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The Intersection Of Urban Heat Islands And The CDC Social Vulnerability Index In Two Border Cities

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Chapter 1: Introduction

With rising temperatures, susceptibility to heat effects has caused concern about thermal comfort and health risk, particularly in urban settings during the summer. Urban landscapes can intensify heat in surrounding areas due to structures such as buildings, roads, and other infrastructures that absorb and re-emit the sun's heat, as well as reduced greenery (EPA, 2022), causing what are called Urban Heat Islands (UHIs). Prior work has indicated that UHIs can cause adverse health outcomes that can be exacerbated depending on geographic location, race-ethnicity, housing characteristics, and socioeconomic disparities. Historically, research has concluded that redlining techniques have disproportionately placed people of color in hazardous environments, and more recent research has identified that historically redlined neighborhoods continue to have elevated land surface temperatures (Hoffman et al., 2020). Further literature has indicated that thermal inequities are still prevalent in the U.S, particularly in poor urban areas.

Most research on UHIs analyzes the intersection of UHI landscapes and vulnerable populations. The NIHHIS/NOAA UHI Mapping Campaign conducted throughout the U.S has supported more than 70 communities to identify the disproportionate heat effect. Much of this data is in the early stages of being incorporated into studies. Researching cities involved in the NIHHIS/NOAA UHI mapping campaign combined with social-spatial data can help increase our understanding of thermal inequities.

The UHI effect has become an environmental health concern as being exposed to extreme temperatures can compromise human health including heat, stroke, exhaustion, and cardiovascular issues (Wald, 2019). With these health risks in view, environmental justice scholars have identified those parts of communities (e.g., elderly) specifically most vulnerable to extreme heat due to the unequal distribution of heat hazards. The effects of extreme heat can be exacerbated in cities, and as we begin to see extreme temperatures increasing in frequency and duration, we must acknowledge that it poses a serious problem to human health (WHO, 2022).

Previous research has used social spatial analyses using heat data and socio-demographic data to help identify areas and people who are most vulnerable. The intersection between social data and UHI landscapes is significant when approaching research from an environmental justice standpoint. Several studies have shown the intersection between heat data and social data that show the spatial distribution of both variables to identify disadvantaged communities (Dialesandro et al., 2021). Given that spatial analyses are important in identifying vulnerable communities, this can be used to target communication about heat information to prevent mortality and morbidity during high temperatures. This study will take an environmental justice perspective to examine areas most vulnerable to heat and ways in which we can improve heat communication which was an important goal in my work with the National Weather Service's Weather Forecasting Offices.

As these cities continue to grow and develop, they are facing significant changes in their built environment and land use patterns, which can contribute to the urban heat island (UHI) effect. This study will investigate the relationship between urbanization and the UHI effect, and how it impacts the high-vulnerability communities in these borderland cities. The study will analyze the spatial distribution of urban heat, taking into consideration the distinctive ethnic patterns in the borderland, and how the UHI intersects with heightened risk due to the high prevalence of ethnic minorities with potential language barriers. The results of this analysis will assist in identifying communities that are highly vulnerable to the UHI effect for improving resilience and risk communication.

Chapter 2: Geographic Setting

This thesis will investigate two borderland cities to give depth to the different social dimensions in the U.S-Mexico border. Since this thesis is for an M.A. in Latin American and Border Studies, the focus cities will be San Diego and El Paso as they are U.S- Mexico border cities with culturally and racially diverse populations. See Figures 2.1 and 2.2 for the geographical location of San Diego and El Paso. Incorporating borderland cities into this study will give depth into the environmental injustices surrounding minority communities. Borderland cities tend to have a large percentage of Hispanic populations living in poverty and a relatively high percentage of immigrant households. This is particularly important due to the limited English proficiency some immigrant households may have. The goal of this thesis is to identify high-risk spatial areas and social compositions for improved risk communication strategies that are tailored to the unique social and demographic profiles of high-vulnerability communities in borderland cities, with the aim of increasing their preparedness and resilience in the face of environmental and public health risks.

Figure 2.1: Geographic Location of El Paso, TX.

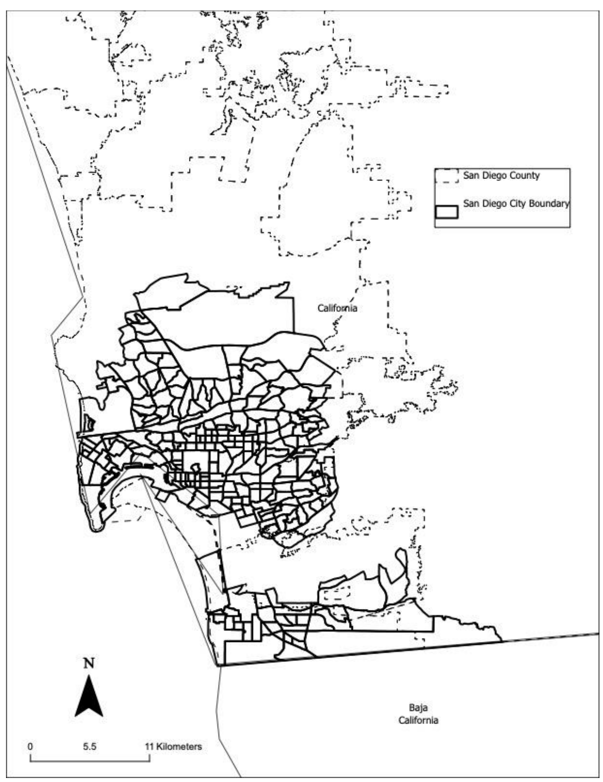


Figure 2.2: Geographic Location of San Diego, CA.

2. 1 Historical Background

U.S-Mexico border cities are characterized by their proximity to the border which results in cultural, economic, and social influences from both the U.S. and Mexican sides. Most importantly, border regions are also characterized by their arid climate affecting "architecture, diet, attire, leisure, socialization, and travel" (Ganster & Collins, 2021, p.21). This process has been shaped by a range of historical developments that have led to cross-border interactions. Although these influences date back to colonial periods with the arrival of various European and indigenous groups inhabiting the U.S- Mexico border this paper will elaborate on post-colonial history that resulted in the growth of cross-border interactions.

The historical background of the U.S.-Mexico border was obtained from Ganster & Collins (2021), a standard source. Economic trends have been a driving force for large-scale Mexican immigration to the U.S. borderlands since the late 19th and early 20th centuries. In turn, the Bracero Program of 1942 brought a large influx of Mexican laborers to work in the U.S. during World War II. The Bracero Program had a significant impact on the geography of the U.S.-Mexico border region as approximately 200,000 Mexican laborers made their way into the U.S. during 1942-1947 (Ganster & Collins, 2021, p. 99). This impact was most notable in California with an economic boom and population growth. The program led to the development of new cultural patterns as transnational communities established ties on both sides of the border. As a result of the Bracero Program, Mexican border cities also experienced a large influx of Mexican migration. With new economic opportunities in agriculture and mining on both sides of the border the U.S-Mexico border became an attractive destination for economic opportunity.

Growth in both cultural and economic trends continued after the 1950s. The post-war economic boom on the border resulted from the growth of both manufacturing and service sectors on both sides of the border. This can be attributed to the role the U.S. and Mexican governments played in establishing a binational program that initiated a globalized economy. The maquiladora boom began in the 1970s and drastically increased by 1990. It is estimated that by 1996 there were approximately 1500 maquiladora operations (Ganster & Collins, 2021, p.119). Many of these maquiladoras were concentrated in border cities such as Tijuana and Ciudad Juarez.

As a result, the maquiladora boom not only resulted in rapid population growth in Mexican border cities but had an impact on the urban geography of U.S. borderland cities. Border cities attracted an influx of border migration on both sides of the border. Even though many Mexican people moved to the Mexican border for maquiladora work. Mexican migration was also prevalent in the U.S as migrants sought better opportunities in U.S border cities. U.S. border states experienced significant urban growth in the 1990s with California being the highest urbanized state at 95%, followed by Arizona at 89.8%, and Texas at 84.7% (Ganster & Collins, 2021, p. 142). Given that inequalities and differentiations are evident between Mexico and the U.S. this attracts a flow of Mexican migrants to U.S. border cities both legal and illegal (Heyman, 2007). The long history of borderland relations has resulted in rapid urbanization in border cities that can often have adverse effects on the social, economic, and environmental aspects of these cities.

It is evident that the interrelations between the U.S. and Mexico have had a significant effect on the way border cities are shaped. As previously mentioned, the large influx of Mexican migrants into U.S. border cities has impacted the socio-demography of the borderlands. Having culturally and racially diverse populations can have adverse effects when it comes to heat messaging and mitigation. Studies have emerged that analyze how redlining techniques have left many residents in hazardous environments (Hoffman et al., 2020). Yet, little is known about the structural racism that has shaped neighbourhoods in the borderland.

2.2 Borderland Geography

San Diego is located in the Southern part of California near the Mexican border. As of 2021, San Diego currently has approximately 1.4 million residents. It is estimated that by the year 2035, there will be a population increase of 710,269 people (San Diego Association of Governments, 2021, p.17). This can affect the current land use and regional development as increased density will affect housing density (San Diego Association of Governments, 2021, p.17). Furthermore, a growth in population will result in an expansion of urbanization, therefore, increasing impervious surfaces which can contribute to the UHI effect (Dialesandro et al., 2021).

The city's topography is characterized by "low-lying coastal plain, foothills, mountains, and lowlands of the desert" (San Diego Association of Governments, 2021, p.1). The climate in San Diego is tempered by the Pacific Ocean, thus, rarely having freezing temperatures (National Weather Service, n.d.). San Diego's difference in climate can be attributed to cooler areas being near the Pacific Ocean and gradually getting warmer near inland valleys. San Diego is characterized by a Mediterranean climate, yet its UHI effect results from its topography consisting of mesas and canyons.

El Paso is located west of Texas bordered by Ciudad Juarez Mexico. The city is in the northern part of the Chihuahuan Desert with unique topography consisting of mountains that surround the city ("One Water", n.d.). The UHI phenomenon is influenced by El Paso's geography and desert climate. Ozone pollution has been a prevalent issue in the El Paso and Ciudad Juarez region which is mainly affected by anthropogenic emissions (Karle et al., 2021). Ultimately, air pollution can contribute to the UHI effect by affecting the balance of the climate system.

El Paso's population has had an increase since the year 2000 to the present time. El Paso County has a population of 800,000 residents and is expected to increase to over one million residents by 2030 (City of El Paso, Texas Comprehensive Plan, 2012, p. 19). With rapid population increases it is important to understand the implications of future urban development to ensure a sustainable environment (Moyer & Raheem, 2020).

Borderlands face inequality when it comes to poverty, minority status, and other social-economic variables. For example, with the exception of San Diego County, U.S. residents along the border have fewer financial resources than residents of other U.S. regions; 22 of the 23 U.S. counties bordering Mexico exceed the national average below the federal poverty level in 2020. Some 57 percent of the border county population is Hispanic; it is 84 percent when the highly urbanized, somewhat more Anglo (non-Hispanic white) counties of San Diego, California, (43.8% Anglo) and Pima, Arizona (50.3% Anglo)[1] are excluded (U.S Census Bureau, 2020).

Like other borderland cities, social inequality is a pervasive issue in El Paso, TX. According to the U.S Census Bureau (2021), the median household income is about three-quarters of the national income. Approximately 20% of the population lives below poverty, and 23% of the population is foreign-born (U.S Census Bureau, 2021). With a high percentage of struggling households and potential language barriers El Paso population is susceptible to the adverse effects of high temperatures.

The U.S-Mexico border city of San Diego, CA has distinct social characteristics compared to other border cities. While San Diego does have a diverse population, it does remain

[1] Although it is a border county, Pima County has no substantial urban settlement on the boundary; its large city, Tucson, is well north of the border.

predominately White (42%) followed by the Hispanic population (29%). According to the U.S. Census Bureau (2021), San Diego's median household income is 10% higher than other cities in California. Yet, social inequality is still prevalent as 12% of the population lives in poverty, 37% of the population has language barriers, and 24% of the population is foreign-born (U.S Census Bureau, 2021). Although San Diego has distinct characteristics compared to other borderland cities it is evident that disparities persist among these communities. With San Diego having a relatively high cost of living, economic disparities can have adverse effects on low-income communities.

Furthermore, border cities have a significant legacy of unequal urban development. The San Diego redlining map of 1935 has shown how historic redlining policies have left brown, black, and immigrants in the most toxic environments. In a recent article, Burris (2020) argues that 90 years later San Diego still suffers from segregation and these maps are still similar in recent times.

Similarly, El Paso's redlining map shows evidence that homes in South Central were categorized as the most hazardous with a high concentration of Mexican people which is still relevant today. Li et al. (2022), investigated whether the effects of redlining were still prevalent in 11 Texas cities including El Paso. The study concluded that historically redlined neighbourhoods experienced higher levels of land surface temperature compared to non-redlined neighborhoods (Li et al., 2022). The city has also acknowledged the legacy of redlining in El Paso through a strategic plan which will prioritize the improvement of redlined areas. The city of El Paso (2020) demonstrates a side-by-side comparison of the redlined map (1930) to a current map of El Paso (2020) to demonstrate how redlined neighborhoods have the lowest economic investment and lowest home equity. Additionally, redlined neighborhoods still house the city's poorest residents (El Paso, 2020). Although there is limited research on the effects of redlining policies and its association to elevated exposure to urban heat historical urban policies are still prominent in El Paso.

This diversity in borderland cities has important implications for the distribution of environmental and public health risks, and the ways in which these risks are perceived and communicated. For example, cultural differences, language barriers, and low levels of media access and literacy can impact the effectiveness of risk communication efforts. This study will examine the geographic locations and social covariates of these factors shaping the risk perceptions and preparedness behaviors of high-vulnerability communities in borderland cities. By examining the complex social and cultural dynamics of these communities, this study will aim to shed light on the ways in which border urbanization has contributed to heightened vulnerability to environmental and public health risks in borderland cities and represents the first step toward addressing these factors through improved risk communication strategies.

Given ethnic patterns in borderland cities, it is important also to analyze the spatial distribution of urban heat. This study will take into consideration the distinctive ethnic patterns in the borderland to analyze the UHI. For example, this study will examine the intersection of heat with heightened risk due to the high prevalence of ethnic minorities with potential language barriers. Given the aforementioned context regarding UHI and heightened vulnerability in certain populations, this study will aim to analyze the UHI effect throughout the city of San Diego and El Paso by performing a spatial analysis combining physical and social vulnerability data. In addition, the study will examine how border-specific social information can be used by National Weather Service (NWS) Weather Forecast Offices (WFO) and their partners to create more effective heat products and messaging.

This research started as part of the NOAA Experiential Research and Training Opportunities (NERTO) program. Some data has already been gathered and will be incorporated into this study. The informational interviews with WFO meteorologists and their partners that were already done during that summer will be used to provide information based on UHI and social vulnerability census data that can address WFO concerns with effective targeting and messaging in a borderlands context.

Chapter 3: Literature Review

The UHIs are characterized by their unique environment with large impervious surfaces and low vegetation. These features typically have elevated land surface temperatures compared to surrounding areas. Research has identified how thermal inequity is still prevalent in many cities throughout the U.S. (Dialesandro et al., 2021) including border cities such as El Paso (Li et al., 2022). As a result, some research has focused on the impact high temperatures have on specific populations who may lack physiological tolerance or adaptive capacity such as limited access to air conditioning.

A substantial literature addresses the UHI phenomena and its impact on vulnerable populations. Given the amount of literature regarding the impacts of heat, this section will focus on the effects that heat has on human health and comfort. There are numerous factors that play roles in identifying those most vulnerable to high temperatures. Exposure, sensitivity, and adaptive capacity are elements used to identify vulnerability (U.S. EPA, 2018). Given the potential impact of hazards such as elevated temperatures, the Social Vulnerability Index (SVI) tool developed by the CDC has been an additional resource to help identify vulnerable populations. The SVI tool can be used for preparedness and recovery from natural disasters. This literature review will briefly identify some of those vulnerable populations.

3.1 Background

Rising temperatures have caused concern throughout the United States as extreme heat has been the leading weather hazard that has caused the most fatalities in recent decades (Wong et al.,2013). As a result, the UHI phenomena can exacerbate heat hazards due to the uneven distribution of heat whereby urban areas tend to have higher temperatures than surrounding areas (Leal Filho et al., 2017). Urban landscapes can intensify heat in surrounding areas due to structures such as buildings, roads, and other infrastructures that absorb and re-emit that sun's heat (EPA, 2022). This UHI effect has become an environmental justice concern as research has determined that temperatures can vary as much as 10 degrees Celsius in urban areas (Shandas et al., 2019).

Identifying those who lack adaptive capacity is essential to prevent a significant threat to their human health. During extreme heat, socioeconomic status, household composition, disability, minority status, language, housing type, and transportation are key components that play a role in adaptive capacity and, most importantly, human suffering (CDC 2021). Understanding the disproportionate effect of heat and identifying those who may suffer in greater amounts has been the emphasis of environmental justice research. Thus, considering the disproportionate burden of heat, research conducted on the matter has identified the range of detrimental factors impacting environmental, energy, economic, and human health (EPA, 2022).

Risk perception and attitudes toward high temperatures are significant factors determining whether populations recognize their susceptibility to heat extremes. Findings have suggested that survey participants are aware of the health risks driven by climate change that are disproportionately affecting populations (Sarfaty et al., 2016). Minority residents have also recognized that climate change will worsen existing health conditions and potentially cause people to develop new health problems (Estrada-Martinez et al., 2020). People are subjectively aware of the adverse health effects of heat, but clinical professionals have also become concerned with heat-related health effects on patients (Sarfaty et al., 2014). Diverse populations are becoming aware of the adverse health effects of heat extremes which is fundamental in risk reduction if individuals and health professionals recognize risks. Taking protective measures during high temperatures such as seeking cooling centers, reducing physical activity, drinking sufficient water, and staying in an air-conditioned environment during hot weather will likely suppress heat hazards (Smoyer-Tomic & Rainham 2001; Bouchama, 2007). Yet, potential barriers may prevent low-income households from seeking the appropriate mitigation tactics during heat waves. Low-income households may lack the adequate sources and income to reduce heat wave casualties, thus increasing human suffering. Studies have found that individuals with higher income did not perceive heat risks as threatening, as they may have good adaptive behaviors preventing them from experiencing the negative health consequences of heat extremes (Akompab et al., 2013; Frewer, 1999; O'Connor et al., 1999).

Risk perception of heat is detrimental to a population's response to heat mitigation strategies. Populations who do not perceive heat as a risk may not take the adequate protection measures during high temperatures. Prolonged exposure to heat can ultimately have physiological effects to an individual's health.

Although heat effects can be influenced by a person's perceived heat risks there are other factors that also play a role in heat mitigation. Energy burden refers to the high proportion of income spent on household energy and utility bills, also known as the "poverty tax" (Lewis et al., 2019). Lower-income households may have trouble keeping appliances (such as air conditioners and perhaps even fans) on during high temperatures, feeling the need to shut off appliances to keep utility bills low. Additionally, financial stressors may prevent access to cooling appliances leading to thermal discomfort which can exacerbate health conditions (Lewis et al., 2019). Madrigano et al. (2018), found some New York residents who did not own AC units due to financial strains, and a portion of participants who did own AC units abstained from turning them on to prevent heightened electricity bills.

3.2 Vulnerable Populations

Extensive research on the impacts of heat has found numerous factors leading to morbidity and mortality among specific populations. First, we must analyze the historical effect of housing policies that left many residents, particularly, poor black communities in areas with exacerbated heat and poor housing conditions due to redlining techniques. The role of historical housing policies through relining was the start of creating racial segregation in communities by neglecting specific populations from safe environments through the refusal of home loans or insurance (Hoffman et al., 2020). The effects of redlining are still prominent in recent times as redlined neighborhoods experience elevated land surface temperatures compared to non-redlined areas (Hoffman et al., 2020). Redlining may also affect Hispanic and Asian populations, specific histories that may be relevant to the U.S.-Mexico borderlands. Furthermore, poor communities and people of color are displaced in hazardous environments, exacerbating morbidity and mortality among these populations.

Given that there are numerous interconnected factors that influence vulnerability, successful communication of heat messages is crucial in protecting communities. The climate gap is prevalent among communities of color given that redlined techniques have neglected people of color from accessing safe home environments. To overcome barriers and minimize heat-related illnesses effective heat risk communication and delivery can help minimize this gap (VanderMolen et al., 2022).

Effectively communicating heat messages has been an ongoing concern for National Weather Service (NWS) and partners. Hansen et al. (2013) evaluated the issue of ethnicity influencing vulnerability to extreme heat, and ethnic minorities with language barriers were a subpopulation at risk. One of the main issues is that emergency alerts in the U.S are transmitted in English. There are relatively few Weather Forecasting Offices (WFOs) that have started to incorporate messages in Spanish. Given that border towns primarily consist of ethnic minorities this can increase vulnerability for non-English speaking households. With the recent increase of migrants coming to border cities, language barriers may prevent ethnic minorities from understanding heat warning messages. This can also prevent ethnic minority language groups from taking adaptive behaviours (Uejio et al., 2011). Hansen et al., (2011), found that linguistic barriers can emerge as potential social isolation for elderly migrants in Australia. Migrants face the potential increase of heat health effects due to their social isolation in a new country, additionally, race, ethnicity, and linguistic isolation may also cause cultural isolation as they may be concerned about their familiarity with public spaces or have concerns that about their immigration status (Sampson et al., 2013).

Extreme heat can often target specific populations. Health, age, and prolonged exposure can be critical factors in determining who is at greater risk of high temperatures. Growing literature underlines the importance of studying the effects on both children and elderly groups. Age has become a significant indicator of vulnerability to atmospheric changes (Zahran et al., 2008). Heat-related mortality in children is the most lethal subtype of death by forces of nature, particularly for infants (Zahran et al., 2008). Young children's susceptibility to heat extremes, mainly younger children, may result from their dependence on their parents. Moreover, like young children, older adults' adaptive capacity to extreme heat can be compromised due to their inability to adjust to sudden temperature changes (CDC, 2022).

Urban Heat islands are prone to intensifying temperatures (Lee & Shaman 2017), particularly around areas with structures such as buildings, roads, and other infrastructures (Environmental Protection Agency, 2022). Thus, outside workers are highly vulnerable to the effects of heat. Excess heat exposure has been linked to heat strokes, exhaustion, and respiratory and cardiovascular issues (Wald, 2019). Heat has been a contributing hazard to outside workers, leading to heat-related fatalities. In 2018, the U.S Bureau of Labor and Statistics reported 173 fatalities among construction workers due to harmful environments (U.S Bureau of Labor Statistics, 2018).

Literature has identified pregnant women as another vulnerable group. Exposure to heat can have adverse health effects on pregnant women and their fetuses. Association between adverse birth outcomes such as pre-term, low birth, and stillbirth has been associated with heat exposure among pregnant women (Bekkar et al., 2020). Bekkar et al. (2020) also concluded that most women at risk were primarily minority groups, especially black women. Additional articles demonstrate the adverse effects of pregnant women exposed to high temperatures. Other literature has addressed how temperature above 90°F can accelerate births by 5%, which decreases the gestation period for fetuses and impacts babies' cognitive development (Barreca & Schaller, 2020, Almond & Currie, 2011).

Although there are numerous populations at risk, low-income households are also highly vulnerable to heat hazards. The low-income households will be a population of interest for this study. Income and poverty have been associated with heat morbidity and mortality in the U.S. (Madrigano et al., 2013). Adaptation to extreme heat requires that individuals are not only aware of heat risks but have the ability to reduce these risks. Low-income individuals may not only face financial barriers such as turning on their AC or owning an AC (Madrigano et al., 2018) but may not receive adequate medical care during a heat event (Zhang et al., 2009). Furthermore, low-income households may face inferior housing conditions that can include deteriorated housing. The lack of high-quality housing structures may pose additional financial stressors as there can be an increase in the costs of performing basic household functions (Lewis et al., 2019). There are numerous burdens that low-income individuals face that can heighten vulnerability. Harlan et al. (2006) found that warmer neighborhoods also consisted of populations that had fewer resources, therefore being more vulnerable due to their limited ability to cope with extreme heat.

Additionally, as energy prices have heightened, low-income households have struggled with utility bills by spending 25% of their income on energy bills in 2006 yet consuming significantly less energy than higher-income households (Carlson, 2008). Energy insecurity is the "inability to meet basic household energy needs," primarily affecting low-income and minority households whose housing conditions do not meet thermal comfort (Hernandez et al., 2016; Lewis et al., 2019). Furthermore, deteriorated housing, such as "poor insulation, air leaks, poorly maintained HVAC systems, and outdated appliances," have led disadvantaged households to spend significantly more to keep homes cool during the summer (Drehobl & Ross, 2016; Hernandez & Phillips, 2015; Reames 2016; United Census Bureau, 2015). Energy injustices have led to increased human suffering in lower-income households and communities of color. Resource-limited communities are not only experiencing elevated land surface temperatures but may lack the economic means to protect themselves during the summer. Disadvantaged homes are prone to hazardous environments, thus putting low-income households at greater risk.

The changes that have occurred through rapid urbanization and climate change in cities have become an increasing concern as literature has identified that those most vulnerable are experiencing excessive heat. Mitchell & Chakraborty (2018) use the concept of thermal inequity to understand how marginalized individuals experience additional heat burdens such as higher temperatures compared to other individuals. The characteristics of thermal inequity stem from the uneven distribution of heat and social structures that often place specific communities at greater risk through their inability to mitigate heat hazards (Mitchell & Chakraborty, 2018).

Recognizing that there are social disparities in the UHI phenomenon is critical in environmental justice research. As previously mentioned, populations can be vulnerable through their lack of physiological tolerance, but scholars are also recognizing that there is a disproportionate impact of climate change specifically among those most vulnerable which makes it hard to cope with rising temperatures.

Research that has incorporated spatial analyses have been able to identify the uneven distribution of heat to UHI and its connection to marginalized communities. For example, the development of heat vulnerability indexes (HVI) has been used to identify high-risk areas and identify climate gaps (Reid et al., 2009). The objective of HVI and its spatial distribution has been used to find connections among vulnerable populations and high temperatures. When incorporating the concept of thermal inequity in spatial analyses has become prevalent as this can help scholars understand how heat and social data interact and are spatially distributed. When conducting spatial analysis with heat data and social variables researchers can display which areas are of high-heat risk, and therefore be used in multifaceted approach of incorporating results into decision-making and policymaking and therefore address the thermal inequity gap.

Prior research have developed indices to evaluate the connection of marginalized individuals and environmental hazards. The creation of vulnerability indices have been developed as a means of detecting areas of high vulnerability and ultimately implement more resources. For example, Lenhert et al. (2020) found that there's a link between social vulnerability and heat-related health problems like emergency department visits and death rates. The link was not the same everywhere and some groups, like older men and black people, were more affected. The study also identified places with high social vulnerability and heat-related health problems. Similarly, Fahy et al. (2019) studied the link between flooding and heat in

Portland. They found that the relationship between the two varied across the city and that some areas may experience severe effects. East Portland had the largest concentration of these issues. The study also showed that different groups of people were affected differently by the combined hazard of flooding and heat across the city.

Nayak et al. (2018) focused on developing a HVI for New York state (NYS). The study revealed vulnerability to heat varied spatially in NYS with the HVI showing that metropolitan areas were most vulnerable, with language barriers and socioeconomic disadvantage contributing to the most vulnerability. Johnson et al. (2012) studied how heat and socio-economic factors are distributed in an area to create an index for extreme heat vulnerability (EHVI). They used Principal Components Analysis to combine the factors and found that areas with high risk have more heat-related deaths, while areas with low risk have fewer deaths. Other indices have become a widely used method for measuring vulnerability in hazard preparedness and planning. Studies have come up with innovative approaches to examine heat vulnerability. For example, Reid et al. (2009) created a vulnerability index that considered 10 vulnerability variables, including the presence of people with diabetes.

Sanchez and Reames (2019) used socio-spatial analysis to find a correlation between lack of green infrastructure and heat vulnerability in Detroit, Michigan. They discovered that low-income residents were close to cooling centers but not part of green initiatives, while green roofs were present in affluent, predominantly white areas. Johnson & Wilson (2008) studied the link between the distribution of vulnerable populations, UHI, and heat-related deaths during a 1993 heatwave in Philadelphia. Results showed deaths concentrated in areas of higher UHI intensity, suggesting UHI and poverty are key factors in measuring extreme heat risk.

The utilization of spatial analysis has proven to be an effective methodology for investigating the socio-spatial vulnerabilities in relation to extreme heat. This approach allows for the identification of areas that require improved risk communication and allocation of resources. The analysis of the CDC SVI index (see below) and the NWS urban heat campaign data builds upon previous research that considers both social and environmental factors to comprehensively assess health vulnerabilities in the context of extreme heat.

Previous research identifies that the prevalence of thermal inequity is an additional hurdle that vulnerable populations face. Thermal inequity can be mitigated through a collective effort of climate actions and policy changes that protects those most vulnerable. Yet, the importance of effective heat risk communication can be a first step in decreasing morbidity and mortality among those most vulnerable. The process of sharing heat information and ways to reduce heat exposure has been an ongoing concern for WFOs and partners. Heat messages and warning has been a critical tool in protecting community members and investigating how heat risk recommendations can have a positive impact has been a focal point for WFOs.

Heat waves are one of the deadliest extreme weather events that have a negative impact on vulnerable populations. During the Chicago Heat Wave of 1995, there were approximately 536 deaths (Klinenberg, 2015). While social disparities were the leading impact of morbidity and mortality, effectively communicating heat risks could have reduced the increased risk of high temperatures.

During my summer internship at the NWS my research focused on working with WFO meteorologist and their partners on how to provide useful information based on the combination of UHI and social vulnerability data for effective heat communication. Researchers have investigated the effects of heat risk communication to improve public responses (Lambrecht et al., 2021). Lambrecht et al. (2021) investigated the ongoing challenge of heat risk communication and found that communities that live in hot climates often “normalize heat” and use heat as a “marker of community identity”. Communicating heat risks to a population who live in hotter climates is very challenging as people often tend to minimize potential health risks that heat can cause (Abrahamson et al., 2009).

In Morgan et al. (2022) risk communication book the authors elaborate on the complexity of understanding risk communication. The authors argue that when receiving risk communication messages, the receiver typically goes through three phases: try to comprehend the message, try and connect the relevance of the message to their own lives, and communicate their views (Morgan et al., 2022, p.2). The process of receiving risk messages can often involve technical information which can be challenging to some individuals. For example, in the interview phase of my summer internship with the NWS office, a primary concern was effectively communicating risks to communities with language barriers. Having limited literacy or familiarity with a non-native message can prevent an individual from making an informed decision about their well-being. For example, research conducted on health emergency messages were not adequate for immigrants due to their cultural and language differences (Kreps et al., 2008).

Effective risk communication can be challenging when populations have pre-existing beliefs about a risk which is often influenced by a person’s socioeconomic status, cultural background, and health (Blendon et al., 2008). A study performed on older individuals found that participants did not perceive themselves as vulnerable to heat effects (Sheridan, 2007). The aim of this thesis does not focus on the development of effective risk communication but demonstrates where vulnerability is concentrated, in both social and geographic terms. This is important as studies have identified that people are aware of heat risk messaging, but mitigation tactics are driven by economic factors (Sheridan et al., 2007). Effective heat risk communication is one factor that can prevent adverse effects of heat, but another important task by NWS partners is to adequately identify these groups and locations to allocate the appropriate resources. Effective heat messaging, proper identification of vulnerable groups, and identification of place-specific organizations are complementary factors for heat risk management strategies.

In conclusion, previous studies in the field have been centered around the identification of populations susceptible to heat risk through various methodologies. This literature review provides a background on the impact of urban heat on vulnerable populations. Recognition and mitigation of thermal inequities is essential in promoting health and well-being in urban settings, and in reducing the adverse effects of heat on vulnerable populations in the context of a changing climate.

This study aims to further the existing literature on the assessment of environmental hazards through the utilization of data obtained from the NOAA NIHHIS UHI campaign. The findings of Lenhert et al., (2020), which used the CDC vulnerability index and heat-related health emergency department visits data to conduct a spatial analysis of Georgia, will serve as a model for this research. The objective of this study is to use the CDC vulnerability index to identify areas of high priority where physical heat and social vulnerability intersect, thus facilitating the targeted delivery of heat-related messages. Not every variable mentioned in the literature review is easily accessed by me, using the American Community Survey; my selection of social variables is presented below.

Overall, previous research conducted on the impact that urban heat has on vulnerable populations highlights the impact that high temperatures have on the health and well-being of certain populations. The literature suggests that there is a disproportionate effect of urban heat among racial and ethnic minorities and low-socioeconomic individuals (Mitchell and Chakraborty, 2018). These findings are relevant to this current research, which seeks to investigate general thermal inequity, UHIs, and their social characteristics for targeted heat messaging in the borderlands. Previous literature has identified the contributing factors to vulnerability and urban heat. This current research will use existing literature to inform the development of methodology and identify social variables.

Chapter 4: Research Questions

First, we want to investigate the social characteristics between heat and social demographic data by asking; *What are the distributions of physical (heat) and social characteristics throughout the Cities of San Diego and El Paso?* For this research question, the NWS heat index will be distributed across U.S. census tracts, and a series of social variables were picked from my previous interviews with WFOs and partners. This research question establishes the basic data set for my research. The second question aims to identify the correlation between selected social variables and heat data to identify "global" thermal inequities affecting specific vulnerable groups: *Are there any overall patterns of intersection to the covariation of heat and selected social variables?* The third question aims to identify if there is a presence of spatial clustering in both cities: *Are there patterns of heat clustering throughout El Paso and San Diego that indicate the presence of UHIs?* If UHIs are identified, the research will perform a "local" analysis to identify selected social characteristics of hot clusters by contrast with non-hot clusters. This will be used to identify whether there is a presence of local thermal inequity.

My last research questions aim to incorporate the results of this study into WFOs operations. Given that this research was started during my summer internship at the NWS the aim was to do targeted heat messaging for highly vulnerable areas. My focus will not be on communication content or methods as such, but rather on the role of social geography, and the identification of key sites and key social groups for refinement of communications methods that would be directed to them. Therefore, my last research question asks; *Examining the social correlates of heat islands, how can results be used to improve the targeting of heat risk communication strategies and formulate best practices and recommendations for WFOs to support urban areas?*

Table 4.1 Research Questions.

Research Questions	
1.	What are the distributions of physical (heat) and social characteristics throughout the Cities of San Diego and El Paso?
2.	Are there any overall patterns of intersection to the covariation of heat and selected social variables?
3.	Are there patterns of heat clustering throughout El Paso and San Diego that indicate the presence of UHIs?
4.	Examining the social correlates of heat islands, how can results be used to improve the targeting of heat risk communication strategies and formulate best practices and recommendations for WFOs to support urban areas?

These research questions seek to understand the UHI phenomena to decrease the impacts of heat. This study will help understand social inequalities regarding the UHI phenomena and ways we can improve heat messaging for vulnerable populations to prevent morbidity and mortality.

Chapter 5: Methodology

5.1 Data

The NOAA/NIHHIS UHI Campaigns has supported more than 70 communities across the United States. CAPA Strategies is a private company that started the UHI mapping campaigns in 2017. Each city was mapped using citizen science initiatives to obtain heat data throughout each city. Data was collected using remote sensing technologies where participants hooked up the remote sensing monitor to their vehicles and drove the same route in the morning, afternoon, and evening. The sensors measured temperature and humidity which was used to map urban air temperatures and humidity across each city. The heat data used for this study was collected in a single day. Although it does not show an average temperature of multiple heat days, the data used for this study does portray moments of peak risk. The NOAA/NIHHIS UHI campaign worked with NWS to identify a day that accurately depicts a day of high heat risk.

For this study, the heat data variable was obtained from the NOAA/NIHHIS data sets for El Paso and San Diego. The NOAA/NIHHIS heat data comes in both heat index and temperature (Fahrenheit). Temperature data was provided in Fahrenheit and heat index is a combination of temperature and humidity. For this study, the afternoon heat index raster data was used as the heat variable given that heat index measures a higher degree of vulnerability to heat as “this is what temperatures feel like to the human body” (National Weather Service, n.d.). For this study afternoon temperature was used as this is typically displays the highest temperature. During my informational interviews this summer, many of the WFOs offices were using heat indexes. Therefore, using heat index is suitable for this study as it will follow the WFOs protocols and will accurately convey heat data and the level of discomfort it displays to a person. It is important to note that the heat index obtained from NOAA/NIHHIS portray both direct observations and interpolations of the heat data measurements of spaces not directly measured. The interpolation methods were replicated from Shandas et al. (2019) study of heat predictions using ground measurements.

The heat data was provided in raster format. The aim of this research is to identify degrees of vulnerability per census tract. In order to have an estimate of heat temperature per census tract the raster data set was converted into vector data. First, using ArcGIS Pro, both data sets for each city were imported into the program as well as a census tract map of each city from the U.S Census Bureau. Using the tool Zonal Statistics, a mean temperature was calculated per census tract. Additionally, the sample tool was used to acquire a table from the mean temperature. Lastly, a join between the census tracts and the output table was performed to have a map that displays heat per census tract.

Additionally, seven variables were obtained from the American Community Survey (ACS). All variables obtained were percentages of the population and were from the ACS five-year estimates of the years 2017-2021. See table 5.1 for a list of these variables. These variables were obtained to find specific degrees of vulnerability to heat data. Additionally, some of the variables are distinctive to the borderland (e.g. limited English proficient (LEP)) as there is a relatively high percentage of minority populations with potential language barriers. Other variables such as 65 and older were analyzed given the elderly's high risk to high temperatures. Using the non-compiled variables allows us to get a deeper examination of groups that are vulnerable to target heat messaging. A primary concern from NWS and partners was to find vulnerable groups who may be disproportionately placed in hotter environments. By analyzing separate variables, this allows us to identify what groups are most vulnerable to high temperatures which allow WFOs and partners to allocate more heat messages or resources.

Table 5.1: Variables Used to Perform the Bivariate Analysis.

Data	Variables						
ACS data	Percent Age 65 or older	Percent Below Poverty Level	Percent Asian	Percent Native Hawaiian & Other Pacific Islander	Percent Hispanic	Foreign Born	Speaks English “less than well"
Heat data	NOAA/NIHHIS UHI data for San Diego & El Paso	________	______	________	_______	______	______

Table 5.1: Variables Used to Perform the Bivariate Analysis.

The CDC SVI was developed to prepare communities for hazardous events (CDC, 2022). The CDC SVI has been used as a tool in research to allocate emergency preparedness for natural disasters (CDC, 2022). The CDC SVI was downloaded from its public website. This analysis uses census tract-level CDC data for the city of El Paso and San Diego from the most current year, 2020. Table 5.2 provides a comprehensive listing of the social variables taken from the CDC SVI. The study will leverage the SVI indicators compiled by the CDC, with the components being comprised of various variables from the American Community Survey (ACS) (e.g., the component housing type and transportation is made up of group quarters and mobile home data from the ACS). The CDC SVI is compiled of four variables which were also analyzed separately.

The CDC SVI data set provides the data in percentile rankings of every U.S census tract where the scores range from 0 to 1, with 1 indicating the highest degree of vulnerability. The data had to be converted into percentages for the SVI and four themes. Some tracts had no data. The census tracts with no data were set to -999 in the SVI, leading to statistical distortions.

Instead, for the statistical analysis, the census tracts with no data were eliminated.

For this study, the unit of analysis will be census tracts. The purpose of census tracts is to develop a representation of geographic units (U.S Census Bureau, 2021). Census tracts have been used in research to understand the social characteristics of small geographical units. This study aims to incorporate the CDC SVI, and heat data like Lenhert et al. (2020) and also replicate their unit of analysis. Additionally, some of the variables from the ACS were only provided in census tracts, therefore, in order to have uniformity across all variables, census tracts were most suitable for this study. The NOAA/NIHHIS UHI campaign reported data within city boundary, in this study the cities of San Diego and El Paso. Census tracts follow major municipal boundaries.

Table 5.2: Social Vulnerability Indicators (CDC, 2021).

Components	Variables			
Socioeconomic Status	Below Poverty	Unemployed	Income	No Highschool Diploma
Household Characteristics & Disability	Age 65 or Older	Aged 17 or Younger	Civilian with a Disability	Single-Parent Household
Minority Status and Language	Minority	Speaks English "Less than Well"	____________ _	______________
Housing Type and Transportation	Multi-Unit Structures & Group Quarters	Mobile Homes	Crowding	No Vehicle

5.2. Spatial Autocorrelation Analysis

For this study, univariate spatial autocorrelation was used using the Anselin Local Moran's I tool on ArcGIS Pro to detect whether there was a presence of spatial clustering in the UHI data set. This was a preliminary step to determine whether our data sets had heat clustering, and therefore proceed with our hot and non-hot clustering analysis. Anselin Local Moran's I tool is used to determine whether the patterns within a dataset are clustered, dispersed, or random. A series of maps were produced with different spatial relationships. The inverse distance was used for the local analysis as this gives more weight to features closer together.

The given z-score reflects whether a census tract is part of a hot spot (areas with high values) or a non-hot spot (areas with low values). After this tool was performed, a map was produced of areas of hot spots and non-hot spots. A table with both values was obtained for the statistical analysis.

5.3 Statistical Analyses

A bivariate analysis was performed to identify the relationship between selected social variables and heat data throughout the city of San Diego and El Paso. Performing a bivariate analysis this study aims to understand global thermal inequities throughout both cities. Using SPSS statistics, selected social variables, and heat data per census tract were downloaded and imported into SPSS. The bivariate analysis included heat with the seven selected variables. A bivariate analysis was used to determine the strength of the relationship between the two variables. For this analysis a null hypothesis tests whether there was a significant difference from no relationship between the variables. Additionally, Pearson correlation was reported to determine the strength of the linear association. The bivariate comparison is listed below:

- Analyzing heat with percent Asian, percent Hispanic, percent Native Hawaiian and other

Pacific Islander populations, LEP, and foreign-born gives us a global analysis of social characteristics that are unique to the borderlands (Asian and Pacific variables were included as being suited to San Diego). This analysis examines which of the populations with these social characteristics is vulnerable given that the border cities tend to have large minority populations, language barriers, and a large percentage of foreign-born populations.

- Analyzing heat with percent of the population below poverty and age 65 and older was selected to identify vulnerable populations to heat due to their impaired adaptive capacity.

Additionally, a bivariate ordinary least square (OLS) regression was performed to model the relationship between the total CDC SVI, SVI themes, and heat data by creating a linear regression model (see table 5.2 for a list of the components). Performing a bivariate OLS regression can produce changes in the dependent variable. For the bivariate OLS, the heat index was the dependent variable, and SVI total and themes were the independent variables. For this analysis a null hypothesis was reported as well as the strength of the relationship. Additionally, a coefficient was reported to analyze changes in the dependent and independent variables.

Lastly, an independent t-test was performed to determine if the means of social variables differ statistically between urban heat islands (the method for identifying is described above) and non-heat island areas. For the t-test the analysis selected variables, the CDC SVI, and SVI themes were all tested. Using the data that was produced from my local Moran's I on ArcGIS Pro a table was downloaded separating hot census tracts and non-hot census tracts. For the t-test analysis non-hot census tracts were labeled as "1" and hot census tracts were labeled as "2". There was a total of twelve t-test analyses. The social variables were the test variables, and the heat index was the grouping variable. For this part of the study, a t-test was conducted on San Diego and El Paso. For this analysis, the goal was to determine whether there is a presence of local thermal inequity between hot and non-hot census tracts. This analysis reported changes in the mean between hot and non-hot census tracts.

Chapter 6: Results

For this study, both a global and local analysis will be reported. The goal is to identify whether there is global thermal inequity in each city as well as a presence of heat clustering (UHIs) and further investigate the social characteristics of UHIs. These analyses will report results for both El Paso and San Diego and will seek to answer the research questions proposed earlier in this paper. Results will be organized first with a series of univariate maps that introduce the variables. Secondly, the study will report a global analysis of both cities. Next, results will report whether there is a presence of heat clustered tracts in both cities. Last, if there is a presence of heat clusters a local analysis will be performed.

6.1 Descriptive Mapping

Univariate maps were first produced to portray visually the spatial distribution of the variables within El Paso and San Diego city. UHI data for both El Paso and San Diego were only provided inside city limits. For this study, census tracts outside of city limits were not utilized for both cities since no heat data was available, therefore this study will only focus on analyzing data inside city limits. On these maps, darker colors represent higher levels of the selected variable (heat, overall vulnerability, specific vulnerability components as defined by the CDC).

Figures 6.1 to 6.6 provide an overview of the spatial distribution of our heat data and sociodemographic variables for the city of El Paso, TX. Overall, high temperatures are widely distributed across the city. Figures 6.2 to 6.6 displays the spatial distribution of CDC SVI variables and their components are broken down into four themes. Overall, social vulnerability is widely distributed although there is a concentration of vulnerability in South Central El Paso. For the El Paso study 143 census tracts were analyzed.

Table 6.1 shows descriptive statistics and spatial autocorrelation results for El Paso and

6.2 shows results for San Diego. Moran's I with values higher than 0.5 and low p-values indicate spatial clustering. Therefore, this suggests caution is needed in interpreting the bivariate results.

Table 6.1: El Paso Descriptive Statistics & Moran's I results.

Variables	Descriptive Statistics			Spatial Autocorrelation	
	Mean	Median	Standard Deviation	Moran's Index	p-value for Moran's Index
Heat Index	104.48	104.61	0.47	0.15	0.000004
Percent Asian	1.14	0.4	1.91	0.547385	0.013941
Percent Hispanic	81.79	85.65	16.81	0.295233	0.000000
Percent Native Hawaiian & other Pacific Islander	0.18	0	0.85	0.589776	-0.023264
LEP	14.21	11.5	10.07	0.136871	-0.000546
Percent Foreign Born	24.20	23.35	8.88	0.359703	0.00000
Percent Age 65 & older	13.70	14.45	6.55	-0.000546	0.136871
Percent Below Poverty	20.89	17.85	14.12	0.415119	0.00000
SVI	68.44	74.85	25.86	-0.000996	0.000813
Theme 1	66.70	73.6	24.61	-0.000907	0.000676
Theme 2	70.32	75.2	24.61	-0.001137	0.001075
Theme 3	80.57	83.1	14.60	-0.000987	0.000772
Theme 4	54.29	53.95	29.47	-0.001039	0.000901

Table 6.2: San Diego Descriptive Statistics & Moran's I results.

Variables	Descriptive Statistics			Spatial Autocorrelation	
	Mean	Median	Standard Deviation	Moran's Index	p-value for Moran's Index
Heat Index	75.74	77.77	1.76	0.676313	0.00000
Percent Asian	11.37	8.3	10.90	0.420860	0.00000
Percent Hispanic	11.16	8.05	10.84	0.420860	0.00000
Percent Native Hawaiian & other Pacific Islander	0.36	0	0.82	0.064219	0.001941
LEP	57.33	60.25	29.85	0.461502	0.00000
Percent Foreign Born	23.28	22.1	12.41	0.460737	0.00000
Percent Age 65 & older	7.52	4.95	7.46	0.461074	0.00000
Percent Below Poverty	12.84	10.7	9.02	0.215540	0.00000
SVI	37.88	31.45	23.73	0.631105	0.00000
Theme 1	43.24	43.1	32.05	0.449865	0.00000

Theme 2	71.37	71.4	19.07	0.648989	0.00000
Theme 3	58.80	60.6	28.65	0.222276	0.00000
Theme 4	56.70	61.2	30.68	0.474021	0.0000

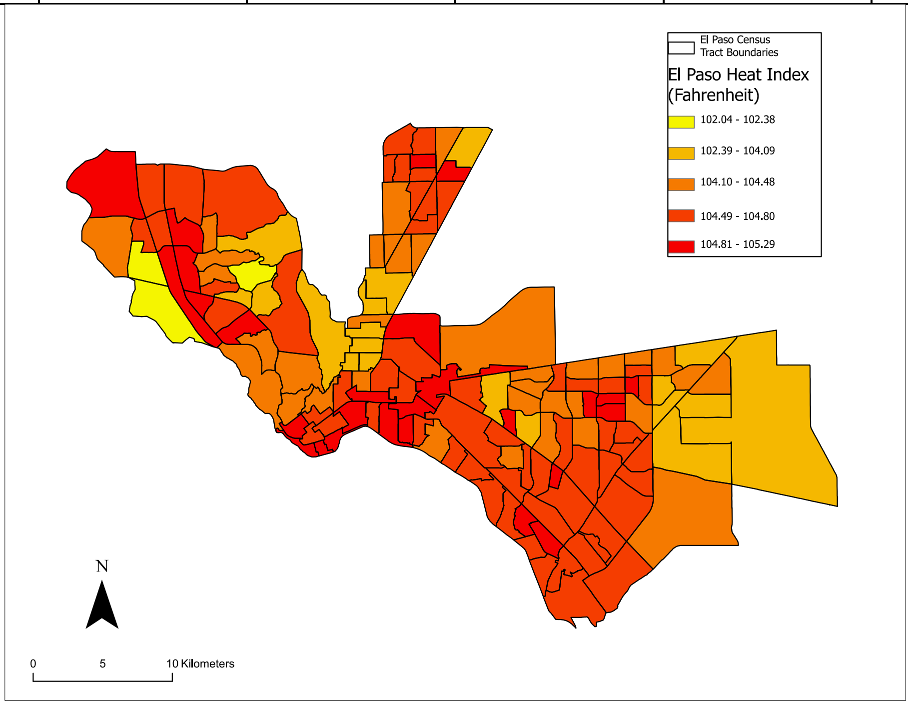


Figure 6.1: El Paso Heat Index.

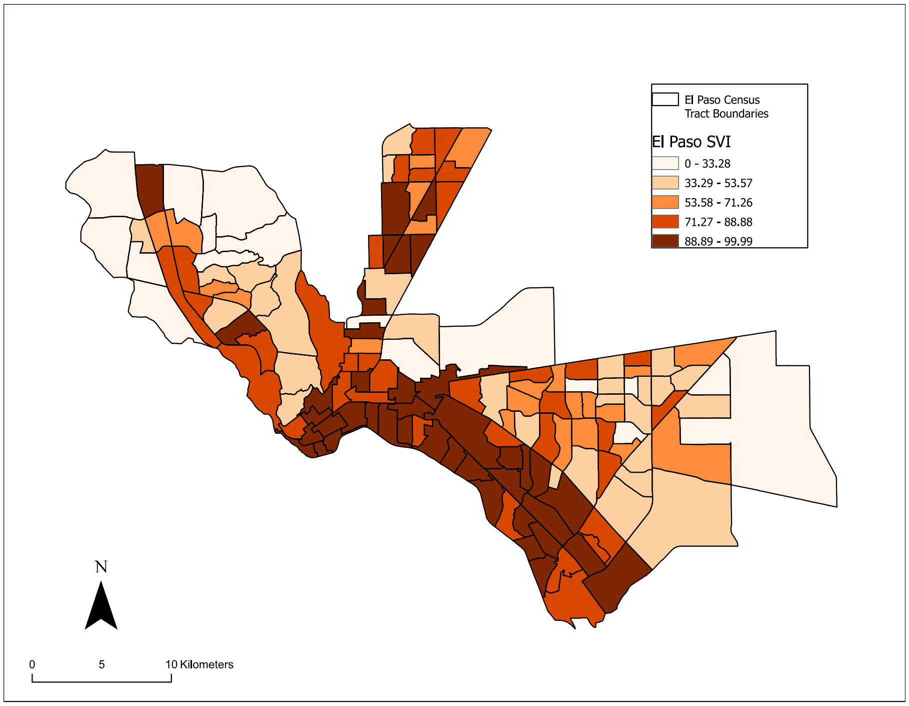


Figure 6.2: El Paso CDC SVI.

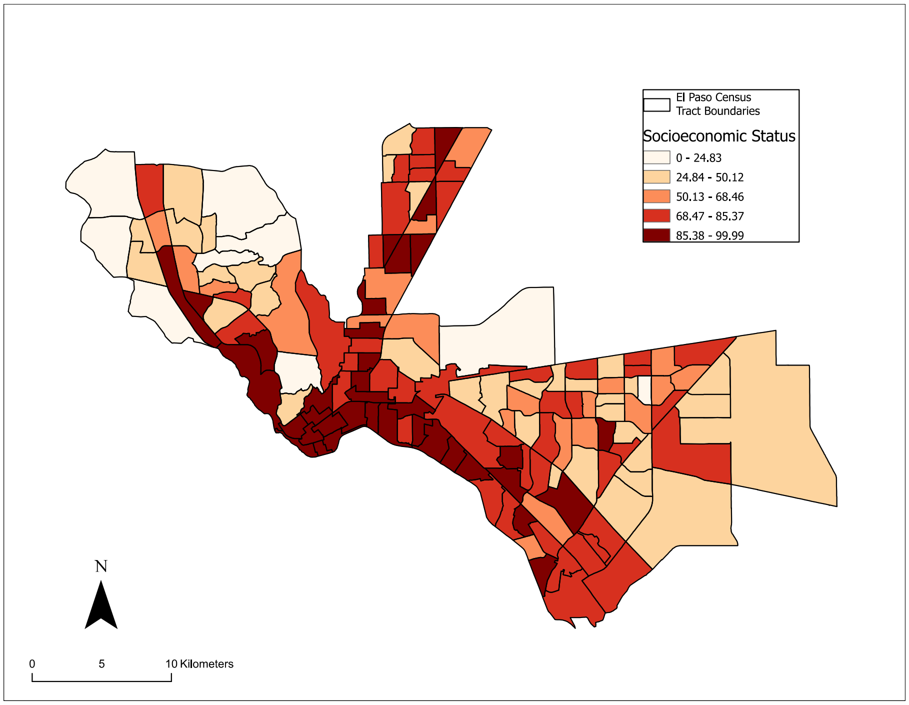


Figure 6.3: El Paso Theme 1: Socioeconomic Status.

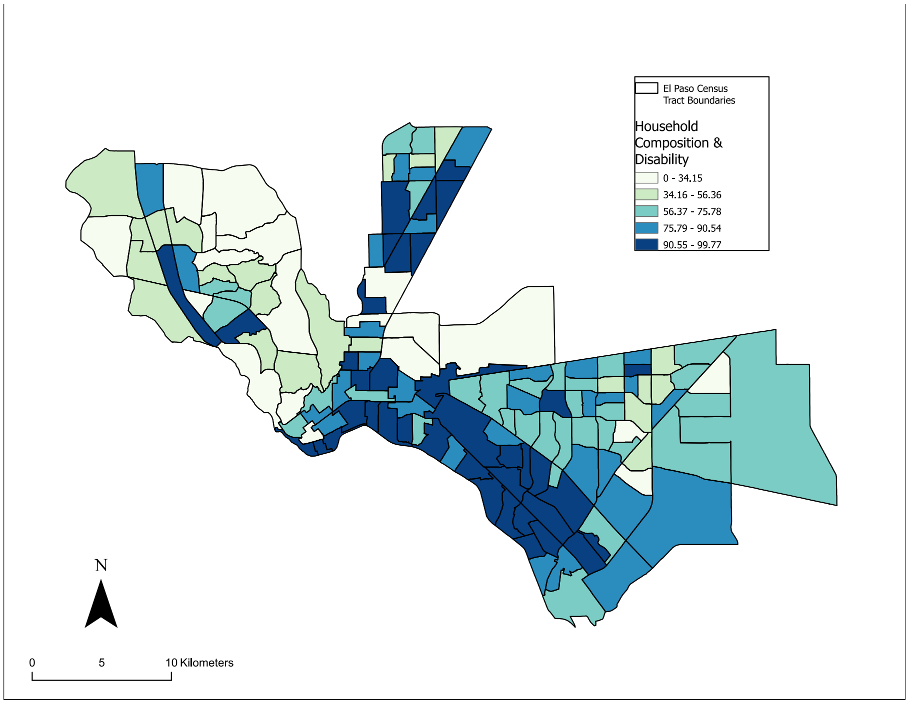


Figure 6.4: El Paso Theme 2: Household Composition & Disability.

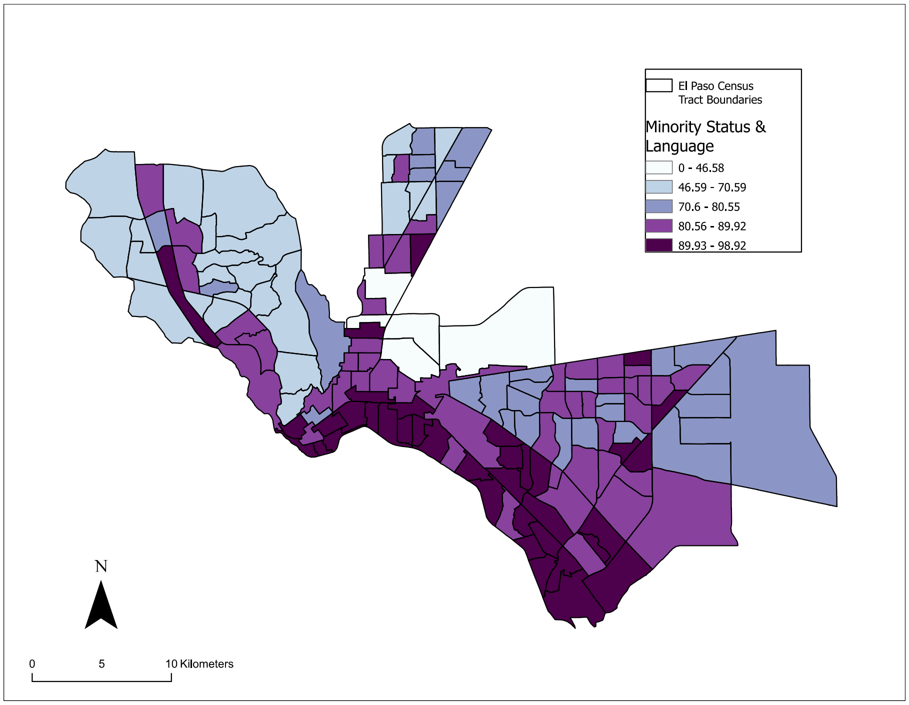


Figure 6.5: Theme 3: Minority Status and Language.

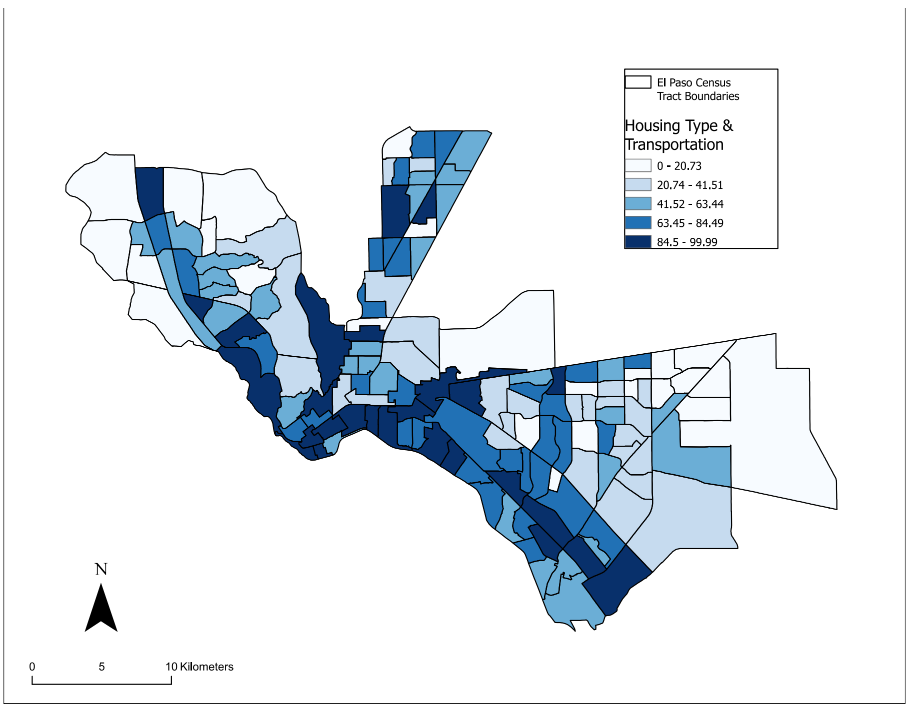


Figure 6.6: El Paso Theme 4: Housing Type & Transportation.

Figures 6.7 to 6.13 provides the spatial distribution of selected variables for El Paso, TX. Figure 6.7 shows the spatial distribution of LEP which portrays some vulnerable census tracts in south-central El Paso. Figure 6.8 shows that older individuals are also widely distributed. For the univariate maps of minority populations (figures 6.9 to 6.11) Asian and Native Hawaiian and Other Pacific Islander populations are widely distributed except for Hispanics and Latinos which are highly concentrated in south-central El Paso. Similarly, populations below poverty and foreign-born (figures 6.12 to 6.13) high percentage of these populations are concentrated in south-central El Paso.

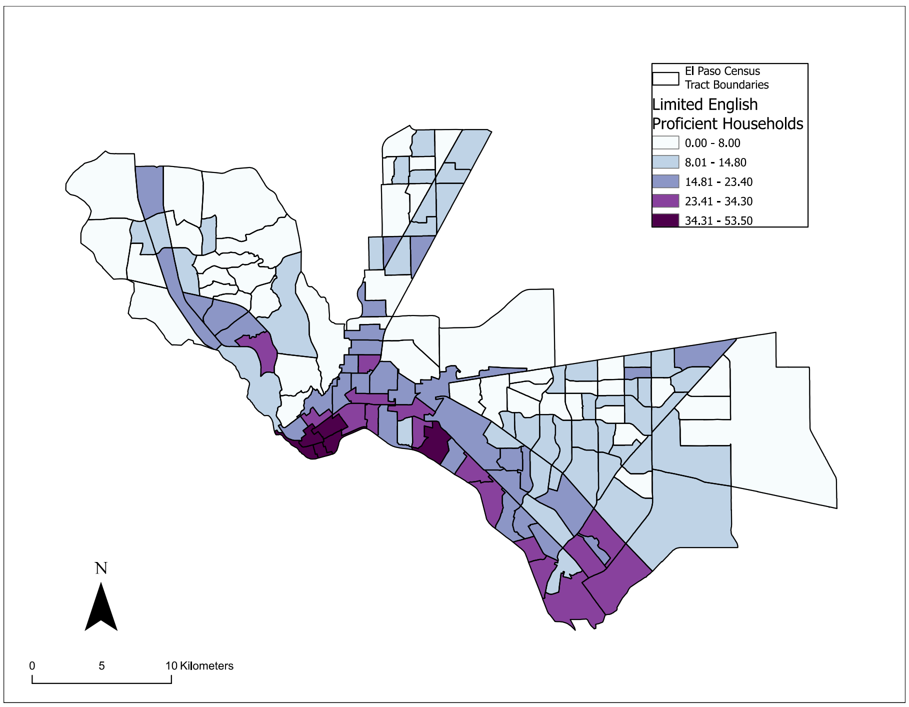


Figure 6.7: El Paso Percentage of Limited English-Proficient Households.

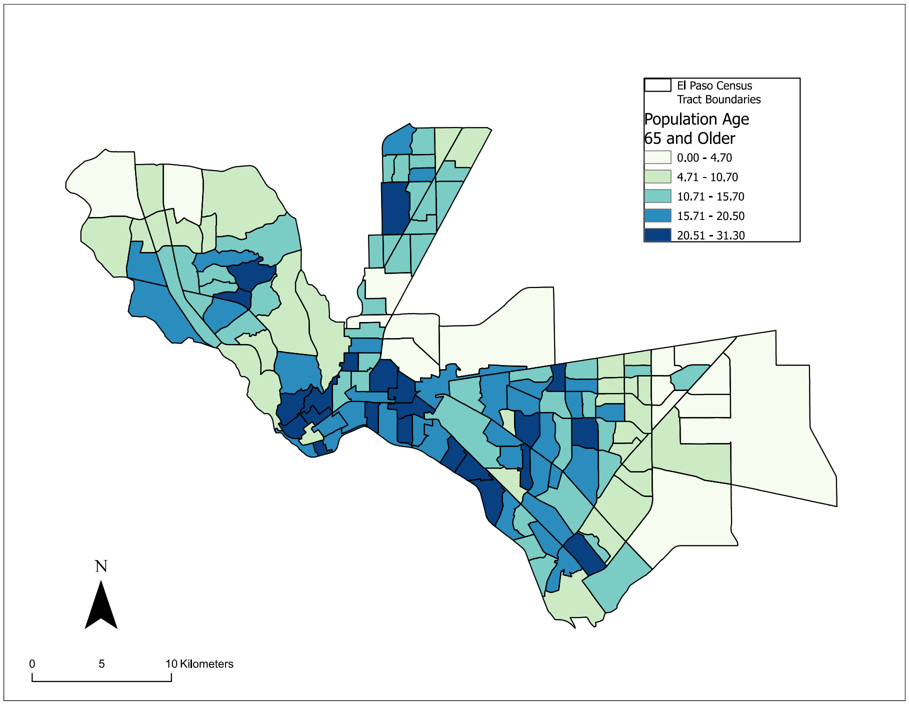


Figure 6.8: El Paso Percentage of Age 65 and Over.

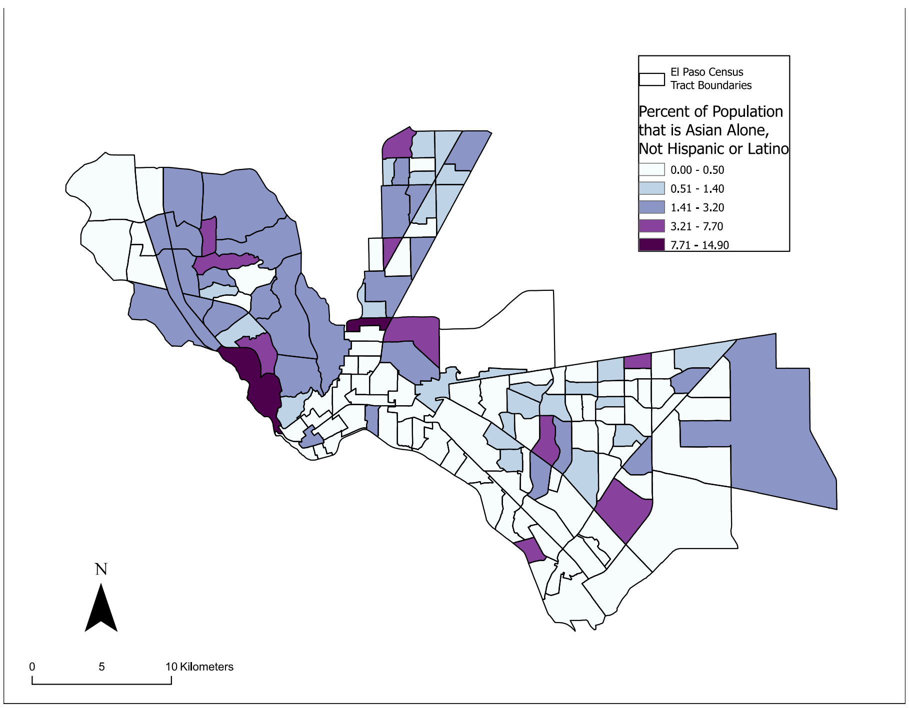


Figure 6.9: El Paso Percentage of Asian.

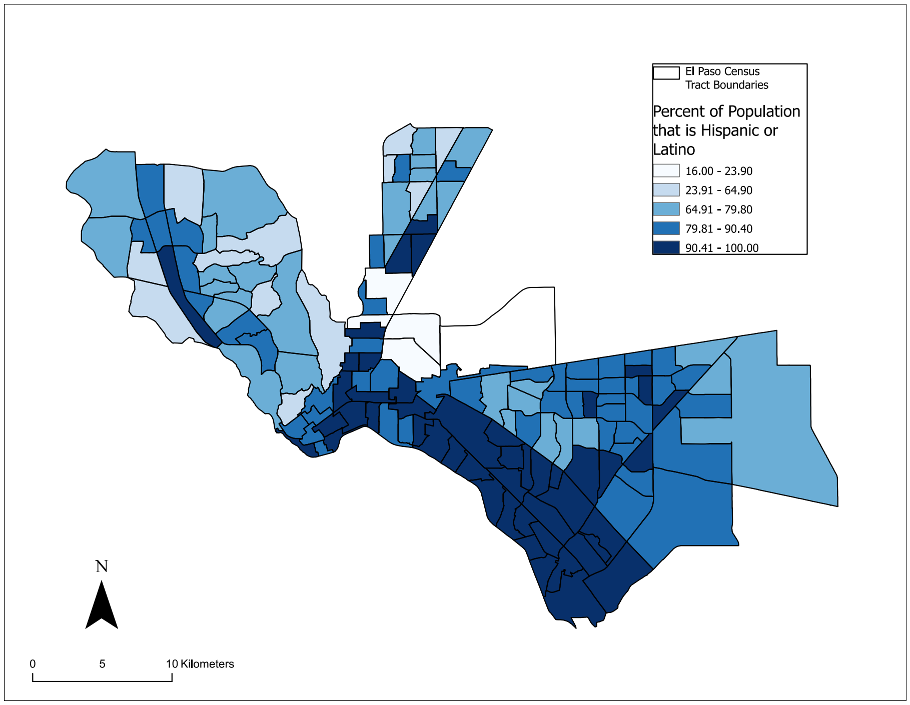


Figure 6.10: El Paso Percentage Hispanic or Latino.

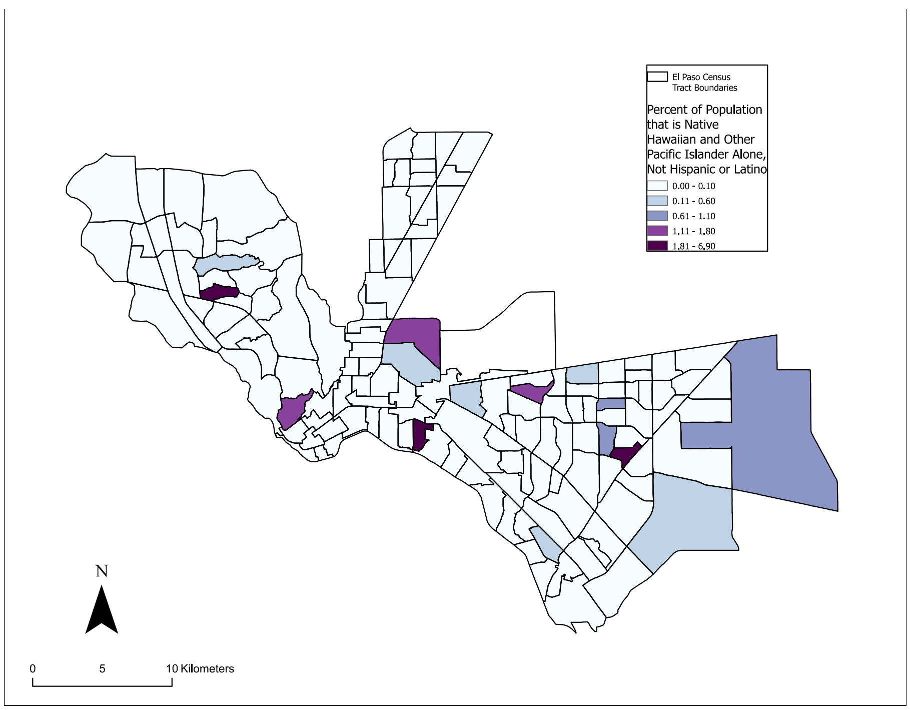


Figure 6.11: El Paso Percentage Native Hawaiian and Other Pacific Islander.

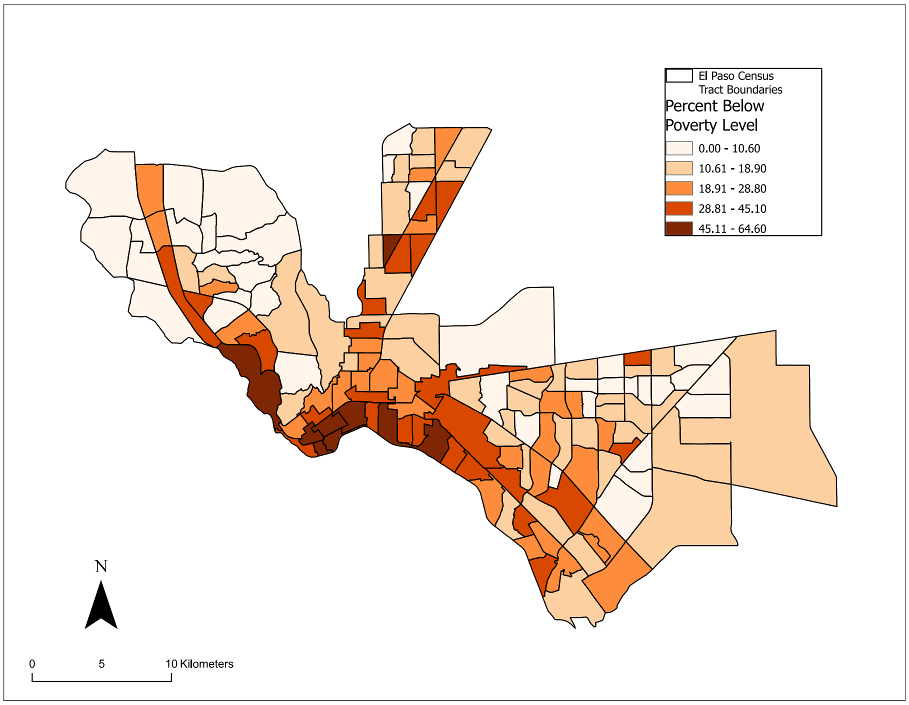


Figure 6.12: El Paso Percentage Below Poverty.

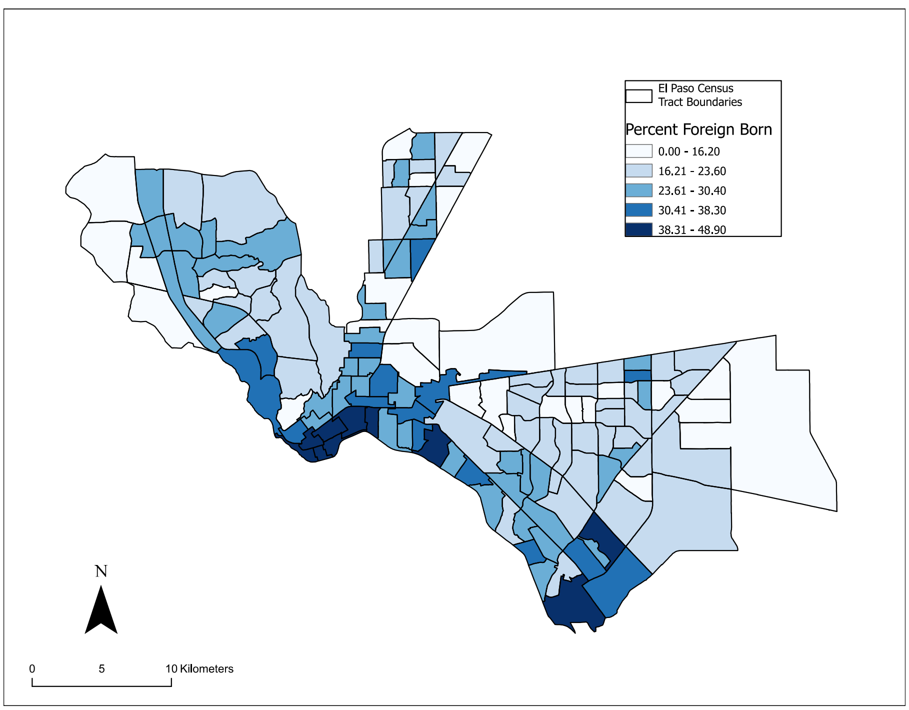


Figure 6.13: El Paso Percentage Foreign-born.

Figures 6.14 to 6.19 displays an overview of the variables used for the San Diego, CA study. San Diego heat data is displayed in Figure 6.14. Overall, heat is widely distributed in the city, but there is a concentration of high temperatures in southeastern San Diego. For the CDC SVI (Figure 6.15) and socioeconomic status, data (Figure 6.16) vulnerability seems widely distributed with a small concentration in southern San Diego. Figure 6.17 displays results for theme 3 which has a large percentage of vulnerability in southern San Diego. Figure 6.18 displays the minority status and language data in which there is a large concentration of vulnerability in southern San Diego. Figure 6.19 displays the housing type and transportation data in which high and low vulnerability is widely distributed across San Diego. For the San Diego study 264 census tracts were studied.

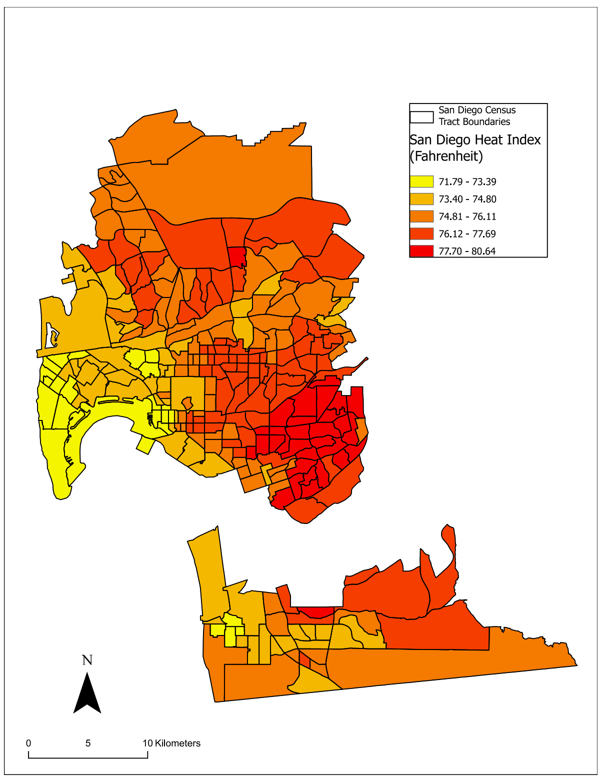


Figure 6.14: San Diego Heat Index.

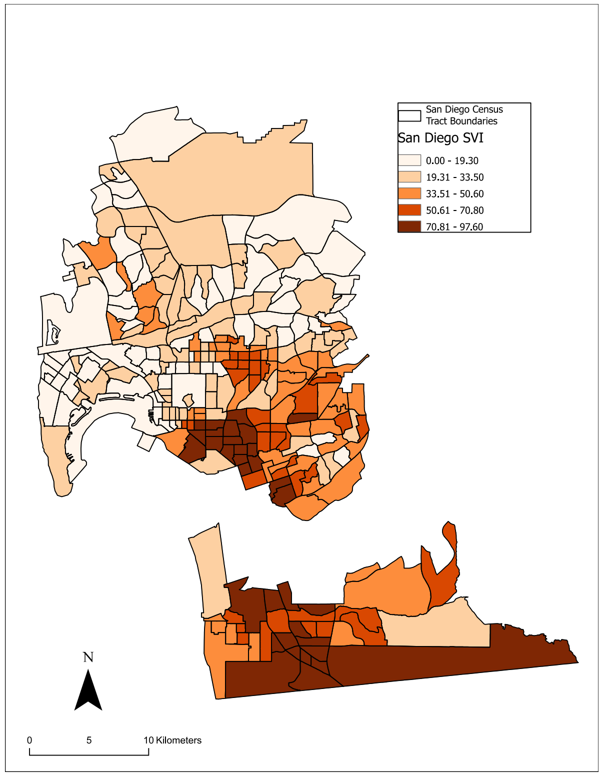


Figure 6.15: San Diego CDC SVI.

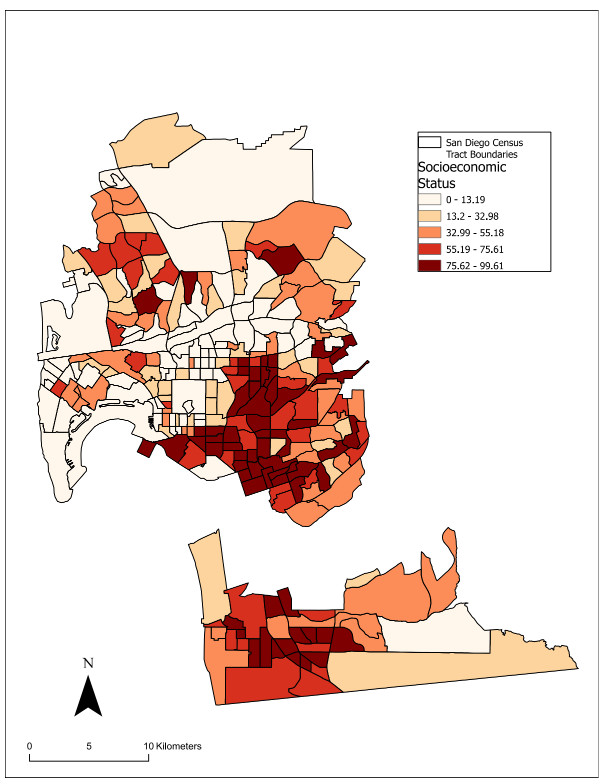


Figure 6.16: San Diego Theme 1: Socioeconomic Status.

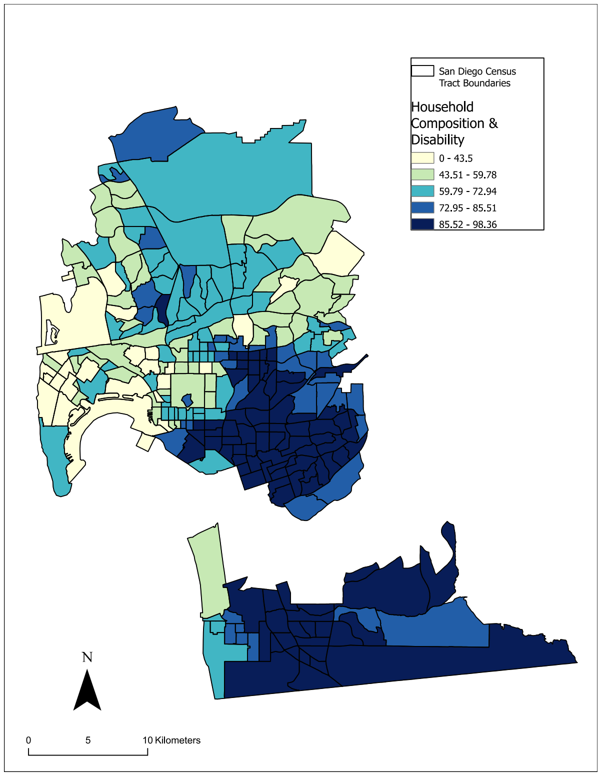


Figure 6.17: San Diego Theme 2: Household Composition & Disability.

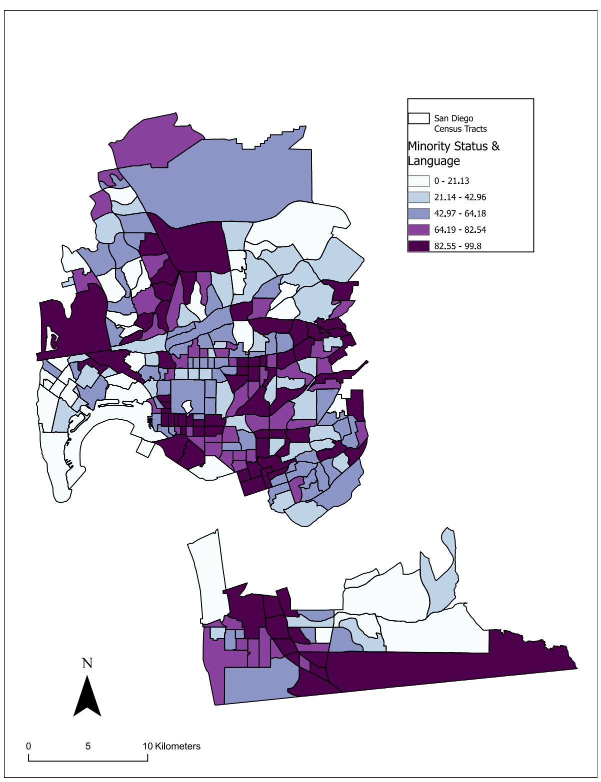


Figure 6.18: San Diego Theme 3: Minority Status & Language.

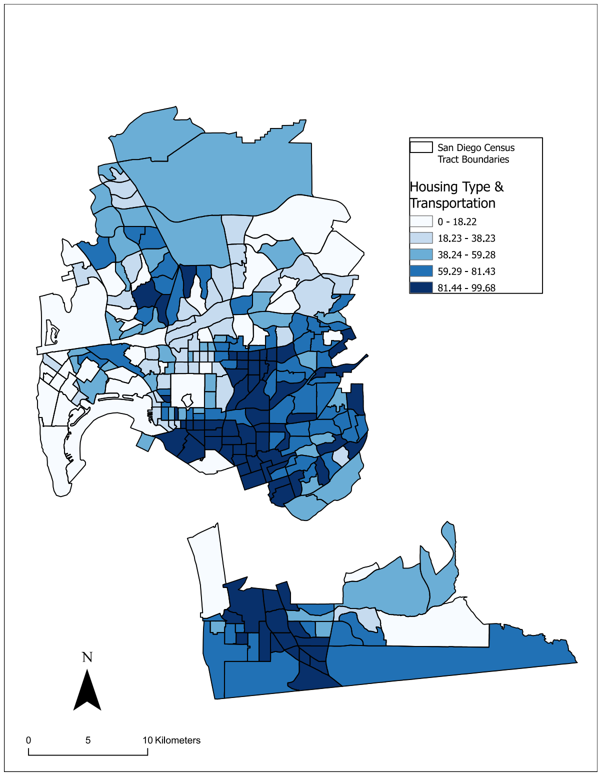


Figure 6.19: San Diego Theme 4: Housing Type and Transportation.

Figures 6.20 to 6.27 shows the geographical distribution of selected variables for San Diego, CA. Figure 6.20 shows that LEP households are widely distributed with some vulnerability in southern San Diego. Figure 6.21 also displays a minimal concentration of elderly in southern San Diego. Minority groups seem to be widely distributed (figures 6.22 to 6.24). Figure 6.25 displays percentage of populations living below poverty, overall, vulnerable groups are widely distributed. Last, figure 6.26 that foreign-born populations are widespread, yet there is some concentration in southern San Diego.

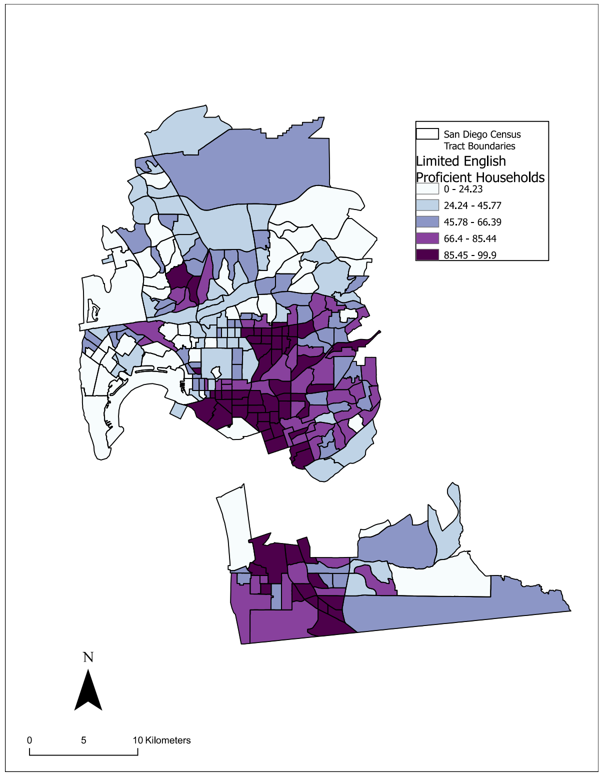


Figure 6.20: San Diego Percentage of Limited English-Proficient Households.

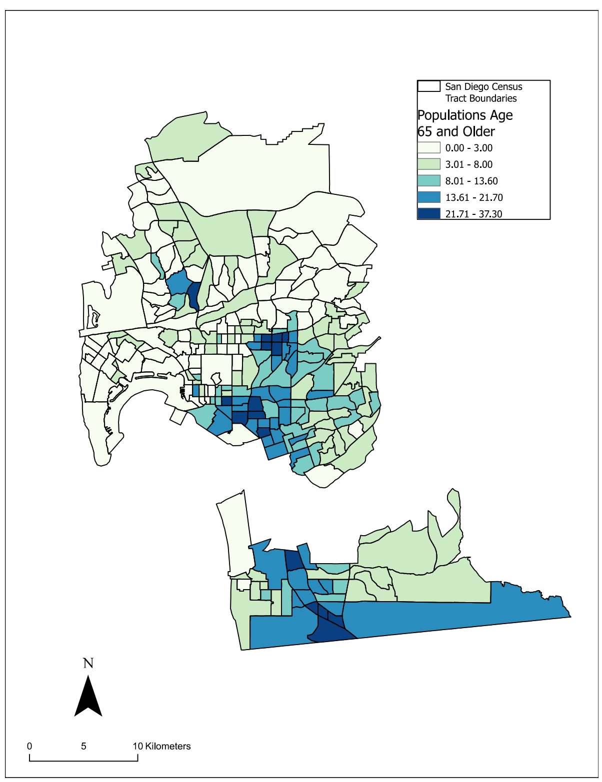


Figure 6.21: San Diego Percentage of Age 65 and Over.

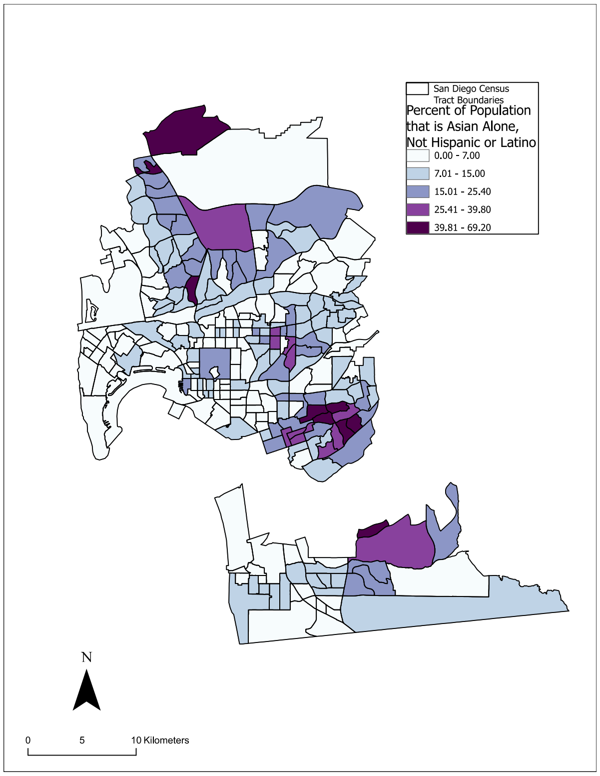


Figure 6.22: San Diego Percentage of Asian.

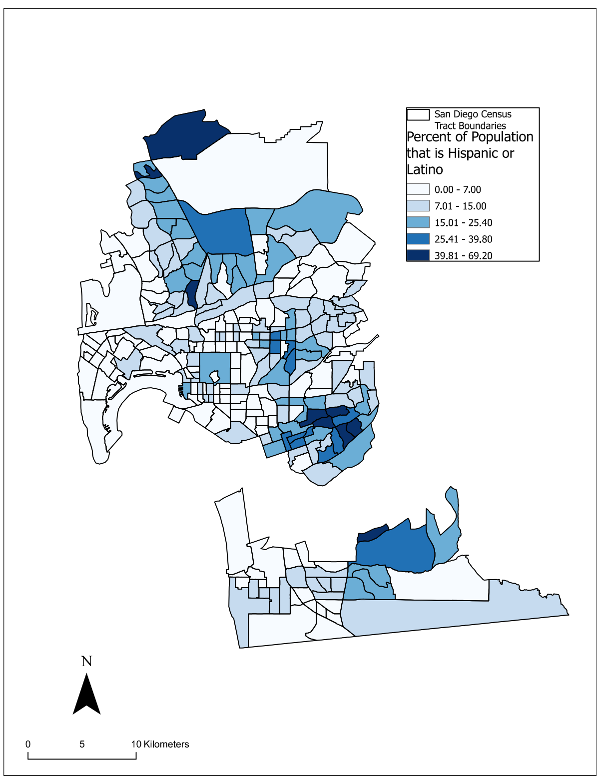


Figure 6.23: San Diego Percentage Hispanic or Latino.

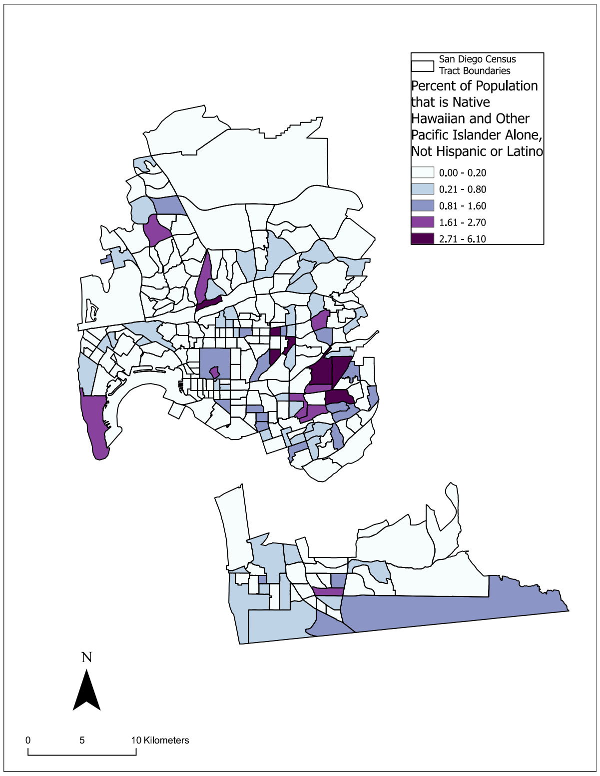


Figure 6.24: San Diego Percentage Native Hawaiian and Other Pacific Islander.

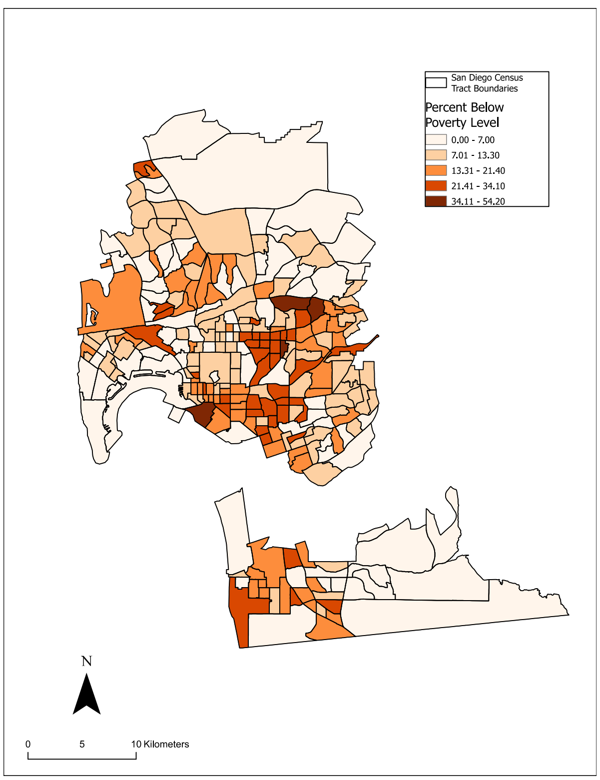


Figure 6.25: San Diego Percentage Below Poverty.

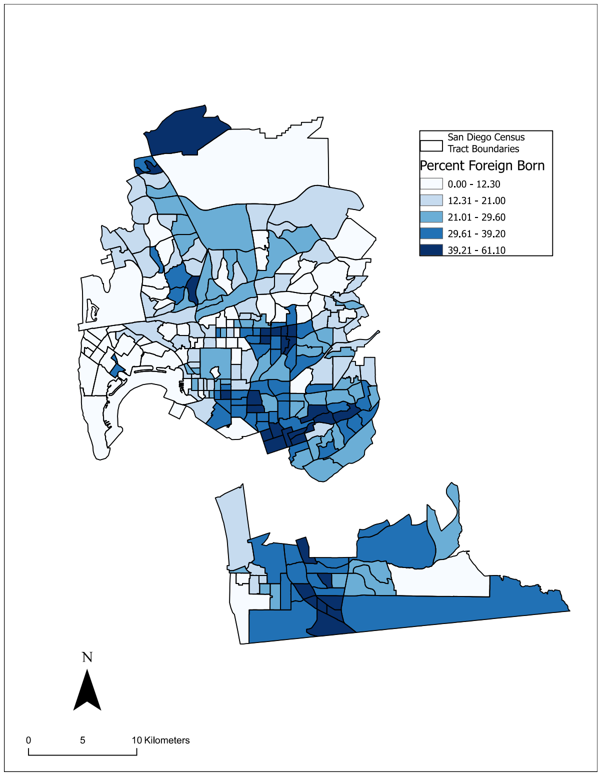


Figure 6.26: San Diego Percentage Foreign-born.

This section provides an overview of the spatial distribution of the data. A further examination of vulnerability and heat clustering in El Paso and San Diego will be discussed in the following sections.

6.2 Global Bivariate Analysis

For this phase of the analysis, the goal was to understand if there was a global thermal inequity in both selected cities. First, a bivariate analysis was performed for selected variables. These variables were selected to understand vulnerability for specific vulnerable populations which can be used by NWS and partners for targeted heat communication or allocation of resources.

Table 6.1 shows the global bivariate results for El Paso, TX with selected variables and heat data. The analysis indicates that LEP, Hispanics, below poverty level, and foreign-born all prove to be significant (sig <.05) with a positive relationship between both selected variables and heat data. All these significant results showed a moderate positive relationship. Figure 6.27 to 6.33 displays a scatterplot to portray the strength of the relationship. Even though all significant relationships displayed similar results, populations with LEP displayed the strongest correlation. These bivariate results conclude that there is a degree of vulnerability to heat for these groups. Overall, Asian, Native Hawaiian and other Pacific Islander, and Age 65 and older did not prove to be significant. Even though some variables did not display a significant relationship, this does not assume these populations are not vulnerable to heat. Figures 6.31 to 6.33 displays the scatterplots for non-significant variables.

Table 6.3: Bivariate results for El Paso TX.

Bivariate Analysis for El Paso, TX				
	Coefficient	Sig	Pearson Correlation	N
Heat Index & Limited English Proficient	0.01	<.001	.282	143
Heat Index & Asian population	-0.02	.366	-.076	143
Heat Index & Native Hawaiian & Other Pacific Islander population	0.02	.612	.043	143
Heat Index & Hispanic population	0.007	.002	.256	143
Heat Index & Age 65 and over	0.004	.563	.049	143
Heat Index & Below Poverty Level	0.008	.004	.241	143
Heat Index & Foreign Born	0.01	.002	.259	143

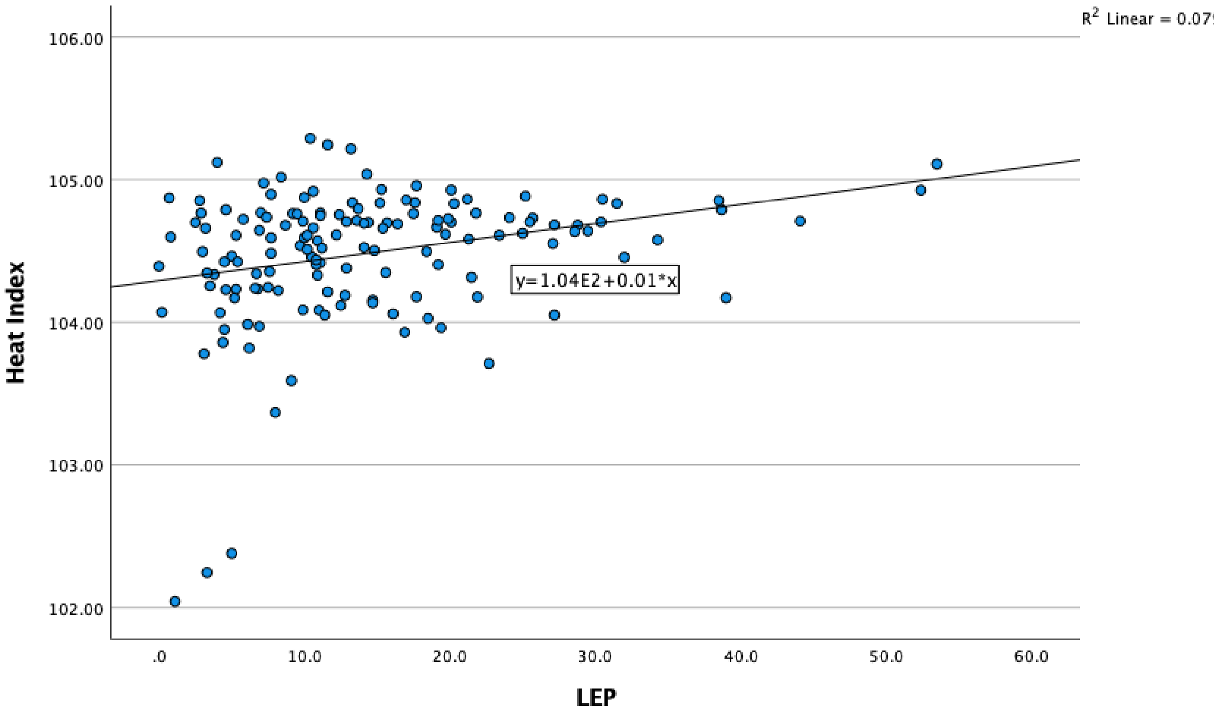


Figure 6.27: EL Paso, LEP & HI.

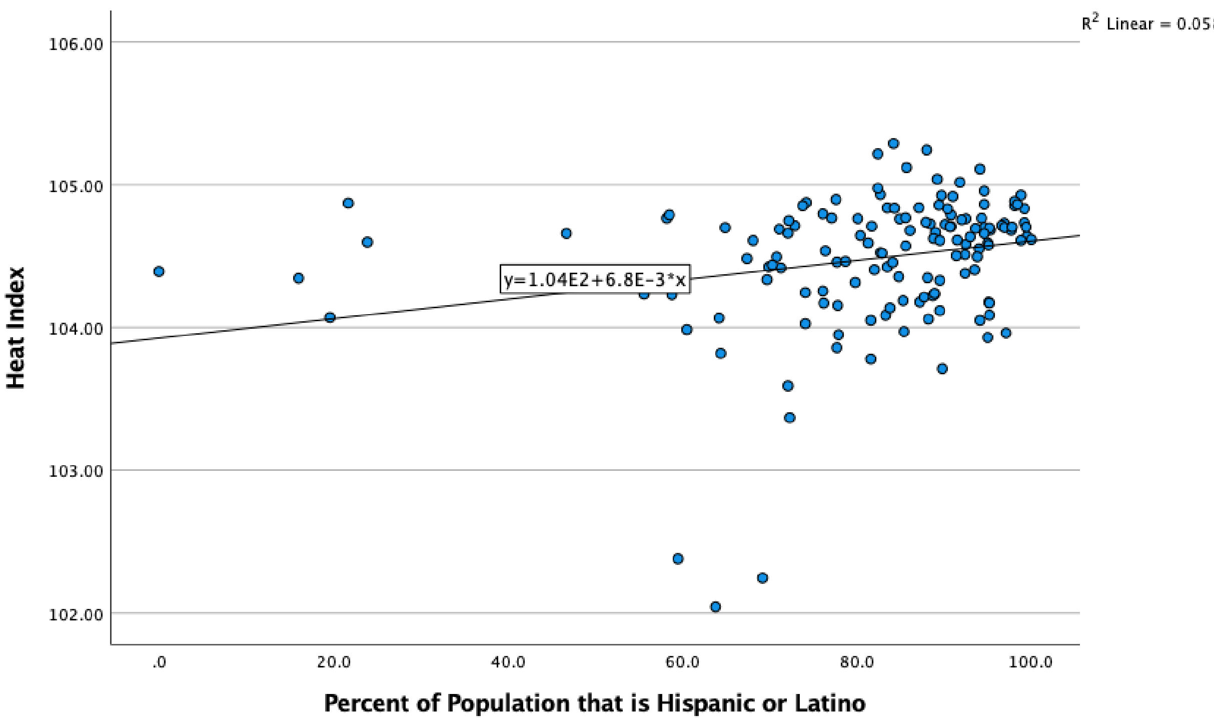


Figure 6.28: El Paso, Hispanic & HI.

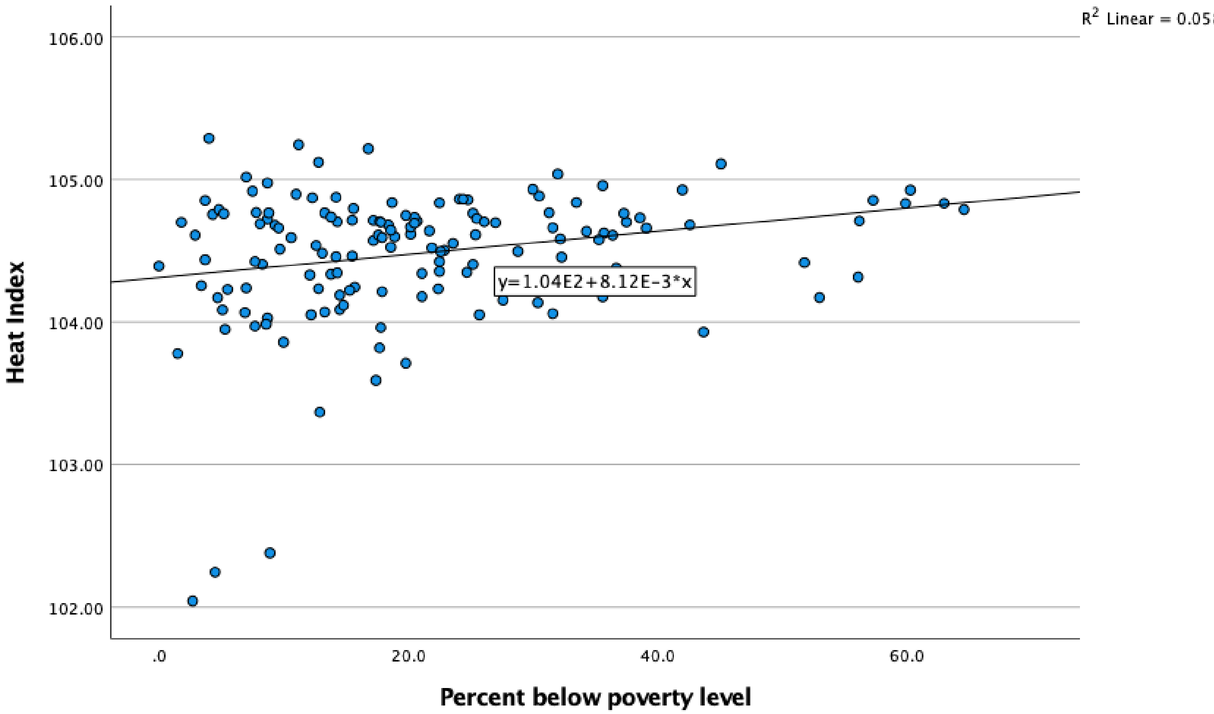


Figure 6.29: El Paso, Below Poverty & HI.

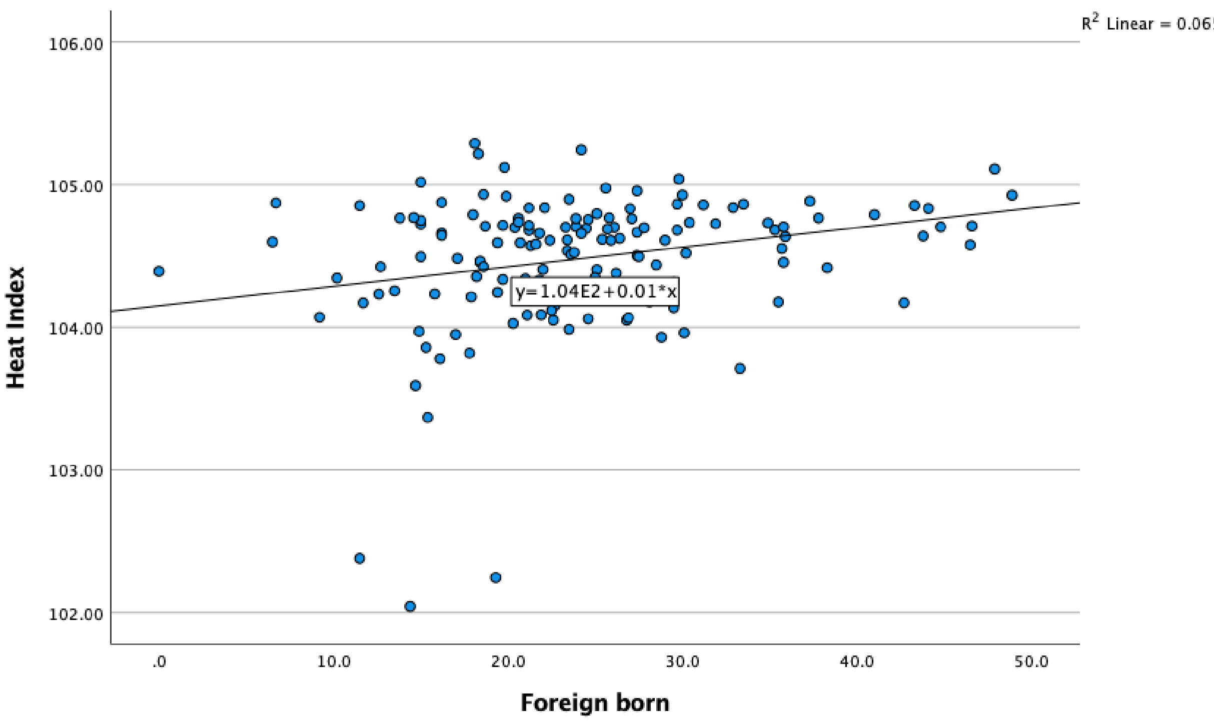


Figure 6.30: El Paso, Foreign-born & HI.

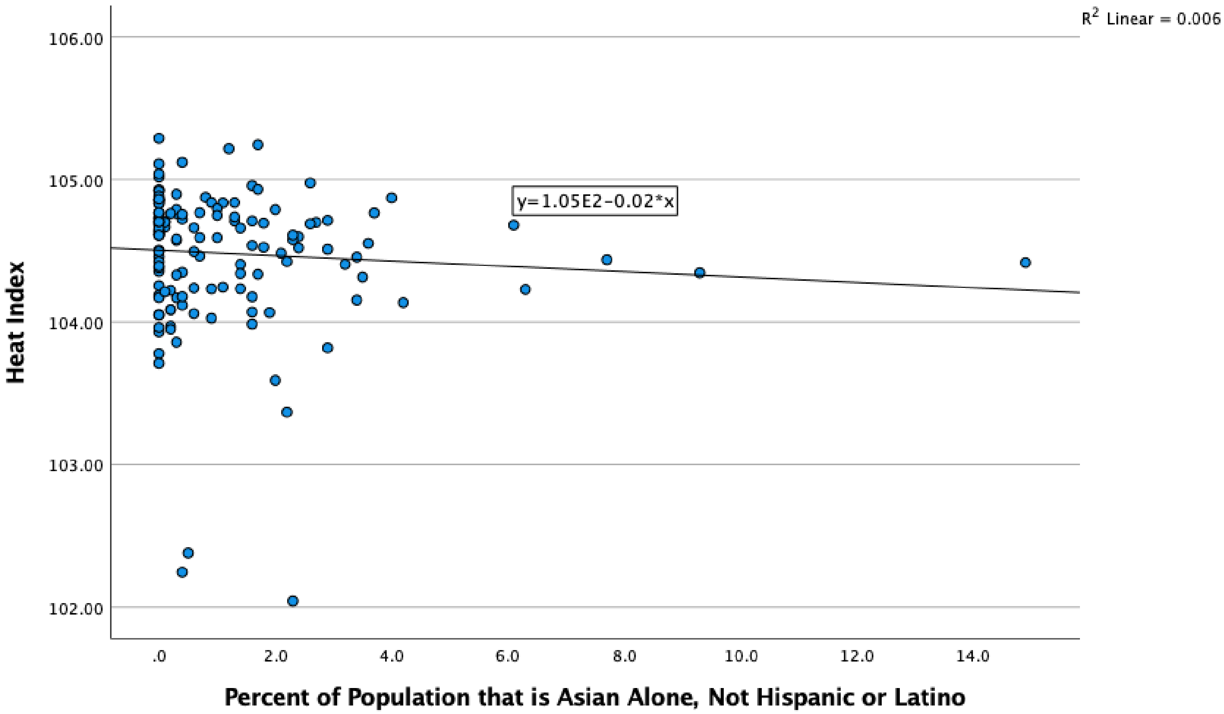


Figure 6.31: El Paso, Asian & HI.

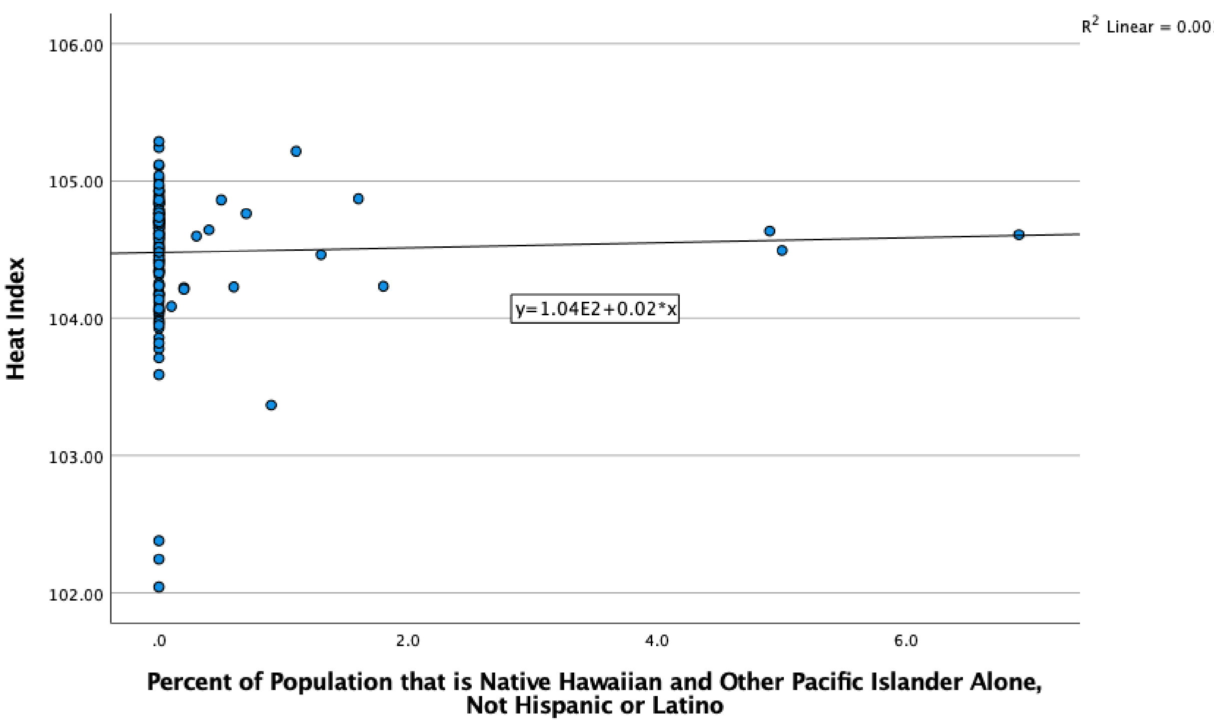


Figure 6.32: El Paso, Native Hawaiian and other Pacific Islander & HI.

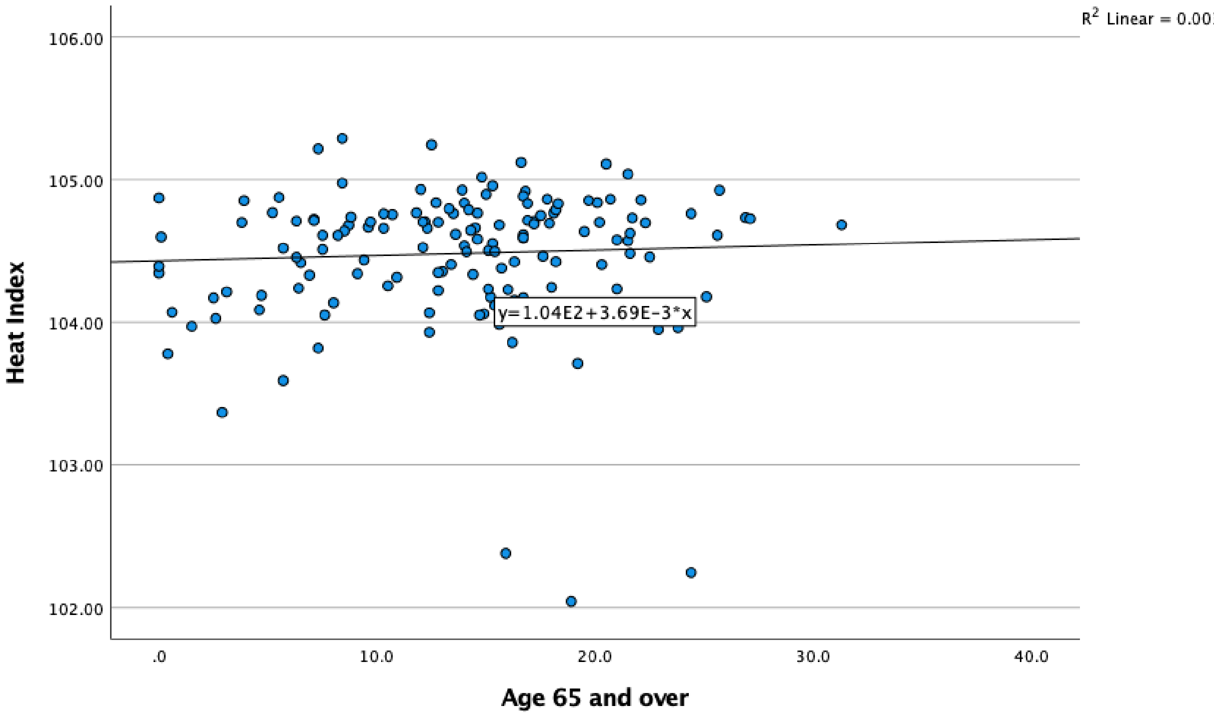


Figure 6.33: El Paso, Age 65 and older & HI.

Additionally, a bivariate least square regression was performed for the CDC SVI. The four components that make up the SVI were also analyzed separately. A bivariate least square analysis was used for these variables as this is a stronger analysis. As shown in Table 6.2, the SVI proves to be significant with a moderate positive relationship. For every one-unit increase in SVI, the heat variable increases by .005. Similarly, theme 1 which consists of socioeconomic status also proved to be significant with a positive moderate relationship. For theme 1, every one-unit increase showed a .005 increase in heat. Theme 2 also displayed very similar results, except that for every one unit increase in theme 2, there is a .004 increase in heat. Theme 3 displayed the highest degree of vulnerability. Theme 3 proved to be significant with a moderate positive relationship. For theme 3, for every one-unit increase, there is a .012 increase in heat. Lastly, theme 4, proved to be significant with a moderate positive relationship. For every one-unit increase in theme 4, there is an increase of .004 of heat.

Table 6.4: Bivariate Least Square Analysis.

Bivariate Least Square Regression for El Paso, TX				
	Coefficient	Sig	Pearson Correlation	95% CI
Theme 1: Socioeconomic Status & Heat Index	.005	.006	.230	.001-.008
Theme 2: Household Composition and Disability & Heat Index	.004	.007	.225	.001-.007
Theme 3: Minority Status and Language & Heat Index	.012	<.001	.320	.006 -.018
Theme 4: Housing Type and Transportation & Heat Index	.004	.003	.249	.001-.007
Overall CDC SVI & Heat Index	.005	<.001	.282	.002-.008

Table 6.3 shows the global bivariate analysis for San Diego, CA. Selected variables were identical to the El Paso study. Overall, San Diego results proved to be significant (sig <.05) for all variables except for populations below poverty level. As displayed in Table 6.3, LEP, Asian, Native Hawaiian and other Pacific Islander, Hispanic, Age 65 and older, and foreign-born all displayed to be significant (sig <.05), with moderate positive relationships. Figures 6.34 to 6.40 displays a scatterplot of variables with significant results. For San Diego, there was only one variable that did not have significant results, Figure 6.40 displays a scatter plot of percent below poverty and heat index.

Table 6.5: Bivariate Analysis for San Diego, CA.

Bivariate Analysis for San Diego, CA				
		Sig	Pearson Correlation	N
Heat Index & Limited English Proficient	0.02	<.001	.318	257
Heat Index & Asian population	0.05	<.001	.304	257
Heat Index & Native Hawaiian & Other Pacific Islander population	0.54	<.001	.270	257
Heat Index & Hispanic population	0.05	<.001	.304	257
Heat Index & Age 65 and over	0.06	<.001	.226	257
Heat Index & Below Poverty Level	0.02	.314	.063	257
Heat Index & Foreign Born	0.05	<.001	.307	257

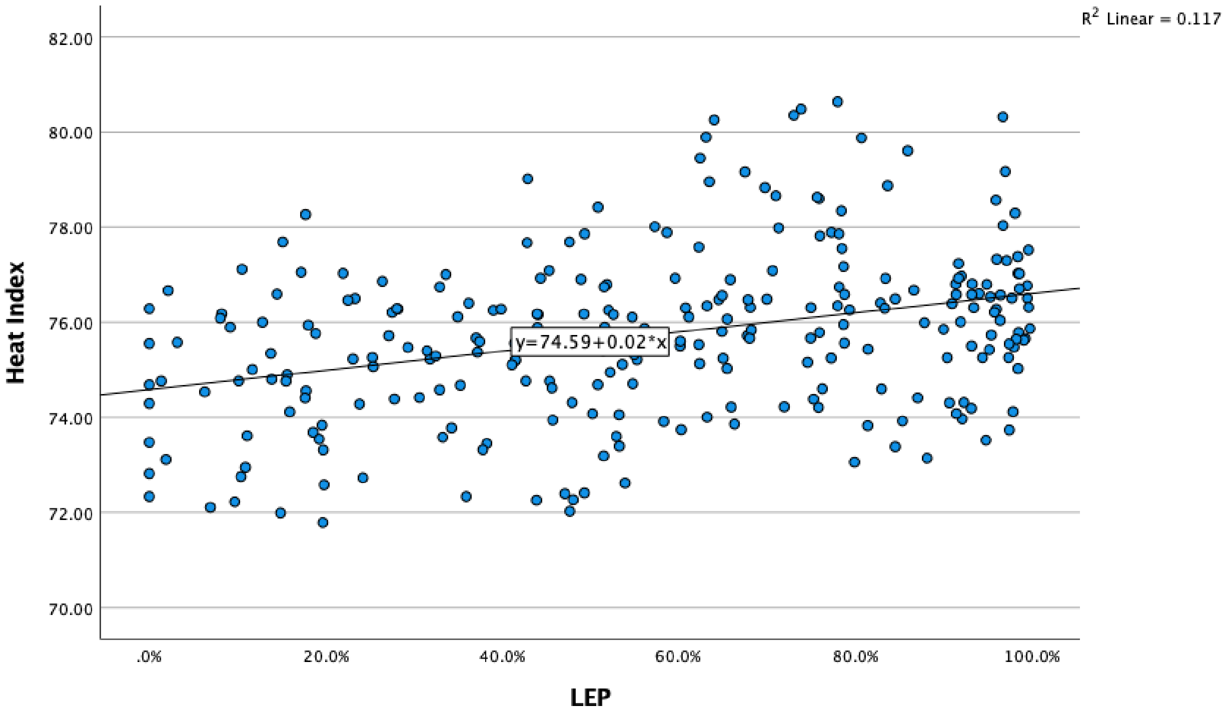


Figure 6.34: San Diego, LEP & HI.

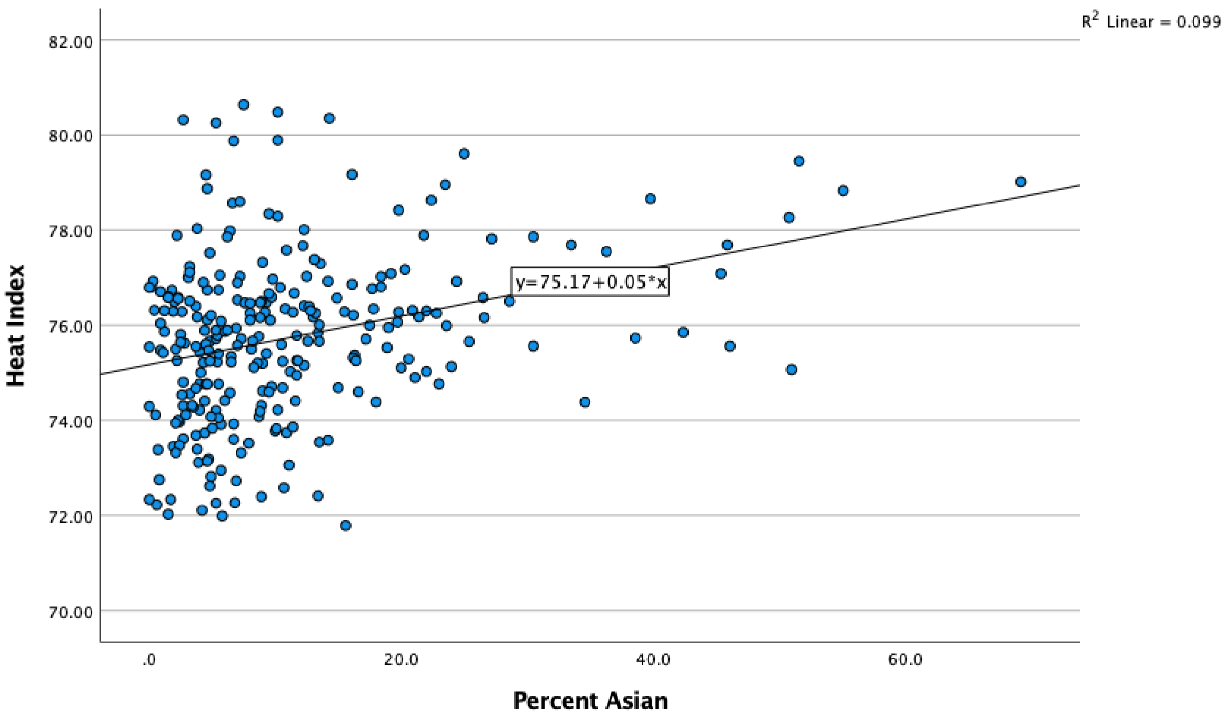


Figure 6.35: San Diego, Asian & HI.

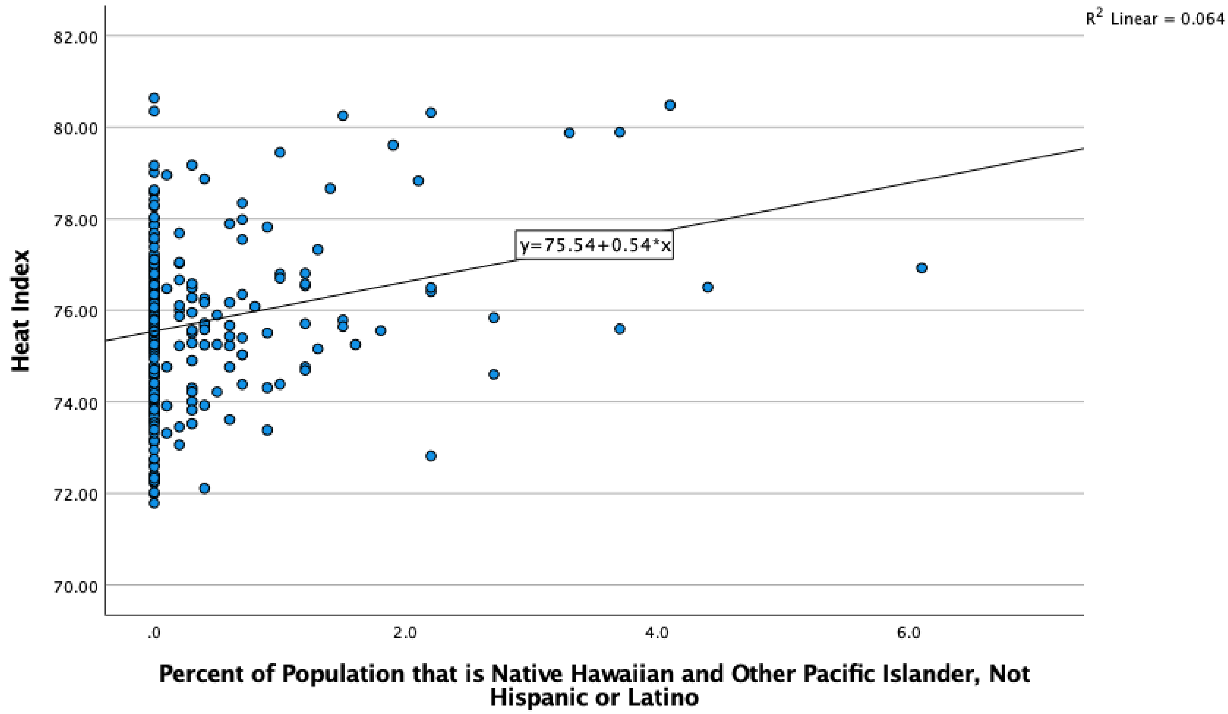


Figure 6.36: San Diego, Native Hawaiian and other Pacific Islander & HI.

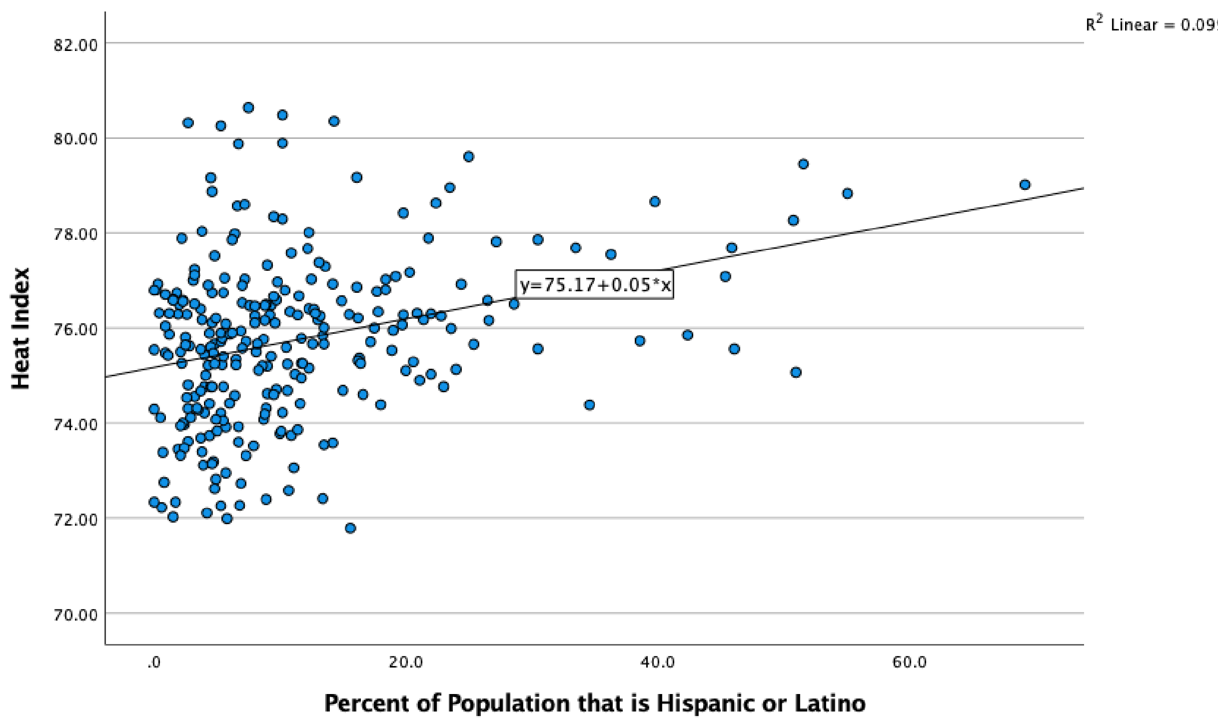


Figure 6.37: San Diego, Hispanic & HI.

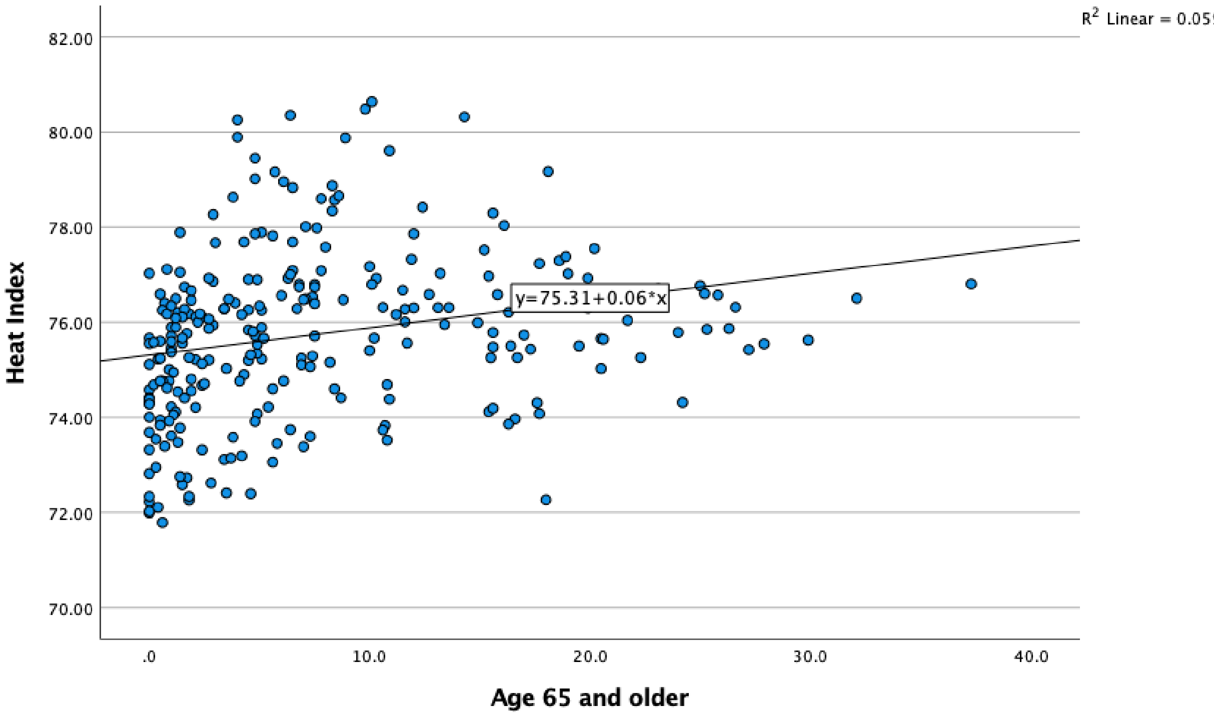


Figure 6.38: San Diego, Age 65 and older & HI.

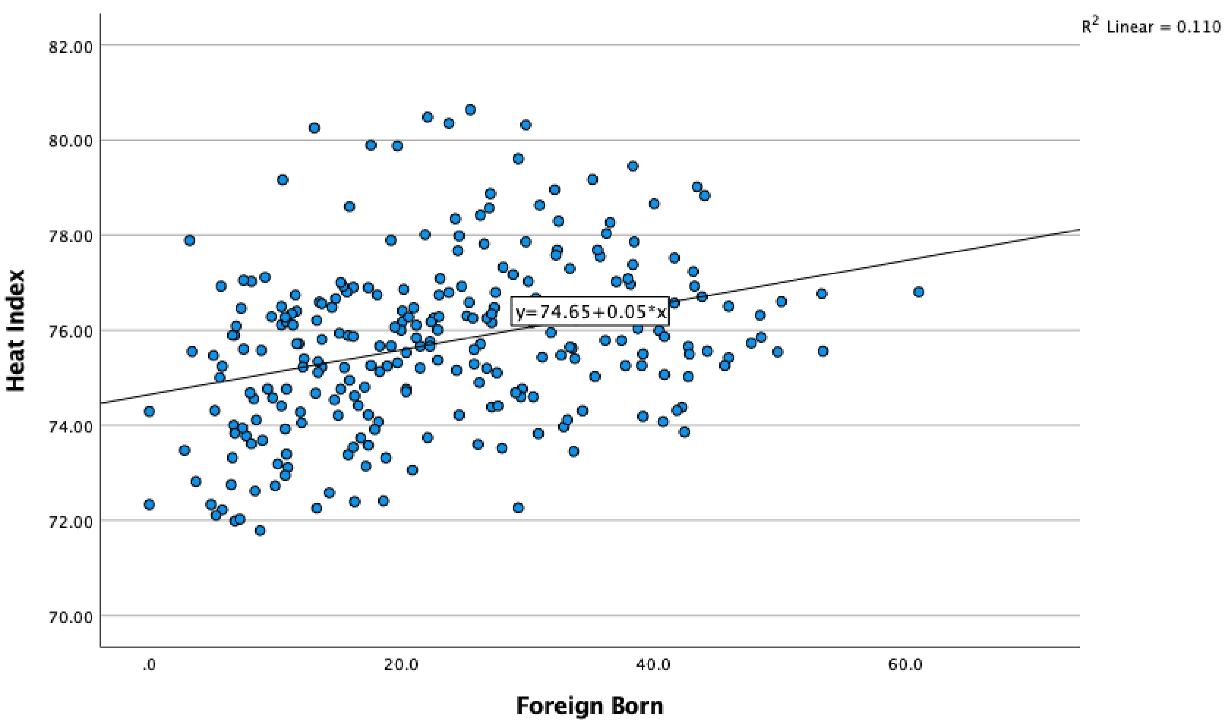


Figure 6.39: San Diego, Foreign-born & HI.

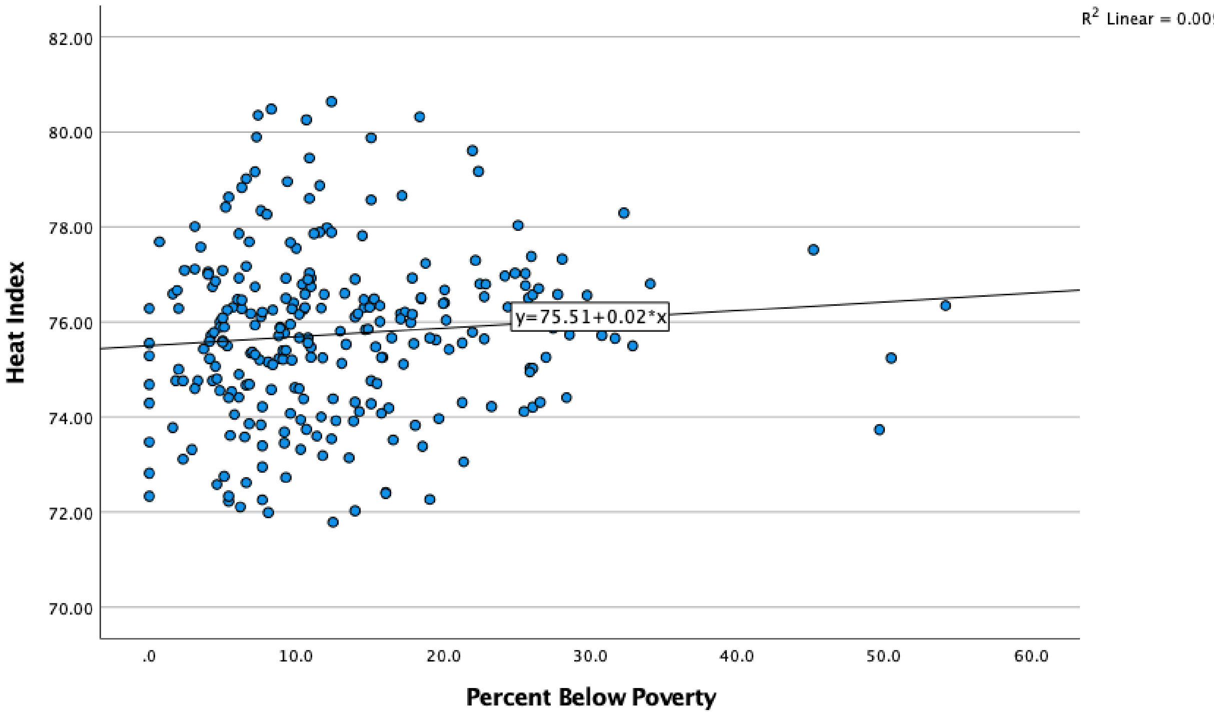


Figure 6.40: San Diego, Below Poverty & HI.

For the San Diego study a bivariate least square analysis was also performed with the heat index and CDC SVI and four components; Table 6.4 displays the results. San Diego had distinct results as only four variables showed significant results. First, the CDC SVI proved to be significant (sig <.05) with a moderate positive relationship. For every one-unit increase in SVI there is a coefficient increase of .020 in heat. Theme 1 also proved to be significant (sig <.05) with a moderate positive relationship. For every one unit increase in theme 1, there is .014 coefficient increase in heat. Theme proved to be significant (<.05) with a strong positive relationship (p= .515). Theme 3 was the only component that did not display significant results (sig .529). Lastly, theme 4 proved to be significant (sig <.05) with a moderate positive relationship. For every one-unit increase in theme 4, there is a .018 coefficient increase in heat.

Table 6.6: Bivariate Least Square Analysis.

Bivariate Least Square Regression for San Diego, CA				
	Coefficient	Sig	Pearson Correlation	95% CI
Theme 1: Socioeconomic Status & Heat Index	.014	<.001	.258	.008-.021
Theme 2: Household Composition and Disability & Heat Index	.048	<.001	.515	.038-.058
Theme 3: Minority Status and Language & Heat Index	.003	.529	.039	-.005-.010
Theme 4: Housing Type and Transportation & Heat Index	.018	<.001	.299	.011-.025
Overall CDC SVI & Heat Index	.020	<.001	.268	.011-.028

6.3 Spatial Autocorrelation

To identify whether there is a presence of UHI (heat clustering) in both San Diego and El Paso, a series of spatial autocorrelation tests were performed. For this part of the analysis, ArcGIS pro was used to perform the spatial clustering tests. The goal was to perform the same process for both cities and identify whether there was a presence of heat clustering tracts. The Local Moran's I tool was used to identify heat clustering values. Given that there are different ways to cluster values the inverse distance option was used as this gives a higher weight to features closer together. All other options were performed, and maps are included in the appendix. All maps displayed similar hot census tracts. Figure 6.42 displays the results for El Paso with some clustering in east and south-central. For San Diego the same process was performed, the inverse distance map was also used. Figure 6.41 shows displays the final map that identifies the spatial clustering of UHIs in San Diego. As shown, heat clustering values are concentrated in southern San Diego. Hot clusters are in medium red and identified as high-high clusters on the legend for both figures 6.41 and 6.42.

The focus of this study is not to concentrate on cool islands. Non-hot census tracts are shaded in blue and dark red. High-low outliers have contiguity with hot census tracts and low-high outliers have contiguity with cool census tracts. The local Moran's I tool was able to identify hotspots therefore the rest of the census tracts will be identified as non-hot census tracts. To obtain data that separates hot census tracts and non-hot census tracts a query was built to separate values. This new data set was used for the local analysis.

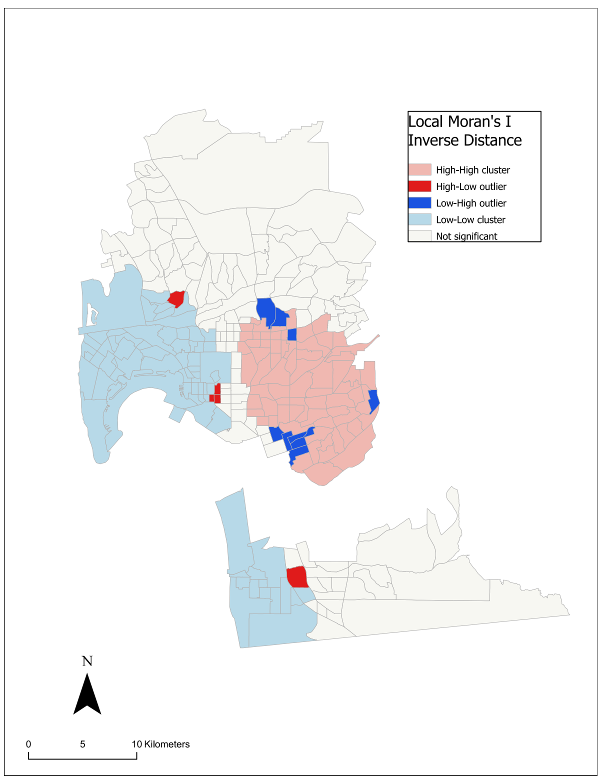


Figure 6.41: Local Moran's I analysis of San Diego, CA.

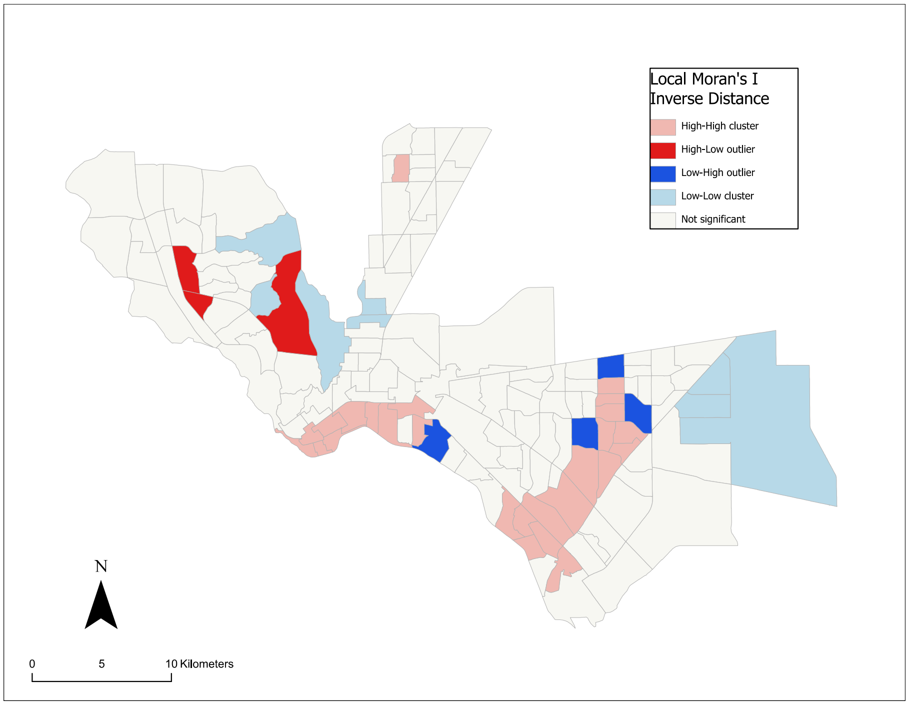


Figure 6.42: Local Moran's I analysis of El Paso, TX.

6.4 Local T-Test Analysis

To analyze vulnerability locally, a t-test analysis was used to analyze the mean difference in vulnerability between hot and non-hot census tracts. First, a local analysis of SVI and the four components was conducted. Selected variables were also locally analyzed to find specific socio-characteristics that may be vulnerable at the local scale. SPSS statistics was used to perform the local t-test analysis. When performing a t-test analysis, SPSS statistics automatically produces results depending on the data, and in this analysis, the software assumed my data was "equal variance assumed".

Table 6.5 to 6.16 shows the results of the t-test analysis of SVI, SVI themes, and selected variables for San Diego. Overall, results for SVI and SVI themes indicated that hot spots have a higher degree of vulnerability compared to non-hot census tracts. The CDC SVI (Table 6.5) indicates that social vulnerability has a higher mean in hot-census tracts and a significant difference in the mean (sig <.05). Additionally, themes 1 to 4 also had a higher mean in hot census tracts (Table 6.6 to 6.9). The SVI four themes also indicated there is a significant difference in the mean (sig <.05).

Table 6.7: San Diego T-test Analysis for SVI.

SVI			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	34.22	48.04	
Std. Deviation	24.66	17.42	
Sig. Two-Sided p			<.001
F			9.83
df			255
Mean Difference			13.82
Std. Error Difference			3.20
95% CI of the Difference Lower			7.51
95% CI of the Difference Upper			20.13

Table 6.8: San Diego T-test Analysis for Theme 1.

Theme 1: Socioeconomic			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	36.68	61.41	
Std. Deviation	31.51	26.11	
Sig. Two-Sided p			<.001
F			8.42
df			262
Mean Difference			24.72
Std. Error Difference			4.21
95% CI of the Difference Lower			16.43
95% CI of the Difference Upper			33.01

Theme 6.9: San Diego T-test Analysis for Theme 2.

Theme 2: Household Composition & Disability			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	65.98	86.30	
Std. Deviation	18.99	8.35	
Sig. Two-Sided p			<.001
F			40.53
df			262

Mean Difference			20.32
Std. Error Difference			2.35
95% CI of the Difference Lower			15.70
95% CI of the Difference Upper			24.95

Table 6.10: San Diego T-test Analysis Theme 3.

Theme 3: Minority Status & Language			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	56.54	65.03	
Std. Deviation	30.22	22.80	
Sig. Two-Sided p			.033
F			9.23
df			262
Mean Difference			8.48
Std. Error Difference			3.97
95% CI of the Difference Lower			0.66
95% CI of the Difference Upper			16.29

Table 6.11: San Diego T-test Analysis Theme 4.

Theme 4: Housing Type & Transportation			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	49.46	76.73	
Std. Deviation	30.93	18.83	
Sig. Two-Sided p			<.001
F			6.855
df			255
Mean Difference			-23.50
Std. Error Difference			3.94
95% CI of the Difference Lower			19.52
95% CI of the Difference Upper			35.03

The local t-test analysis was also conducted on selected variables (6.10 to 6.16). A local analysis of selected variables was conducted to identify specific socio-characteristics of hot cluster census tracts. Conducting a local analysis of the CDC SVI and four components is relevant in identifying overall vulnerability inside UHIs. Breaking down the variables into single variables is beneficial in identifying specific vulnerable groups to UHIs.

Table 6.10 shows results for LEP which had a significantly higher mean in hot census tracts compared to non-hot census tracts than the rest of the selected variables (Tables 6.11 to 6.16). The selected variable LEP indicated a significant difference in the mean (sig<.05). All other selected variables indicated a higher mean in the hot census tracts compared to non-hot census tracts (6.11 to 6.16). Selected variables in Tables 6.11 to 6.16 also indicated a significant difference in the mean (sig <.05).

Table 6.12: San Diego T-test Analysis LEP.

LEP			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	50.04	77.53	
Std. Deviation	29.67	19.27	
Sig. Two-Sided p			<.001
F			22.39
df			262
Mean Difference			27.49
Std. Error Difference			3.81
95% CI of the Difference Lower			19.99
95% CI of the Difference Upper			34.99

Table 6.13: San Diego T-test Analysis Asian.

Percent Asian			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	9.43	15.94	
Std. Deviation	9.44	14.22	
Sig. Two-Sided p			<.001
F			19.97
df			262
Mean Difference			6.51
Std. Error Difference			1.46
95% CI of the Difference Lower			3.63
95% CI of the Difference Upper			9.38

Table 6.14: San Diego T-test Analysis Native Hawaiian & Other Pacific Islander.

Percent Native Hawaiian & Other Pacific Islander			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	.244	.707	
Std. Deviation	.534	1.27	
Sig. Two-Sided p			<.001
F			48.26
df			262
Mean Difference			.46
Std. Error Difference			.11
95% CI of the Difference Lower			.24
95% CI of the Difference Upper			.68

Table 6.15: San Diego T-test Analysis Hispanic.

Percent Hispanic			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	9.44	15.94	
Std. Deviation	8.75	14.22	
Sig. Two-Sided p			<.001
F			19.97
df			262
Mean Difference			6.51
Std. Error Difference			1.46
95% CI of the Difference Lower			3.63
95% CI of the Difference Upper			9.38

Table 6.16: San Diego T-test Analysis Age 65 and older.

Age 65 and older			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	6.14	11.32	
Std. Deviation	7.05	7.33	
Sig. Two-Sided p			<.001
F			.107
df			262
Mean Difference			5.18
Std. Error Difference			.99
95% CI of the Difference Lower			3.22
95% CI of the Difference Upper			7.13

Table 6.17: San Diego T-test Analysis Below Poverty.

Percent Below Poverty			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	11.84	15.63	
Std. Deviation	8.78	9.15	
Sig. Two-Sided p			.002
F			2.16
df			262
Mean Difference			3.79
Std. Error Difference			1.24
95% CI of the Difference Lower			1.35
95% CI of the Difference Upper			6.22

Table 6.18: San Diego T-test Analysis Foreign Born.

Foreign Born			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	20.92	29.81	
Std. Deviation	12.37	10.03	
Sig. Two-Sided p			<.001
F			6.42
df			262
Mean Difference			8.89
Std. Error Difference			1.64
95% CI of the Difference Lower			5.65
95% CI of the Difference Upper			12.13

Additionally, a local analysis was performed for El Paso. First, a t-test analysis was performed on the CDC SVI total and four components followed by selected variables. Tables 6.17 to 6.21 show results for the t-test analysis of SVI and four components. Overall, the CDC SVI (Table 6.17) indicated social vulnerability in hot census tracts. Hot census tracts have a higher mean compared to non-hot census tracts with significant results. All four themes also indicated higher means in hot census tracts with significant results.

Table 6.19: El Paso T-test Analysis for SVI.

SVI			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	65.07	87.73	
Std. Deviation	25.87	19.86	
Sig. Two-Sided p			<.001
F			6.18
df			142
Mean Difference			18.67
Std. Error Difference			5.40
95% CI of the Difference Lower			7.99
95% CI of the Difference Upper			29.36

Table 6.20: El Paso T-test Analysis Theme 1.

Theme 1: Socioeconomic			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	63.83	79.73	
Std. Deviation	24.54	20.72	
Sig. Two-Sided p			.003
F			1.96
df			142
Mean Difference			15.90
Std. Error Difference			5.18
95% CI of the Difference Lower			5.65
95% CI of the Difference Upper			26.14

Table 6.21: El Paso T-test Analysis Theme 2.

Theme 2: Household Composition & Disability			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	67.76	81.89	
Std. Deviation	25.47	22.46	
Sig. Two-Sided p			.01
F			1.99
df			142
Mean Difference			14.13
Std. Error Difference			5.41
95% CI of the Difference Lower			3.43
95% CI of the Difference Upper			24.82

Table 6.22: El Paso T-test Analysis Theme 3.

Theme 3: Minority Status & Language			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	78.44	90.25	
Std. Deviation	15.06	6.32	
Sig. Two-Sided p			<.001
F			6.91
df			142
Mean Difference			11.81
Std. Error Difference			3.02
95% CI of the Difference Lower			5.85
95% CI of the Difference Upper			17.78

Table 6.23: El Paso T-test Analysis Theme 4

Theme 4: Housing Type & Transportation			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	50.81	70.05	
Std. Deviation	29.06	26.46	
Sig. Two-Sided p			.002
F			.682
df			142
Mean Difference			19.24
Std. Error Difference			6.20
95% CI of the Difference Lower			6.98
95% CI of the Difference Upper			31.49

The local t-test analysis was also on selected variables (Table 6.22 to 6.28). The same as in San Diego, selected variables were also analyzed in El Paso to identify the socio-characteristics of hot cluster census tracts.

Table 6.25 shows results for Hispanic which had a significantly higher mean in hot census tracts compared to non-hot census tracts than the rest of the selected variables. Additionally, all other variables indicated a higher mean in the hot census tracts compared to non-hot census tracts except for percent Asian and age over 65 (Table 6.23 and 6.26). Additionally, these two variables also did not have significant results.

Table 6.24: El Paso T-test Analysis LEP.

LEP			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	12.30	22.87	
Std. Deviation	7.83	14.04	
Sig. Two-Sided p			<.001
F			21.37
df			142
Mean Difference			10.57
Std. Error Difference			2.00
95% CI of the Difference Lower			6.62
95% CI of the Difference Upper			14.53

Table 6.25: El Paso T-test Analysis Asian.

Percent Asian			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	1.26	.550	
Std. Deviation	2.04	.924	
Sig. Two-Sided p			.085
F			-3.53
df			142
Mean Difference			-.714
Std. Error Difference			.411
95% CI of the Difference Lower			-1.53
95% CI of the Difference Upper			.0987

Table 6.26: El Paso T-test Analysis Native Hawaiian & Other Pacific Islander.

Percent Native Hawaiian & Other Pacific Islander			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	.105	.542	
Std. Deviation	.529	1.62	
Sig. Two-Sided p			.017
F			19.33
df			142
Mean Difference			.44
Std. Error Difference			.18
95% CI of the Difference Lower			.08
95% CI of the Difference Upper			.79

Table 6.27: El Paso T-test Analysis Hispanic.

Percent Hispanic			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	79.70	91.26	
Std. Deviation	17.72	5.60	
Sig. Two-Sided p			.001
F			10.37
df			142
Mean Difference			11.56
Std. Error Difference			3.52
95% CI of the Difference Lower			4.60
95% CI of the Difference Upper			18.53

Table 6.28: El Paso T-test Analysis Age 65 and older.

Age 65 and older			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	13.31	15.44	
Std. Deviation	6.77	5.15	
Sig. Two-Sided p			.134
F			2.11
df			142
Mean Difference			2.13
Std. Error Difference			1.41
95% CI of the Difference Lower			-.66
95% CI of the Difference Upper			4.92

Table 6.29: El Paso T-test Analysis Below Poverty.

Percent Below Poverty			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	18.24	32.93	
Std. Deviation	11.69	17.81	
Sig. Two-Sided p			<.001
F			13.39
df			142
Mean Difference			14.68
Std. Error Difference			2.81
95% CI of the Difference Lower			9.13
95% CI of the Difference Upper			20.24

Table 6.30: El Paso T-test Analysis Foreign Born.

Foreign Born			
	Non-hot spot	Hot spot	Equal Variance Assumed
Mean	22.85	30.33	
Std. Deviation	7.83	10.76	
Sig. Two-Sided p			<.001
F			8.65
df			142
Mean Difference			7.49
Std. Error Difference			1.83
95% CI of the Difference Lower			3.88
95% CI of the Difference Upper			11.10

Chapter 7: Limitations

The current study faces some limitations in the data and methodology. The UHI maps for San Diego and El Paso are not measured by census tracts. A mean calculation using zonal statics per census tract was performed to develop an UHI map per census tract. Final heat maps displayed larger pixels that exceed the census tract boundaries. Additionally, heat maps are also limited to city boundaries, due to the methodology of the original UHI measurement campaign. This means that outlying poorer or richer areas are not considered. Furthermore, the UHI map of El Paso has missing values in the downtown area. These data sets were developed in a different map that was not incorporated into this study. Interpolation methods were able to obtain values for these census tracts but can be a weaker form of data. Lastly, during the NOAA/NIHHIS UHI campaign all data was measured in one day. The UHI data does not display a mean average temperature during the summer or multi-day hot spells, although it does display data for a day with high temperatures.

Chapter 8: Discussion

Studies have indicated that populations categorized as most vulnerable tend to live in hotter environments (Dialesandro et al., 2021, Hoffman et al., 2020, Li et al., 2022). Mitchel and Chakraborty (2018) have termed this as “thermal inequity” in which populations who are vulnerable face additional heat burdens. This thesis sought to contribute to the growing literature that investigates thermal inequity at the global and local scale. By identifying vulnerable groups to high temperatures, results can be incorporated into NWS operations to better communicate heat messages to targeted groups. Additionally, NWS partners can help identify vulnerable groups to heat to implement more resources that can help prevent morbidity and mortality.

Results indicated that at the global scale, some groups tend to be most vulnerable than others. Both El Paso and San Diego displayed some degree of vulnerability in which selected groups proved to be significant while others did not. The first research question focused on identifying the physical (heat) and social characteristics throughout both border cities. First, for El Paso, the bivariate comparison indicated that certain socio-demographics are vulnerable at the global scale. For El Paso, LEP, Hispanics, populations below the poverty level, and foreign-born all proved to be significant. All the populations that proved to be significant are all unique socio-characteristics of the borderlands. Additionally, for El Paso, the bivariate analysis for Asian, Native Hawaiian and other Pacific Islander populations, and populations age 65 and over did not prove to be significant. While minority populations have been identified as vulnerable to the UHI effect, Asian and Native Hawaiian and other Pacific Islander populations in El Paso did not display vulnerability. In El Paso, these are small populations. Populations age 65 and over were included in the study given their inability to regulate their body temperature when exposed to high temperatures for long periods of time. Populations age 65 and over did not prove to be significant, yet this does not indicate elderly populations are not at risk to high temperatures in El Paso. For El Paso, bivariate least square regression was performed on the CDC SVI and the four components that make up the SVI. The SVI, socioeconomic status. Household composition and disability, minority status and language, and housing type and transportation all proved to be significant. These results also indicated that for every one unit of the SVI, there was an increase of .005 coefficient. The coefficient ranged from .005 to .012 for the four themes.

Results for San Diego at the global scale indicated that all variables except for populations below the poverty level were significant. Groups that proved to be significant are also unique characteristics of the borderlands except for populations age 65 and over. The selected variable populations below poverty level did not prove to be significant, but this does not mean that some people in these populations are not at risk of high temperatures. Additionally, in the bivariate least square analysis of San Diego of the CDC SVI, socioeconomic status, household composition and disability, and housing type and transportation all proved to be significant. Theme three which consists of minority status and language did not prove to be significant for this city. For every one unit of SVI, there is a .020 increase in coefficient. The coefficient ranged from .003 to .048 for the rest of the variables.

All these results indicate that at the global scale, there are some degrees of vulnerability for specific socio-demographics for El Paso and San Diego. A degree of vulnerability was identified for both border cities. Even though not all variables showed significance with this we can conclude that some populations are at higher risk than others. While this is a global analysis that does not necessarily identify geographic sites of high vulnerability, results at the global scale indicate the need for a local analysis for targeted heat messaging and implementation of resources. There are some limitations of only including a global analysis. NWS and partners main concern was identifying high heat and vulnerable sites to implement adequate resources and information to prevent morbidity and mortality.

The second research question focused on identifying the correlation between selected variables and heat data to identify global thermal inequities. For El Paso, LEP, Hispanics, populations below the poverty level, and foreign-born all showed moderate positive correlations. Asian populations showed a negative correlation and Native Hawaiian and other Pacific Islander population and populations age 65 and older showed a weak positive linear relationship. El Paso has a large percentage of Hispanic population and people living poverty. With moderate positive correlations this indicates the need for more resources in these communities. Additionally, identifying that populations with LEP helps inform WFOs and partners of the need for more diverse heat messaging. Although Asian populations, Native Hawaiian and other Pacific Islander population and populations age 65 and older did not show a strong correlation this does not indicate that some of these populations are not of high risk in El Paso.

For San Diego all variables (LEP, foreign-born, Hispanic, Age 65 and older, Asian, Native Hawaiian and other Pacific Islander population) except for populations below poverty level showed a moderate positive linear relationship. Populations below poverty and heat showed a weak positive linear relationship. These findings point to a global thermal inequity affecting specific vulnerable groups. While El Paso and San Diego display thermal inequities affecting specific vulnerable groups, most groups being affected overlap in both cities. This points that LEP, Hispanics, and foreign-born populations are vulnerable in these two border cities which are unique characteristics of borderland cities. Even though there were differences of global thermal inequities in both cities, results indicate that vulnerable groups that overlapped are of high risk in the borderlands.

The third research question aims to identify if there is a presence of heat clustering throughout El Paso and San Diego which may indicate the presence of UHIs. Using ArcGIS Pro tools, two tests were conducted to ensure the heat data displayed patterns of clustering. Both cities indicated the presence of heat clustering.

For El Paso there was a presence of heat clustering in east and south central census tracts. There was also a presence of spatial clustering in San Diego. In order to identify whether there is a presence of thermal inequity, a local analysis was performed to identify specific social characteristics of hot census tracts. Being able to identify heat clusters is essential in identifying high heat risk areas. Heat clustering in both cities indicates that there is a presence of UHIs, a further local analysis can indicate specific social characteristics of these heat islands and identify whether thermal inequity is prevalent.

The last research question focused on performing a local analysis of hot and non-hot census tracts in in both cities and identify vulnerable groups. The goal was to use the results of this study to improve the targeting of heat risk communication for WFOs operations. First El Paso had the majority of variables concentrated in hot census tracts compared to non-hot census tracts. Results for the Asian population did not indicated a higher mean in hot census tracts and the elderly population did not have significant results.

For San Diego, results indicated that hot census tracts are more vulnerable than non-hot census tracts. All socio-demographic groups and the CDC SVI and four components have a significantly higher mean in hot census tracts. While some variables had higher means than others, results indicate that there is a need to identify areas where there is higher vulnerability to better communicate heat messages. For the San Diego WFO, targeting community organizations and institutions in the identified heat island may be a helpful strategy. The t-test analysis also reveals that performing a local analysis on vulnerable groups can be beneficial for WFOs and partners. Even though some variables did not show significance at the global scale, being able to identify specific socio characteristics of hot census tracts is important as all variables proved to be vulnerable to the UHI. With these findings WFOs can move towards targeted heat messaging for minority populations with potential language barriers. Additionally, WFOs can include the physiological implications of populations age 65 and over who are based in hotter environments. Lastly, with these finding WFOs and partners can work together to implement more resources in these communities who may have financial barriers to mitigate heat effects.

The study indicated that performing both a global and local analysis in the borderlands can be significant in identifying vulnerable groups. For the global analysis, some groups did not display significant results yet specific characteristics of the borderlands such as minority populations, LEP populations, and foreign-born did display significant results. This shows that distinctive socio-demographics of the borderlands may require targeted messaging. Additionally, by performing a local analysis of UHIs, the study was able to uncover that all variables used were identified as vulnerable groups.

Chapter 9: Conclusion

This thesis aims to investigate the thermal inequity phenomenon in two border cities. The goal was to identify locations of high vulnerability areas. This study started through a summer internship with the NWS that conducted interviews with WFOs about their knowledge of vulnerable populations to heat and how to better communicate heat messages to specific groups. Much of the NOAA/NIHHIS UHI data is in the early stages of being incorporated into studies. This study incorporates the NOAA/NIHHIS UHI data to identify specific areas of high socio-vulnerability and heat. While there are studies that have investigated thermal inequities in the U.S., this study is distinct as it investigates two border cities at the global and local scale.

Previous research has shown that certain populations are at higher risk than others to natural hazards, so this study incorporates some of those populations while also identifying socially vulnerable populations in the borderlands. The aim was to identify areas of high vulnerability. Since both border cities displayed heat clusters, WFOs can use the results to further refine heat communication in these areas. Li & Howe (2023), found personalizing heat messages can create the perception that the message is relevant to the reader. Identifying groups and communicating that they may be at risk to high temperatures and personalizing heat messages to a targeted audience is something that WFOs and partners plan on incorporating into their operations. Also, since heat islands are geographically located, this analysis may help with risk reduction campaigns that are place-based, such as working with key local community organizations and institutions.

This study was able to identify vulnerable groups to heat at the global scale (in this case, whole cities) and identify specific social characteristics of high temperatures. For this thesis, only two border cities were investigated. The NOAA/NIHHIS UHI mapping campaign has mapped more than 70 cities across the U.S. This study only covers a minimal portion of UHI cities throughout the U.S. Future studies can investigate more cities and work with local WFOs to incorporate results into their operations.

Additionally, this study identified social groups that are distinctive to border cities. Cities throughout the U.S have specific socially vulnerable groups that may require targeted heat messaging. Future studies can investigate the UHI phenomenon at the global and local scale with the distinctive socially disadvantaged people residing in these cities. While this study used the data provided by the NWS, future studies can acquire more refined heat data that may display a higher degree of vulnerability. Additionally, this study was limited to working inside city limits. Future studies can investigate beyond city limits by acquiring heat data for the rest of the urban area.

In conclusion, thermal inequity is a prevalent issue throughout the U.S. As this thesis has shown, there is a need to address thermal inequities and work with agencies that can help close this climate gap. This thesis sought to investigate this complex issue affecting those most vulnerable. Approaching thermal inequities requires a multifaceted approach to prevent morbidity and mortality. This study was first produced in collaboration with the NWS, yet collaborative work can go beyond heat messaging. The study introduces ways in which collaborative research can help address thermal inequities.

Chapter 10: References

Abrahamson, V., Wolf, J., Lorenzoni, I., Fenn, B., Kovats, S., Wilkinson, P., ... & Raine, R. (2009). Perceptions of heatwave risks to health: interview-based study of older people in London and Norwich, UK. Journal of Public Health, 31(1), 119-126.

Almond, D., & Currie, J. (2011). Killing me softly: The fetal origins hypothesis. *Journal of economic perspectives*, *25*(3), 153-72.

Akompab, D. A., Bi, P., Williams, S., Grant, J., Walker, I. A., & Augoustinos, M. (2013). Heat waves and climate change: Applying the health belief model to identify predictors of risk perception and adaptive behaviors in Adelaide, Australia. *International journal of environmental research and public health*, 10(6), 2164-2184.

Barreca, A., & Schaller, J. (2020). The impact of high ambient temperatures on delivery timing and gestational lengths. *Nature Climate Change*, *10*(1), 77-82.

Bekkar, B., Pacheco, S., Basu, R., & DeNicola, N. (2020). Association of air pollution and heat exposure with preterm birth, low birth weight, and stillbirth in the US: a systematic review. *JAMA network open*, 3(6), e208243-e208243.

Blendon, R. J., Koonin, L. M., Benson, J. M., Cetron, M. S., Pollard, W. E., Mitchell, E. W., ... & Herrmann, M. J. (2008). Public response to community mitigation measures for pandemic influenza. Emerging infectious diseases, 14(5), 778.

Bouchama, A., Dehbi, M., Mohamed, G., Matthies, F., Shoukri, M., & Menne, B. (2007). Prognostic factors in heat wave–related deaths: a meta-analysis. *Archives of internal medicine*, 167(20), 2170-2176.

Burris, B., (2020). A legacy of discrimination: redlining in San Diego. Regional EDC. Retrieved January 30, 2023, from https://www.sandiegobusiness.org/blog/a-legacy-of-discrimination-redlining-in-san-diego/

Carlson, A. E. (2008). Heat waves, global warming, and mitigation. *UCLA J. Envtl. L. & Pol'y*, 26, 169.

Centers for Disease Control and Prevention. (2021, August 30). *CDC/ATSDR Svi Fact sheet*. Centers for Disease Control and Prevention. Retrieved May 3, 2022, from https://www.atsdr.cdc.gov/placeandhealth/svi/fact_sheet/fact_sheet.html

City of El Paso, Texas Comprehensive Plan. (2012, March 6). Retrieved March 29, 2023, from https://www.elpasotexas.gov/assets/Documents/CoEP/Planning-and-Inspections/Applications/Zoning-Applications/PZDS_Fillable_2018-v2.pdf

Drehobl, A., & Ross, L. (2016). Lifting the high energy burden in America’s largest cities: how energy efficiency can improve low income and underserved communities. *American Council for an Energy Efficient Economy*, 56.

Dialesandro, J., Brazil, N., Wheeler, S., & Abunnasr, Y. (2021). Dimensions of thermal inequity: neighborhood social demographics and urban heat in the Southwestern US. *International journal of environmental research and public health*, *18*(3), 941.

El Paso. (2020). Improvement Rollout Strategic Plan Goal: Enhance and Sustain El Paso's Infrastructure Network [PDF file]. Retreived March 29, 2023, from https://www.elpasotexas.gov/assets/Documents/CoEP/Capital-Improvement/Capital-Plans-Public-Safety-Rollout.pdf

Environmental Protection Agency. (2022). (n.d.). *Climate Change Indicators: Heat Waves*. EPA. Retrieved May 3, 2022, from https://www.epa.gov/climate-indicators/climate-change-indicators-heat-waves

Environmental Protection Agency. (2022). (n.d.). *Learn About Heat Islands*. EPA. Retrieved May 4, 2022, from https://www.epa.gov/heatislands/learn-about-heat-islands

Fahy, B., Brenneman, E., Chang, H., & Shandas, V. (2019). Spatial analysis of urban flooding and extreme heat hazard potential in Portland, OR. *International journal of disaster risk reduction*, *39*, 101117.

Frewer, L. (1999). Risk perception, social trust, and public participation in strategic decision making: Implications for emerging technologies. *Ambio*, 569-574.

Gamble, J. L., Schmeltz, M. T., Hurley, B., Hsieh, J., Jette, G., & Wagner, H. (2018). *Mapping the Vulnerability of Human Health to Extreme Heat in the United States*. Environmental Protection Agency, Office of Research and Development, National Center for Environmental Assessment.

Hansen, A., Bi, P., Nitschke, M., Pisaniello, D., Newbury, J., & Kitson, A. (2011). Perceptions of heat-susceptibility in older persons: Barriers to adaptation. *International journal of environmental research and public health*, *8*(12), 4714-4728.

Harlan, S. L., Brazel, A. J., Prashad, L., Stefanov, W. L., & Larsen, L. (2006). Neighborhood microclimates and vulnerability to heat stress. *Social science & medicine*, *63*(11), 2847-2863.

Hernández, D. (2016). Understanding 'energy insecurity' and why it matters to health. *Social science & medicine*, 167, 1-10.

Hernández, D., & Phillips, D. (2015). Benefit or burden? Perceptions of energy efficiency efforts among low-income housing residents in New York City. *Energy Research & Social Science*, 8, 52–59. https://doi.org/10.1016/j.erss.2015.04.010.

Heyman, J. (2007). Environmental Issues at the U.S-Mexico Border and the Unequal Territorialization of Value. In A. Hornberg, J.R McNeill, & J. Martinez-Alier (Eds.), Rethinking Environmental History (pp. 327-343). Rowman Altamira

Hoffman, J. S., Shandas, V., & Pendleton, N. (2020). The effects of historical housing policies on resident exposure to intra-urban heat: a study of 108 US urban areas. *Climate*, 8(1), 12.

Johnson, D. P., & Wilson, J. S. (2009). The socio-spatial dynamics of extreme urban heat events: The case of heat-related deaths in Philadelphia. Applied geography, 29(3), 419-434.

Karaye, I. M., & Horney, J. A. (2020). The impact of social vulnerability on COVID-19 in the US: an analysis of spatially varying relationships. *American journal of preventive medicine*, *59*(3), 317-325.

Klinenberg, E. (2015). Heat wave: A social autopsy of disaster in Chicago. University of Chicago press.

Kreps, G. L., & Sparks, L. (2008). Meeting the health literacy needs of immigrant populations. Patient education and counseling, 71(3), 328-332.

Lambrecht, K., Hatchett, B. J., VanderMolen, K., & Feldkircher, B. (2021). Identifying community values related to heat: recommendations for forecast and health risk communication. Geoscience Communication, 4(4), 517-525.

Leal Filho, W., Icaza, L. E., Neht, A., Klavins, M., & Morgan, E. A. (2018). Coping with the impacts of urban heat islands. A literature based study on understanding urban heat vulnerability and the need for resilience in cities in a global climate change context. *Journal of Cleaner Production*, *171*, 1140-1149.

Lee, W. V., & Shaman, J. (2017). Heat-coping strategies and bedroom thermal satisfaction in New York City. *Science of the total environment*, 574, 1217-1231.

Lehnert, E. A., Wilt, G., Flanagan, B., & Hallisey, E. (2020). Spatial exploration of the CDC's Social Vulnerability Index and heat-related health outcomes in Georgia. *International journal of disaster risk reduction*, *46*, 101517.

Lewis, J., Hernández, D., & Geronimus, A. T. (2019). Energy efficiency as energy justice: addressing racial inequities through investments in people and places. *Energy Efficiency*, 1-14.

Li, D., Newman, G. D., Wilson, B., Zhang, Y., & Brown, R. D. (2022). Modeling the relationships between historical redlining, urban heat, and heat-related emergency department visits: An examination of 11 Texas cities. Environment and Planning B: Urban Analytics and City Science, 49(3), 933-952.

Li, Y., & Howe, P. D. (2023). Universal or targeted approaches? an experiment about heat risk messaging. *Natural Hazards*, 1-18.

Madrigano, J., Lane, K., Petrovic, N., Ahmed, M., Blum, M., & Matte, T. (2018). Awareness, risk perception, and protective behaviors for extreme heat and climate change in New York City. *International journal of environmental research and public health*, 15(7), 1433.

Madrigano, J., Mittleman, M. A., Baccarelli, A., Goldberg, R., Melly, S., Von Klot, S., & Schwartz, J. (2013). Temperature, mycardial infarction, and mortality: effect modification by individual and area-level characteristics. Epidemiology (Cambridge, Mass.), 24(3), 439. Epidemiology;24(3):439–46. Study of characteristics of vulnerability to temperature-associated myocardial infarction and mortality in Worcester, Massachusetts, identifying area-level poverty as a potential characteristic of vulnerability to extreme heat in this population.

Mitchell, B. C., & Chakraborty, J. (2018). Thermal inequity: The relationship between urban structure and social disparities in an era of climate change. In Routledge handbook of climate justice (pp. 330-346). Routledge.

Morgan, M. G., Fischhoff, B., Bostrom, A., & Atman, C. J. (2002). Risk communication: A mental models approach. Cambridge University Press.

Moyer, J. M., & Raheem, A. A. (2020). Study of Past and Future Spatiotemporal Patterns and Impact on Electricity Consumption for Sustainable Planning: A Case Study of El Paso, Texas. Sustainability, 12(20), 8480.

National Weather Service. (n.d.). *San Diego climate*. National Weather Service. Retrieved April 18, 2023, from https://www.weather.gov/sgx/san-san

Nayak, S. G., Shrestha, S., Kinney, P. L., Ross, Z., Sheridan, S. C., Pantea, C. I., ... & Hwang, S. A. (2018). Development of a heat vulnerability index for New York State. *Public Health*, *161*, 127-137.

O'Connor, R. E., Bard, R. J., & Fisher, A. (1999). Risk perceptions, general environmental beliefs, and willingness to address climate change. *Risk analysis*, 19(3), 461-471.

Reames, T. G. (2016). Targeting energy justice: exploring spatial, racial/ethnic and socioeconomic disparities in urban residential heating energy efficiency. *Energy Policy*, 97, 549–558. https://doi.org/10.1016/j.enpol.2016.07.048

Reid, C. E., O'neill, M. S., Gronlund, C. J., Brines, S. J., Brown, D. G., Diez-Roux, A. V., & Schwartz, J. (2009). Mapping community determinants of heat vulnerability. Environmental health perspectives, 117(11), 1730-1736.

Renteria, A. C., Gibson, L. J. (2019). The U.s. And Mexico: Borderland Development And The National Economies. United Kingdom: Taylor & Francis.

Shandas, V., Voelkel, J., Williams, J., & Hoffman, J. (2019). Integrating satellite and ground measurements for predicting locations of extreme urban heat. Climate, 7(1), 5.

Sampson, N. R., Gronlund, C. J., Buxton, M. A., Catalano, L., White-Newsome, J. L., Conlon, K. C., ... & Parker, E. A. (2013). Staying cool in a changing climate: Reaching vulnerable populations during heat events. *Global Environmental Change*, *23*(2), 475-484.

Sampson, N. R., Gronlund, C. J., Buxton, M. A., Catalano, L., White-Newsome, J. L., Conlon, K. C., ... & Parker, E. A. (2013). Staying cool in a changing climate: Reaching vulnerable populations during heat events. *Global Environmental Change*, *23*(2), 475-484.

San Diego Association of Governments*: Final 2021 regional plan*. SANDAG. (2021). Retrieved March 28, 2023, from https://www.sandag.org/regional-plan/2021-regional-plan/final-2021-regional-plan

Sanchez, L., & Reames, T. G. (2019). Cooling Detroit: A socio-spatial analysis of equity in green roofs as an urban heat island mitigation strategy. Urban Forestry & Urban Greening, 44, 126331.

Sarfaty, M., Mitchell, M., Bloodhart, B., & Maibach, E. W. (2014). A survey of African American physicians on the health effects of climate change. *International journal of environmental research and public health*, 11(12), 12473-12485.

Sarfaty, M., Kreslake, J. M., Casale, T. B., & Maibach, E. W. (2016). Views of AAAAI members on climate change and health. *The Journal of Allergy and Clinical Immunology: In Practice*, *4*(2), 333-335.

Shandas, V., Voelkel, J., Williams, J., & Hoffman, J. (2019). Integrating satellite and ground measurements for predicting locations of extreme urban heat. *Climate*, *7*(1), 5.

Sheridan, S. C. (2007). A survey of public perception and response to heat warnings across four North American cities: an evaluation of municipal effectiveness. International journal of biometeorology, 52, 3-15.

Smoyer-Tomic, K. E., & Rainham, D. G. (2001). Beating the heat: development and evaluation of a Canadian hot weather health-response plan. *Environmental health perspectives*, 109(12), 1241-1248.

Uejio CK, Wilhelmi OV, Golden JS, Mills DM, Gulino SP, Samenow JP. Intra-urban societal vulnerability to extreme heat: the role of heat exposure and the built environment, socioecono-mics, and neighborhood stability. Health Place 2011; 17: 498507.

U.S. Bureau of Labor Statistics. (2022, May 3). U.S. Bureau of Labor Statistics.Retrieved May 4, 2022, from https://www.bls.gov/

United States Census Bureau. (2015). American Housing Survey. Retrieved from https://www.census.gov/programssurveys/ahs/data/interactive/ahstablecreator.html#?s_areas=a00000&s_year=n2015&s_tableName=Table5&s_byGroup1=a7&s_byGroup2=a1&s_filterGroup1=t1&s_filterGroup2=g1&s_show=S

U.S. Bureau of Labor Statistics. (2022, May 3). U.S. Bureau of Labor Statistics.Retrieved May 4, 2022, from https://www.bls.gov/

UTEP. (n.d.) One Water: *One water cluster*. (n.d.). Retrieved March 28, 2023, from https://www.utep.edu/onewater/our-region/geographic-focus.html

VanderMolen, K., Kimutis, N., & Hatchett, B. J. (2022). Recommendations for increasing the reach and effectiveness of heat risk education and warning messaging. *International Journal of Disaster Risk Reduction*, *82*, 103288.

Wald, A. (2019). Emergency Department Visits and Costs for Heat-Related Illness Due to Extreme Heat or Heat Waves in the United States: An Integrated Review. *Nursing Economic$*, *37*(1).

Wong, K. V., Paddon, A., & Jimenez, A. (2013). Review of world urban heat islands: Many linked to increased mortality. *Journal of Energy Resources Technology*, *135*(2).

World Health Organization (WHO). (2022). Heatwaves. https://www.who.int/health-topics/heatwaves#tab=tab_1.

Zahran, S., Peek, L., & Brody, S. D. (2008). Youth mortality by forces of nature. *Children Youth and Environments*, 18(1), 371-388.

Zhang, Y., Nitschke, M., & Bi, P. (2013). Risk factors for direct heat-related hospitalization during the 2009 Adelaide heatwave: a case crossover study. *Science of the total environment*, *442*, 1-5

Appendices

A. CDC SVI Theme 1 Component

Theme 1: Socioeconomic Variables from ACS				
Persons below poverty estimate, 2014-2018 ACS	Civilian (age 16+) unemployed estimate, 2014-2018 ACS	Persons (age 25+) with no high school diploma estimate, 2014- 2018 ACS	Per capita income estimate, 2014-2018 ACS	Unemployment Rate estimate
Percentage of persons with no high school diploma (age 25+) estimate	Percentile Percentage of persons below poverty estimate	Percentile Percentage of civilian (age 16+) unemployed estimate	Percentile per capita income estimate	Percentile Percentage of persons with no high school diploma (age 25+) estimate

B. CDC SVI Theme 2 Component

Theme 2: Household Composition and Disability Variables from ACS				
Persons aged 65 and older estimate, 2014- 2018 ACS	Persons aged 17 and younger estimate, 2014-2018 ACS	Civilian noninstitutionalized population with a disability estimate, 2014- 2018 ACS	Single parent household with children under 18 estimate, 2014-2018 ACS	Percentage of persons aged 65 and older estimate, 2014- 2018 ACS
Percentage of persons aged 17 and younger estimate, 2014-2018 ACS	Percentage of civilian noninstitutionalized population with a disability estimate, 2014-2018 ACS	Percentage of single parent households with children under 18 estimate, 2014- 2018 ACS	Percentile percentage of persons aged 65 and older estimate	Percentile percentage of civilian noninstitutionalized population with a disability estimate
Percentile percentage of civilian noninstitutionalized population with a disability estimate	Percentile percentage of single-parent households with children under 18 estimate	___________________	________________	________________

C. CDC SVI Theme 3 Component

Theme 3: Minority Status and Language Variables from ACS				
Minority (all persons except white, non-Hispanic) estimate, 2014-2018 ACS	Persons (age 5+) who speak English "less than well" estimate, 2014-2018 ACS	Persons (age 5+) who speak English "less than well" estimate MOE, 2014-2018 ACS	Percentage minority (all persons except white, non-Hispanic) estimate, 2014-2018 ACS	Percentage of persons (age 5+) who speak English "less than well" estimate, 2014-2018 ACS
Percentile percentage minority (all persons except white, non-Hispanic) estimate	Percentile percentage of persons (age 5+) who speak English "less than well" estimate	________________	________________	________________

D. CDC SVI Theme 4 Component

Theme 4: Housing Type and Transportation Variables from ACS				
Housing in structures with 10 or more units	At household level (occupied housing	At household level (occupied housing	Households with no vehicle available	Persons in institutionalized group

estimate, 2014- 2018 ACS	units), more people than rooms estimate, 2014- 2018 ACS	units), more people than rooms estimate, 2014- 2018 ACS	estimate, 2014-2018 ACS	quarters estimate, 2014-2018 ACS
Percentage of housing in structures with 10 or more units estimate	Percentage of mobile homes estimate	Percentage of occupied housing units with more people than rooms estimate	Percentage of households with no vehicle available estimate	Percentage of persons in institutionalized group quarters estimate, 2014- 2018 ACS
Percentile percentage housing in structures with 10 or more units estimate	Percentile percentage mobile homes estimate	Percentile percentage households with more people than rooms estimate	Percentile percentage households with no vehicle available estimate	Percentile percentage of persons in institutionalized group quarters estimate

E. El Paso Variables by Census Tracts (Heat Index, theme 1 to 2)

Census Tract Number	Heat Index	Socioeconomic	Household Composition & Disability
48141000800	103.93	90.5%	85.3%
48141004307	104.46	66.8%	71.4%
48141004309	104.71	40.4%	82.3%
48141004310	104.36	70.6%	86.7%
48141004311	104.46	49.5%	72.9%
48141010303	104.57	42.7%	75.1%
48141010312	104.59	34.5%	72.6%
48141010316	104.42	75.0%	62.0%
48141010317	105.02	54.4%	90.3%
48141001400	104.42	96.9%	32.2%
48141004317	104.88	58.8%	62.9%
48141004313	104.54	62.7%	61.6%
48141000208	103.59	64.7%	80.3%
48141003402	104.84	81.7%	93.6%
48141000207	104.84	84.5%	95.6%
48141001114	104.84	74.8%	95.9%
48141001115	104.46	89.2%	53.8%
48141010218	104.85	7.2%	41.6%
48141000600	104.06	97.5%	99.1%
48141010338	104.68	38.5%	83.9%
48141010337	104.72	48.5%	14.2%
48141010336	104.51	49.5%	50.9%
48141004318	104.09	36.0%	71.2%
48141003904	104.55	65.9%	97.7%
48141010226	104.70	38.3%	24.4%
48141010368	103.78	40.6%	59.7%
48141003905	104.68	97.6%	89.9%
48141010366	104.05	73.7%	64.7%
48141004008	104.64	70.2%	59.4%

48141010354	104.03	79.7%	68.3%
48141010355	104.19	59.8%	53.5%
48141004007	104.62	71.4%	97.9%
48141010228	104.67	79.3%	87.3%
48141010353	104.40	59.4%	75.8%
48141010367	104.17	47.4%	31.6%
48141010369	103.37	39.1%	59.3%
48141010350	104.77	82.5%	92.7%
48141001002	104.05	98.6%	79.5%
48141001900	104.93	100.0%	98.3%
48141001112	104.34	37.5%	56.4%
48141010214	104.07	14.5%	34.0%
48141010327	105.22	48.4%	78.1%
48141001111	104.71	56.6%	18.3%
48141010329	104.09	78.8%	77.6%
48141004312	104.15	80.6%	62.9%
48141003702	104.73	88.9%	97.4%
48141003801	104.73	83.1%	93.8%
48141000112	104.52	78.4%	84.6%
48141000204	104.66	85.4%	97.4%
48141000205	104.77	91.4%	97.7%
48141000206	104.50	60.5%	89.4%
48141000302	104.18	94.4%	99.6%
48141000403	104.12	78.8%	85.7%
48141000404	104.32	99.9%	99.1%
48141001001	103.96	72.3%	93.3%
48141003803	104.71	75.1%	94.8%
48141003804	104.93	97.3%	98.7%
48141003901	104.86	77.4%	95.0%
48141003902	104.61	77.6%	90.5%
48141001501	104.42	23.9%	54.6%
48141004201	104.40	86.4%	97.3%
48141003501	104.58	84.9%	99.6%
48141004004	104.68	80.6%	94.6%
48141004103	104.70	95.1%	97.8%
48141004314	104.76	86.6%	71.9%
48141004316	104.71	72.3%	86.1%
48141010103	104.60	30.9%	11.9%
48141010307	104.23	71.1%	91.0%
48141002202	104.62	97.2%	88.1%
48141010102	104.87	60.2%	7.5%

48141001107	104.23	17.1%	20.0%
48141000301	104.38	99.3%	96.8%
48141001502	104.23	40.3%	28.4%
48141001110	103.99	35.4%	52.4%
48141002201	104.18	91.0%	75.3%
48141001109	102.25	45.5%	36.6%
48141003601	104.64	89.5%	63.5%
48141004104	104.70	56.4%	98.1%
48141004105	104.61	81.7%	99.5%
48141004106	104.69	83.0%	99.5%
48141004107	104.92	48.5%	63.3%
48141004202	104.59	79.1%	76.9%
48141004303	104.24	65.9%	77.9%
48141010311	104.22	77.2%	82.7%
48141000106	104.77	41.3%	71.6%
48141000107	104.80	73.5%	72.5%
48141000108	104.34	91.0%	52.3%
48141000109	104.90	75.9%	47.3%
48141000110	104.75	80.8%	87.9%
48141001202	105.24	62.8%	78.7%
48141001301	102.38	33.2%	53.4%
48141001302	102.04	13.7%	52.4%
48141001600	104.86	89.9%	67.3%
48141001700	104.71	99.6%	33.1%
48141000111	104.66	44.8%	51.1%
48141001800	105.11	98.7%	96.3%
48141002000	104.85	99.7%	99.7%
48141002100	104.79	99.9%	83.3%
48141002300	104.50	82.0%	82.0%
48141002400	104.35	89.1%	97.4%
48141002500	104.73	75.7%	94.2%
48141002600	104.88	95.9%	73.9%
48141002800	104.83	99.2%	99.8%
48141002900	104.58	98.0%	99.3%
48141003000	104.83	97.7%	99.7%
48141003100	105.04	83.6%	98.0%
48141003200	104.86	94.4%	89.5%
48141003300	104.70	82.0%	89.3%
48141003403	104.64	49.0%	68.0%
48141003404	103.86	38.0%	70.7%
48141003502	104.66	96.7%	98.8%

48141003602	104.17	99.1%	99.0%
48141003701	104.76	88.6%	89.7%
48141010349	105.29	32.8%	82.7%
48141010348	104.76	24.8%	54.2%
48141010602	104.07	57.5%	22.5%
48141000113	104.79	50.1%	74.4%
48141010352	103.97	57.4%	41.6%
48141010601	104.34	51.3%	24.3%
48141000902	103.82	81.7%	43.8%
48141010229	104.26	6.2%	14.7%
48141004006	104.70	74.2%	88.0%
48141010230	104.76	35.4%	41.9%
48141010227	104.52	68.5%	37.6%
48141001117	104.69	28.5%	72.8%
48141000901	103.71	76.3%	43.6%
48141001204	104.96	87.6%	95.5%
48141001118	103.95	69.6%	68.5%
48141001116	104.93	89.9%	34.2%
48141001119	104.49	57.2%	62.9%
48141010351	104.14	80.4%	82.2%
48141010328	104.33	58.9%	55.1%
48141004320	104.61	81.8%	62.1%
48141010217	104.44	29.0%	26.1%
48141010213	104.61	12.3%	28.5%
48141980000	104.39	0.0%	0.0%
48141010225	104.98	45.3%	52.3%
48141010370	104.21	47.8%	77.5%
48141000114	104.48	76.4%	94.4%
48141004005	104.70	74.3%	64.6%
48141010322	104.24	38.7%	63.6%
48141010323	104.77	61.8%	47.2%
48141010326	105.12	48.2%	68.9%
48141004319	104.74	33.3%	13.1%

F. El Paso Variables by Census Tracts (Theme 2 to 3, SVI total, LEP)

Census Tract Number	**Minority Status & Language**	**Housing Type & Transportation**	**SVI**	**LEP**
48141000800	92.7%	86.1%	93.9%	16.9
48141004307	75.2%	18.9%	55.4%	10.5

48141004309	88.1%	24.3%	51.4%	9.9
48141004310	76.0%	60.4%	76.6%	7.6
48141004311	72.7%	67.3%	64.5%	5
48141010303	81.8%	88.2%	71.3%	10.9
48141010312	73.3%	3.6%	28.7%	7.7
48141010316	84.6%	39.3%	66.1%	4.5
48141010317	83.7%	28.1%	61.5%	8.4
48141001400	83.1%	90.6%	88.1%	11.1
48141004317	78.3%	36.7%	57.3%	10
48141004313	77.3%	67.3%	67.9%	9.7
48141000208	78.7%	46.6%	67.4%	9.1
48141003402	87.2%	93.8%	95.4%	17.6
48141000207	79.6%	55.8%	86.7%	13.3
48141001114	81.2%	89.0%	92.4%	15.2
48141001115	88.8%	66.2%	80.6%	32
48141010218	68.1%	6.4%	13.0%	2.8
48141000600	89.0%	84.5%	99.1%	16.1
48141010338	89.8%	24.7%	51.5%	8.7
48141010337	89.1%	34.0%	38.5%	5.8
48141010336	90.9%	41.5%	53.5%	10.2
48141004318	76.8%	9.1%	35.1%	11
48141003904	93.6%	84.5%	90.6%	27.1
48141010226	64.4%	6.2%	20.5%	2.5
48141010368	79.9%	14.6%	38.4%	3.1
48141003905	97.1%	49.6%	91.0%	28.8
48141010366	78.5%	55.4%	70.2%	11.4
48141004008	98.6%	84.2%	80.3%	29.5
48141010354	75.6%	18.7%	60.9%	18.5
48141010355	73.8%	18.5%	47.7%	12.8
48141004007	96.4%	51.0%	84.4%	19.7
48141010228	82.7%	99.6%	96.6%	19.1
48141010353	83.1%	7.2%	46.7%	10.8
48141010367	80.6%	13.3%	33.3%	5.2
48141010369	75.2%	3.2%	26.8%	8
48141010350	89.3%	15.9%	70.5%	21.8
48141001002	89.6%	44.1%	87.1%	27.2
48141001900	94.8%	88.2%	99.8%	52.4
48141001112	59.6%	47.4%	47.4%	3.8
48141010214	59.2%	35.6%	26.2%	4.2
48141010327	79.4%	27.9%	53.6%	13.2
48141001111	66.8%	24.3%	37.1%	13.6

48141010329	93.4%	50.7%	76.8%	9.9
48141004312	81.4%	76.7%	80.8%	14.7
48141003702	94.0%	82.9%	96.4%	25.7
48141003801	97.7%	73.2%	91.1%	24.1
48141000112	83.1%	78.7%	86.2%	14.1
48141000204	72.7%	44.5%	85.0%	10.6
48141000205	69.3%	97.6%	98.9%	11.1
48141000206	86.5%	20.0%	60.8%	14.8
48141000302	95.4%	48.4%	94.9%	21.9
48141000403	84.4%	73.8%	85.3%	12.5
48141000404	89.9%	72.4%	99.3%	21.5
48141001001	86.2%	45.3%	77.5%	19.4
48141003803	85.9%	55.9%	82.5%	19.2
48141003804	95.7%	73.6%	98.0%	20.1
48141003901	92.8%	94.7%	95.4%	21.2
48141003902	96.7%	58.4%	83.4%	12.2
48141001501	68.2%	40.2%	38.5%	5.4
48141004201	92.7%	72.4%	93.6%	19.2
48141003501	86.9%	81.2%	96.9%	21.3
48141004004	89.6%	94.5%	95.7%	27.2
48141004103	89.3%	74.1%	96.7%	20.1
48141004314	81.8%	65.0%	81.9%	9.2
48141004316	84.8%	59.1%	78.2%	12.9
48141010103	46.6%	30.9%	23.5%	0.8
48141010307	82.8%	83.5%	87.0%	5.3
48141002202	78.2%	79.0%	94.7%	25
48141010102	45.1%	34.6%	34.6%	0.7
48141001107	61.4%	42.4%	25.6%	4.6
48141000301	81.2%	82.7%	98.5%	12.9
48141001502	58.8%	59.0%	44.2%	6.8
48141001110	67.6%	59.9%	50.4%	6.1
48141002201	83.8%	94.3%	94.3%	17.7
48141001109	63.8%	20.7%	36.0%	3.3
48141003601	94.8%	82.0%	88.1%	28.6
48141004104	94.4%	95.8%	92.8%	14.4
48141004105	97.1%	72.5%	95.1%	23.4
48141004106	92.4%	80.7%	96.6%	14.1
48141004107	84.5%	14.2%	43.0%	10.6
48141004202	96.2%	38.5%	73.4%	10
48141004303	73.6%	36.2%	63.9%	7.5
48141010311	85.2%	77.0%	84.8%	8.2

48141000106	68.5%	8.2%	35.3%	2.9
48141000107	73.6%	66.8%	75.1%	13.7
48141000108	68.5%	81.6%	83.9%	6.7
48141000109	77.0%	30.8%	59.1%	7.7
48141000110	79.2%	63.4%	83.2%	11.1
48141001202	81.8%	78.0%	77.1%	11.6
48141001301	55.5%	14.9%	30.6%	5
48141001302	60.5%	16.7%	22.9%	1.1
48141001600	91.8%	82.1%	88.9%	17
48141001700	83.1%	100.0%	98.1%	44.1
48141000111	70.3%	28.6%	43.8%	3.2
48141001800	91.8%	98.5%	99.8%	53.5
48141002000	96.7%	53.4%	98.3%	38.5
48141002100	90.5%	88.7%	98.5%	38.7
48141002300	86.5%	35.2%	74.0%	18.4
48141002400	84.6%	68.5%	93.3%	15.6
48141002500	84.0%	51.9%	81.1%	19.9
48141002600	95.7%	35.6%	81.3%	25.2
48141002800	97.3%	99.7%	100.0%	31.5
48141002900	98.9%	99.2%	100.0%	34.3
48141003000	95.4%	88.8%	99.7%	20.3
48141003100	96.2%	77.2%	94.7%	14.3
48141003200	97.8%	97.0%	98.6%	30.5
48141003300	87.8%	78.1%	89.3%	15.7
48141003403	78.0%	92.9%	74.5%	6.9
48141003404	73.9%	29.1%	46.8%	4.4
48141003502	91.2%	99.3%	99.9%	15.4
48141003602	96.4%	97.9%	100.0%	39
48141003701	86.1%	98.5%	97.7%	17.5
48141010349	89.3%	3.1%	31.9%	10.4
48141010348	89.1%	33.2%	39.3%	12.4
48141010602	39.0%	38.1%	40.6%	0.2
48141000113	61.4%	45.9%	57.1%	4.6
48141010352	82.7%	11.4%	39.5%	6.9
48141010601	20.5%	18.7%	28.5%	3.3
48141000902	71.5%	86.6%	79.9%	6.2
48141010229	70.6%	4.3%	5.9%	3.5
48141004006	98.9%	93.1%	92.3%	30.4
48141010230	70.4%	63.0%	49.4%	9.5
48141010227	73.0%	66.5%	64.2%	11.2
48141001117	69.5%	42.5%	46.8%	16.4

48141000901	85.0%	51.6%	66.1%	22.7
48141001204	91.8%	42.8%	86.1%	17.7
48141001118	56.1%	22.0%	55.2%	4.5
48141001116	70.4%	90.3%	83.0%	15.3
48141001119	73.4%	48.4%	59.7%	3
48141010351	92.1%	77.0%	86.8%	14.7
48141010328	86.5%	22.8%	51.4%	10.9
48141004320	92.8%	26.9%	66.2%	10.2
48141010217	67.9%	13.4%	22.3%	10.8
48141010213	68.6%	0.0%	7.4%	5.3
48141980000	0.0%	0.0%	0.0%	0
48141010225	83.8%	53.3%	54.7%	7.2
48141010370	81.4%	27.7%	53.4%	11.6
48141000114	67.2%	92.4%	92.1%	7.7
48141004005	92.6%	62.6%	74.6%	25.5
48141010322	81.9%	43.4%	51.3%	6.6
48141010323	88.3%	26.7%	52.7%	7
48141010326	78.1%	54.5%	59.5%	4
48141004319	80.6%	25.5%	27.2%	7.4

G. El Paso Variables by Census Tracts (Asian, Native Hawaiian & other Pacific Islander, Hispanic, Elderly)

Census Tract Number	Percent of Population that is Asian Alone, Not Hispanic or Latino	Percent of Population that is Native Hawaiian and Other Pacific Islander Alone, Not Hispanic or Latino	Percent of Population that is Hispanic or Latino	Age 65 and over
48141000800	0	0	95	12.4
48141004307	0	0	77.7	22.5
48141004309	1.3	0	90.8	17.2
48141004310	0	0	84.8	13
48141004311	0.7	1.3	78.7	17.6
48141010303	0.3	0	85.6	21.5
48141010312	1	0	81.3	16.7
48141010316	0	0	83.5	16.3
48141010317	0	0	91.8	14.8
48141001400	14.9	0	71.3	6.5
48141004317	0.8	0	74.2	5.5
48141004313	1.6	0	76.4	14
48141000208	2	0	72.1	5.7
48141003402	0.9	0	87.1	20.1

48141000207	1.3	0	83.5	12.7
48141001114	1.1	0	84.3	14
48141001115	3.4	0	84.1	6.3
48141010218	0	0	73.8	3.9
48141000600	0.6	0	88.2	14.9
48141010338	6.1	0	86.1	8.7
48141010337	0.4	0	90.1	7.1
48141010336	2.9	0	92.4	7.5
48141004318	0.2	0	83.3	22.3
48141003904	3.6	0	94	15.3
48141010226	2.7	0	64.9	3.8
48141010368	0	0	81.6	0.4
48141003905	0	0	97.7	15.6
48141010366	0	0	81.6	7.6
48141004008	0	0	99.5	8.5
48141010354	0.9	0	74.1	2.6
48141010355	0	0	85.3	4.7
48141004007	0	0	100	13.6
48141010228	0.1	0	89	9.6
48141010353	3.2	0	82	13.4
48141010367	0.3	0	76.2	2.5
48141010369	2.2	0.9	72.3	2.9
48141010350	0	0	94.3	14.6
48141001002	0	0	94.1	14.7
48141001900	0	0	89.7	25.7
48141001112	1.7	0	69.7	14.4
48141010214	1.9	0	64.2	12.4
48141010327	1.2	1.1	82.4	7.3
48141001111	2.9	0	72.9	7.1
48141010329	0.2	0.1	95.2	4.6
48141004312	3.4	0	77.8	16.3
48141003702	0	0	96.9	21.7
48141003801	0	0	99.2	26.9
48141000112	1.8	0	82.7	12.1
48141000204	0.6	0	72.1	14.5
48141000205	0.7	0	77.1	11.8
48141000206	0	0	91.4	15.1
48141000302	1.6	0	95.1	15.2
48141000403	0.4	0	89.5	15.4
48141000404	3.5	0	79.8	10.9
48141001001	0	0	97.1	23.8

48141003803	0	0	96.6	16.9
48141003804	0	0	98.8	13.9
48141003901	0	0.5	94.6	17.8
48141003902	0	0	91.5	16.7
48141001501	2.2	0	69.9	18.2
48141004201	1.4	0	93.5	20.3
48141003501	0.3	0	92.5	14.6
48141004004	0	0	95.3	31.3
48141004103	0	0	94.6	12.8
48141004314	0.3	0.7	80.1	13.5
48141004316	0.1	0	90.7	12.2
48141010103	2.4	0.3	23.9	0.1
48141010307	0.9	0	88.9	15.1
48141002202	0	0	88.8	21.6
48141010102	4	1.6	21.7	0
48141001107	6.3	0.6	58.8	16
48141000301	0	0	92.4	15.7
48141001502	1.4	1.8	55.6	21
48141001110	1.6	0	60.5	15.6
48141002201	0.4	0	87.2	25.1
48141001109	0.4	0	69.2	24.4
48141003601	0	4.9	93	19.5
48141004104	0.1	0	96.9	20.2
48141004105	0	0	98.8	25.6
48141004106	1.8	0	93.6	17.9
48141004107	0	0	91	16.8
48141004202	0.7	0	95	16.7
48141004303	1.1	0	74.1	18
48141010311	0.2	0.2	88.7	12.8
48141000106	3.7	0	58.2	18.1
48141000107	1	0	76.1	13.3
48141000108	1.4	0	58.4	9.1
48141000109	0.3	0	77.6	15
48141000110	1	0	72.2	17.5
48141001202	1.7	0	88	12.5
48141001301	0.5	0	59.5	15.9
48141001302	2.3	0	63.8	18.9
48141001600	0	0	89.4	22.1
48141001700	1.6	0	81.7	6.3
48141000111	1.4	0	46.7	12.3
48141001800	0	0	94.1	20.5

48141002000	0	0	98.1	19.7
48141002100	0.3	0	90.8	18.2
48141002300	0	0	93.8	15.4
48141002400	0.4	0	88.1	12.8
48141002500	0	0	88.4	27.1
48141002600	0	0	98.1	16.7
48141002800	0	0	99.2	16.9
48141002900	2.3	0	95.1	21
48141003000	0	0	90.4	18.3
48141003100	0	0	89.2	21.5
48141003200	0	0	98.4	20.7
48141003300	0	0	95.2	22.3
48141003403	0	0.4	80.4	14.3
48141003404	0.3	0	77.7	16.2
48141003502	0	0	94.6	10.3
48141003602	0	0	95.2	16.7
48141003701	0.2	0	92.5	24.4
48141010349	0	0	84.2	8.4
48141010348	0.4	0	92	10.7
48141010602	1.6	0	19.6	0.6
48141000113	2	0	58.5	14.2
48141010352	0.2	0	85.4	1.5
48141010601	9.3	0	16	0
48141000902	2.9	0	64.4	7.3
48141010229	0	0	76.1	10.5
48141004006	0	0	99.4	12.1
48141010230	0	0	84.9	10.3
48141010227	2.4	0	82.9	5.7
48141001117	2.6	0	71.1	17.2
48141000901	0	0	89.8	19.2
48141001204	1.6	0	94.6	15.3
48141001118	0.2	0	77.9	22.9
48141001116	1.7	0	82.7	12
48141001119	0.6	5	70.8	14.1
48141010351	4.2	0	83.8	8
48141010328	0.3	0	89.5	6.9
48141004320	0	6.9	89.5	8.2
48141010217	7.7	0	70.3	9.4
48141010213	2.3	0	68.1	7.5
48141980000	0	0	0	0
48141010225	2.6	0	82.4	8.4

48141010370	0.1	0.2	87.7	3.1
48141000114	2.1	0	67.4	21.6
48141004005	0	0	97.8	9.7
48141010322	0.6	0	88.9	6.4
48141010323	0	0	85.6	5.2
48141010326	0.4	0	85.7	16.6
48141004319	1.3	0	87.9	8.8

H. El Paso Variables by Census Tracts (Poverty & Foreign Born)

Census Tract Number	Percent below poverty level	Percent Foreign born
48141000800	43.7	28.8
48141004307	14.2	18.4
48141004309	20.7	18.7
48141004310	22.5	18.2
48141004311	15.5	18.4
48141010303	17.2	21.3
48141010312	10.6	20.7
48141010316	22.5	12.7
48141010317	7	15
48141001400	51.8	38.3
48141004317	14.2	16.2
48141004313	12.6	23.4
48141000208	17.4	14.7
48141003402	33.5	32.9
48141000207	18.7	22.1
48141001114	22.5	21.2
48141001115	32.3	35.8
48141010218	3.7	11.5
48141000600	31.6	24.6
48141010338	9.3	21.2
48141010337	8.7	15
48141010336	9.7	23.6
48141004318	5.1	21.1
48141003904	23.6	35.7
48141010226	1.8	20.4
48141010368	1.5	16.1
48141003905	42.6	29.7
48141010366	12.2	22.6
48141004008	21.7	43.8

48141010354	8.7	20.3
48141010355	14.5	21.3
48141004007	20.2	25.4
48141010228	20.2	27.4
48141010353	8.3	22
48141010367	4.7	11.7
48141010369	12.9	15.4
48141010350	13.3	37.8
48141001002	25.7	26.8
48141001900	60.3	48.9
48141001112	13.8	19.7
48141010214	6.9	26.9
48141010327	16.8	18.3
48141001111	17.2	21.2
48141010329	14.5	21.9
48141004312	27.6	22.7
48141003702	38.6	34.9
48141003801	20.5	30.4
48141000112	18.6	23.8
48141000204	31.6	16.2
48141000205	31.3	25.8
48141000206	22.9	27.4
48141000302	35.6	35.5
48141000403	14.8	22.5
48141000404	56.1	29.5
48141001001	17.8	30.1
48141003803	15.5	19.7
48141003804	42	30
48141003901	24.1	29.7
48141003902	25.4	23.4
48141001501	7.7	18.6
48141004201	25.2	25.1
48141003501	32.2	21.6
48141004004	18.4	35.3
48141004103	37.5	23.3
48141004314	25.2	20.6
48141004316	17.7	23.9
48141010103	18.9	6.5
48141010307	22.4	12.6
48141002202	35.7	26.4
48141010102	12.3	6.7

48141001107	5.5	26.9
48141000301	36.7	26.2
48141001502	12.8	15.8
48141001110	8.6	23.5
48141002201	21.1	28.1
48141001109	4.5	19.3
48141003601	34.3	35.9
48141004104	17.8	26.1
48141004105	17.6	29
48141004106	20.5	24.5
48141004107	7.5	19.9
48141004202	17.9	19.4
48141004303	15.7	19.4
48141010311	15.3	21.3
48141000106	8.8	13.8
48141000107	15.6	25.1
48141000108	21.1	21
48141000109	11	23.5
48141000110	19.8	15
48141001202	11.2	24.2
48141001301	8.9	11.5
48141001302	2.7	14.4
48141001600	24.8	31.2
48141001700	56.2	46.6
48141000111	9.6	21.8
48141001800	45.1	47.9
48141002000	57.3	43.3
48141002100	64.6	41
48141002300	28.8	27.5
48141002400	24.7	25
48141002500	25.5	31.9
48141002600	30.5	37.3
48141002800	63	44.1
48141002900	35.3	46.5
48141003000	59.9	27
48141003100	32	29.8
48141003200	24.4	33.5
48141003300	27	27.8
48141003403	18.6	16.2
48141003404	10	15.3
48141003502	39.1	24.2

48141003602	53	42.7
48141003701	37.3	23.9
48141010349	4	18.1
48141010348	4.3	24.6
48141010602	13.3	9.2
48141000113	4.8	18
48141010352	7.7	14.9
48141010601	14.3	10.2
48141000902	17.7	17.8
48141010229	3.4	13.5
48141004006	26.1	35.8
48141010230	5.2	27.1
48141010227	21.9	30.2
48141001117	8.1	25.7
48141000901	19.8	33.3
48141001204	35.6	27.4
48141001118	5.3	17
48141001116	30	18.6
48141001119	22.6	15
48141010351	30.4	29.5
48141010328	12.1	21.8
48141004320	36.4	25.9
48141010217	3.7	28.5
48141010213	2.9	22.4
48141980000	0	0
48141010225	8.7	25.6
48141010370	17.9	17.9
48141000114	13.1	17.1
48141004005	14.3	44.8
48141010322	7	22.5
48141010323	7.8	14.6
48141010326	12.8	19.8
48141004319	13.8	20.6

I. San Diego Variables by Census Tracts (Heat Index, theme 1 to 2)

Census Tract	**Heat Index**	**Socioeconomic**	**Household Composition & Disability**
6073010015	75.50	25.2%	92.9%
6073000400	73.58	7.5%	67.1%

6073000500	74.58	2.3%	46.7%
6073000600	75.23	3.7%	58.2%
6073003103	80.48	52.5%	90.8%
6073003105	80.64	18.9%	88.0%
6073002902	76.41	5.8%	70.8%
6073002903	76.79	17.4%	74.7%
6073009901	72.82	0.0%	61.8%
6073010103	74.30	65.8%	88.6%
6073009505	76.18	48.0%	59.8%
6073006200	74.29	0.0%	38.1%
6073012200	78.57	74.6%	89.5%
6073005900	75.21	18.8%	56.9%
6073003208	77.82	94.0%	89.3%
6073000700	75.34	21.0%	48.6%
6073000800	76.11	7.0%	48.7%
6073001000	75.40	6.7%	66.6%
6073001100	75.23	1.6%	60.8%
6073001400	76.40	2.0%	35.5%
6073001500	76.74	5.6%	54.6%
6073014002	78.60	47.1%	79.8%
6073014101	80.25	58.2%	74.4%
6073014102	80.35	43.8%	91.5%
6073014200	79.89	41.1%	83.3%
6073014601	75.25	85.0%	64.5%
6073001600	76.53	32.9%	82.5%
6073001700	76.74	8.9%	68.8%
6073014804	74.08	73.9%	57.3%
6073008902	74.42	0.7%	57.8%
6073007100	72.22	7.7%	19.1%
6073006802	73.91	15.3%	58.3%
6073014300	77.98	53.7%	80.4%
6073014500	76.90	63.6%	78.7%
6073003207	77.09	43.2%	81.1%
6073005000	73.97	69.4%	90.3%
6073003003	79.88	57.2%	85.0%
6073006801	73.19	43.0%	60.4%
6073002301	76.68	46.3%	82.2%
6073002709	77.52	93.3%	90.1%
6073002302	76.51	75.0%	92.1%
6073002401	76.97	56.9%	80.9%
6073002402	76.77	78.8%	94.8%

6073002501	77.03	56.5%	88.3%
6073002705	77.55	79.1%	85.9%
6073002707	76.81	85.0%	90.2%
6073002708	75.66	88.5%	91.7%
6073003114	79.45	30.1%	93.1%
6073003115	78.66	96.1%	93.3%
6073009509	74.90	7.2%	67.3%
6073010012	76.60	78.6%	98.4%
6073001900	75.94	7.0%	55.5%
6073002001	74.77	12.7%	36.9%
6073011902	76.31	93.8%	87.1%
6073014400	76.80	99.6%	88.3%
6073009103	74.56	26.8%	46.3%
6073006500	74.22	36.9%	59.6%
6073004501	75.67	5.5%	70.9%
6073003204	77.67	48.6%	79.0%
6073009706	75.72	43.8%	50.7%
6073009704	76.21	41.8%	53.5%
6073003401	77.17	78.8%	87.4%
6073009502	76.28	30.2%	58.0%
6073002601	76.58	82.9%	92.4%
6073009400	75.60	9.0%	68.6%
6073002602	77.30	83.0%	89.3%
6073002702	76.39	33.0%	80.6%
6073002710	76.93	77.9%	88.5%
6073002801	75.24	0.9%	59.7%
6073002905	76.49	45.8%	67.5%
6073003201	77.89	87.4%	88.5%
6073003202	78.34	77.9%	87.9%
6073010005	75.50	98.6%	96.9%
6073002002	75.47	8.6%	50.8%
6073002100	76.26	26.1%	74.0%
6073002201	77.02	68.8%	91.0%
6073002202	76.57	94.5%	92.8%
6073000100	73.11	65.5%	39.5%
6073003107	78.96	78.7%	86.0%
6073003108	75.16	60.1%	83.7%
6073008376	75.03	6.7%	68.6%
6073008375	75.56	2.0%	74.5%
6073008511	76.16	6.2%	72.3%
6073009507	75.76	77.3%	61.6%

6073007800	74.76	10.5%	59.5%
6073008503	76.74	56.7%	63.2%
6073009902	72.34	0.0%	0.0%
6073010104	73.74	89.5%	81.0%
6073003601	75.48	74.0%	96.9%
6073002703	76.30	48.0%	85.5%
6073003109	79.02	48.3%	92.3%
6073003111	79.61	93.2%	94.2%
6073003112	78.42	73.4%	93.3%
6073003113	78.83	54.3%	93.4%
6073022000	74.38	85.6%	89.0%
6073009305	76.86	25.1%	62.3%
6073009306	76.26	9.7%	67.9%
6073009510	77.89	47.6%	63.5%
6073002711	76.92	57.7%	86.3%
6073000201	72.73	36.6%	33.0%
6073003304	79.17	89.6%	92.9%
6073014806	76.11	21.0%	76.9%
6073009511	76.93	24.1%	69.1%
6073011700	75.99	96.4%	89.4%
6073011801	75.03	77.7%	92.6%
6073013308	77.86	60.4%	93.8%
6073008344	76.00	47.7%	52.9%
6073008345	75.37	47.8%	46.9%
6073003213	78.27	36.0%	90.6%
6073003209	77.08	23.0%	93.1%
6073003211	78.01	63.8%	87.2%
6073003212	77.86	36.7%	90.4%
6073005601	72.41	51.2%	68.9%
6073008502	75.67	51.7%	54.1%
6073008504	76.50	62.3%	52.5%
6073008505	75.71	28.2%	65.0%
6073014701	77.03	3.5%	59.8%
6073014702	76.93	88.9%	69.8%
6073010201	75.72	54.1%	67.6%
6073010202	72.62	43.6%	72.9%
6073009307	75.20	2.7%	63.5%
6073009203	76.18	6.7%	66.9%
6073009204	77.05	6.8%	62.2%
6073009308	75.59	1.8%	61.7%
6073007401	74.00	7.4%	49.8%

6073007303	71.99	1.9%	41.3%
6073021401	73.78	41.3%	66.3%
6073005201	75.67	0.9%	66.0%
6073005403	72.26	18.2%	37.2%
6073005402	71.79	8.5%	51.7%
6073005301	72.39	5.4%	66.5%
6073005802	72.58	2.3%	54.2%
6073005801	73.60	2.3%	43.5%
6073004102	76.49	4.9%	69.5%
6073000902	75.40	52.7%	62.5%
6073004101	76.47	19.1%	70.3%
6073005202	74.21	24.7%	65.6%
6073001202	76.17	3.3%	66.4%
6073000901	75.21	1.3%	71.0%
6073021402	73.45	40.4%	57.4%
6073001802	76.90	5.8%	74.0%
6073005302	72.27	51.1%	68.6%
6073001302	75.89	2.7%	65.0%
6073001201	76.48	9.8%	80.9%
6073010016	76.29	0.0%	77.6%
6073013326	77.69	18.1%	87.9%
6073010019	75.29	38.2%	84.1%
6073009109	74.31	0.0%	57.7%
6073007402	73.61	4.1%	37.5%
6073010110	73.83	85.5%	89.5%
6073010111	75.42	83.6%	94.2%
6073010112	74.12	87.0%	92.5%
6073010300	73.06	56.4%	76.5%
6073010401	73.38	77.3%	80.1%
6073008301	74.76	14.4%	49.0%
6073010402	73.52	70.5%	85.2%
6073010501	74.22	60.9%	66.6%
6073010502	73.14	77.6%	84.3%
6073010601	74.54	19.7%	51.3%
6073013205	75.26	81.3%	94.8%
6073010109	75.43	61.2%	90.0%
6073008307	75.26	46.1%	57.4%
6073011100	72.34	89.9%	35.1%
6073013206	77.23	96.5%	90.9%
6073004200	77.00	24.4%	61.0%
6073002904	76.35	3.1%	58.8%

6073002502	77.33	83.8%	80.3%
6073000202	73.32	20.1%	42.4%
6073002712	76.28	85.7%	89.3%
6073003305	78.30	92.5%	94.7%
6073003214	78.63	72.0%	92.0%
6073003301	76.80	70.4%	95.6%
6073003303	78.04	95.9%	91.5%
6073003403	76.29	69.8%	88.6%
6073008506	75.32	65.8%	60.6%
6073008507	75.11	66.1%	75.0%
6073008509	76.25	22.7%	63.4%
6073008510	75.53	71.4%	69.7%
6073008512	76.46	67.6%	52.3%
6073003404	77.38	81.0%	94.0%
6073003501	75.87	77.0%	92.9%
6073003502	76.71	93.7%	96.0%
6073003602	76.58	92.5%	96.2%
6073003603	75.79	77.6%	94.4%
6073008513	76.59	23.8%	48.6%
6073008600	76.21	79.1%	81.3%
6073008701	75.13	6.5%	71.6%
6073008702	75.84	19.2%	68.7%
6073009108	74.68	70.9%	62.3%
6073003800	74.69	0.0%	70.7%
6073003901	76.04	77.1%	95.3%
6073003902	75.62	82.8%	95.1%
6073004000	76.51	93.7%	95.4%
6073008800	75.85	55.2%	87.1%
6073008901	75.66	13.2%	69.7%
6073013317	77.69	38.8%	90.1%
6073010017	74.76	79.4%	89.6%
6073007304	72.03	0.9%	39.1%
6073005602	74.39	0.4%	53.1%
6073001301	76.28	5.9%	67.6%
6073013319	76.29	39.6%	86.1%
6073009000	76.31	51.5%	78.6%
6073009101	74.80	19.3%	36.5%
6073007911	74.76	1.0%	36.1%
6073007601	74.12	1.3%	13.8%
6073005102	75.11	0.8%	58.2%
6073005101	76.01	41.4%	84.7%

6073010018	74.60	43.8%	91.5%
6073005103	73.74	87.0%	74.2%
6073005401	73.69	3.9%	48.1%
6073000301	74.28	1.0%	52.6%
6073000302	73.94	10.3%	40.8%
6073001801	76.56	48.9%	77.5%
6073008350	75.07	22.4%	79.0%
6073002803	75.95	50.1%	73.9%
6073002804	76.11	1.8%	56.5%
6073003001	79.16	68.8%	87.7%
6073003004	80.32	83.6%	93.4%
6073003101	78.87	31.8%	96.8%
6073014805	74.62	8.3%	48.7%
6073010011	73.86	79.8%	91.8%
6073004300	75.89	19.5%	49.6%
6073004400	75.81	14.7%	57.8%
6073004600	76.58	28.1%	71.2%
6073004700	76.31	40.7%	82.7%
6073004800	76.32	98.3%	89.8%
6073004900	75.64	78.4%	91.3%
6073009102	76.16	12.0%	67.2%
6073009104	75.01	42.8%	38.8%
6073009107	74.95	5.3%	60.6%
6073005500	75.55	0.0%	76.6%
6073005700	74.41	66.0%	68.4%
6073009201	76.07	82.3%	78.8%
6073009301	76.34	46.1%	68.1%
6073009506	76.67	64.4%	56.2%
6073009602	74.41	19.2%	47.6%
6073006000	73.54	31.0%	42.7%
6073006100	74.05	23.4%	63.3%
6073006300	73.47	0.0%	59.7%
6073009603	74.71	8.3%	70.1%
6073009604	75.87	7.9%	61.6%
6073009703	75.90	37.6%	40.7%
6073009705	75.58	11.0%	55.5%
6073009801	76.09	19.8%	45.9%
6073011802	75.26	86.3%	95.0%
6073006600	73.92	14.8%	72.7%
6073006900	73.83	7.8%	42.4%
6073007002	72.95	36.8%	34.8%

6073009805	77.11	27.6%	40.8%
6073010001	77.58	53.6%	87.2%
6073010003	74.69	76.8%	92.1%
6073010004	74.60	66.6%	95.1%
6073012002	75.73	99.2%	93.7%
6073012003	75.56	80.0%	91.8%
6073007200	72.11	3.0%	39.8%
6073007302	72.75	62.1%	37.7%
6073007501	73.32	0.6%	37.7%
6073007502	73.39	3.0%	47.4%
6073010009	74.31	60.7%	98.3%
6073010010	74.19	99.5%	92.1%
6073010013	75.55	75.6%	97.6%
6073010106	74.08	93.7%	91.0%
6073010107	75.78	40.3%	88.9%
6073012102	75.25	74.9%	92.3%

J. San Diego Variables by Census Tracts (Theme 2 to 3, SVI total, LEP)

Census Tracts	**Minority Status & Language**	**Housing Type & Transportation**	**SVI**	**LEP**
6073010015	85.2%	69.8%	79.9	60.2%
6073000400	88.2%	46.3%	29.4	33.3%
6073000500	62.6%	24.2%	19	32.9%
6073000600	77.6%	33.9%	22	31.9%
6073003103	28.0%	62.5%	42	73.9%
6073003105	49.6%	63.6%	68.6	78.1%
6073002902	94.0%	74.3%	27.7	82.9%
6073002903	34.5%	41.1%	40.7	51.9%
6073009901	0.0%	0.0%	21.3	0.0%
6073010103	95.0%	93.8%	75.3	90.8%
6073009505	11.6%	14.0%	13.4	8.2%
6073006200	0.0%	0.0%	13	0.0%
6073012200	42.5%	84.8%	76.3	96.0%
6073005900	93.8%	65.5%	24.8	55.3%
6073003208	63.3%	85.6%	32.4	76.1%
6073000700	43.0%	21.8%	17.3	13.8%
6073000800	35.1%	23.3%	20.5	35.0%
6073001000	65.1%	34.2%	36.6	31.5%
6073001100	50.4%	16.3%	18.5	23.1%

6073001400	39.3%	16.6%	10.5	36.2%
6073001500	50.3%	27.0%	18	32.9%
6073014002	93.9%	83.8%	43.6	76.0%
6073014101	5.6%	40.9%	36	64.1%
6073014102	56.8%	70.2%	44.9	73.1%
6073014200	48.0%	60.5%	44.2	63.2%
6073014601	89.7%	88.1%	25.6	77.4%
6073001600	62.4%	80.9%	49.7	95.4%
6073001700	71.6%	63.7%	38.8	78.3%
6073014804	81.6%	70.2%	16.5	50.3%
6073008902	39.9%	12.7%	22.4	30.6%
6073007100	36.7%	10.0%	5.3	9.7%
6073006802	87.4%	61.8%	17.5	58.4%
6073014300	69.2%	73.7%	55.8	71.4%
6073014500	76.0%	67.8%	45.3	49.0%
6073003207	54.4%	54.0%	48.2	45.4%
6073005000	93.9%	94.5%	85	92.2%
6073003003	31.8%	68.1%	52.9	80.8%
6073006801	40.2%	48.6%	18.5	51.5%
6073002301	58.2%	76.9%	43.4	86.7%
6073002709	67.2%	96.7%	62.8	99.7%
6073002302	94.8%	98.2%	56.4	99.6%
6073002401	55.5%	81.1%	55.3	92.1%
6073002402	86.6%	97.3%	64.4	99.6%
6073002501	94.4%	95.9%	59	98.6%
6073002705	41.9%	75.5%	28.1	78.6%
6073002707	88.9%	95.5%	44.2	93.4%
6073002708	75.8%	96.5%	45	99.4%
6073003114	34.1%	53.6%	15.5	62.5%
6073003115	85.9%	91.2%	37.4	71.1%
6073009509	34.7%	16.9%	17.4	15.7%
6073010012	66.1%	90.6%	94.7	94.1%
6073001900	59.1%	23.8%	22.5	18.0%
6073002001	3.0%	3.1%	10.7	10.1%
6073011902	91.4%	90.4%	50.6	68.2%
6073014400	97.8%	99.6%	45.9	91.5%
6073009103	50.9%	27.9%	15.3	17.8%
6073006500	94.1%	78.0%	12.9	72.0%
6073004501	57.4%	54.1%	44.9	75.0%
6073003204	41.3%	48.9%	49.3	42.9%
6073009706	34.6%	32.3%	19.8	27.2%

6073009704	38.1%	33.8%	18.8	27.6%
6073003401	94.4%	91.3%	31.7	78.8%
6073009502	23.0%	25.8%	9.3	28.2%
6073002601	94.3%	96.6%	58	93.3%
6073009400	59.6%	49.6%	26.8	60.3%
6073002602	82.5%	95.4%	62.2	97.3%
6073002702	89.5%	86.4%	27.8	91.1%
6073002710	84.8%	92.8%	40.2	91.8%
6073002801	95.9%	53.2%	17.9	65.1%
6073002905	92.5%	78.9%	18	70.1%
6073003201	48.1%	79.5%	36.8	77.4%
6073003202	77.3%	85.1%	64.6	78.5%
6073010005	97.4%	99.5%	95.2	93.3%
6073002002	23.7%	18.2%	21.1	29.3%
6073002100	64.2%	69.3%	36.6	79.4%
6073002201	68.7%	92.0%	52	98.7%
6073002202	94.4%	98.8%	70.8	96.6%
6073000100	6.8%	8.1%	16.8	1.9%
6073003107	59.5%	73.6%	32.2	63.5%
6073003108	79.1%	79.8%	57	74.7%
6073008376	68.2%	53.6%	24.6	65.5%
6073008375	44.9%	25.7%	10.4	41.5%
6073008511	92.8%	54.6%	24	44.1%
6073009507	37.4%	39.0%	20.3	18.9%
6073007800	71.9%	29.5%	30.9	15.5%
6073008503	63.6%	60.7%	34.4	51.6%
6073009902	0.0%	0.0%	0	0.0%
6073010104	73.6%	79.0%	46.1	60.4%
6073003601	65.2%	92.0%	89.5	98.1%
6073002703	71.7%	69.1%	42.3	60.8%
6073003109	57.7%	56.9%	15.3	42.9%
6073003111	97.6%	97.5%	52	86.1%
6073003112	92.0%	79.5%	46.9	50.9%
6073003113	29.4%	61.7%	20.3	69.9%
6073022000	94.7%	91.9%	46.3	75.3%
6073009305	59.9%	37.8%	16.1	26.4%
6073009306	23.3%	31.5%	14.6	52.1%
6073009510	0.0%	22.8%	30.1	58.7%
6073002711	22.2%	66.1%	37.1	83.5%
6073000201	38.4%	27.8%	4.1	24.2%
6073003304	94.7%	98.4%	60.5	97.1%

6073014806	90.5%	66.6%	34.4	54.8%
6073009511	7.9%	24.2%	28	44.4%
6073011700	99.3%	99.0%	57.2	87.9%
6073011801	97.4%	98.5%	75.7	98.5%
6073013308	57.5%	76.5%	83.5	78.2%
6073008344	19.5%	19.5%	6.1	12.9%
6073008345	29.1%	35.6%	7.1	37.2%
6073003213	35.6%	31.5%	17.8	17.7%
6073003209	60.1%	65.1%	26.1	70.7%
6073003211	46.8%	63.1%	60.9	57.3%
6073003212	46.2%	52.9%	38.3	49.4%
6073005601	93.5%	72.2%	21.5	49.4%
6073008502	34.5%	39.8%	20.5	37.1%
6073008504	56.6%	43.1%	19.3	23.3%
6073008505	61.2%	48.8%	23.2	43.2%
6073014701	29.0%	13.7%	25	22.0%
6073014702	68.6%	75.8%	25.5	59.7%
6073010201	80.6%	74.3%	38.8	67.9%
6073010202	39.4%	51.6%	40.9	54.0%
6073009307	54.4%	29.2%	22.5	41.5%
6073009203	24.3%	25.7%	21.6	44.0%
6073009204	7.8%	7.3%	15.6	17.2%
6073009308	55.0%	24.5%	28.9	37.5%
6073007401	45.9%	41.9%	22.5	63.3%
6073007303	5.6%	2.0%	11.9	14.9%
6073021401	50.5%	43.9%	21.3	34.3%
6073005201	96.5%	44.7%	25.6	45.7%
6073005403	52.7%	38.2%	9	43.9%
6073005402	59.3%	25.2%	6.5	19.7%
6073005301	96.3%	57.4%	25.2	47.1%
6073005802	68.9%	21.0%	18.5	19.8%
6073005801	61.0%	32.9%	14.9	53.0%
6073004102	84.8%	69.3%	46	84.6%
6073000902	51.6%	55.5%	17.2	51.5%
6073004101	87.1%	69.4%	30.6	67.9%
6073005202	99.8%	86.0%	22	75.9%
6073001202	80.1%	44.8%	33.4	49.3%
6073000901	45.3%	23.1%	42.2	41.6%
6073021402	23.8%	33.6%	32.9	38.3%
6073001802	40.3%	43.3%	40.1	65.9%
6073005302	91.4%	70.3%	31.5	48.1%

6073001302	52.5%	30.0%	29.4	44.0%
6073001201	40.8%	47.4%	50.3	64.6%
6073010016	0.0%	0.0%	28.3	0.0%
6073013326	0.0%	5.0%	39	15.2%
6073010019	14.5%	29.1%	56	32.5%
6073009109	9.3%	4.8%	19	48.0%
6073007402	19.6%	6.0%	16.4	11.1%
6073010110	76.5%	88.1%	63.6	81.5%
6073010111	90.2%	96.5%	89.8	95.3%
6073010112	79.7%	96.0%	83.5	98.0%
6073010300	50.3%	72.5%	48.3	80.0%
6073010401	48.7%	79.2%	63.8	84.6%
6073008301	11.1%	3.9%	14.2	1.4%
6073010402	78.3%	91.2%	59.5	94.9%
6073010501	70.1%	71.2%	42.1	66.0%
6073010502	74.4%	88.1%	58.5	88.2%
6073010601	6.7%	5.7%	23	6.3%
6073013205	99.4%	99.2%	90.6	97.5%
6073010109	57.7%	77.8%	77.7	81.5%
6073008307	68.0%	45.2%	18.2	25.3%
6073011100	16.8%	39.8%	9.9	36.0%
6073013206	98.1%	99.0%	79	91.8%
6073004200	37.1%	33.0%	22.8	33.6%
6073002904	87.0%	62.0%	16.6	78.1%
6073002502	77.0%	93.4%	46.3	96.1%
6073000202	45.6%	24.7%	14.4	19.7%
6073002712	91.2%	96.9%	41.8	96.1%
6073003305	89.2%	98.3%	61.8	98.2%
6073003214	88.5%	86.9%	34.1	75.8%
6073003301	57.0%	87.4%	74.6	95.0%
6073003303	77.5%	97.0%	74.2	96.9%
6073003403	34.0%	73.6%	76.4	83.4%
6073008506	63.1%	64.0%	21.9	55.0%
6073008507	90.1%	70.7%	31.4	41.1%
6073008509	75.9%	50.2%	24.7	39.0%
6073008510	93.5%	81.4%	26.7	62.4%
6073008512	19.8%	29.3%	19	22.6%
6073003404	76.1%	95.0%	64.6	98.5%
6073003501	74.6%	95.7%	83.1	99.9%
6073003502	47.0%	93.4%	88.6	98.7%
6073003602	74.5%	94.0%	84.6	91.5%

6073003603	64.7%	92.7%	83.5	98.6%
6073008513	8.7%	10.1%	11.2	14.5%
6073008600	78.8%	92.9%	48.1	95.9%
6073008701	93.2%	64.1%	21	62.4%
6073008702	70.7%	62.6%	26.4	68.3%
6073009108	48.6%	50.8%	35.3	35.3%
6073003800	0.0%	0.0%	22.3	0.0%
6073003901	80.0%	94.2%	88.9	96.5%
6073003902	74.4%	95.6%	88.2	99.2%
6073004000	96.4%	99.3%	87.9	97.9%
6073008800	95.4%	92.4%	33.5	90.1%
6073008901	67.6%	59.2%	35	68.1%
6073013317	20.8%	41.6%	45.4	47.7%
6073010017	51.6%	62.3%	47.2	42.7%
6073007304	20.9%	12.2%	16.7	47.7%
6073005602	56.9%	13.7%	14.4	27.8%
6073001301	59.0%	35.7%	29.9	39.9%
6073013319	40.6%	39.4%	56.3	28.1%
6073009000	84.2%	79.6%	49.1	75.1%
6073009101	15.8%	11.1%	10	13.9%
6073007911	35.0%	16.0%	12.3	45.4%
6073007601	85.8%	17.1%	0.7	15.9%
6073005102	66.1%	30.9%	19.8	53.7%
6073005101	98.1%	93.0%	57.6	92.0%
6073010018	31.4%	63.4%	58.5	76.4%
6073005103	98.5%	98.7%	37.6	97.6%
6073005401	59.9%	20.0%	10	18.6%
6073000301	45.4%	12.5%	23.6	23.9%
6073000302	67.8%	41.4%	17.2	45.8%
6073001801	68.3%	69.1%	54.3	65.0%
6073008350	78.4%	46.3%	8.3	25.4%
6073002803	60.9%	73.3%	28.2	78.8%
6073002804	60.3%	37.4%	17.9	61.2%
6073003001	70.0%	76.2%	41.7	67.6%
6073003004	77.8%	94.7%	72.5	96.8%
6073003101	29.5%	64.9%	65.1	83.8%
6073014805	98.2%	59.3%	9.4	45.7%
6073010011	56.7%	75.1%	70.8	66.4%
6073004300	50.8%	44.1%	21.3	51.7%
6073004400	63.8%	55.1%	31.8	65.0%
6073004600	89.6%	78.3%	40.3	78.9%

6073004700	80.6%	86.2%	67.3	93.5%
6073004800	92.6%	99.7%	79.3	99.8%
6073004900	78.7%	94.8%	79.2	98.4%
6073009102	50.3%	43.8%	36.1	52.7%
6073009104	14.9%	14.4%	13.6	11.7%
6073009107	88.3%	52.9%	22.8	52.3%
6073005500	0.0%	0.0%	32.7	0.0%
6073005700	91.9%	89.5%	21.5	87.2%
6073009201	89.9%	84.4%	27.3	65.6%
6073009301	71.3%	67.3%	29.3	63.3%
6073009506	8.0%	10.3%	11.6	2.1%
6073009602	57.4%	27.9%	17.4	17.7%
6073006000	53.1%	30.2%	7.7	19.3%
6073006100	32.3%	41.2%	24.1	53.3%
6073006300	0.0%	0.0%	25	0.0%
6073009603	97.2%	65.4%	27.8	54.8%
6073009604	70.6%	49.5%	23	56.2%
6073009703	12.0%	11.2%	12.6	9.2%
6073009705	19.2%	6.9%	15.5	3.2%
6073009801	86.6%	33.0%	13	8.1%
6073011802	89.4%	96.5%	76.3	94.5%
6073006600	34.1%	58.8%	29.6	85.4%
6073006900	27.4%	14.1%	8.8	19.6%
6073007002	3.1%	6.1%	6.2	10.9%
6073009805	34.9%	18.1%	14.6	10.5%
6073010001	29.1%	56.6%	66.9	62.4%
6073010003	21.1%	54.0%	61.2	50.9%
6073010004	78.7%	86.0%	84.1	83.1%
6073012002	96.3%	99.6%	43.8	95.5%
6073012003	48.4%	78.4%	57.2	78.9%
6073007200	16.4%	3.5%	13.1	6.9%
6073007302	17.5%	18.2%	11.5	10.4%
6073007501	17.4%	7.0%	12.8	37.8%
6073007502	54.1%	33.3%	12.4	53.3%
6073010009	84.4%	91.2%	93	92.4%
6073010010	84.9%	98.5%	78.1	93.3%
6073010013	87.9%	96.1%	97.6	97.5%
6073010106	97.6%	98.4%	83.5	91.6%
6073010107	95.4%	84.6%	70.6	76.0%
6073012102	56.6%	85.2%	74	90.5%

K. San Diego Variables by Census Tracts (Asian, Native Hawaiian & other Pacific Islander, Hispanic, Elderly)

Census Tracts	Percent of Population that is Asian Alone, Not Hispanic or Latino	Percent of Population that is Native Hawaiian and Other Pacific Islander Alone, Not Hispanic or Latino	Percent of Population that is Hispanic or Latino	Age 65 and over
6073010015	8.1	0.9	8.1	16.4
6073000400	14.2	0	14.2	3.8
6073000500	6.4	0	6.4	0
6073000600	5.4	0.2	5.4	5.1
6073003103	10.2	4.1	10.2	9.8
6073003105	7.5	0	7.5	10.1
6073002902	12.3	2.2	12.3	3.9
6073002903	10.4	1	10.4	7.5
6073009901	4.9	2.2	4.9	0
6073010103	2.7	0.3	2.7	17.6
6073009505	21.4	0	21.4	1.8
6073006200	0	0	0	0
6073012200	6.6	0	6.6	8.4
6073005900	4.3	0	4.3	2.1
6073003208	27.2	0.9	27.2	5.6
6073000700	6.5	0	6.5	4.9
6073000800	4.6	0	4.6	2.1
6073001000	5.5	0.7	5.5	1
6073001100	6.5	0.6	6.5	0.4
6073001400	3.7	0	3.7	0.7
6073001500	4.6	0	4.6	1.6
6073014002	7.2	0	7.2	7.8
6073014101	5.3	1.5	5.3	4
6073014102	14.3	0	14.3	6.4
6073014200	10.2	3.7	10.2	4
6073014601	4.8	0.4	4.8	6.9
6073001600	7	1.2	7	7.4
6073001700	1.8	0	1.8	7.5
6073014804	8.7	0	8.7	4.9
6073008902	6	0	6	0
6073007100	0.6	0	0.6	0
6073006802	5.7	0.1	5.7	4.8
6073014300	6.4	0.7	6.4	7.6
6073014500	4.3	0	4.3	4.5
6073003207	19.2	0	19.2	6.5

6073005000	2.4	0	2.4	16.6
6073003003	6.7	3.3	6.7	8.9
6073006801	4.7	0	4.7	4.2
6073002301	11.5	0	11.5	11.5
6073002709	4.8	0	4.8	15.2
6073002302	28.6	4.4	28.6	32.1
6073002401	9.8	0	9.8	15.4
6073002402	17.7	0	17.7	25
6073002501	12.5	0	12.5	13.2
6073002705	36.3	0.7	36.3	20.2
6073002707	18.4	1.2	18.4	37.3
6073002708	25.4	0.4	25.4	20.5
6073003114	51.6	1	51.6	4.8
6073003115	39.8	1.4	39.8	8.6
6073009509	21.1	0.3	21.1	4.3
6073010012	1.5	0	1.5	25.2
6073001900	6.9	0	6.9	2.9
6073002001	4	0.1	4	0.9
6073011902	20.9	0	20.9	10.6
6073014400	0.2	0	0.2	6.8
6073009103	3.2	0	3.2	1.9
6073006500	10.2	0.3	10.2	1
6073004501	4.8	0	4.8	10.2
6073003204	12.2	0	12.2	3
6073009706	5.3	0	5.3	1
6073009704	4.9	0.4	4.9	1.3
6073003401	20.3	0	20.3	10
6073009502	19.8	0	19.8	3.4
6073002601	26.5	0	26.5	22.7
6073009400	4.5	0	4.5	0.5
6073002602	13.6	3.8	13.6	18.6
6073002702	12.7	0	12.7	7.5
6073002710	31.2	6.1	31.2	19.9
6073002801	10.6	0	10.6	0.5
6073002905	9.3	0	9.3	3.6
6073003201	21.8	0.6	21.8	5.1
6073003202	9.5	0.7	9.5	8.3
6073010005	2.1	0.3	2.1	19.5
6073002002	4.7	0	4.7	1
6073002100	8	0	8	4.5
6073002201	18.4	0.2	18.4	19

6073002202	14.9	0	14.9	25.8
6073000100	3.9	0	3.9	3.4
6073003107	23.5	0.1	23.5	6.1
6073003108	12.3	1.3	12.3	8.2
6073008376	22	0.7	22	3.5
6073008375	46.1	0	46.1	1.5
6073008511	26.6	0	26.6	4.2
6073009507	8.7	0	8.7	1.7
6073007800	4.5	0.6	4.5	4.1
6073008503	5.5	0	5.5	6.8
6073009902	0	0	0	0
6073010104	10.9	0	10.9	6.4
6073003601	0.9	0	0.9	15.6
6073002703	22	0	22	12
6073003109	69.2	0	69.2	4.8
6073003111	25	1.9	25	10.9
6073003112	19.8	0	19.8	12.4
6073003113	55.1	2.1	55.1	6.5
6073022000	34.6	0.7	34.6	10.9
6073009305	16.1	0	16.1	2.9
6073009306	22.8	0.4	22.8	0.6
6073009510	2.2	0	2.2	1.4
6073002711	24.4	0	24.4	10.3
6073000201	6.9	0	6.9	1.7
6073003304	16.1	0.3	16.1	18.1
6073014806	9.6	0	9.6	2.4
6073009511	0.3	0	0.3	2.7
6073011700	23.6	0	23.6	14.9
6073011801	11.2	0.7	11.2	20.5
6073013308	6.2	0	6.2	12
6073008344	17.5	0.2	17.5	2.2
6073008345	16.3	0	16.3	1
6073003213	50.8	0	50.8	2.9
6073003209	45.4	0	45.4	7.8
6073003211	12.3	0	12.3	7.1
6073003212	30.5	0	30.5	4.8
6073005601	13.4	0	13.4	3.5
6073008502	8.2	0.6	8.2	1.5
6073008504	8.9	2.2	8.9	1.2
6073008505	17.2	1.2	17.2	7.5
6073014701	7.2	0	7.2	0

6073014702	14.2	0	14.2	6.3
6073010201	7.3	0.4	7.3	4.8
6073010202	4.8	0	4.8	2.8
6073009307	9	0	9	4.5
6073009203	13	0.4	13	2.3
6073009204	5.6	0.2	5.6	1.4
6073009308	10.5	3.7	10.5	1
6073007401	2.3	0.3	2.3	0
6073007303	5.8	0	5.8	0
6073021401	10	0	10	1.4
6073005201	12.6	0	12.6	0
6073005403	5.3	0	5.3	1.8
6073005402	15.6	0	15.6	0.6
6073005301	8.9	0	8.9	4.6
6073005802	10.7	0	10.7	1.5
6073005801	6.7	0	6.7	7.3
6073004102	2	0.3	2	7.1
6073000902	9.3	0	9.3	10
6073004101	7.6	0	7.6	8.8
6073005202	5.3	0	5.3	2.1
6073001202	3.8	0.6	3.8	0.8
6073000901	8.6	0	8.6	2.7
6073021402	1.9	0.2	1.9	5.8
6073001802	7	0	7	4.9
6073005302	6.8	0	6.8	18
6073001302	4.4	0	4.4	5.1
6073001201	8.8	0.1	8.8	7
6073010016	2.6	0	2.6	3.4
6073013326	45.9	0.2	45.9	4.3
6073010019	20.6	0.3	20.6	7.4
6073009109	8.9	0	8.9	0
6073007402	2.7	0.6	2.7	1
6073010110	10.1	0.3	10.1	10.7
6073010111	1.1	0	1.1	27.2
6073010112	2.9	0	2.9	15.4
6073010300	11.1	0.2	11.1	5.6
6073010401	0.7	0.9	0.7	7
6073008301	5.5	0	5.5	0.6
6073010402	7.9	0.3	7.9	10.8
6073010501	4	0.5	4	5.4
6073010502	4.6	0	4.6	3.7

6073010601	2.6	0	2.6	1.3
6073013205	2.2	0.5	2.2	22.3
6073010109	4	0.6	4	17.3
6073008307	11.7	0	11.7	1.8
6073011100	1.7	0	1.7	1.8
6073013206	3.2	0	3.2	17.7
6073004200	3.1	0	3.1	6.4
6073002904	10.8	0.7	10.8	1
6073002502	9	1.3	9	11.9
6073000202	7.3	0.1	7.3	2.4
6073002712	11.4	0	11.4	11.6
6073003305	10.2	0	10.2	15.6
6073003214	22.4	0	22.4	3.8
6073003301	0	0	0	10.1
6073003303	3.8	0	3.8	16.1
6073003403	1.9	0	1.9	19.9
6073008506	16.2	0	16.2	4.6
6073008507	20	0	20	6.9
6073008509	13.2	0	13.2	5.1
6073008510	18.9	0	18.9	4.9
6073008512	8	0	8	1.9
6073003404	13.1	0	13.1	18.9
6073003501	1.2	0	1.2	26.3
6073003502	0.9	1	0.9	23.1
6073003602	2.3	1.2	2.3	15.8
6073003603	5.4	1.5	5.4	24
6073008513	9.7	0	9.7	0.5
6073008600	16.2	0	16.2	16.3
6073008701	24	0	24	2.4
6073008702	13.4	2.7	13.4	4.5
6073009108	3.7	0	3.7	2.4
6073003800	10.6	0	10.6	0.2
6073003901	0.9	0	0.9	21.7
6073003902	2.8	0	2.8	29.9
6073004000	3.2	0	3.2	18.4
6073008800	42.4	0	42.4	25.3
6073008901	13.5	0	13.5	5.2
6073013317	33.5	0	33.5	6.5
6073010017	23	0	23	6.1
6073007304	1.5	0	1.5	0
6073005602	18	1	18	0

6073001301	9.2	0.3	9.2	1.6
6073013319	15.5	0	15.5	6.7
6073009000	12.8	0	12.8	13.1
6073009101	2.7	0	2.7	1.9
6073007911	4.6	1.2	4.6	0.5
6073007601	0.5	0	0.5	1.2
6073005102	8.3	0	8.3	0
6073005101	13.5	0	13.5	11.6
6073010018	16.6	0	16.6	5.6
6073005103	4.4	0	4.4	10.6
6073005401	3.7	0	3.7	0
6073000301	3.5	0	3.5	0
6073000302	2.1	0	2.1	0.5
6073001801	2.3	0	2.3	6
6073008350	51	0	51	7.3
6073002803	19	0.3	19	13.4
6073002804	8	0.2	8	1.5
6073003001	4.5	0	4.5	5.7
6073003004	2.7	2.2	2.7	14.3
6073003101	4.6	0.4	4.6	8.3
6073014805	9	0	9	0.8
6073010011	11.4	0	11.4	16.3
6073004300	5.3	0	5.3	1
6073004400	2.5	0	2.5	4.7
6073004600	1.5	0.3	1.5	12.7
6073004700	1.2	0	1.2	13.6
6073004800	0.4	0	0.4	26.6
6073004900	2.5	1.5	2.5	20.6
6073009102	8.8	0	8.8	11.2
6073009104	4.1	0	4.1	0.9
6073009107	11.7	0	11.7	1.1
6073005500	3.7	1.8	3.7	0
6073005700	11.6	0	11.6	8.7
6073009201	19.7	0	19.7	2.7
6073009301	17.8	0	17.8	5
6073009506	9.5	0.2	9.5	1.9
6073009602	4.4	0	4.4	1.6
6073006000	13.5	0	13.5	0.3
6073006100	5.5	0	5.5	1.1
6073006300	2.4	0	2.4	1.3
6073009603	9.7	0	9.7	2.5

6073009604	6	0.2	6	2.7
6073009703	6.2	0.5	6.2	1.2
6073009705	7	0.4	7	0.2
6073009801	5.7	0.8	5.7	1.2
6073011802	16.4	0	16.4	16.7
6073006600	6.7	0.4	6.7	0.9
6073006900	5	0	5	0.5
6073007002	5.7	0	5.7	0.3
6073009805	3.2	0	3.2	0.8
6073010001	10.9	0	10.9	8
6073010003	15	1.2	15	10.8
6073010004	9.5	2.7	9.5	8.4
6073012002	38.6	0	38.6	17
6073012003	30.5	0.3	30.5	11.7
6073007200	4.2	0.4	4.2	0.4
6073007302	0.8	0	0.8	1.4
6073007501	2.1	0	2.1	0
6073007502	3.8	0	3.8	0.7
6073010009	3.4	0.9	3.4	24.2
6073010010	8.8	0	8.8	15.6
6073010013	0	0	0	27.9
6073010106	4.9	0	4.9	17.7
6073010107	11.7	0	11.7	15.6
6073012102	11.8	1.6	11.8	15.5

L. San Diego Variables by Census Tracts (Poverty & Foreign Born)

Census Tracts	Percent Below Poverty	Foreign Born
6073010015	5.3	39.2
6073000400	6.5	17.4
6073000500	8.3	9.8
6073000600	8.8	13.7
6073003103	8.3	22.1
6073003105	12.4	25.5
6073002902	20.1	20.1
6073002903	10.4	23.8
6073009901	0	3.7
6073010103	21.3	34.4
6073009505	6.9	20.1
6073006200	0	0

6073012200	15.1	27
6073005900	9.1	15.5
6073003208	14.5	26.6
6073000700	6.9	13.4
6073000800	7.6	10.5
6073001000	9.1	12.3
6073001100	4.1	12.2
6073001400	9.8	11.7
6073001500	4.3	11.6
6073014002	10.9	15.9
6073014101	10.7	13.1
6073014102	7.4	23.8
6073014200	7.3	17.6
6073014601	11.8	18.9
6073001600	22.8	31.2
6073001700	7.2	23
6073014804	9.6	18.2
6073008902	6.1	16.6
6073007100	5.4	5.8
6073006802	13.9	17.9
6073014300	12.1	24.6
6073014500	14	16.2
6073003207	2.4	23.1
6073005000	19.7	32.9
6073003003	15.1	19.7
6073006801	11.8	10.2
6073002301	20.1	30.7
6073002709	45.2	41.7
6073002302	25.8	46
6073002401	24.2	38.2
6073002402	25.6	53.4
6073002501	24.9	30.1
6073002705	10	35.8
6073002707	34.1	61.1
6073002708	31.7	42.8
6073003114	10.9	38.4
6073003115	17.2	40.1
6073009509	6.1	26.2
6073010012	13.3	50.2
6073001900	7.2	15.1
6073002001	1.8	9.4

6073011902	5.7	38
6073014400	22.5	15.7
6073009103	4.8	8.3
6073006500	23.3	17.4
6073004501	10.8	21.5
6073003204	9.6	24.5
6073009706	4.2	11.9
6073009704	7.7	13.3
6073003401	6.6	28.9
6073009502	6.3	20.6
6073002601	27.8	37.4
6073009400	5	7.5
6073002602	22.2	33.4
6073002702	20	31.4
6073002710	11	43.3
6073002801	50.5	5.8
6073002905	15.3	14.5
6073003201	11.6	19.2
6073003202	7.6	24.3
6073010005	32.9	42.9
6073002002	11	5.1
6073002100	10.5	22.6
6073002201	25.6	37.1
6073002202	26.1	41.7
6073000100	2.3	11
6073003107	9.4	32.2
6073003108	8.1	24.4
6073008376	25.9	35.4
6073008375	21.3	53.5
6073008511	10.2	27.2
6073009507	9.2	22.3
6073007800	3.3	15.2
6073008503	11	18.1
6073009902	0	0
6073010104	10.7	22.1
6073003601	15.4	32.7
6073002703	14.6	25.2
6073003109	6.6	43.5
6073003111	22	29.3
6073003112	5.2	26.3
6073003113	6.3	44.1

6073022000	10.5	42.3
6073009305	4.5	20.2
6073009306	8.4	25.7
6073009510	12.4	3.2
6073002711	9.3	24.8
6073000201	9.3	10
6073003304	22.4	35.2
6073014806	14	21.2
6073009511	6.1	5.7
6073011700	17.8	40.5
6073011801	26.1	42.8
6073013308	11.2	38.5
6073008344	4.8	20
6073008345	7	22.9
6073003213	8	36.6
6073003209	5	38
6073003211	3.1	21.9
6073003212	6.1	29.9
6073005601	16.1	18.6
6073008502	10.2	19.2
6073008504	9.3	10.5
6073008505	8.8	26.3
6073014701	10.9	8.1
6073014702	17.9	15.4
6073010201	30.8	11.7
6073010202	6.6	8.4
6073009307	9.7	26.8
6073009203	14.2	22.4
6073009204	4	7.5
6073009308	4.1	25.8
6073007401	11.7	6.7
6073007303	8.1	6.8
6073021401	1.6	7.7
6073005201	16.5	18.3
6073005403	7.7	13.3
6073005402	12.5	8.8
6073005301	16.1	16.3
6073005802	4.6	14.3
6073005801	11.4	26.1
6073004102	18.5	30.6
6073000902	9.3	33.8

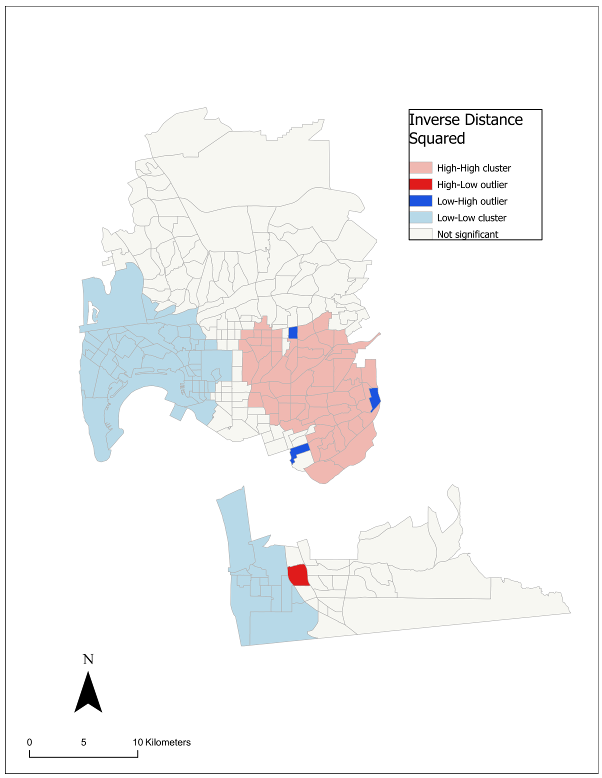
6073004101	14.6	21
6073005202	26.1	15
6073001202	17.1	10.9
6073000901	7.5	21.5
6073021402	9.2	33.7
6073001802	10.8	17.4
6073005302	19.1	29.3
6073001302	4.8	15.8
6073001201	6	27.4
6073010016	0	9.7
6073013326	0.7	35.6
6073010019	0	25.8
6073009109	26.6	5.2
6073007402	5.5	8.1
6073010110	18.1	30.9
6073010111	20.4	46
6073010112	25.5	33.2
6073010300	21.4	20.9
6073010401	18.6	15.8
6073008301	2.3	20.4
6073010402	16.6	28
6073010501	7.7	24.6
6073010502	13.6	17.2
6073010601	5.6	14.7
6073013205	27	39.1
6073010109	3.7	31.2
6073008307	11	17.6
6073011100	5.4	4.9
6073013206	18.8	43.2
6073004200	4	15.2
6073002904	54.2	11.3
6073002502	28.1	28.1
6073000202	2.9	18.8
6073002712	27.4	31.3
6073003305	32.3	32.5
6073003214	5.4	31
6073003301	22.9	27.5
6073003303	25.1	36.3
6073003403	11.7	32.2
6073008506	7.2	19.7
6073008507	8.4	27.6

6073008509	5.3	26.8
6073008510	13.4	20.4
6073008512	6.3	7.3
6073003404	26	38.4
6073003501	27.5	40.9
6073003502	26.5	43.9
6073003602	11.9	34.5
6073003603	22	36.2
6073008513	1.6	13.5
6073008600	17.4	33.9
6073008701	13.1	18.3
6073008702	14.7	21.2
6073009108	6.6	13.2
6073003800	0	8
6073003901	20.2	38.8
6073003902	19.5	33.6
6073004000	18.5	37.3
6073008800	14.9	48.6
6073008901	19.1	22.3
6073013317	6.8	32.4
6073010017	4.3	29.6
6073007304	14	7.2
6073005602	12.5	27.2
6073001301	9.7	10.8
6073013319	2	23
6073009000	10.6	30.3
6073009101	4.6	17.1
6073007911	15.1	10.9
6073007601	14.3	8.5
6073005102	17.3	13.4
6073005101	15.7	22.9
6073010018	3.1	29.5
6073005103	49.7	16.8
6073005401	9.2	9
6073000301	15.1	12
6073000302	10.3	7.4
6073001801	29.8	13.7
6073008350	4.5	40.9
6073002803	9.6	31.9
6073002804	32.6	11.4
6073003001	7.2	10.6

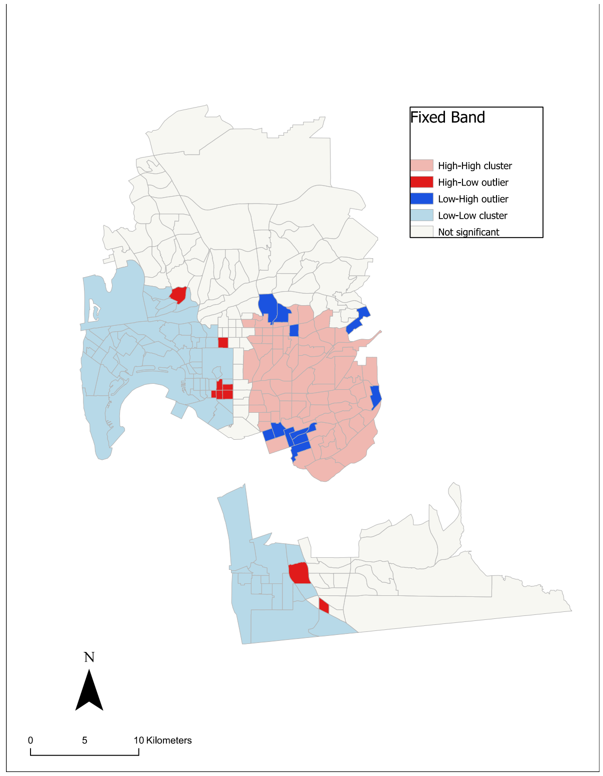
6073003004	18.4	29.9
6073003101	11.6	27.1
6073014805	9.9	16.3
6073010011	6.8	42.5
6073004300	8.9	6.8
6073004400	13	13.7
6073004600	10.6	25.4
6073004700	15	35.4
6073004800	24.4	48.5
6073004900	22.8	33.4
6073009102	17.9	30.4
6073009104	2	5.6
6073009107	25.9	15.9
6073005500	0	3.4
6073005700	28.4	27.7
6073009201	17.1	19.5
6073009301	15.7	27.2
6073009506	1.9	14.8
6073009602	5.4	10.5
6073006000	12.4	16.2
6073006100	5.8	12.1
6073006300	0	2.8
6073009603	15.5	20.4
6073009604	8.9	16.2
6073009703	5.1	6.6
6073009705	5	8.9
6073009801	5	6.9
6073011802	15.9	45.7
6073006600	12.7	10.8
6073006900	7.6	6.8
6073007002	7.7	10.8
6073009805	3.1	9.2
6073010001	3.5	32.3
6073010003	6.8	29.1
6073010004	10.2	30.5
6073012002	28.6	47.8
6073012003	10.8	44.3
6073007200	6.2	5.3
6073007302	5.1	6.5
6073007501	10.3	6.6
6073007502	7.7	10.9

6073010009	14	41.9
6073010010	16.3	39.2
6073010013	18	49.9
6073010106	15.8	40.8
6073010107	4.4	37.5
6073012102	15.8	37.8

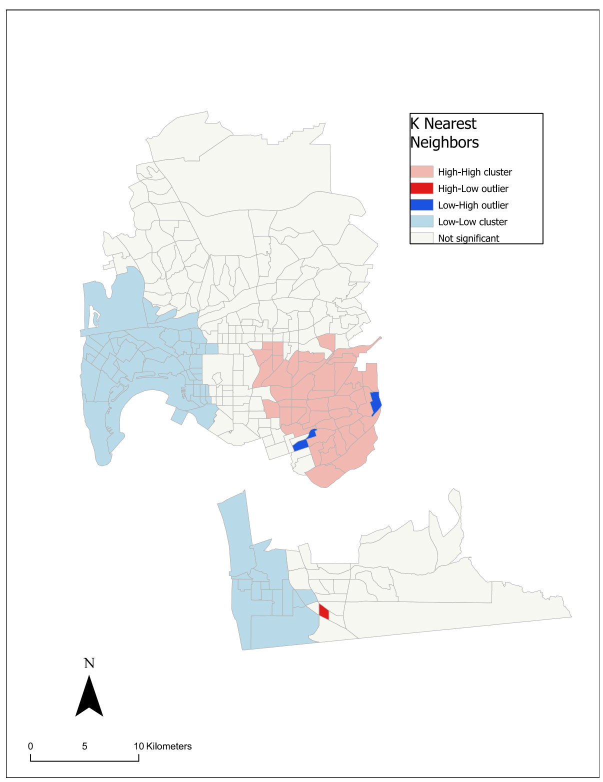
M. San Diego Local Moran's I: Inverse Distance Squared



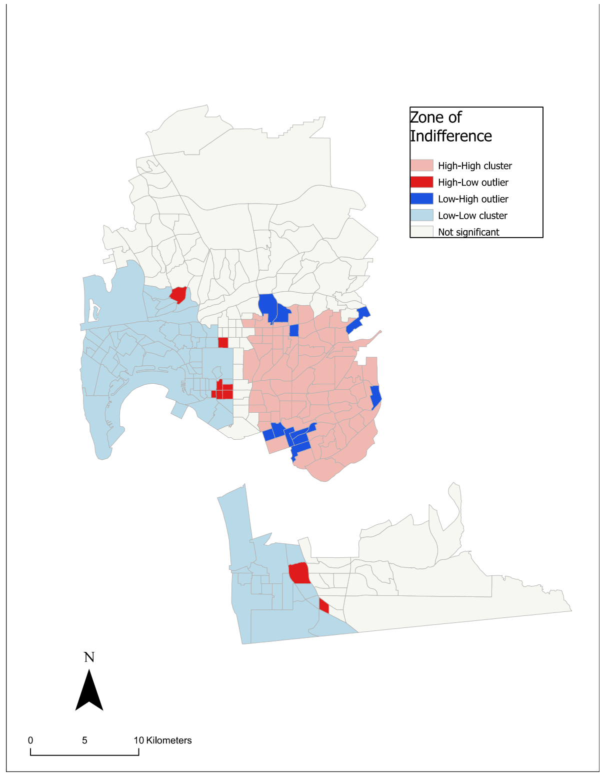
N. San Diego Local Moran's I: Fixed Band



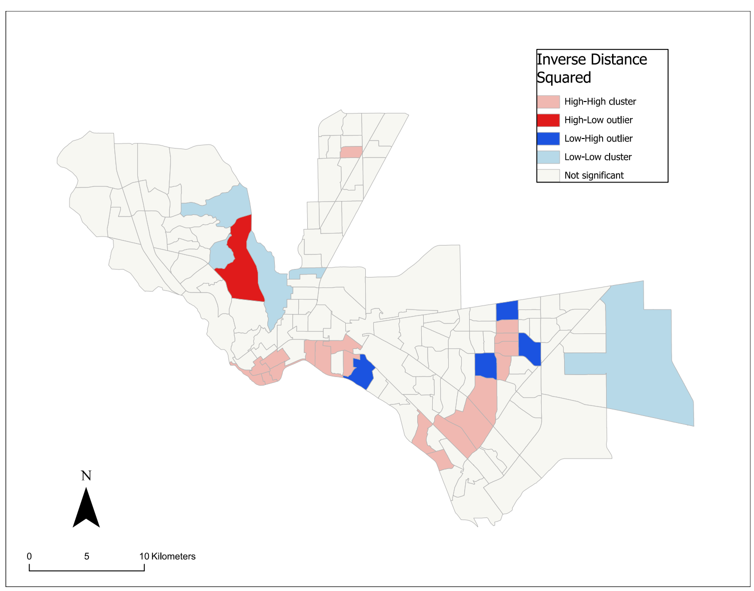
O. San Diego Local Moran's I: K Nearest Neighbors



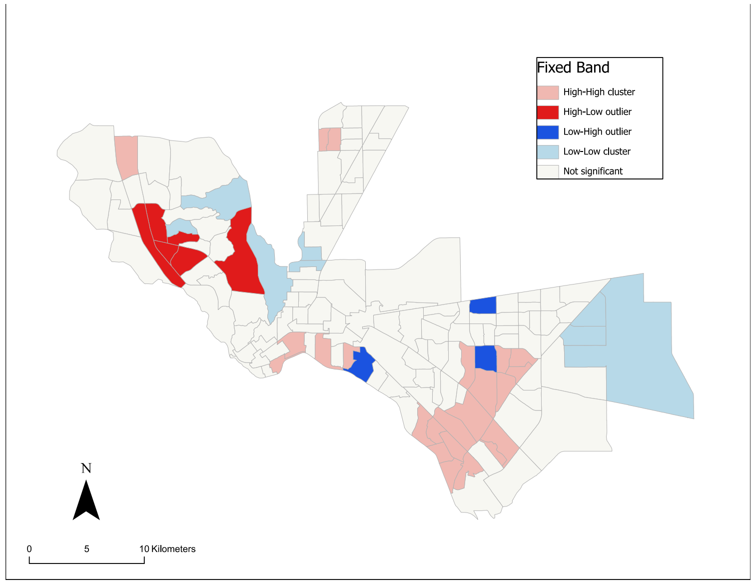
P. San Diego Local Moran's I: Zone of Indifference



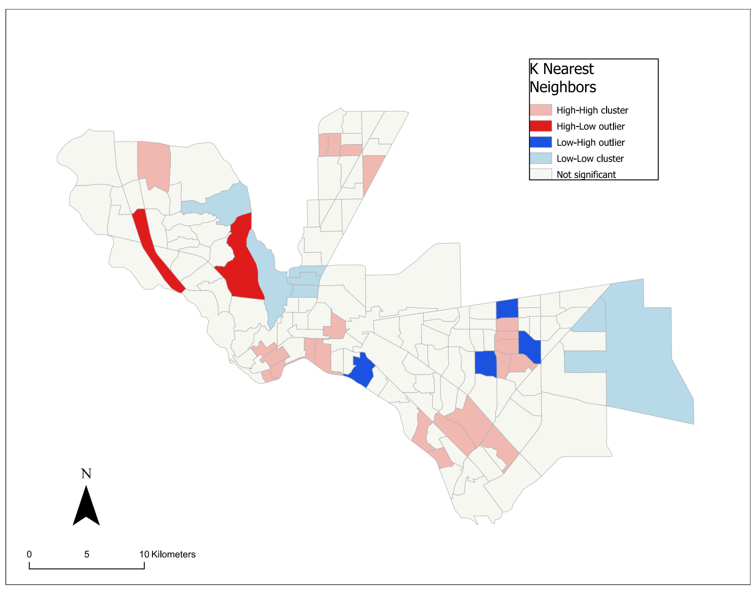
Q. El Paso Local Moran's I: Inverse Distance Squared



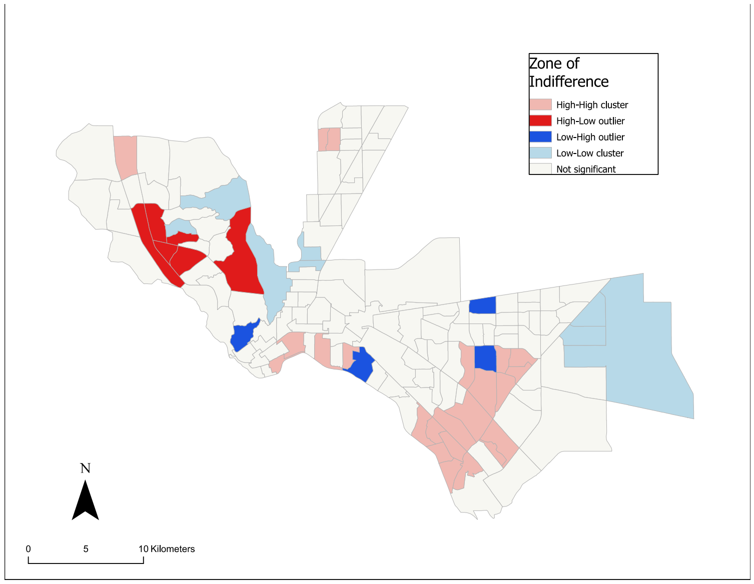
R. El Paso Local Moran's I: Fixed Band



S. El Paso Local Moran's I: K Nearest Neighbors



T. El Paso Local Moran's I: Zone of Indifference



Curriculum Vita

Ileana Morales is an El Paso, Texas native. During her undergraduate and graduate studies, she obtained the NOAA Educational Partnership Program/Minority-Serving Institutions award for Earth System Sciences and Remote Sensing Technologies. After earning her Bachelor of Arts in Sociology and a Minor in Psychology, she became interested in environmental sociology. During her last semester as an undergraduate student, she got accepted into the Latin American and Border Studies master's program. During her graduate studies, she worked with Dr. Josiah Heyman and in collaboration with the city of El Paso to investigate urban heat perceptions of local residents. She also worked as a graduate research assistant under the supervision of Dr. Josiah Heyman. During her graduate studies, Ileana also acquired her geographical information system (GIS) certificate. Through her skills and knowledge acquired during her undergraduate and graduate studies, Ileana is devoted to creating a more equitable and just environment for those experiencing environmental inequalities. She hopes to achieve this by furthering her academic career and starting her Ph.D. in Sociology at CU Boulder in Fall of 2023.