Measuring Vulnerability to Extreme Heat in Lubbock, Tx Using A Heat Vulnerability Index

by

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A Thesis

In

Geography

Submitted to the Graduate Faculty
of Texas Tech University in
Partial Fulfillment of
the Requirements for
The Degree of

MASTER OF SCIENCE

Approved

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May 2018

ACKNOWLEDGMENTS

I would first like to thank my thesis committee chair Dr. Jeffrey Lee. Dr. Lee has been available to me at a moment's notice throughout my career at Texas Tech University. He has also been an outstanding mentor, professor, and boss to me. I'm a better man because of him. Furthermore, The Scientific Endeavor by Dr. Lee is a masterpiece that will live on through me, my future children, and many others.

I would also like to thank committee member Dr. Jennifer Vanos for her continued support throughout my thesis research. Dr. Vanos was enthusiastic about my research ideas from day one, giving me the confidence, I needed to complete this research. Dr. Vanos has also been an outstanding mentor for me. Her work on extreme heat continues to be groundbreaking and is the reason I became interested in the topic.

Additionally, professor and committee member, Dr. Zhe Zhu has fascinated me with his remote sensing expertise. After taking his Remote Sensing of the Environment course, I knew he needed to be on my committee. Of course, he was more than willing and has helped me tremendously in understanding the methods and mathematics involved with remote sensing technology. I will forever cherish the opportunity to have studied under such a prestigious person in their field.

To conclude, I would like to give my most sincere thanks to the Geography advisor, Linda Jones, for putting up with myself and several other colleagues. Her job is not easy, and I will never forget what she has done for me, professionally and emotionally. Last but not least, I want to thank my beautiful fiancé and soon to be wife for the continued support and patience throughout my graduate school career.

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ABSTRACT

Extreme heat has a significant impact on human health and is the leading cause of weather-related mortality in the United States. Climate change is expected to increase the intensity and frequency of extreme heat events in the future. For these reasons, it is essential for municipalities to adopt adaptation and mitigation strategies that will decrease human vulnerability to extreme heat. To adopt such strategies, identifying locations of the most vulnerable communities is critical. A significant approach is to create a heat vulnerability index (HVI). The use of an HVI allows for spatiotemporal analysis of vulnerability to extreme heat at finer spatial scales by combining remote sensing technologies with demographic data. To assess census block group vulnerability to extreme heat, a single-date Landsat 5 Thematic Mapper (TM) scene was utilized. The single-date image was to derive land surface temperature (LST) and Normalized Difference Vegetation Index (NDVI) for Lubbock, Texas. Furthermore, demographic data from American Community Survey (ACS) 5-year estimates (2010-2014) were used in this analysis. Thus, the main focus of this analysis aims to identify census block groups (CBGs) disproportionately affected by extreme heat. This study also aims to identify which social (e.g., socioeconomic status, race, education, etc.) and physical variables (e.g., exposure to high LSTs) contribute most to a CBGs vulnerability to extreme heat.

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LIST OF ABBREVIATIONS

ACS. American Community Survey.

CBG. Census Block Group.

EHE. Extreme Heat Event.

EROS. Earth Resources Observation and Science.

ESPA. Earth Science Processing Architecture.

GIS. Geographic Information Systems.

HVI. Heat Vulnerability Index.

LSE. Land Surface Emissivity.

LST. Land Surface Temperature.

NDVI. Normalized Difference Vegetation Index.

NWS. National Weather Service.

PCA. Principal Components Analysis.

RMSE. Root-Mean-Square Error.

SoVI. Social Vulnerability Index.

UHI. Urban Heat Island.

USGS. United States Geological Survey.

CHAPTER I

INTRODUCTION

Extreme heat is the leading cause of weather-related mortality in the United States (National Weather Service, 2016). As average global temperatures continue to rise, the intensity and frequency of extreme heat events (EHE) are expected to increase (Meehl & Tebaldi, 2004; Intergovernmental Panel on Climate Change, 2012). The urban heat island (UHI) effect is of concern, especially in densely populated areas that contain significant amounts of impervious, heat-retaining surfaces and buildings, causing inner city temperature extremes to be significantly higher than in rural areas. As cities expand, vegetation is often replaced with such impervious material, thus providing less shade and moisture that would keep urban areas cooler than otherwise (Jenerette et al., 2007).

Urban microclimates vary across space and time due to differential heating of surfaces, moisture, vegetation, heating and cooling sources, etc. This differential heating may cause some populations to be more vulnerable than others to negative health impacts associated with extreme heat (Harlan et al., 2006). For instance, elderly populations with pre-existing conditions are highly susceptible to heatstroke, which results in core body temperatures exceeding 40°C (104°F), and negatively affects the central nervous system (Glazer, 2005). One of the most common heat-related illnesses is heat exhaustion (internal body temperature between 37°C (98.6°F) and 40°C (104°F)), which is less severe but can progress into heatstroke if not properly treated (Glazer, 2005).

For these reasons and more, the need to map vulnerability patterns at finer spatial scales is essential to reduce preventable illness and death related to extreme heat (Harlan et al., 2006). Identifying populations most vulnerable to extreme heat can aid decision

makers at the municipality level to allocate resources more appropriately to the most vulnerable (Reid et al., 2009). Due to the advancements of remote sensing technology at refined spatiotemporal scales, measures such as land surface temperatures (LST) and Normalized Difference Vegetation Index (NDVI) are emerging as key explanatory variables in the analysis of vulnerability to extreme heat. LST data shows how the surface temperatures within a neighborhood vary, which can lead to varying microclimates whereas, ground measurements (e.g., weather stations) fail to provide data over large spaces (Li et al., 2013). NDVI is a measure of vegetation and is often categorized as an adaptive capacity for dealing with heat (Harlan et al., 2006). It is well known that such land cover characteristics influence microclimates through surface properties and moisture prevalence (Kovach et al., 2015). Limited vegetation in areas with high densities of materials that absorb solar radiation readily (e.g., concrete and asphalt), cause surface temperatures to increase, contributing to vulnerability (Vanos et al., 2016).

When combined with demographic variables (age, sex, income, etc.) the creation of a heat vulnerability index (HVI) can be utilized to identify the most vulnerable populations within a city. By identifying vulnerability patterns at fine-scale census block groups (CBGs), geographies can implement actions to mitigate and adapt to extreme heat. The consideration of social characteristics among specific communities is vital when examining the effects of extreme heat on communities because mortality and morbidity rates related to extreme heat occur disproportionately among the poor, minorities, and the elderly (Harlan et al., 2006), and areas of high income are less sensitive to outdoor temperatures (Kuras et al., 2015).

Cutter et al. (1996) created one of the first iterations of a heat vulnerability assessment, entitled Hazards-of-Place Model of Vulnerability, thus becoming one of the first researchers to identify locations of vulnerability associated with environmental hazards. Cutter et al. (2003) modified their original model and created a Social Vulnerability Index (SoVI), which allowed for spatiotemporal analysis of vulnerability across U.S. counties.

Using an HVI to measure vulnerability to extreme heat in Lubbock, Texas is expanding on the use of SoVI by Cutter et al. (2003). Due to the expected increase in intensity and frequency of EHEs, along with the absence of adequate heat adaptation/mitigation strategies by the City of Lubbock, Texas, the primary aim of this research seeks to identify specific communities disproportionately affected by extreme heat at the census block group (CBG) scale in Lubbock. Additionally, this research identifies which physical and social predictors contribute most to a community's vulnerability to extreme heat.

To assess how specific CBGs within the city limits of Lubbock are vulnerable EHEs, this analysis derives LSTs and NDVI using Landsat 5 TM imagery from a single-date image during June of 2011. Furthermore, a combination of demographic data from American Community Survey 5-year estimates and a geographic information systems (GIS) were utilized to identify any spatial patterns in vulnerability to extreme heat Lubbock city limits. Producing an extreme heat vulnerability map can provide the City of Lubbock with an adequate tool to allocate resources effectively during future EHEs, contributing to great resiliency within Lubbock communities.

CHAPTER II

BACKGROUND OF LUBBOCK, TEXAS

Lubbock, Texas is located in the region commonly known as the South Plains. Lubbock has a semi-arid climate with an average annual temperature of approximately 16°C (60°F) and receives on average 457 millimeters (18 inches) of precipitation annually (NCDC, 2017). Average summer temperatures approach 27°C (80°F), but average daily maximum temperatures are nearly 33°C (92°F) (NCDC, 2017). Lubbock's hottest summer occurred in 2011 when a record forty-eight 100°F days were recorded (National Weather Service, 2011). Additionally, temperatures reached at least 32°C (90°F) a total of 131 times in 2011, breaking the previous record (1956) of 122 times in a single year (National Weather Service, 2011). During August of 2011, Lubbock experienced nine consecutive days with temperatures exceeding 38°C (100°F) (National Weather Service, 2011).

In Lubbock, one of the few mitigation strategies to extreme heat is the use of heat health warning systems, administered by the National Weather Service (NWS). Heat Advisories are issued when temperatures are expected to increase past 38°C (100°F) within the next 12 hours and stay above 24°C (75°F) during nighttime hours. Excessive Heat Watches are issued when an EHE is expected within the next 24 to 72 hours. For Lubbock, this would mean temperatures could reach up to 41°C (105°F). An Excessive Heat Warning will be issued when temperatures could reach up to 43°C 110°F in Lubbock. In general, these warning systems may benefit residents in the region, but there is a lack of geographical and spatial awareness of microclimates at the city scale (Wolf & McGregor, 2013).

The mean population size for each CBG in Lubbock's city limits is approximately 1,435 with a minimum of 517 and a maximum of 4,942 (**Table 2.1**). For this study, a minority is defined as anyone who identifies as African American, Hispanic or Latino, or other. In this case, it is assumed that people who identify as having two or more races or as other represent a significant portion of the Latino or Hispanic population, due to neither one of these races being provided as a choice on the 2010-2014 ACS 5-year estimates. Therefore, the original variables 'two or more races' and 'other' were combined to create the Hispanic or Latino category in Table 1. Additionally, the original variables 'Native American', 'Asian', and 'Native Hawaiian' were combined to create the Other category in Table 1. It should be noted that Lubbock contains a total of 186 CBGs within its city limits, but two of them have a total population of zero. Therefore, only 184 CBGs were used in this analysis.

In the 1920s, the City of Lubbock implemented an ordinance that prevented people of color from living in specific areas in the city. This resulted in a significant amount of minority populations residing on the east side of the city, where many industrial complexes exist. In this area of Lubbock, fewer trees are found to be present (Sorrensen et al., 2015), reducing the area's adaptive capacity to extreme heat. Though segregation in the region has decreased significantly, many minority populations still live on the east side of Lubbock, which may contribute to the area's vulnerability to extreme heat due to fewer resources to cope.

Furthermore, 22 of the 184 CBGs included in this study, have at least 500 residents who are living without health insurance. Few studies on extreme heat vulnerability use the lack of health insurance as a variable in this context. Additionally,

Harlan et al., 2013 found that being 65 years or older, significantly contributed to one's vulnerability to extreme heat. In this analysis (**Table 2.2**), the total population of elderly (65 or older) with and without health insurance are considered, along with the total population of elderly who are living along, another factor showing strong correlations with extreme heat vulnerability.

Because of this, it is vital to identify vulnerability patterns across the city, so that resources can be allocated appropriately by the City of Lubbock during extreme heat events.

Table 2.1 Summary statistics of census block group race populations, average income, and below poverty populations in Lubbock, TX (mean, standard deviation, minimum, and maximum). Statistics computed in Stata/IC 15.1 using American Community Survey 5-year estimates (2010-2014).

Variable	Mean	Std. Dev.	Min.	Max.
Total Population	1,435.82	746.36	517	4,942
White	1,127.86	671.74	44	4,177
African American	107.9	152.97	0	1,063
Hispanic or Latino*	204.73	191.72	0	1,029
Other	39.7	63.75	0	378
Income	24,549.65	16,702.97	2,813	144,071
Below Poverty	45.09	46.13	0	249

Table 2.2 Summary statistics of census block group young/elderly populations and health insurance characteristics in Lubbock, TX (mean, standard deviation, minimum, and maximum). Statistics computed in Stata/IC 15.1 using American Community Survey 5-year estimates (2010-2014).

Variable	Mean	Std. Dev.	Min.	Max.
No Health Insurance	261.36	177.79	0	876
Health Insurance	1,151.92	668.93	297	4,626
> 65 No Health Insurance	.81	4.58	0	42
> 65 Health Insurance	152.33	105.41	0	571
> 65 Living Alone	45.65	46. 5	0	336
< 5	103.51	98.98	0	649

CHAPTER III

LITERATURE REVIEW

A significant amount of research focused on vulnerability to extreme heat is modeled after the design of Cutter et al. (2003), specifically HVIs. Reid et al. (2009) created an HVI for the entire U.S. at the census tract scale. In this study, researchers divided variables into four categories: social/environmental vulnerability, social isolation, the prevalence of no air conditioning, and proportion of elderly/diabetes. The study found that living below the poverty line, having no high school diploma, and no central air conditioning in the household correlated most to a person's socioeconomic vulnerability to extreme heat (Reid et al., 2009). Because they show correlations with extreme heat vulnerability, education levels were included in this analysis (**Table 3.1**).

Furthermore, using satellite imagery, specifically Landsat data, to analyze vulnerability to extreme heat has become popular within the body of research on the topic. This methodological approach utilizes LST calculations using thermal bands within Landsat imagery. Harlan et al. (2006) completed a hallmark study on vulnerability to heat that examined inequalities related to negative impacts on human health in eight neighborhoods in Phoenix, Arizona. The study found that neighborhoods with lower median incomes experienced higher temperatures during the study period than neighborhoods with higher median incomes (Harlan et al., 2006). Harlan et al. (2013) used NDVI and LST combined with various demographic variables to assess extreme heat vulnerability at the CBG scale in Maricopa County, Arizona. In their study, being a minority or an immigrant negatively affected ones socioeconomic vulnerability to extreme heat (Harlan et al., 2013).

Table 3.1 Summary statistics of census block group education characteristics in Lubbock, TX (mean, standard deviation, minimum, and maximum). Statistics computed in Stata/IC 15.1 using American Community Survey 5-year estimates (2010-2014).

Variable	Mean	Std. Dev.	Min.	Max.
No School	12.67	19.84	0	112
High School	209.96	125.66	0	622
College	201.78	196.09	0	1,124
Graduate School	72.16	77.80	0	458

Jenerette et al. (2011) and Jenerette et al. (2015) also utilized remote sensing data and demographic characteristics in their analysis of extreme heat vulnerability. Jenerette et al. (2011) found that higher levels of median income are directly related to greater values of NDVI (higher amounts of vegetation) and cooler temperatures in Phoenix, Arizona (Jenerette et al., 2011). Similarly, Jenerette et al. (2015) found that neighborhoods with higher percentages of residents living below the poverty line had lower values of NDVI.

Wolf & McGregor (2013) created an HVI for London, United Kingdom by separating heat exposure and sensitivity into categories. HVI values were assigned to census districts in Greater London, where the vulnerability was found to be highest in the city's urban core. Newer studies (Inostroza et al., 2016; Weber et al., 2015) have segregated predictor variables by exposure, sensitivity, and adaptive capacity. Weber et al. (2015) used LST, and temperature data from weather stations in Philadelphia and both were placed in the 'exposure' category. Sensitivity to heat was calculated using demographic variables related to income, age, living alone, etc., along with NDVI being

considered as adaptive capacity. Cutter et al. (2013); Harlan et al. (2013); Inostroza et al. (2016); Johnson et al. (2012); Reid et al. (2009); and Wolf & McGregor (2013) all performed principal components analyses when deriving HVI values, essentially separating variables into specific categories and allowing for overall vulnerability to be analyzed over spatial and temporal scales. Principal components analysis (PCA) is a form of multivariate regression analysis that allows researchers to derive a variance for each variable regarding vulnerability measures (e.g., LST, NDVI, age, education, etc.).

This research takes an approach similar to Inostroza et al. (2016) and Weber et al. (2015), separating exposure, sensitivity, and adaptive capacity. Also, utilizing remote sensing technologies combined with demographic data allows for spatiotemporal analysis of exposure, sensitivity, and adaptive capacity at the CBG scale. For this research, I will take approaches similar to the literature presented here, with the goal of answering the following research questions:

1. Are specific census block groups more vulnerable than others to extreme heat in Lubbock, Texas?
2. What physical and/or social predictors contribute most to a census block groups vulnerability?
3. Will census block groups with high percentages of poverty have less of adaptive capacity and higher exposure to extreme heat than census block groups with low percentages of poverty?

CHAPTER IV

DATA & METHODS

For this study, a single-date Landsat 5 Thematic Mapper (TM) image was collected via the Science Processing Architecture (ESPA) On Demand Interface as part of the United States Geological Survey (USGS) Earth Resources Observation and Science Center (EROS). The Landsat image covers the Lubbock area (WRS Path = 30, WRS Row = 37) and was collected on June 28, 2011 around 5:00 pm central time. Although the air temperature was approximately 32°C (90°F) at the time of the Landsat scene collection, this particular scene is of interest due to the extreme temperatures recorded in the five previous days (all over 100°F). Because Landsat satellites complete coverage of the Earth every 16 days, scenes were not available for the five previous days. Therefore, it is assumed that the thermal characteristics of the study area are proportional to the extreme temperatures recorded in the five days before June 28, 2011.

Before processing, the single-date image was inserted into ArcMap 10.6.1 (Geographic Information Systems software) and clipped to a Lubbock city limits shapefile, acquired from the City of Lubbock GIS & Data Services Department. The clip was performed utilizing the Clip (Data Management) Tool within ArcMap. This allowed for the computation of statistics for only the study area within ENVI 5.4, a remote sensing software package. The processed NDVI image from ESPA contains raw digital numbers that were multiplied by a scale factor of .0001 within ENVI to derive NDVI values between -1 and 1 (USGS, 2017). ESPA uses the following equation to compute NDVI:

$$(NIR - Red) / (NIR + Red) \text{ or } (B4 - B3) / (B4 + B3) \quad (1)$$

where ***NIR*** = Landsat 5 TM near-infrared band (4) and ***Red*** = Landsat 5 TM red band (3).

Additionally, LST was calculated using the at-satellite brightness temperature band (band 6), processed by ESPA using the following equation:

$$T_B = K_2 / \ln (K_1/L_\lambda + 1) \quad (2)$$

where K_2 = the calibration constant in Kelvin (***1260.56***), K_1 = the calibration constant (***Watts/(m²*sr*μm)***) (***607.76***) and, L_λ = spectral radiance in (***Watts/(m²*sr*μm)***). This processed image from ESPA also contains raw digital numbers that were be multiplied by a scale factor of 0.1 within ENVI, resulting in at-satellite brightness temperature in Kelvin (USGS, 2018). To convert to degrees Celsius, the brightness temperature in Kelvin is subtracted by 273.15. There are several ways to compute LST, but for the purposes of this study, the method proposed by Giannini et al., 2015 was adopted due to its simplicity along with a low Root Mean Square Error (RMSE) compared to other methods (Giannini et al., 2015). The RMSE is an indicator of the accuracy of the remote sensing analysis.

Accurately calculating LST requires the consideration of land surface emissivity (LSE), which is "a measure of the inherent efficiency of the surface in transforming the energy accumulated into radiant energy" (Oltra-Carrió et al., 2012). In this study, emissivity, ε, was calculated based on NDVI with the following equation was used by Giannini et al., 2015:

$$\varepsilon = a + b * \ln(NDVI) \quad (3)$$

where, a = 1.0094, b = 0.047 and $\ln(NDVI)$ = the natural logarithm of NDVI. Next, Plank's law is adopted to compute LSTs with the following equation:

$$LST = \frac{T_B}{1 + \left(\frac{\lambda \cdot T_B}{\rho} \right) \cdot \ln(\varepsilon)} \tag{4}$$

where, $\boldsymbol{T_B}$ = brightness temperature, $\boldsymbol{\lambda}$ = central band wavelength of emitted radiance (11.45 μm), $\boldsymbol{\varepsilon}$ = emissivity, $\boldsymbol{\rho} = h*c/\sigma$ ($1.438*10^{-2}$ $m*K$), $\boldsymbol{h}$ = Planck's constant ($6.626*10^{-34}$ $J*s$), $\boldsymbol{c}$ = light velocity ($2.998*10^{8}$ m/s) and, $\boldsymbol{\sigma}$ = Boltzmann constant (1.3810^{-23} J/K).

Once LSTs were derived, the images were converted into the proper file format (GeoTIFF) for compatibility with GIS (ArcMap 10.6.1). To allow for the computation of a minimum, maximum, mean, and standard deviation LST value for all 184 CBGs, Zonal Statistics, an extension of the Spatial Analyst Tool in ArcMap was utilized. This same process was repeated for NDVI values for all 184 CBGs. LST values for all CBGs in this analysis were converted to z-scores

Demographic data were obtained from 2010-2014 American Community Survey 5-Year Estimates via the U.S. Census Bureau's American FactFinder. For this study, several demographic variables were of focus. For instance, socioeconomic status, race, age, and access to healthcare were included in this analysis. Specific demographic characteristics are known to contribute to a person's vulnerability to environmental hazards (Cutter et al., 2003). For instance, people who are 65 and older often have pre-existing health conditions, which, during EHEs, can cause significant damage to organs and increase one's risk of heat stroke (Anderson et al., 2009; Glazer, 2005; Johnson et al., 2012). Additionally, neighborhoods with lower income levels have been found to have higher morbidity and mortality rates during EHEs (Johnson et al., 2012). These data were integrated into a dataset with the LST and NDVI values and separated by exposure,

sensitivity, and adaptive capacity (**Table 4.1**). The dataset was then inserted into ArcMap to visualize any relationship between demographic variables and exposure to high LSTs.

This dataset was also utilized within the statistical software package Stata/IC 15.1 to perform principal components analysis (PCA). The advantage of using PCA is that the analysis does not allow an error-term and all of the variance is used. Also, if latent variables are found, the analysis can be simplified into factor loadings, increasing parsimony and decreasing multi-collinearity. The PCA produces eigenvalues that represent the variances of all variables, allowing for orthogonal rotation of the data, making the variables more interpretable and easier to label. Before performing the PCA, variables were converted to z-scores in Stata, giving all variables a mean of zero and a standard deviation of one. PCA was only performed on sensitivity and adaptive capacity variables, due to the exposure category only containing one variable (LST). The PCA produces an un-rotated factor loading matrix, where only factors surpassing the Kaiser criteria (eigenvalues greater than one) are retained. After retaining *n* PC scores, they are summed using the rotated factor loading matrix. Z-scores were then generated for all 184 CBGs using the sum of *n* PC scores. Next, results for exposure, sensitivity and adaptive capacity were normalized to a scale of zero to one using the following equation:

$$\beta = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad \textbf{(5)}$$

where β = the normalized value, x = the original value, and x_{min} and x_{max} are the minimum and maximum values. After normalization of all variables, we applied an equation from Inostroza et al., (2016) to receive a final vulnerability score for all 184 CBGs in the analysis. The equation is as follows:

$$\boldsymbol{V}_x = E_x + S_x - A_x \quad \textbf{(6)}$$

where V_x is the vulnerability level in census block x, E_x is the exposure level in census block x, S_x is the sensitivity level in census block x, and A_x is the adaptive capacity of census block x.

Table 4.1 All physical and social variables used in this analysis. Variables separated by Exposure, Adaptive Capacity, and Sensitivity.

Exposure
Land Surface Temp.

Adaptive Capacity
NDVI
Health Insurance
No Health Insurance

Sensitivity
Total Population
65 Years or Older
5 Years or Younger
65 w/ Health Insurance
65 w/o Health Insurance
65 and Living Alone
White
African American
Hispanic or Latino*
Other
No School
High School or GED
College
Graduate School
Income
Below Poverty
Above Poverty
Public Transportation
Self-Transportation

CHAPTER V

RESULTS

Figure 5.1 is the result of the LST calculation within the city limits of Lubbock for June 28, 2011. Again, it is assumed that the thermal characteristics of the city are similar to the days leading up to June 28, when air temperatures exceeded 100°F five consecutive days (National Weather Service, 2011).

Low LST values are symbolized by yellow and orange colors, whereas high LST values are dark orange and red. By observing this image, we can see that small portions of the city experience low LST values. The mean LST for all CBGs in the analysis was approximately 39.13°C (102.4°F) (**Table 5.1**). Approximately 18% of CBGs in Lubbock experienced mean LSTs above 40°C (104°F). Also, all CBGs were exposed to an LST maximum of at least 38°C (100°F). Additionally, a significant number of CBGs south of Loop 289, specifically the Lakeridge Country Club community (82nd to 98th Street between Slide & Quaker Ave.), experience some of the lowest mean LST values throughout the city. Interestingly, the income in these CBGs tends to be higher than CBGs with higher mean LST values. A similar correlation exists between mean NDVI values and income.

High NDVI values (high levels of vegetation) are symbolized by green colors, whereas low NDVI values are represented by tan and brown (**Figure 5.2**). As we can see, the higher NDVI values are mainly restricted to residential areas in the city's center and south of Loop 289. Mean NDVI for all CBGs in the analysis was approximately .22 (**Table 5.1**).

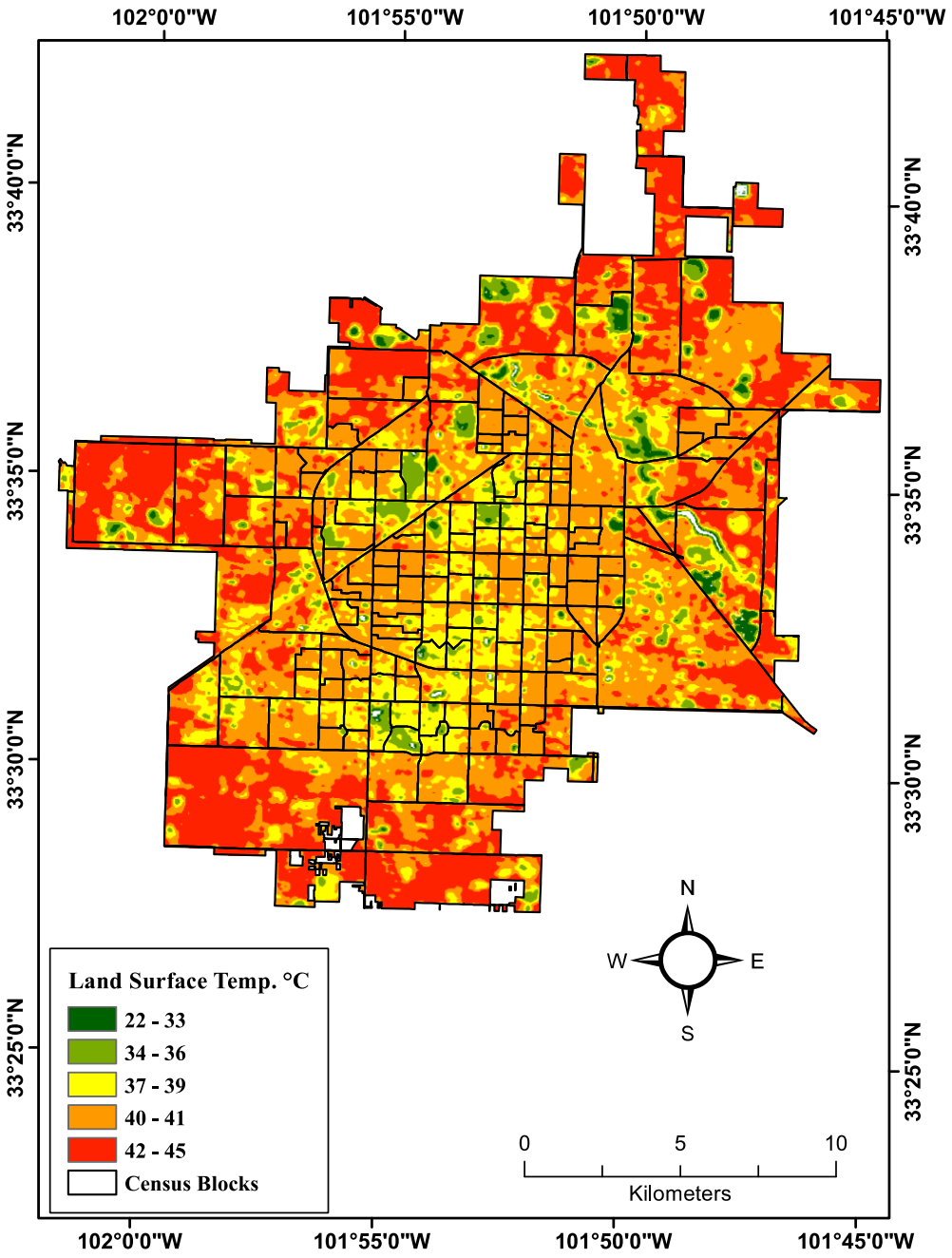

Figure 5.1 Land Surface Temperature (LST) for Lubbock, TX. LST was calculated based on satellite imagery (Eq. 2, 3, & 4) taken from NASA Landsat Program, 2011, Landsat TM, scene LT50300372011179PAC01, USGS, Sioux Falls.

Table 5.1 Summary statistics of census block group LST and NDVI in Lubbock, TX (mean, standard deviation, minimum, and maximum).

Variable	Mean	Std. Dev.	Min.	Max.
LST_{min}	34.9	3.39	21.95	40.65
LST_{max}	41.61	1.39	38.35	45.14
LST Mean	39.13	1.05	35.76	41.41
$NDVI_{min}$	N/A	N/A	N/A	N/A
$NDVI_{max}$	N/A	N/A	N/A	N/A
NDVI Mean	0.22	0.04	0.11	0.38

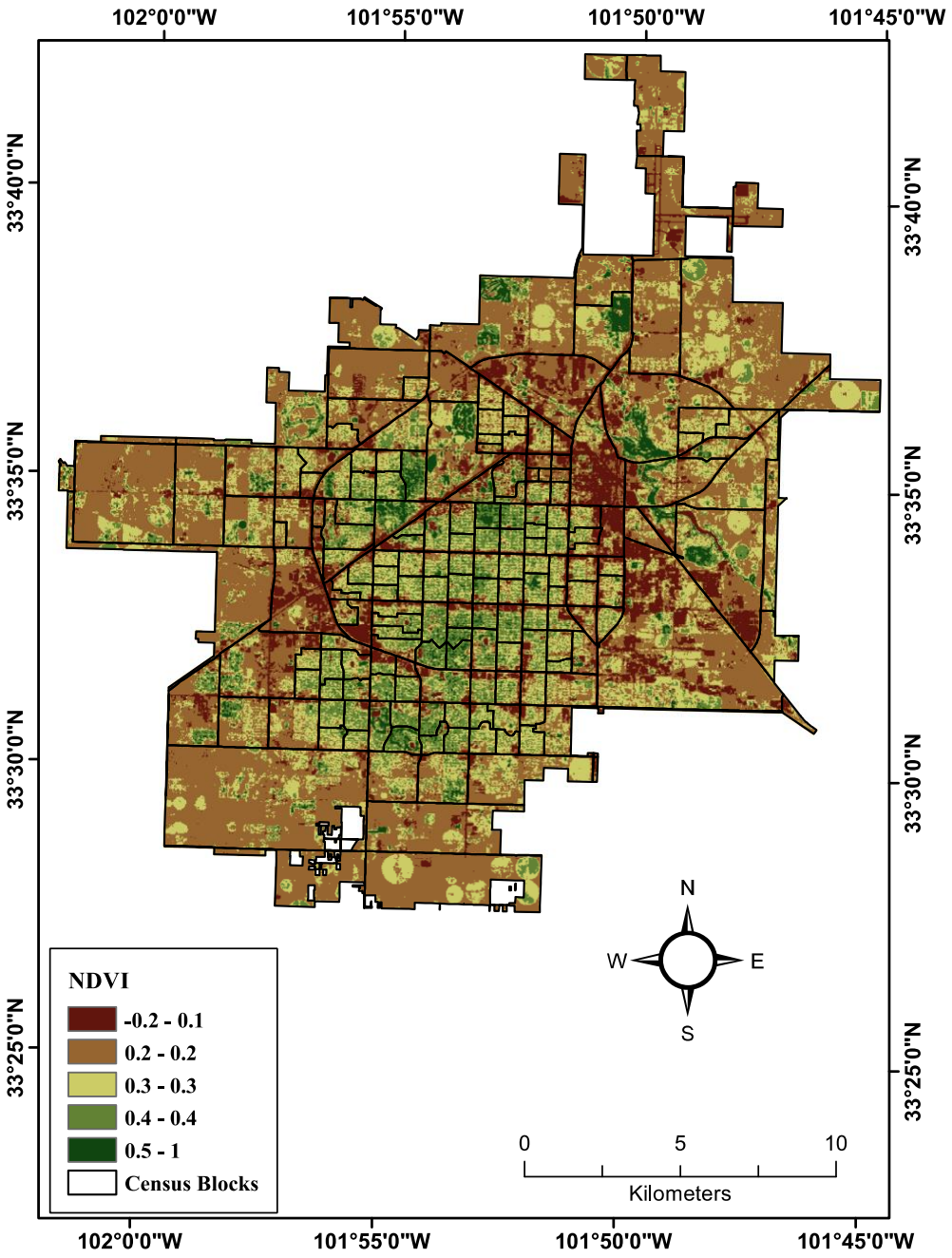

Figure 5.2 Normalized Difference Vegetation Index (NDVI) for Lubbock, TX. NDVI was calculated based on satellite imagery (Eq. 1) taken from NASA Landsat Program, 2011, Landsat TM, scene LT50300372011179PAC01, USGS, Sioux Falls.

Figures 5.3 & 5.4 compare the LST and NDVI for a specific cluster of CBGs in the Lakeridge Country Club community. These CBGs experienced some of the lowest LSTs, the highest abundance of vegetation, along with an average annual income of well above the poverty line. In fact, the CBG directly in the middle of the Country Club (**Figure 5.3**) has an average annual income of $144,071, the highest in the city of Lubbock. Furthermore, of the 745 residents in this CBG, over 98% identify as White, and the remainder of the residents identify as Asian. The combination of this CBG's environmental and social characteristics, likely makes these residents the least vulnerable CBG to extreme heat (not confirmed).

Figures 5.5 & 5.6 compare LST and NDVI in a specific cluster CBGs in Northwest Lubbock that experienced some of the highest LSTs in the study. Previously, it was mentioned that the CBG in Lakeridge Country Club with some of the lowest LSTs has an average annual income of approximately $144,071, yet the CBG in Northwest Lubbock (top CBG in **Figures 5.5 & 5.6**) that experienced some of the highest LSTs, has an average income of approximately $20,379. Additionally, 28% of this CBG's population identifies as a minority, while 72% identify as White. Lastly, approximately 20% of the residents have no form of health insurance. Consequently, the CBG in Northwest Lubbock has very low abundance of vegetation. **Figure 5.7** depicts imagery of the area via the National Agriculture Imagery Program (NAIP) in 2014. The imagery shows various residential areas, where vegetation is sparse, especially in the surrounding patches of barren land. Clearly these two CBGs experience very different levels of exposure to LSTs along with varying levels of income and demographic characteristics. Therefore, we can expect the levels of sensitivity and adaptive capacity to be very

different, creating varying vulnerability levels, as will be concluded at the end of this analysis.

Bivariate regressions between the dependent variable (Mean LST) and several independent variables show significant relationships. For instance, LST has an inverse relationship with NDVI (**Figure 5.8**). Thus, surface temperatures tend to be higher where vegetation is limited. This model explains approximately 46% of the variance in the dependent variable (LST) and is statistically significant. Similarly, LST has an inverse relationship with income (**Figure 5.9**), meaning higher surface temperatures are correlated with lower levels of income (22% of variance explained). For instance, in Lubbock, people who make at least $60,000 annually, experience LSTs under 40°C (104°F). Despite this, several observations were recorded were mean income is below $20,000 and LSTs were under 40°C (104°F). As expected, NDVI and income have a positive relationship (**Figure 5.10**). Thus, as abundance of vegetation increases in CBGs, so does income (26% of variance explained).

Furthermore, being young (<5) or elderly (>65) has been known to be a predictor of vulnerability to high LSTs, but in this analysis, being 65 or older did not know a strong relationship with higher LST values (**Figure 5.11**). The same is true for people 65 or older and are living alone. Despite this, being five years of age or younger showed a positive relationship with LST (**Figure 5.12**). Thus, CBGs with higher numbers of residents five years of age or younger, tend to be more exposed to higher surface temperatures. This bivariate regression explains approximately 12% of the dependent variable and is statistically significant.

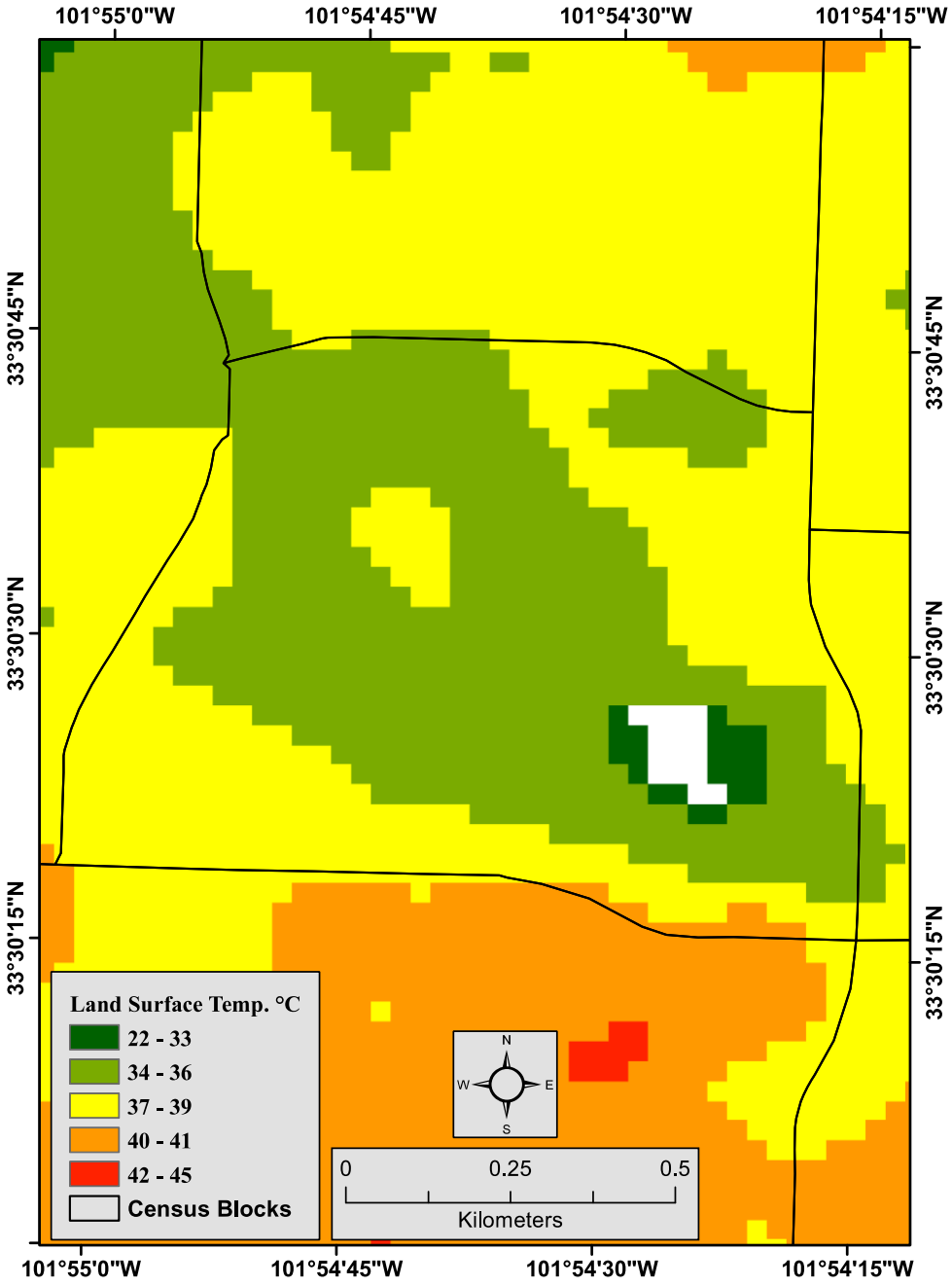

Figure 5.3 Cluster of CBGs in Lakeridge Country Club area that experienced some of the lowest LSTs in Lubbock, TX.

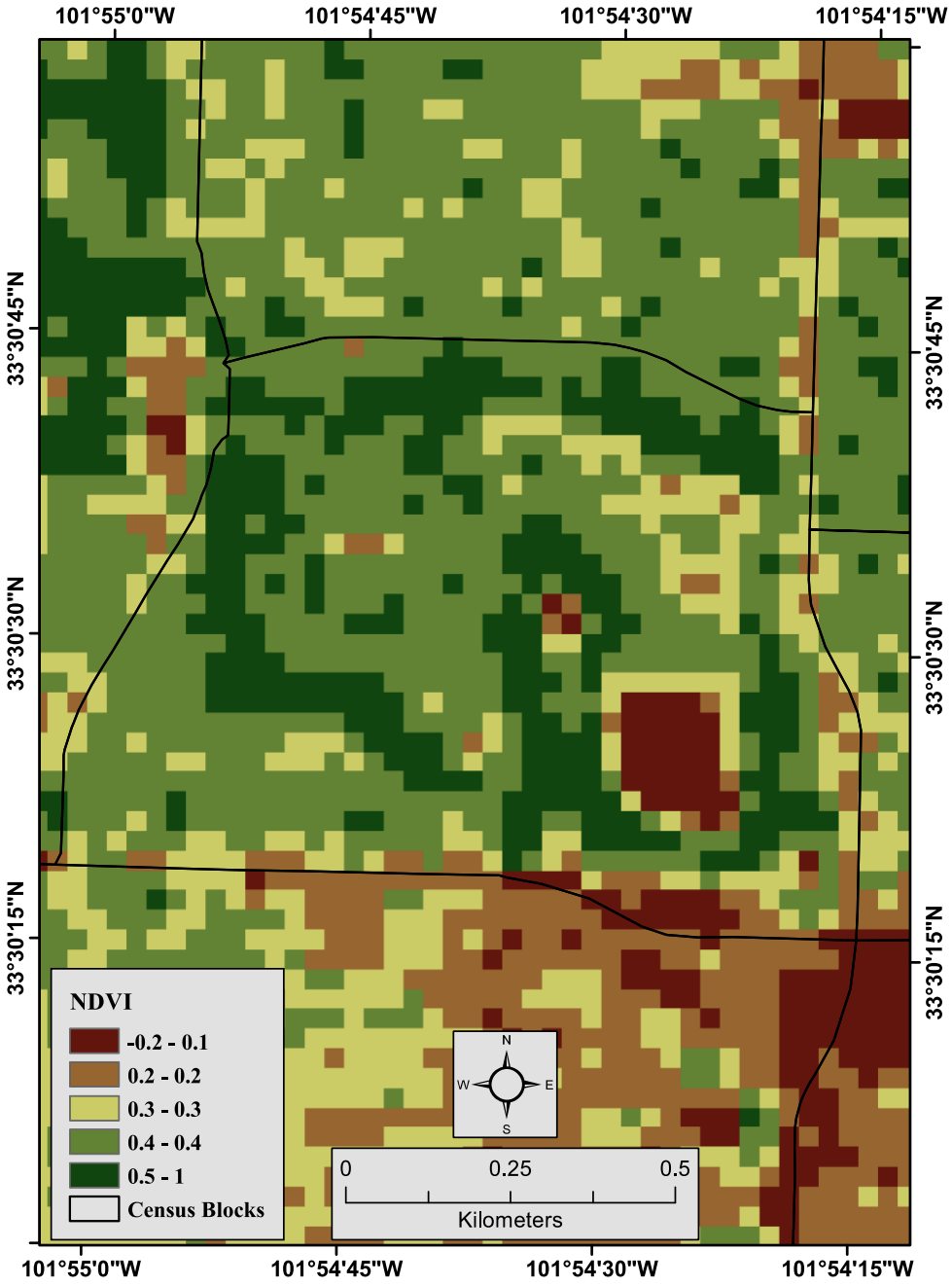

Figure 5.4 Cluster of CBGs in Lakeridge Country Club area that experienced some of the highest NDVI values in Lubbock, TX.

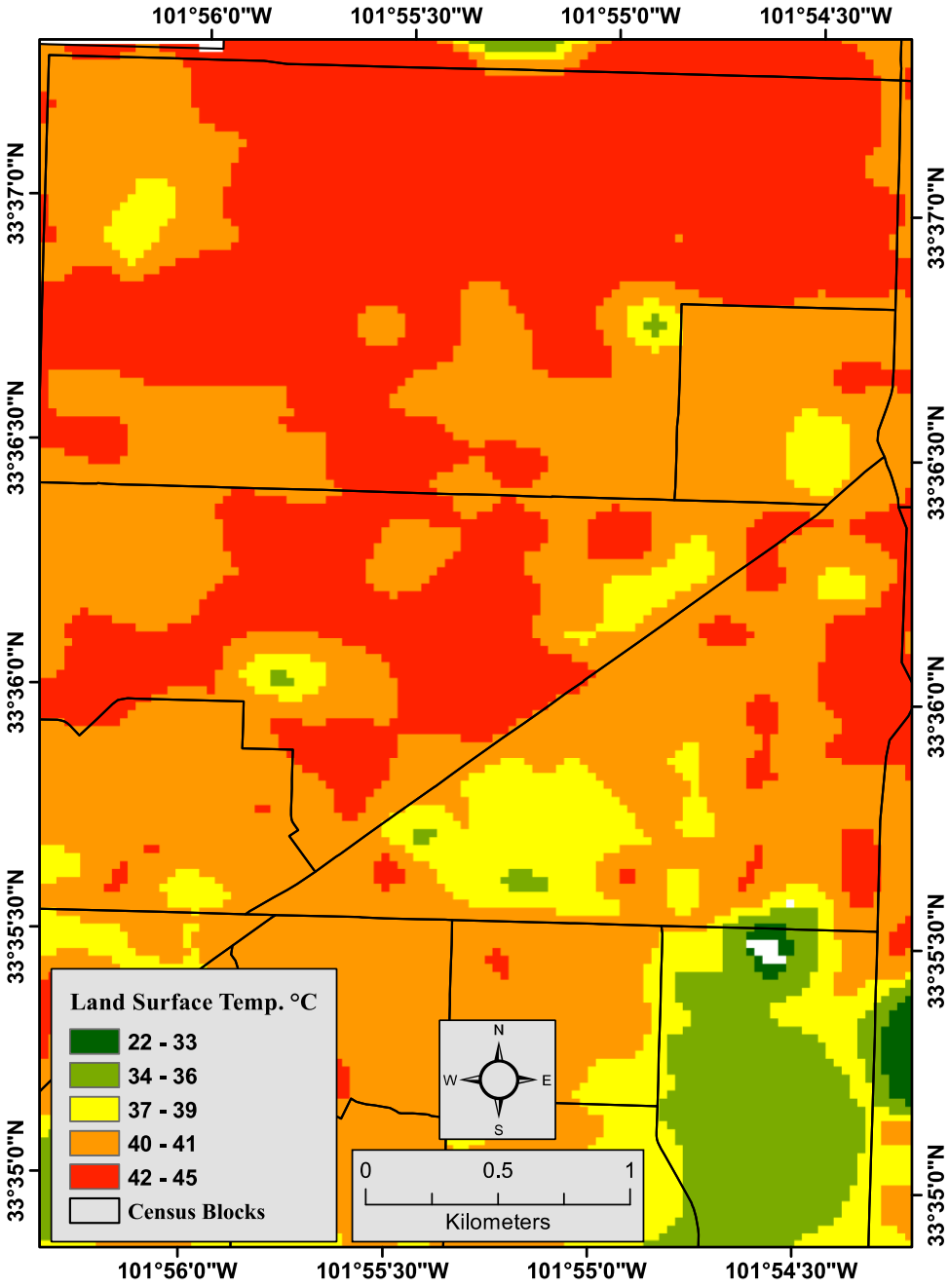

Figure 5.5 Cluster of CBGs in Northwest Lubbock area (N. Slide Rd & Erskine St) that experienced some of the highest LSTs in Lubbock, TX.

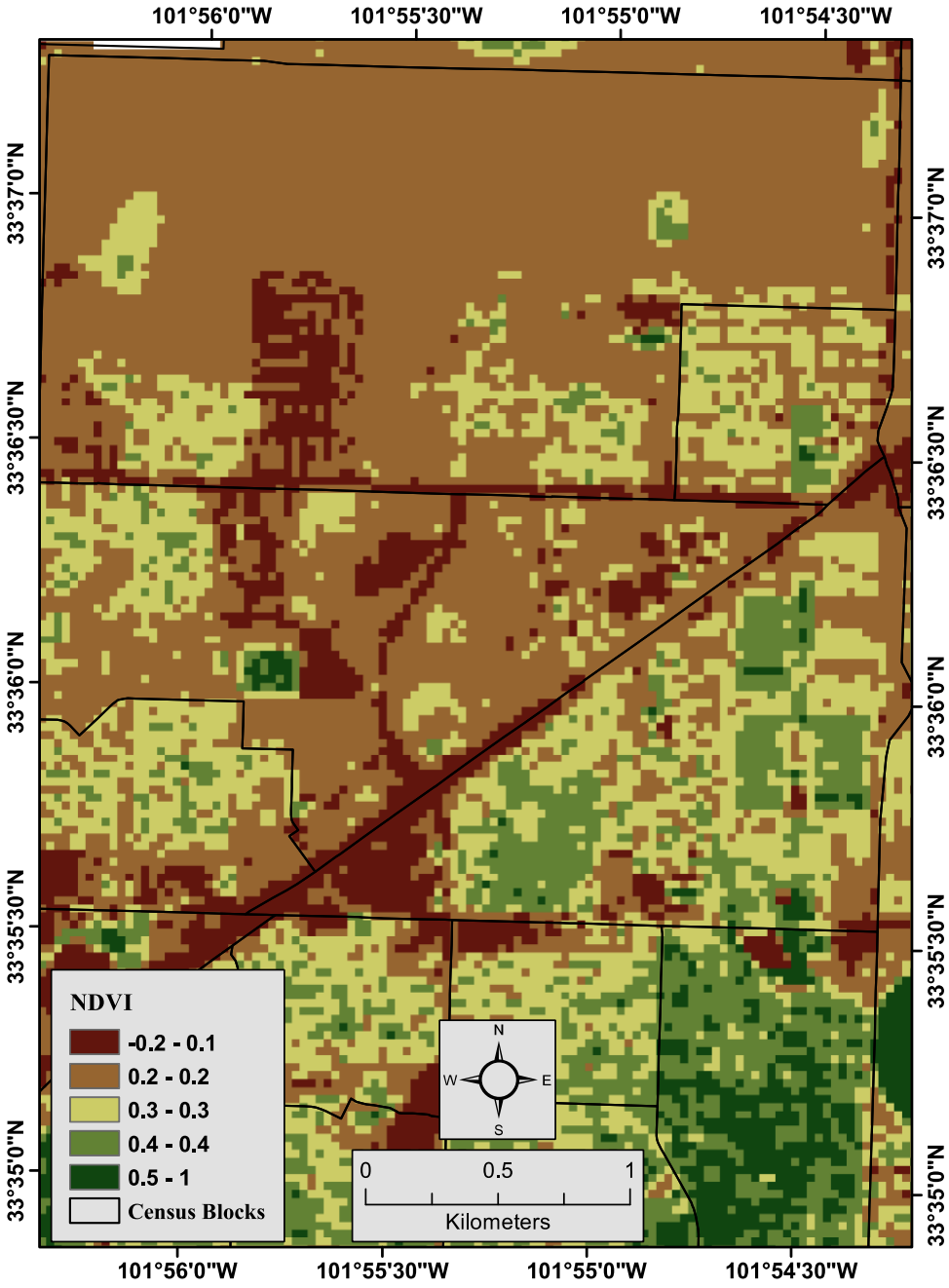

Figure 5.6 Cluster of CBGs in Northwest Lubbock area (N. Slide Rd & Erskine St) that experienced some of the lowest NDVI values in Lubbock, TX.

Figure 5.7 National Agriculture Imagery Program (NAIP) 2014 1m NC/CIR Orthoimagery, United States Department of Agriculture (2014).

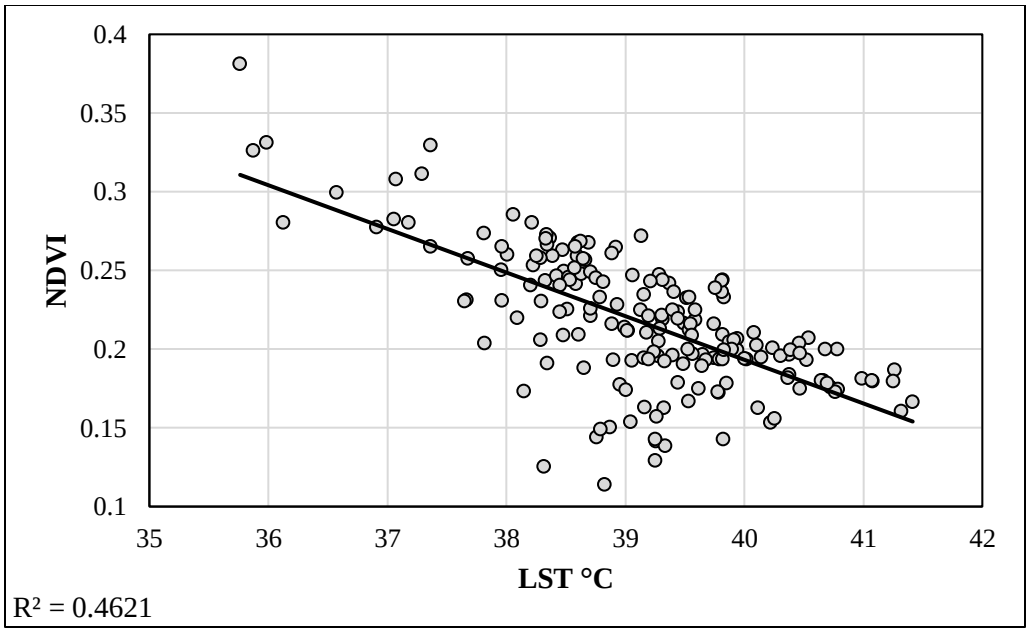

Figure 5.8 Scatterplot of the relationship between LST and NDVI. Statistics calculated using Microsoft Excel 2016.

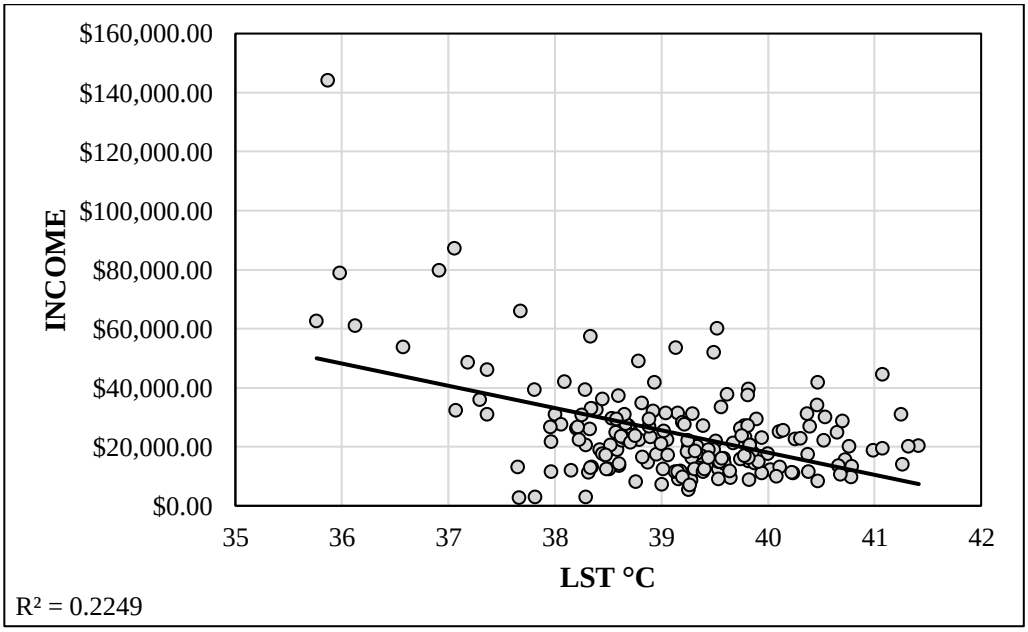

Figure 5.9 Scatterplot of the relationship between LST and income. Statistics calculated using Microsoft Excel 2016.

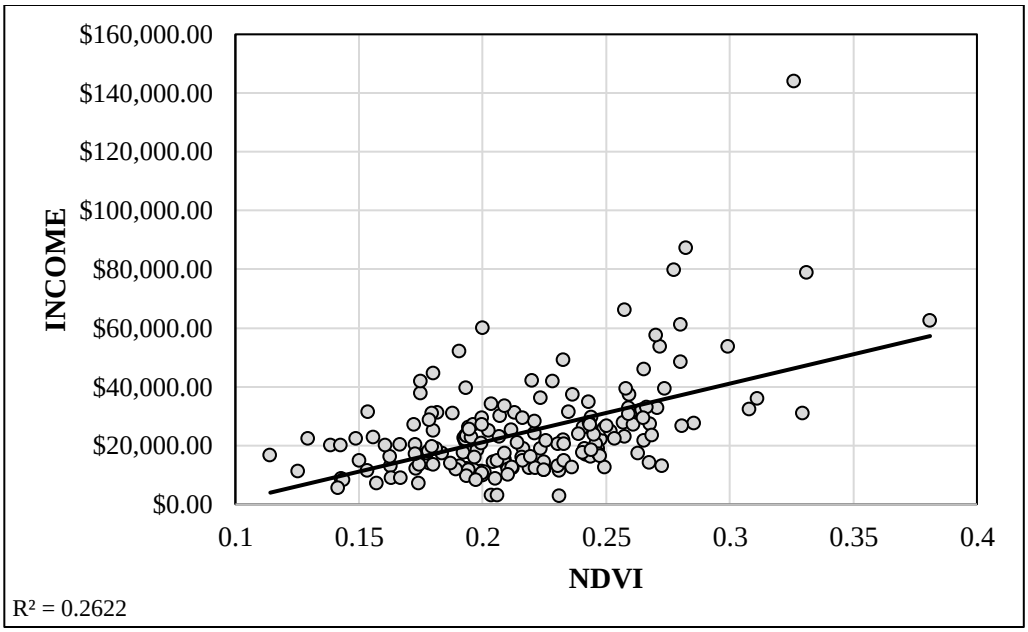

Figure 5.10 Scatterplot of the relationship between NDVI and income. Statistics calculated using Microsoft Excel 2016.

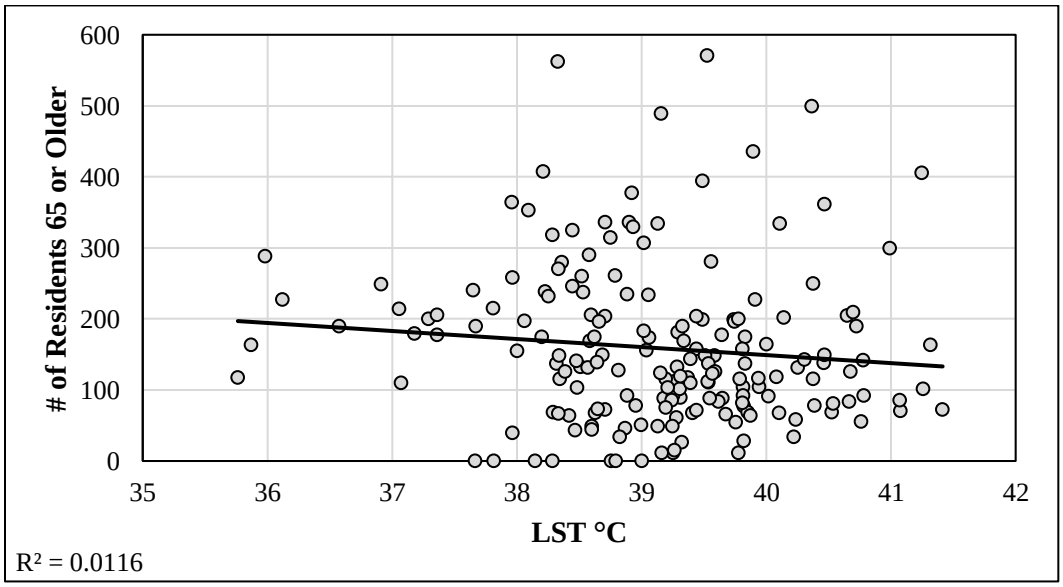

Figure 5.11 Scatterplot of the relationship between LST and the number of residents 65 years of age or older. Statistics calculated using Microsoft Excel 2016.

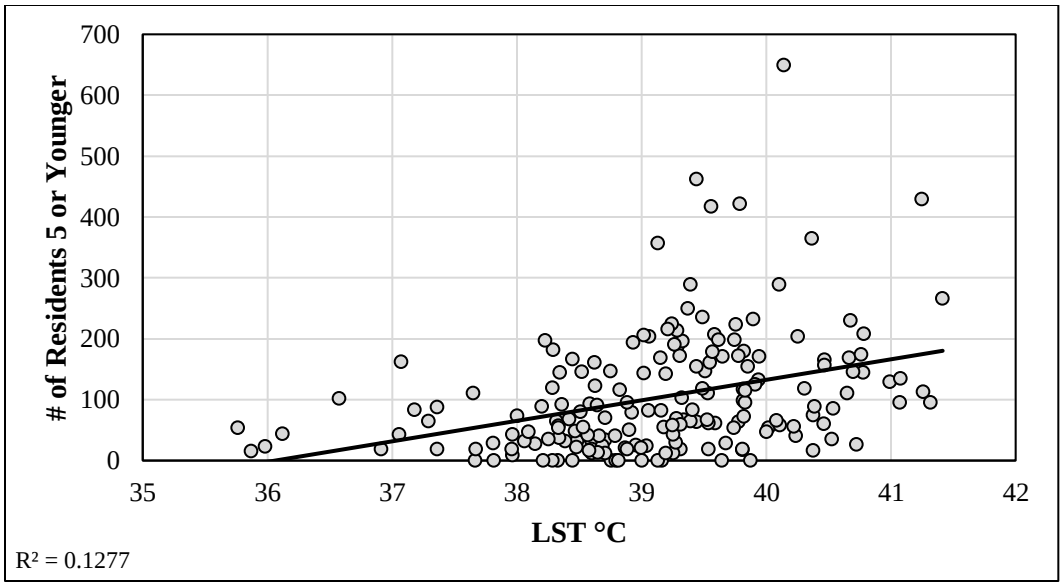

Figure 5.12 Scatterplot of the relationship between LST and the number of residents five years of age or younger. Statistics calculated using Microsoft Excel 2016.

Table 5.2 shows the un-rotated PCA for all sensitivity variables. Like mentioned previously, only components that surpass the Kaiser criteria were retained. In this case, six components were retained, explaining 79.04% of the variance. Additionally, in **Table 5.2**, the first component explains the majority of the variance, while the remaining components explain less and less variance. After an orthogonal rotation was applied, the resulting factor loading matrix (**Table 5.3**) to sum all factors for the six retained components, essentially creating a partial sensitivity score for each CBG in the analysis. This process was repeated for all adaptive capacity variables as well. All values in bold represent statistically significant components at the .05 level. In the first component we can see statistically significant results for educational, race, income, and age characteristics. A similar theme is observed in the second component as well. Components five and six showed no statistically significant values.

Table 5.2 Un-rotated Principal Components Analysis for all sensitivity variables. Statistics computed using Stata/IC 15.1.

Component	Eigenvalue	Variance Explained
PC 1	**6.94133**	**36.53%**
PC 2	**3.24362**	**17.07%**
PC 3	**1.5948**	**8.39%**
PC 4	**1.17422**	**6.18%**
PC 5	**1.05128**	**5.53%**
PC 6	**1.01528**	**5.34%**
PC 7	.771898	*null*
PC 8	.68689	*null*
PC 9	.600603	*null*
PC 10	.44296	*null*
PC 11	.38079	*null*
PC 12	.337181	*null*
PC 13	.251648	*null*
PC 14	.181412	*null*
PC 15	.153446	*null*
PC 16	.0906926	*null*
PC 17	.0593543	*null*
PC 18	.0215638	*null*
PC 19	.00104219	*null*

Table 5.3 Factor loading matrix after orthogonal rotation. Factor loadings were summed together to create a sensitivity score for each CBG in the analysis. Statistics computed using Stata/IC 15.1.

Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6
Total Population	**0.3863**	**-0.0101**	0.0658	0.0287	0.0833	0.0190
No School	-0.0446	**0.0910**	**-0.1295**	0.7174	0.0928	0.0931
High School or GED	**0.2408**	**0.1576**	**0.1679**	**0.2867**	-0.2771	-0.0590
College	**0.3111**	**0.1013**	**-0.1195**	-0.1759	0.0513	0.0594
Graduate School	**0.1773**	**0.1731**	-0.1697	-0.2518	0.1513	0.0208
White	**0.3708**	**0.0220**	**-0.0637**	-0.0134	0.0357	0.0579
African American	-0.0296	**0.0591**	0.6914	-0.2079	0.0401	-0.0146
Hispanic or Latino	**0.2776**	**-0.2250**	-0.0818	0.3834	-0.0294	-0.1693
Other	**0.1444**	-0.0240	-0.0306	**-0.0630**	0.6139	0.1007
65 Health Insurance	**0.0399**	**0.5214**	**-0.0021**	0.0438	-0.0520	-0.0433
65 No Health Insurance	0.0014	-0.0060	0.0015	0.0294	-0.0198	0.9541
65 Living Alone	**-0.0815**	**0.5009**	**0.1151**	0.0783	0.1155	0.0151
65 or Older	**0.0258**	**0.5333**	**0.0064**	0.0536	-0.0687	-0.0093
5 or Younger	**0.3607**	**-0.1311**	**0.2102**	-0.0416	-0.1137	-0.0166
Below Poverty	0.0718	**-0.0032**	**0.5072**	0.1189	0.0389	0.0365
Above Poverty	**0.3462**	0.1064	**-0.0761**	-0.0406	-0.0352	-0.0251
Income	**-0.0078**	**0.1856**	-0.2993	-0.2474	-0.0183	-0.0877
Self-Transportation	**0.3941**	**-0.0332**	**-0.0124**	-0.0336	0.0583	0.0034
Public Transportation	-0.0826	0.0144	0.0877	**0.1480**	0.6789	-0.1367

Figure 5.13 shows the results for the exposure to LSTs at the CBG level for Lubbock. It should be noted that the two CBGs excluded from this analysis are symbolized with grey stripes. This exposure maps shows that a majority of CBGs exposed to very high LSTs are limited to the outside of the city center (or outside of Loop 289). Many of the CBGs exposed to low or very low LSTs are restricted to the Lakeridge Country Club area, Texas Tech University, and a few other areas inside of Loop 289. Interestingly, there are still several CBGs inside of Loop 289 that experience high exposure to LSTs.

Figure 5.14 shows the results for the sensitivity scores at the CBG level for Lubbock. Sensitivity scores are essentially symbolizing the social vulnerability of residents to any environmental hazard, as outlined by Cutter et al., (2003). Again, the most sensitive CBGs are restricted to the outside of Loop 289, mainly in southeast and northwest Lubbock. This observed pattern was surprising due to the fact that much of the African American population resides on the east side of the city (east of Interstate 27). Before this analysis, it was hypothesized that the most sensitive populations would be prevalent in communities with high populations of monitories. Surprisingly, many of the CBGs on the east side show low to medium sensitivity, with the exception of a few. Additionally, we can see that some of the least sensitive populations are again in the Lakeridge Country Club area between 98th and Quaker Ave./Slide Ave.

Figure 5.15 shows the results for the adaptive capacity scores at the CBG level for Lubbock. For this study, adaptive capacity to extreme heat involves high amounts of vegetation (NDVI) and the prevalence of health insurance. As expected, numerous CBGs outside of Loop 289 have a very low adaptive capacity towards extreme heat. Also, the CBGs in the Lakeridge area show very high adaptive capacity due to the large amounts of vegetation provided by the golf course there, along with an abundance of tree canopy cover. Furthermore, the cluster of CBGs in Northwest Lubbock mentioned previously, has low to very low adaptive capacity to extreme heat, a result that was anticipated. CBGs close to Texas Tech University also have high to very high adaptive capacity towards extreme heat. This is likely due to the amount of vegetation on campus, where landscaping is performed year-round.

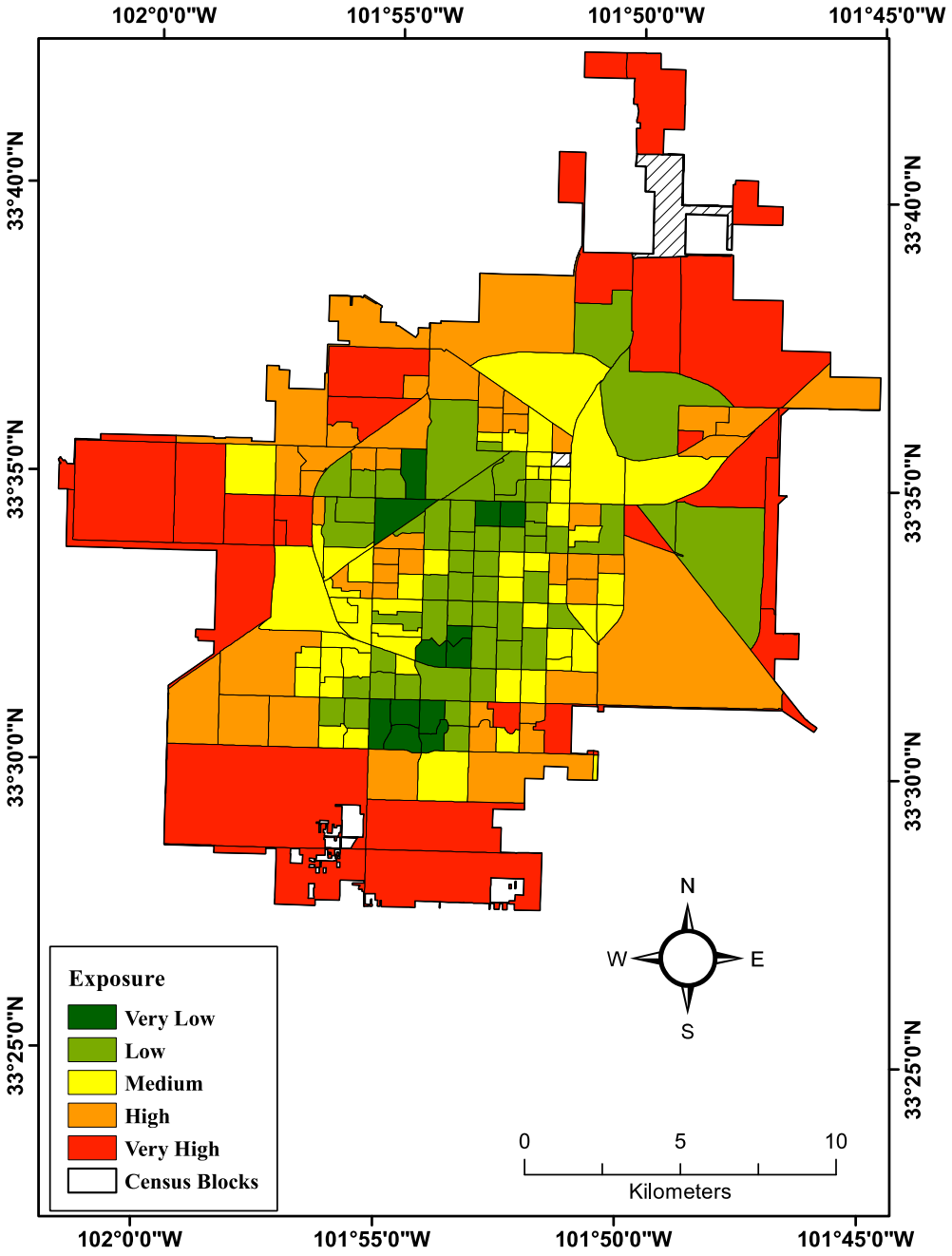

Figure 5.13 Results for exposure at the census block level for Lubbock, Texas.

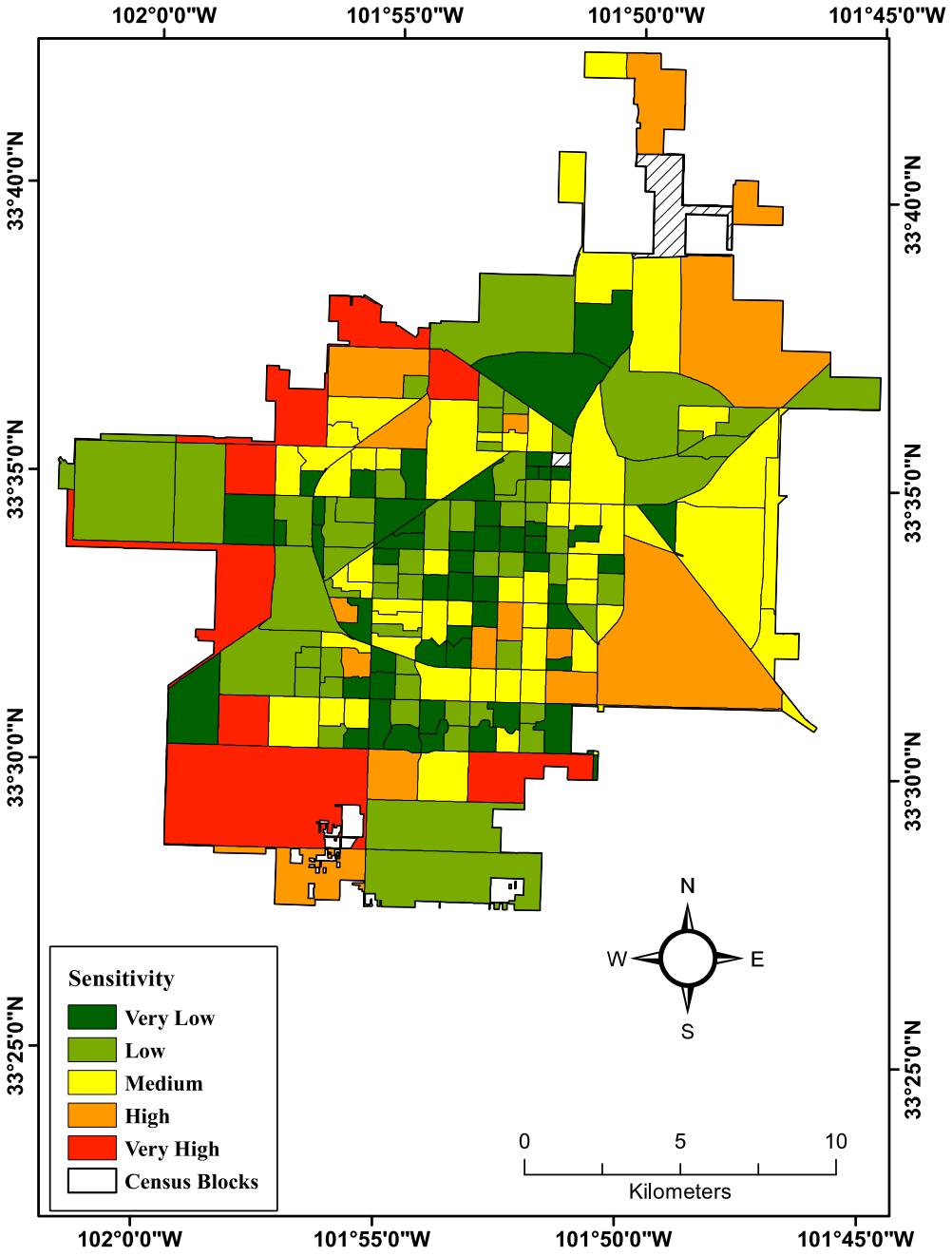

Figure 5.14 Results for sensitivity at the census block level for Lubbock, Texas.

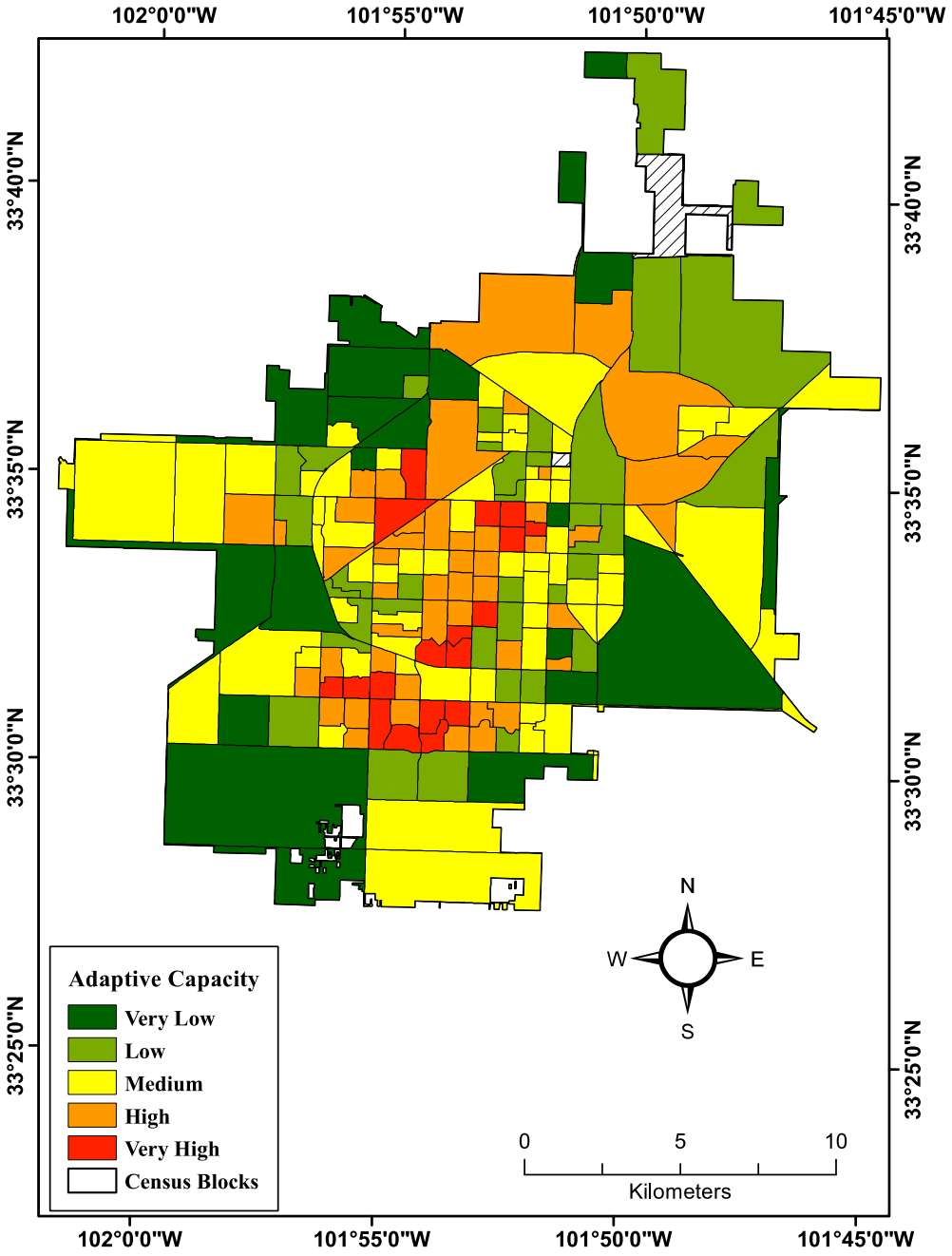

Figure 5.15 Results for adaptive capacity at the census block level for Lubbock, Texas.

Figure 5.16 shows the final heat vulnerability index at the CBG level for Lubbock. Similar to the observed results for exposure, sensitivity, and adaptive capacity, the majority of the most vulnerable communities are restricted to the outside of Loop 289, away from the city's center. This pattern is interesting because typically, urban heat islands are more prevalent in the urban core of a city. This is mainly due to the existence of infrastructure in downtown areas. Many cities in the United States observe this pattern when it comes to LSTs, but Lubbock is somewhat unique in that the most vulnerable communities are not at the city's center. This is likely due to the fact that Lubbock does not have a large downtown area. This area contains Lake Dunbar and several other recreational opportunities with high amounts of vegetation.

Despite this, several CBGs inside of Loop 289 experience high vulnerability. In fact, one CBG (between University Ave. & Ave. P) inside of Loop 289 has a very high vulnerability score. The largest cluster of vulnerability occurs in the northwest portion of Lubbock mentioned previously. The portion of Lubbock contains a high number of children five years or younger and a large Hispanic population, likely leading to high vulnerability scores. CBGs southwest of the Lakeridge area are showing very high vulnerability scores, but the populations in the region are small. This area of Lubbock is undergoing large new developments, where affluent residents are swarming. The landscape in these regions contain a high number of trees, but they are early in the growing process, therefore they are not providing essential canopy cover to mitigate LSTs. Additionally, large amounts of impervious surfaces and barren land exist in new development areas, likely contributing to increased LSTs.

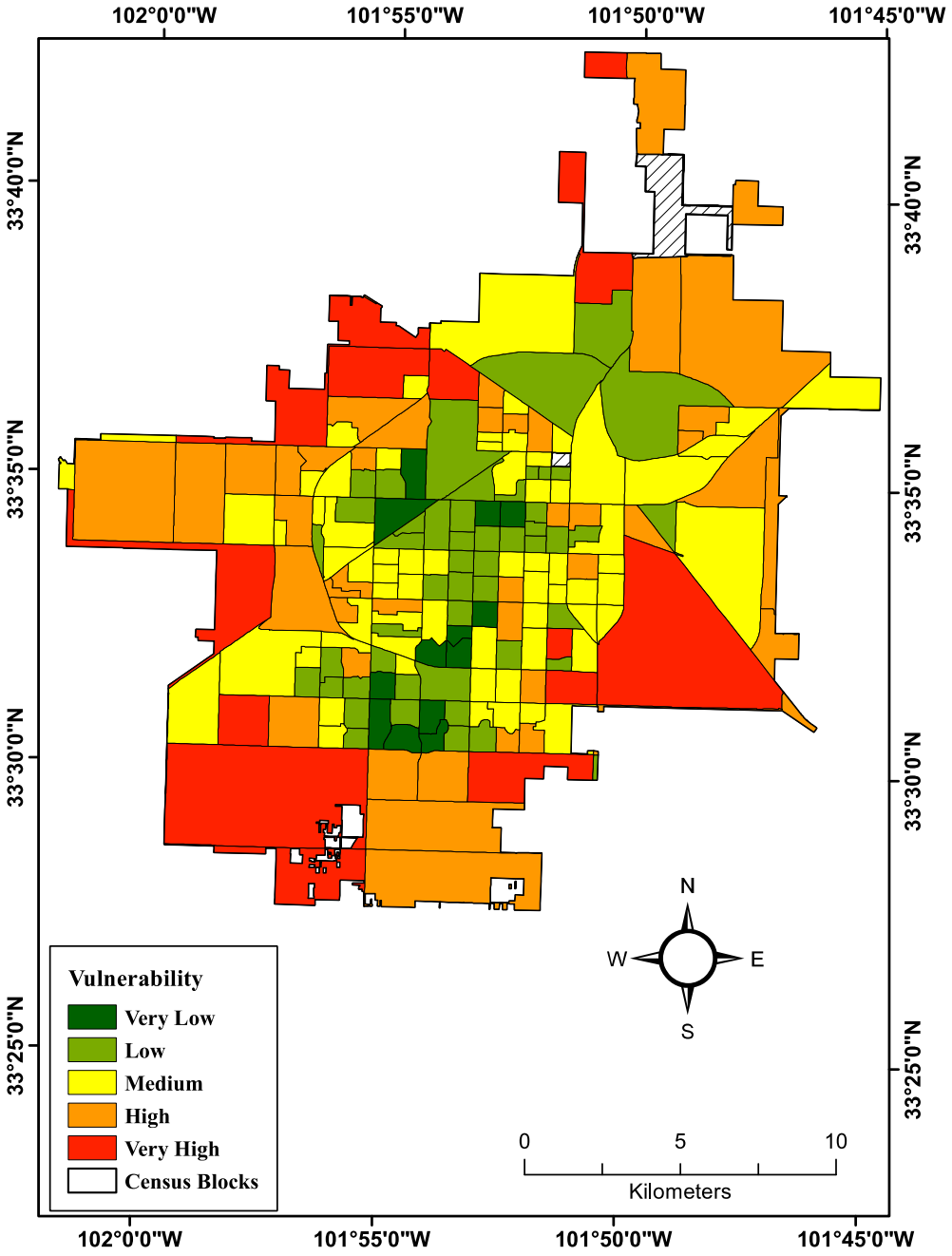

Figure 5.16 Results for heat vulnerability index at the census block level for Lubbock, Texas.

CHAPTER VI

CONCLUSION

In conclusion, CBGs with low-income and low socioeconomic status seem to be more exposed to higher LSTs than CBGs with high-income and high socioeconomic status. Thus, these marginalized groups are the most vulnerable to extreme heat through a combination of exposure, sensitivity, and adaptive capacity. Despite this, there are still large White populations that reside in CBG's with low NDVI and high LST, especially where significant amounts of new development are resulting in rapid residential expansion along with high amounts of impervious surfaces and buildings. In some newly developed areas, vegetation is limited because trees take several years to be effective at providing shade, thus cooling local temperatures. This would mean that some higher income neighborhoods are more exposed to extreme heat than others. Regardless, it can still be concluded by this analysis, that higher income neighborhoods are less exposed and less sensitive to high LSTs. Additionally, it should be noted that while some CBGs (especially on the outskirts of Lubbock city limits) are exposed to extremely high LSTs, the majority of these have a low population, suggesting not many people are actually at risk of being exposed to these extreme temperatures.

Due to this limitation, further statistical analysis is needed on the population density of each CBG. For instance, Johnson et al., 2012 extracted land cover/land use data from the USGS National Land Cover Dataset (NLCD) in Chicago, Illinois with the purpose of identifying areas in which people actually live, basing their vulnerability on residential density. These limitations indicate a need for a higher a temporal resolution, which would aid in observing any trends in LST, whereas this analysis only used a

single-date Landsat image. Future research for this analysis will aim to incorporate higher temporal resolution, along with the addition of Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS).

The primary purpose of this study was to derive LST and NDVI within the city limits of Lubbock, Texas to analyze any spatial patterns of exposure to extreme temperatures within communities and their sensitivity, along with adaptive capacity towards extreme heat. The primary take away from this analysis includes the relationship between LST, NDVI, and specific demographic characteristics (especially income and race). By performing such research, city government can potentially provide extra resources to vulnerable communities.

Additionally, vulnerability maps should be available to the public so that citizens can be more aware of hottest places in the city. Currently, there is no system put in place by local government to identify vulnerable communities to extreme heat. The HVI in this analysis, serves as the only one of its kind in this region of Texas, as there is no knowledge of similar analysis being performed. It is the hope of the researcher that local government and non-profit organizations such as The Salvation Army can utilize this HVI so that cooling centers can be more effectively placed. As climate change occurs, extreme heat events are expected to worsen, making communities more vulnerable than ever, indicating a need to improve vulnerability planning at the city scale. The unequal distribution of vulnerability symbolizes the need for improved planning and should serve as a reminder that environmental hazards affect populations disproportionately.

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APPENDIX A

TABLES

Table 2.1. Summary statistics of census block group race populations, average income, and below poverty populations in Lubbock, TX (mean, standard deviation, minimum, and maximum). Statistics computed in Stata/IC 15.1 using American Community Survey 5-year estimates (2010-2014).

Variable	Mean	Std. Dev.	Min.	Max.
Total Population	1,435.82	746.36	517	4,942
White	1,127.86	671.74	44	4,177
African American	107.9	152.97	0	1,063
Hispanic or Latino*	204.73	191.72	0	1,029
Other	39.7	63.75	0	378
Income	24,549.65	16,702.97	2,813	144,071
Below Poverty	45.09	46.13	0	249

Table 2.2 Summary statistics of census block group young/elderly populations and health insurance characteristics in Lubbock, TX (mean, standard deviation, minimum, and maximum). Statistics computed in Stata/IC 15.1 using American Community Survey 5-year estimates (2010-2014).

Variable	Mean	Std. Dev.	Min.	Max.
No Health Insurance	261.36	177.79	0	876
Health Insurance	1,151.92	668.93	297	4,626
> 65 No Health Insurance	.81	4.58	0	42
> 65 Health Insurance	152.33	105.41	0	571
> 65 Living Alone	45.65	46. 5	0	336
< 5	103.51	98.98	0	649

Table 3.1 Summary statistics of census block group education characteristics in Lubbock, TX (mean, standard deviation, minimum, and maximum). Statistics computed in Stata/IC 15.1 using American Community Survey 5-year estimates (2010-2014).

Variable	Mean	Std. Dev.	Min.	Max.
No School	12.67	19.84	0	112
High School	209.96	125.66	0	622
College	201.78	196.09	0	1,124
Graduate School	72.16	77.80	0	458

Table 4.1 All physical and social variables used in this analysis. Variables separated by Exposure, Adaptive Capacity, and Sensitivity.

Exposure
Land Surface Temp.

Adaptive Capacity
NDVI
Health Insurance
No Health Insurance

Sensitivity
Total Population
65 Years or Older
5 Years or Younger
65 w/ Health Insurance
65 w/o Health Insurance
65 and Living Alone
White
African American
Hispanic or Latino*
Other
No School
High School or GED
College
Graduate School
Income
Below Poverty
Above Poverty
Public Transportation
Self-Transportation

Table 5.1 Summary statistics of census block group LST and NDVI in Lubbock, TX (mean, standard deviation, minimum, and maximum).

Variable	Mean	Std. Dev.	Min.	Max.
LST_{min}	34.9	3.39	21.95	40.65
LST_{max}	41.61	1.39	38.35	45.14
LST Mean	39.13	1.05	35.76	41.41
$NDVI_{min}$	N/A	N/A	N/A	N/A
$NDVI_{max}$	N/A	N/A	N/A	N/A
NDVI Mean	0.22	0.04	0.11	0.38

Table 5.2 Un-rotated Principal Components Analysis for all sensitivity variables. Statistics computed using Stata/IC 15.1.

Component	Eigenvalue	Variance Explained
PC 1	**6.94133**	**36.53%**
PC 2	**3.24362**	**17.07%**
PC 3	**1.5948**	**8.39%**
PC 4	**1.17422**	**6.18%**
PC 5	**1.05128**	**5.53%**
PC 6	**1.01528**	**5.34%**
PC 7	.771898	*null*
PC 8	.68689	*null*
PC 9	.600603	*null*
PC 10	.44296	*null*
PC 11	.38079	*null*
PC 12	.337181	*null*
PC 13	.251648	*null*
PC 14	.181412	*null*
PC 15	.153446	*null*
PC 16	.0906926	*null*
PC 17	.0593543	*null*
PC 18	.0215638	*null*
PC 19	.00104219	*null*

Table 5.3 Factor loading matrix after orthogonal rotation. Factor loadings were summed together to create a sensitivity score for each CBG in the analysis. Statistics computed using Stata/IC 15.1.

Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6
Total Population	**0.3863**	**-0.0101**	0.0658	0.0287	0.0833	0.0190
No School	-0.0446	**0.0910**	**-0.1295**	0.7174	0.0928	0.0931
High School or GED	**0.2408**	**0.1576**	**0.1679**	**0.2867**	-0.2771	-0.0590
College	**0.3111**	**0.1013**	**-0.1195**	-0.1759	0.0513	0.0594
Graduate School	**0.1773**	**0.1731**	-0.1697	-0.2518	0.1513	0.0208
White	**0.3708**	**0.0220**	**-0.0637**	-0.0134	0.0357	0.0579
African American	-0.0296	**0.0591**	0.6914	-0.2079	0.0401	-0.0146
Hispanic or Latino	**0.2776**	**-0.2250**	-0.0818	0.3834	-0.0294	-0.1693
Other	**0.1444**	-0.0240	-0.0306	**-0.0630**	0.6139	0.1007
65 Health Insurance	**0.0399**	**0.5214**	**-0.0021**	0.0438	-0.0520	-0.0433
65 No Health Insurance	0.0014	-0.0060	0.0015	0.0294	-0.0198	0.9541
65 Living Alone	**-0.0815**	**0.5009**	**0.1151**	0.0783	0.1155	0.0151
65 or Older	**0.0258**	**0.5333**	**0.0064**	0.0536	-0.0687	-0.0093
5 or Younger	**0.3607**	**-0.1311**	**0.2102**	-0.0416	-0.1137	-0.0166
Below Poverty	0.0718	**-0.0032**	**0.5072**	0.1189	0.0389	0.0365
Above Poverty	**0.3462**	0.1064	**-0.0761**	-0.0406	-0.0352	-0.0251
Income	**-0.0078**	**0.1856**	-0.2993	-0.2474	-0.0183	-0.0877
Self-Transportation	**0.3941**	**-0.0332**	**-0.0124**	-0.0336	0.0583	0.0034
Public Transportation	-0.0826	0.0144	0.0877	**0.1480**	0.6789	-0.1367

APPENDIX B

FIGURES

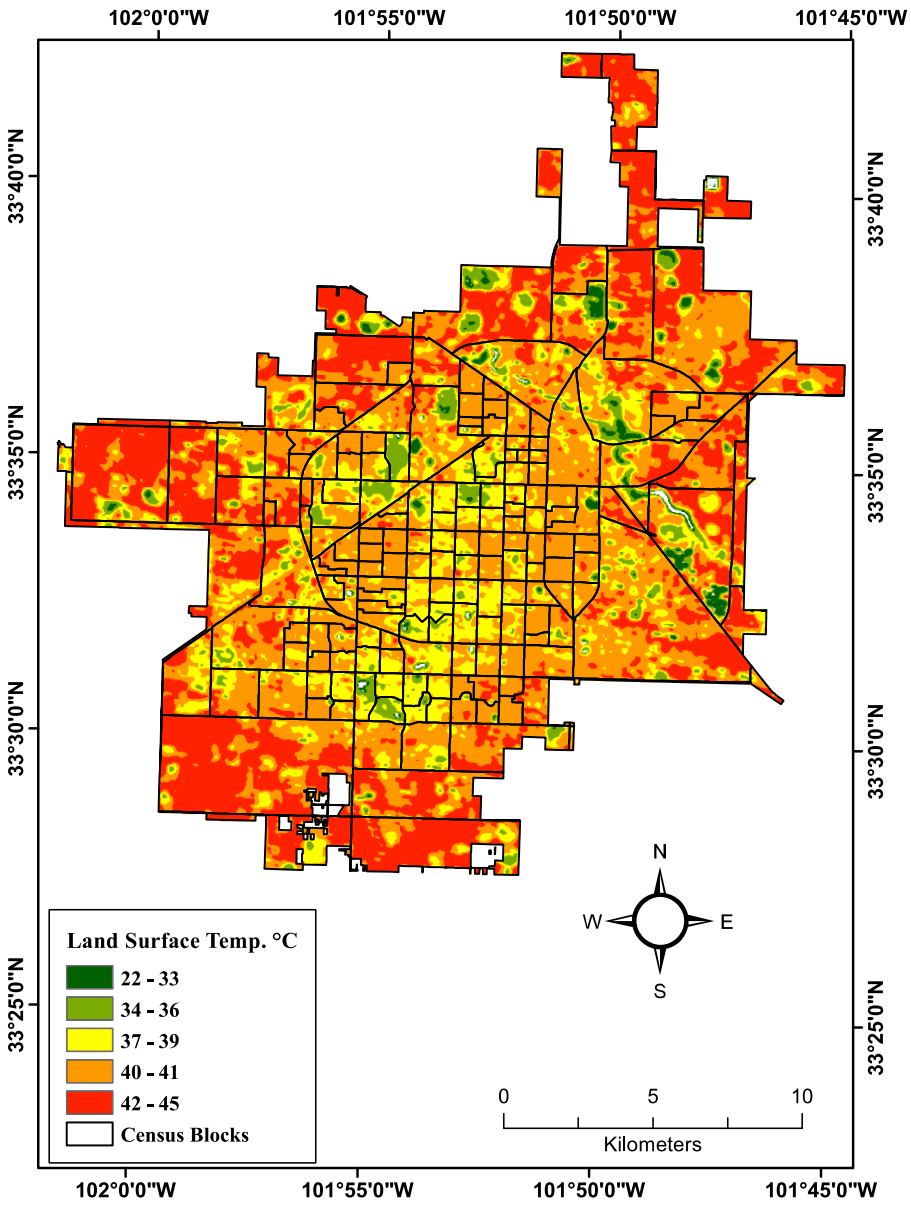

Figure 5.1 Land Surface Temperature (LST) for Lubbock, TX. LST was calculated based on satellite imagery (Eq. 2, 3, & 4) taken from NASA Landsat Program, 2011, Landsat TM, scene LT50300372011179PAC01, USGS, Sioux Falls.

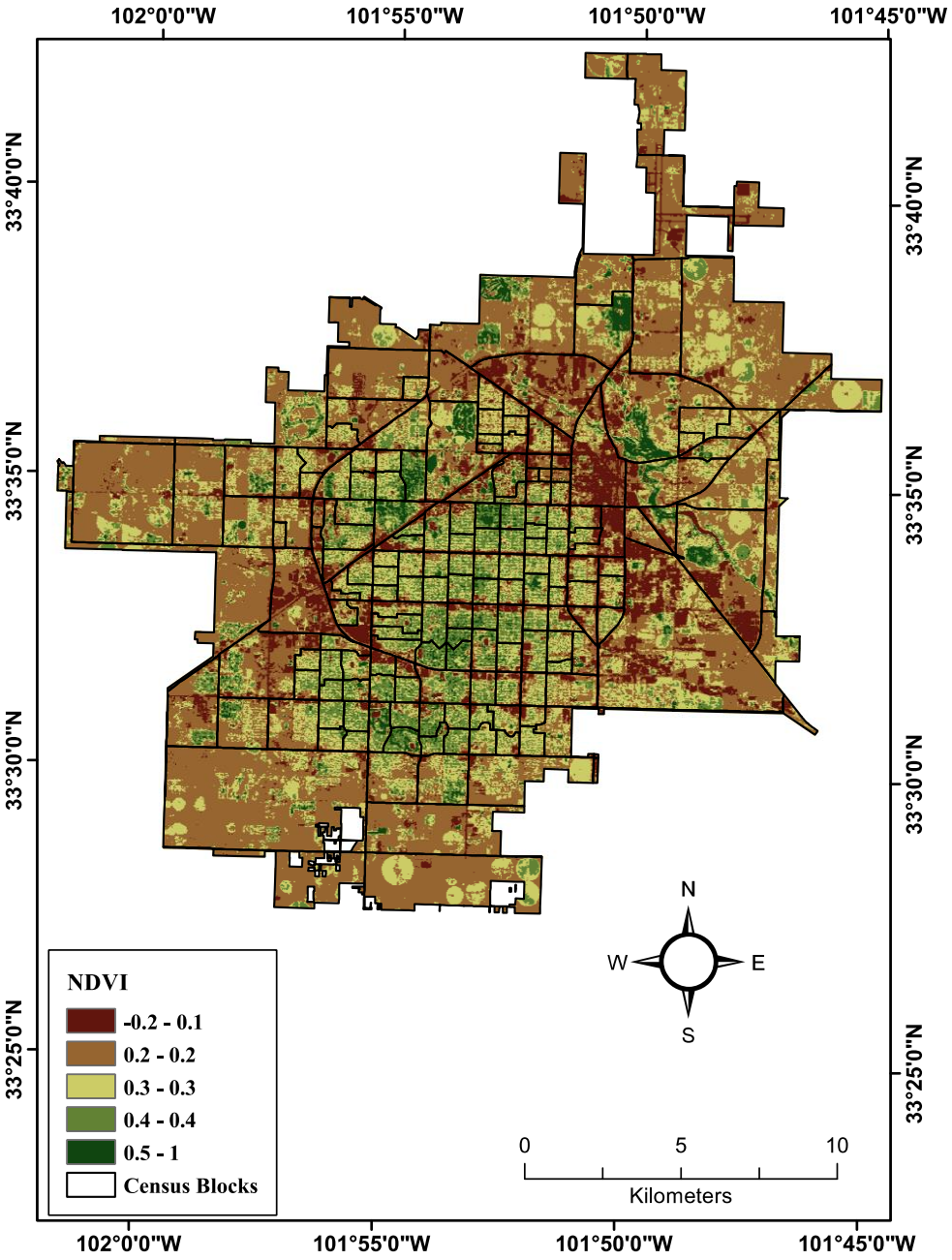

Figure 5.2 Normalized Difference Vegetation Index (NDVI) for Lubbock, TX. NDVI was calculated based on satellite imagery (Eq. 1) taken from NASA Landsat Program, 2011, Landsat TM, scene LT50300372011179PAC01, USGS, Sioux Falls.

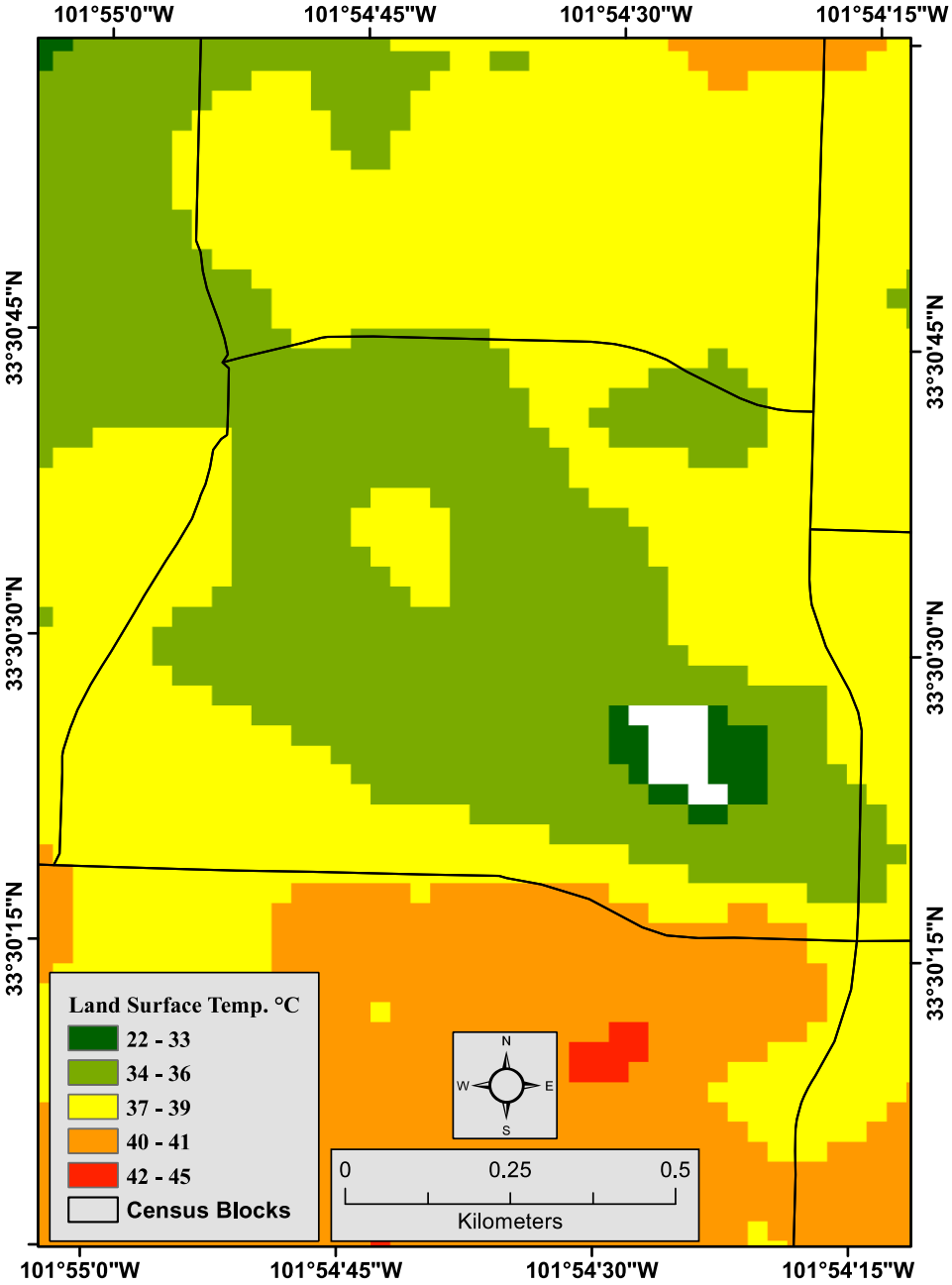

Figure 5.3 Cluster of CBGs in Lakeridge Country Club area that experienced some of the lowest LSTs in Lubbock, TX.

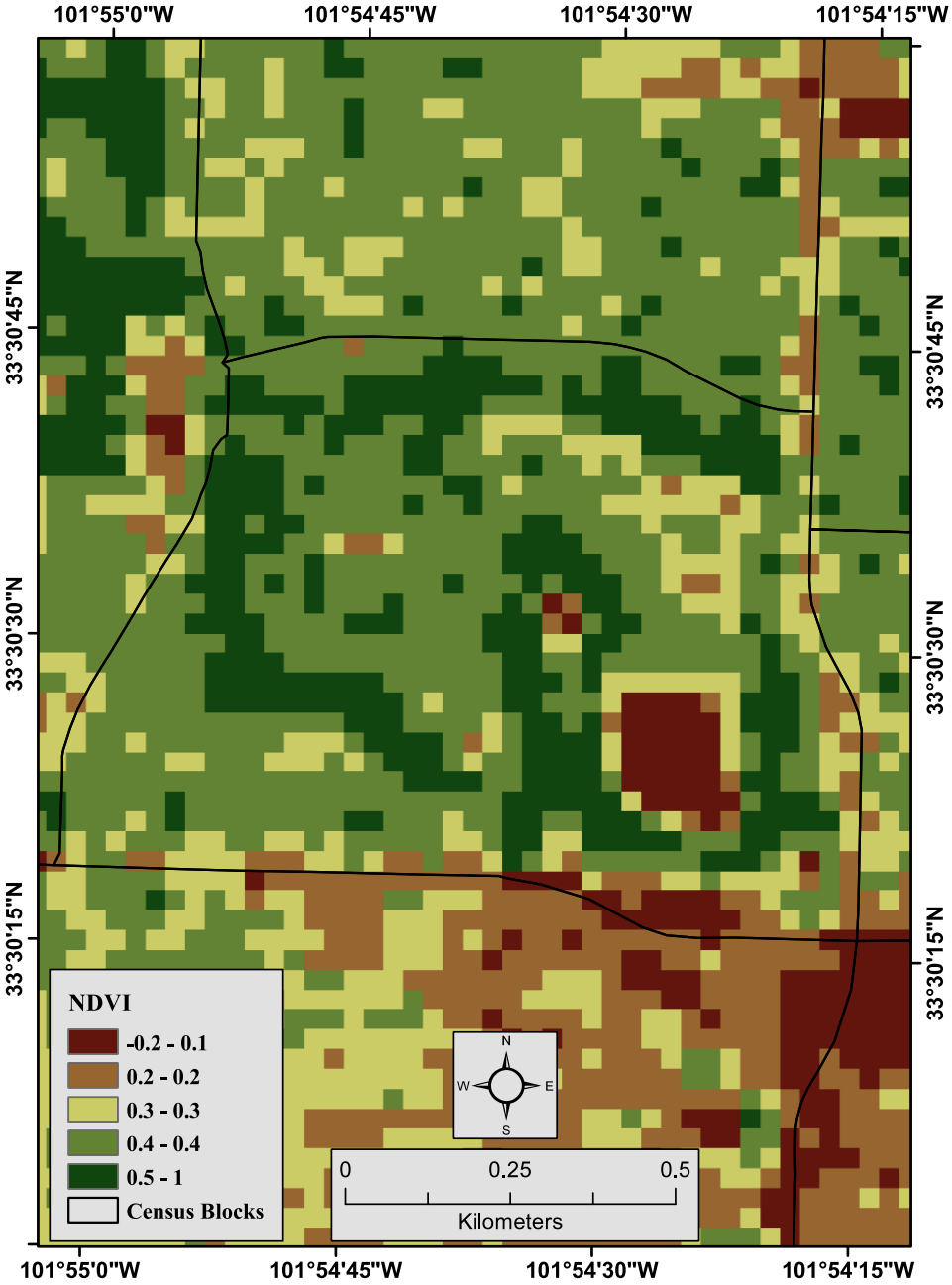

Figure 5.4 Cluster of CBGs in Lakeridge Country Club area that experienced some of the highest NDVI values in Lubbock, TX.

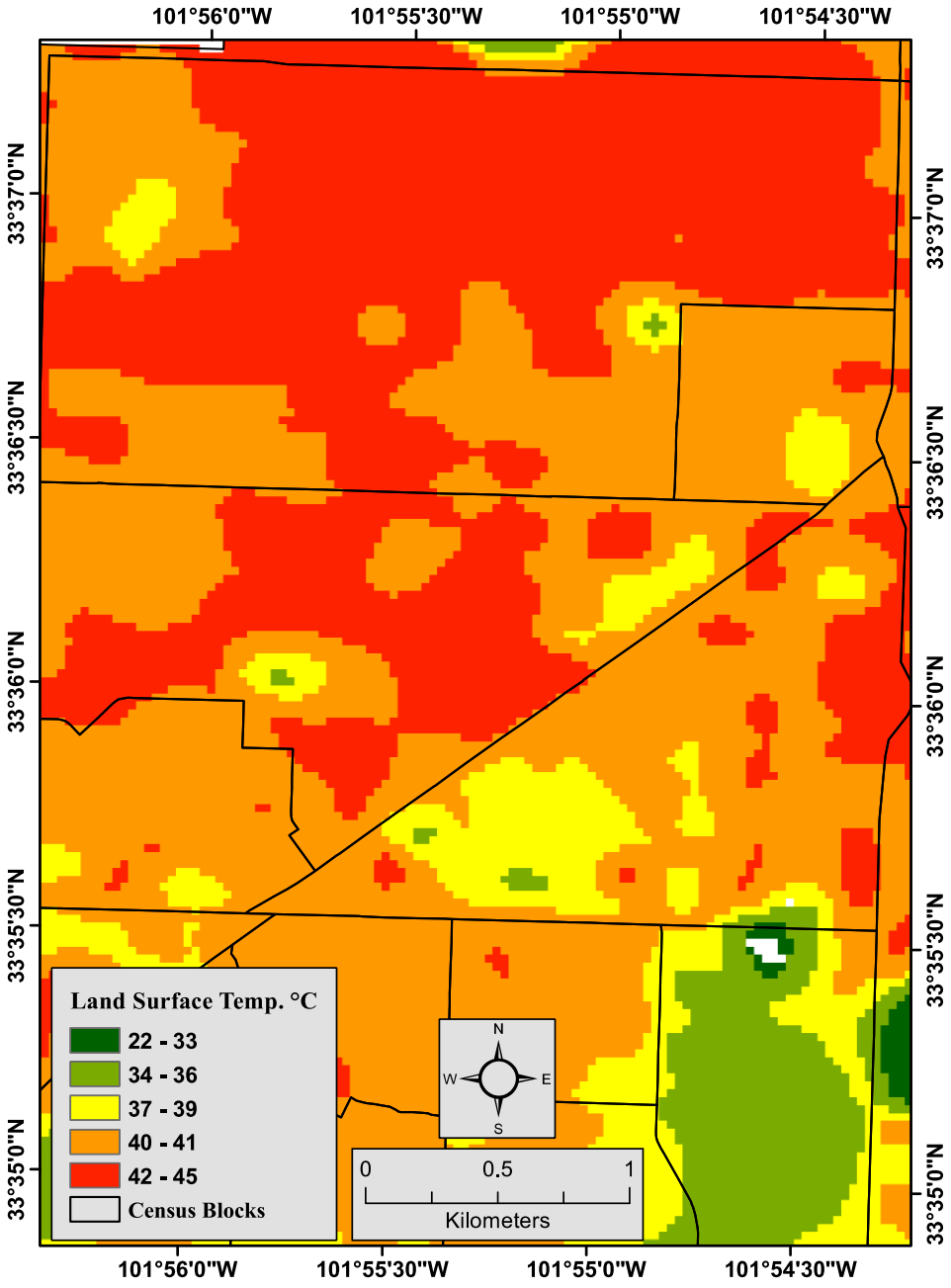

Figure 5.5 Cluster of CBGs in Northwest Lubbock area (N. Slide Rd & Erskine St) that experienced some of the highest LSTs in Lubbock, TX.

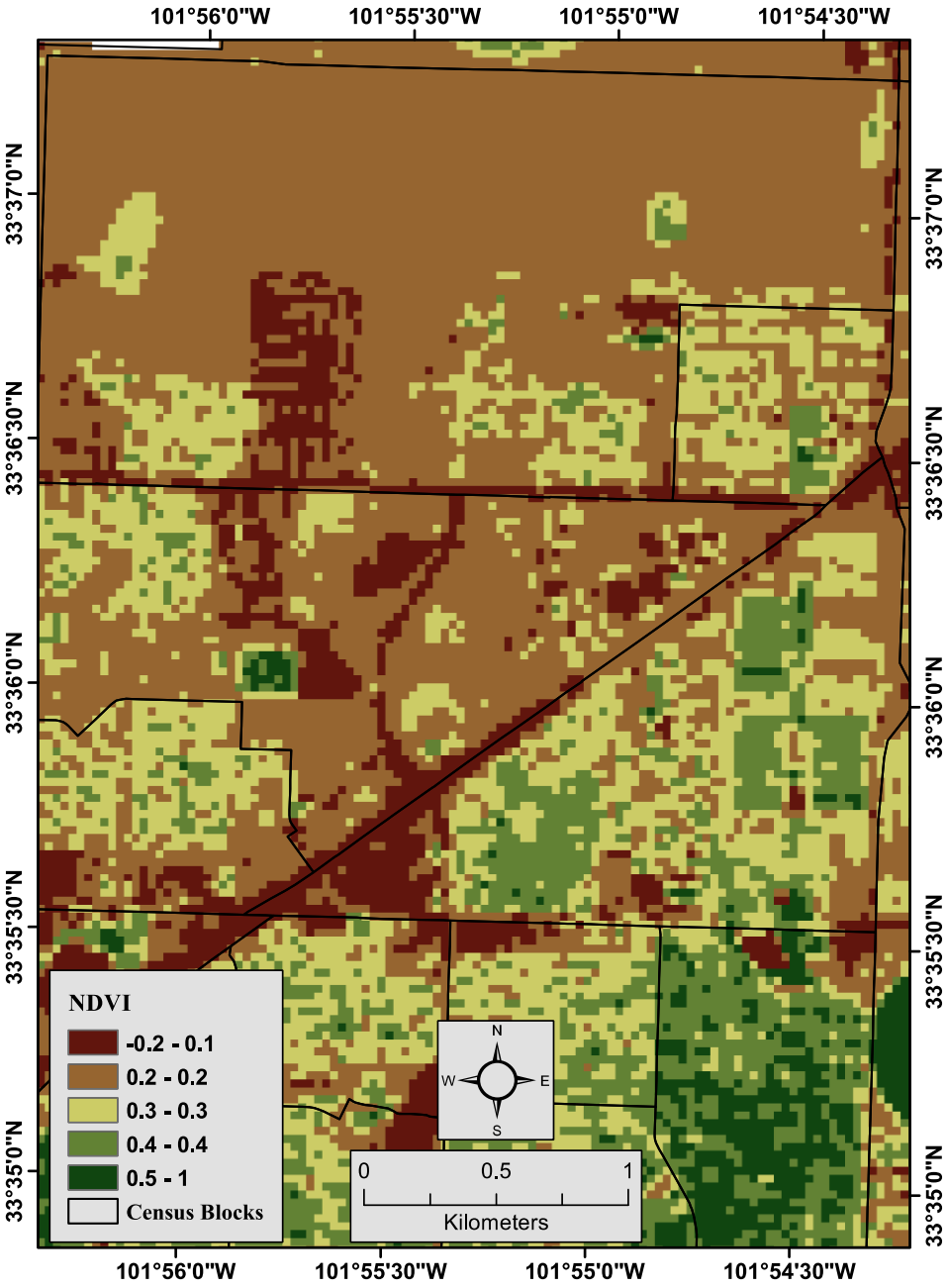

Figure 5.6 Cluster of CBGs in Northwest Lubbock area (N. Slide Rd & Erskine St) that experienced some of the lowest NDVI values in Lubbock, TX.

Figure 5.7 National Agriculture Imagery Program (NAIP) 2014 1m NC/CIR Orthoimagery, United States Department of Agriculture (2014).

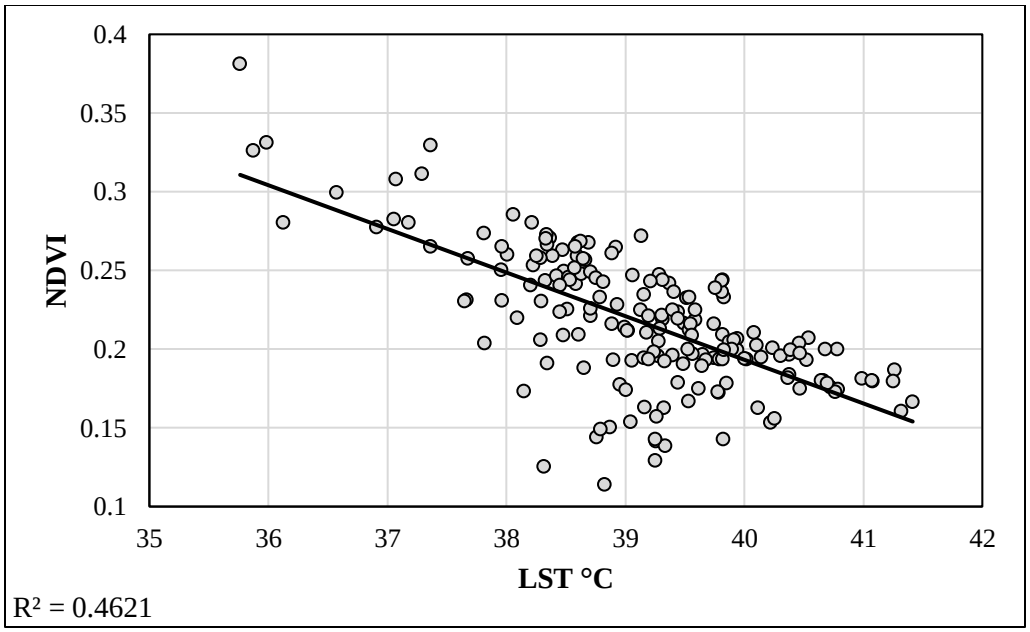

Figure 5.8 Scatterplot of the relationship between LST and NDVI. Statistics calculated using Microsoft Excel 2016.

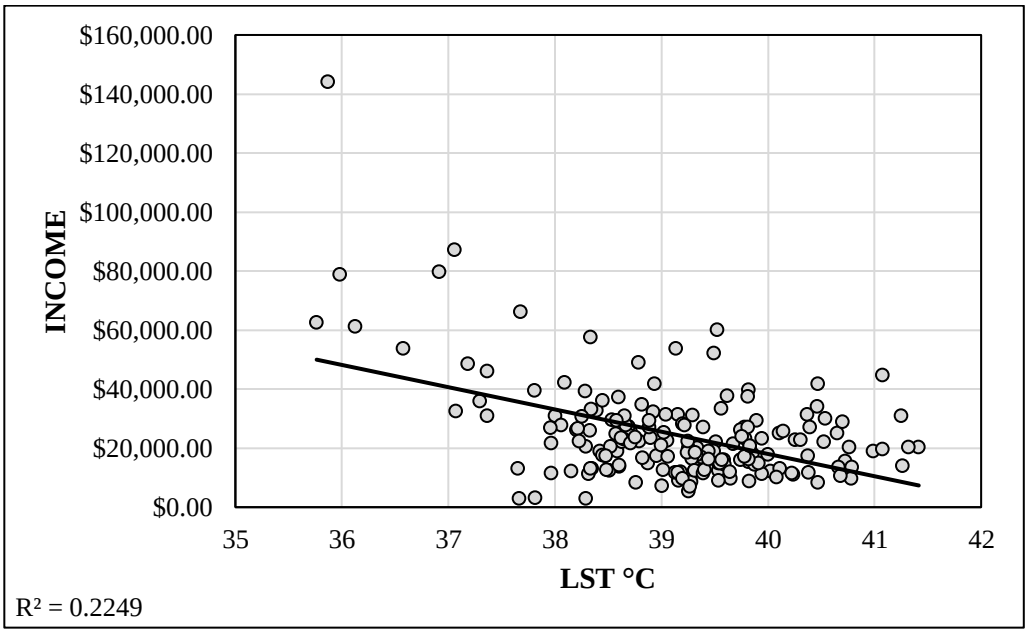

Figure 5.9 Scatterplot of the relationship between LST and income. Statistics calculated using Microsoft Excel 2016.

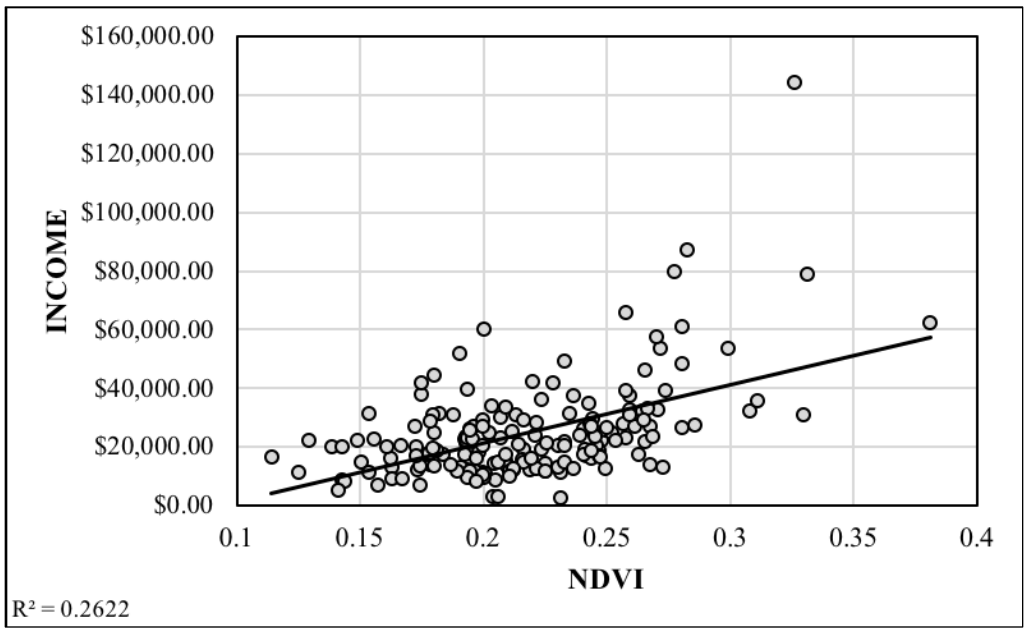

Figure 5.10 Scatterplot of the relationship between NDVI and income. Statistics calculated using Microsoft Excel 2016.

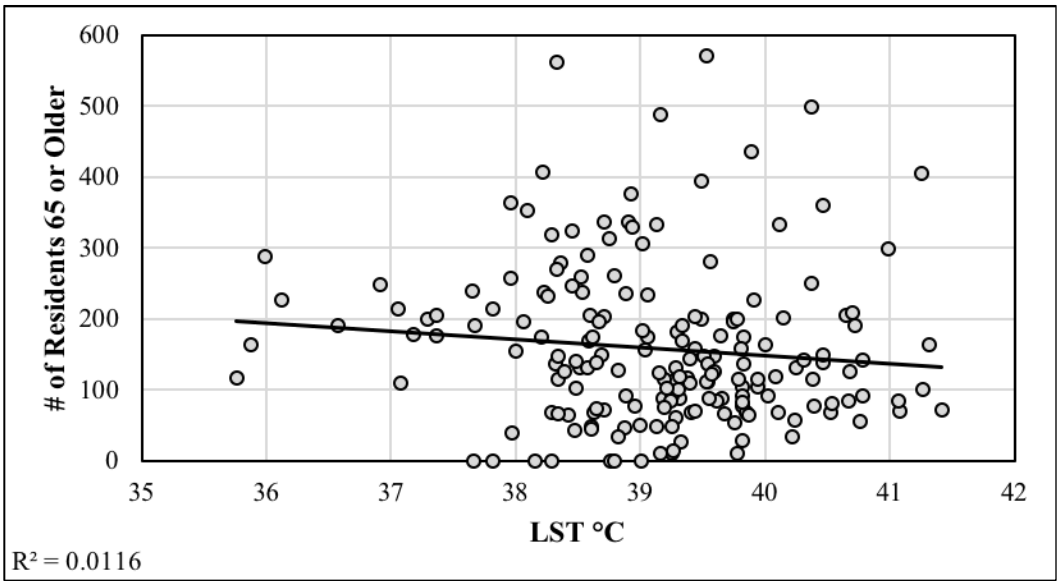

Figure 5.11 Scatterplot of the relationship between LST and the number of residents 65 years of age or older. Statistics calculated using Microsoft Excel 2016.

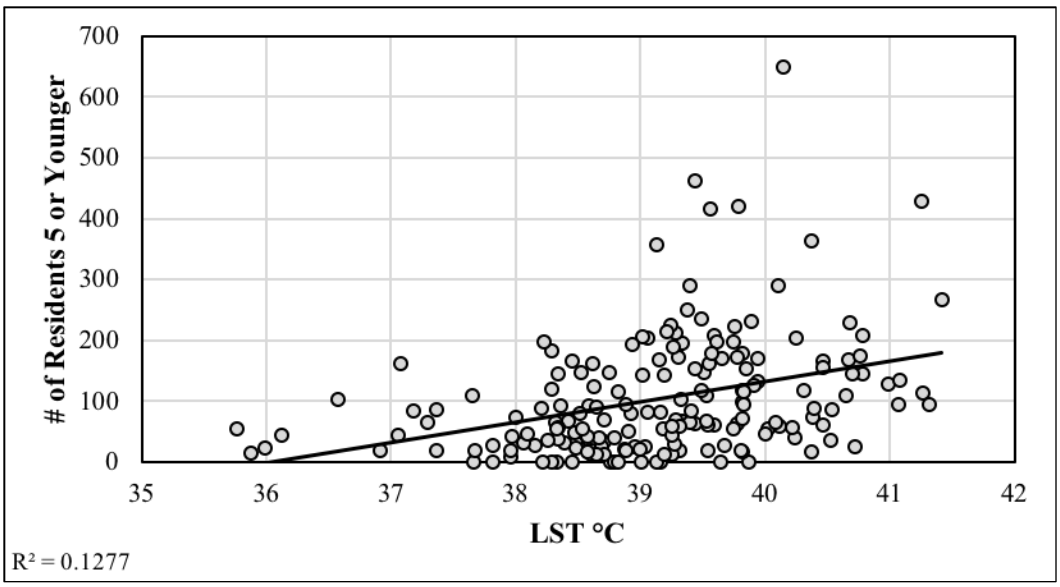

Figure 5.12 Scatterplot of the relationship between LST and the number of residents five years of age or younger. Statistics calculated using Microsoft Excel 2016.

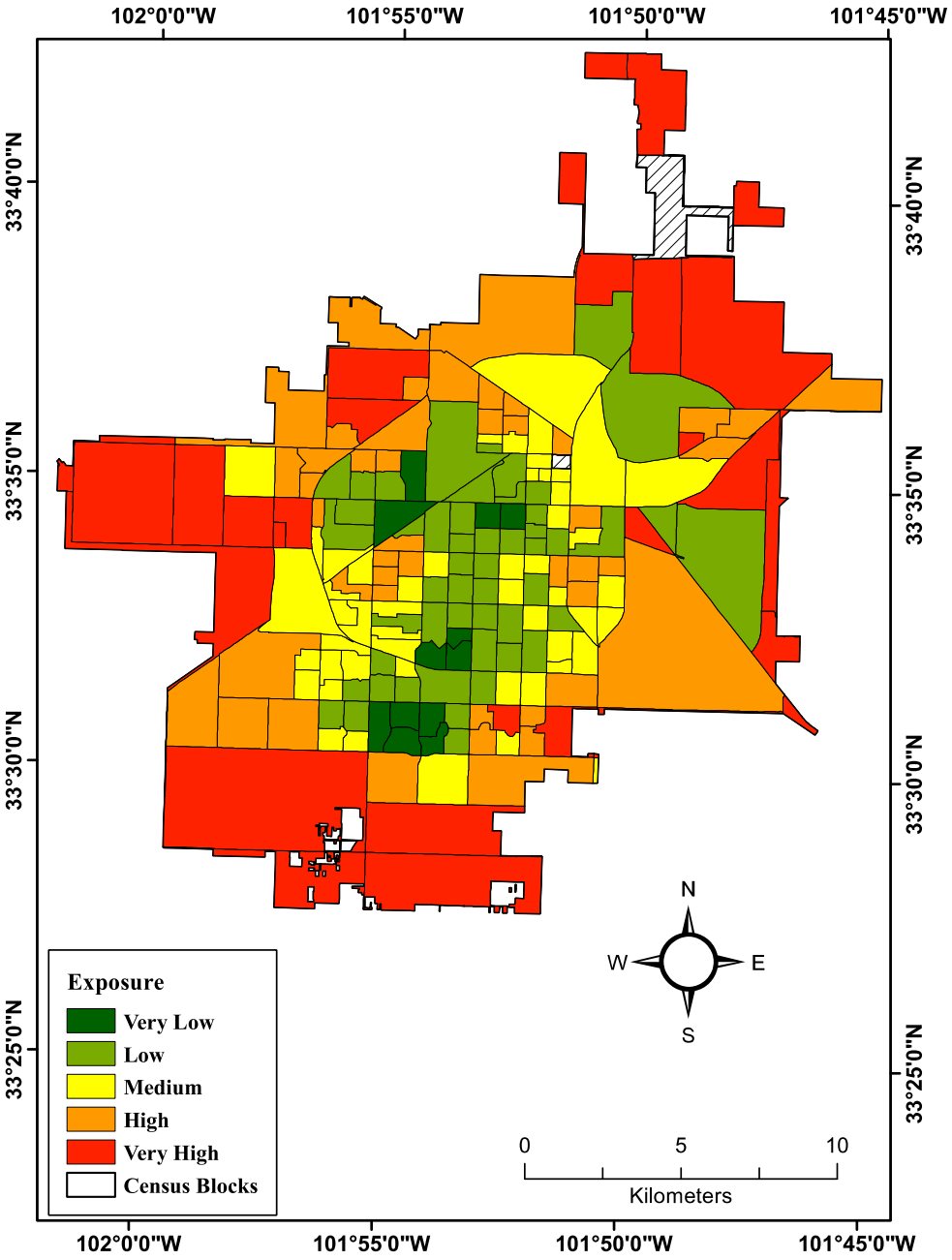

Figure 5.13 Results for exposure at the census block level for Lubbock, Texas.

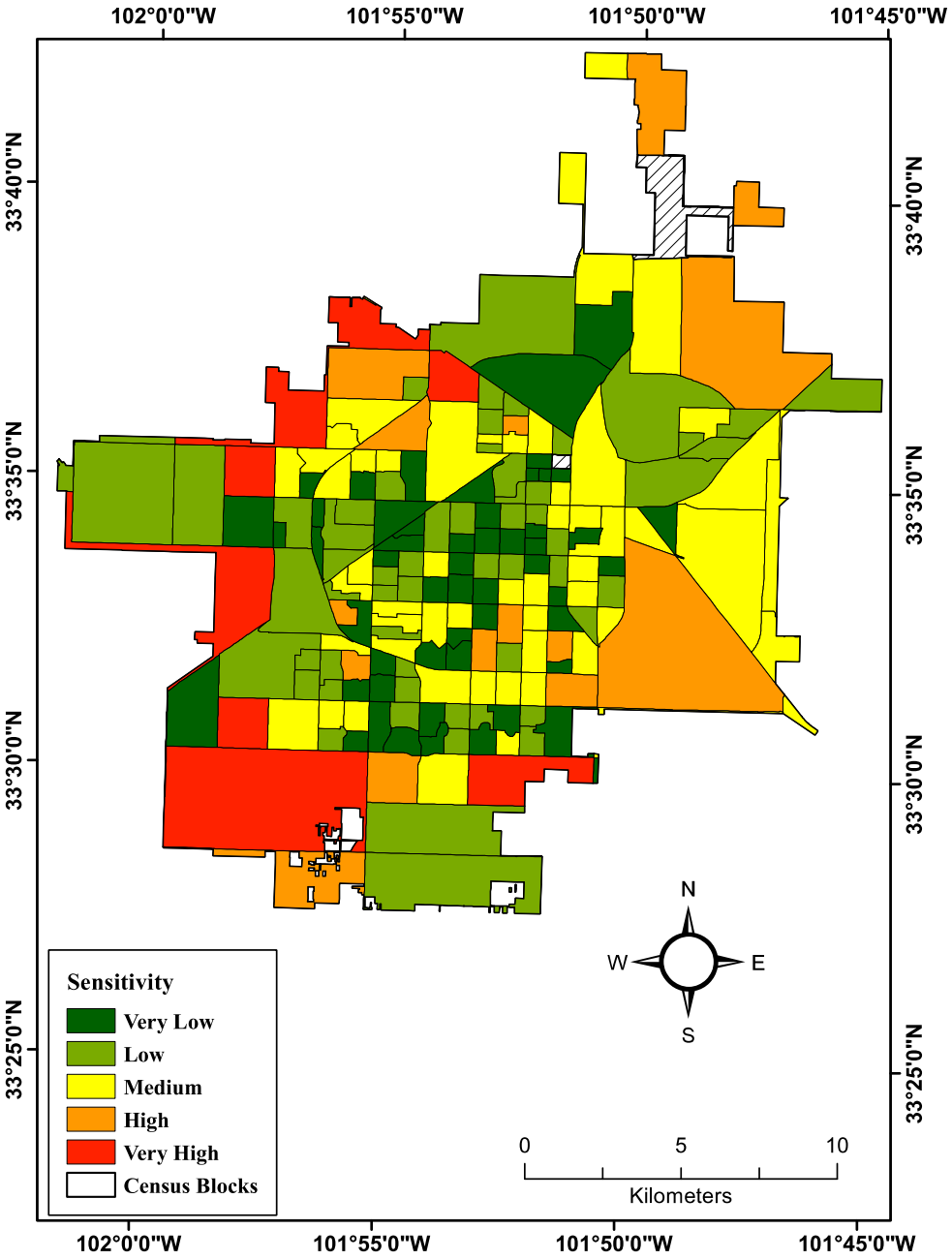

Figure 5.14 Results for sensitivity at the census block level for Lubbock, Texas.

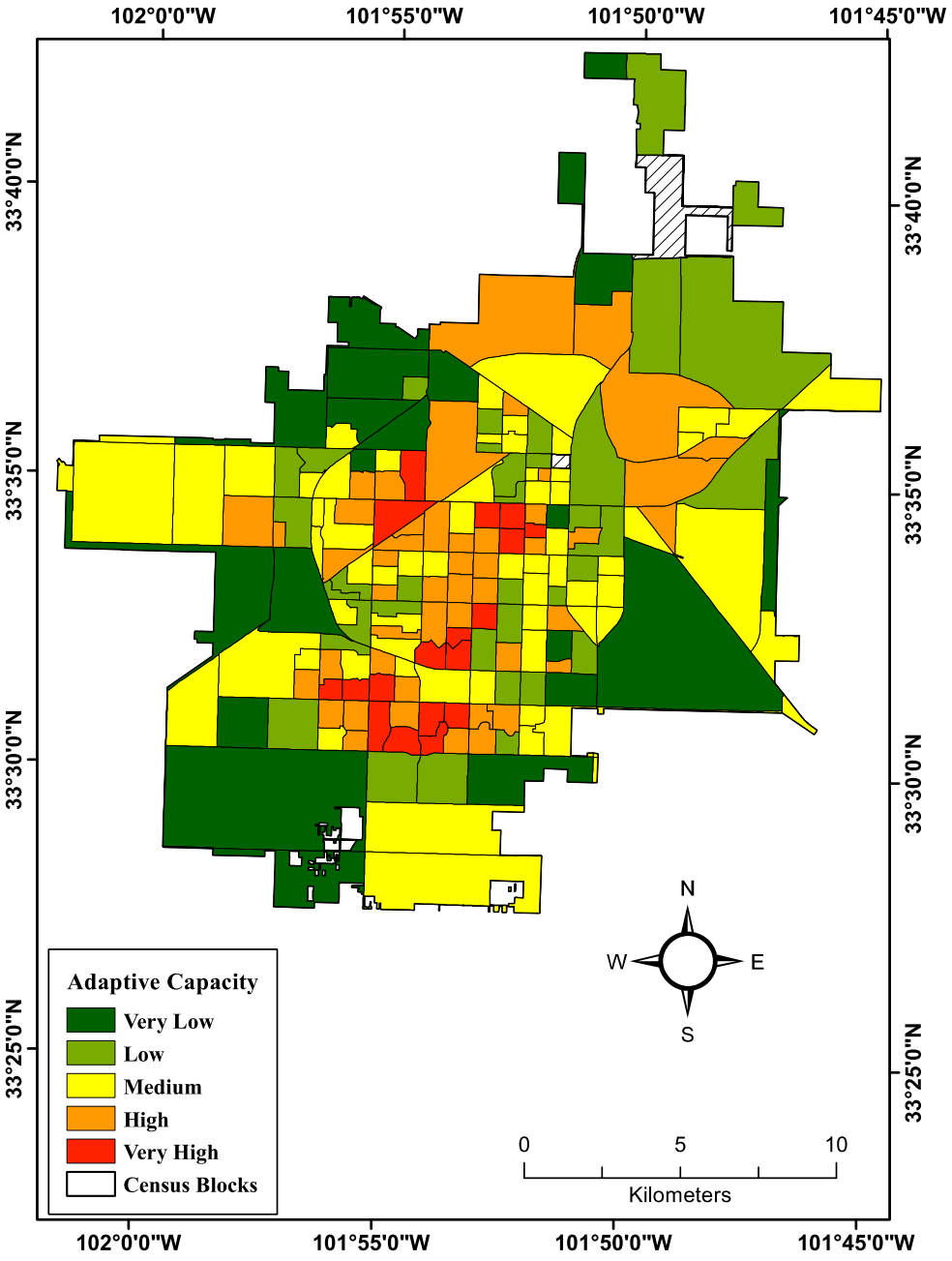

Figure 5.15 Results for adaptive capacity at the census block level for Lubbock, Texas.

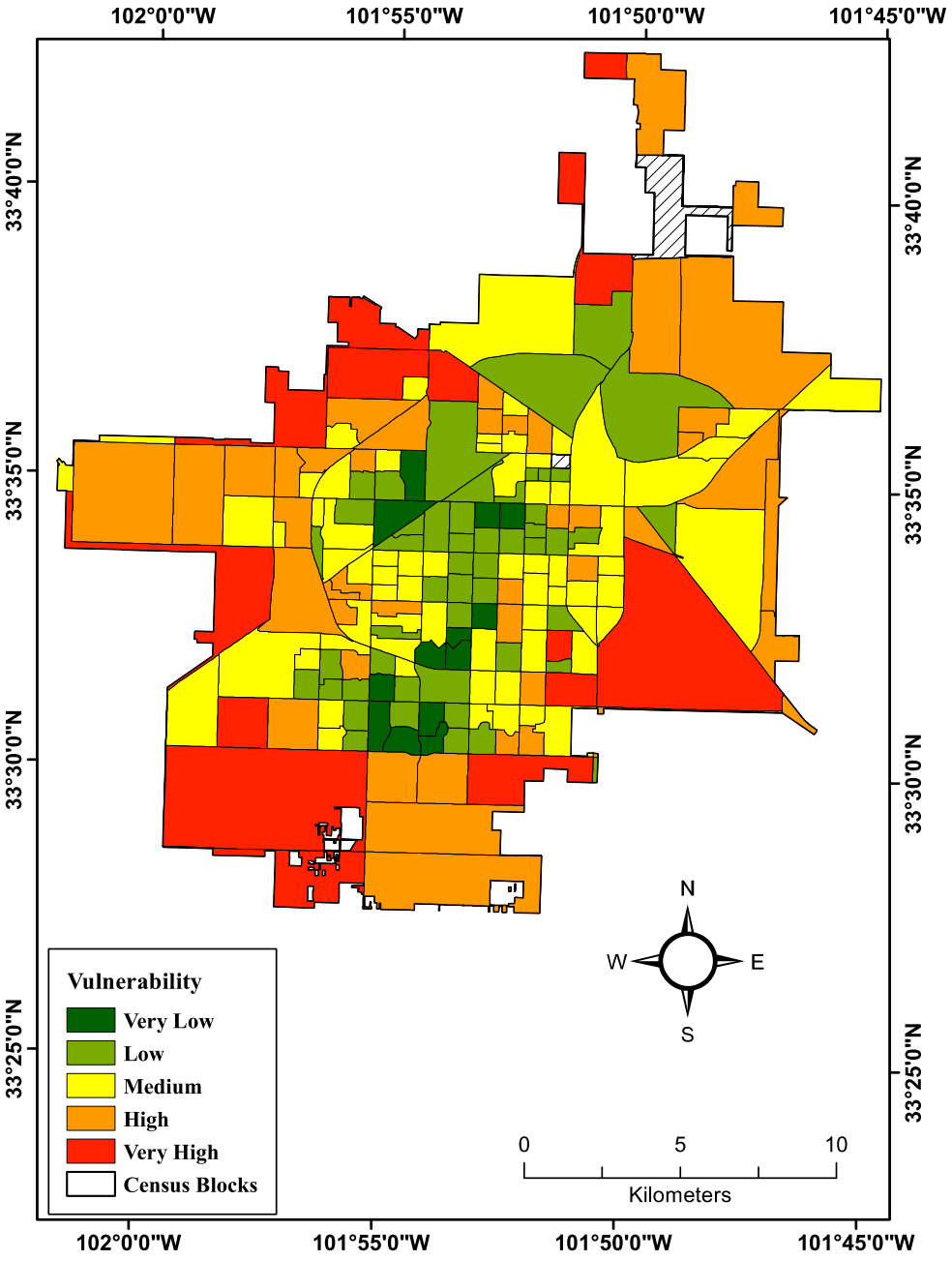

Figure 5.16 Results for heat vulnerability index at the census block level for Lubbock, Texas.