TREE MITIGATION STRATEGIES TO REDUCE THE EFFECT OF URBAN HEAT ISLANDS IN CENTER TOWNSHIP, IN

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ABSTRACT

Michelle C. Rigg

TREE MITIGATION STRATEGIES TO REDUCE THE EFFECT OF URBAN HEAT ISLANDS IN CENTER TOWNSHIP, INDIANA

The purpose of this study was to identify urban heat island locations within Center Township, Indiana and to develop a model to determine areas of high social vulnerability. In addition, an urban heat island mitigation strategy was developed for socially vulnerable and highest temperature locations. Land surface temperature was estimated using Landsat ETM+ satellite imagery. Social vulnerability was estimated using principal components analysis and spatial analysis methods such as kernel density functions. These methods incorporate various socioeconomic variables, land surface temperature, and tree canopy cover. Tree canopy cover was extracted using Quickbird imagery among other techniques. Areas with high social vulnerability, high temperature and low tree canopy cover were analyzed and plantable spaces were assessed. The findings of this study will be shared with Keep Indianapolis Beautiful, Inc. so that they can inform their tree planting campaigns that seek to reduce the effects of urban heat islands on socially vulnerable populations.

Daniel P. Johnson, Ph.D., Chair

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INTRODUCTION

The urban heat island (UHI) effect is the characteristic warmth of urban areas compared to the cooler surrounding non-urbanized areas (Voogt 2002). The urban heat island can be defined as the spatially-averaged temperature difference between an urban area and its surrounding rural area (Magee, Curtis and Wendler 1999). In general, the ambient temperatures in urban areas are several degrees higher than the surrounding rural and suburban areas (Synnefa et al. 2008). During the summer season, many urban areas have daytime temperatures of 1-6^{o}C higher than the surrounding rural areas; this is present for many cities worldwide (Synnefa et al. 2008). In addition, "a key characteristic of the UHI effect are elevated night-time (typically minimum daily) temperatures" (Solecki et al. 2005, 39). Temperatures in the urban environment vary not only from rural surroundings but also within the urban area due to intra-urban differences in land-use and surface characteristics (Hart and Sailor 2009). The UHI is caused by surface and atmospheric modifications that occur throughout urban areas. "Changes to the surface radiation and energy balances lead primarily to reduced cooling rates in urban areas" (Voogt 2002, 1). Warmer urban temperatures is primarily caused by anthropogenic heat released from vehicles, air conditioners and other heat sources, and due to the heat stored and re-radiated by massive and complex urban structures (Rizwan, Dennis and Liu 2008). More solar radiation is stored as sensible heat in urban areas due to the presence of impervious surfaces, the lack of vegetation and the decreased sky view factor in urban areas. The ability of heat release through long-wave radiation in urban areas is typically low due to the canyon geometry of urban areas and the decreased sky view factor; this phenomena results in high heat storage in building structures (Rizwan, Dennis and Liu 2008). Heat islands are characterized into three categories based on the different layers within the urban atmosphere and for the varied surface types; these three layers are the canopy layer, boundary layer, and the surface layer urban heat island. The urban canopy layer extends upwards from the surface to mean building height; the urban boundary layer is located above the canopy layer (Voogt and Oke 2003). The canopy layer heat island and the boundary layer heat island are atmospheric heat islands because they indicate any warming within the urban atmosphere. The surface urban heat island refers to the warmth of the urban surfaces when compared to the surrounding rural and suburban areas (Yuan and Bauer 2007).

Extreme Heat Events (EHEs) are particularly pronounced in cities due to the urban heat island effect. In order to determine EHE days, a heat threshold has been developed for many U.S. cities; several evaluations have found that there is an importance of several consecutive days above a temperature threshold. The National Weather Service uses a heat threshold when daytime heat index values are 105^{o}F or above for more than three hours a day for two consecutive days, or when the daytime heat index exceeds 115^{o}F for any length of time (Kalkstein et al. 1996). Heat-related morbidity and mortality can occur during heat events; these are expected to increase in frequency and severity due to climate change. In addition, death from extreme heat is the number one weather-related killer in North America (Abidine et al. 2007). "Since 1998, heat waves have resulted in more weather-related fatalities annually than any other natural disaster"(Bernard and McGeehin 2004, 1520). Heat stroke is the most common cause of death and severe illness attributable to heat. Heat stroke symptoms are characterized by a body temperature of 105^{o}F (40.6^{o}C) or higher and an altered state of mind. Other causes of death that increase during elevated heat are heart disease, diabetes, respiratory diseases, accidents, stroke, suicide, violence and homicide (McGeehin and Mirabelli 2001). It is estimated that around 240-400 heat related deaths occur annually in the United States. During mid-July 1995, Chicago experienced a five-day heat wave in which temperatures ranged from 93^{o}F to 104^{o}F. During the Chicago heat wave, approximately 525 heat-related deaths occurred (Changnon, Kunkel and Reinke 1996). Approximately 118 deaths occurred in Philadelphia during a heat wave during July 6-14, 1993 (Ebi et al. 2004). In 2003, an estimated 70,000 people died in Europe over several months due to extreme heat (Stone, Hess and Frumkin 2010). Although extreme heat events are the number one weather-related killer, the death count is frequently underestimated because heat waves are multiday events and many of the affected individuals suffer from other health problems. In addition, there is no widely accepted definition of a "heat-death"; this allows medical examiners to define heat deaths differently (Changnon, Kunkel and Reinke 1996).

Various mitigation strategies can help to reduce the amount of heat stored in urban areas. The development of effective mitigation strategies are crucial for the overall health and well-being of people who live in urban areas; this is of increasing importance because of rapid population growth in urban areas, especially in developing countries. UHI mitigation strategies that have been shown to reduce temperatures include tree plantings, developing green roofs and building with cool materials. "Cool materials are characterized by high solar reflectance and infrared emittance values" (Synnefa et al. 2008, 2848). The solar reflectance and the infrared emittance both affect the temperature of the surface. An increase in reflectance and emittance can lower the surface temperature and the surrounding ambient air temperature. Black or dark colored buildings and impervious surface materials have a significantly lower reflectance and emittance characteristics than white building materials and impervious surfaces. For example, “the temperature of a black surface with solar reflectance of 0.05 is about 50^{o}C higher than ambient air temperature. For a white surface with solar reflectance of 0.8 the temperature rise is about 10^{o}C” (Synnefa et al. 2008, 2848). Mitigation strategies that implement tree plantings are particularly appealing because of the relatively low cost, minimal maintenance and long-term benefits involved. Tree planting mitigation has a two-fold benefit because the tree provides cooling shade and trees soak up groundwater, which then creates evapotranspiration, which cools the leaves as well as the surrounding air. The structure of tree and plant canopies and their physiological condition can strongly influence wind flow and transpiration rates. Although planting any type of tree provides benefits, not all trees are equally beneficial. For example, in temperate climates, deciduous trees may be better to plant than evergreens because they are able to provide shade in the summer and they block less of the sun’s warmth during winter.

This research attempted to locate urban heat islands, identify locations of socially vulnerable populations and determine the tree canopy cover in Center Township, Indiana. The identification of socially vulnerable areas, low tree canopy cover and high temperatures helped to develop a tree planting mitigation strategy to increase tree canopy cover and to reduce temperatures and risk levels of vulnerable areas and. Plantable spaces were identified and the results will be provided to KIB, a local non-profit group that organizes tree plantings.

BACKGROUND

Urban Heat Islands

An extensive amount of research on the effects, characteristics and the general causes of the urban heat islands have been published. Much research has also studied various mitigation strategies but many of these strategies are never implemented. The spatial locations of urban heat islands have been well studied and methods have been determined to locate UHIs. In situ sensors can measure air temperature, which can help to locate atmospheric urban heat islands. Satellite infrared remote sensing is able to measure the land surface temperature (LST) component of urban heat islands. "LST has been utilized in various heat-balance, climate modeling and global-change studies since it is determined by the effective radiating temperature of the Earth's surface, which controls surface heat and water exchange within the atmosphere"(Yuan and Bauer 2007, 376).

Several studies have examined the spatial patterns and relationships of various socioeconomic variables and urban heat islands. Johnson and Wilson (2009) investigated the spatial relationship of vulnerable populations, UHI intensities and heat-related deaths that occurred during the 1993 extreme heat event in Philadelphia, PA. They used a standard deviational ellipse (SDE) approach to determine spatial distributions. In addition, they tested the predictability of the spatial distribution of EHE mortality using multiple linear regression, following the exploratory analysis of the SDE (Johnson and Wilson 2009). It was found that the ellipse that contained the most deaths was age 65 and older. In addition, it was found that the only vulnerability measure used in the study that was similar to the total population distribution was age 65 and older (Johnson and Wilson 2009).

Nearly all urban heat island and extreme heat event research has found the same causes of death and illnesses attributable to heat. McGeehin and Mirabelli (2001) concluded that heat stroke is the most common cause of death and serious illness is attributable to EHEs. They also reported that the most common underlying medical conditions after exposure to excessive heat include cardiovascular and respiratory disease, diabetes, renal diseases, and nervous system disorders (McGeehin and Mirabelli 2001).

Saaroni et al. (2000) investigated the spatial variability of UHI intensity in Tel Aviv, Israel. During the daytime, they found both negative and positive heat pockets in the center of the city. The warmer areas were associated with high building densities, heavy traffic flows, various daytime heat sources and low sea-breeze ventilation while the cooler areas were found in open areas such as plazas.

Giridharan et al. found that the most significant land use factors that affect UHI intensity in Hong Kong were albedo, the sky view factor, the height to total floor area ratio and altitude (Giridharan, Ganesan and Lau 2005). Giridharan et al. also determined that the most significant correlation between urban land use parameters and UHI intensity was found on clear days and summer nights (Giridharan et al. 2007).

Socially Vulnerable Populations

As previously stated, urban areas are particularly affected by EHEs; this is of great importance because urbanization is increasing at an unprecedented rate for many cities worldwide. This growth in urbanization also means that the number of people exposed to the urban heat island effect is increasing, especially during EHEs (Voogt 2002). As with most natural disasters, socially created vulnerabilities are largely ignored due to the difficulty in quantifying them; this helps to explain why social losses are typically absent in after-disaster cost/loss estimation reports (Cutter, Boruff and Shirley 2003). "Social vulnerability is partially the product of social inequalities—those social factors that influence or shape the susceptibility of various groups to harm and that also govern their ability to respond (Cutter, Boruff and Shirley 2003, 243)." Social vulnerability also includes place inequalities, which represents the characteristics of communities and the built environment, such as urbanization, growth rates, and economic vitality that contribute to the social vulnerability of places (Cutter, Boruff and Shirley 2003). Previous social science research has found the characteristics that influence social vulnerability include age, gender, race and socioeconomic status. Previous studies have determined that the characteristics that influence social vulnerability to extreme heat events are also age, gender, race, socioeconomic status and education. Johnson and Wilson (2009) defined vulnerable populations in their EHE study as persons below poverty, those with less than a high school education, minority populations, the very young and the very old. In addition, Stone et al. (2010) concluded that the populations vulnerable to heat are the very young and old, those who are homebound, confined to a bed, or unable to care for oneself, those who are socially isolated, lacking air conditioning and suffering from psychiatric or cardiopulmonary disease. The majority of research concludes that the most vulnerable population is persons age 65 and older. In fact, it has been found that more than 70 percent of heat-related deaths occur in persons age 65 and older (Avery 1985). Cutter, Boruff and Shirley (2003) used the Social Vulnerability Index (SoVI) in order to determine the variables that are predictive of vulnerability to various environmental hazards for a particular location. This approach reduces the number of variables using a factor reductionist technique known as principle component analysis (PCA). For their research, PCA was able to reduce the number of variables from 42 to 11; these variables accounted for 76 percent of the variance. The output factors from the PCA were placed into an additive model used to compute a summary score; this summary score is the Social Vulnerability Index. The summary score is based on standard deviations from the mean ranging from -1 to +1 representing low to high vulnerability respectively.

Urban Heat Island Mitigation Strategies

The development and implementation of mitigation strategies could help to lower temperatures in vulnerable areas, which will help to protect people and reduce heat-related deaths and illnesses. A key federal program that plays a leading role to promote heat island mitigation strategies is the Heat Island Reduction Initiative (HIRI). The HIRI includes representatives from programs such as NASA, the US Department of Energy and the EPA. A few examples of strategies that the HIRI promotes include the installation of light-colored reflective roofing and paving materials, planting shade trees and adding more vegetative cover (Solecki et al. 2005). Several studies have reported widely successful strategies and mitigation plans to reduce the urban heat island effects with promising financial and environmental benefits. Most mitigation strategies help to reduce anthropogenic heat release by turning off air conditioners, design of better roofs, or other design factors such as tree plantings (Rizwan, Dennis and Liu 2008). It has also been determined that the increase in albedo and/or vegetation in urban areas can help to reduce urban air temperatures with the associated benefits in terms of air quality and energy consumption (Synnefa et al. 2008).

Several studies have modeled and suggested appropriate mitigation and preventative methods to reduce the effect of UHIs. Kalkstein developed a Hot Weather- Health Watch/Warning System for Philadelphia, PA. Kalkstein used a climatological index for the study. The climatological index is an automated air mass-based index, which categorizes each day based on its meteorological character using a synoptic climatological approach. This type of synoptic procedure groups meteorologically homogenous days based on the following elements: air temperature, dew point temperature, total cloud cover, atmospheric pressure, wind speed and direction. The overall goal of this system is to identify the oppressive air masses that are associated with increased mortality. The format of the system is three-tiered; it produces a health watch, health alert, or a health warning. This system is used by Philadelphia's National Weather Service office. (Kalkstein et al. 1996) The official warnings and "information is transmitted to the Philadelphia Department of Health from the University of Delaware's Center for Climatic Research, and after consultation with the local National Weather Service office, the health commissioner makes the final decision on the issuance of health advisories" (Kalkstein et al. 1996, 1524).

In addition, "several modeling studies have suggested that urban environmental control strategies such as the increase of surface albedo can reduce surface and air temperatures and this effect is the most evident in areas where such surface modifications are most concentrated" (Synnefa et al. 2008, 2847). A study carried out by Taha et al. examined the meteorological impacts of large-scale increases in albedo and vegetation in urban areas for 10 cities. This study found that changes in albedo and vegetation could offset the 1^{o}-2^{o}C urban heat islands found in the majority of cities studied. In a different study, Taha found that large-scale increase in both albedo and vegetative cover could result in a 3^oC-3.5^oC decrease in air temperature during some hours of the day (Taha 2005).

Previous studies that evaluated the effect of shade trees have typically been small-scale experiments that examine the effect of trees on individual buildings or large-scale simulation modeling studies. Akbari et al. were able to quantify the effect of shade trees on the total cooling costs of two comparable houses. For this experiment, 16 potted trees were placed along the south and west walls of the homes; the homeowners kept their houses at the same temperature and used similar lighting. Akbari et al. found that the trees were able to reduce the cooling costs between 26 and 47 percent (Akbari et al. 1997). Akbari and Taha used simulation modeling to determine the effect of trees on energy usage in four Canadian cities. It was concluded that increasing vegetative cover in a neighborhood by 30 percent and increasing the albedo of houses by 20 percent would decrease heating costs by 10-20 percent and decrease cooling costs by 30-100 percent (Akbari and Taha 1992).

Hart et al. used a combination of land-use data, surface cover imagery and weekday/ weekend daytime tree-structured regression models to quantify the land-use and surface characteristics that have the most significant impact and influence on UHI intensity in the Portland metropolitan area. Their results suggested that the most important urban characteristic separating warmer areas from cooler areas was canopy cover. They found that the influence of Portland's Forest Park is greatest during the warmest part of the day when factors such as shading from the dense canopy cover and evapotranspiration are most significant (Hart and Sailor 2009). In addition, Hart et al. also determined the difference of anthropogenic activity on UHI intensity for both weekends and weekdays:

the temperatures in Portland's downtown core experience 1-2^{o}C stronger UHI intensity on weekday afternoons than on weekend afternoons (Hart and Sailor 2009). This difference between UHI intensity during weekends and weekdays is most likely due to differences in anthropogenic heat emissions; emissions are less during the weekends because of a decrease in building maintenance and traffic flows directed downtown (Hart and Sailor 2009).

Rosenfeld et al. developed a simulation model for Los Angeles to determine whether white roofs and shade trees help to reduce temperatures. In addition, this model also proved that UHI mitigation strategies have a lucrative benefit/cost ratio. This model raised the city albedo by 7.5 percent and covered 5 percent of the area with 10 million trees. This model was able to predict that the direct effect of white roofs and shade trees could potentially reduce air conditioning use by approximately 18 percent for buildings that are directly affected (Rosenfeld, Romm and Akbari 1997). Rosenfeld et al. also determined that these mitigation strategies have an indirect effect; it was estimated that if a community drops about 1^{o}F by the use of white roofs and additional shade trees, the air conditioning load would decrease for everyone. These "indirect annual savings would total an additional 12 percent – 0.7 billion kilowatt-hours, or $70 million" (Rosenfeld, Romm and Akbari 1997, 56).

Silva et al. (2009) developed a zero-dimensional energy balance model to be used as a mitigation tool for the study of urban heat islands. The zero-dimensional model helped to show the relative effects of four common mitigation strategies; increasing the overall emissivity, the percentage of vegetation, thermal conductivity, and the albedo of the urban environment. This model can show the increase in each of these strategies in a series of percentage increase s by 5, 10, 15 and 20 percent from the standard baseline values. The overall goal of this model is to determine how the increases in each of the parameters will lead to reductions in the urban temperatures.

Cost-Benefits of Tree Planting

Approximately one-sixth of the electricity consumed in the United States is used to cool buildings; this has an annual power cost of about $40 billion. Mitigation tree planting methods involve planting a large amount of shade trees, but even a single tree planted has a benefit. For example, "a single properly watered tree can evapotranspirate 40 gallons of water in a day – offsetting the heat equivalent to that produced by one hundred 100-watt lamps, burning 8 hours per day"(Rosenfeld, Romm and Akbari 1997, 54). Planting trees can also help to reduce pollutants and smog. Within many urban areas, a 5^{o}F heat island can increase the amount of pollutants; once pollutants are released in the form of ozone, they form the main ingredients of smog (Rosenfeld, Romm and Akbari 1997). The direct reduction of air pollution is because of a decreased use in cooling energy. "Indirect air pollution reductions reflect the fact that the reaction of ozone formation (that produces smog) accelerates at higher temperatures, therefore at lower urban temperatures the probability of smog formation is decreased" (Synnefa et al. 2008, 2847). Although most trees help to reduce smog there are several types that help to create it; these trees should not be used as mitigation trees. Some tree species emit large amounts of volatile organic hydrocarbons (VOC's) that combine with oxides of nitrogen to form smog. Ash and Maple are among the more VOC-free trees, emitting only about one VOC unit. Eucalyptus trees are problematic because of the high amounts VOC emissions (Rosenfeld, Romm and Akbari 1997).

Public Values and Benefits from Trees

Trees can benefit an individual, a group/organization or an entire community (Westphal 2003). Vegetated areas such as gardens, parks and forests have been related to positive social outcomes including crime reductions, health benefits, and advanced childhood development (Tooke et al. 2009). An increase in trees and tree plantings can also improve the physical appearance of an area, improve the environmental quality, and it can have an impact on important social issues such as education, economic development and social disenfranchisement. Research has also found that community tree plantings give citizens a sense of empowerment and it can help to strengthen the social fabric within a community (Westphal 2003). Within urban areas, urban forests play a critical role and can affect people socially, physically and mentally. Urban forests are ecosystems which are characterized by the existence of trees and vegetation in association with human developments (Nowak et al. 2001). The increasing urban populations have put increasing pressure on urban forests, threatening the basic ecological functions such as water and air purification. Several studies have helped to determine how the public values urban forests. Hull determined through surveys that people believe that trees evoke positive feelings and that they serve an important role in improving the community image (Hull 1992). Lohr et al. discovered through surveys that the public typically has positive attitudes towards trees in cities; they also determined that the attitudes were increasingly positive if the subject had participated in garden or outdoor activities during childhood (Lohr et al. 2004). On the other hand, the people who valued trees the least were typically males, young people, poorly educated and those with low incomes. In addition, it was determined that the highest-ranked reason for using trees was for shade and cooling. Overall, it can be determined that trees play a significant role in reducing temperatures, increasing the well-being and beauty of neighborhoods, and positively affecting people socially, educationally, emotionally and economically.

Tree Canopy Estimation

There is an extensive amount of research on methods used to estimate vegetation characteristics and tree canopy coverage within urban areas. Urban areas contain a variety of tree types (species and dimensions), land uses, and manufactured structures and each of these has different spectral reflectance characteristics. The urban mosaic can make urban tree classification very difficult because unlike trees in rural areas that tend to form in continuous canopies, trees in urban settings are often single trees or isolated groups (Avery 1985). The increase of impervious surfaces, bare soil and shadows within cities also make characterizing trees by remote sensing difficult. In cases of such difficult characterization of urban tree canopies, it is important to use high spatial resolution imagery for mapping individual trees (Avery and Berlin 1992).

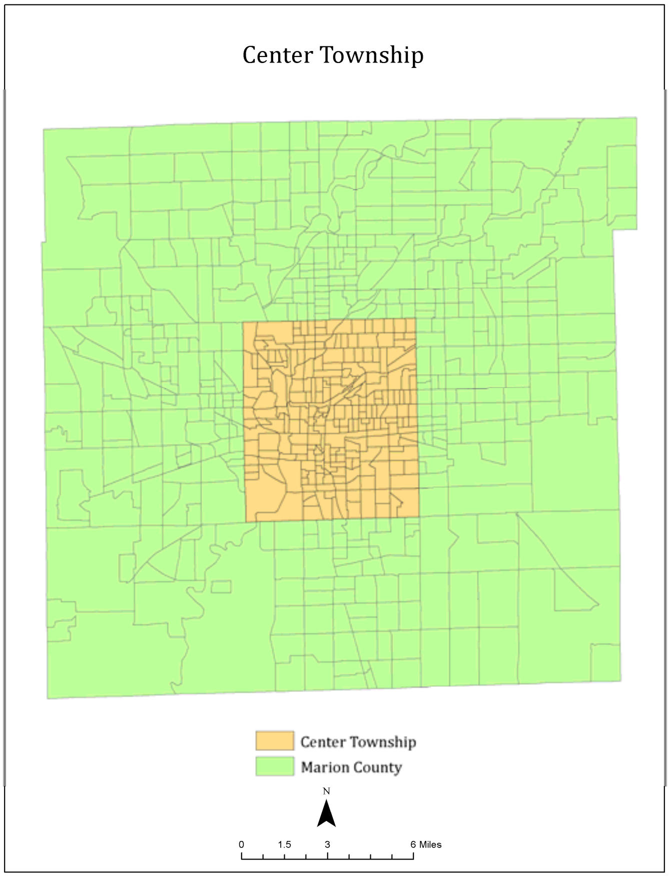
Tooke et al. classified urban vegetation characteristics by the use of spectral mixture analysis and decision tree classification using Quickbird imagery. This study was able to produce vegetation fractions, high albedo substrate and dark features by the use of spectral mixture analysis. This study also estimated shadows using LIDAR (Light Detection and Ranging) data; in addition, the condition and species of the vegetation was collected from observations to provide training data for the decision tree classifications. The results suggested that tree and vegetative ground cover could be accurately separated along the vegetation-dark mixing line with 80 percent and 94 percent of the variance explained respectively. In addition, “more categories with variance explained ranging from 67% and 100%" (Tooke et al. 2009, 398). The research also determined that leaf-off condition of deciduous trees could create pixels that have higher dark fractions due to bare tree branches and exposed soil that dominate the reflectance values.

Xiao et al. (2004) used high-resolution Airborne Visible Infrared Imaging Spectrometer (AVIRIS) data and multiple masking techniques to extract and identify urban vegetation characteristics in Modesto, CA. The AVIRIS data categorized the vegetation based on the spectral character difference and the masking techniques shifted the focus on particular land cover types in order to reduce confounding noise during the spectral analysis. Xiao et al. were able to use low altitude AVIRIS data acquired at 3.5m spatial resolution; this allowed for studying the urban forest at an individual tree level. This study used AVIRIS data, a field survey of all street trees, and various GIS layers (parcels, buildings, roads etc.). Isolated trees were used to avoid spectral mixing among different species, 22 different species were selected from the field sample, and training sites were selected with GIS for validation purposes. Xiao et al. were able to accurately select 16 of the 20 tree species; accuracy increased when the trees had large crowns and dense leaves. Overall, Xiao et al. concluded that isolated tree species could be accurately classified using AVIRIS data.

METHODS

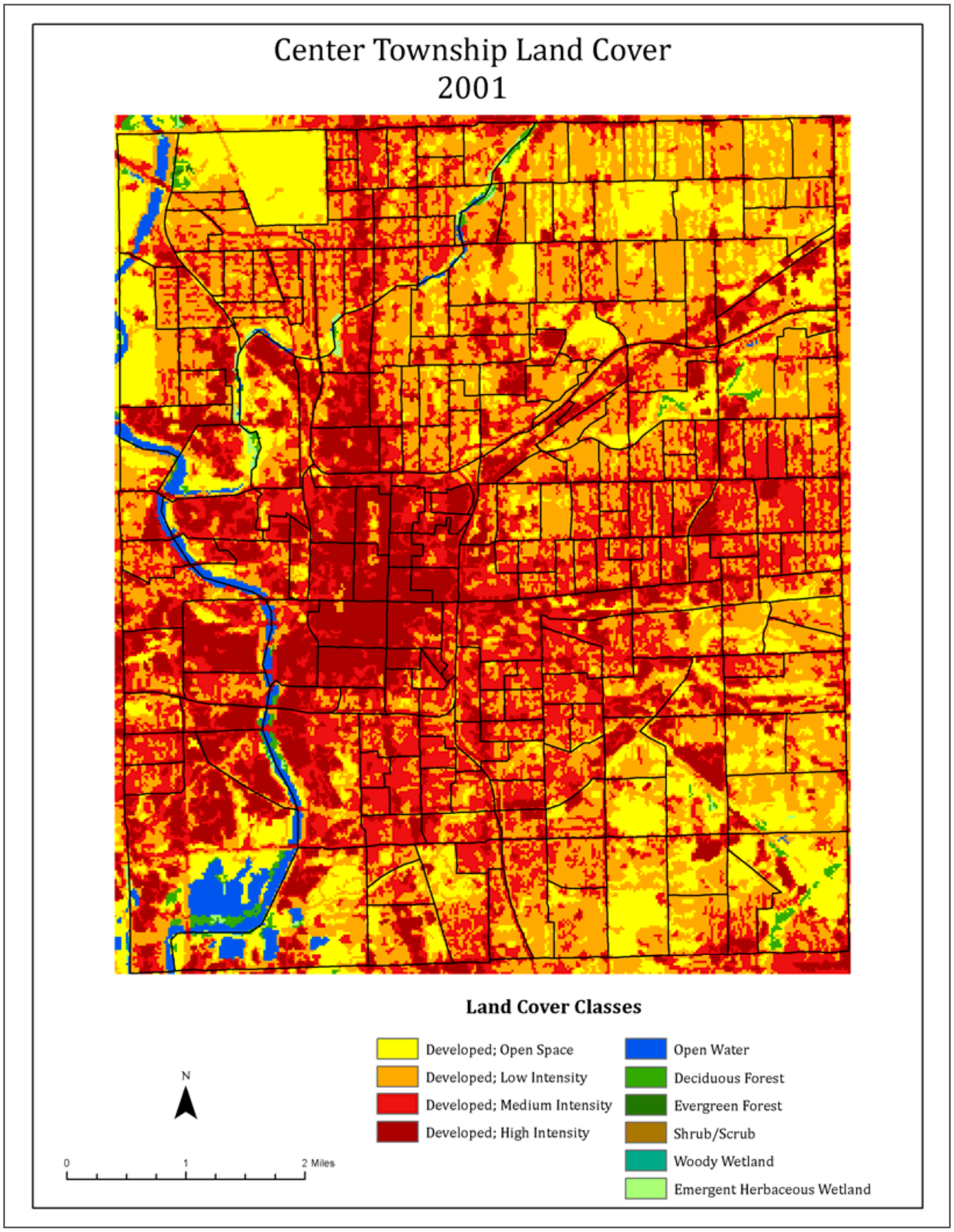
Study Area

Figure 1: Study Area



This study focused on Center Township in Marion County, Indiana (as seen in Figure 1 above), which is located within Indianapolis. It contains the central business district (CBD), Indiana University Purdue University Indianapolis (IUPUI) and several hospitals. In addition, approximately 97 percent of the total land area within Center Township is developed, ranging from open space development to high intensity development (see Figure 2). More specifically, the study focused on Census block groups as units of analysis. A total of 235 block groups are located within Center Township.

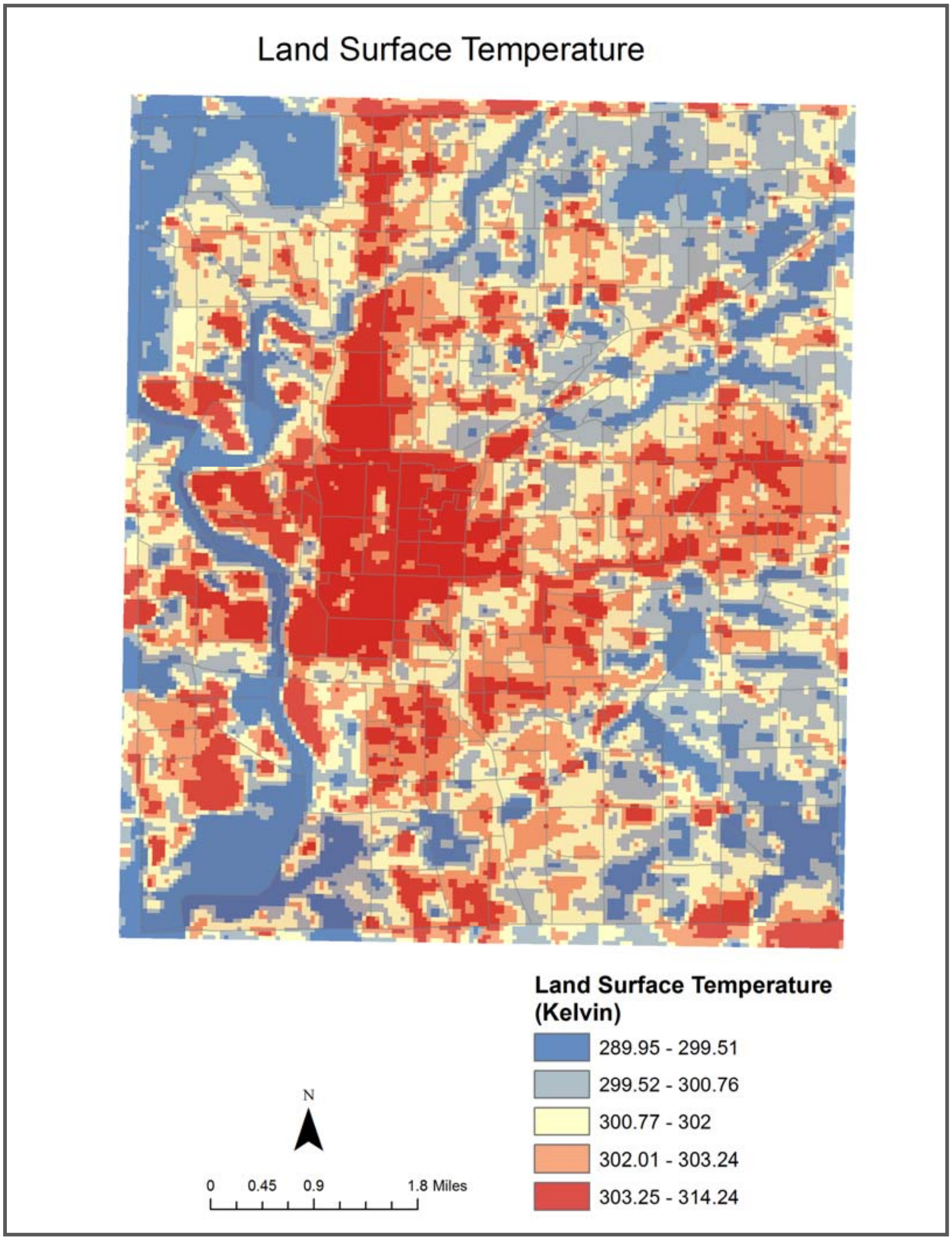
Figure 2: Land Cover Type



Land Surface Temperature

Landsat 7 Enhanced Thematic Mapper Plus (ETM+) imagery was used to determine the land surface temperature (LST) within Center Township. The scan line corrector failure within ETM+ was fixed by an algorithm performed by NASA for this imagery. The Landsat image was collected on June 23, 2009 with 0 percent cloud cover; it was acquired from the USGS Global Visualization Viewer (GLOVIS) http://glovis.usgs.gov/. Landsat collects land surface temperature and stores the information as raw digital numbers; these numbers can be converted to degree Kelvin. In order to determine the LST, methods suggested by Chander et al. (2009) were used; these methods transform the digital numbers to temperature. These methods convert sensor spectral radiance to at sensor brightness temperature. These methods were completed in the ERDAS Imagine modeler. The Kelvin temperatures were then converted to Fahrenheit for ease of use and understanding. The LST values were then mapped to display the land surface temperature variations throughout Center Township.

Figure 3: Land Surface Temperature in Kelvin



Socioeconomic Variables

Socioeconomic variables were selected on the basis of previous research that identified variables associated with populations that are particularly vulnerable during extreme heat events (Johnson and Wilson 2009). Socioeconomic data were acquired from the U.S. Census Bureau's American Factfinder for 2000 at the block group level. The variables selected are the following: total population, Caucasian, African American, other race, Hispanic, persons under the age of 5; persons age 65 and older, median household income, total population below poverty, age 65 and older below poverty, persons with less than a high school education, age 65 and older living alone. The data was joined with a block group shapefile of Center Township and converted from feature to point in order to run the kernel density function.

Density Estimation

A kernel density function (KDF) was run for each of the socioeconomic variables selected. A KDF is capable of transforming data that is associated with geographically discrete features into a continuous or smooth raster. The KDF calculates a magnitude per unit area from point or polyline feature to fit a smoothly tapered surface to each point or polyline (ESRI 2010a). "The kernel weights vary within its 'sphere of influence' according to their distance from the point or polyline as the intensity estimated: the surface value is highest at the location of the geo-feature and diminishes over from the geo-feature" (Li, Wang and Leung 2010, 1764-1765). The KDF is able transform and normalize data in order to represent the densities of each variable and to decrease errors caused by political and geographic boundaries. In addition, the KDF outputs a raster dataset that can then be used to determine the zonal statistics for each of the variables.

Zonal Statistics

Once the KDF's were run for each socioeconomic variable, zonal statistics were then run on each KDF variable and temperature. Zonal statistics can calculate statistics on raster values within the zones of another dataset" (ESRI 2010b). In other words, the zonal statistics were able to use the normalized KDF data and average the pixel values for each block group. This process resulted in a zonal mean for each variable within each block group. The area input for the zonal statistics was the centroid point of each block group, the unique STFID field was chosen as the zone field and the input value raster used was the KDF for each of the socioeconomic variables.

Principal Component Analysis

The next step used the zonal statistic mean output to determine the social vulnerability levels of the block groups within Center Township. A Social Vulnerability Index (SoVI) was used for the block groups of Center Township. The Social Vulnerability Index reduces the number of variables to only those that account for variance using PCA. The SoVI uses the factor outputs from the PCA in an additive model, which results in a score for overall social vulnerability. For this study, the PCA was run on the mean value of the socioeconomic variables. The central idea of the PCA is to reduce dimensionality of a dataset consisting of a large number of interrelated variables, while retaining as much variation as possible present in the dataset (Joliffe 2002). PCA allows for robust and consistent sets of variables to be monitored over time in order to assess any changes in overall vulnerability (Cutter, Boruff and Shirley 2003). For this PCA, the mean values of each socioeconomic variable by block group were used as the independent variables. The output factor loadings of the PCA will help to determine the variables that are predictors of social vulnerability. The Kaiser criterion was used for the determination of which factors to use because of its capability to represent the most variation. The Kaiser criterion retains only the factors that have eigenvalues greater than 1. The idea behind the Kaiser criterion is that unless a factor extracts at least as much as the equivalent of one original variable, it gets dropped (StatSoft 2011). For this research, three factors had eigenvalues greater than 1. These three factors were summed and used to represent the social vulnerability. A choropleth map representing social vulnerability was then created.

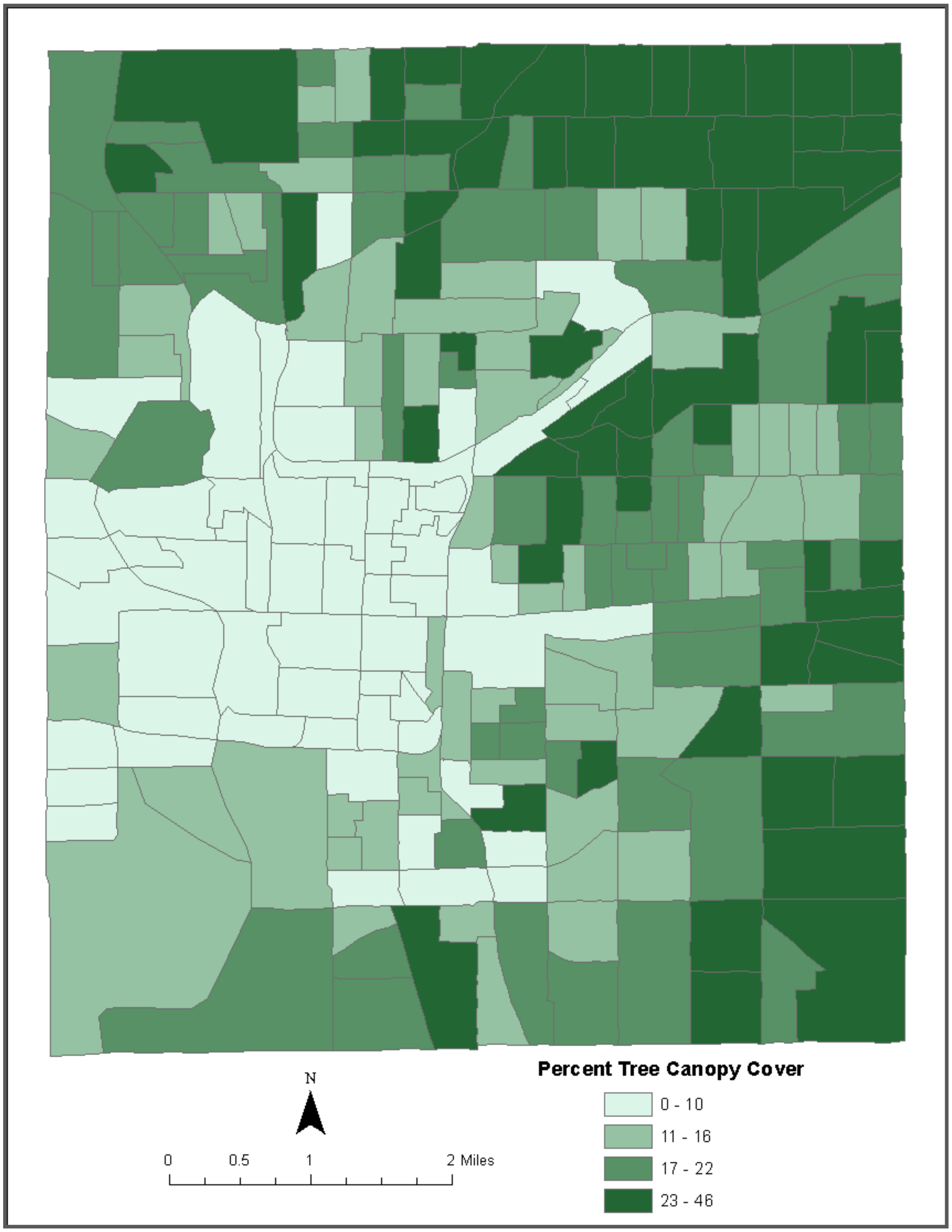
Tree Canopy Assessment

A tree canopy assessment of Center Township completed by graduate students in IUPUI's Department of Geography and Keep Indianapolis Beautiful, Inc. was used to estimate tree canopy coverage in the study area. The tree canopy was created using satellite and aerial imagery. The Quickbird satellite collected the satellite imagery on April 25, 2005. The Quickbird sensor collects multispectral imagery in the blue, green, red, near-infrared portions of the electromagnetic spectrum at a resolution of 2.4m. Additionally, the Quickbird sensor also collects panchromatic black and white imagery at a resolution of 61cm.

The first phase of the tree canopy assessment involved digital image classification of the Quickbird satellite imagery to group the image pixels into 50 categories based on similar spectral qualities. The iterative self-organizing data analysis technique (ISODATA) unsupervised classification algorithm was used for clustering. The resulting clusters were then classified as either tree canopy, other or mixed. The second phase of the assessment involved visual interpretation and on-screen digitizing using the aerial imagery as a backdrop to correct errors and increase the accuracy of the tree canopy map.

Once the canopy assessment was complete, the tree canopy data was imported into ArcMap as a vector file and the percent tree canopy for each block group in Center Township was calculated. To determine the percent tree canopy cover more accurately, the tree canopy polygons were clipped by the extent of each block group. A choropleth map displaying percent tree canopy was then created to visually display the data.

Figure 4: Percent Tree Canopy Cover



Plantable Space Assessment

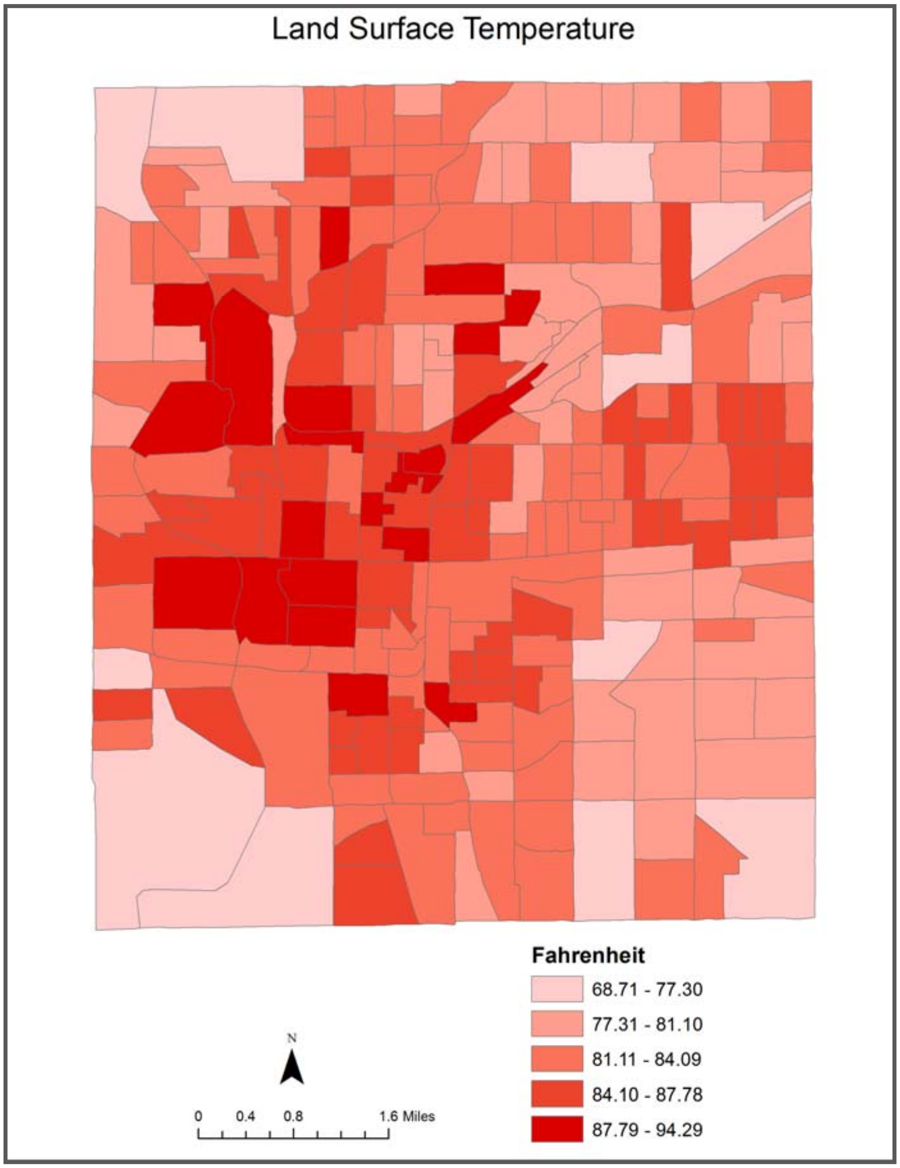
Standard deviation maps were created to represent percent tree canopy cover, land surface temperature and social vulnerability; these maps helped determine which block groups have temperatures and social vulnerability above the mean and tree canopy cover below the mean. The block groups that have a combination of high temperature, high social vulnerability and low tree canopy cover were selected for further analysis; a total of 18 block groups were selected These block groups were assessed and suitable spaces to plant trees were then determined. Plantable spaces were chosen through visual interpretation of aerial imagery, land use/ land cover characteristics, building polygon features, hydrology characteristics and street segment data. Locations with open space to plant (i.e. without impervious surfaces) were selected as plantable spaces. Polygons were digitized to designate plantable spaces and the total area of plantable space for each block group was determined and ranked. This data will be provided to Keep Indianapolis Beautiful, Inc in order to implement tree plantings in these socially vulnerable locations.

RESULTS

Land Surface Temperature Results

Land surface temperatures derived from the Landsat ETM+ image of the study area ranged from 289.95K–314.24K. The highest temperatures were located within the central business district (CBD). Other high temperatures were observed within high-density/high-intensity developed neighborhoods surrounding the CBD. Figure 3 displays the temperature variations within Center Township. Zonal statistics were used to determine the average temperature for each block group. These average land surface temperatures were converted to degrees Fahrenheit. The average temperature in Fahrenheit for each block group ranged from 68.71^{o}F–94.29^{o}F. Figure 4 represents the average temperature in Fahrenheit for each block group.

Figure 5: Land Surface Temperature in Fahrenheit



Social Vulnerability Results

The resulting output is reported in Tables 3-8. Table 5 is highlighted in order to represent how the variables are grouping together in the components. For example, variables Total65_Mean to Hispanic_Mean are grouped into component 1. Total65Alone_Mean to Male65_Mean are grouped into component 2; the remaining variables are grouped into component 3. These components represent either greater or lesser variance. In other words, the most variance in vulnerability is explained in component one, followed by component 2 and then component 3. When the values within the first 3 components are summed, they explain about 80 percent of the total variance in vulnerability. Figure 5 displays components 1-3 summed; this map represents the social vulnerability for the block groups located within Center township.

Table 1: Total Variance Explained

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	9.139	50.771	50.771	9.139	50.771	50.771
2	3.923	21.794	72.564	3.923	21.794	72.564
3	1.346	7.480	80.044	1.346	7.480	80.044
4	.867	4.818	84.862			
5	.707	3.929	88.791			
6	.492	2.735	91.525			
7	.420	2.333	93.858			
8	.358	1.991	95.849			
9	.321	1.786	97.635			
10	.153	.847	98.482			
11	.122	.677	99.159			
12	.056	.313	99.472			
13	.040	.220	99.692			
14	.037	.207	99.899			
15	.018	.101	100.000			
16	2.908E-5	.000	100.000			
17	1.710E-5	9.500E-5	100.000			
18	2.540E-6	1.411E-5	100.000			

Extraction Method: Principal Component Analysis.

Table 2: Component Matrix

Component Matrix[a]

	Component		
	1	2	3
TotalHS_MEAN	.922	-.126	-.140
Total65_MEAN	.921	-.220	-.124
Male5_MEAN	.913	-.202	-.135
Fem5_MEAN	.913	-.235	-.110
FemHS_MEAN	.909	-.016	-.165
MaleHS_MEAN	.848	-.227	-.101
BelPov_MEAN	.839	-.051	-.281
Other_MEAN	.779	-.518	.046
Hispanic_MEAN	.734	-.533	.055
White_Mean	.696	-.410	.507
Male65_MEAN	.643	.569	.058
MHHI_MEAN	.471	-.156	.460
Total65Alone_MEAN	.544	.743	.260
BelPov65_MEAN	.390	.720	.015
Fem65Alone_MEAN	.547	.670	.155
Male65Alone_MEAN	.366	.632	.358
Fem65_MEAN	.582	.612	.044
Black_MEAN	.197	.586	-.682

Extraction Method: Principal Component Analysis.

a. 3 components extracted.

Table 3: Rotated Component Matrix

Rotated Component Matrix[a]

	Component		
	1	2	3
Total65_MEAN	.931	.195	.086
Fem5_MEAN	.925	.182	.103
Male5_MEAN	.920	.204	.068
TotalHS_MEAN	.900	.272	.038
Other_MEAN	.874	-.080	.328
MaleHS_MEAN	.863	.162	.100
FemHS_MEAN	.853	.354	-.025
BelPov_MEAN	.837	.262	-.130
Hispanic_MEAN	.837	-.111	.336
Total65Alone_MEAN	.124	.948	.054
Fem65Alone_MEAN	.184	.860	-.017
Male65Alone_MEAN	-.017	.798	.160
Fem65_MEAN	.267	.797	-.095
BelPov65_MEAN	.064	.795	-.186
Male65_MEAN	.333	.791	-.059
Black_MEAN	.135	.414	-.811
White_Mean	.633	.094	.707
MHHI_MEAN	.350	.197	.545

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Table 4: Component Transformation Matrix

Component Transformation Matrix

Component	1	2	3
1	.883	.451	.134
2	-.383	.855	-.350
3	-.273	.258	.927

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

Table 5: Coefficient Matrix

Component Score Coefficient Matrix

	Component		
	1	2	3
White_Mean	.005	.042	.396
Black_MEAN	.100	.007	-.519
Other_MEAN	.117	-.066	.089
Hispanic_MEAN	.112	-.069	.096
Male5_MEAN	.135	-.025	-.062
Fem5_MEAN	.133	-.027	-.041
Male65_MEAN	-.005	.167	-.001
Fem65_MEAN	-.013	.171	-.016
Total65_MEAN	.136	-.026	-.052
MHHI_MEAN	-.032	.077	.338
BelPov_MEAN	.143	-.023	-.177
BelPov65_MEAN	-.036	.179	-.048
MaleHS_MEAN	.125	-.027	-.037
FemHS_MEAN	.123	.010	-.099
TotalHS_MEAN	.130	-.009	-.071
Male65Alone_MEAN	-.099	.224	.196
Fem65Alone_MEAN	-.044	.203	.055
Total65Alone_MEAN	-.073	.238	.121

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

Component Scores.

Table 6: Covariance Matrix

Component Score Covariance Matrix

Component		1	2	3
dimension0	1	1.000	.000	.000
	2	.000	1.000	.000
	3	.000	.000	1.000

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

Component Scores.

Figure 6: Socially Vulnerable Locations

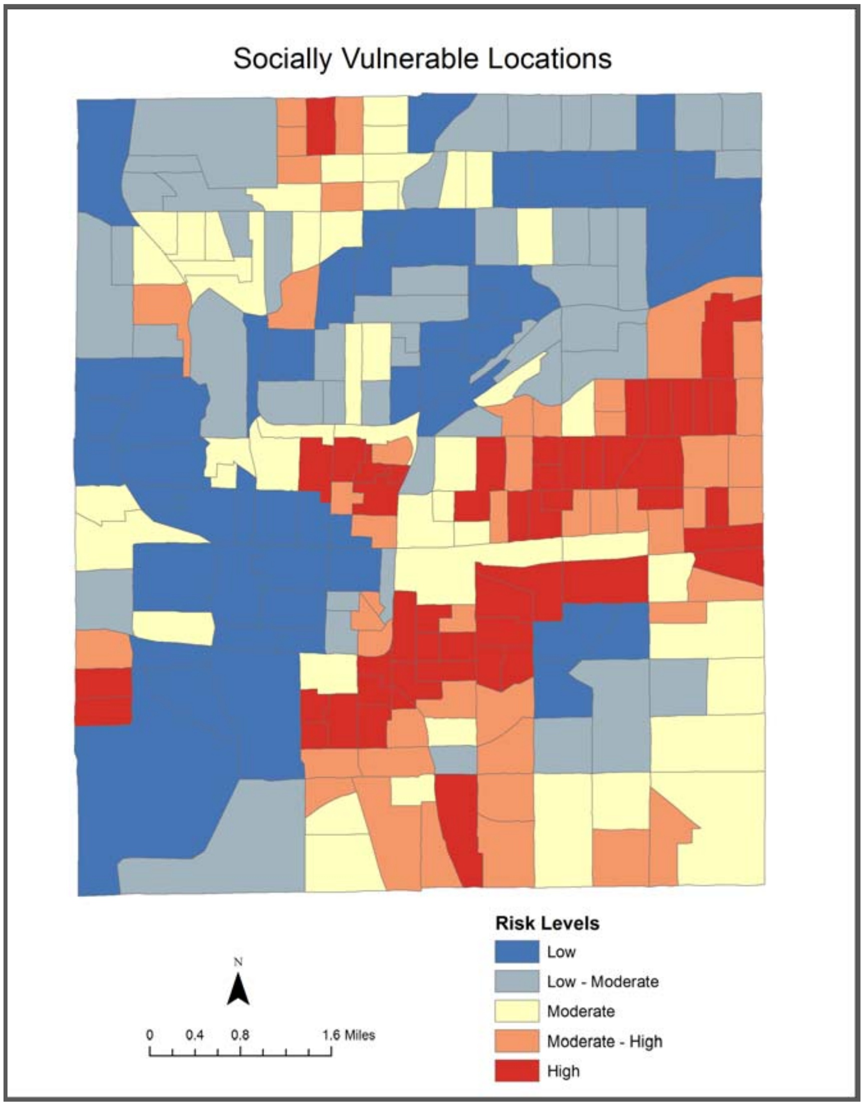
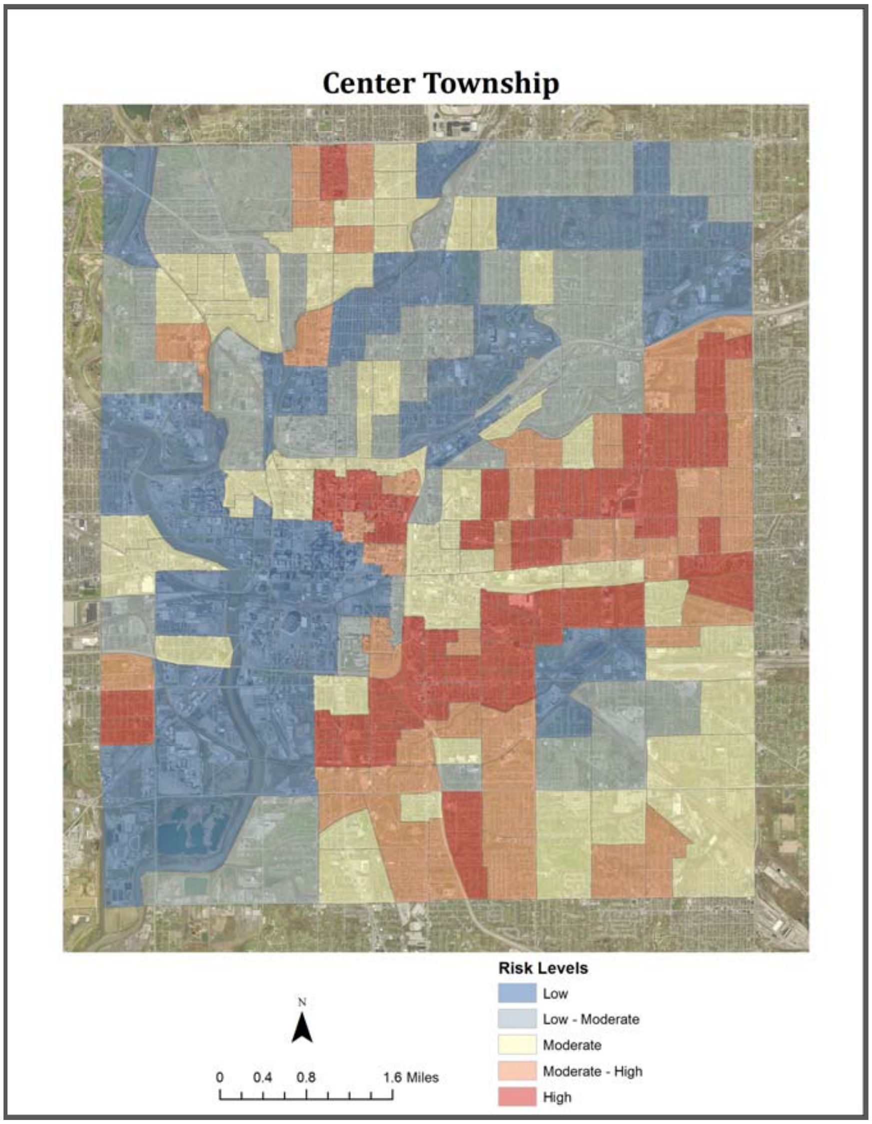


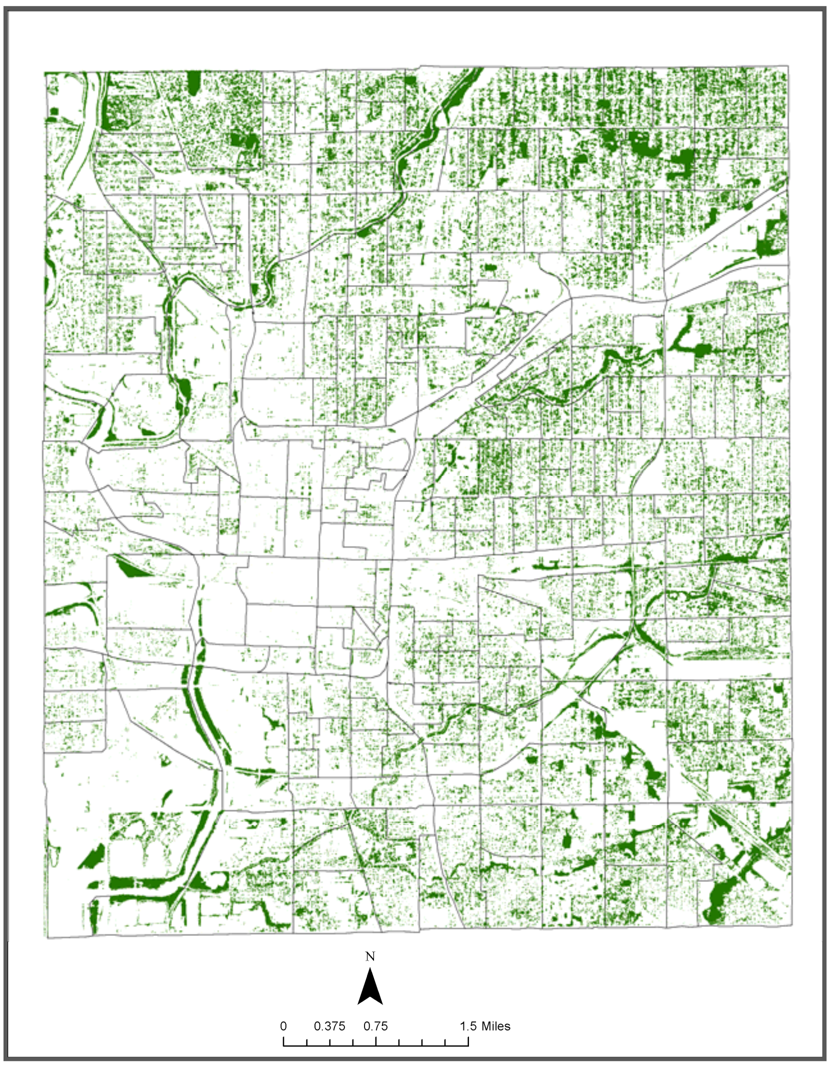
Figure 7: Socially Vulnerable Locations with Aerial Image



Tree Canopy Extraction Results

The tree canopy map provided by the IUPUI Deparment of Geography is displayed in Figure 6. The majority of heavy tree canopy cover is located along water features and within suburban areas surrounding the CBD. There is very little tree canopy cover within the CBD.

Figure 8: Raster Image of Tree Canopy Cover



The range of the percent tree canopy cover within block groups was approximately 0-46 percent. The block group that contained about 0 percent tree canopy cover was an outlier. This block group is only about 1536 square feet and it is located in a median between I-65 North and on a ramp to I-65 North. This block group appears to be an anomaly with a population also of zero. This particular block group was excluded from the classification when the standard deviation maps were completed.

Most Vulnerable Block Groups and Plantable Space Results

The social vulnerability, tree canopy cover and temperature maps were recreated to represent standard deviations. One standard deviation from the mean was used for each map. Block groups with social vulnerability above the mean are mostly located within the central and western and near eastside areas of Center Township (see Figure 9). The block groups with standard deviations above the mean for temperature are located within the center portion of Center Township but some are also found within the southern and western portion of the township (see Figure 9). The block groups with standard deviations below the mean for percent tree canopy cover are located within much of Center Township except or the northwestern corner of the township (see Figure 10). A total of 18 block groups were selected to further study for plantable space locations. These block groups were chosen because they had a combination of low tree tree canopy cover below the mean and high social vulnerability and temperatures aboce the mean. It was found that the percent plantable space for the most vulnerable block groups ranged from approximately 1.47-20.94 percent. See Table 9 for each block groups percent plantable space. In addition, several maps were created to show examples of the plantable space digitizing. Figure 13 represents the block group with the lowest percent plantable space (1.47 percent). This block group has the lowest plantable space percent because it is situated within the CBD where most of the groundcover is impervious surfaces and very little open space. Figure 14 represents the the near average percent plantable space (11.86 percent). This block group has a good deal of open space in which trees can be planted. This block group is a good representation of what the plantable space looks like for the more residential block groups that were selected. Figure 15 represents the block group with the highest percent plantable space (20.94 percent). This block group has a lot of plantable space because a highway exists within it. There is a lot of tree planting potential because there are large amounts of open space surrounding the highways and on the medians.

Figure 9: Social Vulnerability Measured with Standard Deviation

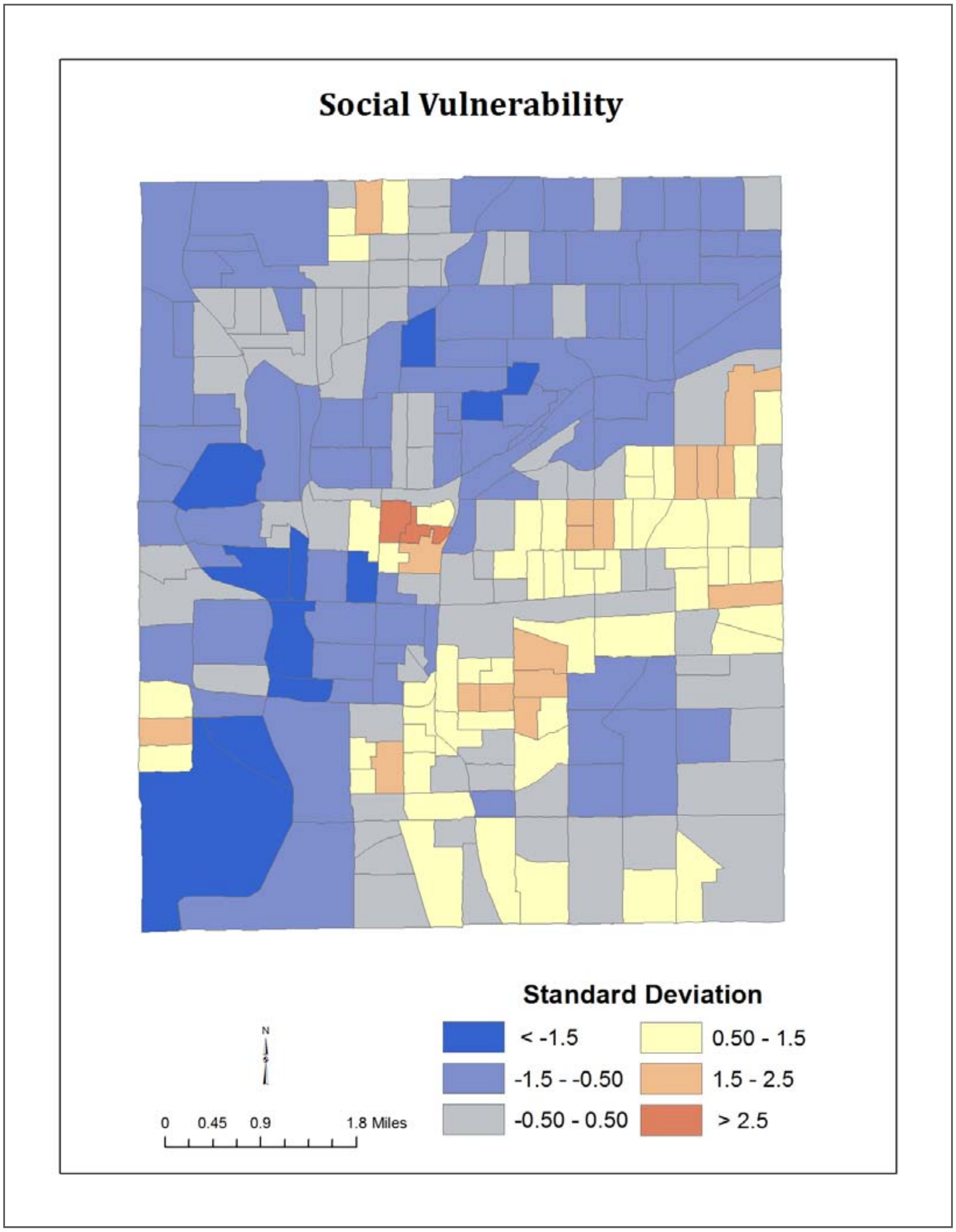


Figure 10: Land Surface Temperature Measured with Standard Deviation

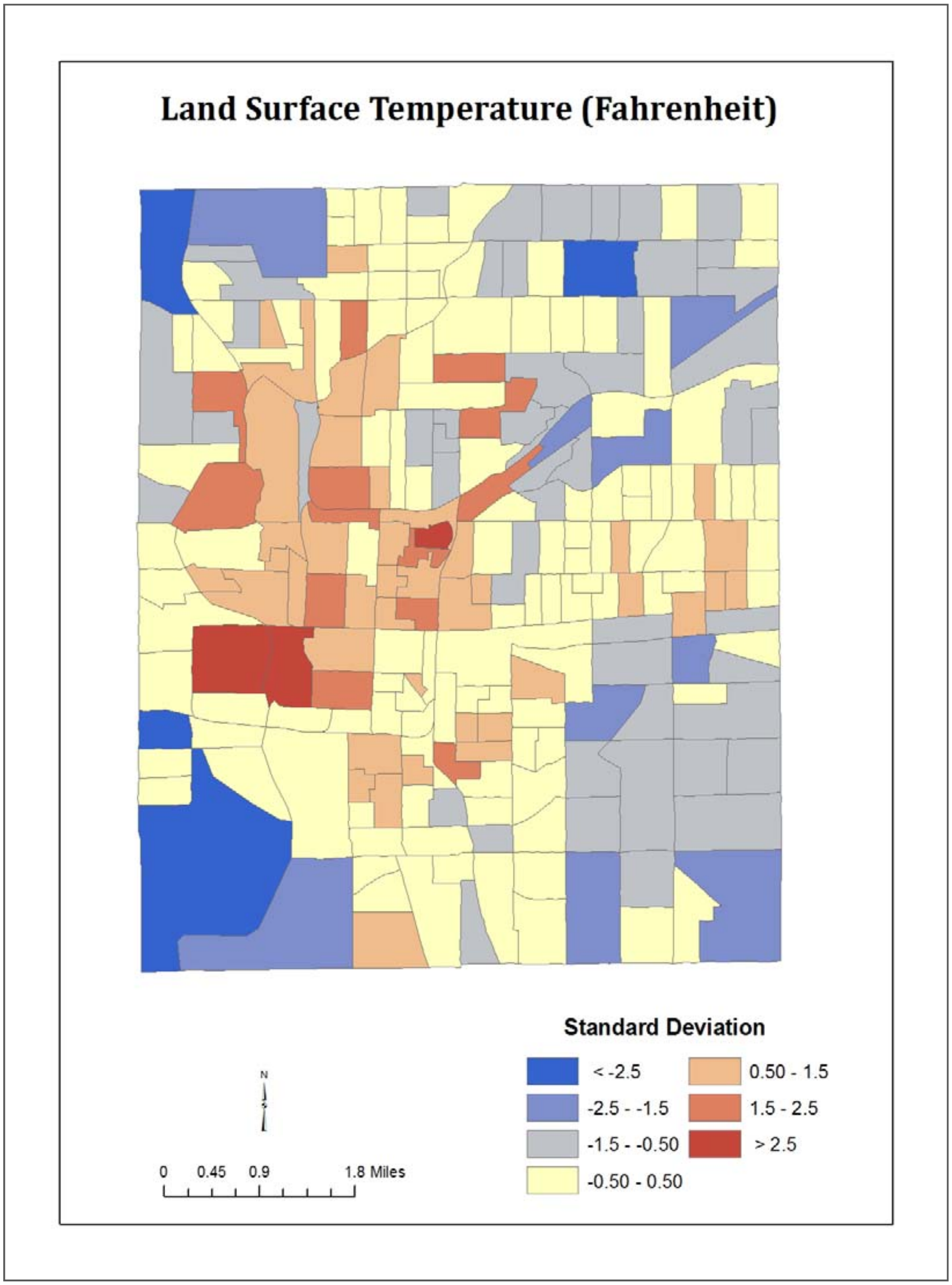


Figure 11: Percent Tree Canopy Cover Measured with Standard Deviation

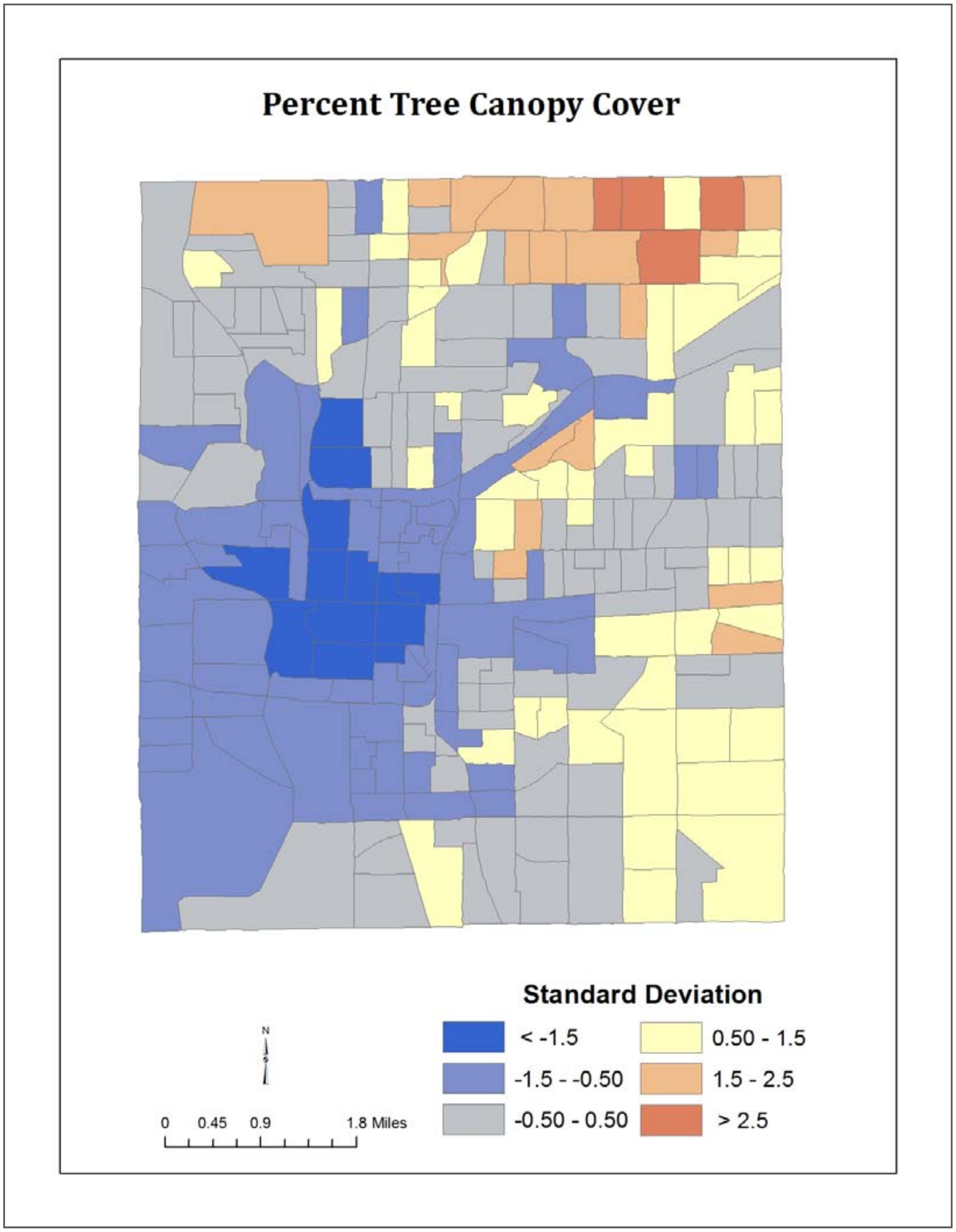


Figure 12: Most Vulnerable Block Groups

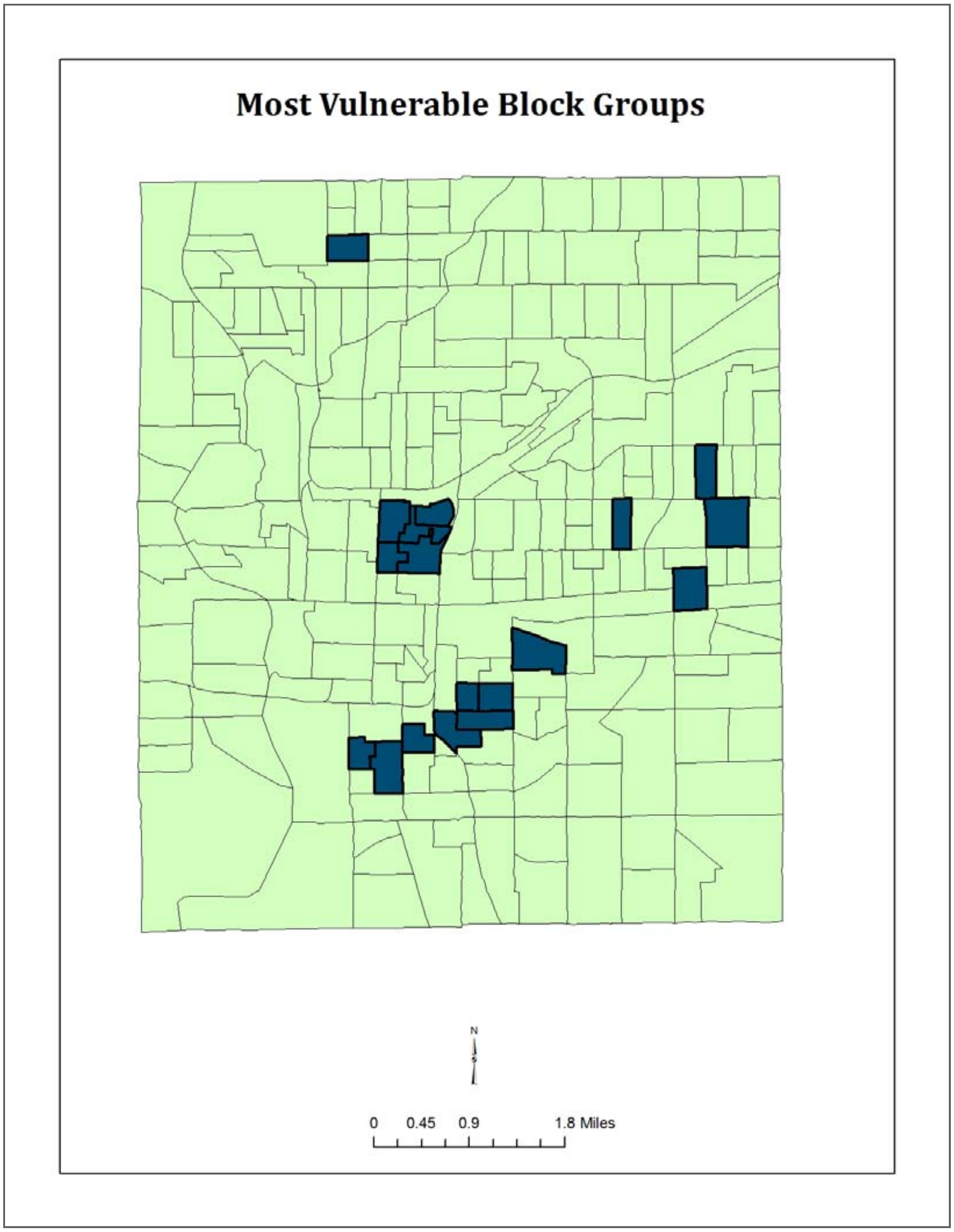


Table 7: Percent Plantable Space Characteristics

Block Group	Plantable Space Area (sq. ft)	Block Group Area (sq. ft)	Percent Plantable Space
180973542005	26271.21	1787995.99	1.47
180973542006	199973.98	2787424.57	7.17
180973542002	255712.55	3352617.26	7.63
180973542008	173880.01	1952589.11	8.91
180973549002	209160.15	2316402.29	9.03
180973542001	220551.47	1993154.87	11.07
180973551002	404524.96	3484563.98	11.61
180973525004	324261.53	2735240.63	11.85
180973553002	613983.98	5176058.42	11.86
180973510001	336680.00	2645185.15	12.73
180973559003	207171.04	1511221.40	13.71
180973570003	275529.42	1963994.58	14.03
180973569003	256425.38	1806855.55	14.19
180973557003	644080.15	4521854.96	14.24
180973571001	372887.56	2591796.29	14.39
180973569001	562965.78	3696775.53	15.23
180973559002	359216.19	2318227.21	15.50
180973571004	587744.01	2806877.93	20.94

Figure 13: Least Plantable Space Block Group

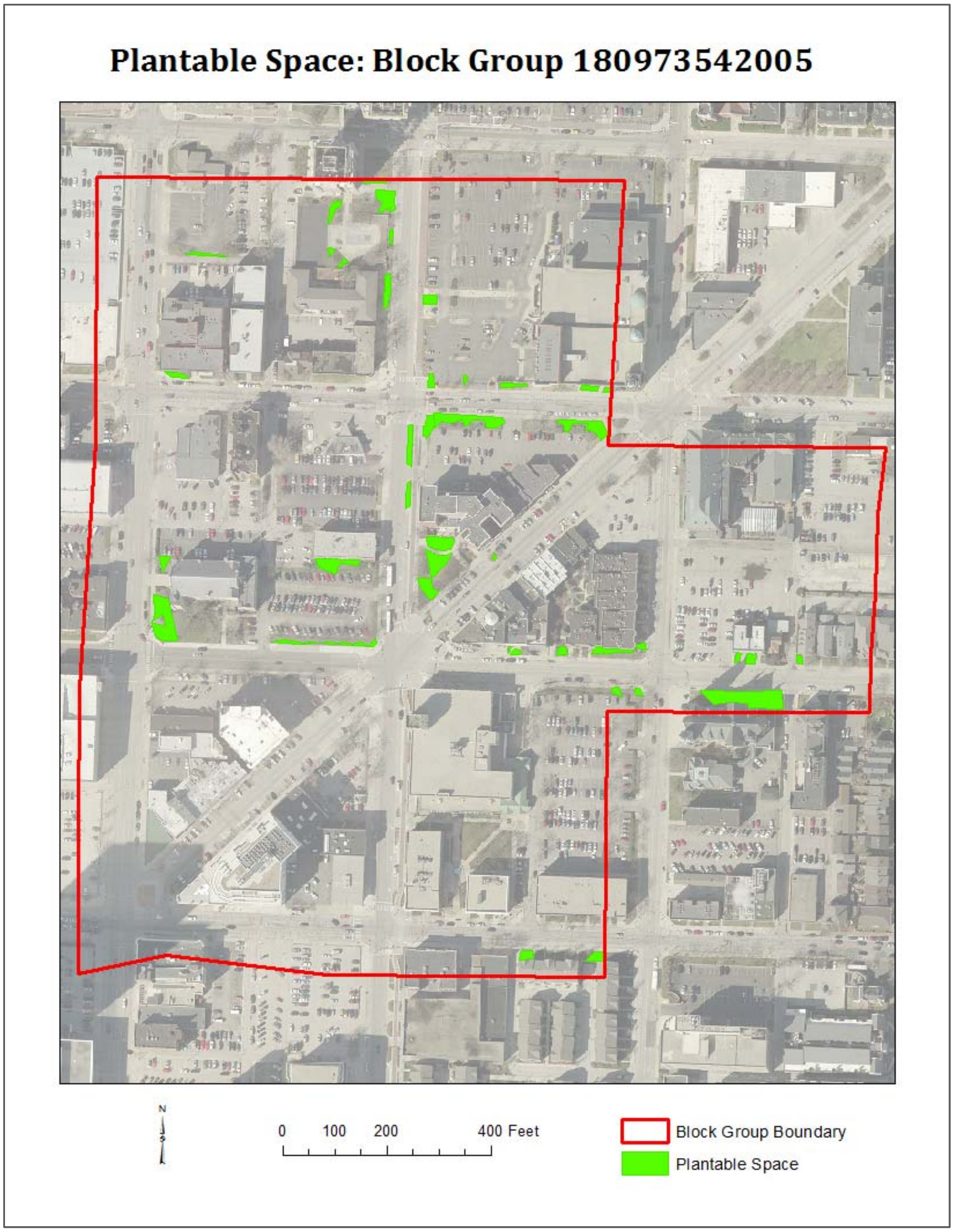


Figure 14: Average Plantable Space Block Group

Figure 15: Most Plantable Space Block Group

CONCLUSION

Locating vulnerable populations and implementing mitigation strategies before and during extreme heat events can help to prevent heat-related illness and death. In addition, tree planting mitigation strategies can also help communities socially, aesthitcally and environmentally. Several methods were implemented in this study to locate vulnerable populations and determine locations to implement tree plantings in order to mitigate the effects of urban heat islands and extreme heat events. The land surface temperature within Center Township was determined first in order to locate the urban heat island within Center Township. The UHI was primarily located within the CBD. The temperatures ranged from 68.71^{o}F-94.21^{o}F throughout Center Township.

The social vulnerability was determined by implementing the Principal Component Analysis. Several socioeconomic variables were used within the PCA; these variables are as follows: total population, Caucasian, African American, other race, Hispanic, persons under the age of 5; persons age 65 and older, median household income, total population below poverty, age 65 and older below poverty, persons with less than a high school education, age 65 and older living alone. The results of the PCA determined that the first three components explain about 80 percent of the total variance for vulnerability. The next method involved determining the location and amount of tree canopy cover. It was found that the percent tree canopy cover ranged from 0-46 percent for the Center Township block groups.

The first three methods determined the land surface temperature, social vulnerability and tree canopy cover; once these were analyzed, the results for each were then tied together. Standard deviation maps helped to determine the 18 high-risk block groups that are particularly vulnerable to high temperatures, low tree canopy cover and high social vulnerability. Further analysis was completed on the block groups to help determine which block groups had areas in which tree plantings could potentially be implemented. The overall findings found that of the 18 block groups further analyzed, 13 had more than 10 percent plantable space. In addition, all but one block group had more than 5 percent plantable space.

Although the overall results and methods of this study were consistent and thoroughly examined, there were several limitations to this study. The first limitation to this study was the inconsistent dates among the data. For example, the thermal imagery was acquired during 2009, the socioeconomic variables were collected from 2000 and the tree canopy cover was extracted from 2005 data. These inconsistencies exist due to the lack of access and time to acquire newer data. This is recognized as a shortcoming for the research and it is suggested that further research use the most updated 2010 Census data along with 2010 thermal imagery and tree canopy imagery. The KDF analysis is a good approach to use but it should be noted that some argue that it can introduce error and it may be based on underlying assumptions that may not apply to Census data. The digitizing of the plantable spaces may have not been the most accurate approach but due to time and data availability constraints it was the most effective and efficient methods for this study. Lastly, tree types were not taken into account due to the extensive nature and expertise of these types of research. Forestry experts at Keep Indianapolis Beautiful will be able to determine tree the types most suitable to planting.

FURTHER RESEARCH

The effectiveness and overall benefits of urban heat island mitigation strategies have not been studied enough to fully understand the best approaches. Further research should study the direct impact of various mitigation strategies to fully comprehend the extent to which they can reduce temperatures. In addition, it would be very informative for further research to extensively study the tree species that should and should not be planted. It would also be interesting for additional research to examine where trees should be planted based on sun angles and locations around buildings; this focus would help to reduce energy costs.

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CURRICULUM VITAE

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Education

Indiana University – Purdue University Indianapolis
M.S., Geographic Information Science
May 2012

Wright State University, Dayton OH
B.A. Geography
November 2008

Professional Experience

Citizens Energy Group, Captial Projects and Engineering--- Indianapolis, IN-- August 2011-Present
Water Distribution Analyst- Capital Projects and Engineering

- Update and analyze GIS data to improve the performance of the hydraulic model.
- Perform water distribution system hydraulic analysis for new development and evaluation of existing systems.
- Audit water distribution hydraulic model on a regular basis: add new mains, facilities, update demand data, adjust roughness, etc. to keep model current and representative of the system.
- Engage in research activities on assigned development studies.
- Assist in the assemling of data and the preparation of exhibits for special projects.
- Creates field surveys and and investigates identified pressure problems within the system.
- Create maps and and update water data to provide to better information about the water network to field services.

Veolia Water Indianapolis--- Indianapolis, IN-- July 2010-August 2011
GIS Analyst-Asset Management

- Update, analyze and edit GIS data to improve the performance of the hydraulic model.
- Create maps for various projects and reports for internal and external purposes.
- Complete statistical and spatial analyses of underground assets.
- Trained asset management personnel in ESRI software and created tutorials.

IUPUI--- Indianapolis, IN-- August 2009-July 2011
Graduate Research Assistant-Department of Geography

- Perform field audits and observations in order to determine the physical activity and neighborhood physical activity access.
- Gathered, analyzed and organized Census data and satellite imagery.
- Analyzed spatial relationships among urban heat islands and various socioeconomic factors.
- Completed a model to determine locations of extreme heat vulnerability within Indianapolis, IN.
- Presented findings at the Annual Association of Geographers conference in April, 2010.

Keep Indianapolis Beautiful--- Indianapolis, IN-- January 2011-May 2011
GIS Analyst-Tree Team

- Updated tree database and organized data.
- Created various tree canopy, soil type and neighborhood maps.
- Helped to determine methods for a statewide tree canopy map.
- Created a model to determine locations to plant trees based on temperature, socioeconomic and tree canopy cover parameters.

Mid-Ohio Regional Planning Commission--- Columbus, OH-- April 2009-August 2009
GIS Intern-GIS and Planning

- Created and edited various maps.
- Digitized tree canopies for the Central Ohio Greenways project.
- Updated land use data for each county.

Wright State University--- Dayton OH-- September 2007-May 2008
Undergraduate Research Assistant, Department of Urban Affairs and Geography

- Studied the urban heat island and its affect on various socioeconomic variables.
- Created maps and analyzed various satellite images.
- Geocoded data for various projects.
- Gathered and organized Census data.
- Presented work findings at the 2007 East Lakes Conference.

Conference Presentations

Rigg, M.R. 2011. Tree Canopy Mitigation of Socially Vulnerable Areas within Urban Heat Islands. Presented at the Association of American Geographers Annual Conference, April 2011 Seattle, WA.

Rigg, M.R. 2007. Identifying Populations Vulnerable to Urban Heat Islands. Presented at the East Lakes Division Association of American Geographers Conference, October 2007 East Lansing, MI.