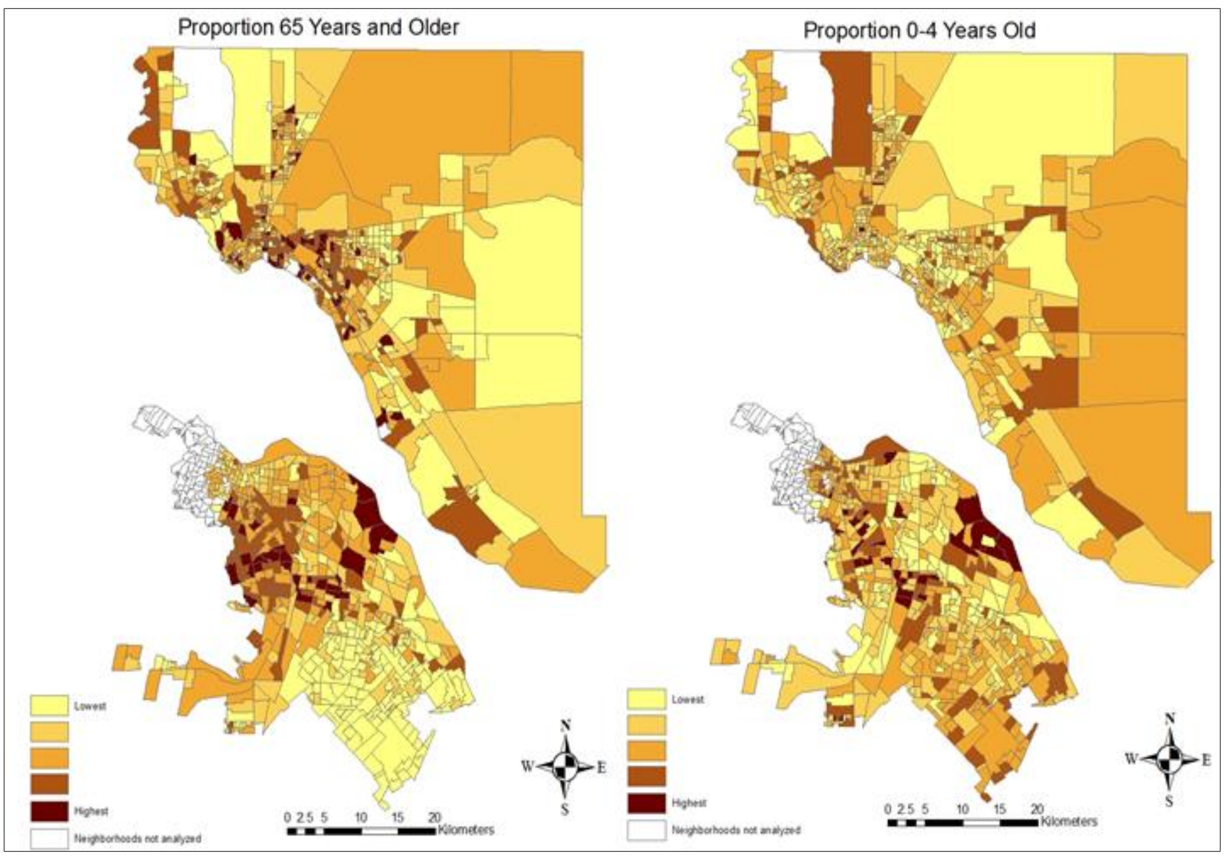


Figure 2.5 people aged 0–4 and 65 and older for El Paso and Juarez

2.4.4 Female-headed households

A female-headed households variable was used in several environmental justice studies along the US–Mexico border (Grineski and Collins 2010; McDonald and Grineski 2011; Grineski et al 2011). Female-headed households have been considered because they are usually disproportionately young, less educated and less skilled, and because female-headed households are more likely to live in poverty (Levernier et al 2000). To calculate the proportion of female-headed households, the number of female-headed households divided by the total number of households (see Fig 2.6).

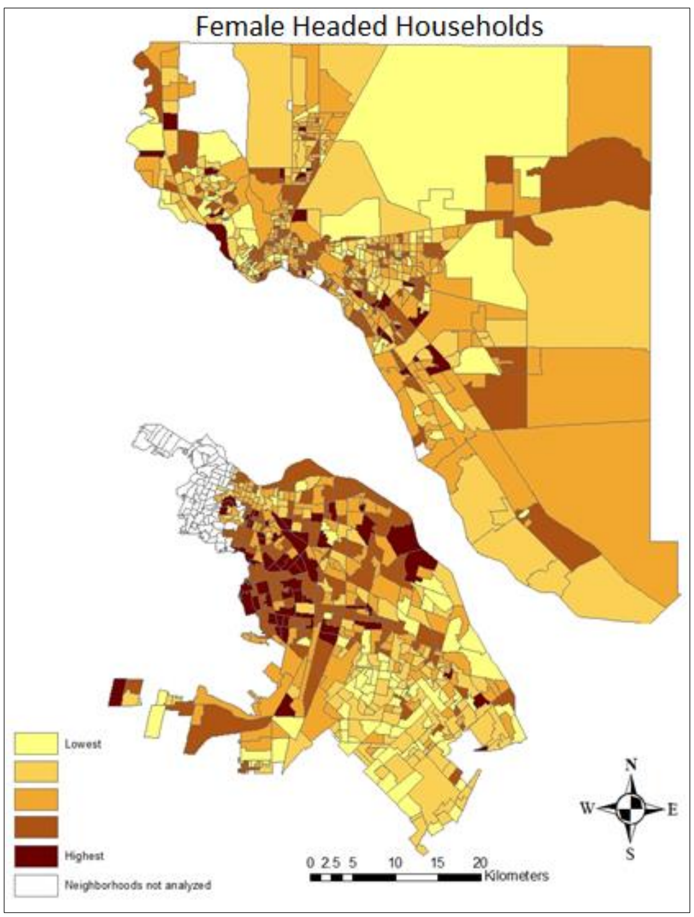


Figure 2.6: Female-headed households for El Paso and Juarez

2.4.5 Mean level of education

While neighborhood income is a more conventional variable in equity studies (see; Mohai and Saha 2006; Szasz and Meuser 1997), it is not included in this study due to differences in the two countries' censuses (see Collins et al. 2009 for more details). The use of education as a social class variable is well supported by several studies, which exhibits a strong relationship between income and education in the study area (McDonald and Grineski 2011; Law and VanDerslice 2011; Blodgett 2006). Both countries collect data useful for creating a variable for the mean years of education completed by the population in the neighborhood. Therefore, I included mean level of education as a variable to measure social class, a fundamental variable in study area (see Fig 2.7).

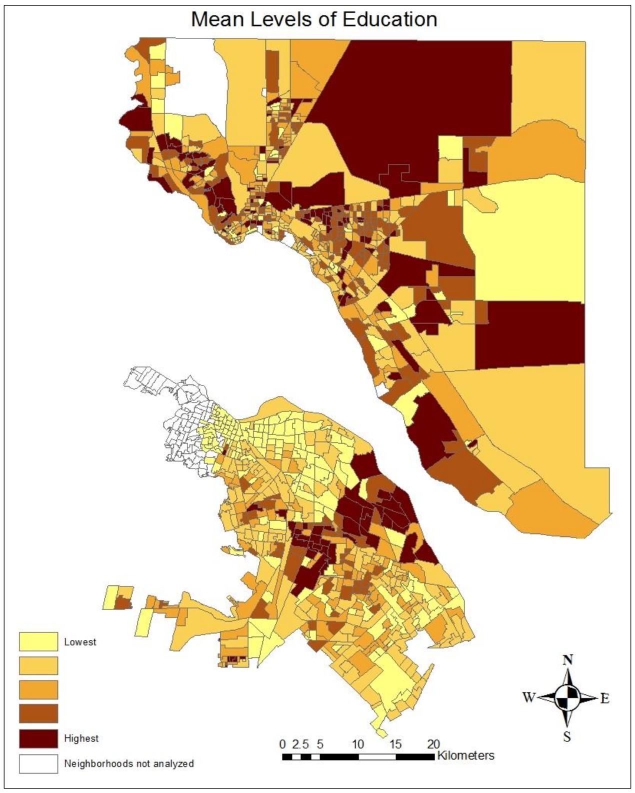


Figure2.7: Mean level of education for El Paso and Juarez

2.5 Statistical strategy

2.5.1 Research question 1-a: Repeated Measures ANOVA

Repeated measures ANOVA are an extension of Paired T-Tests. As such, repeated measures ANOVA gives us the statistic tools to detect whether statistically significant change has occurred over time. T-Tests compare average scores at two different periods of time for a single group of subjects. Repeated measures ANOVA compared the average score at multiple time periods for a single group of Subjects (Vogt, 1999). For studying the greenspace change during the time period of 1984-2010, a repeated measures ANOVA with post hoc t-tests was used to detect whether there is statistically significant change in NDVI between the time periods (1984-1990, 1984-2000, 1984-2010, 1990-2000, 1990-2010, 2000-2010). In this process, there two main steps; first, is to assume that all the means are equal. Second step is however conducted when the assumption in the first step is not satisfied, which called the post – hoc test.

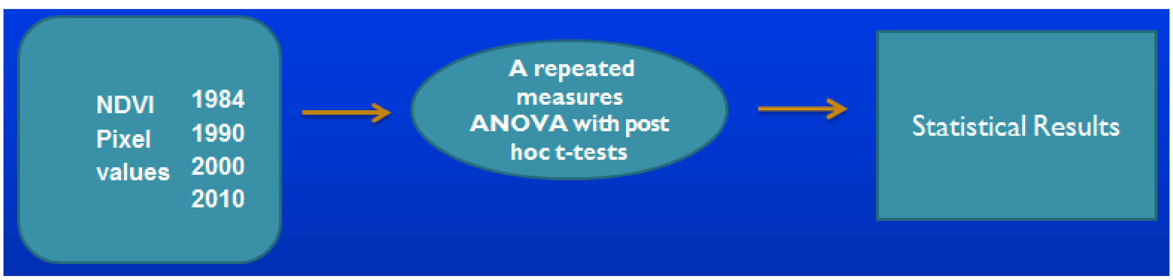


Figure2.8: Analysis processes for Research question 1-a

Step 1

In this step, we assume that the hypothesis that all the NDVI for the various years is the same. This is a general test for the Mauchly's Test of Sphericity. The hypothesis can be written as follows:

H0: $\mu_1 = \mu_2 = \mu_3 = \mu_4$

H1: at least one of the μ_i is different for i=1,…,4

In this case 1, 2, 3, 4 represents years 1984, 1990, 2000 and 2010 respectively.

Step 2

I then further performed a post – hoc test to determine the pairs of years that have the different mean NDVI's. The pairwise selection was done as follows;

1984-1990, 1984-2000, 1984-2010, 1990-2000, 1990-2010, 2000-2010.

The hypotheses for the pairwise tests are as follows:

H0: $\mu_1 = \mu_2$ H1: $\mu_1 \neq \mu_2$

H0: $\mu_1 = \mu_3$ H1: $\mu_1 \neq \mu_4$

H0: $\mu_1 = \mu_4$ H1: $\mu_1 \neq \mu_4$

H0: $\mu_2 = \mu_3$ H1: $\mu_2 \neq \mu_3$

H0: $\mu_2 = \mu_4$ H1: $\mu_2 \neq \mu_4$

H0: $\mu_3 = \mu_4$ H1: $\mu_3 \neq \mu_4$

2.5.2 Research question 1-b: Correlations

To address the relationship between LST and vegetation cover, the NDVI and LST values for each pixel was obtained through ENVI and ArcGIS. A bi-variate correlation coefficient model was used to assess the relationship between LST and NDVI in the study area in the year 2010.

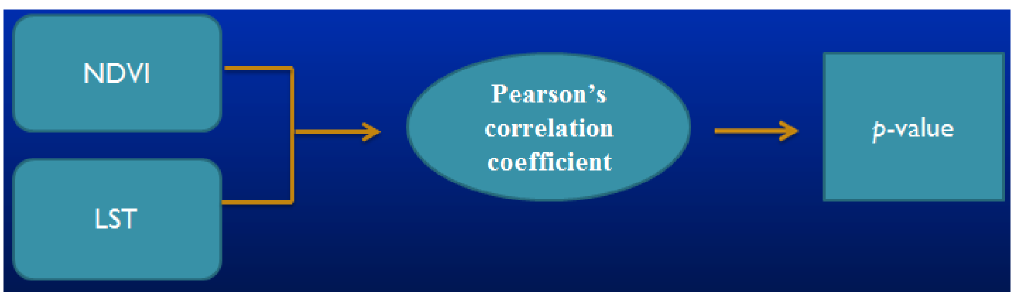


Figure 2.9: Analysis processes for Research question 1-b

2.5.3 Research question 2: Regression Analyses

Instead of working at the level of the pixel, a neighborhood-level analysis was conducted to evaluate whether the distribution of greenspace is statistically associated with socio-demographic variables in the neighborhoods of the cities of El Paso and Juarez in 2010. This study used open source spatial statistics application GeoDa (Anselin, 2004) to conduct the regression analysis for the twin cities separately, using NDVI values as the dependent variable. Descriptive statistics for all variables are presented in Table 2.2. Prior to analysis, two steps were taken in consideration: (1) each independent variable was tested for normality, and (2) checked for the multicollinearity diagnostics which occur as part of the OLS modeling step.

Table 2.2: Descriptive statistics for El Paso and Juarez

Variables	El Paso				Juarez			
	Min	Max	Mean	StdDev	Min	Max	Mean	StdDev
Population density	5.025	9536.9	2062.7.	1326.8.0.	181.12	18561.5	6152.72	3132.5
Owner-occupied	0.001	0.602	0.329	0608	0.142	0.367	0.260	0.021
Proportion 0-4 years	0.000	0.258	0.076	0.0246	0.065	0.398	0.150	0.045
Proportion 65 and older	0.000	0.397	0.121	0.0640	0.002	0.183	0.048	0.034
Proportion female-headed household	0.000	0.745	0.291	0.0766	0.092	0.462	0.259	0.061
Mean Education	7.378	17.29	12.379	1.9766	6.180	14.96	8.956	1.911
NDVI	0.000	0.494	0.1925	.08519	0.000	0.407	0.0818	0.0620

2.5.3.1 Testing for Normality:

To run regression analyses with so many variables of different units, I first attempted to check for distribution normality. When a variable is not normally distributed, a transformed variable was created and tested for normality and then substituted in our analysis (Park, 2008). A q-q plot was used to check and to compare the shapes of distributions, providing a graphical view of how properties such as location, scale, and skewness are similar or different in the two distributions (Tanbakuchi, 2009). In my case, the distribution of variables in both cities is skewed and non-symmetrical, and all of the variable distributions except proportion of owner-occupied for the city of Juarez violated the test of normality in the q-q plot test. To better approximate normality, the study used the square root transformation and the Z-score for improving the normality of all variables, except population density, proportion owner occupied, and proportion female headed households for Juarez (since these variables relatively normal to begin with so the transformation was not needed), and reducing skewedness and kurtosis of these measures in each city and I found that the transformation was effective in improving normality.

2.5.3.2 Testing for Multicollinearity:

Multicollinearity in regression exists when some independent variables in the model are correlated with other independent variables (Schroeder, 1990). GeoDa software, which I used in this study, provides the multicollinearity condition index, which indicates whether multicollinearity was a serious issue in the models (Anselin, 2005; Chakraborty, 2009). Anselin (2005) asserted that a condition index of 30 is indicative of serious collinearity problems. In this case, the condition indices were 3.637 for El Paso and 2.806 for Juarez, which indicate the absence of multicollinearity issues, and suggest that analysis could proceed.

2.5.3.3 Correlations

The correlations between NDVI and the other independent variables were achieved using Pearson's correlation for both cities El Paso and Juarez. The correlation analysis for El Paso and Juarez was performed separately. The results obtained for the city of El Paso show a negative relationship between lower NDVI and higher population density, higher proportion 0-4, higher owner-occupied and higher proportion female-headed households. There was a positive correlational relationship between higher NDVI and an increasing proportion of individuals 65 years old and higher mean level of education. The outputs obtained for the city of Juarez indicate a negative relationship between lower NDVI and an increasing population density, increasing proportion of owner-occupied residences, and increasing female-headed households. While there were a positive associated between higher NDVI with a higher proportion of children aged under 5, higher proportion of individuals 65 years old, and higher levels of mean education.

2.5.3.4 Regression analysis Using GeoDa Software

GeoDa software was built to provide classical ordinary least squares (OLS) regression with diagnostics for non-normality, heteroskedasticity, and spatial dependence. It also provides statistics for helping to choose appropriate models among OLS, Spatial Lag, and Spatial Error models using spatial dependence tests such as the Lagrange Multiplier error test and Lagrange Multiplier lag test (Smirnov and Anselin, 2001; Anselin, 2005). To get these spatial dependence statistics, the OLS model requires a set of neighbor relationships, or a spatial weights matrix, which accounts for variation in the dependent variable explained by values at neighboring locations rather than by explanatory variables (Pastor et al. 2005). In GeoDa, there are two types of spatial weights matrices: the contiguity-based spatial weight matrix and the distance-based

spatial weight matrix (Freisthler at el. 2006; Anselin, 2003; Bowen et al. 2009). Distance-based approaches are more commonly used in environmental justice research (McDonald and Grineski, 2011; Grineski and Collins, 2010; Bowen et al. 2009; Landry and Chakraborty, 2009; Chakraborty, 2009; Grineski and Collins, 2008; Grineski et al. 2010, and Pastor et al. 2005) and are what I used here (more details are provided in the next paragraph).

Following Chakraborty (2009) and Grineski and Collins (2010), OLS regression models were run first to test model residuals for spatial autocorrelation using one of the most common tests in group-level data. That is, the Moran's I statistic, which is calculated from the residual error values from the OLS regression model (Hartselle, 2012). Spatial autocorrelation ''refers to the tendency of variables to be influenced by their neighbors, potentially causing the errors in a regression model to violate the independence assumption associated with the OLS approach'' (Chakraborty 2009: 682). The study used distance method of defining weights has been used, which is considered more appropriate for irregularly-shaped census geography than the rook or queen method (Pastor, Morello-Frosch and Sadd 2005). The process of selecting a bandwidth distance for neighbors is iterative. The spatial distance was tested using 1000 m as the first distance band. Each of the models was run using the 1000 m band and I tested the residuals for spatial autocorrelation using the univariate Moran's I test. For the city of El Paso, the OLS models indicated there was no spatial autocorrelation in the residuals (i.e., I tested Moran's I values at 1,000 m, 2,000 m and 3,000m and they were not significant ; for example, the *p*-value was 0.326 when the spatial weight was 3,000 m, see Fig 2.10). As such, results from OLS regression models have been reported because the data did meet the assumptions of OLS.

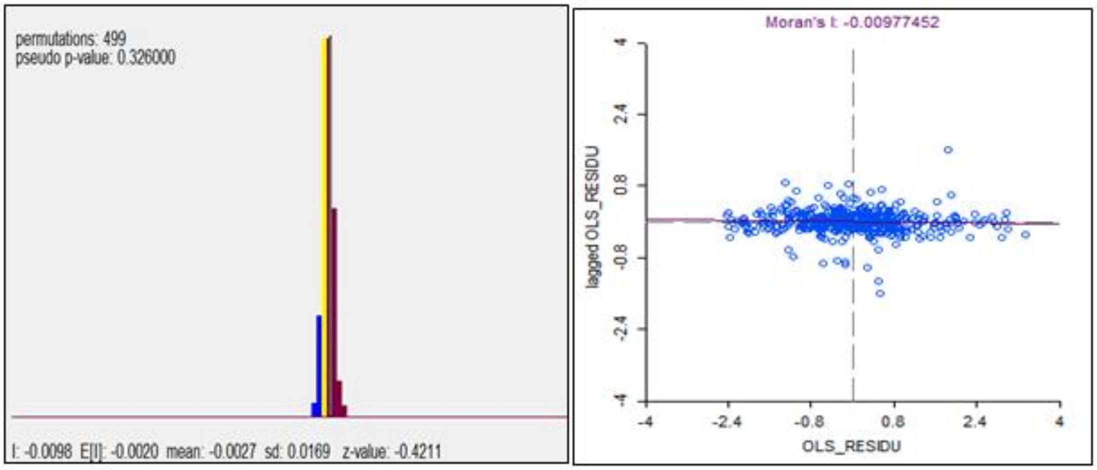


Figure 2.10: *p*-value and Moran's I of OLS test for El Paso with a spatial weight of 3,000 m

In the city of Juarez, the diagnostic tests offered in GeoDa for OLS models indicated a positive spatial autocorrelation in the residuals (i.e., Moran's I values were 0.121 at a *p*-value of 0.001 at 1000 m, see Fig. 2.11); this meant that the data did not meet the assumptions of OLS regression models.

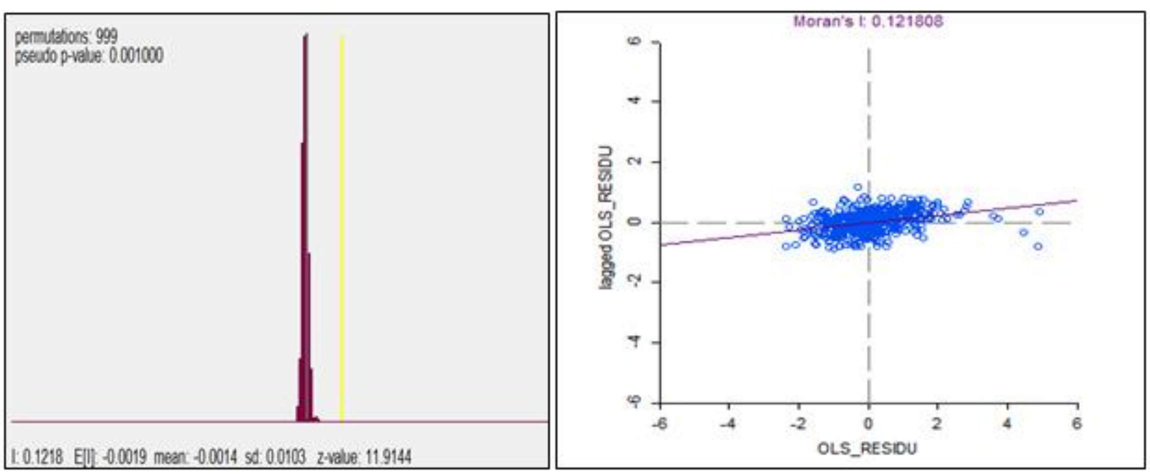


Figure 2.11: *p*-value and Moran's I of OLS test for Juarez with a spatial weight of 1,000 m

The Lagrange Multiplier (LM) and the Robust LM diagnostic tests were used to determine whether the spatial lag model or spatial error model would be used in the final analysis

for the city of Juarez (Anselin 2005). Spatial lag models assume that spatial autocorrelation is present in the dependent variable, while spatial error models assume that the independent variables exhibit spatial dependence (Landry and Chakraborty, 2009; Pastor, Morello-Frosch and Sadd 2005). In this case, the LM tests recommended that the spatial lag models was the best fit (as opposed to spatial error models), and the two models were run with weights matrix of 2000 meters because the spatial autocorrelation was removed at that distance (i.e., Moran's I values became not significant at *p* =0.37 level) see Fig 2.12.

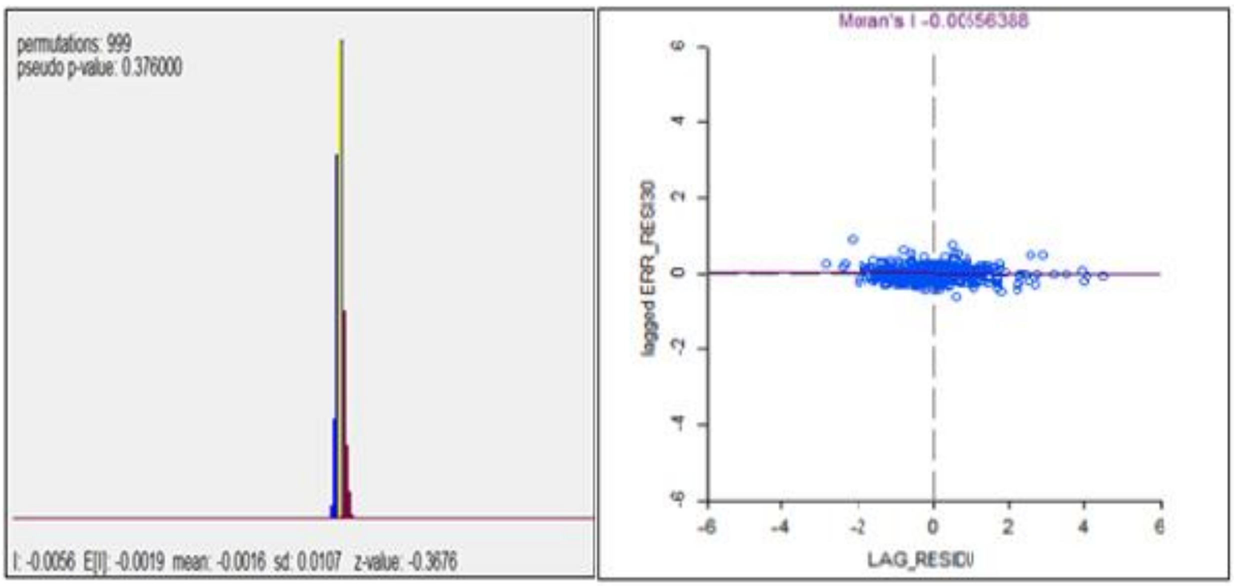


Figure 2.12: p-value and Moran's I of spatial autocorrelation test for Juarez with a spatial weight of 2,000 m

Chapter 3: Results

3.1 Introduction

The main purpose of this study is to determine the relationship between socio-demographic characteristics and greenspace in twin cities neighborhoods El Paso and Juarez and reveal inequities in the distribution of NDVI. Data were extracted from many different sources, and with different units and many processes were followed to prepare these data for analyzing. This chapter describes the change detection which was conducted using Landsat images centered on June, July, August, and September in the years 1984, 1990, 2000, and 2010 for monitoring the past and present vegetation status. It also presents the results of a repeated measure ANOVA with post hoc t-tests was used to detect whether there is statistically significant change in NDVI between 1984 to 2010. A bi-variate correlation coefficient model was used to assess the relationship between LST and NDVI in the study area in the year 2010. In addition, correlation and regression model were also conducted to evaluate whether the distribution of greenspace is statistically associated with socio-demographic variables in the neighborhoods of the cities of the El Paso and Juarez in 2010.

3.2 Vegetation Change Detection (Research Question 1a)

3.2.1 Vegetation change detection for El Paso

Before reporting the results of the ANOVA, I will describe the changes in vegetation. The NDVI change detection results for the city of El Paso can be observed in Table 3.1 and Figure 3.1. Six change detection time periods listed in Table 3.1 were compared and evaluated in this study. As it is evident, during the period 1984 to 1990, El Paso witnessed an increase in vegetation, and as such El Paso had 5.5 square mile increase of vegetation in 1990, and had small

decrease of vegetation of -0.1 square mile in 2000. While in 2010 the area recorded larger increases in vegetation of 10.2 square miles as compared to the year 1984 of 5.5 square miles (3.9 % from the total area).

Table 3.1 : The results of change detection of NDVI images in El Paso per pixel and mile between the time periods 1984-1990, 1984-2000, 1984-2010, 1990-2000, 1990-2010, 2000-2010

Year	Vegetation increase			Vegetation decrease			Net change	No change		
	Pixel	Area (mi sq)	%	Pixel	Area (mi sq)	%	(mi sq)	Pixel	Area (mi sq)	%
1984-1990	19227	6.7	7.1	3616	1.2	1.3	5.5	248381	86.3	91.6
1984-2000	20150	7	7.4	4058	1.4	1.6	5.4	247017	85.8	91
1984-2010	33463	11.6	12.3	4143	1.4	1.6	10.2	233619	81.2	86.1
1990-2000	6064	2.1	2.2	6453	2.2	2.3	-0.1	258708	89.9	95
1990-2010	32721	11.4	12.1	3718	1.3	1.3	10.1	234786	81.6	86.6
2000-2010	23285	8.1	8.6	6893	2.4	2.4	6.2	241047	84	89

Note: Vegetation change is based on five categories

Figure 3.1 depicts, in a visual format, the results of performing change detection by using ENVI and GIS techniques on NDVI image in the period between 1984 to 2010. It shows changes in the vegetation from the period 1984 to 2010. It can be obviously seen that the areas of vegetation increase were generally located in the Upper and Lower Valleys, where irrigated agriculture land uses are common. The areas of decrease occurred in the center of the county and on the northeast side. Small areas which observed a high decrease in vegetation were located in the East and Westside (change detection maps for El Paso 1984-1990 and 1984-2000 are included in appendix).

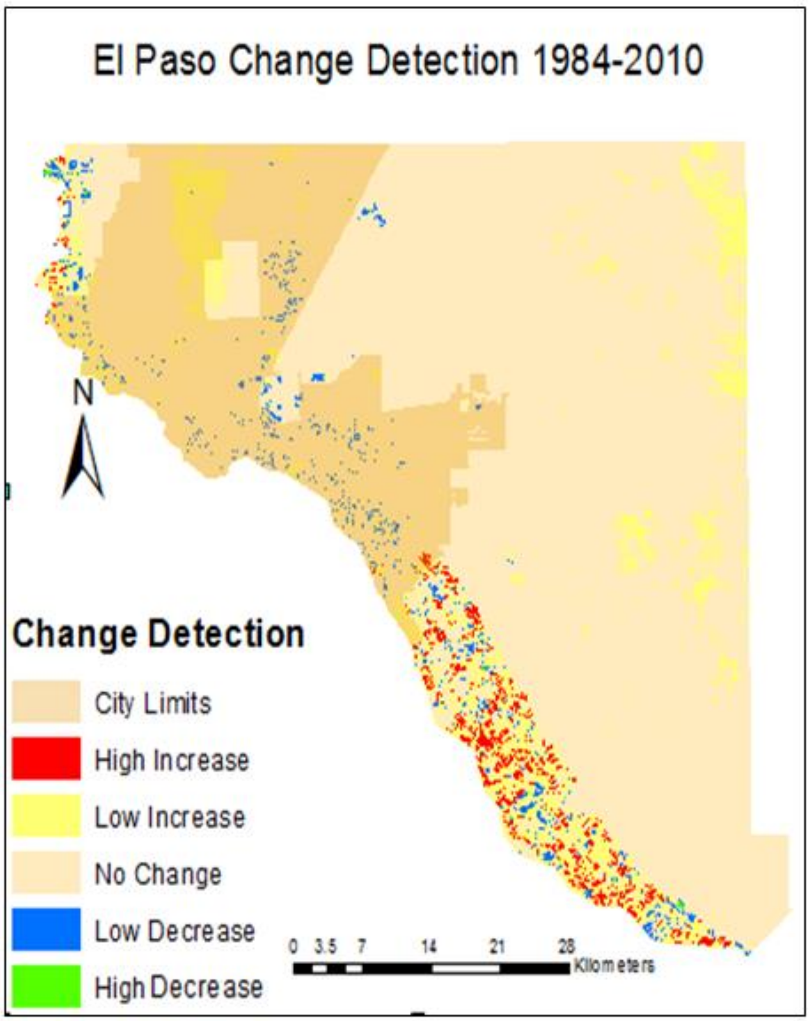


Figure 3.1: Change detection map for El Paso, 1984-2010

Here, I will present the results of a repeated measures ANOVA test. Descriptive statistics for the pixel of NDVI from the city of El Paso are observed and shown in the table 3.2;

Table 3.2: Description of NDVI for El Paso

	Mean	Std. Deviation	N
Time 1_1984	.226	.144	131295
Time 2_1990	.251	.189	131295
Time 3_2000	.243	.176	131295
Time 4_2010	.253	.192	131295

As the table above indicates, the mean and standard deviation for NDVI have increased between the years 1984 and 1990, then they decreased in the year 2000, and then rose again in the year 2010. Table 3.3 shows the results obtained from the post-hoc pairwise comparison.

Table 3.3: Post- hoc Pairwise Comparisons for El Paso

(I) NVDI_effect	(J) NVDI_effect	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a]	
					Lower Bound	Upper Bound
1984	1990	-.026*	.000	.000	-.026	-.025
	2000	-.018*	.000	.000	-.018	-.017
	2010	-.027*	.000	.000	-.028	-.026
1990	1984	.026*	.000	.000	.025	.026
	2000	.008*	.000	.000	.008	.009
	2010	-.001*	.000	.000	-.002	-.001
2000	1984	.018*	.000	.000	.017	.018
	1990	-.008*	.000	.000	-.009	-.008
	2010	-.009*	.000	.000	-.010	-.009
2010	1984	.027*	.000	.000	.026	.028
	1990	.001*	.000	.000	.001	.002
	2000	.009*	.000	.000	.009	.010

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Since the *p*-value is less than the significant level of 0.05 I reject the null hypothesis in favor of the alternate hypothesis. As such, I conclude that there is a significant difference in the post-hoc pair wise comparisons of the mean pixel values of NVDI between all of the time periods (1984-1990, 1984-2000, 1984-2010, 1990-2000, 1990-2010, 2000-2010).

Figure 3.2 shows the estimated marginal means from 1984 to 2010. From 1984, there is a steady marginal increase to 1990. There is a drop from 1990 to 2000. Again we see a further rise in NVDI from 2000 to 2010 where we record the highest estimated the mean pixel values of NVDI.

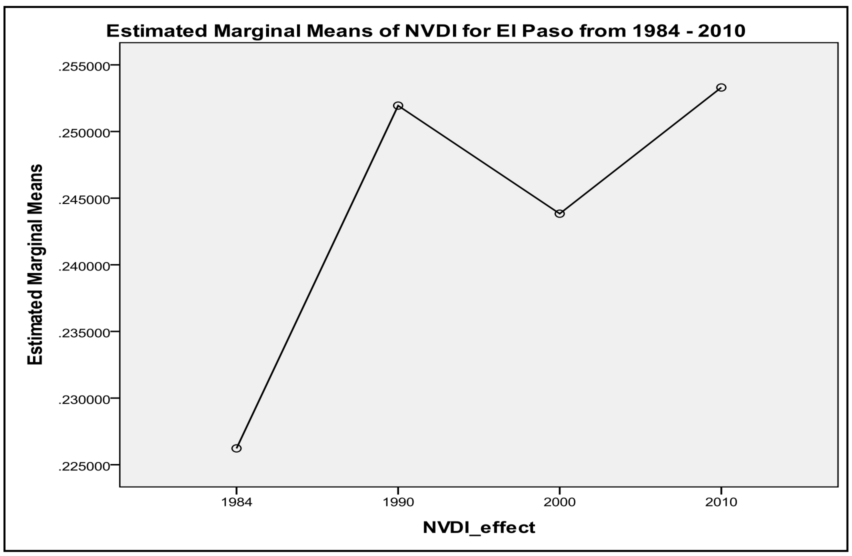


Figure 3.2: Estimated marginal means of NDVI for El Paso from 1984-2010

3.2.2 Vegetation change detection for Juarez

The results of change detection in NDVI for the city of Juarez can be observed in Table 3.4 and Figure 3.3. Juarez had a smaller increase in vegetation compared with El Paso (0.8 % from total area). During the period 1984 to 1990, the study area witnessed an increase in vegetation, and as such, Juarez had 0.5 square miles more of vegetation in 1990 as well as 0.6 square mile in 2000 compared to the year 1984. On the other hand, the area underwent a decline in vegetation from the period 2000 to 2010 which recorded approximately -0.5 square miles of vegetation decrease.

Table 3.4 : The results of change detection of NDVI images in Juarez per pixel and mile between the time periods 1984-1990, 1984-2000, 1984-2010, 1990-2000, 1990-2010, 2000 2010

Year	Vegetation increase			Vegetation decrease			Net change	No change		
	Pixel	Area (mi sq)	%	Pixel	Area (mi sq)	%	(mi sq)	Pixel	Area (mi sq)	%
1984-1990	2687	0.9	7.6	1102	0.4	3.4	0.5	31777	11	89
1984-2000	2927	1	8.2	1039	0.4	3	0.6	31599	11	88.8
1984-2010	1888	0.7	5.3	1792	0.6	5	0.1	31885	11.1	89.7
1990-2000	1418	0.5	4	1358	0.4	3.8	0.1	32790	11.4	92.2
1990-2010	1725	0.6	4.9	1550	0.5	4.3	0.1	32290	11.2	90.8
2000-2010	1062	0.4	3	2529	0.9	7	-0.5	31974	11.1	90

Figure 3.4 illustrates, in a visual format, the results of performing change detection by using ENVI and GIS techniques on NDVI in the period of 1984 to 2010. The map shows small changes in the vegetation, which occurred in the urban area. It can be evidently seen from the

map that areas of vegetation decrease were generally located in the center of the city. It can also be observed that a slight increase of vegetation was dispersedly distributed over the northeast side of the city of Juarez, where irrigated agriculture takes place. (more change detection maps for Juarez 1984-1990 and 1984-2000 are included in appendix).

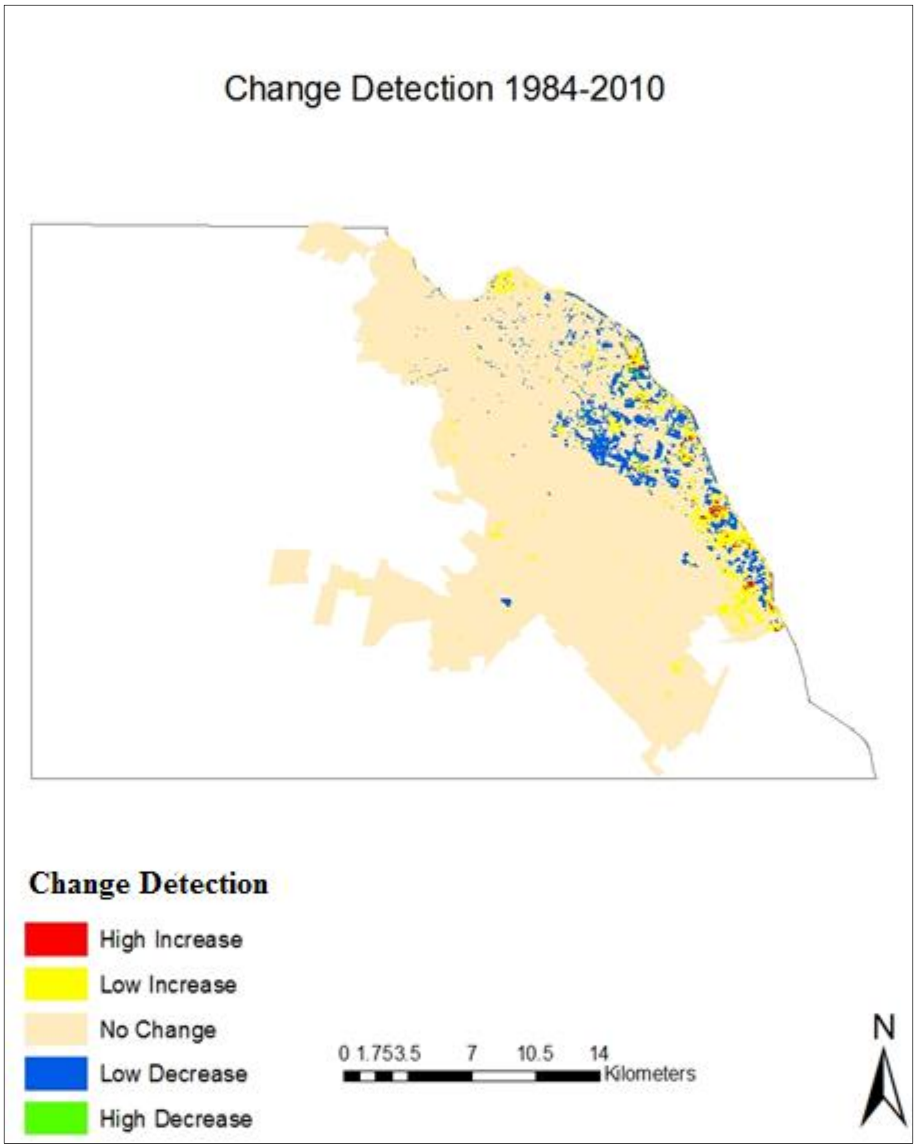


Figure 3.2: Change detection map for Juarez, 1984-2010

Before reporting results of the repeated measures ANOVA, I begin by observing the descriptive statistics for the data from Juarez. The result is as shown in table 3.5.

Table 3.5 : Description of NDVI for Juarez

P	Mean	Std. Deviation	N
Time 1_1984	.156	.104	157888
Time 2_1990	.181	.138	157888
Time 3_2000	.161	.125	157888
Time 4_2010	.147	.115	157888

As the table above indicates, the mean and standard deviation have increased from 1984 to 1990 in NDVI. Then there was a drop in the NVDI after 1990 to 2000 and a further drop in 2010. The following table shows the results obtained from the post-hoc pairwise comparison.

Table 3.6: Post- hoc Pairwise Comparisons for Juarez.

(I) NVDI_effect	(J) NVDI_effect	Mean Difference (I-J)	Std. Error	Sig.a	95% Confidence Interval for Differencea	
					Lower Bound	Upper Bound
1984	1990	-.024*	.000	.000	-.025	-.024
	2000	-.014*	.000	.000	-.005	-.004
	2010	-.009*	.000	.000	-.009	-.010
1990	1984	.024*	.000	.000	.024	.025
	2000	.020*	.000	.000	.019	.020
	2010	-.033*	.000	.000	-.033	-.034
2000	1984	.004*	.000	.000	.004	.005
	1990	-.020*	.000	.000	-.020	-.019
	2010	-.014*	.000	.000	-.013	-.014
2010	1984	.009*	.000	.000	.010	.009
	1990	.033*	.000	.000	.034	.033
	2000	.014*	.000	.000	.014	.013

Based on estimated marginal means

*. The mean difference is significant at the .05 level.
a. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Since the *p*-value is less than the significant level of 0.05 I reject the null hypothesis in favor of the alternate hypothesis. As such there is a significant difference in the post-hoc pair wise comparisons the mean pixel values of NVDI between all of the time periods (1984-1990, 1984-2000, 1984-2010, 1990-2000, 1990-2010, 2000-2010).

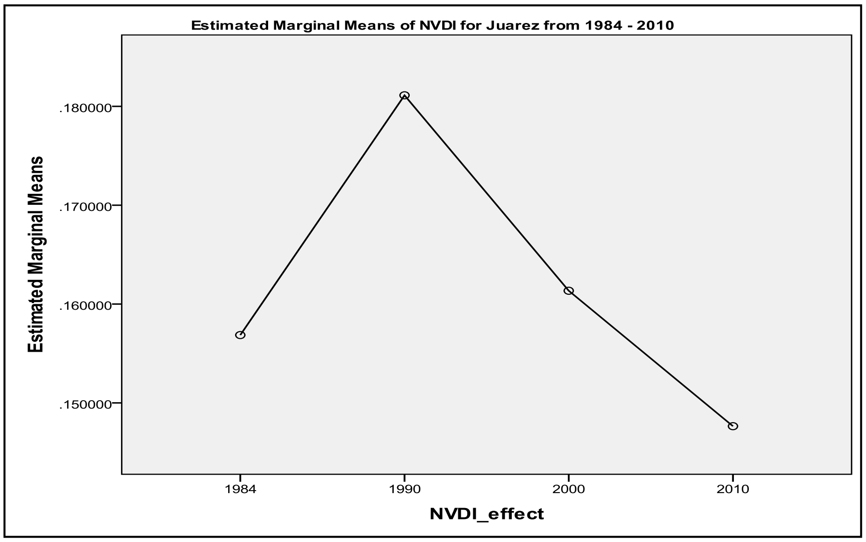


Figure 3 3 Figure 3.4: Estimated marginal means of NDVI for Juarez from 1984-2010

Figure 3.4 shows the estimated marginal means from 1984 to 2010. There is a marginal increase from 1984 to 1990 in NDVI. We then observe a drop in the NVDI after 1990 to 2000 and a further drop in 2010.

3.3 The link between NDVI and land surface temperature (LST) (Research question 1b)

The Landsat satellite images of the study area acquired for summer 2010 is shown in Figure 2.2 and 2.3. From the NDVI map shown in figure 2.2, three primary colors are classified and used (dark green, slight green and white). The dark green color indicates dense vegetated area and the slight green color indicates moderate vegetated area and the white color shows non-vegetated areas for NDVI images. NDVI of study area ranges between [0.0 and 0.8]. As can be

seen from Figure 2.2, NDVI values are high on the west and east sides of El Paso city, and in a small portion of east Juarez. Regions with low NDVI values are mainly located in the center of both cities, where the land surface is covered with city buildings and hardened surface. The region that represents the median NDVI value is located in the northwestern and southeastern of El Paso and southeastern of Juarez with very little green cover.

Figure 2.3 shows the distribution of land surface temperature of the study area. Dark red color indicates low temperature and white color shows high temperature values for thermal image. The mean value of LST in study area is between 89^{o}F and 114^{o}F. As it can be seen from Figure 2.3, low temperature distribution regions are detected in east, west and northeast parts of El Paso, and east and southeastern parts of Juarez which means that they are distributed on the areas with high NDVI value. The high temperature regions are detected at the center of the study area, where low vegetation cover areas co-locate with the urban core area.

In order to quantify the effect of vegetation on surface temperature during the year 2010 in the cities of El Paso and Juarez, the correlation coefficient was computed for each pixel in the study area for each city separately.as shown in Table 3.7.

Table 3.7 : Correlation between the NDVI and LST for El Paso and Juarez at the pixel-level

Pearson Correlation	El Paso		Juarez	
	NDVI	LST	NDVI	LST
NDVI Sig. (2-tailed) N	1 3056444	-.709** .000 3056444	1 1894536	-.523** .000 1894536
LST Sig. (2-tailed) N	-.709** .000 3056444	1 3056444	-.523** .000 1894536	1 1894536

**. Correlation is significant at the 0.01 level (2-tailed).

Based on the output of correlation analysis as shown in Table 3.7, the correlation between NDVI and LST is negative and significantly associated. The results show that vegetation has clear negative relationship with land surface temperature (correlation coefficient value = -0.709 and -0.523, in El Paso and Juarez respectively, and statistically significant at $p < .01$). Lower vegetation coverage is associated with higher temperature and vice versa which supports my hypothesis.

3.4 Greenspace Equity (Research question 2)

3.4.1 Spatial Distribution of NDVI

The spatial distribution of NDVI coverage within the entire study area by neighborhood is illustrated in choropleth maps in Figure 3.5 (see below). For comparative purposes, these choropleth maps are grouped into the same six categories based on the values calculated from ENVI and GIS. A visual comparison indicates that the distribution of NDVI between El Paso and Juarez are different. The results obtained for the city of El Paso show a high NDVI in the Rio Grande valley/floodplain, where irrigated agricultural land uses occur. However, the results of the city of Juarez demonstrate a high level of NDVI in the northeast area.

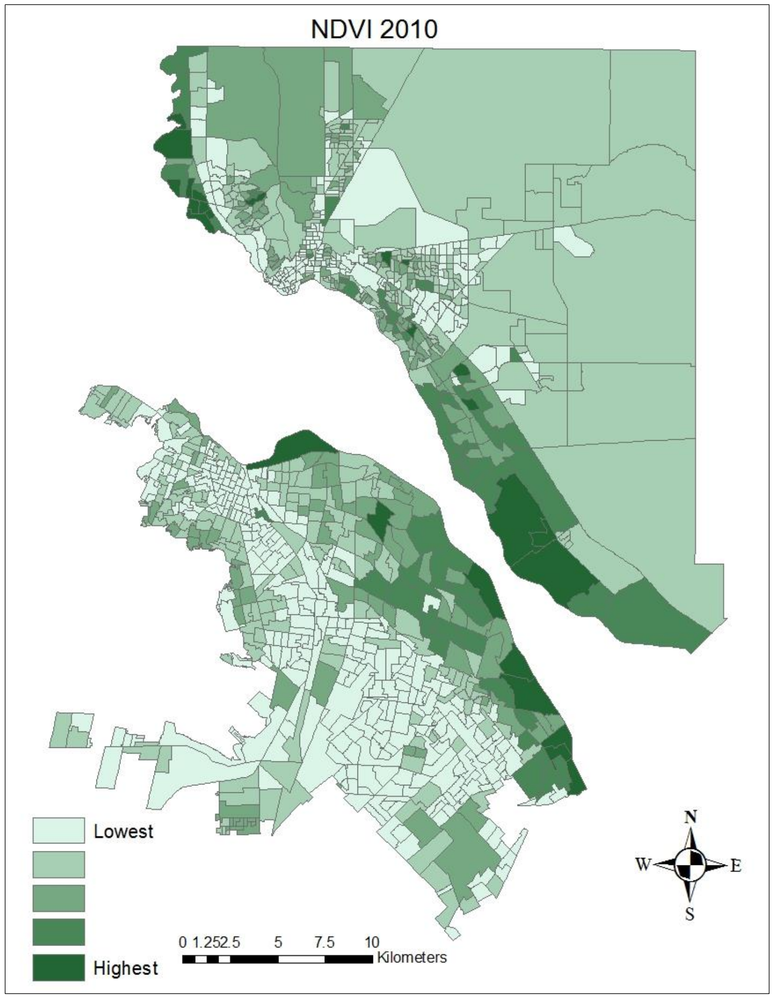


Figure 3.5: 2010 NDVI by neighborhood for El Paso and Juarez

3.4.2 Correlation Results

In order to analyze the relationship between the NDVI and the explanatory variables, the correlation analysis for El Paso and Juarez was performed separately and the statistical results are presented in Table 3.8 and 3.9. The outputs for the city of El Paso show a negative relationship between lower NDVI and higher population density, higher proportion 0-4 (p<.01 for both), higher owner-occupied (p<.05) and higher proportion female-headed households, which is not significant (p>.05). There is a positive correlational relationship between higher

NDVI and an increasing proportion of individuals 65 years old and higher mean level of education which are not significant (p>.05). The Pearson's correlation test obtained for the city of Juarez (shown in Table 3) confirms a negative relationship between lower NDVI and an increasing population density, increasing proportion of owner-occupied residences (p<.05 for both), and increasing female-headed households, which is not significant (p>.05). While a higher proportion of children aged under 5 (p<.01), higher proportion of individuals 65 years old, and higher levels of mean education were a positive associated with higher NDVI, but they are not significant (p>.05).

Table 3.8: Pearson Correlation Coefficients for El Paso

Pearson Correlation	NDVI	Pop Density	P Owner occupied	P 0_4	P 65	P_FHH	Mean Education
NDVI	1	-.375**	-.121**	-.112*	.012	-.129**	.048
Pop Density	-.375**	1	.234**	-.074	.261**	.144**	-.096*
Prop. Owner occupied	-.121**	.234**	1	-.155**	.538**	-.265**	.203**
Prop. age 0_4	-.112*	-.074	-.155**	1	-.550**	.488**	-.198**
Prop. age 65 and over	.012	.261**	.538**	-.550**	1	-.103*	-.080
Prop. Female Headed Household	-.129**	.144**	-.265**	.488**	-.103*	1	-.408**
Mean education	.048	-.096*	.203**	-.198**	-.080	-.408**	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Note: "P" refers to "proportion".

Table 3.9: Pearson Correlation Coefficients for Juarez

Pearson Correlation	NDVI	Pop Density	P Owner occupied	P_0_4	P_65 and Over	P_FHH	Mean Education
NDVI	1	-.518**	-.100*	.170**	.032	-.075	.078
Pop Density	-.518**	1	-.082	-.183**	-.116**	.094*	-.179**
Prop. Owner occupied	-.100*	-.082	1	.063	.161**	.178**	.270**
Prop. Ages 0-4	.170**	-.183**	.063	1	.075	.040	.268**
Prop. 65 and over	.032	-.116**	.161**	.075	1	.741**	.053
Prop. Female Headed Household	-.075	.094*	.178**	.040	.741**	1	-.066
Mean education	.078	-.179**	.270**	.268**	.053	-.066	1

3.4.3 Regression Results

The results obtained of the Ordinary Least Square (OLS) models for El Paso and the spatial error models for Juarez are presented in Tables 3.10 and 3.11, respectively. Model coefficients are presented along with the t-statistic for the OLS model and the z-statistic for the spatial error model. In the spatial error model, the spatial autoregressive coefficient used to supplement the regression model was very large and highly significant ($p < 0:001$). Measures of

model fit are provided by the adjusted coefficient of determination R^2, and the Akaike info criterion (AIC) for both models. The Moran's I-statistic was generated from the residual error values in each model.

Table 3.10: Ordinary least squares model predicting NDVI in El Paso

Neighbor Bandwidth	3000 m		
Condition Index	3.637		
Moran's I-OLS p-value	-0.009 (p = 0.34)		
R Squared	0.174		
Adjusted R2	0.164		
Akaike info criterion (AIC)	-1141.5		
Log likelihood	578.2		
Degrees of Freedom	500		
Model estimates	Coef.	t-Statistic	P
Constant	0.192	55.66	0.000
Population Density	-0.031	-8.538	0.000
Proportion Owner-occupied	-0.013	-2.656	0.008
Proportion 0-4 Years	-0.002	-0.743	0.636
Proportion 65 Years+	0.014	2.490	0.0130
Proportion Female-headed household	-0.006	-1.377	0.169
Mean Education	0.001	0.421	0.673

All variables are Z scores.

Table 3.10 presents the results of the OLS model of the city of El Paso. Decreasing population density, decreasing proportions of owner-occupied housing, and higher proportions of individuals 65 years and older (p <0.05 for all) were associated with higher NDVI. The other three variables were not statistically significant predictors of NDVI.

Table 3.11 describes the results of the spatial lag model for the city of Juarez. It reveals that higher population densities, higher proportions of adults 65 years and older, higher proportion female-headed household, and lower levels of education were significantly associated with higher NDVI (all with p< 0.01); but NDVI was not significantly associated with higher proportion owner-occupied housing and higher proportions of children ages 0-4 years.

Table 3.11: Spatial Lag Model Predicting NDVI in Juarez

Neighbor Bandwidth	2000 m		
Moran's I-OLS (p)	0.12 (p = .001)		
Condition Index	2.806		
Moran's I-Spatial lag (p)	-0.003 (p = 0.38)		
R Squared Spatial Error Model	0.518		
Degrees of Freedom	508		
Log likelihood	-556.07		
Akaike info criterion	1128.14		
Model estimates	Coef.	z-value	P
W_ NDVI	0.747	17.780	0.000
Constant	-0.031	-0.325	0.744
Population Density	0.239	6.495	0.000
Proportion Owner-occupied	0.075	1.812	0.069
Proportion 0-4 Years	0.101	0.292	0.770
Proportion 65 Years+	0.147	4.355	0.000
Proportion Female-headed household	1.038	5.925	0.000
Mean Education	-0.993	-5.687	0.000

All variables are Z scores.

Chapter 4: Discussion

4.1. Green space change

Sufficient greenspace is an important element for a sustainable city. Most studies have demonstrated that green spaces are important for the urban environment and the quality of life. It is widely accepted that greenspaces provide a variety of benefits to urban residents including recreational opportunities, improved air quality, and better public health (Massa et al. 2006; Mitchell et al. 2008; Baker et al. 2002, Patz et al. 2005, Grimmond 2007, Jenerette 2011). The study area has relatively low levels of natural green vegetation due to its hot and dry climatic characteristics. It is necessary to evaluate and characterize greenspace in arid and semi-arid cities due to a large variation in greenness and associated amenity values. GIS and remote sensing technique played a key role in my combining the works from various academic fields to have reliable data and analyses (Han et al. 2004; Wang et al. 2004; Coop et al. 2009; Avelar et al. 2009; Chen et al. 2009; Bagan et al. 2010; Mustapha et al. 2010; Peijun et al. 2010).

The first objective in my dissertation was to examine vegetation change during the period of 1984 to 2010 in the cities of El Paso and Juarez. This study provides another example that change detection techniques can be applied to desert vegetation environments. Use of such change detection techniques may help decision makers and planners to better understand the factors shaping land use and land cover changes in order to take effective and useful measures to increase the amount of green space. The results show an observed change in NDVI across the twin cities during the period included in the study. In the city of El Paso, the findings obtained from the change detection technique and repeated measures ANOVA led me to accept the study hypotheses that greenspace had increased, while in the city of Juarez, this was not the case. As compared to Juarez, El Paso recorded larger increases in vegetation between in the years 2010

and 1984 as vegetation increased to 10.2 square miles from 5.5 square miles. The highest increases in NDVI were associated with the expansion of irrigated agriculture in the Upper and Lower Valleys of the Rio Grande.

These results are consistent with previous studies that have shown tree cover and grassland in some arid environments to have increased due to urbanization process (Al-Gaadi 2011; John et al. 2009; Nowak et al. 2012; Kim 2010; Kadmon et al. 1999). In much of the El Paso metropolitan area, natural desert vegetation has been removed as a consequence of urbanization; El Paso has experienced extensive urbanization from 1970 to 2000 (Pena 2002) and based on the maps, I believe the effect of urbanization led to the increase that I observed in NDVI between 1984 and 2010. Many places in the city especially in the Northwest side along the mountain have been turned into commercial and residential neighborhoods, thus people living there are aware of the need to have more greenspace and they have invested in their yard and planted grass and trees. In addition, the city also played an important role in planting and maintaining trees to improve landscape and quality of life for El Paso residents.

The obtained results from the change detection technique and repeated measures ANOVA for the city of Juarez did not support the study hypotheses. The city witnessed a small increase in vegetation of 0.5 only square miles between 1984 to 2000, and it underwent a decline in vegetation from the period 2000 to 2010, which recorded approximately -0.5 square miles of vegetation decrease. Therefore, I think the decrease of NDVI in Juarez city relates to the following reasons; first, the city has grown by turning croplands into home developments. Second, Juárez has undergone widespread violence between 2006 and 2011, and thus, a significant number of individuals escaped the violence by migrating internally to other parts of México or to the US (Morales et al. 2013). As such, green plants probably died as people

abandoned their homes. Third, scarce water resources as well as drought are considered other factors responsible for loss of vegetation in the city of Juarez. Fourth, there has been less expansion of irrigated agriculture in Juarez (the Valle de Juarez) than in El Paso likely due to the fact that Juarez has a reduced entitlement to Rio Grande/Bravo water as compared to El Paso.

4.2. The Relationship between NDVI and LST

In many places on earth, especially arid and semi-arid regions, vegetation can significantly influence the urban environment through reducing land surface temperature (Miller 1997; Dong et al. 2005; Yuan et al. 2007; Sun and Kafatos 2007; Kim et al. 2005; Ozelkan et al. 2011). Using Landsat TM data and ENVI software, NDVI and LST images were produced (Figures 2.1 and 2.2). Comparing the NDVI images with the LST images, the relationship between them can be clearly understood. The distribution of vegetation cover is low in center and high in edges in both cities. On the other hand, the distribution of LST was opposite to the distribution of vegetation cover, which is high in the center and low in the edges. The hot spots in the 2010 image are mainly concentrated in the downtown and in the barren lands for both cities, while the largest cooling affect from vegetation was on the far East and West sides. The average heat for Juarez was 104° F while the average heat for El Paso was 105° F.

Conducting a correlation analysis between the pixel values of NDVI and LST with the support of SPSS demonstrated that the correlation of the pixel values of NDVI with LST was significant and negative in both cities ($p > 0.01$). This means that vegetated areas tend to have lower surface temperatures. In Juarez, due to the fact that NDVI values are lower in Juarez and exhibit less variability (smaller range) than in El Paso, the correlation is quite a bit weaker than in El Paso and other studies that reported earlier in the literature review (Sun and Kafatos 2007; Kim et al. 2005; Ping et al. 2006; Zhangyan et al. 2006; Ozelkan et al. 2011). NDVI and LST

are considered to be two main indices to study the urban ecological environment and to contribute to further validation of the applicability of relatively low cost, moderate spatial resolution satellite imagery. Therefore, the results of this section seem to support the hypothesis that lower levels of vegetation coverage in the study area will be associated with higher land surface temperatures, and vice versa.

4.3. Equity implications of greenspace distribution

I have sought to address specific limitations of prior environmental equity studies on urban amenities through several methodological improvements. The main purpose of this study is to determine the relationship between socio-demographic characteristics and NDVI in twin city neighborhoods and reveal inequalities in the distribution of NDVI for residents. It is important to note that my results reveal that the percentage of NDVI in the average El Paso neighborhood was nearly 2.3 times higher than for Juarez neighborhoods, meaning that El Paso residents experience higher levels of NDVI relative to Juarez residents. This represents an environmental injustice for Juarez, as it reflects the unequal distribution of greenspace between the twin cities. The results show statistically significant relationships between certain socio-demographic variables and NDVI across twin cities' neighborhoods. Interestingly, I found some associations that followed my hypotheses and some that did not.

The findings obtained from the Pearson correlations indicate that higher neighborhood levels of NDVI for the city of El Paso were significantly correlated with lower population density, lower proportion of owner occupied housing, lower proportion of children ages 0-4 years old, and lower proportion of female-headed household, and NDVI was not significantly correlated with higher proportion of adult ages 65 or higher mean education. In the OLS model, NDVI was negatively associated with population density, owner occupied and positively with

more old people approaching significance ($p < 0.01$for all), and negatively associated with proportion of age 0-4, female-headed household and positive for mean levels of education, but they did not approach significance ($p = 0.63$, $p = 0.17$, $p = 0.67$) respectively (see table 3.10). My lack of significant findings for age 0-4, female-headed households and mean education suggest that there is not an environmental inequity with respect to these variables for the city of El Paso. Some of these results do seem to support an inequity hypothesis by suggesting that neighborhoods with higher population density, less old people, and more owner occupied housing may have less of the distribution of NDVI. However two of the results are in the opposite direction from a traditional inequity hypothesis (i.e., that the socially disadvantaged would have less greenspace): neighborhoods with more renters and more older adults have more greenspace. For population density, the finding indicates a lack of greenspace in densely settled urban neighborhoods.

In the city of Juarez, the findings obtained from the Pearson correlations indicate that neighborhood NDVI was significantly correlated with lower population density, higher proportion of owner occupied, higher proportion of children ages 0-4 years old, and not significantly correlated with higher proportion of adult ages 65, lower proportion of female-headed household, and higher mean education. The results obtained from the spatial lag model indicating that neighborhoods with more adults 65 years and older have a greenspace advantage. The statistical results from the lag model also show a higher NDVI in neighborhoods with a higher population density, higher proportion of female headed households, lower mean levels of education ($p < 0.01$ for all); results were nearly significantly for higher proportion of owner occupied ($p = 0.07$), and the results for higher proportion of children ages 0-4 years did not approach significance ($p = 0.77$) see table 3.11.

However, the analyses of this study revealed that the distinct patterns of environmental injustice related to the lack of access to greenspace that were similar between El Paso and Juarez in some ways, but also different in meaningful ways. In terms of similarities, there was one social variable that demonstrated similar patterns across the cities: proportion of adults 65 years and older of age was a positive predictor of NDVI and statistically significant for both cities. This result opposes other studies that found areas with high number of residents over 65 years of age had lower percentage of NDVI cover (Kerns and Watters 2012). This finding is of particular interest because elderly people are more vulnerable to negative environmental conditions, such as heat, which can be mitigated by the presence of trees (Nowak 1994, 2010; Kinney et al. 2008).

In terms of differences, there were five variables that demonstrated divergent patterns between the two cities: (1) population density, (2) proportion owner-occupied, (3) proportion of children ages 0-4 years, (4) female-headed households, and (5) mean education. First, while lower population density was significantly linked with increased NDVI in El Paso using OLS models, the findings in Juarez using spatial lag models indicate higher population density was significantly linked with increased NDVI. On the other hand, the correlations match in both cities: less density, more NDVI. In Juarez, in the multivariate model, the directionality of the density finding flips from negative to positive, in El Paso it stays negative, meaning that highly-populated neighborhoods in El Paso, where it is probably hotter, have less green spaces. Hence, the lack of access to greenspace may be an added concern for this variable in El Paso. It suggests that improved planning of green space in densely settled urban neighborhoods in El Paso city is needed in future urban developments.

Second, the multivariate results for proportion owner-occupied were negative and significant for El Paso and positive but not nearly significant ($p<.10$) for Juarez. The

correlations were significant in both cities (negative in El Paso and positive in Juarez). The correlation in Juarez does suggest that neighborhoods with more owners do have significantly more greenspace as expected, but the other variables in the multivariate model make this effect less significant. These results (for Juarez) are consistent with previous research that indicates that higher level of tree cover in neighborhoods is associated with a higher percentage of owner-occupied housing (Heynen et al, 2006; Perkins et al, 2004). It is surprising that neighborhoods with fewer owners have more greenspace in El Paso. Given the relatively high rates of home ownership in El Paso, low income residents are often able to buy homes, which may be part of the reason for this relationship. Despite having a median household income that is $12,400 less than the Texas statistic, a similar percent of El Paso County residents own homes (63.6% vs 64.5%) (US Census Bureau, 2013)

Third, the results for proportion of children ages 0-4 years were negative for El Paso and positive for Juarez but were far from significant for both cities. The correlations were significant in both cities (negative in El Paso and positive in Juarez). Therefore, the lack of access to greenspace may be an added health concern for children in El Paso, although this variable was not significant in the multivariate model. While a few EJ research studies have identified young children as being disproportionately distributed with greenspace (Strife and Downey 2009; Germany, 2009), this inequality was only found in the El Paso correlation analysis.

Fourth, in Juarez, greater proportion of female-headed households was positively and significantly associated with more NDVI for the spatial lag model. While in the multivariate model for El Paso, the relationships were the opposite in comparison with Juarez (more female-headed households were associated with a lower percentage of NDVI, although this was not significant). The correlation analyses show that higher percentages of female-headed households

were significantly associated with less NDVI in both cities (although this coefficient was statistically significant only in El Paso); based on a visual inspection of the data and maps of the study area (Figure 2.6), this likely relates to the fact that female-headed households are more likely to live in the developed inner-city in both cities, which has lower percentage of NDVI. In Juarez, accounting for the effects of the other variables, the increased availability of greenspace in neighborhoods with more female-headed households emerges.

Fifth, while the results for mean levels of education were negative and significant for Juarez, they were positive but not significant in El Paso. In the correlations, the findings were not significant but positive in both cities, indicting weak spatial overlap between higher SES neighborhoods and more greenspace. However, in the multivariate model for Juarez, lower mean education is significantly associated with more greenspace. This suggests a greenspace advantage for those neighborhoods with lower SES. This aligns with other studies finding that low-income groups were not systematically disadvantaged from the distribution of greenspace (Nicholls, 2001; Lindsey et al, 2001; Tarrant and Cordell 1999).

Concerning the above, the results of this study related to El Paso did not show much evidence of environmental inequities with respect to socially marginalized groups and a lack of greenspace. First, the most prevalent environmental injustice finding from the OLS model is that the more populated the area is, the less the availability of greenspace. In the correlations, the analysis for El Paso reveals neighborhoods with fewer children and fewer female-headed households are greener, suggesting a spatial imbalance between the benefits of greenspace and the number of children and female-headed households. In Juarez, the findings do reveal one injustice for socially marginalized groups in terms of greenspace: neighborhoods that have fewer

owners and more renters have less greenspace. This finding is almost significant in the lag model.

Second, Juarez faces greater inequities as compared to El Paso related to overall greenspace distribution. In the regression results, the patterns of inequity were stronger in Juarez, evidenced by larger coefficients and greater number of statistically significant findings. In addition, five findings were statistically significant in Juarez, whereas in El Paso, three were significant. However, the findings suggest that it is the socially disadvantaged that have greater greenspace in their neighborhoods. Thirdly, it is important to quantify these injustices in order to give urban greenspace inequity due consideration. Incorporating considerations of equity into greens space planning can uphold environmental justice principles of equal access to environmental burdens and benefits (Flocks et al. 2011). There is also a known positive relationship between urban greenspace services and physical and psychological health, which is a primary concern of the environmental justice movement. Therefore, urban greenspace assessments should join the environmental justice literature in the discussion of urban amenities, and conversely environmental justice research should continue to expand to include studies of urban greenspace distribution and services.

Overall, while EJ literature has previously addressed environmental burdens on the neighborhood level, only a few urban greenspace research studies have been conducted that focus on neighborhoods (Conway 2011; Escobedo 2006; Heynen 2003; Jennings 2012; Kerns and Watters 2012). This study contributes to the environmental justice literature by evaluating the spatial inequalities of NDVI at the neighborhood scale. However, further research is needed to understand the observed spatial disconnect between the urban geography of amenities and disamenities.

4.4 Limitations

One limitation of my study is that it relies on data generated from Landsat 5, which has some limitations in terms of the accuracy when deriving NDVI and LST values. Using remotely sensed information from low-cost optical satellites such as Landsat means that the image information is insufficient for studying the height of the trees, for example. To overcome this problem, active imageries such as RADAR could be used in future studies. While NDVI is a measure of "greenness" produced by the ratio of infrared and red light that is reflected from the surface, other factors like sensitivity to atmospheric conditions and soil background influence the NDVI values (Gao, 1996; Huete et al. 2002). For instance, light from the soil surface, especially in semi-arid and arid environments which tend to have higher cover of bare ground, can affect the NDVI values by a large degree. Heute and Jackson (1988) found that the soil surface impact on NDVI values was greatest in areas with between 45% and 70% vegetative cover. In these cases, it is advisable to use another vegetation measure with better sensitivity to vegetation cover situations such as the Enhanced Vegetation Index.

Other limitations are associated with the equity aspect of my study are summarized in what follows. The current association between NDVI and socio-demographic characteristics does not necessarily reflect neighborhood conditions at the time the vegetation was planted. Identifying specific processes responsible for the observed patterns would require additional and substantial longitudinal analysis that is beyond the scope of the current study. Non-residential areas in neighborhoods, including such as roads, buildings, or industrial parks, could have also affected NDVI distribution in the neighborhood. This has the potential to impact the findings of association between NDVI and neighborhood demographic data. The Mexican 2010 census did not collect income data at the neighborhood level and they did not collect the poverty measure

(related to minimum wage) that was available in 2000 (e.g., Collins et al. 2013; Grineski and Collins 2010; Lara-Valencia et al. 2009). Collecting the 2010 data was difficult in Juarez. Many houses were abandoned during 2010, which created an added challenge. With no mail form, census workers knocked on doors several times to ensure houses were indeed abandoned. Also, the continued violence made it more difficult to keep census workers safe (Licon 2010).

While studies on urban greenspace equity have used multivariate regression analysis, the potential for spatial autocorrelation has not been addressed previously. This means that my results for Juarez may not be directly comparable with those from other studies not using a spatial approach. The spatial dependence in my Juarez data also suggests the need for additional future research because the models probably excluded other relevant explanatory variables (Kissling and Carl, 2008; Lloyd, 2007).

Chapter 5: Conclusion

In this work Landsat TM images of El Paso and Juarez were collected from USGS earth explorer web site. Summer 1984, 1990, 2000, and 2010 were selected to create Normalized Difference Vegetation Index (NDVI) and Land Service Temperature (LST). To characterize the socio-demographics of study area neighborhoods, the data were collected from 2010 Census and American Community Survey (ACS) (2006-2010) for El Paso neighborhoods and 2010 Mexican census data from the Instituto Nacional de Estadística y Geografia (INEGI) for Juarez neighborhoods.

By using modern techniques such as remote sensing (RS), geographic information systems (GIS), and multivariate spatial regression, this research has been conducted to determine the equity distribution of greenspace in 2010 with respect to socio-demographics in the Chihuahua Desert region (El Paso and Juarez). To provide background information, the study first focused on identifying greenspace changes in term of increases or decreases over a twenty six year period from 1984 to 2010. Then the study examined the relationship between neighborhood heat and vegetation cover. The aim of these two descriptive analyses was in relation to my main focus on equity.

The first objective in my dissertation was successful in monitoring vegetation change. The outputs of the analyses indicate that pixel of NDVI values for both cities varied over the course of the study period. The results show an observed change in NDVI across twin cities during the period included in the study. In the city of El Paso, the findings show increases in vegetation during the period from 1984 to 2010, while in the city of Juarez the findings demonstrate decline in vegetation from 1990 to 2010. A statistic test (a repeated measure

ANOVA) was also applied in order to see if statistically there significant change or not compare on NDVI value among years. The results indicate that the changes in NDVI were significant.

The second objective was focused on providing context for my descriptive analysis of the relationship between NDVI and LST in 2012. It is well known that vegetation can significantly influence the urban environment through reducing temperature, improving air pollution, and preserving biodiversity in cities. Several studies showed that more greenspace in urban areas is positively related to mitigating the land service temperature (e.g., Ca, Asaeda, and Abu 1998; Oh and Hong 2005; Zhangyan et al. 2006; Ping et al. 2006; Kim et al. 2005; Ozelkan et al. 2011), which improves the quality of life for urban residents. This makes it an important consideration from an equity perspective. Based on the NDVI and LST images it is clearly understood that land surface temperature is high in urban area compared to suburban areas in both cities. The twin cities are experiencing more heat than the surrounding rural areas mainly due lack of vegetative cover. Low temperature distribution regions are detected in east, west and northeast of El Paso, and east side of Juarez which means they are distributed in the areas with high NDVI value. The high temperature regions are detected at the center of both cities, where lower vegetation cover areas with concentration of population and built-up or core urban area. Also the correlation study shows that vegetation cover and temperature have a significant negative correlation in both cities, meaning that the higher the vegetation coverage, the lower the land service temperature effect, and vice versa.

The primary focus of this study was related to environmental equity and greenspace. Urban greenspace serves as environmental amenities that provide several direct and indirect benefits for urban residents. The equitable distribution of greenspace is an important consideration because planting and management of vegetation is the primary responsibility of

government, and such public investment should be nondiscriminatory. There is a large body of work suggesting a disadvantage in the distribution of greenspace with respect to particular demographic and socioeconomic groups. However, only a few studies have examined these issues in the context of environmental equity (Heynen et al, 2006; Pedlowski et al, 2002; Perkins et al, 2004) and none of these studies has specifically focused on an arid and semi-arid region.

Based on the regression results, in El Paso there are few inequities related to socially vulnerable groups having less access to green space; and serious inequity related to the lack of greenspace in high density urban neighborhoods. In Juarez, the association between neighborhoods with more renters and less greenspace conforms to a traditional pattern of inequity. The only "traditional EJ finding" in Juarez is the association between neighborhoods with more renters and has less greenspace conforms to a traditional pattern of inequity.

The study also shows that Juarez faces greater inequities as compared to El Paso related to overall greenspace distribution. First, based on GIS and remote sensing results, the percentage of NDVI in the average El Paso neighborhood was nearly 2.3 times higher than for Juarez neighborhoods, meaning that El Paso residents experience higher levels of NDVI relative to Juarez residents. According to correlation results for LST and NDVI, greenness resulted in more cooling. Therefore since El Paso witnessed increases in NDVI and few inequities with regards to socially marginalized groups having lower levels of NDVI, there is less of a concern in regards to socially vulnerable groups having less access to green space in this city in the future. While in Juarez, it witnessed a decrease in NDVI and is therefore probably getting hotter. While the regression results showed that socially disadvantaged groups live in greener neighborhoods in 2010, there is more of a concern with respect to socially marginalized groups having less NDVI in the future, if levels of NDVI continue to decrease in the city.

5.2 Practical Implications

The research reported in this dissertation took on the task of examining inequity in greenspace across the El Paso and Juarez metropolitan region. Urban greenspaces serve as environmental amenities that provide several direct and indirect benefits for urban residents. An uneven distribution of greenspace reflects an inequality in the benefits they provides to residents (Kerns and Watters 2012). By providing information on greenspace distribution, the present study was able to present a clear picture of greenspace across the region and infer from this disadvantages and advantages experienced by specific groups and the larger implications of these relative to their health. The contributions of the present dissertation are largely empirical and methodological, with broader implications for the fields of urban geography, environmental justice research, and active living research. A focus on proximity to amenities is limited in environmental justice literature, especially in arid and semi-arid regions, which traditionally focuses on proximity of minority groups to disamenities. This study contributes to literature on environmental equity and urban greenspace in that it assesses the spatial inequalities of urban greenspace distribution by neighborhood in arid region. The twin cities El Paso and Juarez should implement policies to address current disparities by targeting tree planting within available planting areas.

Bibliography

Al-Gaadi. K, Samdani. M, Patil. V, 2011. Assessment of Temporal Land Cover Changes in Saudi Arabia Using Remotely Sensed Data. Middle-East Journal of Scientific Research 9 (6): 711-717, 2011.

Anderton, Douglas L. Andy B. Anderson, John M. Oakes, and Michael R. Fraser. 1994. Environmental equity: The demographics of dumping. Demography 31:229–48.

Anderson, Joan B. 2003. The US–Mexico border: a half century of change Social Science Journal, 40 (4) (2003), pp. 535–554.

Angulo. G, Aldouri. R, Collins. T, Grineski. S, Aguilar. M, Aboargob. F, Eldeb. A, McDonald. Y, Amparán. F, 2012. Characterizing climate change risks and informing adaptation strategies in the Ciudad Juárez-El Paso metropolitan region based on spatial analyses of extreme heat–vegetation abundance–population vulnerability relationships.

Anselin, L. (2003). GeoDa™ 0.9 user's guide. Urbana: Spatial Analysis Laboratory, Department of Agricultural and Consumer Economics, University of Illinois, Urbana- Champaign and Center for Spatially Integrated Social Science.

Atlas, Mark. 2002. Few and far between? An environmental equity analysis of the geographic distribution of hazardous waste generation. Social Science Quarterly 83:365–78.

Avelar, S.; Zah, R. & Tavares-Correa, C. (2009). Linking Socioeconomic Classes and Land Cover Data in Lima, Peru: Assessment through the Application of Remote Sensing and GIS. International Journal of Applied Earth Observation and Geoinformation, Vol.11, No.1, pp. 27-37, ISSN 0303-2434.

Bagan, H.; Takeuchi, W.; Kinoshita, T.; Bao, Y. & Yamagata, Y. (2010). Land Cover Classification and Change Analysis in the Horqin Sandy Land from 1975 to 2007.

Baker, L. A., A. J. Brazel, N. Selover, C. Martin, N. McIntyre, F. R. Steiner, A. Nelson, and L. Mussacchio. 2002. Urbanization and warming of Phoenix Arizona, (USA): impacts, feedbacks, and mitigation. Urban Ecosystems 6:183–203.

Bath. R, 1982. Health and Environmental Problems: The Role of the Border in El Paso-Ciudad Juarez Coordination, Journal of Interamerican Studies and World, Vol. 24, No. 3, Aug., 1982.

Blodgett, A. D. (2006). An analysis of pollution and community advocacy in 'Cancer Alley': Setting an example for the environmental justice movement in St James Parish, Louisiana. Local Environment, 11(6), 647–661.

Boone, C. G., Buckley, G. L., Grove, J. M., & Sister, C. (2009). Parks and People: An Environmental Justice Inquiry in Baltimore, Maryland. Ann. Assoc. Am. Geogr., 99(4), 767-787.

Bowen, William M., Mark J. Salling, Kingsley E. Haynes, and Ellen J. Cyran. 1995. Toward environmental justice: Spatial equity in Ohio and Cleveland. Annals of the Association of American Geographers 85:541–663.

Bowen. William M, Atlas. Mark, Lee. Sugie, 2009. Industrial Agglomeration and the Regional Scientific Explanation of Perceived Environmental Injustice. Agglomeration and Environmental Justice. Annals of Regional Science;Dec2009, Vol. 43 Issue 4, p1013.

Bullard, Robert D, editor, 1994: Unequal protection: environmental justice and communities of color. San Francisco, CA: Sierra Club Books.

Bullard, Robert D. 1996. Environmental justice: It's more than waste facility siting. Social Science Quarterly 77:493–99.

Ca, V., Asaeda, T., and Abu, E. (1998). Reductions in air conditioning energy caused by a nearby park. Energy and Buildings, Vol. 29: 83-92.

Cadenasso M L, Pickett S T A, Schwarz K, 2007, ``Spatial heterogeneity in urban ecosystems: reconceptualizing land cover and a framework for classification'' Frontiers in Ecology and the Environment 5 80 ^ 88.

Cambridge Systematics, Inc. 2010. El Paso Regional Ports of Entry Operations Plan, Commodity Flow and Socioeconomic Profile. Texas Department of Transportation.

Chakraborty J, 2009. Automobiles, air toxics, and adverse health risks: environmental inequities in Tampa Bay, Florida. Annals of the Association of American Geographers. 2009;99(4):647-697.

Chambers . D Samuel , 2002. Application of Spectral Change Detection Techniques to Identify Forest Harvesting Using Landsat TM Data. Thesis submitted to the Faculty of Virginia Polytechnic Institute and State University.

Chen, H.; Chang, N.; Yu, R. & Huang, Y. (2009). Urban Land Use and Land Cover Classification Using the Neural-fuzzy Inference Approach with Formosat-2 Data. Journal of Applied Remote Sensing, Vol.3, pp. 033558, ISSN 1931-3195 .

Comber A, Brunsdon C, Green E, 2008, ``Using a GIS-based network analysis to determine urban greenspace accessibility for different ethnic and religious groups'' Landscape and Urban Planning 86 103 ^ 114

Coops, N. C.; Wulder, M. A. & Iwanicka, D. (2009). Exploring the Relative Importance of Satellite-derived Descriptors of Production, Topography and Land Cover for Predicting Breeding Bird Species Richness over Ontario, Canada. Remote Sensing of Environment, Vol.113, No.3, pp. 668-679, ISSN 0034-4257.

Collins T, Grineski S, Romo L (2009) Vulnerability to environmental hazards in the Ciudad Juárez (Mexico)/El Paso (USA) metropolis: a model for spatial risk assessment in transnational context. Appl Geogr 29:448-461.

Cutter S L, 1995. ``Race, class and environmental justice'' Progress in Human Geography 19 111 -122.

Daniel J. Hayes and Steven A. Sader, 2001. Comparison of ChangeDetection Techniques forMonitoring Tropical Forest Clearing and Vegetation Regrowth in a Time Series. Photogrammetic Engineering & Remote Sensing. GVol. 67. No. $1, Ssptc:nlt)er 2001. 111). 10(i7-1075.

Dajun Dai, 2011. Racial/ethnic and socioeconomic disparities in urban green space accessibility: Where to intervene? Landscape and Urban Planning 102 (2011) 234– 244.

Department for transport, local government and the regions (DTLR) (2002) Green spaces, better places—final report of the urban green spaces taskforce. Eland House, Bressenden Place, London.

Design Center for American Urban Landscape (DCAUL) (2003) Urban green space: effects on water and climate, 1. Rapson Hall, Minneapolis, MN.

Dong-hoon Shin Æ Kyoo-seock Lee, 2005. Use of remote sensing and geographical information systems to estimate green space surface-temperature change as a result of urban expansion, Landscape Ecol Eng (2005) 1: 169–176.

DiGirolamo. P Alrik, 2006. A Comparison of Change Detection Methods in an Urban Environment Using LANDSAT TM and ETM+ Satellite Imagery: A Multi-Temporal, Multi- Spectral Analysis of Gwinnett County, GA 1991-2000. Georgia State University, Department of Anthropology.

Ecological Society of America, 2012. What is Environmental Justice, http://www.esa.org

EPA (U.S. Environmental Protection Agency). 2003. Environmental justice fact sheet: EPA's commitment to environmental justice.Washington, DC: U.S. EPA Office of Environmental Justice.

Fahmy M, Sharples S, Yahia M. LAI based trees selection for mid latitude urban developments: a microclimatic study in Cairo, Egypt. Building and Environment 2010;45:345e57.

Flocks Joan, Francisco Escobedo, Jeff Wade, Sebastian Varela, and Claudia Wald, 2011. Environmental Justice Implications of Urban Tree Cover in Miami-Dade County, Florida. ENVIRONMENTAL JUSTICE Volume 4, Number 2, 2011, DOI: 10.1089/env.2010.0018

Freisthler, B., Lery, B., Gruenewald, P.J., Chow, J. (2006). Methods and challenges of analyzing spatial data for social work problems: the case of examining child maltreatment geographically. Social Work Research, 30,198-210.

Fuller, D.O. 1998. Trends in NDVI time series and their relation to rangeland and crop production in Senagal, 1987-1993. International Journal of Remote Sensing 19(10): 2013-2018.

Fuller. T, and Gatrell. J D. 2007. The Spatial Imperatives of Environmental Justice. Situating Urban Enviromental Risk Using GIScience to Understand Risk in a Midwestern City, Earth and Environmental Science.

Gao, B.C., 1996, (NDWI—a normalized difference water index for remote sensing of vegetation liquid water from space. Remote Sensing of Environment, 58, pp. 257–266.

Germany. B, 2009. Environment and health risks: the influence and effects of social inequalities. Report of an expert group meeting, World Health Organization.

Gilbert A, Chakraborty J, 2008. Health risks from hazardous air pollutants: analyzing environmental injustice in Florida. The Florida Geographer. 2008;39:71-94.

Goetz S J,Wright R K, Smith A J, Zinecker E, Schaub E, 2003, ``IKONOS imagery for resource management: tree cover, impervious surfaces, and riparian buffer analyses in the mid-Atlantic region" Remote Sensing of Environment 88 195 ^ 208.

Greenberg, M.R. 1993: Proving environmental inequity in siting locally unwanted land uses. 4 Risk - Issues in Health and Safety 235, 235-52.

Green, K., D. Lempka, and L. Lackey, 1994. Using remote sensing to detect and monitor land-cover and land-use change, Photogrammetric Engineering 6 Remote Sensing, 60:331-337.

Griffith, D. (2000). A linear regression solution to the spatial autocorrelation problem. J. of Geographical Systems 2, 141-156.

Grimmond, S. 2007. Urbanization and global environmental change: local effects of urban warming. Geographical Journal 173:83–88.

Grineski S, Collins T, Ford P, Fitzgerald R, Aldouri R, Velázquez-Angulo G, Romo L, Lu D (2012) Climate change and environmental injustice in bi-national context. Appl Geogr 31. doi: 10.1016/j.apgeog.2011.05.013.

Grineski S, Collins T (2010) Environmental injustices in transnational context: urbanization and industrial hazards in El Paso/Ciudad Juárez. Environ Plan A 42:1308-1327.

Grineski, S. E., T. W. Collins, L. Romo, and R. Aldouri. 2010. No safe place: Environmental hazards & injustice along Mexico’s northern border. Social Forces 88 (5): 2241–66.

Groenewegen, P. P., A. E. van den Berg, S. de Vries, and R. A. Verheij.2006. Vitamin G: effects of green space on health, well-being, and social safety. BMC Public Health 6: 149.

Grove J M, Troy A R, O'Neil-Dunne J P M, BurchW R, Cadenasso M L, Pickett S T A, 2006a, Characterization of households and its implications for the vegetation of urban ecosystems" Ecosystems 9 578 ^ 597.

Grove J M, 1996 The Relationship Between Patterns and Processes of Social Stratification and Vegetation of an Urban ^ Rural Watershed. PhD dissertation, Department of Social Ecology, Yale University, New Haven, CT

Han, K. S.; Champeaux, J. S. & Roujean, J. L. (2004). A Land Cover Classification Product over France at 1 km Resolution using SPOT4/VEGETATION Data. Remote Sensing of Environment, Vol.92, No.1, pp. 52-66, ISSN 0034-4257.

Hartsell. J Andrew, 2012. Using Forest Inventory Data along With Spatial Lag and Spatial Error Regression to Determine the Impact of Sothern Pine Plantation on Species Diversity and Richness in The Central Gulf Coastal plain, Moving from Status to Trends: Forest Inventory and Analysis Symposium 2012, GTR-NRS-P-105

Heather. E, 2011, An Examination of the Impacts of Urbanization on Green Space Access and Water Resources: A Developed and Developing World Perspective. University of South Florida (USF).

Heyman J, 2007. Environmental issues at the US–Mexico border and the unequal territorialization of value, A. Hornberg, J. McNeill, J. Martinez-Alier (Eds.), Rethinking

environmental history: World-systems history and global environmental change, Altamira Press, New York (2007), pp. 327–341.

Heynen N C, Lindsey G, 2003, ``Correlates of urban forest canopy cover: implications for local public works'' PublicWorks Management and Policy 8 33 ^ 47

Heynen, N., H. Perkins, and P. Roy. 2006. The Political Ecology of Uneven Urban Green Space: The Impact of Political Economy on Race and Ethnicity in Producing Environmental Inequality in Milwaukee. Urban Affairs Review 42 (1):3-25.

Heynen N, 2006, ``Green urban political ecologies: toward a better understanding of inner-city environmental change'' Environment and Planning A 38 499 ^ 516.

Huete, A.R., and Jackson, R.D., 1988. Soil and atmosphere influences on the spectra of partial canopies, Remote Sensing of the Environment 25:89-105.

Huete, A., K. Didan, T. Miura, E. P. Rodriguez, X. Gao, and L. G. Ferreira (2002), Overview of the radiometric and biophysical performance of the MODIS vegetation indices, Remote Sens. Environ., 83, 195– 213.

James, P., K. Tzoulas, M. D. Adams, A. Barber, J. Box, J. Breuste, T. Elmqvist, M. Frith, C. Gordon, K. L. Greening, J. Handley, S. Haworth, A. E. Kazmierczak, M. Johnson, K. Korpela, M. Moretti, J. Niemelä, S. Pauleit, M. H. Roe, J. P. Sadler, and C. Ward Thomson. 2009. Urban Forestry and Urban Greening 8: 65-75.

Jenerette. G, Harlan. S, Stefanov. W, and Martin. C, 2011. Ecosystem services and urban heat riskscape moderation: water, green spaces, and social inequality in Phoenix, USA. Ecological Applications, 21(7), 2011, pp. 2637–2651.

Jensen R, Gatrell J, Boulton J, Harper B, 2004, ``Using remote sensing and geographic information systems to study urban quality of life and urban forest amenities'' Ecology and Society 9(5), http://www.ecologyandsociety.org/vol9/iss5/art5/

John R, Chen J, Lu N and Wilske B 2009 Land cover/land use change and their ecological consequences Environ. Res. Lett. 4 045010.

Kadmon. Ronen, Ruthie Harari-Kremer, 1999. Studying Long-Term Vegetation Dynamics Using Digital Processing of Historical Aerial Photographs, REMOTE SENS. ENVIRON. 68:164–176.

Kasperson, R.E. 1994: Global environmental hazards : political issues in societal responses. In Demko. G.J. and Wood, W.B., editors, Reordering the world: geopolitical perspectives on the 21st century. Boulder, CO: Westview Press, 141-66.

Kerns. P, Watters. M, 2012. Urban forest inequality: Assessing the distribution of trees and their services across Twin Cities neighborhoods. Carleton Environmental Studies program.

Kim. W, Wentz. E, 2010, Complicated Simplicity: A Case Study on Urban Open Spaces in Phoenix Metropolitan Area. University Consortium for Geographic Information Science (UCGIS) 2010. Summer Assembly in Hitlon Head, South Carolina, June 15-16, 2010.

Kim . W, 2011. Understanding Open Spaces in an Arid City. A Dissertation Presented in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy, Arizona State University.

Kim. M, Kim. K,You. K, 2005. A Statistic Correlation Analysis Algorithm Between Land Surface Temperature and Vegetation Index. International Journal of Information Processing Systems Vol.1, No.1, 2005.

Kinney PL, O'Neill MS, Bell ML, Schwartz J, 2008. Approaches for estimating effects of climate change on heat-related deaths: challenges and opportunities. Environ Sci Policy. 2008;11:87–96.

KisslingW D, Carl G, 2008, ``Spatial autocorrelation and the selection of simultaneous autoregressive models'' Global Ecology and Biogeography 17 59 _ 71

Koerner. B, Klopatek. J, 2002. Anthropogenic and natural CO2 emission sources in an arid urban Environment. Environmental Pollution 116 (2002) S45–S51.

Landry, S. M., and J. Chakraborty. 2009. Street trees and equity: evaluating the spatial distribution of an urban amenity. Environment and Planning A 41 (11):2651-2670.

Law, J., & VanDerslice, J. (2011). Proximal and distal determinants to access to health care among Hispanics in El Paso County, Texas. Journal Immigrant Minority Health, 13, 379–384.

Lavelle, M. 1994. Environmental justice. In The 1994 Information Please Environmental Almanac, ed. World Resources Institute, pp. 183-192. Boston, MA: Houghton Mifflin.

Levernier, W., Patridge, M.D., Rickman, D.S., 2000. The causes of regional variations in US poverty: a cross-county analysis. Journal of Regional Science 40, 473–497.

Licón, Adriana Gómez. 2010. "Mexico 2010 census effort a daunting task amid drug violence." El Paso, TX: El Paso Times.

Lindsey G, Maraj M, Kuan S, 2001, ``Access, equity, and urban greenways: an exploratory investigation'' The Professional Geographer 53 332 ^ 346.

Liverman. DM, Varady. R, Chavez. O, Sanchez. R, 1999. Environmental issues along the U.S.-Mexico border - drivers of changes and the response of citizens and institutions. Annual Review of Energy and Environment, Vol 24. p 607-643.

Lloyd C D, 2007 Local Models for Spatial Analysis (CRC Press, Boca Raton, FL).

Lunetta, R.S., J.F. Knight, J. Ediriwickrema, J.G. Lyon, and L.D. Worthy, 2006. Land-cover change detection using multi-temporal MODIS NDVI data. Remote Sens. Environ., in press.

LU. D, MAUSEL. P, BRONDI. E, and MORAN. E, 2004. Change detection techniques, INT. J. REMOTE SENSING, 20 JUNE, 2004, VOL. 25, NO. 12, 2365–2407.

Lyon, J. G., Yuan, D., Lunetta, R. S., and Elvidge, C. D., 1997, A change detection experiment using vegetation indices. Photogrammetric Engineering and Remote Sensing, 64, 143–150.

Maas, J., Spreeuwenberg, P., Van Winsum- Westra, M., Verheij, R. A., M., de Vries, S, Groenewegen, P.P(2009), Is green space in the living environment associated with people's feelings of social safety? Environment and planning A, Vol 41 (7): 1763-1777.

Maas. J, Verheij. R, Groenewegen. P, Vries. S, Spreeuwenberg. P, 2006. Green space, urbanity, and health: how strong is the relation? J. Epidemiol. Community Health 2006;60;587-592.

Zadeh, H. 2006. Digital Change Detection Using Remotely Sensed Data for Monitoring Green Space Destruction in Tabriz, Management and Planning Organization of East Azerbaijan Province, Tabriz, Iran.

Matthew. M, Charlie M. Shackleton, 2010, Public green space inequality in small towns in South Africa, Department of Environmental Science, Rhodes University, Grahamstown 6140, South Africa, Habitat International 34, 244–248.

McDonald. Y, Grineski. S, 2011. Disparities in access to residential plumbing: a binational comparison of environmental injustice in El Paso and Ciudad Juarez. Popul Environ, DOI 10.1007/s11111-011-0154-0.

McDermott, M., S. Mahanty, and K. Schreckenberg. 2011. Defining Equity: A Framework for Evaluating Equity in the Context of Ecosystem Services. Working paper for 'Safeguarding Local Equity as Global Values of Ecosystem Services Rise'project under Ecosystem Services for Poverty Alleviation (ESPA) programme, Natural Environment Research Council (NERC), UK. http://redd-net.org/resourcelibrary/ defining-equity-a-framework-for-evaluating-equity-in-the-co.

Miller RW (1997) Urban forestry: planning and managing urban greenspaces, 2nd edn. Prentice Hall, Upper Saddle River, pp 45–79.

Mitchell, R., & Popham, F. (2008). Effect of exposure to natural environment on health inequalities: an observational population study. Lancet, 372(9650), 1655-1660.

Mohai, Paul, and Bunyan Bryant. 1992. Environmental racism: Reviewing the evidence. Race and the incidence of environmental hazards, ed. Bunyan Bryant and Paul Mohai, 163–76. Boulder, CO: Westview Press.

Mohai, P., & Saha, R. (2006). Reassessing racial and socio-economic disparities in environmental justice research. Demography, 43, 383–399.

Morales. M, Morales. O, Menchaca. A, Sebastian. A, 2013. The Mexican Drug War and the Consequent Population Exodus: Transnational Movement at the U.S.-Mexican Border. www.mdpi.com/journal/societies, ISSN 2075-4698.

Mustapha, M. R.; Lim, H. S. & MatJafri, M. Z. (2010). Comparison of Neural Network and Maximum Likelihood Approaches in Image Classification. Journal of Applied Sciences, Vol.10, No.22, pp. 2847-2854, ISSN 1812-5654.

National Research Council (NRC), 2001. Grand Challenges in Environmental Sciences, National Academy Press, Washington, DC, 2001.

Ng E. Policies and technical guidelines for urban planning of high-density citis- air ventilation assessment (AVA) of Hong Kong. Building and Environment 2009;44:1478e88.

Nicholls, S. 2001. Measuring the Accessibility and Equity of Public Parks: A Case Study Using GIS. Managing Leisure 6 (4):201-219.

Nowak. D, Greenfield. E, 2012. Tree and impervious cover in the United States. journal homepage: www.elsevier.com/locate/landurbplan landurbplan.2012.04.005.

Oh, K. S., and J. J. Hong. 2005. The relationship between urban spatial elements and the urban heat island effect. Reid Journal of Urban Design Institute of Korea 6: 47-63.

Osborne, Jason (2002). Notes on the use of data transformations. Practical Assessment, Research & Evaluation, 8(6). Retrieved January 24, 2013 from http://PAREonline.net/getvn.asp?v=8&n=6 . This paper has been viewed 104,751 times since 5/30/2002.

Ozelkana. E, Papilaa. I, D.Z. Uca Avcia, KARAMAN. M, 2011. Drought Determination by Using Land Surface Temperature and Normalized Difference Vegetation Index. Istanbul Technical University, Center for Satellite Communications and Remote Sensing, Ayazaga Campus, Maslak, Istanbul.

Park. Hun Myoung, 2008. Univariate Analysis and Normality Test Using SAS, Stata, and SPSS. University Information Technology Services. Center for Statistical and Mathematical Computing. Indiana University

Patz, J. A., D. Campbell-Lendrum, T. Holloway, and J. A. Foley. 2005. Impact of regional climate change on human health. Nature 438:310–317.

Pastor M, Morello-Frosch R, Sadd J, 2005. The air is always cleaner on the other side: race, space, and ambient air toxics exposures in California. Journal of Urban Affairs. 2005;27(2):127-148.

Pedlowski M A, Da SilvaVA C, Adell J J C, Heynen N C, 2002, ``Urban forest and environmental inequality in Campos dos Goytacazes, Rio de Janeiro, Brazil'' Urban Ecosystems 6 9 ^ 20.

Pena, S. & Fuentes, C.M., Forster, C. (2005). Land Use Changes in the El Paso del Norte: A Brief History. [Monograph] The U.S.-Mexico Border Environment: Dynamics of Human-Environment Interactions, 11, 321-340.

Peijun DUa, Xingli LIb, Wen CAOa, Yan LUOa, Huapeng ZHANGa, 2010. Monitoring urban land cover and vegetation change by multi-temporal remote sensing information, Mining Science and Technology (China), Volume 20, Issue 6, November 2010, Pages 922–932.

Perkins H A, Heynen N,Wilson J, 2004, ``Inequitable access to urban reforestation: the impact of urban political economy on housing tenure and urban forests'' Cities 21 291 ^ 299.

Ping Tian,et al. Urban Heat Island Effect and Vegetation Cover Index Relation Using Landsat TM Image. Bulletin of Science and Technology. 2006,9,VOL22NO.5,708-713.

Ridgway. John, Piazza. Millie, Saul. Dan, Morris. Joan, Valero. Antonio, Levig. Shirley, Schaefer. Melvin, Westrum. Frank. 1995. A Study on Environmental Equity in Washington State, Department of Ecology. Publication Number 95-413.

Sader, S.A. and J.C. Winne. 1992. RGB-NDVI colour composites for visualizing forest change dynamics. International Journal of Remote Sensing 13(16):3055-3067.

Sader, S.A., D.J. Hayes, J.A. Hepinstall, M. Coan and C. Soza. 2001. Forest change monitoring of a remote biosphere reserve. International Journal of Remote Sensing 22(10): 1937-1950.

Schroeder, Mary Ann. (1990). Diagnosing and dealing with multicollinearity. Western Journal of Nursing Research, 12(2), 175-187.

Singh, A. 1989. Digital change detection techniques using remotelysensed data. International Journal of Remote Sensing 10:989–1003.

Strife. S, Downey. L, 2009. Childhood Development and Access to Nature, A New Direction for Environmental Inequality Research. Published in final edited form as: Organ Environ. 2009 March; 22(1): 99–122. doi: 10.1177/1086026609333340. PMCID: PMC3162362.

Sun. D, Kafatos. M, 2007. Note on the NDVI-LST relationship and the use of temperature-related drought indices over North America. GEOPHYSICAL RESEARCH LETTERS, VOL. 34, L24406, doi:10.1029/2007GL031485, 2007.

Szasz, A., & Meuser, M. (1997). Environmental inequalities: Literature review and proposals for new directions in research and theory. Current Sociology, 5, 99–120.

Taha, H., Modeling the impacts of large-scale albedo changes on ozone air quality in the south coast air basin. Atmosphere & Environment. 31 (1997) 1667.

Talarchek G M,1990, ``The urban forest of New-Orleansöan exploratory analysis of relationships'' Urban Geography 11 65 ^ 86.

Talen, E. 1997. The social equity of urban service distribution: An exploration of park access in Pueblo, Colorado and Macon, Georgia. Urban Geography 18(6): 521- 541.

Tanbakuchi. Anthony, 2009. Introductory Statistics Lectures, Assessing Normality, Department of Mathematics, Pima Community College.

Tarrant, M.A. and Cordell, H.K. 1999. Environmental justice and the spatial distribution of outdoor recreation sites: An application of Geographic Information Systems. Journal of Leisure Research 31(1): 18-34.

Taylor J, Paine C, FitzGibbon J (1995) From Greenbelt to Greenways: four Canadian case studies. Landscape Urban Plan 33:47–64.

Troy A R, Grove J M, O'Neil-Dunne J P M, Pickett S T A, Cadenasso M L, 2007, ``Predicting opportunities for greening and patterns of vegetation on private urban lands'' Journal of Environmental Management 40 394 ^ 412.

Tyrväinen, L. 1997. The amenity value of the urban forest: an application of the hedonic pricing method. Landscape and Urban Planning 37: 211-222.

Tucker, C., 1979, Red and photographic infrared linear combination for monitoring green vegetation. Remote Sensing of Environment, 8, 127–150.

Urbanization and Global Environmental Change (UGEC) 2010. Climatic and Heat Island Effects of Urban Areas. Arizona State University. Tempa, Arizona.

US Census Bureau. (2012). State & County QuickFacts: El Paso County, Texas. Accesed on May 1, 2012 at http://quickfacts.census.gov/qfd/states/48/48141.html.

US Census Bureau. (2013). State & County QuickFacts: El Paso County, Texas. Accesed on July 20, 2013 at http://quickfacts.census.gov/qfd/states/48/48141.html.

Vogt, W. P. (1999). Dictionary of Statistics and Methodology: A Non-Technical Guide for the Social Sciences (2nd ed.). Thousand Oaks, CA: Sage Publications.

Wang, L.; Sousa, W. P.; Gong, P. & Biging, G. S. (2004). Comparison of IKONOS and QuickBird Images for Mapping Mangrove Species on the Caribbean Coast of Panama. Remote Sensing of Environment, Vol.91, No.3-4, pp. 432-440, ISSN 0034-4257.

Williams, Marie, 2008. Linking health hazards and environmental justice: A case study in Houston, Texas. Graduate School Theses and Dissertations. University of South Florida.

Wolch, J. 2005. The Green Visions Recreational Open Space Assessment, Memorandum of Methodology. University of Southern California Center for Sustainable Cities and GIS Research Laboratory, Los Angeles, CA.

Yeshiwondim. K, Gopal. S, Hailemariam. T, Dengela. O, Patel. P, 2009. Spatial analysis of malaria incidence at the village level in areas with unstable transmission in Ethiopia, International Journal of Health Geographics. doi:10.1186/1476-072X-8-5

Yuan F, Marvin E. Comparison of impervious surface area and normalized difference vegetation index as indicators of surface urban heat island effects in Landsat imagery. Remote Sensing of Environment 2007; 106(3): 375–386.

Yue. W, Xu. J, Tan. W, and Xu. L, 2007. The relationship between land surface temperature and NDVI withremote sensing: application to Shanghai Landsat 7 ETM+data. International Journal of Remote Sensing, Vol. 28, No. 15, 10 August 2007, 3205–3226.

Zhangyan Jiang,et al. Heat Island Effect of Beijng Based on Landsat TM Data. Geomatics and Information Science of Wuhan University. 2006,2,VOL31NO.2,121-123.

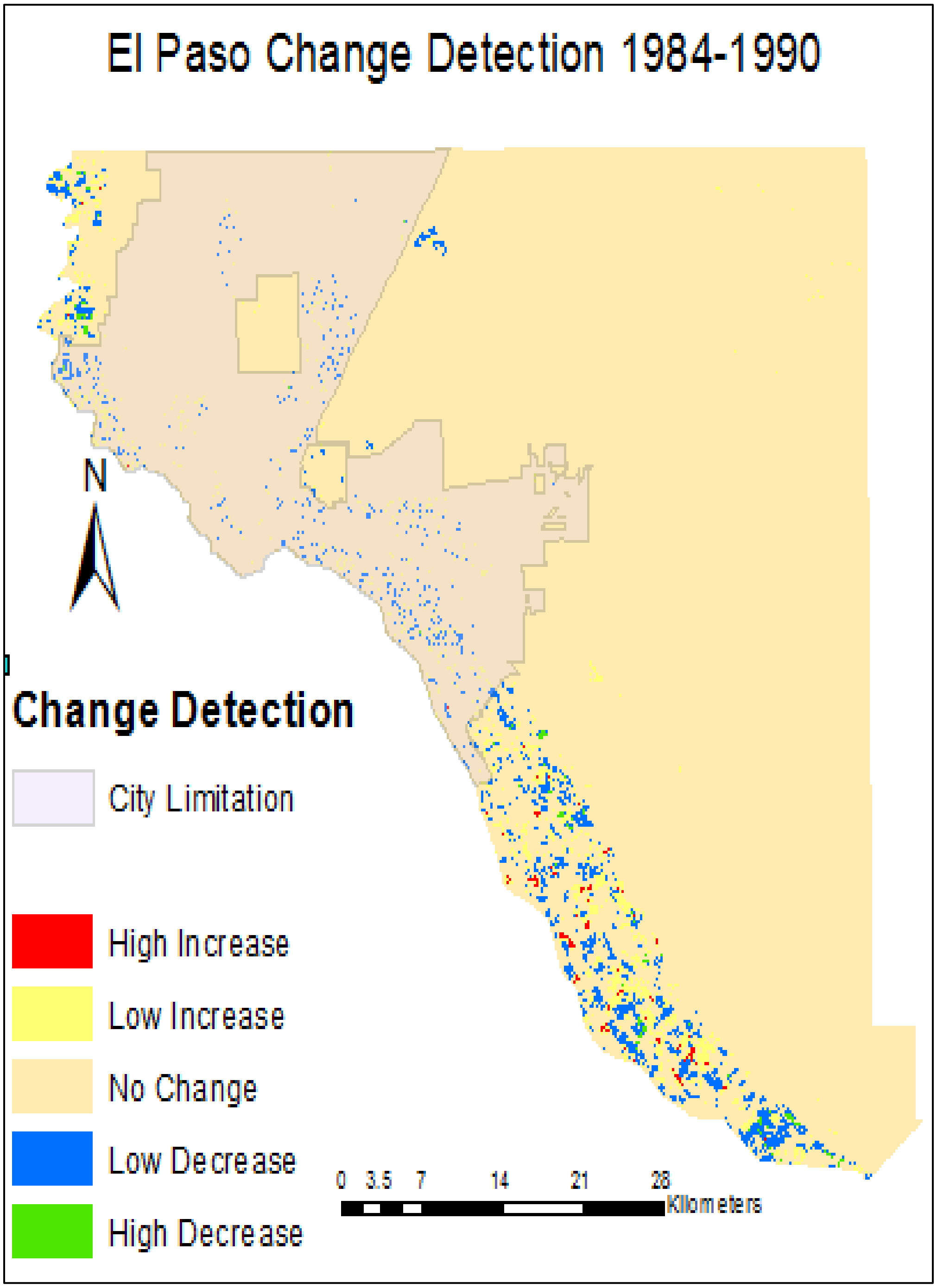
Zhou. X, Wang. Y, 2011. Spatial–temporal dynamics of urban green space in response to rapid urbanization and greening policies, Landscape and Urban Planning 100 (2011) 268–277).

.

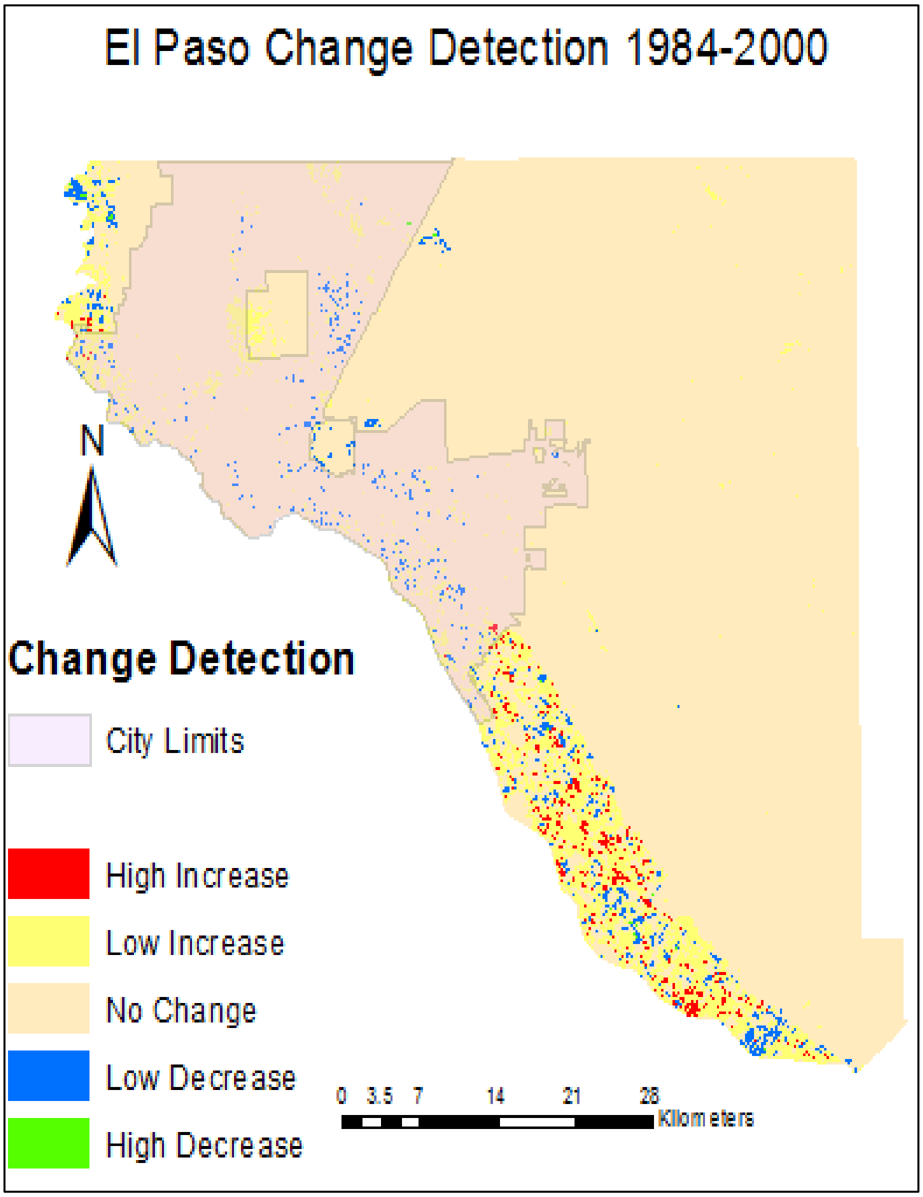
Appendix

Appendix 1:

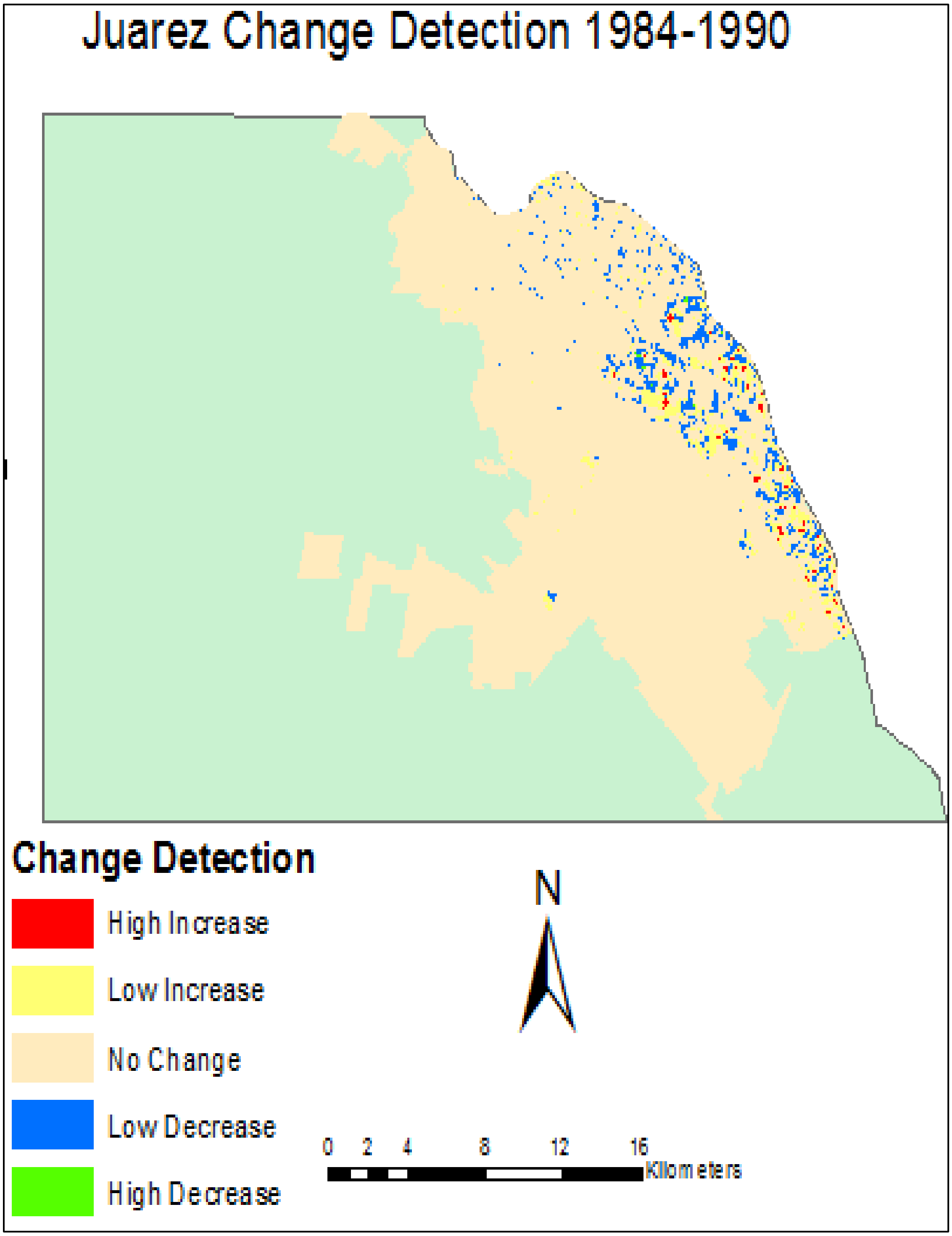
1.1 Change detection map for El Paso, 1984-1990



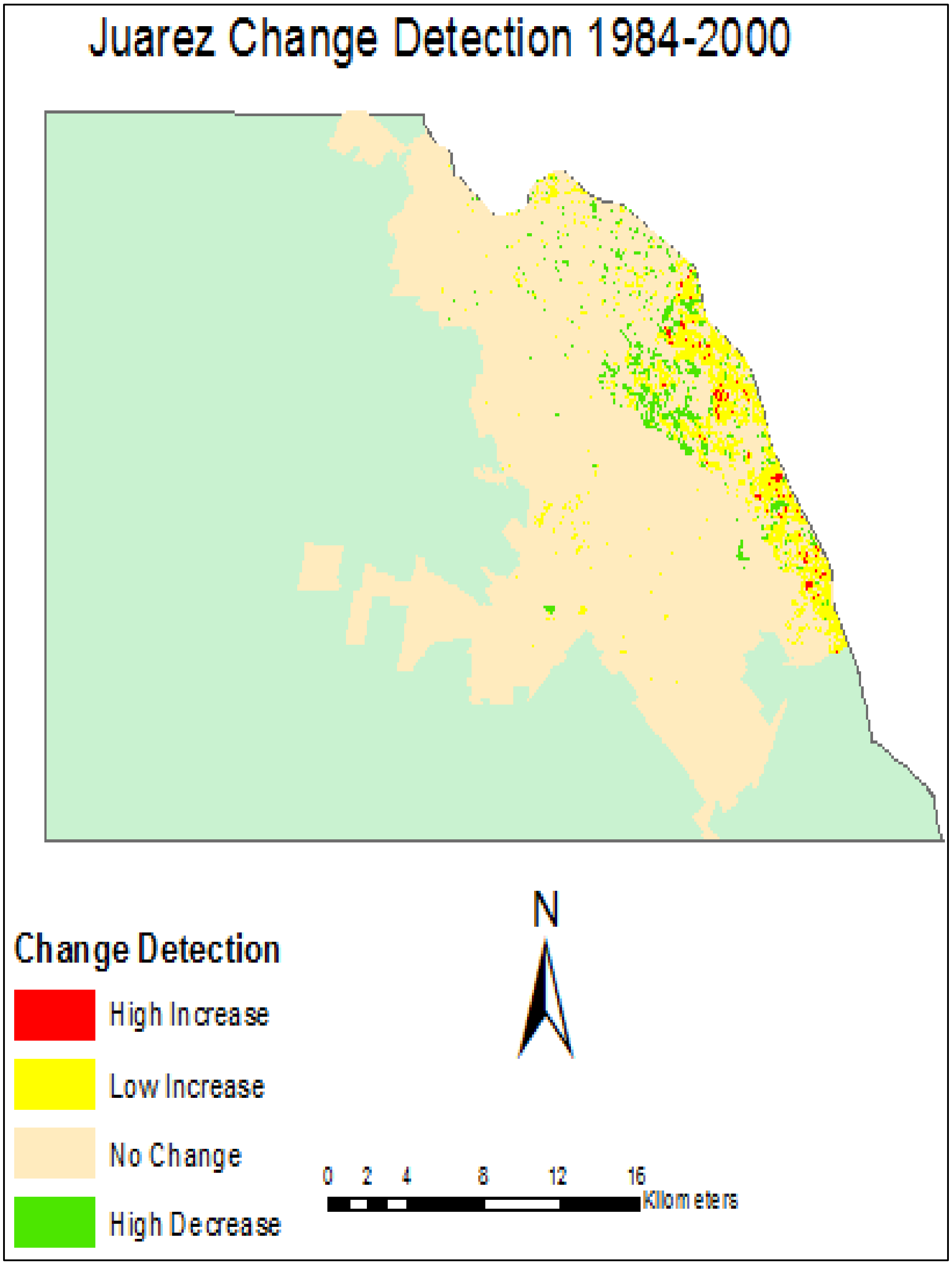
1.2 Change detection map for El Paso, 1984-2000



1.3 Change detection map for Juarez, 1984-1990



1.4 Change detection map for El Paso, 1984-2000



Vita

My name is Abdelatif Bashir Eldeb, and I was born in the first of October, 1968, in Alkhoms, Libya. I received my BSc in Geography from Tripoli University, College of Arts and Science (Libya) in 1992 and my MSc in Geography from Al-Margeb University, Al-Khoms (Libya) in 2005. My Master's thesis was entitled: "Relationship between Alkhoms City and its Suburbs, An Urban Study". After graduation, I worked for four years as a high school geography and environmental sciences teacher and for nine years at the University of Almergeb (Libya) as the Head of Faculty Affairs, as well as a member of the Administrative Committee of the Teachers Training College. From 2005-2008, I worked at the College of Arts and Science at University of Almergeb (Libya) as instructor. In addition to teaching, I worked as a BSc research supervisor. In reward for my hard work and achievements, I was awarded a PhD scholarship from the Ministry of High Education in Libya. I came to the United States in February of 2008 and began a course of study though the English Language Program at the University of Indianapolis, Indiana. In the Fall of 2010, I began my studies in the Environmental Science and Engineering PhD program at the University of Texas at El Paso. My dissertation is entitled "Assessing the equity implications of greenspace distribution in an arid region" and was supervised by Dr. Sara Grineski. While a student at UTEP, I gained skills using techniques such as GIS and remote sensing, and I was also a member of a trans-disciplinary, bi-national research team studying social vulnerability to climate change in El Paso and Juarez. This work has resulted in two forthcoming publications on which I am a co-author. After graduation, I plan to return to Libya to pursue my academic career.

Permanent address: 5450 Suncrest Dr.

El Paso, Texas 79912.

This thesis/dissertation was typed by Abdelatif Eldeb