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Determinants Of Neighborhood Exposure To Extreme Heat: A Spatial Examination Of El Paso And Juárez, 2010

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DETERMINANTS OF NEIGHBORHOOD EXPOSURE TO EXTREME HEAT: A SPATIAL EXAMINATION OF EL PASO AND JUÁREZ, 2010

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DEDICATION

I would like to dedicate this dissertation to my father and the soul of my mother

(May Allah "God" rest her soul in peace)

To my brothers and sisters,

My wife and children,

For their endless sacrifice, love, hope, and belief and for showing me that greatness comes only through hard work

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A SPATIAL EXAMINATION OF EL PASO AND JUÁREZ, 2010

By

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DISSERTATION

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ABSTRACT

Numerous studies have been conducted on the modification of local weather by the urban environment. In studying urban environmental effects on the urban heat island (UHI), researchers have investigated influences such as land use, vegetation density, topography, population density, and neighborhood socioeconomic status. Many studies have used data collected from field observations, while other studies relied solely on computer modeling. This dissertation research used a spatial analysis approach, which has been less widely employed, to investigate neighborhood level biophysical, built environmental and socio-demographic determinants of the El Paso and Juárez UHI. The research utilized inexpensive data obtained from US and Mexican government sources for the study area.

Summer daytime land surface temperature (LST) was examined for the year 2010. High resolution maps of El Paso and Juárez LST were generated using remotely sensed satellite imagery. These maps enabled identification of neighborhood level variation in the intensity of the UHI. Data on previously documented predictors of extreme heat were assembled and analyzed to identify the most important influences on neighborhood level variation in LST. Findings indicate that vegetation density, land use/land cover class, and elderly population concentration were relatively important predictors of LST variation in both cities. Results for elevation, albedo, population density, educational attainment (socioeconomic status) were not stable across the analyses and between the two cities. Results also reveal that the spatial regression modeling approach explained more variation in LST than the OLS regression modeling; thus, spatial regression should be more widely used in studies of extreme heat in cities. Additionally, findings provide practical insights into mitigation strategies to protect vulnerable people from extreme heat exposure. Interventions should aim to protect vulnerable older aged people, particularly in Juárez. Additionally, urban greening programs should be implemented to mitigate extreme heat exposure in neighborhoods with high LST, high population density, and low vegetation density.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF EQUATIONS

LIST OF ABBREVIATIONS

AGDEM……………………….......................................ASTER Global Digital Elevation Model V002
LST……………….. …………… ....Land Surface Temperature
ENVI………………………...Environment for Visualizing Images
FLAASH…………………….......................Fast Line-of-sight Atmospheric Analysis of Hyper-cubes
GIS…………………………..Geographic Information Systems
SRM……………….. ………...Spatial Regression Model
ETM+………………………..Landsat 7 Enhanced Thematic Mapper Plus
LCA……………….. ………..Land Cover Albedo
TM 4, 5………………………...Landsat 4-5 Thematic Mapper
LULC……………………….. Land Use Land Cover
NEM…………………… …...Normalization Emissivity Method
NDVI…...Normalized Difference Vegetation Index
OLS………………………...…............ Ordinary Least Squares
ROI……………………...……............... Region of Interest
ASTER…………………….. Thermal Emission and Reflection Radiometer
TIR……………………….. Thermal Infrared
UHI………………………...…............... Urban Heat Island
NGOs………………………...Non-Governmental Organization
HIA…………………………..Heat island area
RQ …………………………..Research Question
Hs…………………………...…............Hypotheses
USGS………………………...United States Geological Survey
SES……………………...……...............Socioeconomic Status
AGEBs…..Áreas Geoestadísticas Básicas in Mexico
BGs…………………………...Census Block Groups in USA
NIR…...Reflectance in the Near Infrared Band
RED………………………...Reflectance in the Red Band
RMS………………………...…..................Root Mean Squared
BIP…………………………………........................Band-Interleaved-by-Pixel or Pixel-Interleaved

BIL……………………………………….........................Band-Interleaved-by-Line or Row-Interleaved

ANOVA ………………………..Analysis of Variance

LM……………………………...Lagrange Multiplier

SAR Lag…..Spatial Lagged Regression

SARee…...Spatial Error Regression

Tukey's HSD…...Tukey's HSD (Honestly Significant Difference) Test

SRM..Spatial Regression Model

RSSR……………………………..R Square Spatial Regression

CHAPTER 1: INTRODUCTION

Rapid urbanization and human population growth in urban environments has led to increased scientific consideration of causal forces and potential effects. The proportion of the human population worldwide living in cities now exceeds 50%. The United Nations Population Fund (UNFPA, 2007) projected this number will increase to 60% by 2030. Increased temperatures due to global climate change and urban heat island (UHI) formation are associated with increased human exposure to extreme heat in cities and an increased risk for negative health outcomes. Governments, the private sector, NGOs and academia have begun to direct attention to the economic and environmental impacts of climate change on human populations. This study focuses specifically on clarifying determinants of extreme heat exposure across urban neighborhoods, due to the acute effects extreme heat may have on the health and productivity of people living in particular urban settings (Crowe, 2009). Neighborhoods within the El Paso County and Ciudad Juárez urban area, which stretches across the US-Mexican border, are examined.

This study aims to identify the main factors affecting exposure to excessive heat at the neighborhood level in the sister cities of El Paso (Texas, USA) and Ciudad Juárez (Chihuahua, Mexico). In terms of study methods, remote sensing, GIS and (spatial) statistical analysis techniques are used to clarify factors influencing fine-scale spatial variation in land surface temperature (a measure of extreme heat exposure) for El Paso County and Ciudad Juárez. Results can potentially inform mitigation and adaptation responses in the study area and beyond.

1.1 Problem Statement

There are several factors that have been shown to influence spatial variation in extreme heat distribution. My research will focus on spatial variation in land surface temperature, which has traditionally been examined by physical geographers at much broader spatial scales. Urban climatologists have advanced understanding to focus on intra-urban variation in temperatures, and have documented the "urban heat island" effect. My work connects with and expands upon research on the UHI by examining fine-scale variation in land surface temperature. I will focus on the relative effects on land surface temperature (LST) of a wider range of biophysical, built environmental and socio-demographic factors than have not previously been examined together in individual studies, and for two cities located in two countries (one high income country and one middle income country). The overall goal is to provide new insights into the factors controlling fine-scale exposure to extreme heat.

1.2 Research Objectives

The specific research objectives are:

1. To accurately map extreme heat exposure and hypothetical determinants at a fine spatial scale (the neighborhood level).
2. To examine elevation, vegetation density, land use/land cover class, land cover albedo, population density, concentration of the older aged population, and socioeconomic status (education level) as factors related to variation in extreme heat exposure at the neighborhood level.
3. To examine and identify predictors of neighborhood level extreme heat exposure for the year 2010 within two cities situated in two countries (Ciudad Juárez, Mexico and El Paso, United States)
4. To clarify how neighborhood predictors of variation in extreme heat exposure differ by city/country.

1.3 Research Questions and Hypotheses

1.3.1 Research Questions

The following research questions (RQs) will be addressed in my research. By addressing these questions, I will identify local biophysical, built environmental and socio-demographic determinants of land surface temperature in the El Paso County-Ciudad Juárez study area.

RQ1: What is the relationship between elevation and land surface temperature (LST) in the study area?

RQ2: What is the relationship between vegetation density and LST in the study area?

RQ3A: What is the relationship between land use/land cover class and LST in the study area?

RQ3B: What is the relationship between land cover albedo and LST in the study area?

RQ4: What is the relationship between population density and LST in the study area?

RQ5: What is the relationship between the distribution of older aged people (based on the percentage of the neighborhood population above 64 years of age) and LST in the study area?

RQ6: What is the relationship between socioeconomic status (based on measures of educational attainment) and LST in the study area?

RQ7: Taken together, which of the factors identified in RQ1 through RQ6 (i.e., elevation, vegetation density, land use/land cover class, land cover albedo, population density, older age, socioeconomic status) are relatively more (or less) important in predicting LST in the study area?

RQ8: Are the relationships between the factors identified in RQ1 through RQ6 (i.e., elevation, vegetation density, land use/land cover class, land cover albedo, population density, older age, socioeconomic status) and LST stable between El Paso County and Ciudad Juárez?

1.3.2 Hypotheses

Based on results from prior research covered in the literature review, I am proposing the following hypotheses (Hs), which correspond with each of the research questions:

H1: There is a significant negative relationship between elevation and land surface temperature.

H2: There is a significant negative relationship between vegetation density and land surface temperature.

H3A: Land surface temperature varies significantly by land use/land cover class. Some land use classes have significantly higher (e.g., commercial and industrial), and other land use classes significantly lower (e.g., agricultural), mean land surface temperatures.

H3B: There is a significant negative relationship between land cover albedo and land surface temperature.

H4: There is a significant positive relationship between population density and land surface temperature.

H5: There is a significant positive relationship between the concentration of older aged people and land surface temperature?

H6: There is a significant negative relationship between socioeconomic status and land surface temperature.

H7: Factors that directly physically influence land surface temperature (i.e., elevation, vegetation density; land use/land cover class), are relatively more important predictors of surface temperature than factors that indirectly influence land surface temperature (i.e., population density, socioeconomic status).

H8A: Relationships for the factors that physically influence land surface temperature (i.e., elevation, vegetation density, and land use/land cover class) are stable between El Paso and Juárez.

H8B: Relationships between the factors that indirectly influence land surface temperature (i.e., population density, socioeconomic status) are unstable (i.e., substantially vary) between El Paso and Juárez.

CHAPTER 2: LITERATURE REVIEW

This literature review focuses identifying the most important determinants of local variation in land surface temperature and exposure to extreme heat in cities. First, I review the literature on variables associated with biophysical determinants of land surface temperature variation. Second, I focus on built environmental determinants. Third, I identify variables associated with socio-demographic determinants and land surface temperature variation in cities based on the extant literature. See Appendix 1 for detailed a summary chart of the relevant literature.

2.1 Biophysical Determinants

2.1.1 Topography

It is well known that elevation is negatively related to temperature; the higher the elevation, the lower the temperature. In the literature on local temperature variation in cities, studies that have examined elevation have confirmed this relationship (Charabi & Bakhit, 2011; Grossman et al., 2010; Valade, 2006; Hawkins, 2003) (See Appendix 1). For example, the urban heat island in Muscat, Oman varies spatially because of the rugged mountain topography of the city. The temperature decreases at higher elevations on steep slopes surrounding the city center, due primarily to adiabatic processes and secondarily to the reduced density of urban development (Charabi & Bakhit, 2011). As another example, Phoenix, Arizona (like El Paso County-Ciudad Juárez) is located in a desert river valley, with urban development occurring in the flood plain and in surrounding mountainous areas. In this context, Jenerrette et al. (2006) found that higher elevation neighborhoods had substantially lower mean land surface temperatures than lower elevation neighborhoods. One limitation of existing elevation data relates to the resolution of available digital elevation models (DEMs), especially when conducting research at very fine scales (Kestens et al., 2011). However, for the purposes of this dissertation research, the spatial resolu-

tion of existing DEMs (i.e., 30 m) is adequate. Topography also produces shade and moisture effects that can significantly reduce local temperatures in cities. For example, the urban area of Muscat, Oman is bordered by mountains that separate it from the sea on one side, and on the other side from a narrow accumulation plain, of 6–20 km width in average, which is built mainly by the numerous wadis (i.e., arroyos) that drain the surrounding slopes in a predominantly SW–NE direction. The effect is that cool moist breezes coming from the sea are blocked, which tends to increase temperatures throughout the city. On the other hand, the urban area is kept in shade for much of the day due to the mountain range, which reduces local temperatures in shaded areas of the city (Charabi & Bakhit, 2011).

2.1.2 Vegetation Density

Vegetation is directly correlated with local temperature; the higher the density of vegetation, the lower the temperature. Studies on local temperature variation in cities have provided substantial empirical support for this relationship (Murphy, 2009; Sullivan, 2010; Memon, 2007; Buyantuyev & Wu, 2009; Jin et al., 2005; Murphy, 2007; Mallick et al., 2008). Denser vegetation is associated with high rates of evapotranspiration and, hence, is associated with increased moisture and higher rates of evaporative cooling, which lowers temperatures. Vegetation can also provide shade, which protects against insolation and helps maintain soil moisture, lowering temperatures. For example, studies of cities in North America, the Caribbean and Asia have shown that areas of lower UHI temperatures are significantly associated with areas of lower percentages of impervious (non-vegetated) surface and higher vegetation density (Sullivan, 2010; Grossman et al., 2010; Goggins, 2009; Memon, 2007; Murphy, 2007; Small & Balstad, 1997). In the literature on local temperature variation in cities, studies have conventionally measured vegetation density effects using the Normalized Difference Vegetation Index (NDVI) (Buyantuyev & Wu, 2009; Stefanov, 2005; Xian and Crane, 2006; Murphy, 2009;

Kestens et al., 2011; Jenerette et al. 2006; Hardegree, 2006; Jin et al., 2005; Murphy, 2007; Zhang et al., 2010; Goggins, 2009).

2.2 Built Environmental Determinants

2.2.1 Land Use and Land Cover

An important human influence on land surface temperature, especially in urbanizing regions is extensive land use/land cover change, as it plays a major role in regional and local scale heat variation. Previous research has classified the urban environment into residential, commercial and industrial areas or their subcategories using high-resolution remotely sensed data (Sullivan, 2010). Most of the heat differences in urban areas related to human activities are associated with land use/land cover (LULC) variations defined by the presence and density of attributes such as vegetation (e.g., associated with park or agricultural land uses) or materials used in the built environment. These include, for example, impervious surfaces or high rise glass and metal structures (Kim, 2009; Prado, 2010). In Tampa, Florida and Phoenix, Arizona, for example, residential land use classes have been shown to have lower mean temperatures than commercial and industrial land use classes (Prado, 2010; Stefanov et al., 2003).

Other studies have focused on land cover and surface heat island formation in different metropolitan regions. Land cover types common to urban areas (such as dark colored pavement, brick and asphalt with low albedo) absorb radiation during the day and release it during the evening, causing maximum temperature differences for UHIs by land cover type that are typically greatest at nighttime (Stefanov et al., 2003; Stone & Norman, 2006; Murphy, 2007). Vegetation has been shown to be linked to LULC, such that strong negative correlations have typically been observed between NDVI values (i.e., vegetation density) and land surface temperatures based on different LULC classes. Regression models integrating LULC parameters have been estimated, indicating that surface temperatures in some contexts can be accurately predicted if NDVI values are also known (Mallick, et al. 2008). Vegetation impacts by

LULC type are clearly evident as low temperature values have been observed over agricultural cropland, dense vegetation (forest) and sparse vegetation (grass/park) classes in comparison to urban land use classes (Chow, 2011; Ani et al., 2009; Rosenthal, 2010; Mallick et al., 2008). For example, in Paris and Hong Kong, daytime temperatures are significantly higher in densely built industrial areas than in higher vegetation density urban areas, such as parks (Dousset et al., 2010; Nicholet et al., 2009). The replacement of natural vegetation and agricultural lands with impervious surfaces (concrete, asphalt, roof tops, and dense buildings in residential, commercial and industrial areas) has been shown to amplify extreme heat in many cities (Buyantuyev & Wu, 2009; Dousset et al., 2010; Goggins, 2009; Yan Kestens et al., 2011; Rajasekar & Weng, 2008). On the other hand, increasing the albedo of building surfaces as well as implementing green building and landscaping approaches (such as painting building surfaces white, installing green roofs, and/or planting street trees) have been shown to mitigate extreme heat within high density urban areas (Ani et al., 2009; Chow, 2011; Taha et al., 1988)

2.2.2 Land Cover Albedo

Land cover albedo is an important factor controlling the amount of energy available to drive daytime surface-atmosphere exchange processes. Albedo determines the total amount of energy available for evaporation, sensible heat flux and gas exchange (Houldcroft et al., 2009). Albedo is the biophysical indicator that influences the surface temperature by affecting land surface energy distribution and balance. Numerous studies demonstrate that there is a strong negative relationship between surface albedo and radiative heat; as albedo increases, the radiation absorbed by the surface decreases, which causes cooling. Surprisingly few studies have quantified the relationship between land cover albedo and land surface temperature (except for Houldcroft et al., 2009; Cho et al., 2012; Bhattacharya et al, 2009a). For example, a study of Dubai and Abu Dhabi (hot-dry environments similar to El Paso-Ciudad Juárez) used ASTER imagery to evaluate variation of surface temperature and albedo and found albedo was higher in

nonurban areas, as compared to urban areas, and that surface temperatures were correspondingly lower in nonurban areas (Frey & Parlow 2007). Scott and Voogt (2010) examined impacts of changing roof albedo on near surface air temperature in neighborhoods with different degrees of urbanization in Chicago; they found that the average temperature decreased by -1°C as roof albedo increased 0.59% in the summer daytime.

2.3 Socio-demographic Determinants

2.3.1 Population Density

The problem of extreme heat is amplified in major cities with large populations and extensive, densely settled built environments (Ahmed et al., 2007). Population density is measured as the number of people per unit of area, usually per square kilometer or mile. Empirical studies conducted throughout the world (e.g., in San Francisco, Phoenix, and large Western European cities) have shown population density to be positively correlated with temperature in cities; the greater the population density, the higher the temperature (Jeanerette et al., 2007; Dousset et al., 2010). In large cities, the population has twofold effects on heat generation: a direct effect associated with greater population density and greater metabolism and an indirect effect due to the design and number of buildings, vehicles, factories, and other features of the built environment (Memon et al., 2007; Sullivan, 2010). For example, Zhang and Wang (2008) conducted correlation and regression analyses to study relationships between the heat island area (HIA) and related factors in the Pearl River Delta region of China; results showed that while HIA was significantly correlated with urban size (r=0.95) and development area (r=0.83), it was most highly correlated with population density (r=0.97).

2.3.2 Distribution of Older Age Population

Neighborhood characteristics may modify the effects of exposure to hazards, acting as buffers that reduce or stressors that amplify their harmful effects. Related research on heat vulnerability suggests that the elderly are especially vulnerable to extreme heat exposure. For example, in the 1995 Chicago heat wave, elderly populations experienced heightened risk of death (Klinenberg, 2002; Stanforth, 2011). Because the elderly population is especially vulnerable to extreme heat exposure, it is important to examine relationships between the spatial concentration of elderly residents and land surface temperature at the neighborhood level (i.e., based on the percent of the population age >64 in neighborhoods).

2.4 Socioeconomic Status (SES)

Studies have revealed an association whereby higher socioeconomic status (SES) neighborhoods tend to be negatively related to temperature; the higher the neighborhood SES (in terms of level of education and/or income), the lower the local temperature. In the literature on local temperature variation in cities, studies that have examined SES have confirmed this relationship. In Phoenix, previous studies have shown a strong correlation between temperature and variables affecting its spatial and temporal variation, and revealed that lower SES groups were more likely to live in warmer neighborhoods with greater exposure to heat stress (Buyantuyev & Wu, 2010). Examining eight diverse neighborhoods in Phoenix during the summer of 2003, it was noted that neighborhoods with higher "settlement density, sparse vegetation, and having no open space…were significantly correlated with higher temperatures" and that minority ethnic and lower income groups were more likely to live in these warmer neighborhoods (Harlan et al., 2006). Overall, every $10,000 increase in neighborhood annual median household income was associated with a 0.28 degree C decrease in surface temperature on an early summer day in Phoenix (Jenerette et al., 2006). Lower educational attainment has also been associated with higher extreme heat exposure in both El Paso and Juárez (Grineski et al. 2012, 2013).

CHAPTER 3: METHODOLOGY

To examine the research questions and hypotheses, multiple sources and techniques were used to assemble and analyze the data. Figure 3.1 depicts the general methodological approach employed. This chapter begins with an overview of the study area and then provides a description of the data and their sources for El Paso, Texas, USA as well as Ciudad Juárez, Chihuahua, Mexico. Additionally, the technical details of data transformation procedures (e.g., remotely sensed image pre-processing) are described in this chapter. These procedures were used to prepare the data for analysis of the dependent and independent variables, including land surface temperature (LST), elevation (based on digital elevation models, DEMs), vegetation density (based on the Normalized Difference Vegetation Index, NDVI), land use/land cover (LULC, based on a classification procedure), land cover albedo (LCA), population density, distribution of older aged people, and socioeconomic status (education). Next, the statistical analysis procedures are described. They include descriptive statistics and Pearson correlations to examine distributions of each of the variables as well as the basic relationships of LST with the suite of biophysical, built environmental and socio-demographic independent variables. One-way ANOVA was used to examine the relationship between LULC class and LST. Those analyses were achieved using SPSS v. 20. Next, spatial regression was used to model multivariate determinants of daytime surface temperature using GeoDa software. In this procedure LST was the dependent variable leaving the other six variables as independent. Methodological details are described in what follows.

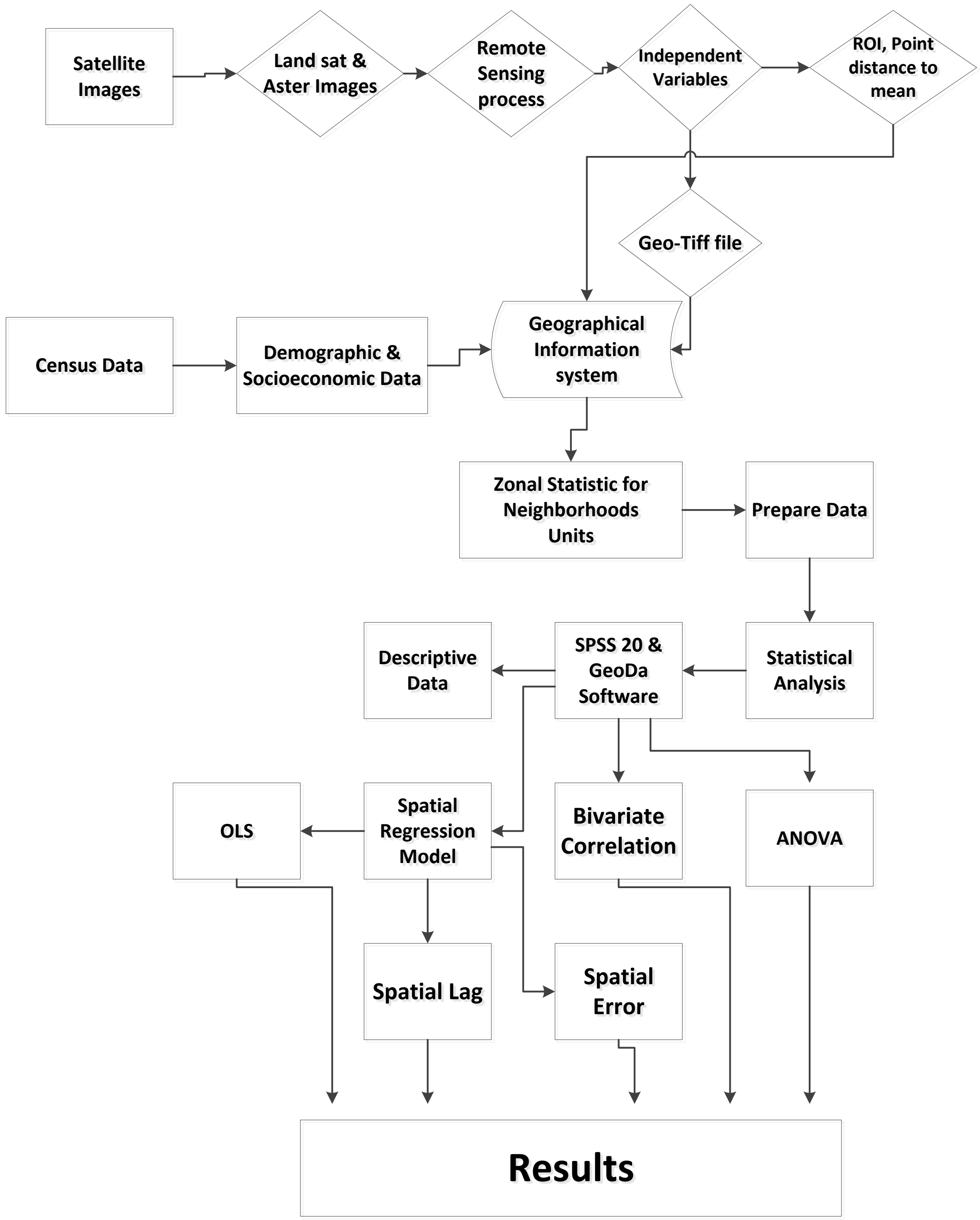


Figure 3.1 Methodology Overview

3.1 Study Area

Understanding the locational characteristics of the El Paso County and Ciudad Juárez urban area at the US-Mexico border is important for examining local temperature related variables and for interpreting analysis results. The twin border urban areas of El Paso County, Texas, and Ciudad Juárez, Chihuahua, were known in the 16th century as a single city. Since then, El Paso del Norte has changed in every aspect: geographically, demographically, politically, culturally, and economically. Today the two cities are characterized by distinct economies as a result. Furthermore, they clearly represent the economic differences that exist along the entire US-Mexico border (Federal Reserve Bank of Dallas El Paso, 2001). The US-Mexico border region is unique because it is characterized by the large number of people who migrate to the region, including many from central Mexico coming to the northern border (Mondragon & Brandon, 2004). Juárez is located in the north of Mexico. It is the most populated city of the Mexican state of Chihuahua and is the fifth largest city in México with approximately 1,600,000 inhabitants. It was rapidly growing with an economy dominated by industrial production until narco-violence and the global recession slowed immigration and commerce beginning in 2008. Juárez 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 Juárez was $9,890 while the statistic for Mexico was $11,460 (pesos converted to US dollars) (Grineski and Collins, 2010). Juárez is bordered to the north by the city of El Paso, Texas. Together, Juárez and El Paso form one the largest bi-national metropolitan areas in the world. El Paso County is a majority-minority context with 82% of residents being Hispanic and a median household income of $36,333 (based on 2006-2010 estimates), which is well below the US national average (US Census Bureau 2012). See Figure 3.2 for a map of the study area.

Figure 3.2 Study Area (Source: USGS 2012)

The focal area for this study is El Paso County, USA and Ciudad Juárez, México with focus on the summer months of 2010. El Paso and especially Juárez have experienced a period of rapid population growth, along with a conversion of desert lands to urban use. Accompanying this, land cover change has generally been defined by an increase in buildings, roads, and other impervious surfaces common in the urban environment as well as local increases in vegetation density associated with irrigated agriculture and other human land uses.

3.2 Unit of Analysis

The primary spatial unit of analysis was the neighborhood (census block groups [BGs] in the US and áreas geoestadísticas básicas [AGEBs] in Mexico, based on 2010 spatial boundaries). The neighborhood unit includes 618 AGEBs in Ciudad Juárez and 513 BGs in El Paso County (see Figure 3.3). In this analysis I used all block groups and AGEBs with more than 500 residents. This included 540

AGEBs in Ciudad Juárez and 510 block groups in El Paso County. I refer to the AGEBs and census block groups as ‘neighborhoods’ instead of ‘block groups’ and ‘AGEBS’. The highest Juárez neighborhood population density was 14726 per km^2 compared with the high for El Paso of 9536 per km^2. A zonal statistic method in ArcMap was performed to calculate mean LST, LSA, NDVI, and elevation levels for each neighborhood, and those data were spatially joined to the BG and AGEB shape files. To examine the relationship between land use/land cover class and land surface temperature, the 30 m by 30 m pixel was used as a secondary unit for analysis of variance (ANOVA) testing (described in the analysis methodology section).

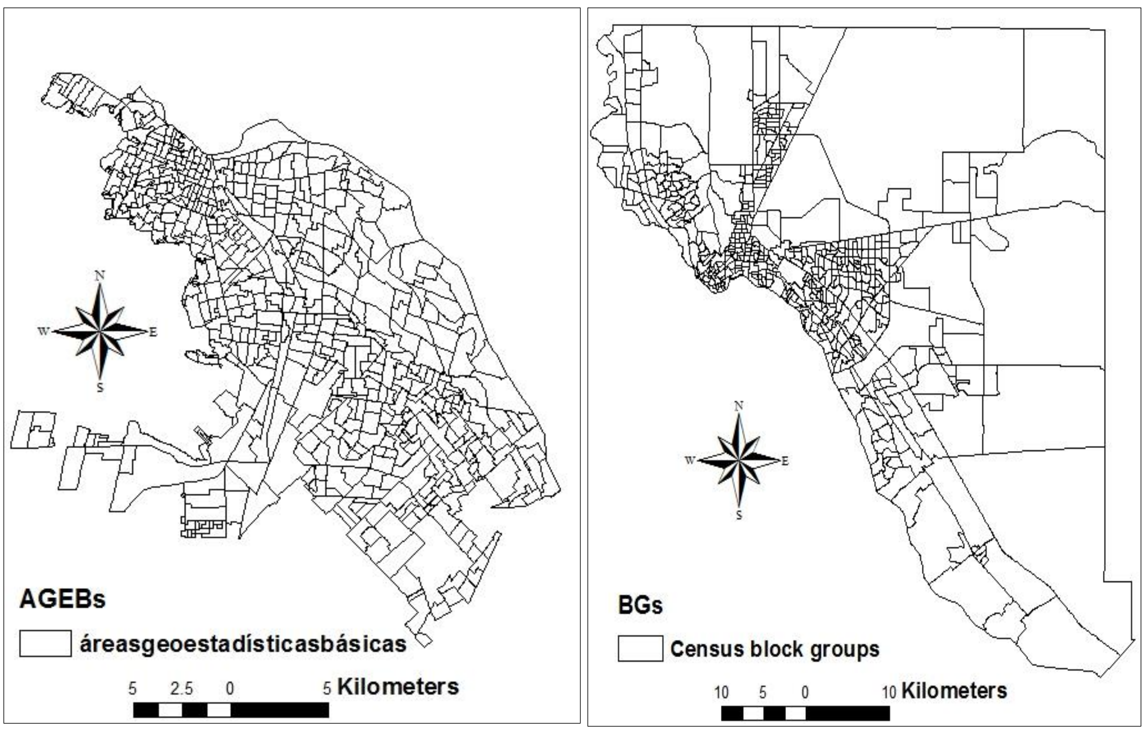


Figure 3.3 Analysis Neighborhoods of Ciudad Juárez (AGEBs) and El Paso County (BGs)

3.3 Data Sources and Variable Construction Procedures

Data from several sources were used to construct the analysis variables, including but not limited to satellite imagery (from which land surface temperature, vegetation density, land cover albedo, and

other measures were derived), census statistics, and digital elevation models (from which elevation measures were derived). Together these spatial data were overlaid using a geographic information system and relationships between the analysis variables (specifically those relationships addressed by the RQs and Hs) were examined using (spatial) statistical analysis techniques. See Table 3.1.

Table 3.1 Analysis Variables: Date, Scale and Source

Variable	Date	Scale/Resolution	Source
Land Surface Temperature Mean (Y)	2010 Average	30 m /120m	Landsat TM /ETM (USGS)
Elevation Mean (X1)	2010	30 m	ASTER Global Digital Elevation Model (USGS)
Vegetation Density Mean (X2)	2010 Average	30 m/120	Landsat TM/ETM (USGS)
Land Cover Albedo Mean (X3)	2010 Average	30 m/120	Landsat TM/ETM (USGS)
Population density (X4)	2010	Neighborhood: block groups (BGs) in the US and áreas geoestadísticas básicas (AGEBs) in Mexico	US Census Bureau and Mexican Census Bureau (INEGI)
Over age 64 (X5)	2010	Neighborhood: block groups (BGs) in the US and áreas geoestadísticas básicas (AGEBs) in Mexico	US Census Bureau and Mexican Census Bureau (INEGI)
Education Level (X6)	2010	Neighborhood: block groups (BGs) in the US and áreas geoestadísticas básicas (AGEBs) in Mexico	US Census Bureau and Mexican Census Bureau (INEGI)
Land use & land cover (X7; not used for correlation and regression)	2010 August 17	30 m	Landsat TM/ETM (USGS)

3.3.1 Land Surface Temperature

Landsat 4-5 Thematic Mapper (TM) includes images from a multispectral scanning radiometer carried on board Landsat’s 4 and 5. Landsat TM images were downloaded from the NASA website and

data were acquired for cloud free summer days in the year 2010 (see Table 3.1). This study used Band 6 with a spatial resolution of 30 m for LST calculations to increase the accuracy and the interpretability of the digital data. Several preprocessing procedures were required including, atmospheric, radiometric, and geometric corrections to reduce the dust and fog in the imagery caused by factors such as atmospheric disturbances, differences in illumination angle, or errors in sensor calibration (Agapiou and Hadjimitsis, 2011) (see Figure 3.4).

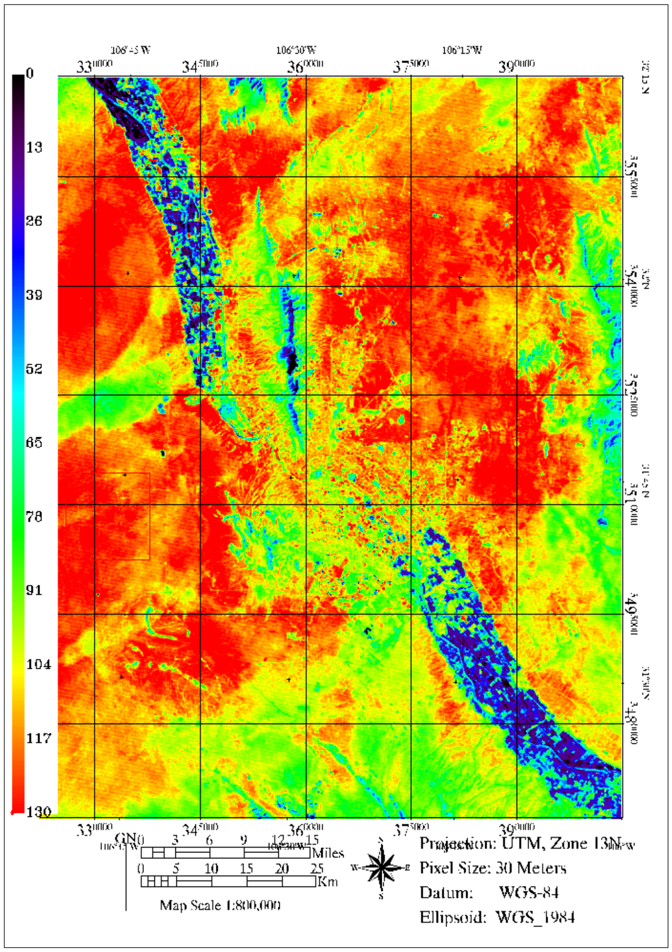


Figure 3.4 Example of LST Map Used to Measure Extreme Heat Exposure

Landsat images with very little or no cloud cover for 5 extreme heat events were selected (centered on the year 2010). The selection of images was determined by the five highest maximum and mean temperature days during 2010 for which cloud-free images were available. The final land surface tem-

perature variable used in analysis was based on images for five dates (6/14/2010, 7/13/2009, 7/29/2009, 8/17/2010, and 9/2/2010), which were combined in order to obtain as stable a dependent variable as was possible; mean land surface temperature values were first calculated for each day for each neighborhood individually and then averaged across the five dates to create the dependent variable. The images were calibrated and the pixel values were converted to temperature first in Kelvin and then Fahrenheit. Next, the mean LST for all pixels within each neighborhood was calculated. ENVI software was used for zonal calculations of mean LST for all pixels within each neighborhood to map intra-urban variation in extreme heat exposure for all neighborhoods in the study area (see Figure 3.5below). More specifically, the following procedures were implemented to obtain mean LST values for study area neighborhoods, which were use in subsequent analyses:

Equation 3.1 Calibration Landsat

$$L_{\lambda}= \left(\frac{LMAX_{\lambda}\text{-}LMIN_{\lambda}}{QCALMAX_{\lambda}}\right) QCAL+QCALMIN_{\lambda}$$

Where QCAL is the calibrated and quantized scaled radiance in units of digital numbers (DNs), $LMIN_{\lambda}$ is the spectral radiance at QCAL = 0, $LMAX_{\lambda}$ is the spectral radiance at QCAL = $QCALMAX_{\lambda}$,$QCALMIN_{\lambda}$ is the minimum quantized calibrated pixel value in DN, and $QCALMAX_{\lambda}$ is the maximum quantized calibrated pixel value in DN (Chander & Markham 2003).

I used the Normalization Emissivity Method (NEM), which separates the emissivity and temperature information from TIR radiance data in Kelvin degrees. This was done as follows:

Equation 3.2 Convert Radiance Value to Degrees Kelvin

$$T_K = \frac{K_2}{\ln[\frac{K_1}{P_R}+1]}$$

Where Tk=Kelvin Temperature, PR=pixel Radiance value, K1=607.76 and K2=1260.56 (http://cires.colorado.edu/).

Then, I converted degrees Kelvin to degrees Fahrenheit for each pixel using the following formula:

Equation 3.3 Convert Degrees Kelvin to Fahrenheit

$$\mathbf{T_{f=(B1-273)^{*}1.8+32}}$$

Where B is the TIR band

Next, the zonal statistic calculation method in ArcMap was performed to obtain estimated mean LST values for each neighborhood. See Figure 3.5.

Table 3.2 Descriptive Statistics for LST Derived from Landsat TM Images

Images	Sensor	Daytime	El Paso LST by Pixel		Juárez LST by Pixel	
			Mean	St Dev	Mean	St Dev
16/14/2010	Landsat 5 TM		113.4	3.0	111.9	2.8
7/13/2009	Landsat 7 ETM+		109.3	2.9	108.8	2.3
7/29/2009	Landsat 7 ETM+		103.3	3.1	101.9	2.5
8/17/2010	Landsat 5 TM		95.6	4.0	94.8	3.7
9/2/2010	Landsat 5 TM		106.3	3.3	105.4	2.8

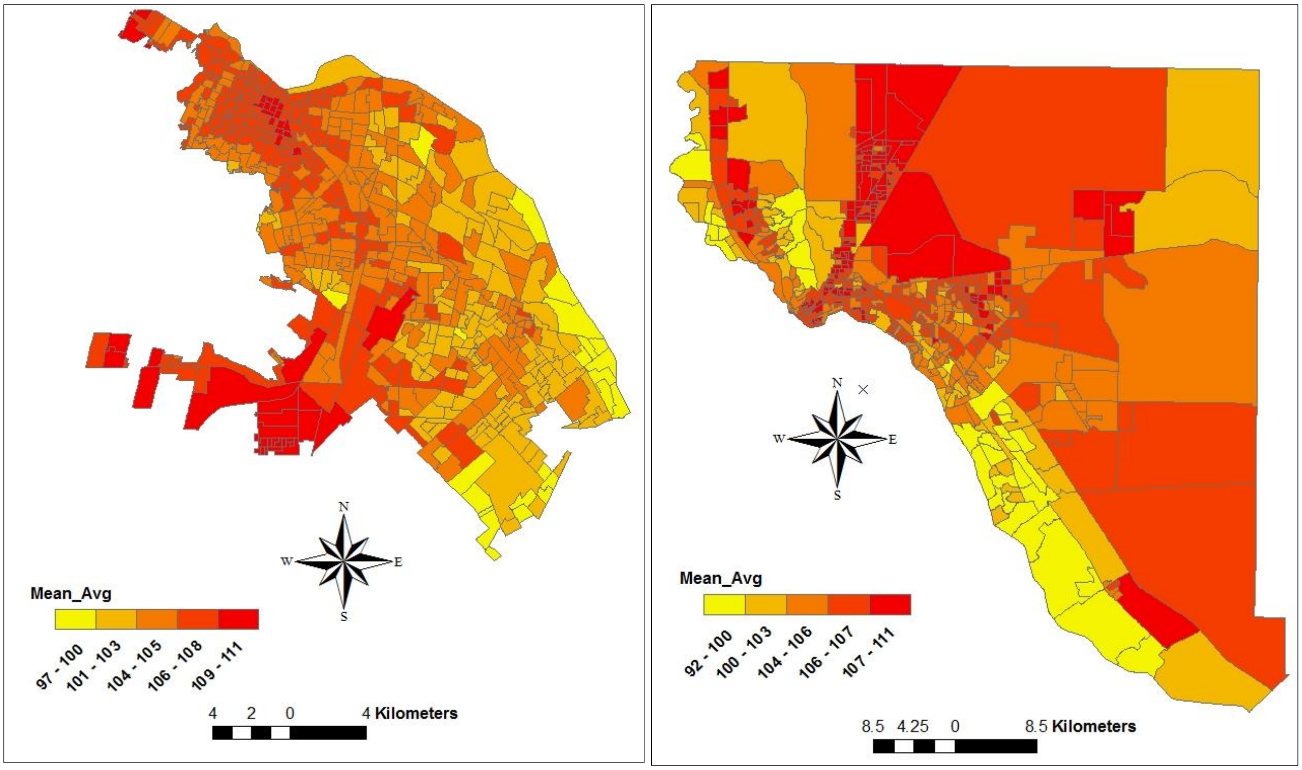


Figure 3.5 Estimated Mean LST for Study Area Neighborhoods

3.3.2 Biophysical Determinants

3.3.2.1 Topography

Data were derived directly from the United States Geological Survey (USGS) native format and ASTER Global Digital Elevation Model V002 (USGS 2010) (Figure 3.6). ASTER Global Digital Elevation Model data files (derived from DEMs produced by the USGS) are digital representations of cartographic information in a raster form. DEMs consist of a sampled array of elevations for a number of ground positions at regularly spaced intervals. To construct the analysis variables, the mean elevation in meters for each neighborhood was calculated using the zonal statistic technique ArcMap 10.1 (see Figure 3.7).

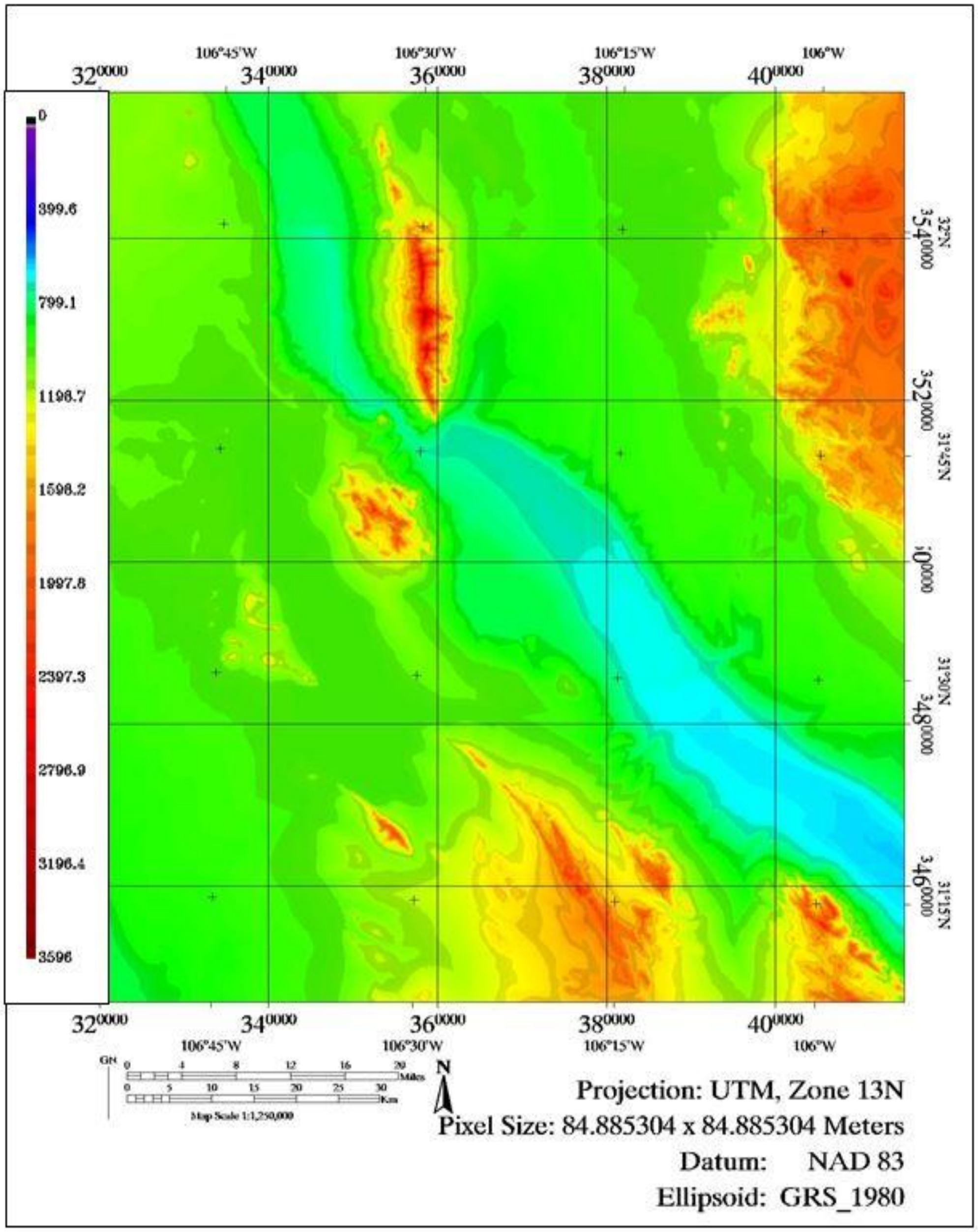


Figure 3.6 Digital Elevation Model Used to Measure Elevation

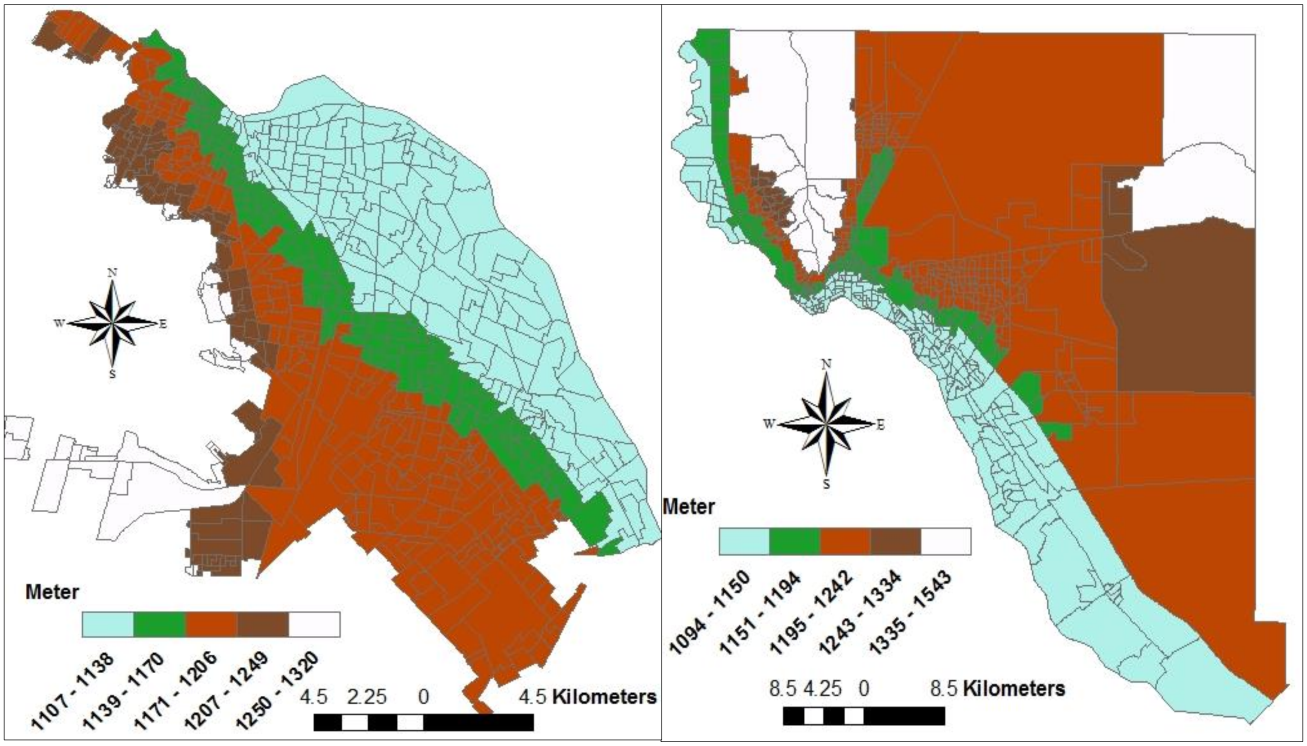


Figure 3.7 Mean Elevation for Study Area Neighborhoods (Meters)

3.3.2.2 Vegetation Density (NDVI)

Remotely sensed imagery from the Landsat TM and the enhanced thematic mapper plus (ETM+) was transformed using ENVI software to calculate and map vegetation density throughout the study area (see Figure 3.8). To measure vegetation density for the El Paso and Ciudad Juárez area, the Normalized Difference Vegetation Index (NDVI) was used.

The NDVI measures vegetation presence by relating near infrared (NIR) and visible (RED) bands; it is calculated using the following formula:

Equation 3.4 NDVI

$$NDVI = (NIR - RED) / (NIR + RED) = (Band4 - Band3) / (Band4 + Band3)$$

Where NIR = reflectance in the near infrared band and RED = reflectance in the red band.

The raw images were clipped to smaller images covering the El Paso County-Ciudad Juárez area. In order to calculate the mean NDVI for each BG/AGEB any pixel values outside of the vegetation range were masked and assigned values of zero. The neighborhood shapefiles were overlaid on each NDVI image and converted to region of interest (ROI); then the statistical parameter of interest was calculated (mean NDVI). The data for multiple images were combined to create the mean NDVI values for all neighborhoods (BGs, AGEBs) in the study area. Valid values range between -1 and 1 and common range for green vegetation was 0.2 – 0.8 (Rouse et. al., 1973). See Figure 3.9.

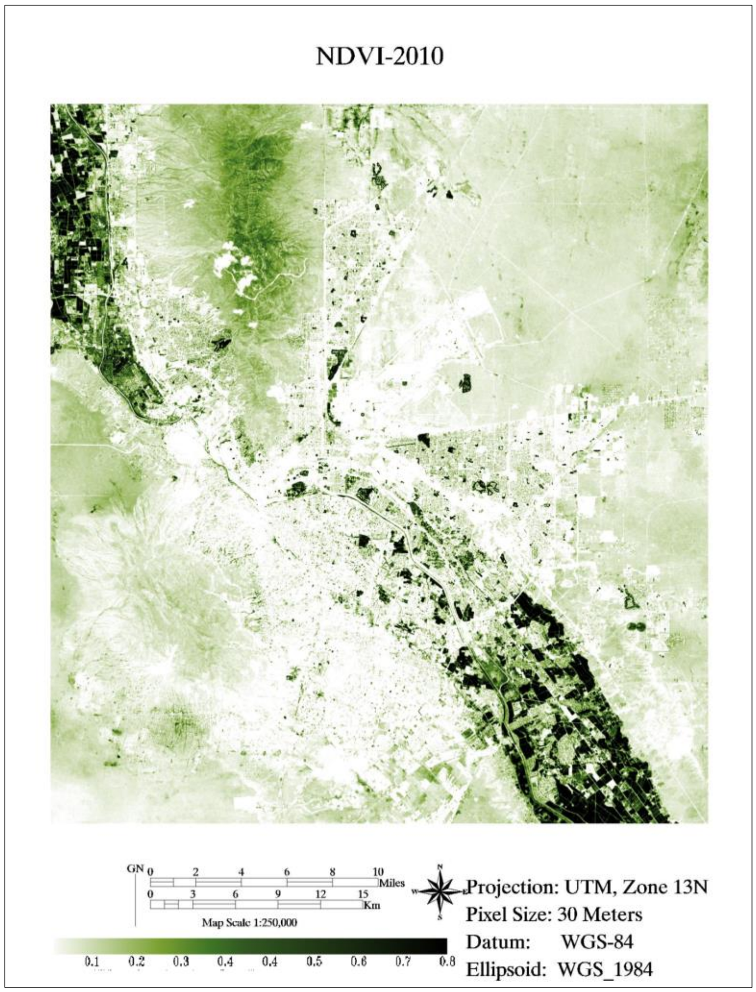


Figure 3.8 Image Used to Measure Normalized Difference Vegetation Index

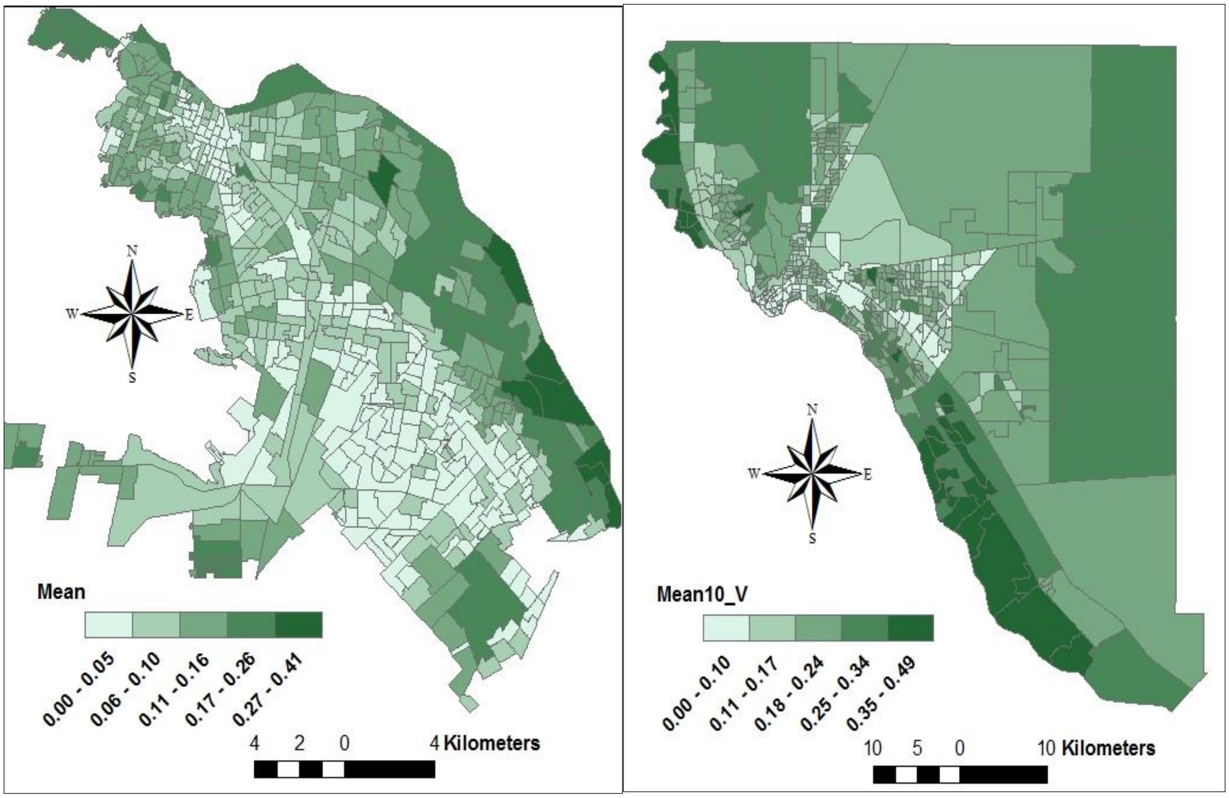


Figure 3.9 Mean NDVI for Study Area Neighborhoods

3.3.3 Built Environmental Determinants

3.3.3.1 Land Use/Land Cover (LULC)

The method presented in this study was motivated by the need for comparable land use/land cover (LULC) characterization for El Paso County and Ciudad Juárez using remote sensing. A Landsat image for 2010 was used to classify LULC using the supervised classification technique. A summer scene was selected since it was subject to the relatively low variability and was better for distinction between LULC and temperature distributions. A supervised classification processes was used to classify LULC in El Paso and Juárez.

The supervised classification technique involves ground-truthing sample point locations (using 100 points, i.e., training areas) to test data for accuracy as well as using the minimum distance to mean method to define land use classes of all pixels in the study area based on the Landsat image. The supervised classification process was performed using bands 2, 3, and 4 (wavelengths: 0.565-0.825 micrometers) and by taking field sample points as training sites to represent each LULC category. The minimum distance to the mean method involves calculating the Euclidean distance for each pixel in the image to each class based on the following:

Equation 3.5 Euclidean Distance

$$D_{i(\chi)} = \sqrt{(x-m_i)^T (x-m_i)}$$

Where D = Euclidean distance, i = the ith class, x = n-dimensional data (where n is the number of bands), and m_i = mean vector of a class.

In the supervised classification the most common errors were found in the classification of forest. Seven LULC classes were established using minimum distance classification, which generated a better classification than the maximum likelihood method. The LULC classes established include the following: (1) bare rock, sand, and clay; (2) commercial, industrial, and transportation; (3) cultivated row crops; (4) grasslands (herbaceous), (5) residential, (6) water, (7) shrub land. See Figures 3.10 and 3.11, and Table 3.3. The assessment was performed using the confusion matrix technique with a ground-truthed image, taking points as samples for each class. The reference data were collected from different locations. The average accuracy of classification and the Kappa coefficient were found to be 94.0% for accuracy and 0.92.5 for kappa coefficient respectively in both cities.

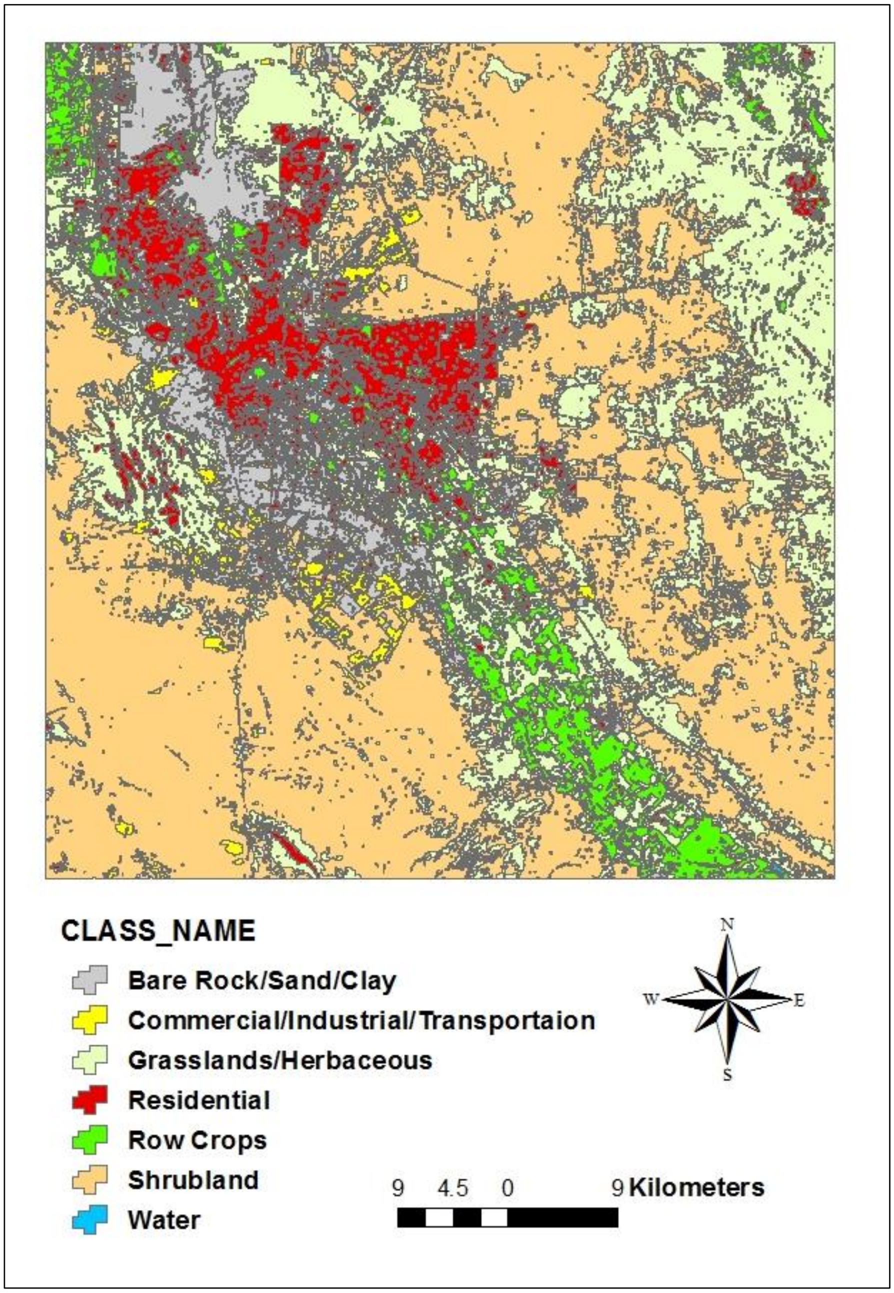


Figure 3.10 Image Used to Classify LULC

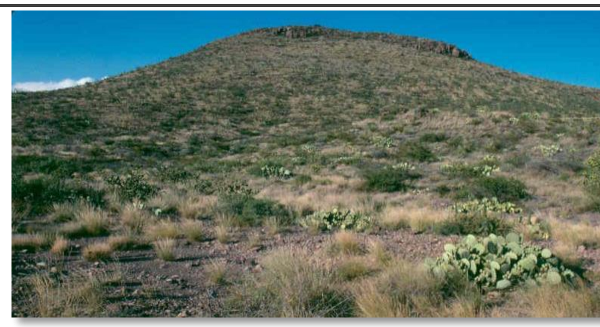
1-Bare/ Rock/Sand/Clay	2-Commercial/Industrial/Transportation
	
3-Row Crops	4-Grasslands/Herbaceous
	
5-Residential	6-Water
	
7-Shrub land	
	

Figure 3.11 Land Use/Land Cover Types in the Study Area

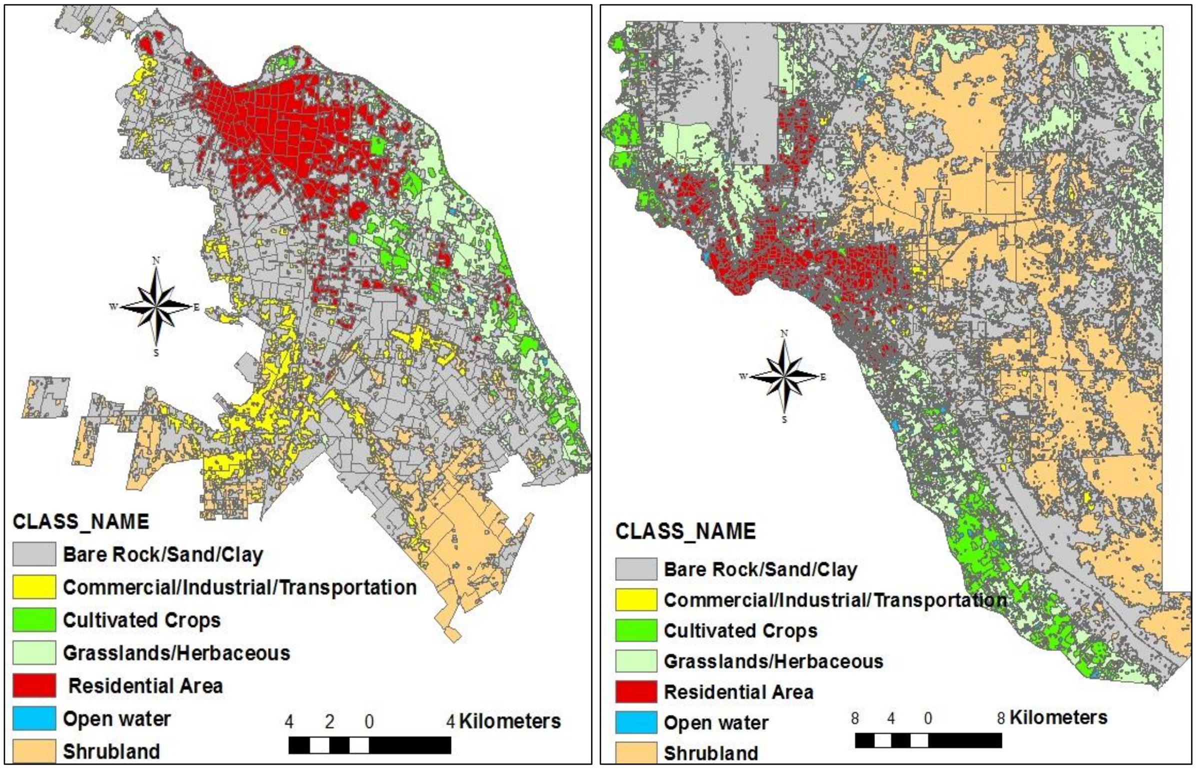


Figure 3.12 Supervised Land Use/Land Cover Classification for El Paso and Juárez

Table 3.3 Areal Coverage of Land Use/Land Cover Classes in the Study Area, 2010

LULC Class	Areal Coverage
Row Crops	166 km^2
Commercial/Industrial/Transportation	99 km^2
Residential	547 km^2
Shrub land	1112 km^2
Bare Rock/Sand/Clay	61 km^2
Grasslands/Herbaceous	985 km^2
Water	4 km^2

3.3.3.2 Albedo

Raw albedo data were extracted from three Landsat images (5 TM and 7 ETM+) for the year 2010, using bands 1, 3, 4, 5, and 7 wavelengths (0.485 to 2.22 micrometers). These images already have the geometric, radiometric, and atmospheric measures corrected (see Figure 3.13). The following equation was used to calculate land cover albedo (LCA):

Equation 3.6 Calculate Land Surface Albedo

*(a=0.356*b1+0.13*b3+0.373*b4+0.085*b5+0.072*b7-0.0018)

Where b is the band used from the image.

The radiance for each image was initially calibrated and then converted to BIL format, which was required in order to perform the atmospheric correction using the following Fast Line-of-sight Atmospheic Analysis of Hyper-cubes (FLAASH) formula:

Equation 3.7 Fast Line-of-sight Atmospheric Analysis of Hypercube (FLAASH)

$$L = \left(\frac{Ap}{1 - p_e \quad S}\right) + \left(\frac{Bp_e}{1 - p_e \quad S}\right) + L_a$$

Where p is the pixel surface reflectance, p_e is an average surface reflectance for the pixel and the surrounding region S is the spherical albedo of the atmosphere, $L_a$is the radiance back scattered by the atmosphere, A and B are coefficients that depend on atmospheric and geometric conditions and not on the surface.

The region of interest (ROI) and stats tools in ENVI were then used to calculate mean LCA for each neighborhood with values exported as a text file, then saved as a CSV file, and joined with the neighborhood (BG/AGEB) ArcGIS shapefile. This effectively integrated the mean LCA variable into the analysis database (see Figure 3.14). Mean LCA ranged from 0.1554 to 0.436588. Note, that the mean LCA for each neighborhood is based on the reflection percentage of all pixels within each neighborhood (with a 30 m resolution).

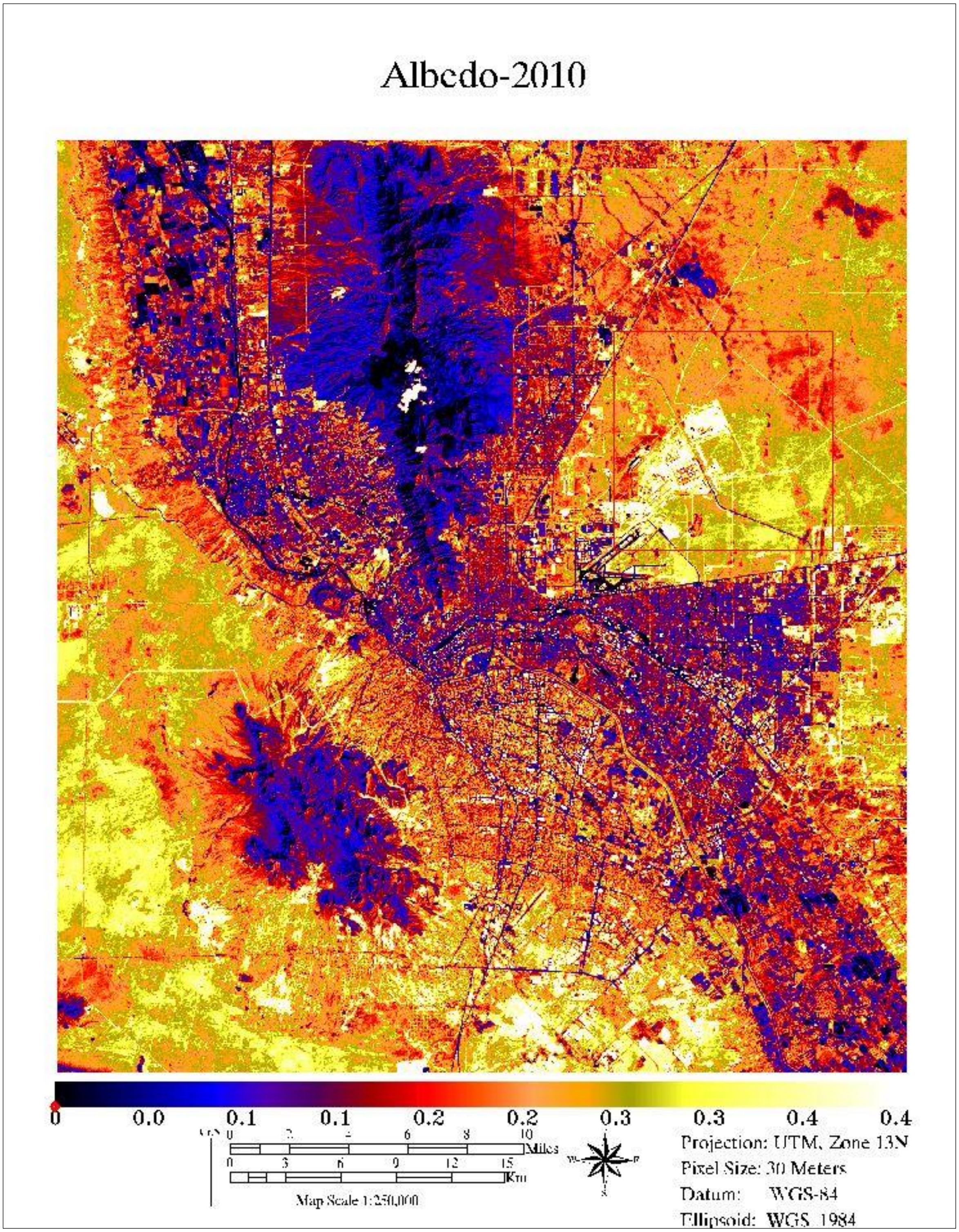


Figure 3.13 Image Used to Measure Albedo

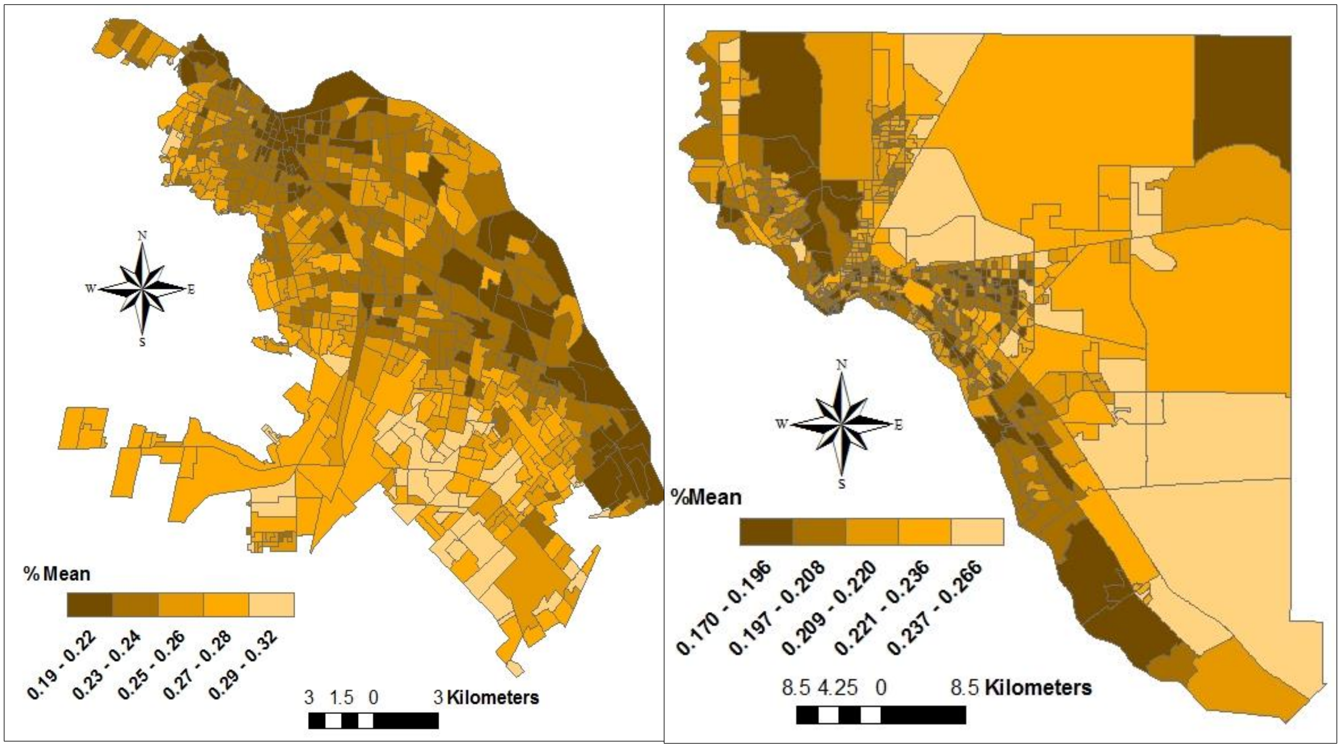


Figure 3.14 Mean LCA for Study Area Neighborhoods

3.3.4 Socio-demographic Determinants

3.3.4.1 Demographic Factors

Census data for 2010 (specifically for census block groups in the US and áreas geoestadísticas básicas in Mexico) were used to examine human population density and the percentage of the population older than 64 years of age.

3.3.4.1.1 Population Density

Population density was calculated by dividing the total neighborhood population by the surface area of the neighborhood. The population density for El Paso County neighborhoods ranged between

0.08 and 9,537 per km^2, while population density for Juárez neighborhoods ranged from 0 to 14,726 per km^2 (Figure 3.15).

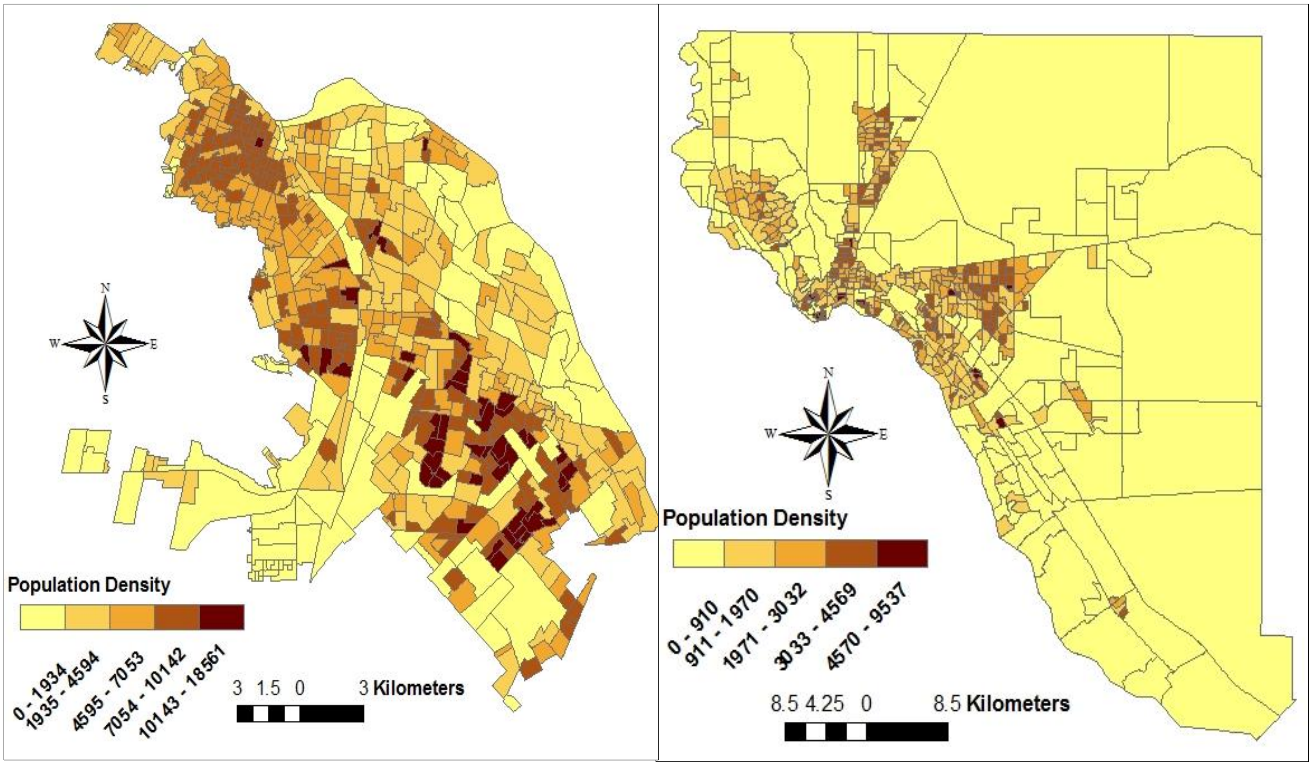


Figure 3.15 Population Density for Study Area Neighborhoods

3.3.4.1.2 Percentage of Population Over 64 Years of Age

Percent of the population age 65 years or older was calculated by dividing the number of neighborhood residents >64 years of age by the total population of the neighborhood based on census data for the year 2010. The values were then mapped for El Paso and Juárez neighborhoods using ArcMap. See Figure 3.16

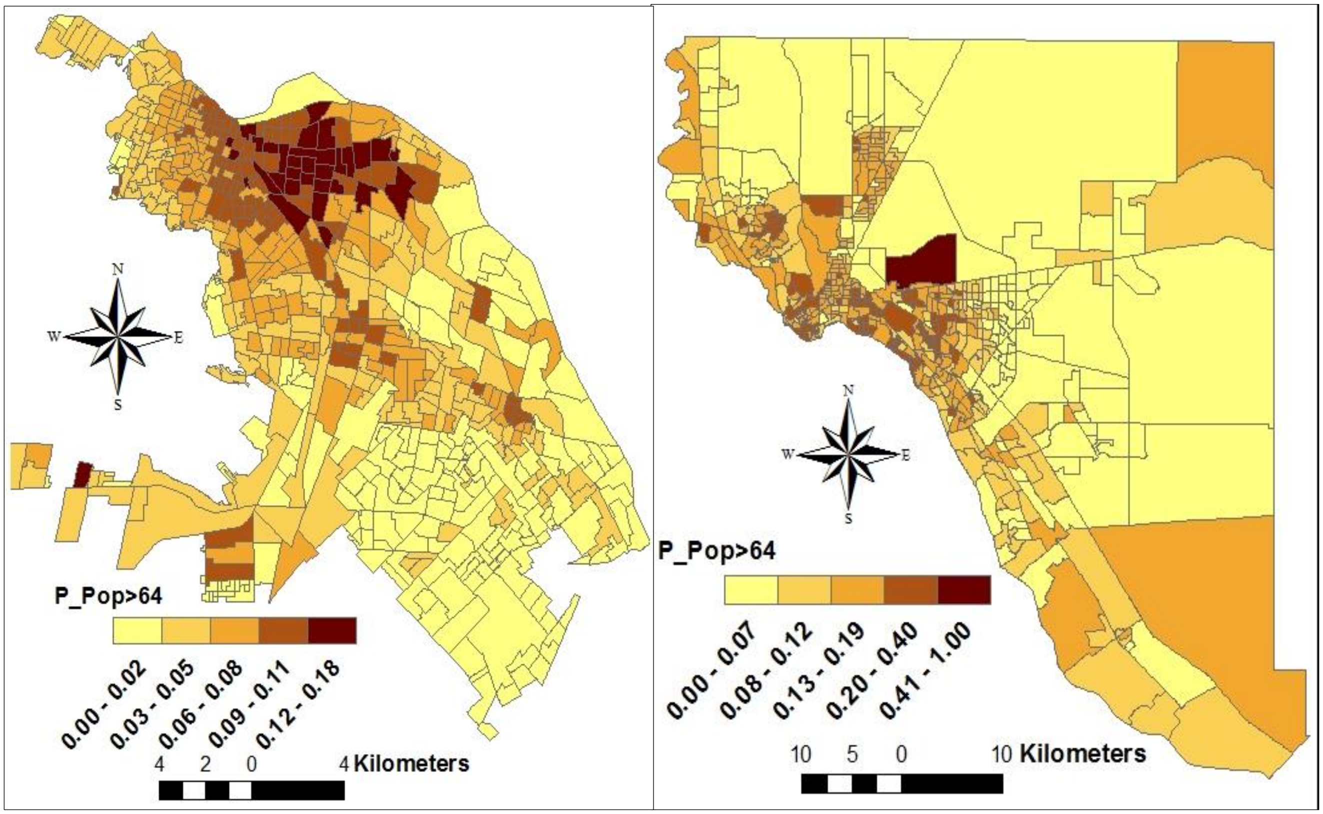


Figure 3.16 Proportion of the Population Age 65 or More for Study Area Neighborhoods

3.3.4.2 Socioeconomic Status (SES)

The census dataset was also used to examine relationships between socio-economic status and land surface temperature in the study area for 2010. Specifically a variable for mean years of education was examined as a measure of socioeconomic status (as per Collins, Grineski and Romo, 2009). Socio-economic status (mean years of education) was calculated based on the mean number of years of formal schooling completed by residents of each neighborhood. Values were mapped for El Paso and Juárez neighborhoods using ArcMap (Figure 3.17).

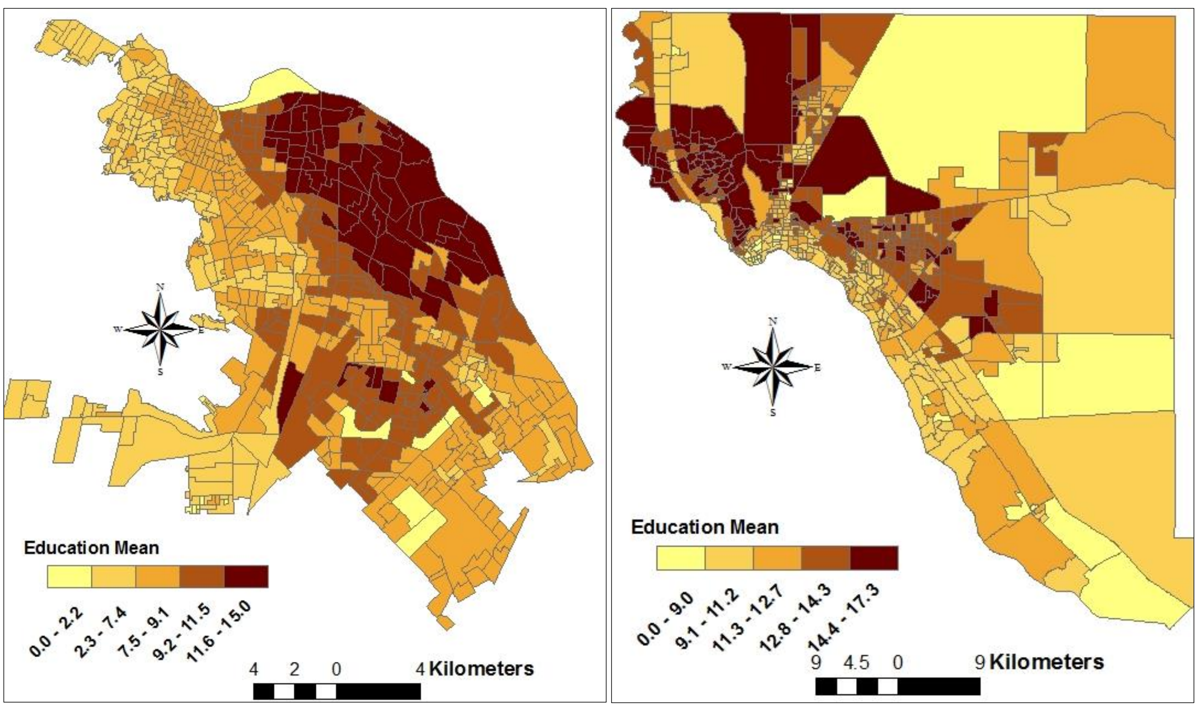


Figure 3.17 Mean Years of Education for Study Area Neighborhoods

3.4 Analysis Methodology

Univariate descriptive statistical analysis was used to examine the distributions of LST and the independent variables. I tested each of the variables for skewness and kurtosis and used transformations if applicable for the dependent variables (LST) or independent variables for El Paso and Juárez. For subsequent analyses, all variables were Z-scored to center them. The processes of inferential statistical analysis of local variation of LST in the study area that followed were divided into three phases. The first phase consisted of bivariate a correlation analysis between the independent and dependent variables. The second phase focused on determining differences in LST by land use/land cover class using analysis of variance (ANOVA) testing. The third phase involved computing spatial regression models for each of the two cities with LST as a dependent variable for each city for the two models. To conduct analyses, SPSS version 20 and the open source software GeoDa (available at http://geodacenter.asu.edu) were utilized.

To clarify determinants of land surface temperature at the neighborhood level during 2010, descriptive and inferential statistical analyses were conducted using the variables described previously including:

- Land surface temperature, mean (dependent variable)
- Elevation, mean (independent variable)
- Vegetation density, mean (independent variable)
- Mean albedo (independent variables)
- Population density (independent variable)
- Percent of the population age 65+ years of age (independent variable)
- Socioeconomic status: mean years of education (independent variable)

See Figure 3.18.

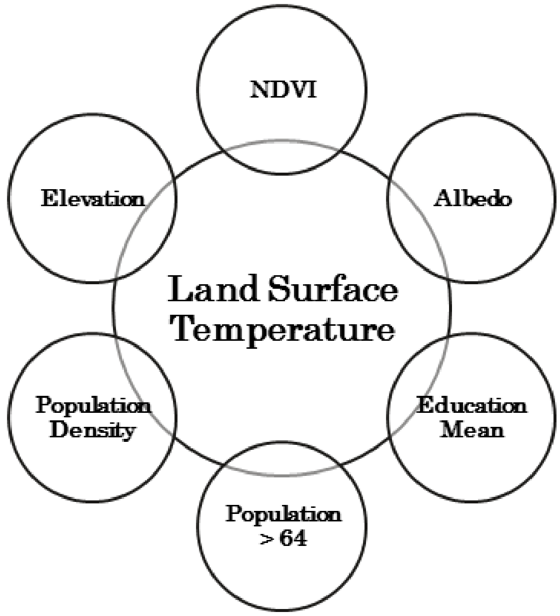


Figure 3.18 Dependent and Independent Variables

3.4.1 Univariate Analysis

Univariate analysis (including the calculation and examination of variable frequency distributions and descriptive statistics such as the mean, standard deviation, minimum, maximum, and range) was used in order to detect and correct errors in the data and to assure that the assumptions of the inferential statistical tests to be employed were met. Errors and inaccuracies may be produced by user and system errors through the process of database management. Such errors in data values affect results, thus the database had to be cleaned to ensure that analysis results were not impacted. Additionally, the statistical tests and models to be developed were based on specific assumptions about the analyzed data. In order to generate valid inferences about statistical analysis results it was required that variables meet the assumptions required by the statistical tests. Univariate data analysis was used to identify variables that did not meet the requirements of the statistical tests. Transformations were made to variables in order to assure that they met the requirements. SPSS was applied for the univariate analysis.

3.4.1.1 Accuracy of Data

In this case, the main sources of errors in data relate to entry in the database. To assess the accuracy of the data, I checked the minimum and maximum value for each variable to ensure that all values for each variable were valid. Corrections were applied to cases that displayed invalid values. There was no missing data for the variables included in the analysis.

3.4.1.2 Normality

Data were checked for normality of distribution. Histograms were constructed and visually inspected, and skewness and kurtosis were also calculated for each variable. For El Paso County, variables distributed normally included LST, NDVI, elevation, Albedo, population over age64 and education level. Only population density was not normally distributed. Thus, the population density variable for El Paso was subjected to a square root transformation. Juarez variables such as LST, elevation, education level and albedo, were distributed normally, but NDVI, population density and population over age 64 were skewed negatively. Those three variables were subjected to square root transformations.

3.4.2 Bivariate Analysis

After the descriptive statistics step, I explored basic relationships using bivariate correlations for El Paso and Juárez separately between the dependent variable (LST) and six independent variables. Bivariate correlations were calculated to determine the direction and strength of basic relationships between the analysis variables, and specifically to partially address research questions number 1, 2, 3B, 4 and 5. Pearson product-moment correlation analysis was used to investigate the relationship of the suite of biophysical, built environmental and socioeconomic independent variables with LST across both cities using SPSS version 20.

3.4.3 Analysis of Variance (ANOVA)

To address question 3A and test the hypothesis that LULC significantly influences LST, I employed ANOVA testing using the land use/land cover classes to comprise the grouping (independent) variable and LST as the dependent variable. There are seven LULC classes: (1) commercial/industrial/transportation, (2) grasslands/herbaceous, (3) residential, (4) rock/sand/clay, (5) row crops, (6) shrub land, and (7) water. Results clarified which LULC classes were significantly warmer, significantly cooler, or had mean LST values that were not significantly different from the others. SPSS was applied for ANOVA testing.

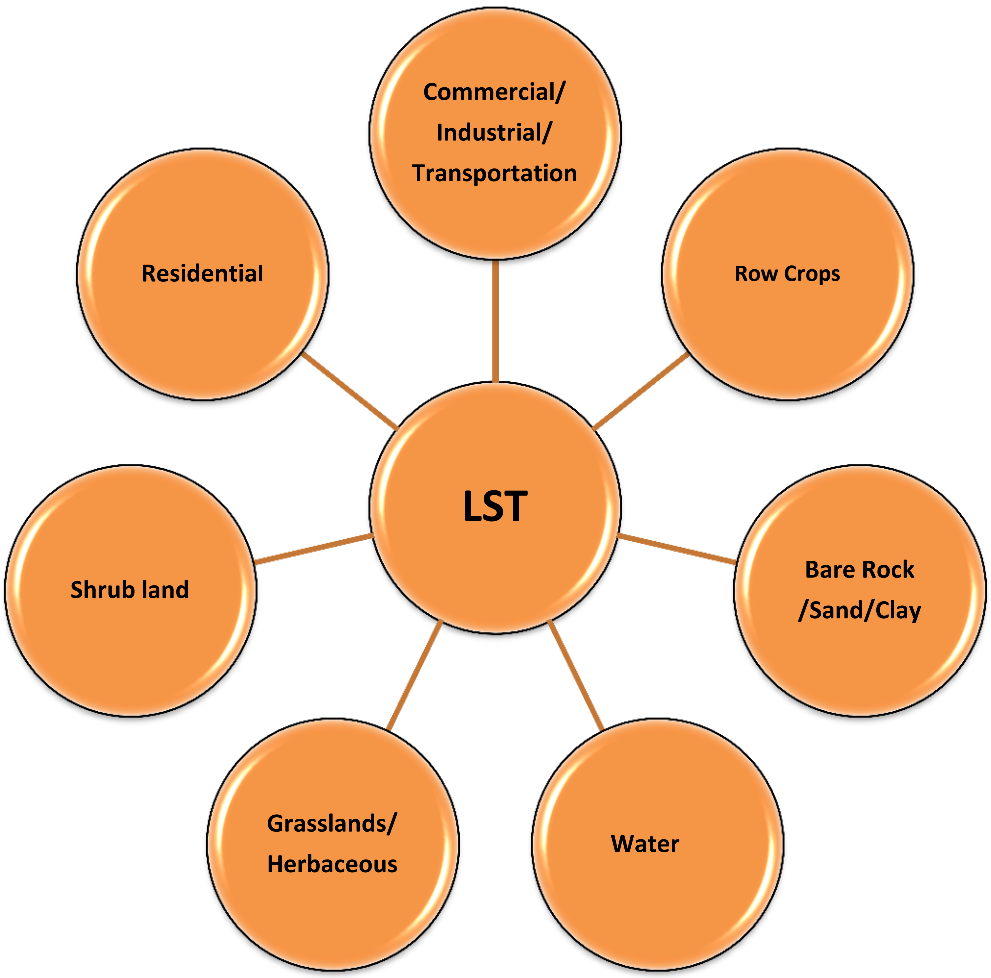


Figure 3.19 Land Use Types

3.4.4 Multivariate Regression Modeling

Ordinary Least Squares (OLS) and spatial regression modeling were used to examine the relative strength of the independent variables in predicting mean LST, adjusting for the effects of other independent variables. SPSS and GeoDa were used for OLS regression modeling, while GeoDa was used for spatial regression modeling (http://geodacenter.asu.edu).

OLS is a useful tool for examining the relationship between two or more interval/ratio variables, and is based on the following:

Equation 3.8 Ordinary Least Squares (OLS) Model

$$Y_i = \beta_0 + \sum_k \beta_k X_k + \varepsilon$$

Where: Y is the dependent variable, X represents independent variables, ε is the error term, and β is the contribution that each independent variable makes to predict the value of dependent variable (Hao, 2008).

OLS models for El Paso and Juárez predicting mean LST (2010) using the six independent variables were run as part of the analysis. OLS regression assumes that there is a linear relationship between the two variables. It does not take into account spatial dependence.

3.4.4.1 Spatial Regression Modeling

As a modification of traditional regression, spatial regression modeling (SRM) was developed to reach accurate conclusions that account for local spatial variation. This technique has been widely applied to different fields dealing with the problem of spatial autocorrelation and variation in spatial data. Spatial regression modeling was conducted with GeoDa software. This software was chosen because it was designed to support SRM, it offers helpful diagnostics, and it has a dynamic cartographic interface that is useful for spatial data/analysis visualization.

In this study, neighborhood-level LST data for El Paso and Juárez were added separately to GeoDa as dependent variables. The independent variables were neighborhood-level elevation, NDVI, LCA, population density, population age≥65 years and mean education. The data were standardized to address any predictor unit of measurement effects.

Spatial regression modeling techniques were developed to work with variables that exhibit spatial dependence. The two types of models of spatial dependence that were analyzed by using GeoDa are spatial lag and spatial error. Spatial lag models assume that spatial autocorrelation is present in the dependent variable (Chakraborty, 2009); while spatial error models assume that the independent variables exhibit spatial dependence (Pastor, Morello-Frosch, &Sadd, 2005).

I used the Lagrange Multiplier (LM) and the Robust LM diagnostic tests to identify whether spatial lag or spatial error models were appropriate (Anselin, 2005). In this case, the LM tests suggested that the spatial error model was best for the model predicting LST differences in El Paso, and the spatial lag model was best for the models predicting LST in Juárez. The third specification diagnostic offered by GeoDa in OLS regression is the multicollinearity condition index. The condition index measures the stability of the regression results due to multicollinearity (Anselin, 2005; Chakraborty, 2009). Anselin (2005) suggests that a condition index of 30 is indicative of serious collinearity problems. In this case, the condition indices were 2.95 for the Juárez model and 2.123 for the El Paso model; these values indicate an absence of multicollinearity in the models.

I used the Moran's I test statistic for spatial autocorrelation. There are two separate functions, Moran's I test, where inference is based on a randomization assumption, and moran.mc, for a permutation based test. Both take a variable name or numeric vector and a spatial weights list object (listw), in that order, as mandatory parameters (Anselin, 2005). The permutation test also requires the number of permutations as a third mandatory parameter.

I used the distance method of defining weights, following Chakraborty (2009). This method is more appropriate for irregularly-shaped census geography than the rook or queen method (Pastor, Morello-Frosch and Sadd 2005). To evaluate (SRM) model fitting, comparisons between OLS and spatial lag and spatial error were performed.

3.4.4.1.1 El Paso Spatial Regression Modeling Process

Spatial Weight: 1000 m

I started using a distance band at 1000 m; 129 neighborhoods had no neighbors (Figure 3.20).

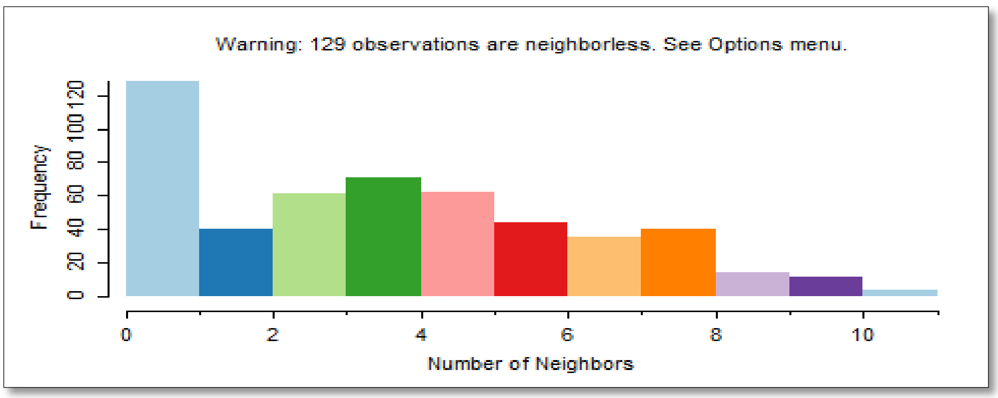


Figure 3.20 Number of Neighbors in El Paso with 1000 m Distance Band

First, I ran an OLS regression model predicting LST (natural log) with Lagrange Multiplier (LM) and the Robust LM diagnostic tests to aid in model specification (Anselin 2005). I began by testing model residuals for spatial autocorrelation using the univariate Moran's I test, following Chakraborty (2009). After running an OLS Model with a 1000 m distance band, the Moran’s I statistic for the residuals of that model was 0.173924, which is significant, since it has a p-value of 0.001 (see Figure 3.21). This indicates the presence autocorrelation in the residuals, which violates the assumptions of OLS regression.

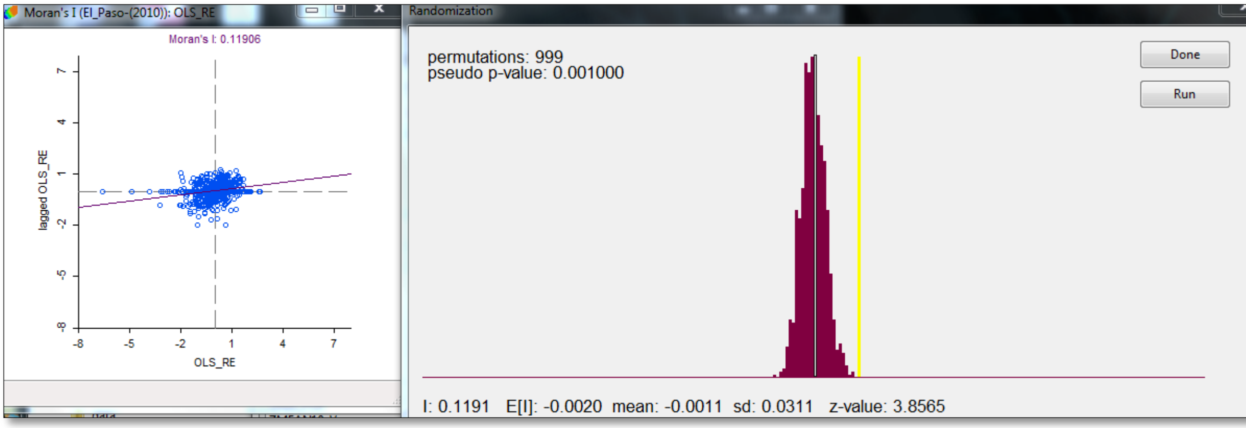


Figure 3.21 El Paso OLS Moran's I Value and P-value

I then ran the spatial model with a 1000 m distance band to see if autocorrelation still existed in the spatial model, and I used the Lagrange Multiplier (LM) and the Robust LM diagnostic tests to determine of which of the spatial model specifications should be used (Anselin, 2005) (see Table 3.4). In this case, the LM tests suggested that the spatial error model was best for the model predicting LST (i.e., the value for error was greater than for lag). The Moran's I test for the spatial lag model was -0.00960777, which is not significant (p=0.335) and indicates the absence of autocorrelation of the residuals (Figure 3.22). This model as selected as the final model for El Paso.

Table 3.4 Lagrange Multiplier (LM) and Robust LM Diagnostic Tests

Moran's I (error)	0.119060	N/A	N/A
Lagrange Multiplier (lag)	1	7.1175245	0.0076334
Robust LM (lag)	1	0.0309404	0.8603735
Lagrange Multiplier (error)	1	14.8645001	0.0001155
Robust LM (error)	1	7.7779160	0.0052889
Lagrange Multiplier (SARMA)	2	14.8954404	0.0005828

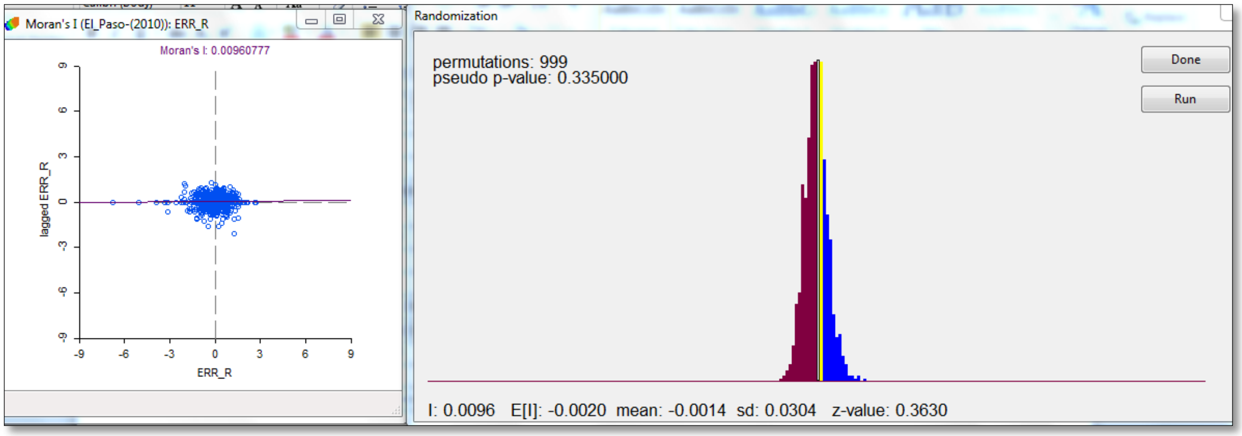


Figure 3.22 El Paso Spatial Error Regression Model at 1000 m, Moran's I value and p-value

3.4.4.1.2 Juárez Spatial Regression Modeling Process

Spatial Weight: 1000 m

I started using the spatial distance at 1000 m; Only 22 neighborhoods had no neighbors (Figure 3.23).

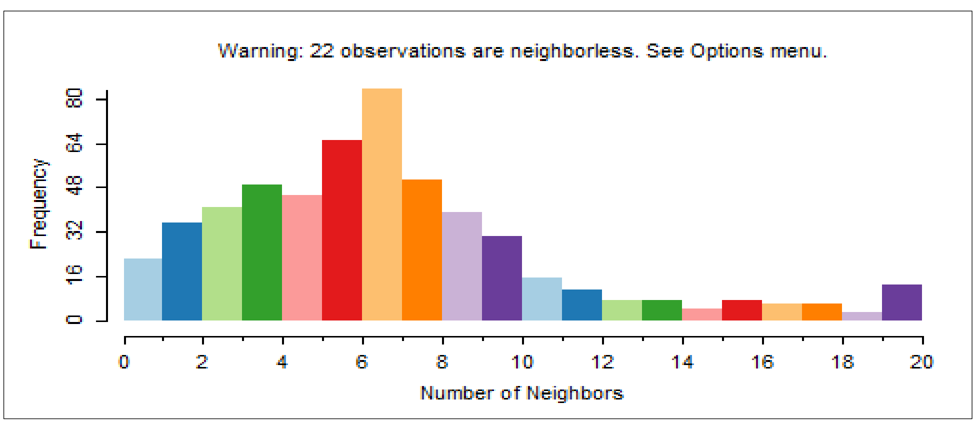


Figure 3.23 Number of Neighbors in Juárez with 1000 m Distance Band

I began by testing model residuals for spatial autocorrelation using the univariate Moran's I test, following Chakraborty (2009). After running an OLS Model with a 1000 m distance band, the Moran's I statistic for the residuals of that model was 0.173, which is significant, since it has a p-value of

0.001. This indicates the presence autocorrelation of the residuals, which violates the assumptions of OLS regression.

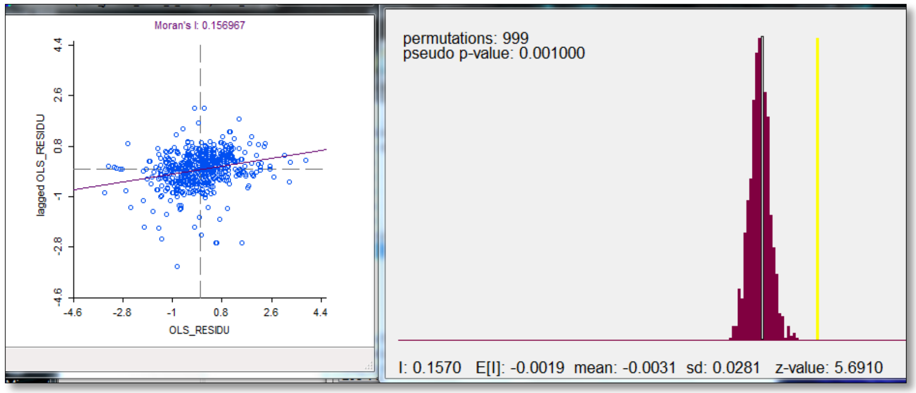


Figure 3.24 Juárez OLS Model at 1000 m, Moran's I value and p-value

I then ran the spatial regression model at 1000 m to see if it addressed the autocorrelation problem. I used the Lagrange Multiplier (LM) and the Robust LM diagnostic tests to determine of which the spatial model specification should be used (Anselin, 2005). In this case, the LM tests suggested the spatial lag model was best for the models predicting LST in Juárez (i.e., the value for lag was greater than for error).

Table 3.5 Lagrange Multiplier (LM) and Robust LM Diagnostic Tests

TEST	MI/DF	VALUE	PROB
Moran's I (error)	0.156967	N/A	N/A
Lagrange Multiplier (lag)	1	68.8468163	0.0000000
Robust LM (lag)	1	43.1802944	0.0000000
Lagrange Multiplier (error)	1	29.2280828	0.0000001
Robust LM (error)	1	3.5615609	0.0591321
Lagrange Multiplier (SARMA)	2	72.4083772	0.0000000

After running the spatial lag model with a 1000 m band, the Moran's I statistic for the residuals was -0.083, which is significant, since it has a p-value of 0.002000. This indicates that autocorrelation in the residuals remained problematic. Thus, I increased the distance band to 1,500 m to attempt to iteratively address the autocorrelation problem, using the same steps described above. The Moran's I statistic for the spatial autocorrelation in the residuals of the spatial lag model with a 1500m distance band is -0.03966, which is significant, since it has a p-value of 0.035000. Again, this indicates that spatial autocorrelation had not been adequately accounted for in the model.

I then increased the distance band to 2000 m and ran another spatial lag model. With a distance band of 2000 m, all neighborhoods had neighbors (Figure 3.25).

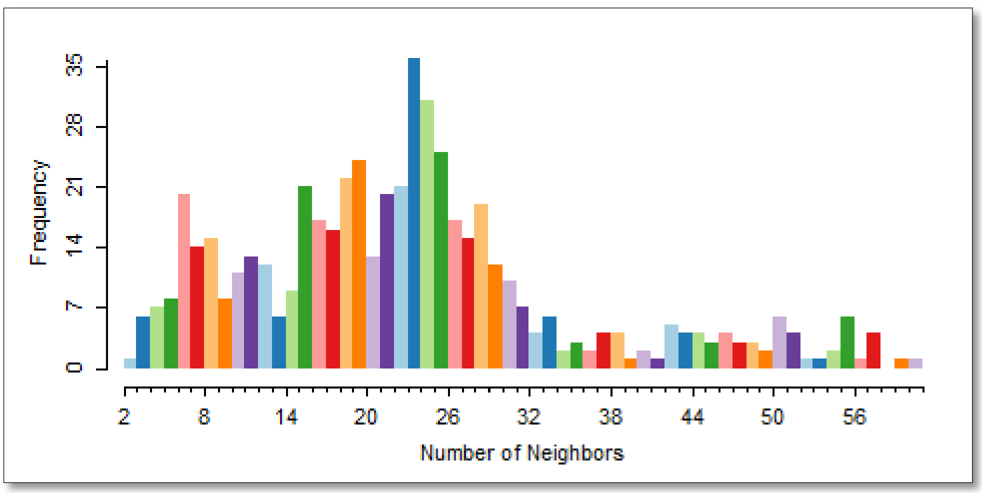


Figure 3.25 Number of Neighbors in Juárez with 2000 m Distance Band

I used the Lagrange Multiplier (LM) and the Robust LM diagnostic tests to determine which spatial model specification should be used (Anselin, 2005). Since the value of the LM (lag) is greater than that of the LM (error), I ran a spatial lag model. The Moran's I test of spatial lag model with a

2000 m distance band is 0.0155, which is not significant (p=0.195000) and indicates the absence of autocorrelation in the residuals. Thus, this was selected as the final model for Juárez.

Table 3.6 Lagrange Multiplier (LM) and Robust LM Diagnostic Tests

TEST	MI/DF	VALUE	PROB
Moran's I (error)	0.168692	N/A	N/A
Lagrange Multiplier (lag)	1	163.7512878	0.0000000
Robust LM (lag)	1	54.9792638	0.0000000
Lagrange Multiplier (error)	1	120.9231100	0.0000000
Robust LM (error)	1	12.1510860	0.0004906
Lagrange Multiplier (SARMA)	2	175.9023738	0.0000000

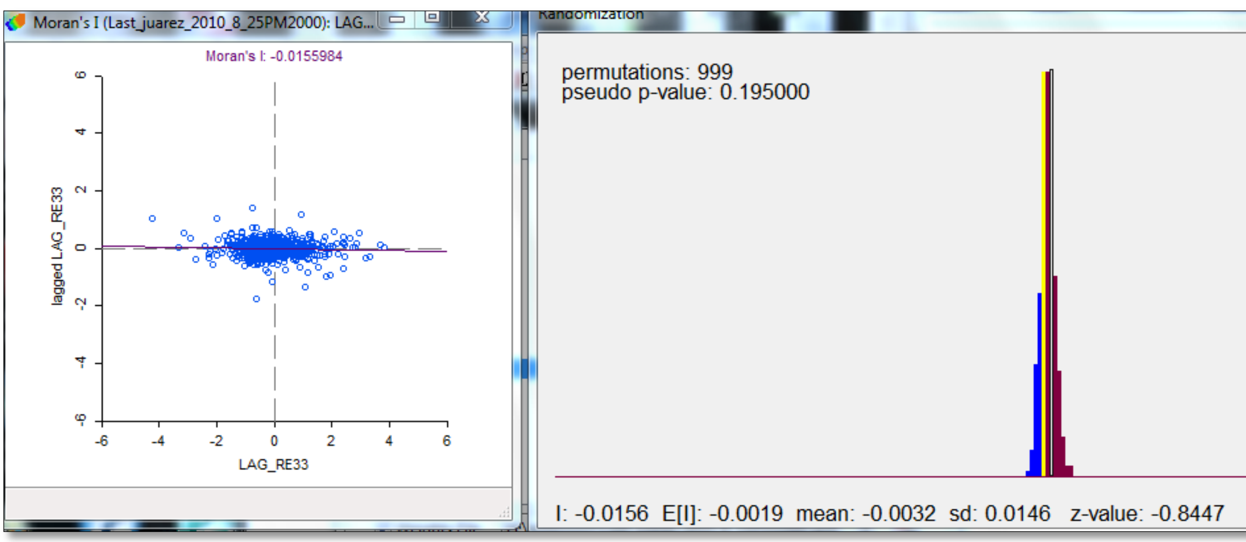


Figure 3.26 Juárez Spatial Lag Regression Model at 2000 m, Moran’s I Value and P-value

In total, four final models were specified corresponding with the year 2010, which are reported in the Results chapter:

1) OLS regression model predicting mean LST using the six independent variables for El Paso with a 1000 m distance band.
2) Spatial regression model predicting mean LST using the six independent variables for El Paso with a 1000 m distance band.
3) OLS regression model predicting mean LST using the six independent variables for Juárez with a 1000 m distance band.
4) Spatial regression model predicting mean LST using the six independent variables for Juárez with 2000 m distance band.

CHAPTER 4: RESULTS

The main purpose of this study is to clarify the spatial distribution of land surface temperature (LST) and local determinants of LST variation for El Paso TX, USA and Juárez, Chihuahua, Mexico. This chapter reports results for bivariate correlations, ANOVA tests of land use/land cover classes, as well as OLS and spatial regression modeling.

4.1 Bivariate Correlations

I begin by reporting bivariate relationships between the independent and dependent variables, which specify associations for the biophysical, built environmental and socio-demographic variables with LST.

4.1.1 El Paso

The bivariate relationships between the independent variables and LST for El Paso are reported in Table 4.1. NDVI was negatively and statistically significantly correlated with LST, while population density and albedo were positively and significantly correlated with LST; neighborhoods with less vegetation density as well as greater population density and higher albedo were hotter. Education was negatively and insignificantly associated with LST; that is, neighborhoods with populations having lower education (mean years) tended to be hotter. Population over age 65 and elevation were not correlated with LST (see Table 4.1).

Table 4.1 El Paso Bivariate Correlations

Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1-LST	-						
2-Elevation	-0.003	-					
3-Vegetation	-0.65***	-0.12**	-				
4-Albedo	0.29***	-0.045	0.16***	-			
5-Population-D	0.33***	-0.051	-0.26***	-0.26***	-		
6- Pop>64	-0.0001	0.003	0.10*	-0.23***	0.084	-	
7-Education	-0.050	0.44***	0.031	-0.06	-0.092*	0.031	-

*p<.05; **p<.01; ***p<.001

4.1.2 Juárez

Bivariate relationships between the independent variables and LST for Juárez are reported in Table 4.2. In terms of the basic relationships between LST (2010) and the explanatory variables for Juárez, NDVI and albedo had significant and negative relationships with LST, while elevation was significantly and positively correlated with LST. In terms of the socio-demographic variables, higher population density, higher proportions of residents over 64 years of age and lower levels of education were significantly associated with higher LST in Juárez. See Table 4.2.

Table 4.2 Juárez Bivariate Correlations

Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1-LST	-						
2-Elevation	0.124**	-					
3-Vegetation	-0.18***	-0.188***	-				
4-Albedo	-0.32***	0.469***	-0.409***	-			
5-Population-D	0.098*	0.199***	0.089*	-0.000	-		
6- Pop>64	0.485***	-0.387***	0.022	-0.51***	-0.041	-	
7-Education	-0.25***	-0.547***	0.112**	-0.024	-0.19***	0.103*	-

*p<.05; **p<.01; ***p<.001

4.2 Analysis of Variance (ANOVA)

For both cities, the highest mean LSTs were for the following LULC classes: Grasslands/Herbaceous, Shrub Land, Residential, Commercial/ Industrial/Transportation, and Bare Rock/Sand/Clay. On the other hand, the lowest mean LSTs were associated with the Row Crops, Water, and Forests LULC classes. See Table 4.3.

Table 4.3 Land Use/Land Cover Classes: Descriptive Statistics

LULC Classes	El Paso	El Paso	Juárez	Juárez
	Mean	SD	Mean	SD
Commercial/Industrial/Transportation	104.32	5.6	102.7	2.75
Grasslands/Herbaceous	107.2	8.6	109.9	4.5
Residential	104.8	5.8	105.3	3.6
Bare Rock/Sand/Clay	99.1	3.2	108.4	4.03
Row Crops	91.9	4.7	92.9	2.2
Shrub Land	106.3	7.4	108.2	4.9
Water	95.5	4.7	95.6	6.2
Total	101.38	7.9	103.3	7.3

Mean differences in LST were compared using one-ANOVA testing separately for the seven El Paso and seven Juárez land use/land cover classes. This enabled me to test the hypothesis that LULC classes are significantly different in terms of mean LST (hypothesis 3A). As Tables 4.4 and 4.5 indicate, the differences in mean LST across the LULC classes in El Paso and Juárez are significant. Post-hoc comparisons using Tukey's HSD indicated whether differences in mean LST for each paired comparison among the LULC classes for both El Paso and Juárez were significant (see Tables 4.4 and 4.5).

Table 4.4 ANOVA Results: LST by LULC Class in El Paso

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1209.340	6	201.557	6.747	.000
Within Groups	836.420	28	29.872		
Total	2045.760	34			

Table 4.5 ANOVA Results: LST by LULC Class in Juárez

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1334.00	6	222.333	12.644	.000
Within Groups	492.358	28	17.584		
Total	1826.35	34			

Table 4.6 Multiple Comparisons of LST by LULC class in El Paso

(I) LULC	(J) LULC	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Dependent Variable: LST Tukey HSD						
1-Commercial/ Industrial/ Transportation	Grasslands/Herbaceous	-2.19	3.24	.997	-12.66	8.29
	Residential	2.07	3.24	.998	-8.41	12.55
	Bare Rock/Sand/Clay	7.77	3.24	.275	-2.71	18.25
	Row Crops	14.97 *	3.24	.001***	4.5	25.45
	Shrub land	.106	3.24	1.000	-10.4	10.58
	Water	11.82 *	3.24	.018**	1.344	22.30
2-Grasslands/ Herbaceous	Comm/Indust/Transport	2.19	3.24	.997	-8.29	12.67
	Residential	4.26	3.24	.886	-6.22	14.74
	Bare Rock/Sand/Clay	9.96	3.24	.072	-.521	20.44
	Row Crops	17.16*	3.24	.000***	6.67	27.64
	Shrub land	2.30	3.24	.996	-8.18	12.77
	Water	14.01*	3.24	.003**	3.52	24.49
3-Residential	Comm/Indust/Transport	-2.07	3.24	.998	-12.55	8.41
	Grasslands/Herbaceous	-4.26	3.24	.886	-14.74	6.22
	Bare Rock/Sand/Clay	5.70	3.24	.649	-4.78	16.18
	Row Crops	12.90*	3.24	.008*	2.41	23.37
	Shrub land	-1.96	3.24	.999	-12.45	8.51
	Water	9.75	3.24	.083	-.73	20.23
4-BareRock/ Sand/Clay	Comm/Indust/Transport	-7.77	3.24	.275	-18.25	2.71
	Grasslands/Herbaceous	-9.96	3.24	.072	-20.4	.52
	Residential	-5.70	3.24	.649	-16.18	4.78
	Row Crops	7.20	3.24	.364	-3.3	17.67
	Shrub land	-7.66	3.24	.290	-18.14	2.81
	Water	4.05	3.24	.909	-6.43	14.53
5-Row Crops	Comm/Indust/Transport	-14.97 *	3.24	.001***	-25.45	-4.48
	Grasslands/Herbaceous	-17.16*	3.24	.000***	-27.64	-6.67
	Residential	-12.90*	3.24	.008	-23.37	-2.41
	Bare Rock/Sand/Clay	-7.20	3.24	.364	-17.67	3.28
	Shrub land	-14.86 *	3.24	.001***	-25.3	-4.38
	Water	-3.15	3.24	.975	-13.6	7.33
6-Shrub land	Comm/Indust/Transport	-.106	3.24	1.000	-10.58	10.37
	Grasslands/Herbaceous	-2.30	3.24	.996	-12.77	8.18
	Residential	1.97	3.24	.999	-8.51	12.44
	Bare Rock/Sand/Clay	7.66	3.24	.290	-2.81	18.14
	Row Crops	14.86 *	3.24	.001***	4.38	25.34
	Water	11.71 *	3.24	.020*	1.23	22.19
7-Water	Comm/Indust/Transport	-11.82 *	3.24	.018**	-22.30	-1.34
	Grasslands/Herbaceous	-14.01*	3.24	.003**	-24.48	-3.52
	Residential	-9.75	3.24	.083	-20.23	.73
	Bare Rock/Sand/Clay	-4.05	3.24	.909	-14.53	6.43
	Row Crops	3.15	3.24	.975	-7.33	13.63
	Shrub land	-11.71 *	3.24	.020*	-22.19	-1.23

*p<.05; **p<.01; ***p<.001

Table 4.7 Multiple Comparisons of LST by LULC class in Juárez

Dependent Variable: V3
Tukey HSD

(I) V2	(J) V2	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-Commercial Industrial/ Transportation	Grasslands/Herbaceous	-7.32	2.65	.120	-15.7	1.09
	Residential	-2.68	2.65	.947	-11.1	5.73
	Bare Rock/Sand/Clay	-5.75	2.65	.343	-14.1	2.66
	Row Crops	9.73*	2.65	.016**	1.31	18.14
	Shrub land	-5.57	2.65	.380	-13.9	2.8
	Water	7.09	2.65	.143	-1.32	15.5
2-Grasslands/ Herbaceous	Comm/Indust/Transport	7.32	2.65	.120	-1.09	15.73
	Residential	4.63	2.65	.592	-3.78	13.05
	Bare Rock/Sand/Clay	1.57	2.65	.997	-6.85	9.98
	Row Crops	17.04*	2.65	.000***	8.63	25.46
	Shrub land	1.75	2.65	.994	-6.66	10.16
	Water	14.41*	2.65	.000***	5.99	22.82
3-Residential	Comm/Indust/Transport	2.68	2.65	.947	-5.73	11.10
	Grasslands/Herbaceous	-4.63	2.65	.592	-13.0	3.78
	Bare Rock/Sand/Clay	-3.07	2.65	.904	-11.4	5.34
	Row Crops	12.41*	2.65	.001***	3.99	20.82
	Shrub land	-2.88	2.65	.926	-11.3	5.53
	Water	9.77*	2.65	.015**	1.36	18.19
4-Bare Rock/ Sand/Clay	Comm/Indust/Transport	5.75	2.65	.343	-2.66	14.17
	Grasslands/Herbaceous	-1.57	2.65	.997	-9.98	6.85
	Residential	3.07	2.65	.904	-5.34	11.48
	Row Crops	15.48*	2.65	.000***	7.06	23.89
	Shrub land	.18	2.65	1.000	-8.23	8.60
	Water	12.84*	2.65	.001***	4.43	21.25
5-Row Crops	Comm/Indust/Transport	-9.73*	2.65	.016**	-18.1	-1.31
	Grasslands/Herbaceous	-17.04*	2.65	.000***	-25.4	-8.63
	Residential	-12.41*	2.65	.001***	-20.8	-3.99
	Bare Rock/Sand/Clay	-15.48*	2.65	.000***	-23.8	-7.06
	Shrub land	-15.29*	2.65	.000***	-23.7	-6.88
	Water	-2.64	2.65	.951	-11.0	5.77
6-Shrub land	Comm/Indust/Transport	5.57	2.65	.380	-2.84	13.98
	Grasslands/Herbaceous	-1.75	2.65	.994	-10.1	6.66
	Residential	2.89	2.65	.926	-5.53	11.29
	Bare Rock/Sand/Clay	-.18	2.65	1.000	-8.59	8.23
	Row Crops	15.29*	2.65	.000***	6.88	23.71
	Water	12.66*	2.65	.001***	4.25	21.07
7-Water	Comm/Indust/Transport	-7.09	2.65	.143	-15.5	1.32
	Grasslands/Herbaceous	-14.41*	2.65	.000***	-22.8	-5.99
	Residential	-9.77*	2.65	.015**	-18.2	-1.36
	Bare Rock/Sand/Clay	-12.84*	2.65	.001***	-21.2	-4.43
	Row Crops	2.64	2.65	.951	-5.78	11.05
	Shrub land	-12.66*	2.65	.001***	-21.1	-4.25

*p<.05; **p<.01; ***p<.001

4.3 Multivariate Regression Model Results

4.3.1 OLS and Spatial Error Models Predicting LST in El Paso

The OLS model (see Table 4.8) revealed that higher population density, albedo, percent of the population over age 64 years and education level, as well as lower NDVI and elevation, were associated with higher extreme heat. The spatial error model (Table 4.8) revealed similar statistically significant results for four of the variables (NDVI, albedo, elevation, population density); there were not statistically significant relationships for percent of the population age >64 and education level with extreme heat in the spatial error model.

Table 4.8 OLS and Spatial Regression Models for El Paso

INFORMATION	MODEL1 : Current Model		MODEL2 : Current Model	
	El Paso OLS Results		El Paso SRM (Error) Results	
Neighbor Bandwidth	1000 m		1000m	
Moran's I Value P-value	0.173924 0.001000		0.00960777 0.335	
Condition Index	2.123258		2.123258	
R Square	0.717011		0.732123	
	Parameter	P	Parameter	P
Lambda			0.29	0.000***
Constant	-0.001696	0.944	-0.01	0.750
NDVI	-0.68	0.000 ***	-0.693	0.000***
Albedo	0.23	0.000***	0.20	0.000***
Elevation	-0.13	0.000***	-0.15	0.000***
Population density	0.26	0.001***	0.24	0.000***
Population over age 64	0.062	0.012*	0.04	0.107
Education	0.063	0.020*	0.038	0.168

*p<.05; **p<.01; ***p<.001

4.3.2 OLS and Spatial Lag Models Predicting LST in Juárez

The OLS model (Table 4.9) revealed that higher population density and elevation – as well as lower NDVI, albedo and education – were associated with higher mean LST. There was not a statistically significant relationship between population density and mean LST, although the relationship was positive. The spatial lag model (Table 4.9) revealed similar statistically significant results. Note that while the relationship between population density and LST remained insignificant, it flipped in direction to negative in the spatial lag model.

Table 4.9 OLS and Spatial Regression Models for Juárez

INFORMATION	MODEL1 : Current Model		MODEL2 : Current Model	
	Juárez OLS Results		Juárez SRM (Lag) Results	
Neighbor Bandwidth	2000 m		2000m	
Moran's I P-value	0.16 0.001000		0.01559 0.195000	
Condition Index	2.953153		2.953153	
R Square	0.38		0.525701	
	Parameter	P	Parameter	P
Constant	-0.001	0.97	0.003	0.91
NDVI	-0.20	0.000***	-0.16	0.000***
Albedo	-0.24	0.000***	-0.04	0.000***
Elevation	0.27	0.000***	0.19	0.000***
Population density	0.03	0.380	-0.04	0.250
Population over age 64	0.44	0.000***	0.24	0.000***
Education	-0.18	0.000***	-0.13	0.000***

*p<.05; **p<.01; ***p<.001

CHAPTER 5: DISCUSSION

This chapter discusses the results presented in Chapter 4 in reference the research questions and hypotheses, and in the context of the extant literature on determinants of land surface temperature. Some hypotheses are supported by results while others are not. Comparing the findings between the two cities reveals differences in patterns of land surface temperature distribution and extreme heat exposure related to biophysical, built environmental and socio-demographic factors. To begin, this discussion must be premised with the point that some neighborhoods are exposed to substantially higher temperatures that others (see Figures 5.1 and 5.2). The range of mean land surface temperature for neighborhoods in both El Paso and Juárez is ~20°F for each of the selected dates. The remainder of the discussion focuses on evaluating determinants of land surface temperature variation.

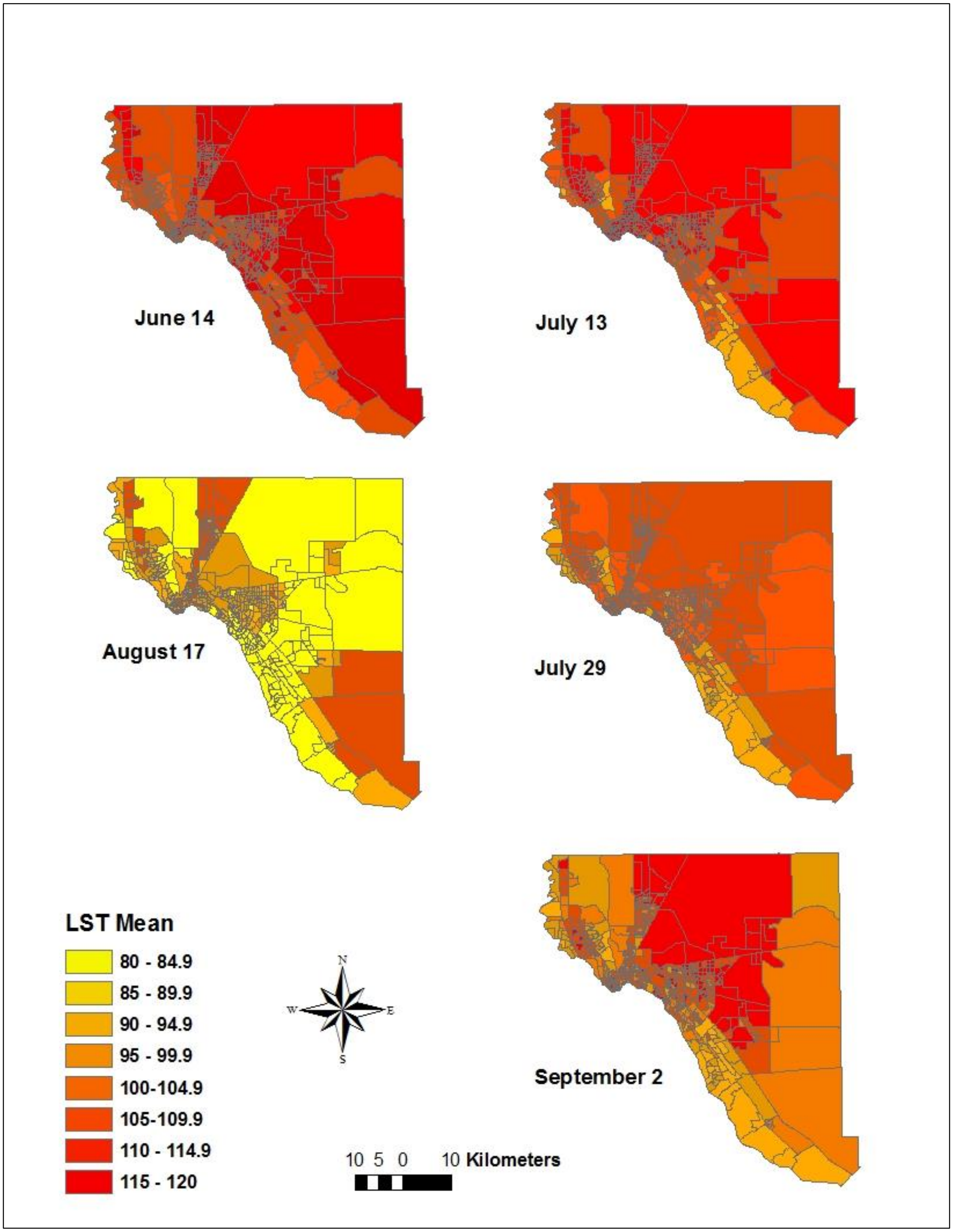


Figure 5.1 El Paso Land Surface Temperature Distribution, 2010

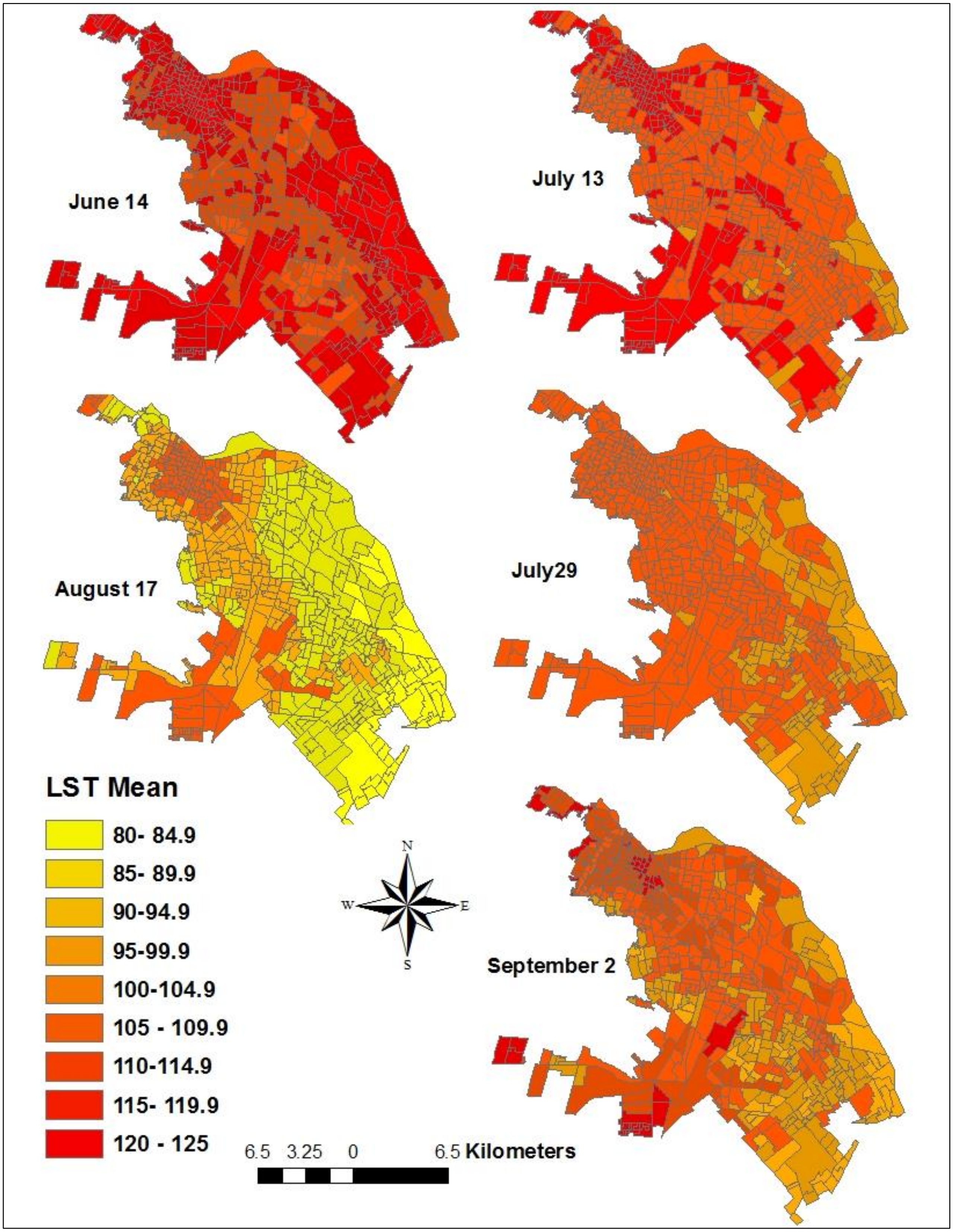


Figure 5.2 Juárez Land Surface Temperature Distribution, 2010

5.1 Research Question 1

What is the relationship between elevation and land surface temperature in the study area? Considering results from the correlation and spatial regression analysis (Tables 4.1, 4.2, 4.8 and 4.9), elevation in El Paso was associated with LST as hypothesized. There was a significant negative association between elevation and LST in El Paso, meaning that higher elevation neighborhoods had substantially lower temperatures. These results align with prior research (Jenerrete et al., 2006; Charabi & Bakhit, 2011; Grossman et al., 2010), and support Hypothesis 1.

On the other hand, results reveal that elevation had a positive relationship with LST in Juárez, meaning that higher elevation neighborhoods had substantially higher temperatures. This contradicts expectations (and Hypothesis 1) and suggests that another variable not adequately measured in the analysis may affect land surface temperatures in Juárez neighborhoods. It is plausible that the dark color of the volcanic rock cover in higher elevation neighborhoods located in the Sierra de Juarez influences relatively higher absorption of solar radiation as compared to lower elevation Juárez neighborhoods located on (lighter colored) sedimentary material in the Rio Bravo/Grande Valley. High elevation, high heat neighborhoods in Juárez are identified in Figure 5.3. Although land surface albedo was included as an independent variable in the regression models, it may not have adequately captured the role of geologic substrate as an influence on solar radiation absorption. It is notable that, in El Paso, higher elevation neighborhoods are primarily located on relatively lighter colored, limestone substrates that are prevalent in the Franklin Mountains. This may explain the divergent findings for elevation between the two cities.

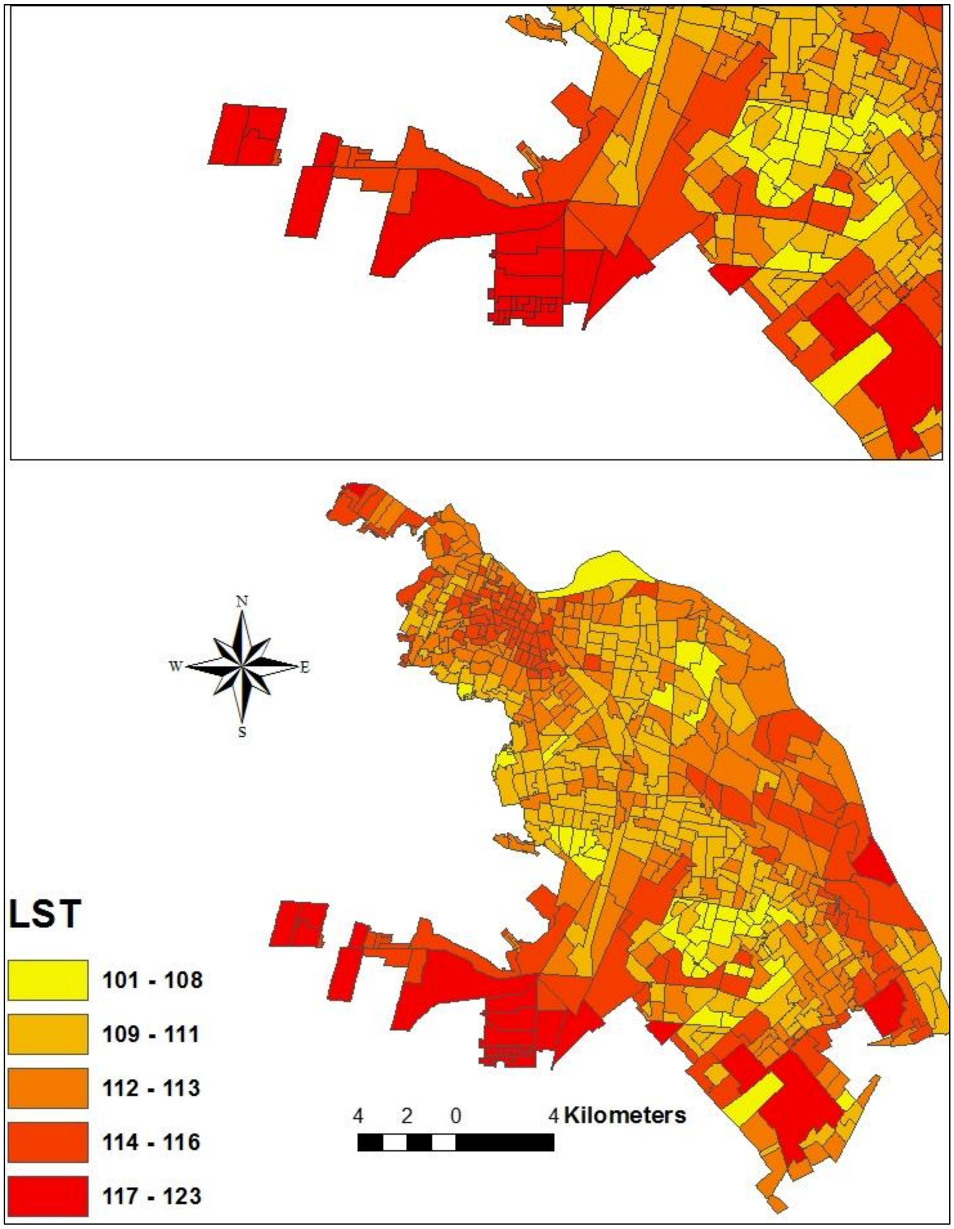


Figure 5.3 Higher Elevation-Higher Heat Neighborhoods in Juárez

5.2 Research Question 2

What is the relationship between vegetation density and land surface temperature in El Paso and Juárez? Results show that neighborhoods with higher vegetation density had lower mean LST in both cities, which supports Hypothesis 2. The relationship between LST and NDVI was significant and nega-

tive in all statistical tests for both cities. More specifically, results indicated that the relationship between NDVI and LST was stronger for El Paso than for Juárez, most likely due to the fact that most of the highest NDVI neighborhoods are located on the US side of the international border, adjacent to the Rio Grande/Bravo. These results generally align with the literature (Xian and Crane, 2006; Buyantuyev & Wu, 2009; Zhang & Wang, 2007; Stefanov, 2005; Mallick et al., 2008; Jenerette et al., 2007; Zhang et al., 2010; Hardegree, 2006; Weng et al., 2004; Goggins, 2009; Murphy, 2007). It is important to note that these relationships were quantified using regression techniques that adjust for spatial autocorrelation inherent in these data. Thus, this study represents an advance from conventional regression techniques that have been used frequently in previous studies. Conventional OLS regression techniques are not adequate, because they are based on the assumption of independent observations.

5.3 Research Question 3A

What is the relationship between land use/land cover and land surface temperature in the study area? ANOVA test results revealed some significant differences in LST across the land use/land cover (LULC) classes, which generally supports Hypothesis 3A. In terms of urban LULC types, results indicate that commercial/industrial/transportation and residential LULC classes were associated with relatively higher LST and that row crop and water LULC classes were associated with relatively lower LST. These LST differences are attributable to differences across the LULC classes in terms of heat absorption, moisture and evaporative cooling. These results generally align with the literature (Clarke et al. 2010; Sullivan 2010; Kim 2009; Taha et al. 1988; Prado 2010; Kestens et al. 2011; Chow 2011; Dousset et al. 2010; Goggins 2009).

Notably, the grassland/herbaceous and shrub land LULC class were surprisingly hot (in fact, they were the hottest LULC classes); this is because study area grasslands are dry, meaning that humidity and associated evaporative cooling effects are lower than for wet grassland types prevalent in other regions. This highlights an important difference between El Paso- Juárez and the vast majority of other

urban contexts where determinants of LST have been examined: Whereas wildland areas surrounding most other large cities are substantially cooler than corresponding urbanized areas, Chihuahua Desert natural landscapes surrounding El Paso- Juárez are often hotter on high-heat summer days than corresponding urbanized landscapes. Finally, there were striking differences in mean LST for the bare rock/sand/clay LULC class between El Paso and Juárez (and to a lesser degree, for the grassland and shrub land LULC classes) (Figure 5.4). This provides another indication that differences in heat absorption between El Paso and Juárez non-urban LULC types based on geologic substrate (e.g. limestone vs. basalt) may influence distinctions in LST between the two cities.

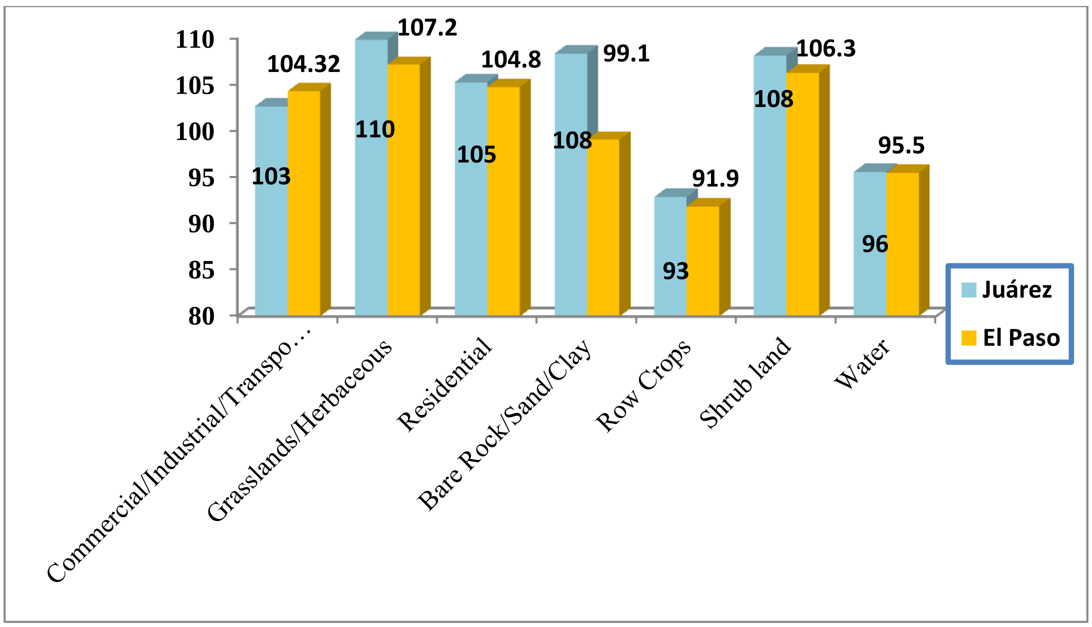


Figure 5.4 Mean LST by LULC Class for Juárez and El Paso, 2010

5.4 Research Question 3B

What is the relationship between land surface albedo and land surface temperature in the study area? Results diverged between Juárez and El Paso notably. In Juárez, LCA was associated negatively and significantly with LST at the neighborhood level (see Tables 4.2 and 4.9). These results provide support hypothesis 3B and they generally align with the literature (Frey and Parlow 2007, Houldcroft et al. 2009; Cho et al. 2012; Bhattacharya et al. 2009a; Scott and Voogt 2010).

In contrast, LCA was associated positively and significantly with LST in El Paso, which runs counter to hypothesis 3B (see Tables 4.1 and 4.8). There are a few possible reasons for this. First, there is less neighborhood-level variability in albedo for El Paso than in Juarez, and this may have dampened the influence of mean LCA on mean LST in El Paso (see Figure 3.14). However, that does not explain the significant and positive relationship found here. A second factor could be the influence exerted by a set relatively high albedo-high heat (lower elevation and highly arid) Chihuahua Desert landscapes that predominate across census block groups in the large northeastern portion of El Paso County.

5.5 Research Question 4

What is the relationship between population density and land surface temperature in El Paso and Juárez? Results for the relationship between population density and LST provide some support Hypothesis 4, although results for Juárez were mixed. In El Paso, there were significant and positive relationships between population density and mean LST across all results. In other words, higher population density neighborhoods were significantly hotter, which was also found to be the case in Phoenix, Arizona (Jeanerette et al. 2007). In fact, this relationship generally aligns with the extant literature (Sullivan 2010; Jeanerette et al. 2007; and Zhang & Wang 2008). The direction of the relationship between population density and LST reversed across the analyses conducted for Juárez neighborhoods. Counter to expectations, the spatial regression results for Juárez (See Table 4.9) revealed a weak negative (insignificant) association between population density and LST (for the year 2010). This counterintuitive result

may be explained in part by the depopulation that occurred as many residents fled from densely built-up (and previously densely populated) neighborhoods due to the drug violence (beginning in 2007 and extending well past 2010 [the year for which population density data apply]) (see Grineski et al. 2013). This is an area for further research.

5.6 Research Question 5

What is the relationship between the distribution of older aged people (based on the percentage of the population above 64 years of age) and land surface temperature in the study area? Results for the relationship between percent older aged and LST provide some support Hypothesis 5, although results for El Paso were mixed. In Juárez, the association between proportion of older adults and LST was positive and significant across all results. In El Paso, there was no association for the bivariate correlation; however, the OLS model revealed a positive and significant relationship and the spatial regression model yielded positive association that approached significance. These results suggest generally increasing risk for this already vulnerable group when accounting for the other variables in the models. In sum, results suggest that older people tend to be disproportionately represented in neighborhoods where they must cope with greater exposure to extreme heat. These results provide some support for Hypothesis 5, and align with a small literature indicating that neighborhoods with greater older age composition may be exposed to relatively higher temperatures in some U.S. cities (Jeanerette et al. 2007). For the public health sector, these results should raise concerns due to the well-documented vulnerability of older people to morbidity and mortality during extreme heat events (Naughton et al. 2002; Schifano et al. 2009; Semenza et al. 1999; Stafoggia et al. 2006).

5.7 Research Question 6

What is the relationship between socioeconomic status (based on measures of educational attainment) and land surface temperature in the study area? Results indicate that mean education was associated with mean LST in both cities at the neighborhood level. Lower mean education was signifi-

cantly associated with mean LST in the bivariate correlations for Juárez and El Paso (see Table 4.2). Additionally, in the OLS and spatial regression models for Juárez, mean education was associated negatively and significantly with LST (see Table 4.9), which supports Hypothesis 5. These results also align with the literature (Buyantuyev & Wu 2010; Murphy 2009; Rosenthal 2010; Stanforth 2011; Harlan et al. 2006). On the other hand, in the spatial regression model for El Paso, mean education was associated positively and insignificantly with LST. It is unclear why mean education spatial regression results diverged between Juárez and El Paso (see Table 4.8).

5.8 Research Question 7

Taken together, which of the factors identified in RQ1 through RQ6 (i.e., elevation, vegetation density, land use/land cover class, land surface albedo, population density, older age, socioeconomic status) are relatively more (or less) important in predicting land surface temperature in the study area? The results of bivariate correlations and spatial regression models for both cities are summarized in Figures 5.5 and 5.6. Based on the bivariate correlations, in El Paso, the variables most strongly associated with mean LST at the neighborhood level were vegetation density, population density, and albedo. On the other hand, the variables with the weakest bivariate correlations with LST were elevation, older age, and education (SES) (Figure 5.5). Results from the multivariate spatial regression model (which adjusts for the effects of other independent variables as well as spatial dependence in the data) indicate that, in El Paso, vegetation density is by far the most important predictor of LST, followed by population density, albedo, and elevation. Older age and education exhibit the weakest associations with LST relative to the other predictors examined here. In sum, all analyses point toward vegetation density as the most powerful determinant of LST at the neighborhood level in El Paso. This suggests also that land use/land cover class plays an important role in LST in El Paso.

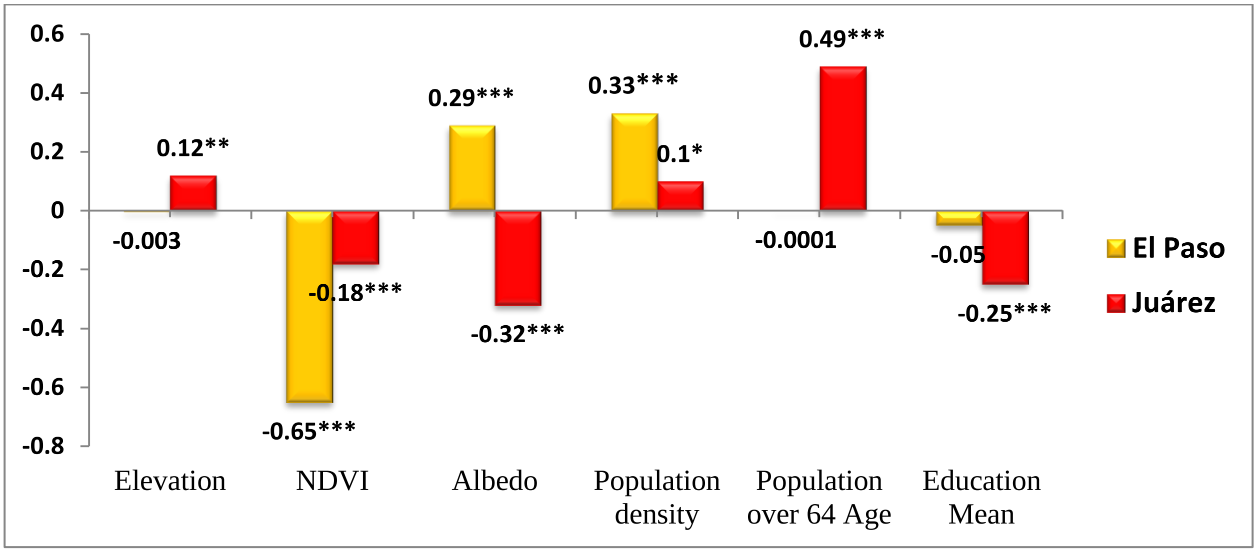


Figure 5.5 Bivariate Correlation Coefficients with LST for El Paso and Juárez, 2010

Based on the bivariate correlations, in Juárez, the variables most strongly associated with mean LST at the neighborhood level were older age, albedo (in the direction opposite from that hypothesized) and education. NDVI, elevation and population density had weaker bivariate correlations with LST in Juárez; however those relationships were still statistically significant (Figure 5.6). Results from the multivariate spatial regression model indicate that, in Juárez, older age is the most important predictor of LST, followed closely by elevation, vegetation density, and education (all significant in the model). Population density and albedo exhibit weak associations with LST relative to the other predictors. In sum, analyses point toward multiple variables being inter-correlated with LST in Juárez, which diverges from findings for El Paso.

I reference to hypothesis 7, in El Paso, the factors that more directly physically influence land surface temperature (i.e., NDVI, elevation, albedo, population density) were relatively more important predictors in the multivariate models than the factors that indirectly influence land surface temperature (i.e., population over age 64, education level). Note that the relationship with albedo ran counter to expectations based on physical science knowledge. El Paso results thus provide some limited support for

hypothesis 7. In Juarez, in contrast, results provide little support for hypothesis 7, since the indirect factors (older age, education) were among the strongest predictors in the multivariate models.

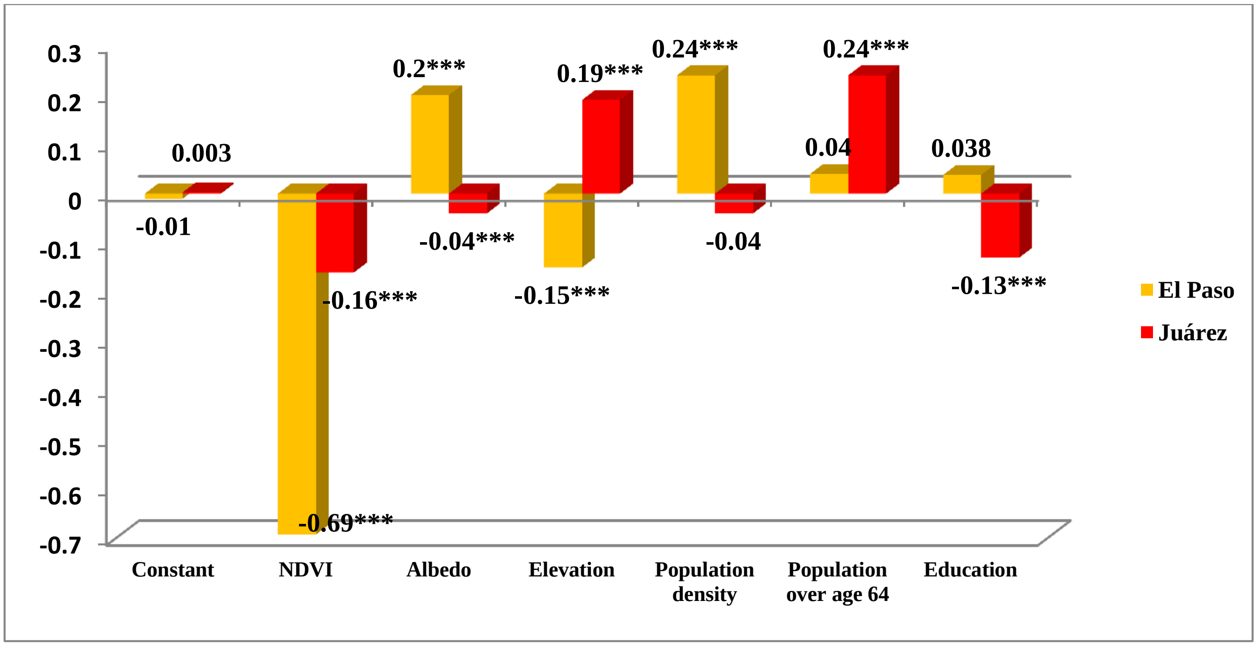


Figure 5.6 Spatial Regression Parameters for El Paso and Juárez, 2010

5.9 Research Question 8

Are the relationships between the factors (i.e., elevation, vegetation density, land use/land cover class, land cover albedo, population density, older age, socioeconomic status) and land surface temperature stable between El Paso County and Ciudad Juárez? Relationships for some variables exhibit relative stability based on results for El Paso as compared to Juárez while relationships for other variables do not. Vegetation density was stable with negative and significant relationships with LST in both cities. Older age also exhibited a relatively stable positive relationship with LST across all but one result. In Juárez, the association between proportion of older adults and LST was positive and significant across all results. In El Paso, there was no association for the bivariate correlation; however, the OLS model revealed a positive and significant relationship and the spatial regression model yielded positive association that approached significance.

In addition, most of the land use/land cover classes exhibited stability in terms of mean LSTs between the two cities. This includes the commercial/industrial/transportation, residential, row crops and water LULC classes. Grasslands/herbaceous and shrub land were slightly less stable in terms of the mean LSTs. Bare rock/sand/clay was the only LULC class that did not exhibit stability between El Paso and Juárez (there was a 9°F mean LST difference between El Paso and Juárez for this LULC class). Possible explanations for these differences are discussed above.

Results for albedo were highly unstable between El Paso and Juárez. In Juárez, albedo was associated negatively and significantly with LST, as expected. In contrast, albedo was associated positively and significantly with LST in El Paso. Additionally, results for elevation were highly unstable between El Paso and Juárez. In Juárez, elevation was associated positively and significantly with LST, which countered expectations. In contrast, elevation was negatively and significantly associated with LST in El Paso. Results for population density also exhibited instability between El Paso and Juárez. The bivariate correlations for population density were positive and significant in both cities, but for the spatial regression models, the results were not stable between El Paso and Juárez; in Juárez, the relationship with LST was negative and insignificant, but in El Paso the result was positive and significant. Likewise, the relationship between education and LST was not stable. Bivariate correlations revealed negative relationships with LST for both El Paso and Juárez. The spatial regression model results, however, diverged between El Paso and Juarez; the relationship between education and LST was positive and insignificant for El Paso while the relationship between education and LST was negative and significant for Juárez.

Results do not support hypotheses 8A and 8B. Relationships for factors that physically influence vs. indirectly influence LST exhibited similar levels of (in)stability between El Paso and Juárez. For example, elevation and albedo, two variables that physically influence LST, were found to be highly unstable between El Paso and Juárez, while older age was relatively more stable between the two cities.

CHAPTER 6: CONCLUSION

This study aimed to determine the spatial distribution and determinants of exposure to extreme heat in El Paso and Juárez for the year 2010. The main research questions of this study focused on clarifying the relative importance of elevation, vegetation density, land use/land cover class, albedo, population density, the distribution of older aged people (based on the percentage of the neighborhood population above 64 years of age), and socioeconomic status (based on measures of educational attainment) in predicting extreme heat exposure (based on estimated land surface temperatures) at the neighborhood level. In addition, emphasis was placed on evaluating the stability of variable relationships with extreme heat exposure between El Paso County and Ciudad Juárez. Data were obtained from various sources and inferences were supported based on results from multiple data analysis techniques. In terms of analysis techniques, the spatial regression modeling approach was successful in terms of explaining more variation in LST than the spatial OLS models. This increased explanatory power indicates that spatial regression modeling should be more widely used in GIS-based analyses of determinants of the urban heat island and extreme heat exposure at the local level in future studies.

6.1 Study Limitations

This study has limitations that need to be acknowledged. Firstly, I was not able to obtain finer-scale (e.g., 30*30 m pixel) data for the socio-demographic variables. The resolution of those data necessitated a coarser-scale, neighborhood-level analysis. The second limitation relates to causality. Similar to other studies in this vein, this is a cross-sectional study and causality cannot be determined based on the relationships between the independent variables and LST determined at one-point-in time. The third limitation of this study was the lack of compatible data for other potentially relevant socio-demographic variables between Juárez and El Paso (e.g., income).

6.2 Future Research and Practical Importance

The focus of this study was to evaluate the distribution and determinants of LST in the border area between the US and Mexico within the cities of El Paso and Juárez. A future research project that is well-deserving of attention would be to assess how populations in different contexts (such as the US and Mexico) cope with and adapt to excessive heat exposure. In terms of practical importance, results of this study could be used by urban planners and public health officials to determine the most effective types of measures to implement in specific locations to mitigate heat exposure. Based on the results of this study, interventions should aim to protect vulnerable older aged people, particularly in Juárez. Additionally, high mean LST neighborhoods in both El Paso and Juárez – with low NDVI and high population density – could be targeted with urban greening projects to most efficiently and effectively mitigate extreme heat impacts (see Velázquez-Angulo et al. 2013). Indeed, it is my hope that such knowledge will be used to better protect vulnerable populations from exposure to extreme heat in the El Paso-Juárez metropolitan area in the future, and that the approach used here will be applied by scholars in other contexts where human vulnerability to extreme heat is a pressing concern.

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APPENDIX

Appendix 1. Detailed Summaries of the Literature

Factors	Prior studies (citation)	Location	Data Source	Methods: Data transformation & analysis	Results	Resolution
Topography	Charabi & Bakhit 2011	Muscat Oman	•Meteorological observations •Mobile measurements	• The study describes: - The form, the location and the spatial distribution of the urban heat island (UHI) using a spatial network of weather observations. -The intensity or the magnitude of UHI and its temporal variability at different temporal scales - The main factors that shape Muscat's UHI.	**Topographically, this valley is surrounded by mountains formed of dark-colored rocks such Ophiolites that absorb short wave radiation and contribute, to the emergence of this warm urban core.**	• Station 1: elevation 8.40 m, distance 3000 m • Station 2: elevation 4.08 m, sea distance 100 m
Topography	Jenerrete et al. 2006	Phoenix USA	•ETM+ at 60 m/pixel •Census statistics, •Digital elevation model(DEM)	• Topographic and vegetation independent variables • To adjust for normality the following variables were transformed: SAVI-mean (log), SAVI-SD (log), temperature-SD (log), and slope. • Surface temperature dependent variable • Path analysis used to extend regression by allowing models that include multiple dependent and independent variables.	**Higher elevation neighborhoods had substantially lower temperatures**.	Emitted energy in the mid-infrared wavelengths (10.4–12.5 lm) is acquired by ETM+ at 60 m/pixel
Topography Aspect-shade	Grossman et al. 2010	Phoenix USA	•Model of WRF Simulations •Comparison of measured near-surface temperatures	• Extreme heat event (EHEs) are investigated for the arid Phoenix, Arizona, metropolitan area • Using the Weather Research and Forecasting Model (WRF)	**During daytime the flow is reversed and heating of the air on the mountain slopes causes predominantly westerly anabatic winds and characteristic surface a hot wind flows to low area in Phoenix. The study also included topography contours. The lowest areas were hotter than others.**	1^0 resolution at every 6 hours for each EHE
Vegetation	Buyantuyev & Wu 2009	Phoenix USA	•Data from 2ASTER •Using the search and retrieval tools provided by the Land Processes Distributed	•Use the expert classification system in the initial image classification the system was developed for Landsat data in ERDAS Imagine 8.7	**Mean NDVI was the most significant explanatory variable of daytime surface temperature, but the correlation was notably weaker at night.**	Resolution required combining on average 3,300 NDVI pixels (15 m) or approximately 90

			Active •LST. Autumn data) •US Geologic Survey (USGS) digital elevation models •Landsat data in ERDAS Imagine 8.7.	•Land-use map, normalized difference vegetation index (NDVI), NDVI / (NIR- RED)=(NIR + RED) •Images computed by a 3 9 3 pixel moving window. • Using the temperature emissivity separation hybrid approach developed by the ASTER. •Using geographically weighted regression (GWR)		Temperature pixels (90 m).
Vegetation	Xian and Crane 2006	Tampa Bay&Las Vegas USA	•Remote sensing data •Land sat 5 •Land sat 7 systems	•Land sat TM and ETM+ images from 1994–1995 and 2002 for paths 17, and 16, rows 40, and 41 for Tampa Bay •1984 and 2002 images for path 39, row 35 for Las Vegas. •Determination of Tb and NDVI from TM and ETM+ •The measurement of LST	**Temperature increased in association with lower density of vegetation.**	Nominal spatial resolution of 1 m. Training pixels classified as urban and non-urban in 1 m grids from the DOQQ were used to calculate percent ISA and converted to 30m resolution each pixel.
Vegetation	Zhang & Wang 2007	10 cities (in China)	•Two scenes of Landsat TM/ETM+ remotely sense imagery •Weather station data from: http://www.rsgs.ac.cn	• A systematical geometric and radiometric correction were Performed to the image data. •Extracted from Classification Images using bands 1–5 and 7 • Classification map was checked with the random •Sampling method and 25 samples for each land cover category •Using Land cover components of high temperature area in 1990 and 2000 (%	**Both 1990 and 2000, showed lower temperature on vegetation cover and other high temperature on other cover in the urban area.**	The Landsat TM image 1990 was further registered to the ETM+ image 2000 with the resultant root mean square error being less than 0.5 pixels, so that both TM/ETM+ images of the two years had same spatial resolution and covered the same area.(1m2).
Vegetation	Stefanov 2005	Phoenix USA	••Landsat ETM+ data • NASA MASTER airborne sensor •Satellite-based MODIS and ASTER instruments •version WINVICAR	•Using linear-least squares regression •Modeling of physical and climatic variables. improve the NCAR/UCAR MM5 meso-scale climate model •All data were dereferenced to UTM Zone 12 using the NAD83	**A strong negative correlation between surface temperature and vegetation density (r2 = -0.673) was obtained between 2000 MASTER surface temperature and 2000 ETM+ SAVI data at the neighborhood scale.**	Region varies from 5 – 1 depending on aircraft hei

				datum		
Vegetation	Mallick et al. 2008	Delhi India	•Landsat-7 ETM+ •Landsat visible and NIR channels •Minimum Noise Fraction (MNF)	• In the study an attempt has been made to derive emissivity by taking the fraction of vegetation cover per pixel (FVC) in conjunction with NDVI. • The vegetation and bare soil proportions are obtained from the NDVI of pure pixels • NDVI is estimated using proportion vegetation cover	**Strong correlation is observed between surface temperature with Normalized Difference Vegetation Index (NDVI) over different LU/LC classes and the relationship is moderate with fractional vegetation cover (FVC). A regression relation between these parameters has also been estimated indicating that surface temperatures can be predicted if NDVI values are known.**	90-m resolution
Vegetation	Jenerette et al. 2007	Phoenix USA	•Satellite images: - Landsat ETM+ - EROS Data - Electromagnetic spectrum in six bands •US Census statistics •USGS digital elevation models	• Used a GIS approach • Computed the mean and standard deviation for both temperature and vegetation across all neighborhoods and then estimated correlation coefficients between vegetation and temperature variables. • The correlation structure between these variables was then examined primarily through a multivariate regression approach.	**Mean surface temperature and vegetation (SAVI) were strongly and negatively correlated for Phoenix neighborhoods, and higher density neighborhoods were associated with decreased vegetation variability**	30 m/pixel ground resolution
Vegetation	Zhang et al. 2010	Beijing China	•Technologies of remote sensing and GIS •Land sat 5 TM image -TM image Includes 7 bands – used to extract NDVI	• Remote sensing image combined with meteorological data used to extract land surface temperature to study the relationship between urban heat island and NDVI • NDVI= (NIR-R)/ (NIR+R) • Combined seven single bands to generate a multi band image to extract NDVI in the study area • Used regression analysis to examine relationship between average brightness temperature and average NDVI	**• The stronger the negative correlation between brightness temperature (Tb) and normalized difference vegetation index (NDVI.**	30m

Vegetation	Hardegree 2006	Baton Rouge USA	•Airborne & satellite multispectral data - Sensor (ATLAS) - Land sat •Meteorological data •Color Infrared Orthophotography LDEQ,COOP	•Verification that altering amounts of vegetation within a given land cover over time can reveal changes in surface temperature values, thus providing a means to reconstruct and predict future SHIs •Calculate mean , maximum of vegetation with masking Veg map •Regression equations predicting surface temperatures from known NDVI values	**•Regression equations were developed to predict surface temperature from known NDVI; it was negative relation between them.** **•Local surface temperatures and NDVI-surface correlation was related as the vegetarian type and density.**	Spatial resolution of 10 meters..
Vegetation	Weng et al. 2004	Indianapolis USA	•Remote sensing NDVI spectral mixture model •Landsat 7 Enhanced Thematic Mapper Plus (ETM+) image (Row/Path: 32/21) •USGS Earth Resource Observation Systems Data Center	•Examination of Landsat enhanced thematic mapper plus (ETM+) image of Indianapolis •Using the Normalized Difference Vegetation Index (NDVI) • Estimation of vegetation abundance using LSMA 1 Image processing, 2 End member selection, 3 Unmixing solution and evaluation of fraction images	**•Some hot spots, or urban heat islands, can be easily identified. The most extensive UHI was distributed in the central part of the CBD. There were also many smaller UHIs along Highway** **•The highest negative correlation was found in cropland (_0.7265 at 30 m) and forest (_0.7156 at 30 m).**	- Resolution was 30 to 960m - Correlations reached their strongest at the 120m resolution
Vegetation	Goggins 2009	Starkville, Birmingham and Atlanta. USA	• Landsat-7 ETM+ satellite data (http://glcf.umiacs.umd.edu/index.shtml - The image for Path 19, Row 37 (Atlanta) was downloaded from USGS and the Global Visualization Viewer. (http://glovis.usgs.gov • GIS Data Acquisition	•UHI is analyzed and investigated in preprocessing of satellite data Classification of satellite imagery. •This analysis described trends that relate the impact of vegetation coverage to the overall temperature budget within an urban area. •Landsat TM/ETM's band 6 is a thermal-infrared (TIR) band that has been commonly used for surface temperature mapping	**Average surface temperature reduction of 2°C with only 15% forest coverage within a 1km 2 area. Results obtained can be useful as a potential monitoring tool that can characterize relationships between amount and percentage of urban tree cover and surface temperature.**	- The resolution was 60 meter. - Thermal band only has a resolution of 120 meters.
Vegetation	Murphy 2007	Northeastern Puerto Rico	• Using mobile and fixed-station transects •Mapping software x data	••Regression analysis of upwind vegetation vs. average temperature was used to predict temperature based on	**Comparisons of diel temperature trends at urban, grassland, and forests sites indicate that canopy cover is reduced daytime UHI effects**	Resolution was 30 meters

			- IDRISI mapping software x data • Remotely sensed data (ATLAS) •Meteorological station data	land-cover change over time. •Effects of urbanization, especially the effects of Urban Heat Islands		
LULC	Sullivan 2010	Tampa USA	•Landsat TM •US Geological survey, FLUCCS •Department of Transportation land use, cover and forms classification system 1999. •U.S. Census 2000 •Sampling network study	• Classification of LULC based upon standardized methods • The State of Florida produces the Florida Land Use Land Cover Classification System (FLUCCS) series of maps • The goal of these maps is to classify LULC based upon standardized methods and overlaying the impervious surface layer of the Tampa Bay Region • Spatial and temporal analysis used to examine the relationship between impervious surfaces and the generation of the UHI	**The results showed that simultaneous increases in Albedo and vegetation cover would decrease air temperatures by 2-5°C , over urban region**	The resolution was 4 by 4 kilometer ground pixel in the thermal infrared band is a limiting factor in UHI studies
LULC	Kim 2009	Columbus USA	•Using Landsat-5 remote-sensing data. •US Geological survey statistics for the estimated temperatures •Statistical models of local temperature changes	•Statistical methods used to analyze thermal dynamics with remotely sensed data sets •The MalaretSobrino and USGS methods converts the digital number (DN) in the thermal band into RST •TM images is to use the NDVI	**Their applicability to land-use planning and regulation is illustrated by simulating hypothetical land-use changes in part of the CMA, and computing the resulting temperature effects. The results clearly demonstrate that it is possible to reduce temperatures in residential and urban areas through a judicious siting of green areas.**	The resolution was : Band 1- 5) is (30 M*30 m). In the case of the TM Thermal band (band 6), the size of a pixel is (120 m*
LULC	Taha et al. 1988	Sacramento USA	•Lawrence Berkeley Laboratory. •Weather database -Using the DOE-2.1C program and TMY weather tapes for Sacramento, California. •Surface characteristics, geometry and building surfaces and	•Modeling domains and heat and cool islands in Sacramento. •Used the WTHCHANGE to simulate evapotranspiration from vegetation canopies •URBNET to determine the effects of albedo •Used an albedo of 90% to represent a whitewashed exterior finish, 43% to represent a medium yellow paint, and 12 % to repre-	**•The residential-commercial area is generally warmer than the residential area. The effective albedo of the surroundings (neighboring houses, streets, vegetation etc).** **•The buildings can result in direct savings of up to 14% and 19% on cooling peak power. Modifying the overall urban albedo, in addition to whitewashing, can result in total savings of up to 35% and 62% respectively.** **•Maximum temperature amplitude can be reduced by 15°C when moving from black to grey,**	LULC resolution was 200-m

			components. •Remote sensing data	sent a dark brown paint. Then calculated an area weighted "effective" albedo by multiplying the albedo of component surfaces by their area percentages.	**and by a further 22°C when moving from grey to white.**	
LULC	Prado 2010	El Paso, Dallas-Ft. Worth, Houston, and San Antonio USA	•Thermal data from ---Terra and Aqua satellite images obtained using the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor •http://daac.ornl.gov/cgibin/MODIS/GLBVIZ_1_Glb/modis_subset_order_global_col5.pl	•Converted from digital numbers to real temperatures through the Band Math tool. •ROI must be created so that statistics can be plotted for each area of the cities. •Create shape files •Using Arc Map and creating new features for each zone that match up to the highway layers •The MODIS image is used to limit the size of the rural area.	**•The day time images contain large amounts of cloud contamination in Dallas-Ft. Worth, Houston, and San Antonio •UHI consistently appears in night time images in El Paso-Juárez • The downtown zone showed the largest variation in standard deviations amongst the images • Improvement in the 95% and 99% confidence intervals with El Paso-Juárez having the greatest improvement during the day time observations. This is due to the higher temperature variability of the day time observations.**	14,126 mi2 (36,590 km2.
LULC	Kestens et al. 2011	Quebec Canada	•Records from Meteorological stations •Satellite images TM 15 LAND SAT 5 and LAND SAT 7images	• Generalized linear model (GLM is a flexible generalization of ordinary linear regression was used to estimate surface temperatures using 15 LANDSAT 5 and LANDSAT 7 and spanning the months of June to August. •The images encompassed both rural and urban landscapes and predictors included: -Historical Weather Data - Normalized Differential Vegetation Index (NDVI) - Land cover (built and bare land, water, or vegetation). - Latitude, longitude - Week of the year	**•The model explained 77% of the variance in surface temperature, accounting for both temporal and spatial variations. •NDVI had the strongest effects, with a 95% effect range of 9°C - or, in other words, 95% of the variation in NDVI explained up to 9°C variation in surface temperature. heat exposure within a density population of urban area.**	The spatial resolution Was 60 m
LULC	Chow 2011	Phoenix	•Meteorology and	•Using ArcView 9.3 GIS, to cre-	**•The heat was different between residential are-**	TR-72U sensors were

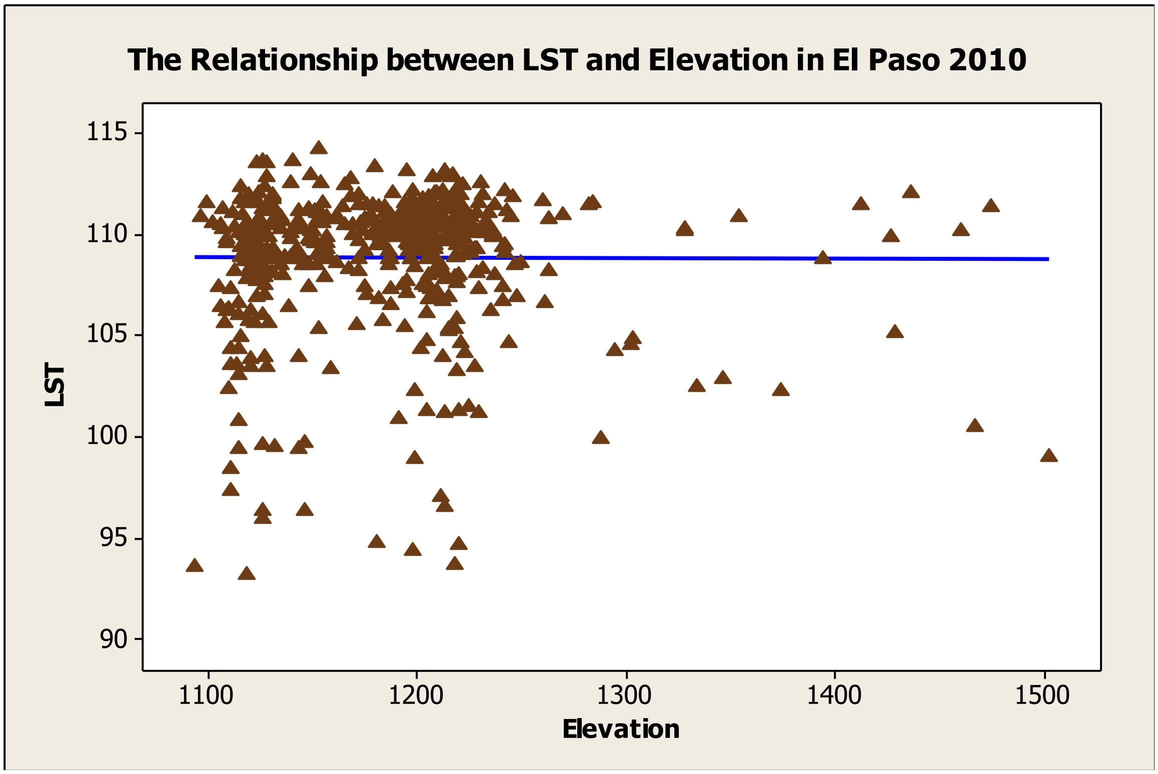
		USA	climatology in Arizona's. National Weather Service (temperature data) •.Radiosonde data •Landsat TM •Remote sensing data •GIS models data	ate a 3-dimensional (3-d) model by digitizing an aerial photograph of the study area •Used the TR-72U temperature /relative humidity sensor-data logger and examined the horizontal and vertical impacts of a small park on nocturnal near-surface temperatures at micro- and local-scales though a mobile traverse, and through simulations with the ENVI-Met 3.1 model. •ENVI-Met urban microclimate model (version 3.1 to simulate soil, surface and vegetation interactions within the urban canopy layer •Ran a model simulation for 24 h starting from sunrise (0600-0600 h;Oct 27-28, 2007) with updated surface data every 60s •Evaluation of ENVI	**as with differing surface vegetation cover (mesic vs. xeric), evaluated with hourly temperatures from meteorological stations within each study area.** **•Warming from increased xeriscaping occurred over mesic residential neighborhoods. These results suggest a need for further evaluation of urban climate models in simulating mitigation scenarios across different spatial scales.** **•Fastest growing urban areas, with population increasing from 1.04 to 4.36 million residents from 1970-2009**	attached to a metal pole before being vertically mounted to a bicycle at 0.01, 1, 2, and 3 m and 10m
LULC	Dousset et al. 2010	Paris France	•Remotely sensed data: -NOAA-AVHRR acquisition -Processing SPOT HRV -4 •Meteorological data •logistic regression model	•land cover classification derived from the four visible and near-infrared channels, which yielded six classes corresponding to water, densely built urban areas, suburban residential areas, light bare soils, forest and lawns and fields .•logistic regression model to test their use as heat exposure indicators, based on risk factors. Over the period 1–13 August •Population density of ~20 000 Inhabitants/km2 in the city.	**•Negative correlation with vegetation** **In the rural areas north of Paris, LST decreased by~4 °C,** **•In downtown the temperatures decreased slowly as the heat stored in buildings** **•The densely of building and industrial suburbs, conveying mostly variations of the surface heat balance between dry and comparatively moist surfaces** **•The northeast region quickly warmed because of the heavy traffic and industries.**	The 20-m resolution classified

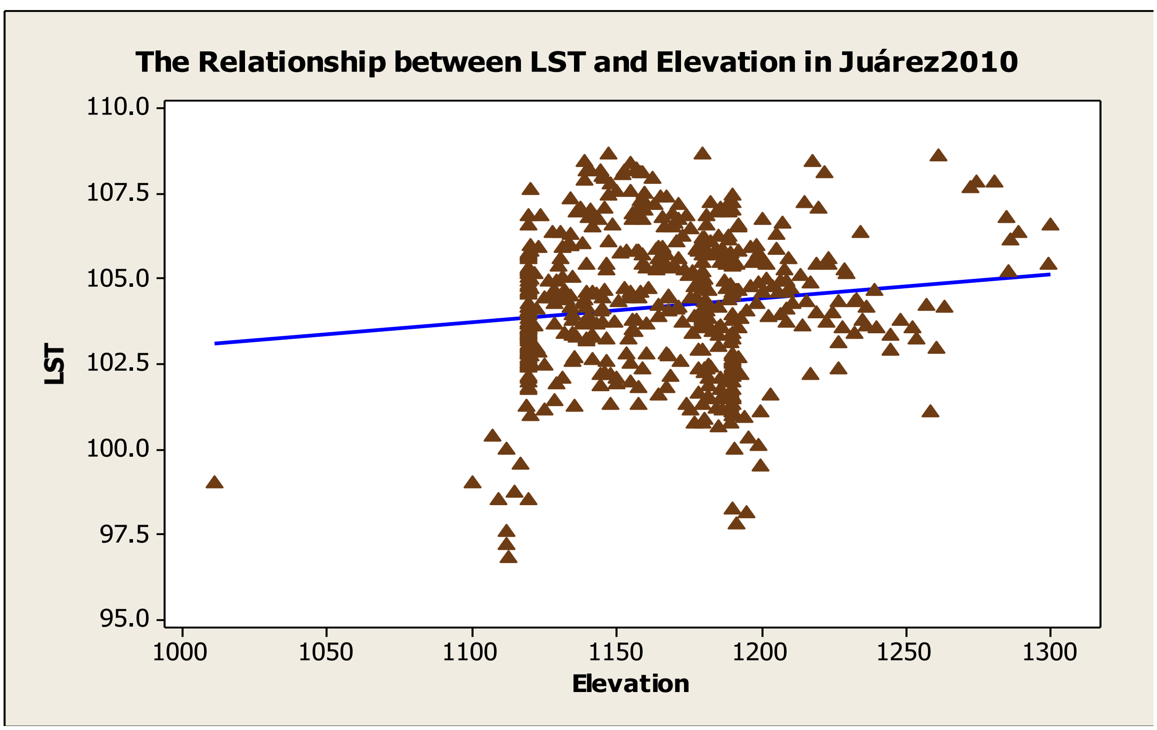
LULC	Goggins 2009	Starkville, Birmingham and Atlanta, USA	•Land sat Satellite Data •Reference •GIS Data •Weather Station Data •http://www.census.gov/geo/www/tiger/).	•UHI is analyzed and investigated in preprocessing of satellite data Classification of satellite imagery. •This analysis described trends that relate the impact of vegetation coverage to the overall temperature budget within an urban area. •GIS polygon layers for each of the study area cities were acquired for the local scale analysis and for the sub setting of the satellite imagery.	**•Temperature profiles based on percentage of vegetation coverage, and LULC classification which exposed to heat such as soil and very bright high-density urban buildings and roof-tops** **•The reduction of open surfaces due to buildings in urban areas reduces the radiative loss of heat and results in higher temperatures than rural areas and the thermal response at the community-level was consistent with the amount of impervious surface present**	The resolution was 30 Meter.
Population density and heat distribution	Sullivan 2010	Tampa USA	•U.S. Census 2000). •NOAA Geo-stationary Operational Environmental Satellites (GOES) •Geographic Information Systems GIS data •Sampling data	•Use GIS database use spatial and temporal analysis. •Remote sensing to create the map of temperature from the satellite images and use regression model •Examines the relationship between impervious surfaces and the generation of the UHI.	**•This results in an urban area that is warmer than the surrounding rural area. These studies suggest that the percentage of impervious surface in an urban area is a useful source of data to interpret urban thermal patterns and Land Surface Temperature** **•Results indicate the storage heat flux is a significant component of the surface energy balance at all sites and is the greatest at downtown and light industrial sites.**	Resolution of 30 by 30 meters
Population density and heat distribution	Jeanerette et al. 2007	Phoenix USA	•Land sat ETM+ •US Census 2000 http://www.census.gov. •Statistics models •Geographic information system GIS •Remote sensing	•Population density for all 634 census tracts in the Phoenix metropolitan statistical area. •Using ERDAS Imagine 8.5 commercial imaging software •The correlation and regression approach. •A single tract generally contains between 1,000 and 8,000 people, with a target size of 4,000 people. •Use(UTM) Coordinate System using the NAD83 datum •Using the MODTRAN 4 radiative transfer code implemented by a commercial software package, ATCOR 2.0	**•Mean surface temperature was strongly and positively correlated for Phoenix population density** **•The social correlates with mean temperature were median household income (positive)**	At 30 m /pixel ground resolution. Emitted energy in the mid-infrared wavelengths (10.4– 12.5 lm) is acquired by ETM+ at 60 m/pixel
Population	Zhang	Pearl River	•US Geological	•Method was proposed to com-	**Results showed that temperature is highly and**	Different resolutions

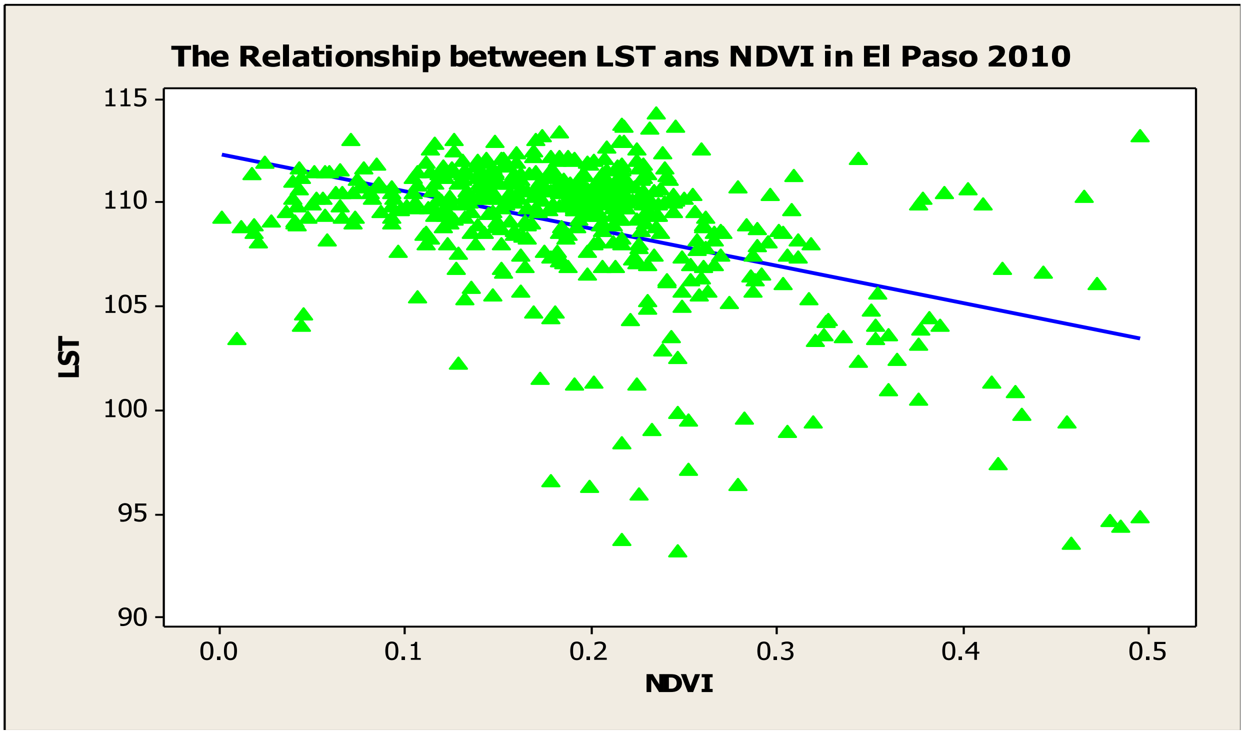
density and heat distribution	&Wang 2008	Delta cities China	Survey, •Remote Sensing •Ground Station •Statistical method and analyzing •Landsat TM/ETM+ band 6 for 1990 -2000	pute high temperature area HTA for each city from the retrieved LST •Two scenes of Landsat TM/ETM+ image, date 13 October 1990 and 1 November 2000, •A systematical geometric and radiometric correction were performed to the image data using the calibration parameter file and NDVI value	**positively correlated with urban size (r=0.95), population density (r=0.97) and development area (r=0.83**	91 km in the north -south and 33 km in the west-east directions
Socio -economic status	Buyantuyev & Wu 2010	Phoenix USA	•Land Processes Distributed Active Archive Center -Land sat data in ERDAS Imagine 8.7 -ASTER data	•ASTER data processing created land-cover maps. •Statistical analyses such as using regression OLS •Obtained atmospherically corrected level 2ASTER Data and GIS maps.	**•The high positive correlation between daytime temperatures and median family income** **•Both GWR and OLS predict temporally stable and warmer cluster of block groups in the area around the Sky Harbor International Airport**	Between 15-90m
Socio -economic status	Murphy 2009	Philadelphia USA	•Remote Sensing Thermal Infrared (TIR) Thematic •Land sat 7 ETM+ data •Geological Survey •http://landsat.usgs.gov/). •Weather stations	• Thermal Infrared TIR Visible and Near Infrared • Spectral Mixture Analysis (SMA) • Exploratory statistics to examine correlations between temperature and land-cover • Hierarchical cluster analysis • Simulation modeling	**The study showed Poverty scores close behind high temperature. Population density and pre 1960s housing score close together with low density of green vegetation are correlated to high temperature.**	
Socio -economic status	Rosenthal 2010	New York USA	•US Census 2000 •Department of City Planning Department of Housing. •Daytime Landsat 7 and one nighttime ASTER observation of NYC (10/3/05) • Geographical information system	•Neighborhood-level poverty. Using multivariate regression, analysis. •Census 2000 data aggregated from census tracts to the district level. •There are 42 United Hospital Fund (UHF) designated neighborhoods in the city, defined by several adjoining zip codes. •Housing quality..	**The percent of population in poverty and measures of educational attainment are so very strongly correlated Positively to heat (r = 0.89) at the neighborhood scale. These correlations among variables were used to select one or two correlated metrics of the similar factors to the heat**	15- to 90-meter
Socio -economic	Stanforth2011	Chicago USA	•Statistical processes •Landsat 7 ETM+	•The Normalized Difference Built-up Index (NDBI)	**The people whom living in poverty typically have lower education attainment and take up**	All wavelengths are collected at 30 m x 30 m

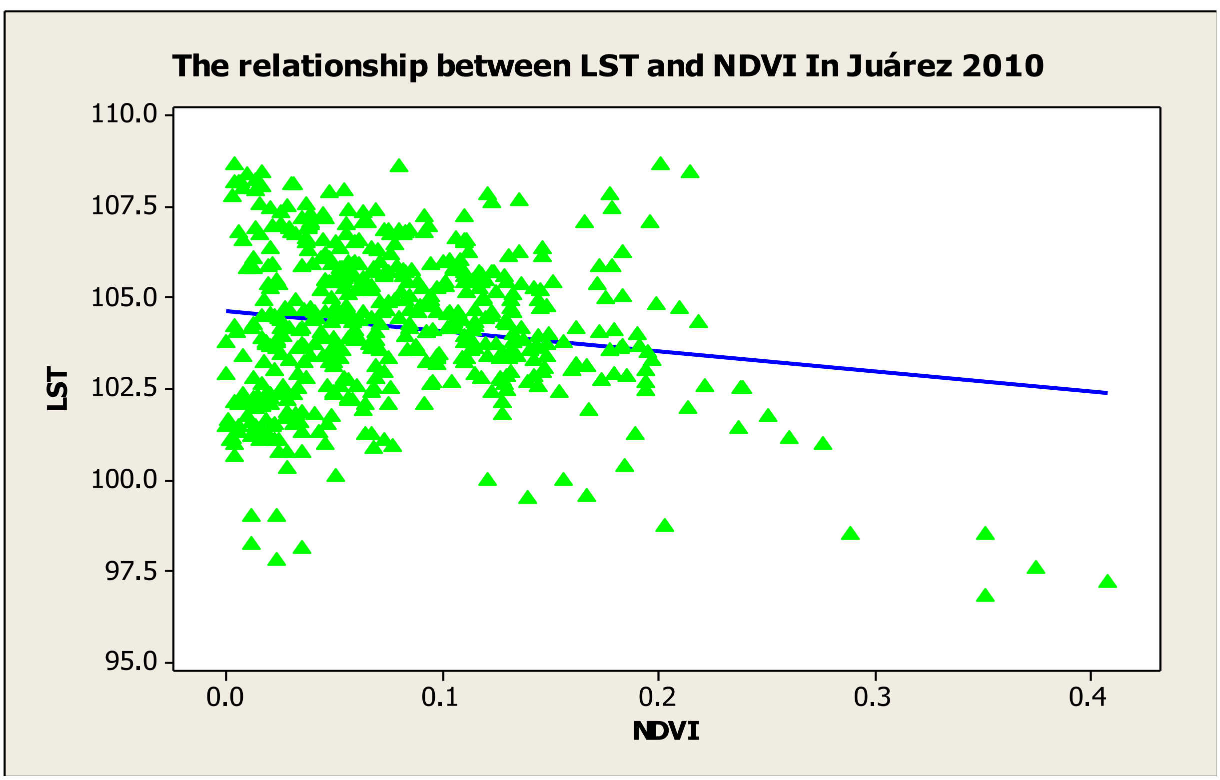
status			image and Landsat 5 TM data • U.S. Geological Survey (USGS) National Land Cover Dataset (NLCD) Residential -Mortality data •US Census 2000	•Spatial Resolutions of Analysis •Building codes, or zone IDs, are an identification tool utilized by government officials to distinguish potential uses for buildings. • The study was conducted by the statistical program PASW& The full PCA outputs. • Using Geographical information system maps and models such as buffer and polygons	**residence in lower rent habitations, such as older buildings with less insulation or adjacent vegetation are correlated with higher temperature**	resolution except the thermal band, which is collected at 120 meters (re-sampled to 60 m pixels by the proprietors
Socio -economic status	Harlan et al. 2006	Phoenix USA	•206 sites -Maricopa County where field data were collected through the Central Arizona–Phoenix Long-Term Ecological Research Project (CAP LTER) (CAP LTER) •Landsat ETM+	•Neighborhood population characteristics at the block group level from the 2000 US Census, including median income, percent of population below the US government federal poverty guideline, educational attainment, ethnicity, and age • Statistical models ANOVAs and Pearson correlations	**Lower income live in warmer neighborhoods and fewer social and material resources to cope with extreme heat. Hispanics, mainly of Mexican origin, are the largest ethnic minority in Phoenix that was mean most of them positively exposed to the extreme heat**	30m2 plots, 46 were in residential areas

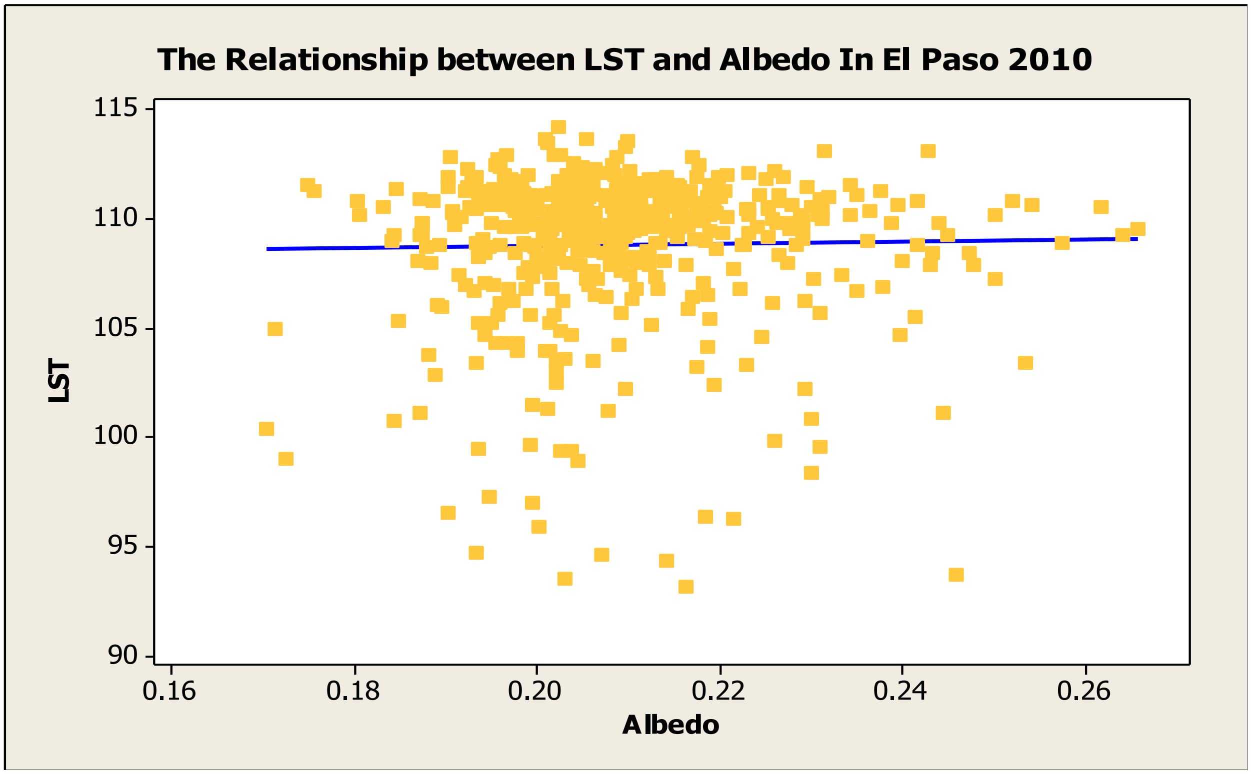
Appendix 2. Bivariate Correlation Scatterplots

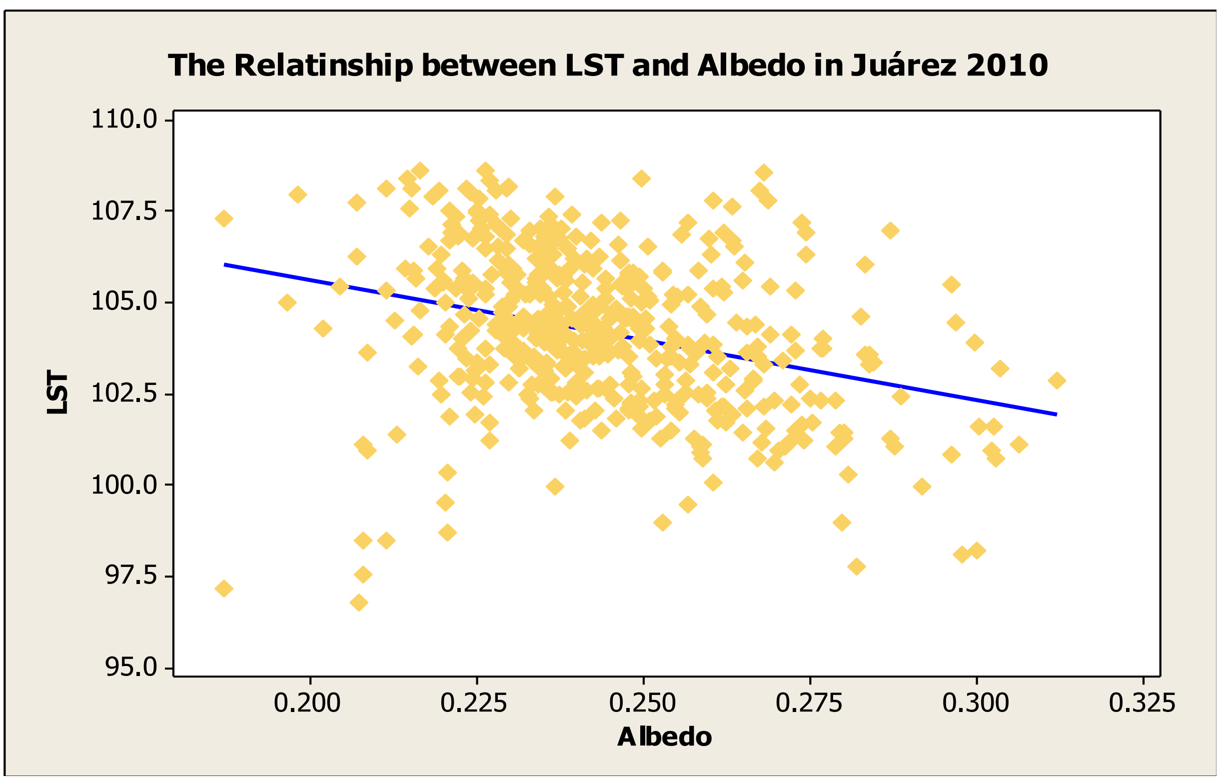


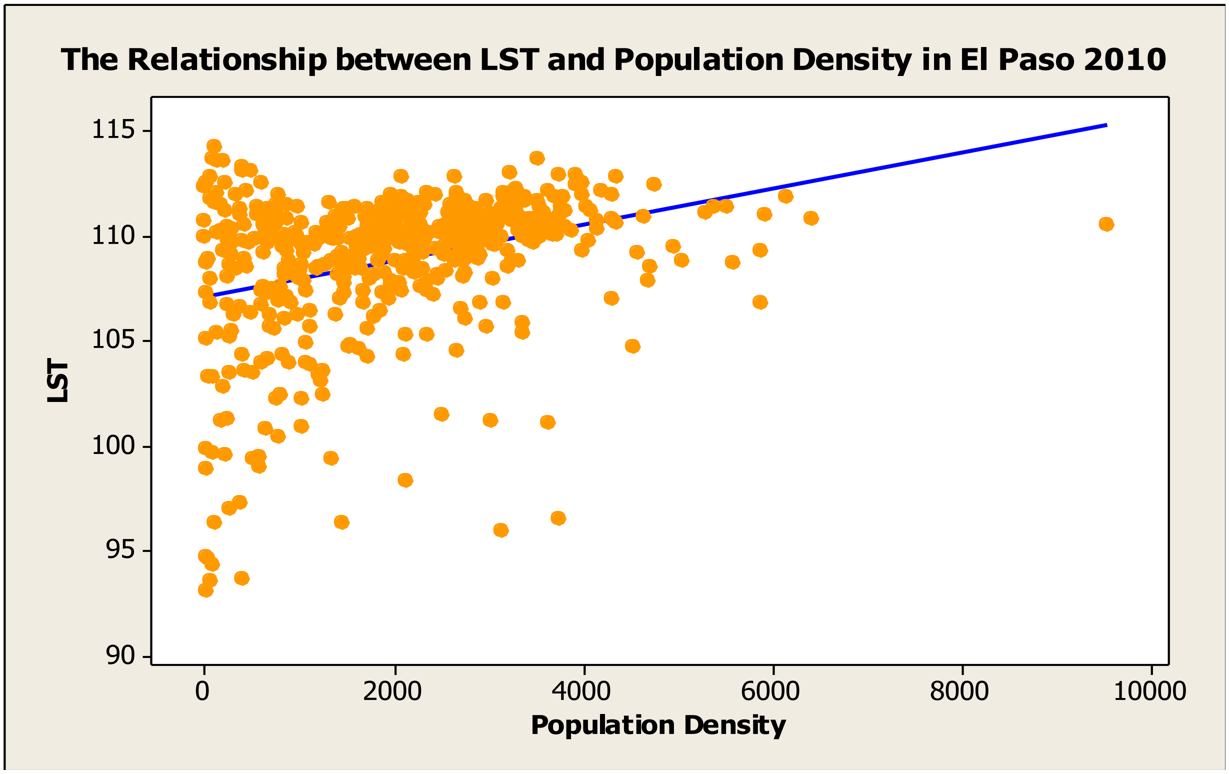


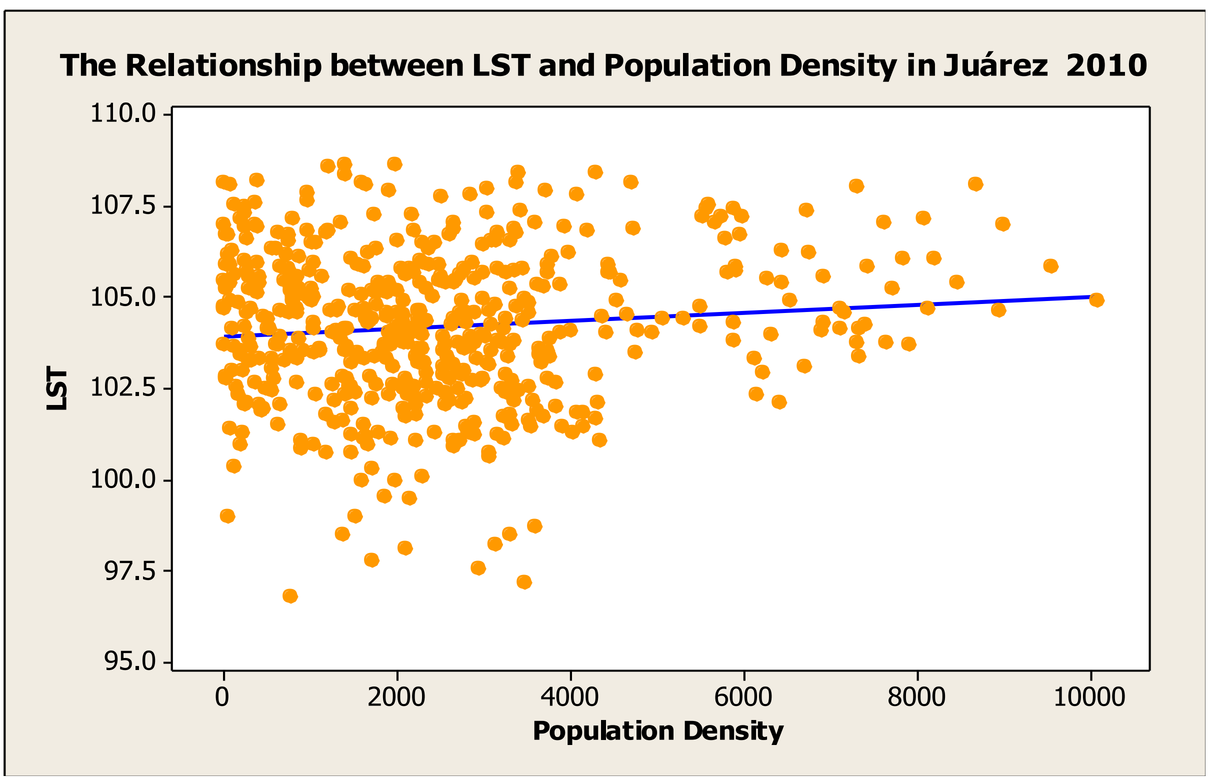

The Relationship between LST ans NDVI in El Paso 2010
LST
NDVI
115
110
105
100
95
90
0.0
0.1
0.2
0.3
0.4
0.5

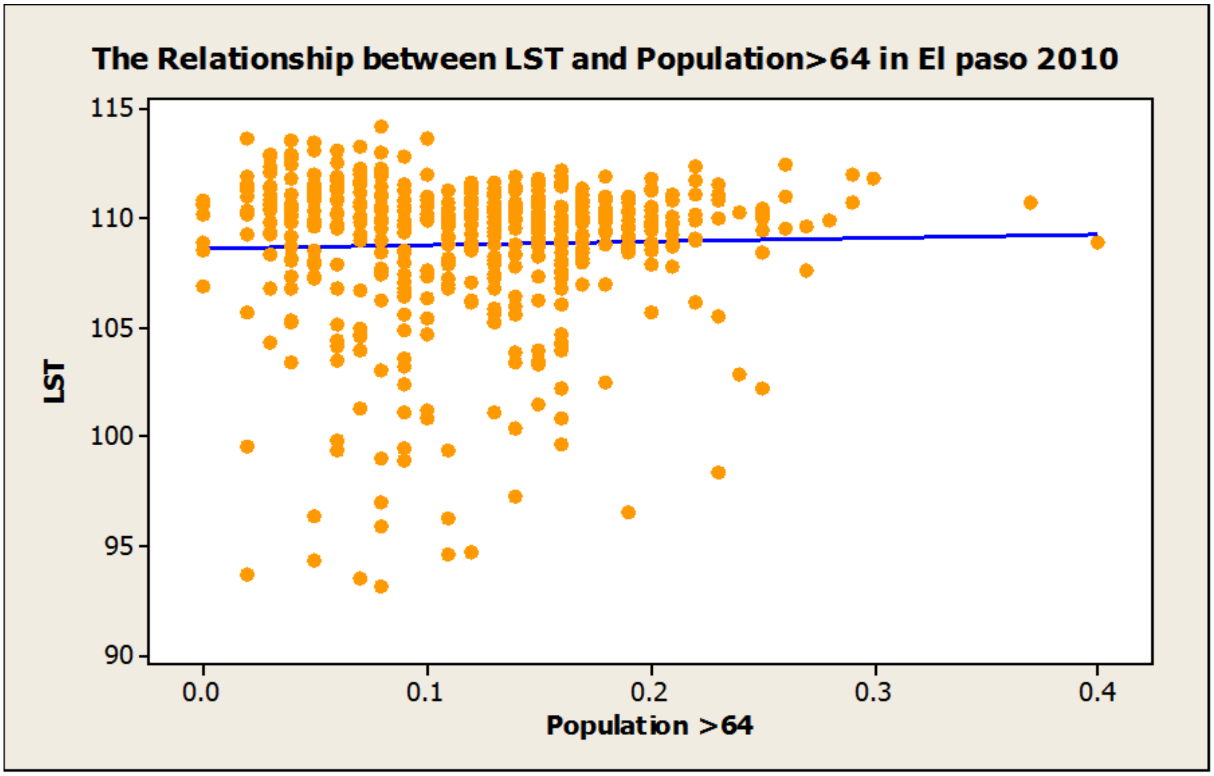

The relationship between LST and NDVI In Juárez 2010
LST
NDVI
110.0
107.5
105.0
102.5
100.0
97.5
95.0
0.0
0.1
0.2
0.3
0.4

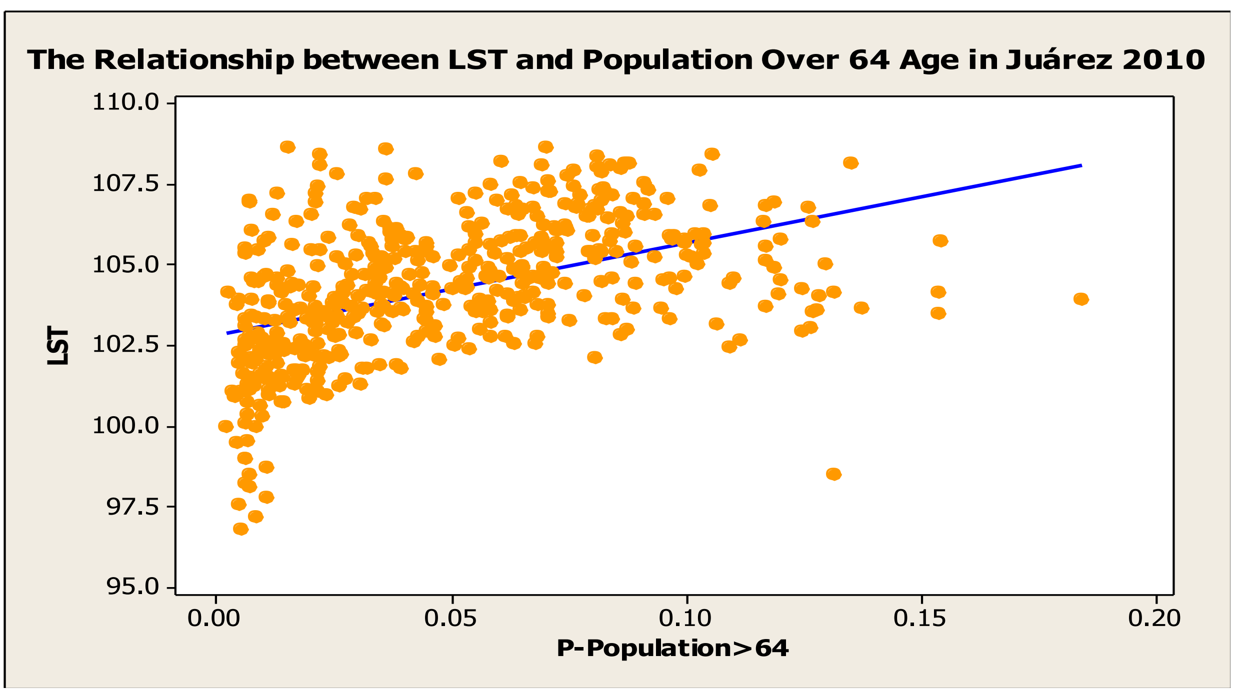

The Relationship between LST and Albedo In El Paso 2010
LST
Albedo
115
110
105
100
95
90
0.16
0.18
0.20
0.22
0.24
0.26

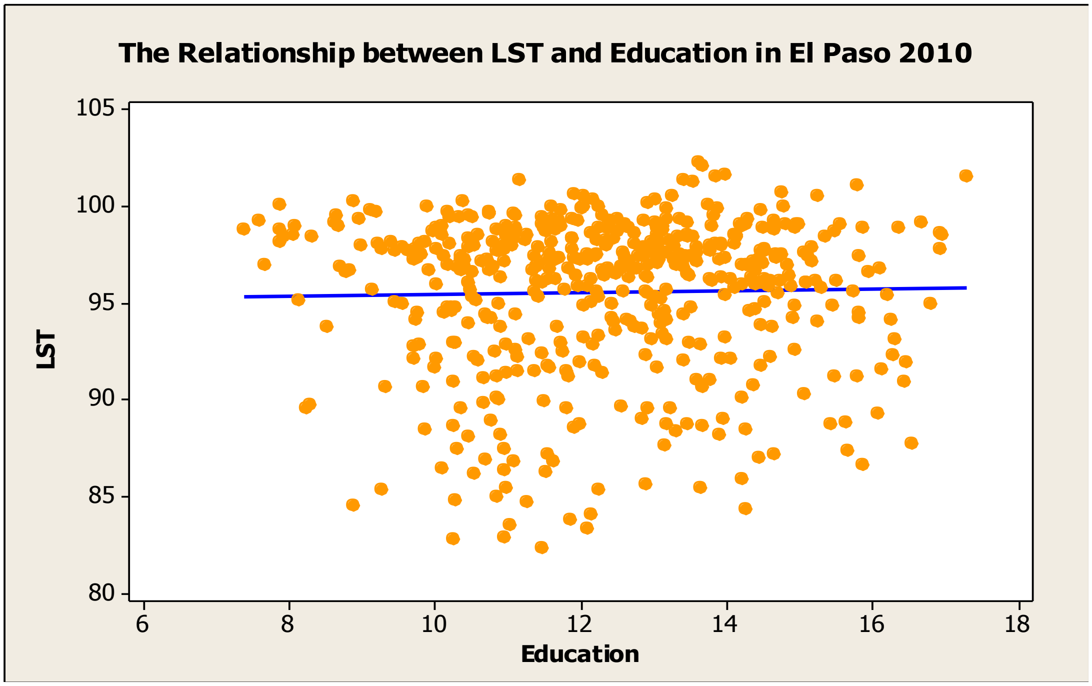

The Relatinship between LST and Albedo in Juárez 2010
LST
Albedo
110.0
107.5
105.0
102.5
100.0
97.5
95.0
0.200
0.225
0.250
0.275
0.300
0.325


The Relationship between LST and Population Density in El Paso 2010
LST
Population Density
115
110
105
100
95
90
0
2000
4000
6000
8000
10000

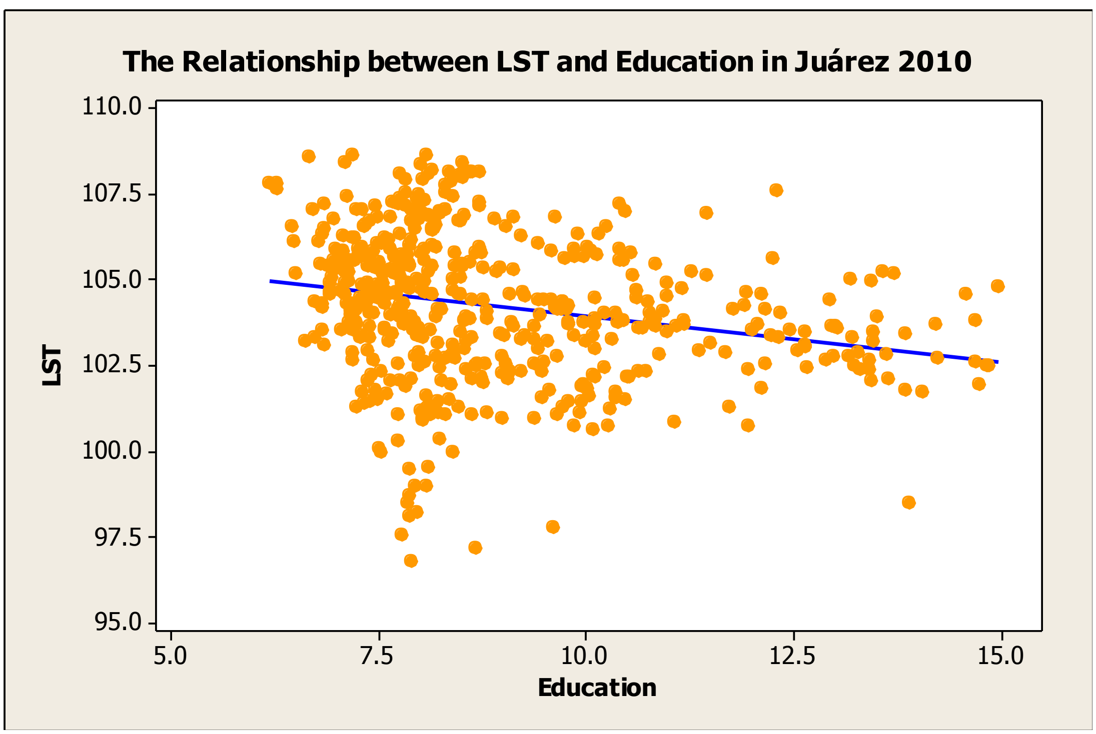

The Relationship between LST and Population Density in Juárez 2010
LST
Population Density
110.0
107.5
105.0
102.5
100.0
97.5
95.0
0
2000
4000
6000
8000
10000


The Relationship between LST and Population>64 in El paso 2010
LST
115
110
105
100
95
90
0.0
0.1
0.2
0.3
0.4
Population >64


The Relationship between LST and Population Over 64 Age in Juárez 2010
LST
110.0
107.5
105.0
102.5
100.0
97.5
95.0
0.00
0.05
0.10
0.15
0.20
P-Population>64



The Relationship between LST and Education in El Paso 2010
LST
Education
105
100
95
90
85
80
6
8
10
12
14
16
18



The Relationship between LST and Education in Juárez 2010
LST
Education
110.0
107.5
105.0
102.5
100.0
97.5
95.0
5.0
7.5
10.0
12.5
15.0

VITA

Faraj Mohamad Aboargob was born in 1964 in Libya and graduated from high school in 1982. He earned his Bachelor of Science degree in Geography from Benghazi University-Libya in 1986. He received his Master of Science degree in Geographical Science in 2003 from The University of Zawia-Libya. His thesis research focused on the spatial distribution of elementary schools in the city of Gharian, Libya.

In 2006 Dr. Aboargob joined the College of Science at the Aljabel Algharbi University in Gharian, Libya, where he worked as an instructor for three years. During this period of time he taught many courses (such as Water & Wastewater Treatment and Solid Waste Management). In addition to teaching, he worked as a Bachelor of Science research supervisor. Faraj Aboargob has been the recipient of numerous honors and awards, including ones from the Libyan Ministry and the University of Tripoli-Libya. Dr. Aboargob earned a scholarship from the Libyan Ministry of Higher Education to pursuedoctoral training in the USA.

In 2010, Dr. Aboargob joined the doctoral program in Environmental Science and Engineering at the University of Texas at El Paso. He has worked as a graduate research assistant as part of a US EPA Southwest Consortium for Environmental Research and Policy (SCERP) funded interdisciplinary research team examining social vulnerability to climate change in El Paso and Ciudad Juárez. As part of that research project, Dr. Aboargob has coauthored two peer-reviewed publications (one book chapter and one journal article). His dissertation, "*Determinants of neighborhood exposure to extreme heat: A spatial examination of El Paso and Juárez, 2010*" was supervised by Dr. Timothy W. Collins. Upon graduation, Dr. Aboargob plans to pursue a career in the United States.

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