SPATIAL MISMATCH BETWEEN HIV INFECTION AND ACCESS TO HIV SERVICE FACILITIES IN TEXAS

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Since 2004, the number of people living with HIV (PLWH) has steadily increased by about 5% and currently, the number in Texas is about 86,000. Though the National HIV/AIDS Strategic Plan seeks to ensure “unfettered access to quality healthcare”, barriers to access still exist especially among minority populations. This study examines the relationship between HIV infection rates and the geographic location of HIV service centers with a focus on 4 counties: namely, Dallas, Denton, Harris and Tarrant. The goal is to show whether there is a spatial mismatch between HIV rates and service providers. Are service facilities located in zip codes where they are most needed?

Using the vulnerability framework and the Inverse Care Law (ICL), we address the research question using demographic variables (race/ethnicity, sex, poverty, education attainment) and HIV data. Our results show that extreme vulnerable zip codes have high HIV rates and closest proximity to HIV service providers.

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CHAPTER 1

INTRODUCTION

Human immunodeficiency virus (HIV) was first reported in the United States in 1980. For 33 years, about 600,000 people have died from the disease (ONAP, 2010). The US Centers for Disease Control and Prevention (CDC) estimates that 1,178,350 people were living with HIV/AIDS in the United States in 2008 (CDC, 2011), but twenty percent of these people is unaware of their infection (CDC, 2010). HIV infection has become more of a chronic infection than the terminal disease it used to be (TDSHS: HIV/STD, 2012; Levi & Kates, 2000) and particularly with the introduction of the Highly Active Antiretroviral Therapy (HAART) in 1995, infected people are living much longer (CDC, 2011; Levi & Kates, 2000; TDSHS, 2011; TDSHS: HIV/STD, 2012). While HAART has prolonged and improved the quality of people's lives, access to HAART or any form of HIV medical care is not uniformly distributed in space.

HIV mortality is high among the poor due to their poor access to quality health care (Levi & Kates, 2000). The unequal distribution of HIV infection across race/ethnic lines, sex, mode of spread, age, socioeconomic status, access to quality care, and insurance suggest the existence of some vulnerable populations. According to the Institute of Medicine (2002), minority populations regardless of health insurance have poor access to healthcare. In a state which is a "minority-majority" (i.e., percent Black + percent Hispanic is more than percent White), poor access to healthcare for minorities may result in high rates of any kind of disease including HIV (Mullins et al., 2005).

HIV infection is highest in the metropolitan areas of Texas including Houston, Fort Worth and Dallas. Based on total population, new cases of HIV infection and need for HIV funding for treatment, Dallas, Houston and Fort Worth have been classified by the Health Resources and

Services Administration (HRSA) as Emerging Metropolitan Areas (EMAs) and Transitional Grant Areas (TGAs) (TDSHS, 2012). Consequently, more than half of the PLWH in 2010 lived in Dallas and Houston EMAs. EMAs and TGAs also had the highest rates of HIV infection compared to the places which were not classified as such and thus bringing into question the issue of access to quality HIV care in these metropolitan areas. Whereas Houston has the most HIV service centers within the study area, the Houston EMA recorded the highest HIV prevalence rate of about 393.1/100,000 whilst the region with the lowest rate was along the border counties and other rural parts of Texas. Fort Worth TGA had the lowest rate among the EMAs and TGAs with 184.9/100,000.

This paper applies the vulnerability framework to examine whether there is a spatial mismatch between HIV service centers and HIV infection. It uses access to HIV service facilities and HIV rates to show whether people who need HIV service have access to it. What is the geography of HIV rates and of the location of service centers in the study area? The Inverse Care Law (Hart, 1971) suggests that quality health care is inversely related to the population who need it. Hence, people who need medical care the most are often those with the least access to it. Is the Inverse Care Law relevant in the study area? Using explanatory variables such as race/ethnicity, poverty rate and education, we analyze how these different demographic variables influence the spatial variation in access to HIV care. We argue that adverse conditions which make people susceptible to HIV infection are not distributed equally in space and will further influence HIV rates and access to service facilities.

CHAPTER 2

LITERATURE REVIEW

The first reported case of HIV in the United States was in 1980. In July 2010, the government set up the National HIV/AIDS Strategy (NHAS) to ensure better results in dealing with the infection. The vision of this comprehensive action plan targeted for 2015 is to make the United States:

"… a place where new HIV infections are rare and when they do occur, every person regardless of age, gender, race/ethnic, sexual orientation, gender identity or socio-economic circumstances will have unfettered access to high quality life-extending care, free from stigma and discrimination." (ONAP, 2010)

In ensuring the success of this strategy, a number of goals have been set which includes: reducing new infections by 25%, increasing access to HIV care and improving health of people already living with the disease as well as reducing HIV care disparities (ONAP, 2010; Yehia & Frank, 2011). Knowledge of the geography of HIV rates, HIV service centers and access is therefore critical if these targets are to be achieved.

2.1 Access to HIV Service Facility

Access is essential for efficient healthcare delivery yet it is not clearly defined (Aday & Anderson, 1974; Penchansky & Thomas, 1981; Guagliardo, 2004; Cromley & McLafferty, 2002). It is not surprising that, *The Discursive Dictionary of Health Care* published by the U.S. House of Representatives at a point could not even define healthcare "access". Accessibility, availability and acceptability were difficult to separate thus the difficulty in coming up with a good definition for health "access" (Penchansky & Thomas, 1981). Access is defined both as a verb and a noun, thus a multidimensional concept (Cromley & McLafferty, 2002). The Oxford

English Dictionary (2012) defines access as the opportunity to benefit from a service (noun); or as a verb, to gain admission to something. The verb definition of “access” has been used by some researchers in healthcare studies to mean entry into a facility (Salkever, 1975). In the context of health, access can be grouped under 2 broad categories: spatial and aspatial access. Spatial access describes geographical measures such as travel distance, and travel time necessary to get to a facility whilst aspatial access looks at the socioeconomic aspect of healthcare delivery such as costs of healthcare (Guagliardo, 2004), health insurance, among others.

This research defines access to HIV service facility/center as the “potential for healthcare use and the act of using healthcare” (Guagliardo, 2004; Penchansky & Thomas, 1981). According to Guagliardo, there is a potential for healthcare access if a population (demand) has a facility (supply) within its borders that is willing to offer services. A service facility is “used” after all barriers have been overcome which include cost, availability of facility, travel distance, among others. In their seminal work on *The Concept of Access (1981),* Penchansky and Thomas identify availability, accessibility, affordability, accommodation and acceptability of a service facility as critical components of access. To them, access describes “a fit between the patient and the health care system”. Essentially, how we define access to health facilities for instance will determine how we respond to the health needs in those places.

Accessibility is the geographic distance between a health care facility (supply center) and a population in need of health care (demand center). For accessibility to exist there should first be the existence of a health facility which is willing to offer services to the population in need. This concept is what they termed availability. Adversely, affordability is defined as the relationship of price of services of health care to health insurance, median income of the patient. Again, this is to show whether the patient can afford the cost of that health care he is receiving.

Accommodation refers to how the facility is setup to receive clients such as: working hours, language, how they treat patients, among others. Acceptability refers to clients attitudes towards the facility vis-a-vis the facility's acceptable characteristics of clients. Some variables used to show acceptability are age, sex, and race/ethnicity.

Our research applies the first 3 dimensions of access: availability, accessibility, and affordability. Of these accessibility and availability are spatial whilst affordability is aspatial. We limited our access definitions to these 3 due to data available to us for this research. Analyzing accommodation and acceptability will require detailed information on clients' behavior and the facilities in our study area. This dataset is unavailable to us now.

Previous research on healthcare access has predominantly focused on the aspatial component with much emphasis on the economic cost of a disease and health insurance (Betancourt & Maina, 2004; Guagliardo, 2004; Levi & Kates, 2000; TDSHS, 2012). Consequently, most works on spatial accessibility to healthcare have been in the rural areas with very little in the urban centers (Chan et al., 2006; Huang et al., 2009; Guagliardo, 2004). Accordingly, comparable research on urban accessibility is needed.

Emphasis on access to healthcare has been a priority since the 19^{th} century (Hunter et al., 1986; Guagliardo, 2004). Easy access to healthcare has been found to correlate positively with better health outcomes (Chan et al., 2006; Guagliardo, 2004). In a study on women's access to mammogram facilities in Kentucky, Huang et al. (2009) identified that rural women with longer travel distance reported worse breast cancer diagnostic outcomes compared to their counterparts residing in the urban areas who had shorter distances to mammogram facilities. Similarly, Fortney et al. (1995) confirmed that travel distance impacts health outcomes: the closer one is to the facility, the better their health outcome is. Chan et al. further add that, certain people will not use a health facility which is over 20 miles away even if it was free. However, travel distance does not constrain those who have the means to access better healthcare, such as seeing a specialist at a farther distance. Research suggests that, patients who seek HIV treatment from specialist physicians have a better chance of undergoing HAART early and surviving for a longer time compared to those who meet generalist physicians (Heslin et al., 2004). Hence, longer travel distance to see a specialist physician will not necessarily mean poor access to health facility.

Access to HIV care is a key goal in the 2010 NHAS which is to be achieved by 2015. These goals are meant to help the country reduce the disease burden on both government and patients by reducing access difficulties. For instance, by 2015, the NHAS expects to increase the number of patients who receive clinical care within 3 months after diagnosis from the current 65% to 85%. Also, to help support needy patients, the strategy aims to increase the number of patients who receive permanent housing support from the Ryan White program by 4% (ONAP, 2010).

Congress first enacted Ryan White CARE (Comprehensive AIDS Resources Emergency) Act in 1990 which has later become known as the Ryan White Program. It has undergone 4 legislative amendments and reauthorizations (1996, 2000, 2006 and 2009) (HRSA, 2013 (d)). Also, it is the largest federally funded program focusing on HIV/AIDS in the United States and its territories. The program provides HIV related services to people who cannot afford HIV treatment due to insufficient financial resources (HRSA, 2013 (a)). In addition, the program works with cities, states and other organizations to provide these HIV related programs to about half a million people annually. Funds from Ryan White mostly support primary medical care with little for technical assistance. Per the Ryan White legislation, the program is divided into 5 main parts namely: A, B, C, D and F. Part A offers emergency assistance to Emerging Metropolitan Areas

(EMAs) and Transitional Grant Areas (TGAs) (HRSA, 2013 (c)) whilst part B provides funding for all 50 U.S. states including the District of Columbia, Puerto Rico, U.S. Virgin Islands, Guam and other territories in the pacific. Additionally, part C provides comprehensive primary care for PLWH and part D offers a family oriented HIV care for women, infants, children and others with the infection. Finally, part F provides funding for various programs (HRSA, 2013 (b)).

Adversely, minority populations usually have low median incomes, low education, high percent poverty, no health insurance, high unemployment rate, among others which further contribute to their poor access to health care resulting in very poor health results (Ryn & Fu, 2003; Levi & Kates, 2000; Heslin et al., 2004; Mullins et al., 2005). Inequality in access to health care is explicitly shown by a national study conducted by the Institute of Medicine in 2003. In the said report, minority populations face discriminations even during clinical trials.

2.1.1 Measuring Accessibility

Measuring access to a service facility is difficult to define (Cromley & McLafferty, 2002; Penchansky & Arday, 1981). Geographical accessibility considers the spatial aspects of access usually using measures such as travel distance and travel time. Previous literature show that travel distance is the commonest measure of spatial accessibility (Hewko et al., 2002; Chan et al., 2006; Guagliardo, 2004; Huang et al., 2009; Oppong & Hodgson, 1997). Using location allocation models, it is assumed people will travel to the nearest facility for service utilization (Oppong & Hodgson, 1997) but other factors may cause a person to bypass a facility located within reach for a distant one. Factors such as income, health insurance, access to transportation, terrain, climate, type of care needed (primary or specialty care), stage of infection, anonymity, among others may influence whether a person uses the closest or farthest facility. The poor person is likely to attend a facility which is within reach than to go to a distant location for health care (Cromley & McLafferty, 2002) whilst the rich can afford to go the extra mile to seek quality service. Additionally, research also suggests that patients are likely to forgo health care stationed outside a 20 mile radius even when it is free (Chan et al., 2006). As distance increases, people are unlikely to access a service facility unless the facility has a huge attractiveness. Attractiveness in this case is defined using the quality of service and range of services provided, price, among others (Cromley & McLafferty, 2002). Measuring spatial access to HIV/AIDS service facilities like other health care goes beyond the physical locations of demand (population at risk) and supply (health facilities).

Though travel distance is an easy measure of accessibility, the Euclidean distance approach like other methods is not without limitations (Guagliardo, 2004; Chan et al., 2006; Huang et al., 2009; Hewko et al., 2002; Oppong & Hodgson, 1997). Ideally, sparse rural lands allow the use of this method as a measure of spatial accessibility because it measures distance from the zip code centroid to the nearest facility which in most cases is miles away from the place of residence. On the other hand, closely packed urban centers make computing travel distance difficult because, distance from a zip code centroid to a facility within that same zip code will be zero though there is some distance covered. Freyer et al. (1999) suggest that all distances need to be considered when using this approach as a measure of spatial accessibility thus zero limits our ability to predict exact distances. However, per our data which is at the zip code level, it is appropriate to use the spatial join method in the join function of ArcMap to get Euclidean distances from zip code centroids to nearest facilities.

Other researchers have used the network analyst tool in ArcGIS to develop travel time, distance and even cost to closest facility. This approach has been found to be a better measure than the regular Euclidean distance because it reflects the geography or terrain of the area. The widely used spatial accessibility method has been the use of the gravity model especially in locating and allocating facilities to demand areas. This is because it reduces the likelihood of overestimation or underestimation of distances. According to the model, a person's access to a service facility is directly proportional to its attractiveness and inversely proportional to its distance. To compute this, one needs a very fine level data such as number of physicians, number of hospital beds or nurses (Guagliardo, 2004; Oppong & Hodgson, 1997) to represent the service capacity. Again, we could not go this route due to data challenges.

2.2 HIV Infection in Texas

About 86,000 people are living with HIV in Texas out of which 17,000 are unaware of their status (TDSHS: HIV/STD, 2012) thus confirming CDC's statement that about 20% of PLWH are unaware of their status. Between 2005 and 2011, the number of PLWH increased from 51,938 to 69,212, representing 34% increment and a steady increase in the number of PLWH by about 5% per year since 2004 (TDSHS, 2012). Increase in the number of PLWH has been attributed to improvements in the healthcare system (TDSHS, 2012; Levi & Kates, 2000 ;). Despite these improvements in healthcare, Texas still recorded about 4180 new cases and 1470 deaths during the last 7 years. HIV infection is not uniformly distributed across Texas as mortality rate is high among minority populations especially Blacks. This brings to question whether HIV/AIDS is a minority disease (Dean et al., 2005; Madden et al., 2011; TDSHS, 2012; TDSHS: HIV/STD, 2012; Betancourt & Maina, 2004; CDC, 2011). Though Blacks comprise just 12% of the Texas population, they represent 38% of PLWH in Texas (TDSHS, 2012).

2.2.1 Geography of HIV in Texas

Texas is only behind Alaska and California in terms of land mass and population respectively (TDSHS, 2012). The vast nature of the state coupled with its rapid minority population (especially Hispanics) and economic growth create good conditions for increase in HIV infection. Metropolitan areas, areas of high minority presence, Texas Department of Criminal Justice (TDCJ) units are among places which normally have high HIV infection rates (TDSHS, 2011; TDSHS, 2012). Among the metropolitan areas, Houston and Dallas over the period have recorded the highest cases of HIV infection in the state. According to the Texas HIV Second Quarterly Report of 2012, health regions 3 and 6 reportedly had the most HIV infections from January to June 2011 and 2012. Health region 3 contains the DFW Metroplex whilst health region 6 contains the Houston Metropolitan area. For the period under review, region 3 reported 654 and 614 cases of HIV infection for 2011 and 2012 respectively. Region 6 on the other hand reported 715 and 734 cases for the same period. It is not surprising that regions 3 and 6 altogether formed over 50% of the HIV infection cases in Texas for the periods January to June 2011 and 2012 (TDSHS, 2012) and this has been the case for previous years as captured by the quarterly reports. Overall, cases for HIV infection are high in all the big cities in the state: Austin, San Antonio, El Paso, Dallas, Houston and Fort Worth. HIV in the rural parts of Texas is usually low compared to those from the urban centers.

Other areas such as the Colonias and East Texas compared to the other regions within the state happen to have high HIV infection cases due to the high minority populations in those places. That notwithstanding, TDCJ facilities also reportedly have high HIV cases. Using population and number of HIV cases within places, the Health Resources and Services Administration (HRSA) classified some places as either EMAs or TGAs. In Texas, 5 out of the 6 cities with a population of over 500,000 together with their surrounding counties have been classified as either EMA or TGA. The growing new cases of HIV in these areas make this classification important as it is also geared towards helping in effective resource allocation for PLWH who rely on the Ryan

White program for HIV medical care. Hence, there is the Dallas EMA, Austin TGA, Houston EMA, Fort Worth TGA and the San Antonio TGA. Out of the 65,077 PLWH in Texas in 2010, Dallas EMA and Houston EMA comprised 56% (TDSHS, 2012). Aside the EMAs and TGAs, only TDCJ units, US-Mexico Border and East Texas had 6% each of PLWH in 2010 with the remaining regions recording 3% or less (TDSHS, 2012).

Table 1 PLWH in Texas by Region, 2010

Region	Number of Cases	Percentage
Houston EMA	20,824	32%
Dallas EMA	15,618	24%
Austin TGA	4,555	7%
San Antonio TGA	4,555	7%
Fort Worth TGA	3,905	6%
TDCJ	3,905	6%
East Texas	3,905	6%
US-Mexico Border	3,905	6%
North & Central Texas	1,952	3%
South & West Texas	1,302	2%
Panhandle	651	1%

2.2.2 Mode of Exposure

People are exposed to HIV infection differently. From 2004 to 2010, men who have sex with men (MSM) has been the dominant mode of exposure of HIV representing about 55% of PLWH in 2010, having increased from 52% in 2004. This is followed by injection drug use (IDU) and heterosexuals which compose 14% and 24% respectively (TDSHS, 2012). Between 2004 and 2010, IDU has decreased steadily by more than 15% whereas MSM increased by 3% within the same period. Different race/ethnicities tend to be exposed to the infection differently. Whereas the Hispanic population is more likely to be exposed to the disease through heterosexual means, Blacks are likely to contract that through IDU. Going by the current trend with regards to mode of exposure as well as increase in the Hispanic population of Texas, Heterosexuals as a mode of exposure to HIV is likely to increase slightly until something is done to control the rate of HIV infection and Hispanic population growth in the state.

2.3 Place Vulnerability and HIV in Texas

Vulnerability is woundability. When a person is vulnerable, he or she is susceptible to a potential loss of life or property from hazards (Cutter et al., 1997). Rao & Thakur (2007) define it as “able to be easily hurt”. Others have defined the concept of vulnerability as both internal and external acquaintance to risks and shocks (Kantor & Nair, 2005; Chambers, 1988). Vulnerability varies across geographical space, time and does not occur randomly (Oppong & Harold, 2009; WHO Bulletin, 2005; Rao & Thakur, 2007; Cutter et al., 2003). Most of previous literature on vulnerability has focused on vulnerable populations but little has been done on vulnerable places. For instance, Cutter et al. (2003) in their paper on *Social Vulnerability to Environmental Hazards,* created a social vulnerability index (SVI) to show the variations in vulnerability at county level in the United States. This idea stems partly from the fact that, little research has been done in the area of social vulnerability. Prior to this research, Cutter et al. (1997) created a social vulnerability index for vulnerable populations using census blocks for the entire country. Demographic and other socioeconomic variables such as age, race/ethnicity, median income, health insurance, type of dwelling units have been mostly used as a means of measuring vulnerability (Oppong & Harold, 2009; Cutter et al., 2003; WHO Bulletin, 2005; Rao & Thakur, 2007; Kantor & Nair, 2005;).

Whereas some of these variables increase vulnerability, some decrease it. For instance, increased percent Black and Hispanic populations in a zip code is likely to increase vulnerability. Also, high poverty rate and low educational attainment increases vulnerability whereas low poverty or high median income decreases it. These variables are not uniformly distributed in space thus creating an environment of social and spatial inequalities which are further associated with social vulnerability. Using the social vulnerability framework, Cutter et al. (2003) contextualized the idea of place vulnerability to be the overall interaction between the social and biophysical vulnerabilities in a place. Thus place vulnerability takes into account the holistic susceptibility of a spatial unit not only limiting it to the populations living in there.

Oppong and Harold (2009) contend that vulnerability is tied to a place. Vulnerable people create their vulnerability in space. Residents in vulnerable places are likely to be poor, with low level education, no health insurance and low median income. The men are likely to be unemployed and will thus do anything to survive. These conditions intertwined with other behavioral and environmental factors create adverse life conditions which increase the risk of dwellers for contracting health infections including HIV. For instance, a study conducted in 1993 showed that poverty and unemployment were highly responsible for the high HIV/AIDS prevalence in Ghana (Adjei et al., 1993).

Research also suggests that vulnerability is dire at the poorest parts of metropolitan areas (Cutter et al., 2003). Within vulnerable places are more vulnerable places. In fact, Cutter et al. (2003) found the most vulnerable spatial units clustered in the metropolitan areas especially in east and south Texas. What in east or south Texas makes those places more vulnerable? Probably the high percent Black and Hispanic populations coupled with the low socioeconomic status among these race/ethnic groups might be important factors to consider.

2.3.1 Race/Ethnicity

Race/ethnic minority groups are known to have very poor access to health care (Heslin et al., 2004; Ryn & Fu, 2003) which translates into poor health outcomes. For both communicable and non-communicable diseases in the country, minority populations seem to have the largest share of mortality and prevalence rates. In fact, a report by the Institute of Medicine in 2004 stated that 3 out of the 5 large landfill sites in the country are located in minority communities which increase their risk of asthma in the area. In the same report, minority patients were more likely to receive little analgesic medication for bone fractures and cancer. In the light of the above, minority populations with health insurance are even treated below par compared to their White counterparts (Heslin et al., 2004; Betancourt & Maina, 2004; Montoya et al., 1999). Also, Cunningham et al. (2007) show that, minority race/ethnic groups receive fewer HIV services which includes HARRT. HIV/AIDS unequally affects minority populations in the country (TDSHS, 2012; Dean et al., 2005; Levi & Kates, 2000). Out of the about 348,799 PLWHA in 2003, 61% were from minority race/ethnic groups (Dean et al., 2005).

From 1981 when the first case of HIV was reported in the country to now, the infection has more significantly affected the minority race/ethnic groups than it has the White populations. For instance, between 1981 and 1982, only 37% of about 400 diagnosed cases of AIDS reported by the CDC were from minority populations yet, about 78% of estimated 43,171 cases in 2003 were in minority communities (Dean et al., 2005).

Between 2004 and 2007, HIV/AIDS cases increased substantially among all the race/ethnic groups in Texas from 11,530 to 17,274 for Hispanics, 17,820 to 21,876 for Whites and 17,993 to 24,938 for Blacks. Much of the increase in cases of PLWH came from the Hispanic populations. However, rate for the infection was very high among the Black populations. Whereas rate of PLWH was 852.4/100,000 for Blacks, that of Hispanics was 175.4/100,000 whilst Whites recorded 191.2/100,000 (TDSHS, 2012). HIV disproportionally affects Blacks in Texas. Over the past 7 years, HIV rates for Blacks are about 2 - 5 times higher than that of Hispanics and Whites. Though Blacks make up 12% of the state's population, they comprise about 40% of new cases and 38% of HIV prevalence in Texas (TDSHS, 2012; TDSHS: HIV in Blacks, 2013).

Vulnerable conditions such as low incomes, no insurance, low education can be said to contribute to these high rates among the minority populations. Despite the decline in the rate of HIV incidence among the Black population in Texas between 2004 and 2011, the fact still remains that 1 in 117 Black is living with HIV which adds up to about 27000 Black Texans with the infection (TDSHS: HIV in Blacks, 2013). Similarly, a research which analyzed HIV/AIDS and AIDS diagnosis data from 1999 – 2003 for 32 states found increasingly high diagnosis rate among Blacks non- Hispanic populations than other race/ethnic groups (Dean et al., 2005).

2.3.2 Socioeconomic Status (SES): Education and Poverty

Low Socioeconomic Status (SES) is associated with mortality of almost every disease (McFarland et al., 2003). Education and poverty are key indicators for measuring a person's socioeconomic status. It is most likely that people with low level of education will have low socioeconomic status, low income, no health insurance and further result in high rates of any kind of disease (TDSHS, 2012) holding all other variables constant.

2.3.2.1 Education

All over the world, knowledge about a disease helps in making informed decisions regarding ways to avoid contracting it. In the United States, previous research suggests that people with more education tend to have better health compared to those with less education. In fact, low level education has been associated with high mortality rate for almost every disease (TDSHS, 2012). People with less than high school education in Texas are those with the highest HIV mortality rates. Minority race/ethnic groups in Texas are the ones with high percent less than high school education and thus reflective of their HIV mortality rates. As of 2009, percent White population had the highest level of education with about 92% with at least 9th grade education whilst that of Blacks and Hispanics was 86% and 60% respectively.

As part of the vulnerability index calculation, we added percent of the population with a bachelor's degree since this has been found to decrease vulnerability.

2.3.2.2 Poverty

Poverty is an important factor in the development of every disease and it is tied to health (Murray, 2006; Wagstaff, 2002), yet it increased steadily from 2009 to 2011 in Texas (Census Bureau, 2012). Poverty limits the chances of individuals from seeking preventive care and even accessing available health care. Some even consider poverty as "the number one killer in the world today" (Rowson, 2001). In the United States where almost every individual needs a health insurance for efficient health care, poverty makes it near impossible for such people to receive HIV care. According to the CDC, poverty is the single most important variable for explaining HIV infection and HIV mortality in the country. Besides, HAART which has contributed to prolonging the lives of PLWH (Levi

& Kates, 2000; McFarland et al., 2003) is not cheap to use. Levi & Kates (2000) estimate the cost of an annual HAART to be between $10,000 and $12,000. Whereas the rich can easily afford this efficient treatment, the poor and vulnerable are often unable to access it (Levi & Kates, 2000) thus leading to a higher rate of mortality (Murrain & Baker, 1997).

2.3.3 Median Income

Median Income is related to health care (Wagstaff, 2002) and access to health care is usually tied to the income of the person involved. People with high median income are likely to have health insurance which is very vital to receiving treatment (McFarland et al., 2003). Low income people are less likely to have health insurance since they are constrained by limited resources to only fend for themselves and not necessarily seek preventive care. With an increasing rise in health care costs in the country, low income people are likely not to have health insurance and thus unable to access HIV care (Murrain & Baker, 1997). In 2008, Texas was the state with the highest proportions of uninsured residents but this was not uniform either. Blacks and Whites were tied at 26% for percent insured whilst the rate was 37% for Hispanics (TDSHS, 2012). Essentially, low median income makes it harder for a person to travel to access quality health care.

2.3.4 Employment Status

Employment status influences a person's susceptibility to health in a lot of ways. When a person is employed, he is able to afford good health care, live in a less vulnerable environment and even eat well. Previous research shows that, there is a positive relationship between employment and good health, all other things held constant. That is to say, an employed person can access health care in the event that he falls sick compared to an unemployed person. HIV is an infection which requires lots of money if one wants to survive longer. It is in this quest that a number of governmental and non-governmental organizations are helping people gain access to quality care. It is estimated that the annual cost of HAART for 2010 was $23,000 (CDC, 2012) thus making it difficult for people with no support to live longer with the infection. Consequently, instead of going for social support as offered by Medicaid, Ryan White program among others, people out of fear of been stigmatized will not access these social supports (Schuster et al., 2000; Sowell et al., 1997; Montoya et al., 1999) thus putting them in a dire situation. Also, unemployed PLWH have a higher risk of HIV mortality than those who are employed (Cunningham et al., 2005). Additionally, unemployed PLWH are less likely to follow-up on HIV treatment which is essential for containing the infection (Jones et al., 2005).

2.3.5 Means of Transport

Easy access to transportation facilitates accessibility to health facilities including HIV service providers. Early access to HIV services has proven to reduce the cost of treatment of the infection (Montoya et al., 1999; Levi and Kates, 2000). Previous studies suggest that people with poor access to transport are less likely to seek regular HIV care and thus are more vulnerable to HIV (Kempf et al., 2010). For instance, a study conducted in Harris County focusing on access to HIV services among the 3 main race/ethnic groups found lack of transportation to be an important factor which limits their access to these facilities. Among the Hispanic population, 43% of respondents said transport was their frequent problem whilst African American respondents said 34% of their problem was lack of transport and 20% for Whites (Montoya et al., 1999). In the same research, Hispanics diagnosed with AIDS were likely to be having transportation problems.

A related research conducted in 23 counties in southeastern Alabama also showed that transportation was a huge impediment to accessibility to HIV facilities. This is even worsened by increased distances to the facility and price hikes in transportation fuel (Kempf et al., 2010). In cases where PLWH have been provided with transportation vouchers or money for transportation, visits to HIV service facilities have improved and little did these people miss their appointments (Kempf et al., 2010; Jones et al., 2005)

2.4 Inverse Care Law and HIV in Texas

The Inverse Care Law (ICL) suggests that there is an inverse relationship between availability of quality health care and the population within which it serves (Hart, 1971). In other words, persons or places which need health care the most are those likely not to have access to it.

From the surveyed literature, we ask the following questions to help address some of the areas among HIV infection and access to service centers. So far, no research has addressed the issue of the ICL with HIV infection and access to service facility. We therefore explore that area to see whether ICL is even applicable to our research. Also, though some work have been conducted on spatial accessibility to health care facilities and diseases (especially breast cancer), very little has been done on HIV infection and service facilities especially in Texas. Again, we show where HIV service facilities are located within the study area since not all service providers are health care facilities. However, the primary objective is to see whether there is a spatial mismatch between access to HIV service facilities and HIV infection in the study area.

2.5 Research Questions

1. *What is the geography of HIV service facilities and HIV infection rates in the study area?*

HIV service facilities vary in size, function, and numbers across space. Whereas some offer only testing services, others provide HIV education, pantry services, shelter, financial assistance as well as free legal service. There are others which offer more than one service too.

2. *Does the Inverse Care Law apply to HIV services?*

   The inverse care law says available good health care is inversely related to the population in need.

   Hypothesis 1: *HIV service facilities will be located in zip codes with low HIV rates.*

   Since ICL just looks at availability of good health care, we expect zip codes with high presence of HIV service facilities to have the lowest HIV rates and vice versa.

3. *Does access to HIV service facilities vary with neighborhood characteristics?*

   Vulnerable neighborhoods and populations attract diseases and usually have worse access to health care resulting in high morbidity and mortality rates. A vulnerable neighborhood is unable to fight off diseases. Socioeconomic and demographic variables such as education, median income, poverty rate, marital status, employment status, age, race/ethnicity, either increases or decreases a person's or place's vulnerability to accessing health care. Hence the following hypotheses:

   Hypothesis 2: *Zip codes with high percent below poverty level will have poor accessibility to HIV service facilities*

   Previous studies draw a strong linkage between poverty and HIV. Though there have been varying views on SES and HIV rates, most literature maintain that poverty stricken areas often have high HIV rates compared to less poor areas. Poor people are less likely to afford the regular checkups and cost of medication associated with HIV treatment. In that regard, we expect zip codes with high percent poverty rates to have high rates of average HIV rates.

Hypothesis 3: *Zip codes with low median income will have worse access to service facilities*

People with low median income are less likely to have health insurance and are thus most vulnerable to high rates of HIV. We expect those zip codes with low median income to have very poor access to HIV service facilities.

Hypothesis 4: *More vulnerable areas will have worse access to HIV service facilities.*

Vulnerability is not uniformly distributed. A concentration of vulnerable variables will create an extremely vulnerable areas compared to places with less of such variables.

4. *Does access to transport influence susceptibility to HIV rates?*

Previous research suggest that people without easy access to transport usually miss health care appointments and are less likely to go for regular medical checkup. We expect zip codes with better access to transportation to have less susceptibility to HIV rates whilst zip codes with poor transport access to have increased HIV rates.

CHAPTER 3

STUDY AREA AND METHODOLOGY

3.1 Study Area

This study is situated in four counties in Texas namely: Dallas, Denton, Harris, and Tarrant. The study area (fig 1) contains some of the largest cities in Texas and is also home to lots of the PLWH in the state. According to the TDSHS, Houston EMA and Dallas EMA constituted a little over 50% of all PLWH in 2010. Houston and Dallas are 2 of 6 cities in Texas with over 500,000 people. These counties, especially Dallas, Harris, and Tarrant also happen to have a large number of HIV service centers in the state.

Dallas County has a population of about 2,368,139 and covers a landmass of about 871.28 square miles. Dallas has 26 cities including Addison, Cedar Hill, Dallas, Garland and Irving. The City of Dallas is the most dominant city in the county with a population of about 1,197,816 (City of Dallas, 2013). According to the 2010 Census report, the county has 807,621 households and 533,837 families. Hispanics constitute about 38.9% of the Dallas population whilst Whites make up 32.8% with percent Blacks being 22.5%. Median age in Dallas County in 2011 is 31 years whilst median household income for the period 2007-2011is $48,942. In addition, about 13.4% of the population is below the poverty level.

Denton County is about 30 minutes north of Dallas County. The County covers an area of about 878.43 square miles with a 2010 population of 662,614. Hence, Dallas County is about 3 times that of Denton County in terms of population size. Race/ethnicity in the county is predominantly White. About 63.7% of the population is White whereas 18.7% is Hispanic and 8.9% Black. In terms of education, about 40% of the population has Bachelor's degree or higher. There are about 231,355 households in Denton with an estimated (2007-2011) median household income of \$72,305 with 7.9% of the population below poverty level. The City of Denton which is the County's capital has a population of about 113,383 (2010). Meanwhile, median household income for the city was \$46,151 (2007-2011). Furthermore, about 36.5% of the population in the city of Denton have a Bachelor's degree or higher.

Harris County is located close to the southeastern coast of the state of Texas. It is one of the largest counties in Texas with a population of about 4,092,459. The county extends over a landmass of 1703.48 square miles. Unlike Dallas and Denton Counties, Harris County has a high percent Hispanic population of about 41.4% (2011). Percent White population is about 32.7% whilst percent Black population in 2011 is 19.3%. Although median household income (2007-2011) was \$52,675, about 17.3% live below the poverty level. Also, Harris has a huge presence of foreign-borns. Almost a quarter of Harris County residents were born outside the United States. The county is made up of 35 cities including Houston, Pasadena and La Porte. Houston is the largest city in Harris County with about half of the population of the county. In 2010, the city had a population of about 2,099,451 the following race/ethnicity distributions: 43.8% Hispanics, 25.6% Whites and 23.7% Blacks. The percent of the population below the poverty level was fairly higher than that of the county. Whereas the county reported about 17.3% below poverty level, Houston recorded 21.5%. Again, median household income was a little below that of the county. Houston's estimated income (2007-2011) was \$44,124 compared to \$52,675 for Harris County for the same period.

Adjacent Dallas is Tarrant County. In 2010, Tarrant had a population of 1,809,034 and covers an area of 863.61 square miles. About 51% of the population is White whilst Hispanics and Blacks constitute 27.3% and 15.3% respectively. The county has a median household income of about \$56,178 whilst 14.2% of the population lives below poverty level. In terms of education, about

28.9% of the population have bachelor's degree or higher. Fort Worth is the largest city in the county with a total population of 741,206. Median income in this city is estimated at about $50,456 whilst about 18% are living below poverty level. Table 2 below compares the study area averages to that of the state.

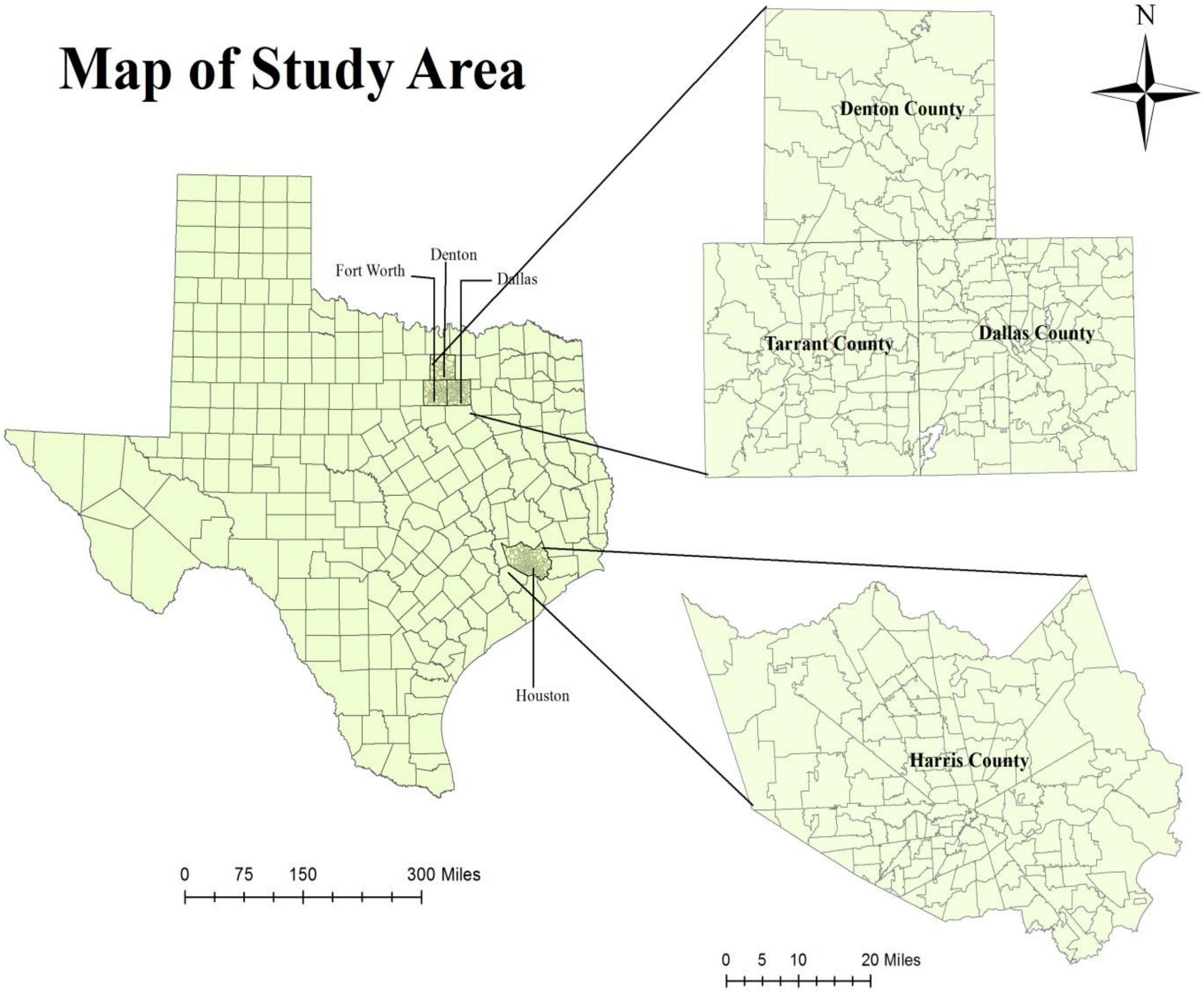

Figure 1 Map of Study Area

Table 2 Descriptive Summary of Study Area

Variables	Study Area Average	State Average
HIV Rate/100,000	4.82	16.7 (2010)
Poverty	22.3	18.5 (2011)
Percent <Grade 9	9.9	10
Median Income ($)	60,255.80	49,649.3 (2011)
Percent White	42.9	45.1 (2010)
Percent Black	17.6	11.5 (2010)
Percent Hispanic	32.3	38.8 (2010)

3.2 Data and Methodology

This study is conducted at the zip code level using Zip Code Tabulation Area (ZCTA) demographic information obtained from the Census Bureau. According to the Census Bureau, ZCTAs are not same as zip codes as delimited by the United States Postal Service (USPS); rather they are areal approximations of USPS's zip codes. The study area comprises 346 ZCTAs. Demographic data such as total population, race/ethnicity, median income, percent of adults 25 years and over with less than 9th grade education, percent below poverty level were thus downloaded from the census at the ZCTA level which is a finer spatial resolution compared to counties. Whereas the total population and race/ethnicity data came from the 2010 Census SF1 data, poverty, income and education was derived from the American Community Survey (ACS) 5 year estimate (2007-2011).

Data for HIV service facilities came from the Texas HIV/STD Community Resource Directory (2012). This directory which is a document from the TDSHS contains information on all HIV service facilities located in Texas as of the date of the publication. Facilities within the study area were thus recorded. In all, 145 facilities were identified in 74 zip codes. Most of the service centers in Texas are located in the study area.

Furthermore, the research used Geographic Information Systems (GIS) operations to conduct analysis in our study area. Geocoding, distance measures, choropleth maps and WebDMAP were undertaken using GIS. Geocoding is the process whereby street addresses are converted to XY coordinates to make them usable in maps. This process was made possible using TIGER street file downloaded from the US Census Bureau. Using US Address–Dual Ranges, we matched the street address of the HIV service facilities to the TIGER street file dataset. In the case where not all addresses matched, we manually geocoded the facility address using Google Earth.

Since spatial accessibility is an important element in this research, an efficient means for measuring distance from HIV patient to HIV service facility is equally important. We used the spatial join tool in Arc Map to calculate Euclidean distances from the centroid of the zip code to the closest service facility though this method also has some limitations.

Also, using ArcMap 10.0, we created choropleth maps to show the spatial distribution of the explanatory variables across the study area whilst we used WebDMAP for creating a smoothing map for HIV rates. A choropleth map uses shaded colors, graduated or proportional symbols which corresponds with the numerical attributes of variables been displayed. These maps were created using the quantiles classification method because it shows equal representation on the map and offers a clear differentiation among the different categories it offers on the map. Quantiles are also good for showing highly skewed data (Cromley and McLafferty, 2002).

WebDMAP is a web-based spatial analysis system which applies GIS functions and spatial analysis methods to help create continuous surface maps (Talbot et al., 2000; Tiwari and Rushton, 2010; Rushton, 2009). Disease burdens do not change abruptly across different spatial boundaries (Rushton, 2009; Tiwari and Rushton, 2005); there is generally a continuous distribution of diseases. A good approach to presenting disease rates is by using continuous surface/smoothing maps which eliminates the effect of ecological fallacy and small numbers problem. One key component of WebDMAP is its use of spatially adaptive filters. Spatial filters or kernels are usually circular in shape and placed at predetermined grid points which cover the entire study area. This helps in creating the continuous surface maps as the overlapping filters are the basis for the disease rate calculation (Tiwari and Rushton, 2009). In WebDMAP, disease rates are calculated by dividing disease cases (cases file) by the number of population controls (control file). Essentially, spatially adaptive filters control the size of the filters as urban centers have denser populations and thus more population controls than sparse rural centers and are thus more effective than the traditional spatial filters (Talbot et al., 2000; Tiwari and Rushton, 2005; Tiwari and Rushton, 2010). Small population sizes are largely responsible for small numbers problem which result in unstable disease rates. For instance: assuming both counties A and B have 10 HIV cases but county A has a population of 1000 whilst county B has 100. What happens is that, the rates (per 1000) for the counties will be 10 a 100 respectively. From this scenario, county B's low population has overestimated the disease rate thus making it unstable. Ecological fallacy is when a rate in one spatial unit (example: zip code, census tract) is assumed to be representative of the entire unit without accounting for spatial variations. WebDMAP further provides a better geographic detail.

HIV rates were calculated using the formula below:

$$\frac{([(Total\ Cases) \div \ \ Population\ at\ Risk\ \times 11\ years)] \times 100{,}000)}{11}$$

We use reported newly diagnosed HIV cases from January 1 1999 to December 31 2009. A total of about 38,866 individual cases were reported in the 11 year period. HIV data was then aggregated at the zip code level to make it easy for ZCTA analysis in ArcMap. Using

WebDMAP, we calculated the disease rates for each zip code within the study area. Throughout this research, the cumulative average HIV incidence rate will be referred to as HIV rate.

Using SPSS 20.0, we ran statistical techniques including kruskal-wallis H Test, spearman's rank correlation, shapiro-wilk test for normality, regression models, to provide an overall description of the dataset and association between the dependent and independent variables. The dependent variable for this research is HIV rate whilst the independent variables include race/ethnicity, median income, percent below poverty level, percent less than 9th grade education and distance from zip code centroid to HIV service facility. We used Spearman rho correlations to show the direction and strength between the independent and dependent variables. This method was arrived at after a normality test showed that the dataset was not normally distributed. A Kruskal-Wallis H Test was further used to show whether variations exist between and within independent variables in relation to HIV rates. The linear geographically regression (GWR) approach was used to model the relationship between the dependent and independent variables in the study area. We chose this method because it recognizes that relationship between the dependent and independent variables may vary in space and thus creates a model which accounts for varying relationships in every part of the study area.

In addition to the above, we created 3 indexes to show vulnerability and percent below poverty level within the study area. Using Weeks et al.'s (2007) approach for calculating slum index in Accra, Ghana, we created a vulnerability index (VI) to show susceptibility to HIV rate in the study area. We calculated the index using the following independent variables: median income, percent below poverty level, education (percent less than 9th grade and percent with bachelor's degree), race/ethnicity (percent White, Black and Hispanic), percent unemployment, percent employment, means of transportation (percent who own cars, trucks and van; percent who walk), percent males and females and HIV service facilities count. We first converted these variables into standard z-score values because of the different units the variables are in. We then summed up the z-scores for each zip code and found the average. This average then becomes the vulnerability index for that particular zip code. Essentially, zip codes with above average socioeconomic indicators will have less vulnerability to HIV whilst those with poor socioeconomic indicators will have high vulnerability to HIV.

Vulnerability Index (VI) = $\dfrac{\Sigma\,(z\text{−}scores\ of\ variables)}{Number\ of\ variables}$

After the VI was calculated for all zip codes in my study area, I grouped VI into 4 categories using the quantile classification method: -2.9 to -0.1 as less vulnerability, 0 as average vulnerability, .01 as high vulnerability and 0.2 to 0.6 as extreme vulnerability. From the research, it is clear that vulnerability is not uniformly distributed.

Using the poverty measure created by Kneebone et al. (2011), percent poverty in a zip code from 40% is categorized as extreme poverty, 20% - 39% is moderate poverty whilst below 20% is low poverty. Since poverty is an underlying factor for almost every disease, it will be interesting to see how the different poverty classifications influence rates of HIV and people’s access to service facilities.

Median Income, education, and distance were also classified to help us draw comparisons between different categories in the independent variables.

Table 3 Classification of Some Explanatory Variables

Median Income ($)	% less than 9th Grade Education	Distance (miles)
15,000-24,999	0-2	< 5
25,000-49,999	3-5	5 – 9
50,000-99,999	6-9	10 – 14
100,000-149,999	10-18	>= 15
150,000-199,999	19-39	

CHAPTER 4

ANALYSES AND RESULTS

4.1 Geocoding

Geocoding results varied across the study area. Dallas County recorded the highest for automatic match up with 87% whilst Denton County had the lowest of 67%. However, a manual approach was used to match most of the addresses which could not match automatically as shown in the table (4) below.

Table 4 Geocoding Results

Match Type							
County	Total	M	U(A)	M%	Tied	M(GE)	U (M)
Dallas	61	53	8	87	-	6	2
Denton	3	2	1	67	-	1	-
Harris	66	51	15	77	-	14	1
Tarrant	19	13	5	72	1	4	1

In the table 4 above, the column named total shows the number of HIV service facilities in the different counties within the study area. From the dataset, Dallas County has 61 facilities, Denton has 3, Harris has 66 and Tarrant has 19. The column named M represents the total number of facilities which were matched using the geocoding tool in ArcMap whilst U(A) means the number of facilities which were unmatched automatically. M% in the table means the percent of the total facilities which were matched automatically whereas the column Tied showed that more than one address in my spatial data matched a street address of a facility. After the automatic geocoding processes, I used Google Earth (GE) to manually match those addresses which were not matched by the ArcMap tool. Overall, 25 out of 29 addresses were matched using the manual approach. Hence about 3% (4) of HIV service facilities did not match with the address during the geocoding process.

4.2 HIV Service Facilities

HIV service facilities varied across the various counties as well as zip codes and offered varying services. Some of the services rendered by the facilities include: HIV testing, TB testing, pantry services, free legal advice, HIV street outreach, HIV education, peer education, financial support, shelter, personal skill development, among others. It would have been ideal to classify and analyze the facilities based on the type of services offered but we are limited in this regard by data. Though we could show where these different services are located, we have no knowledge about who uses which service and will therefore classify the different HIV service irrespective of their size, function and services as the same and equal in service provision.

Whereas some zip codes have as many as 8 facilities, most of them have 0. The table below shows that 272 zip codes out of 346 zip codes in the study area have no facilities whilst 49 zip codes have 1 facility.

Table 5 HIV Service Facilities in Study Area

Counties	**ZCTAs**	**Facilities**
Dallas	94	59
Denton	37	3
Harris	141	65
Tarrant	74	18
Total	346	145

Table 6 Percent Facilities in Study Area

Counties	Number of ZCTAs (%)	
	With F (%)	Without F (%)
Dallas	22 (23.4%)	72 (76.6%)
Denton	3 (8.1%)	34 (91.9%)
Harris	38 (27%)	103 (73%)
Tarrant	11 (14.9%)	63 (85.1%)
Total	74 (21.4%)	272 (78.6)

From the study area, HIV service facilities (Figures 2 and 3) are located in 74 out of 346 zip codes with 49% of these zip codes having only 1 facility. Harris County had the most service facilities with 38 whilst Denton County recorded 3 facilities. Most HIV service facilities are located at the central most parts of the Counties, usually in the zip codes with high percent minority populations and low median income.

Additionally, HIV rates are high in zip codes with HIV service facilities. From our analysis, whereas the mean HIV rate for zip codes without facilities was 3.34 per 100,000, those with facilities recorded 10.04 per 100,000 (more than 2 times that of the study area average). As of now, we cannot say the facilities are causing the high rates but our results suggest the presence of HIV facilities in an area correlates with increased HIV rates. Our spearman's rank correlation for HIV rates and service facilities was .432**.

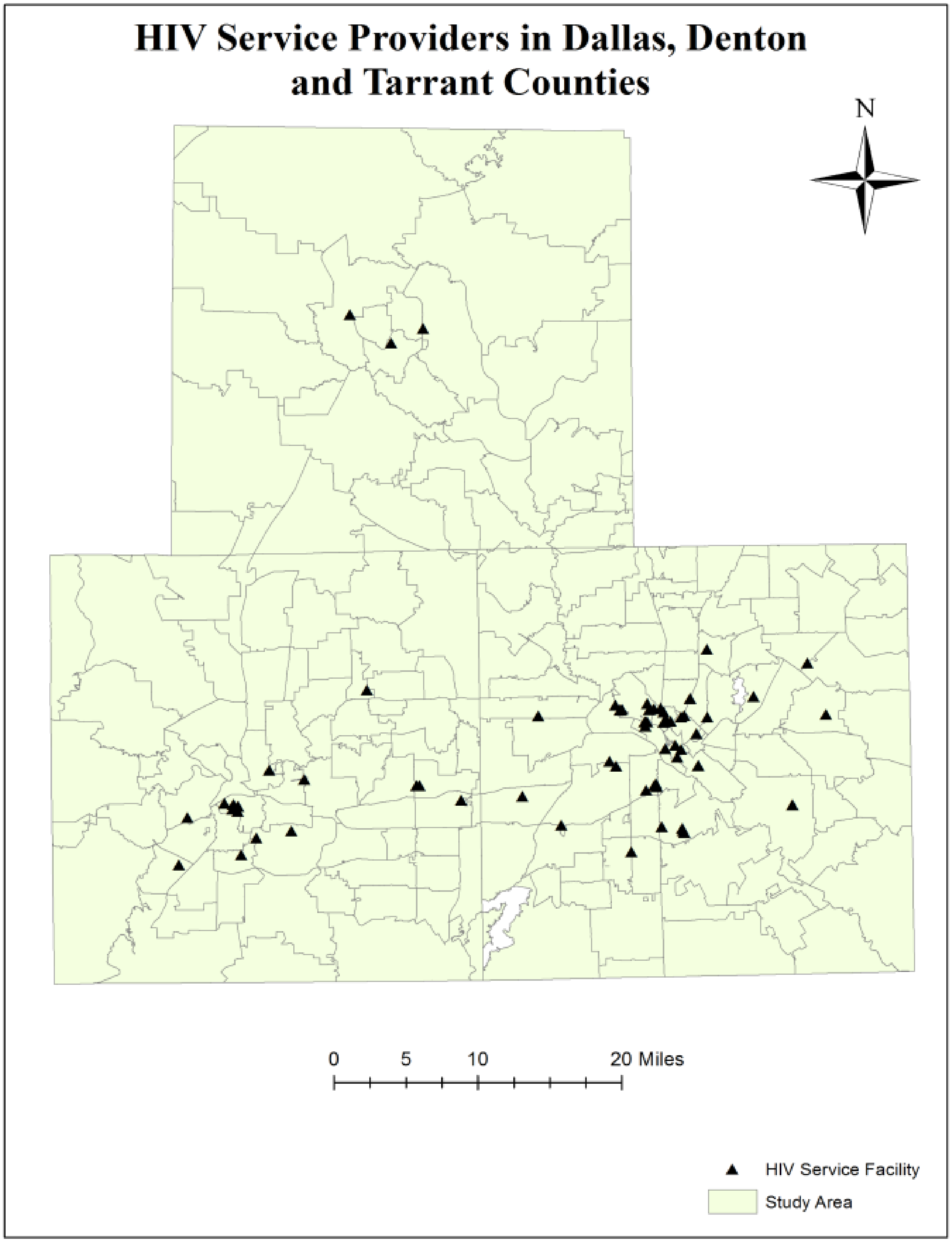

Figure 2 HIV Service Facilities in Dallas, Denton and Tarrant Counties

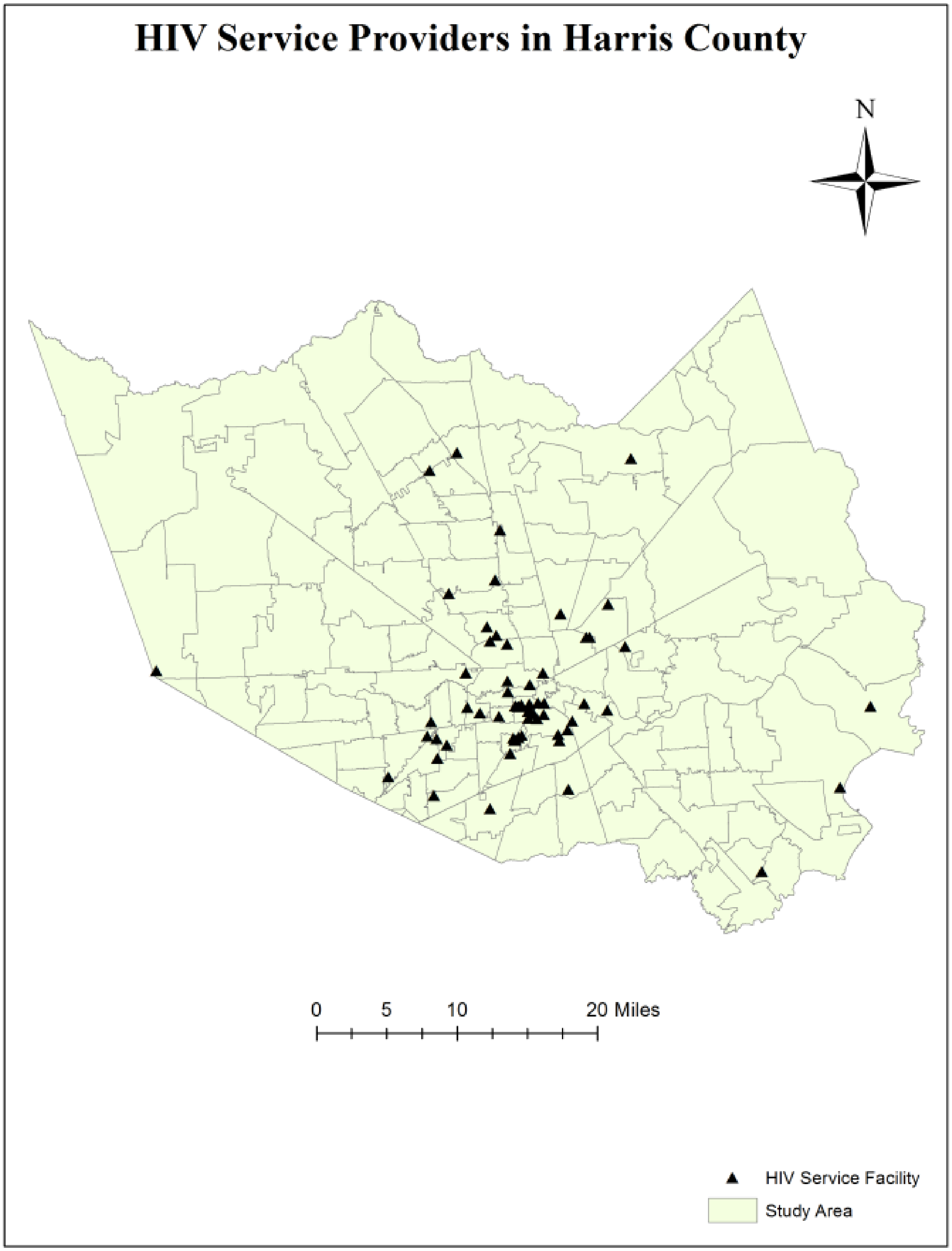

Figure 3 HIV Service Facilities in Harris County

4.3 HIV Rate

Throughout this research analysis, average cumulative HIV rate is used as the dependent variable. HIV rate for the period was not uniform for all the zip codes and counties (Figures 4 & 5). Whereas the state average was 16.7 per 100,000 in 2010, the average for the study area was 3.48 per 100,000 with 13 zip codes recording rates above the state average and 234 zip codes with rates below the study area average. Average HIV rates in the study area appear to be high in and around the major cities such as Dallas, Fort Worth and Houston. Zip code 75247 in Dallas County reported the highest HIV rate of 63.5 per 100,000 which is about 3 times that of the state average and 18 times that of the study area average.

HIV rate maps were constructed using WebDMAP. Unlike choropleth maps, these are continuous surface maps which helps eliminate small number problems as well as ecological fallacy from the study area. Dallas County recorded the highest average rate of 6.73 per 100,000 whilst Denton, Harris and Tarrant counties recorded 0.8 per 100,000, 4.25 per 100,000 and 2.14 per 100,000 respectively. The quantile range for the classification is as follows: 0.05-0.49 as lowest (lighter color), 0.5-1.15, 1.16-2.03, 2.04-4 and 4.01-56.06 as highest (darker color).

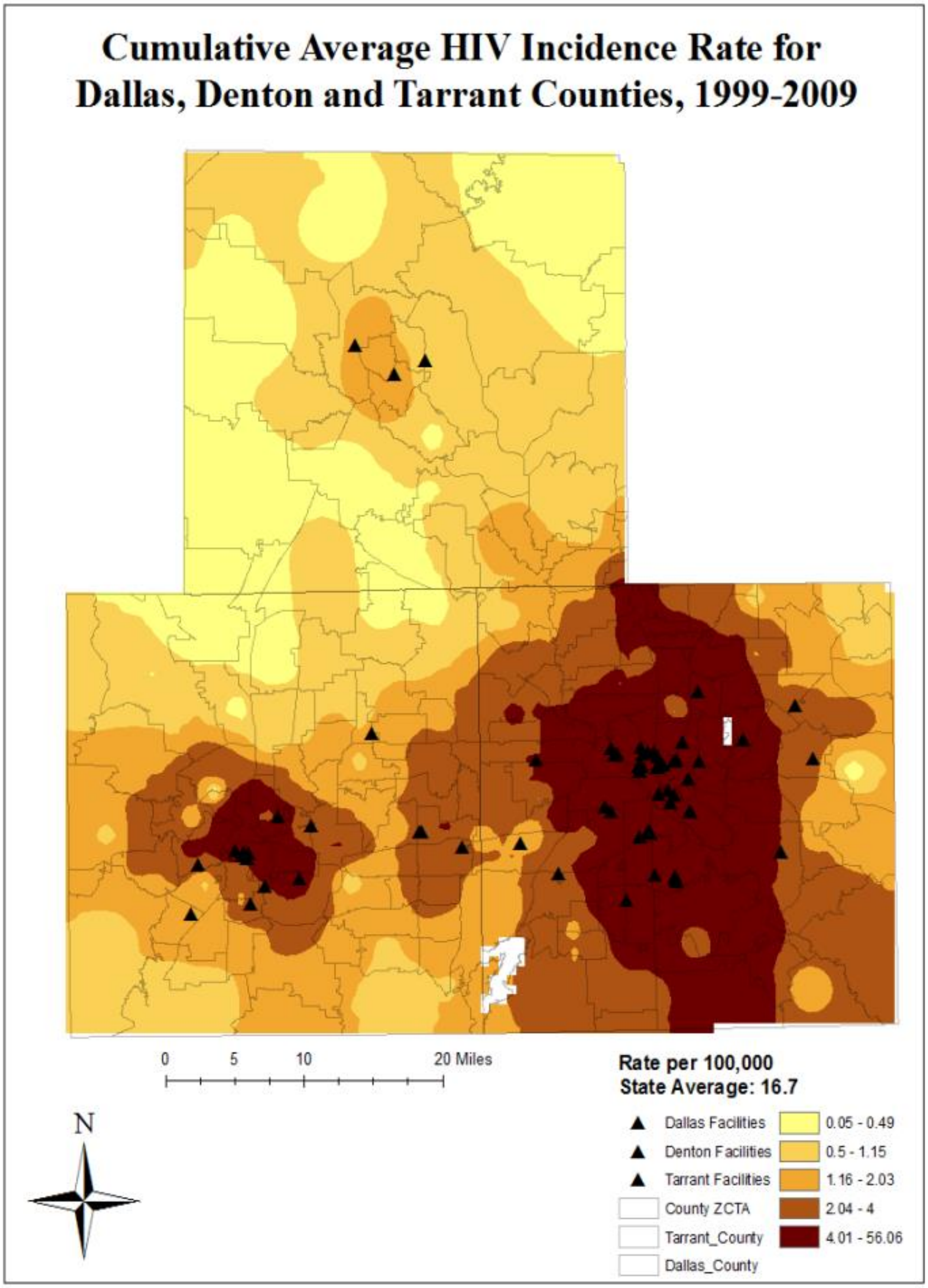

Figure 4 HIV Rates for Dallas, Denton and Harris Counties, 1999-2009. Source: TDSHS

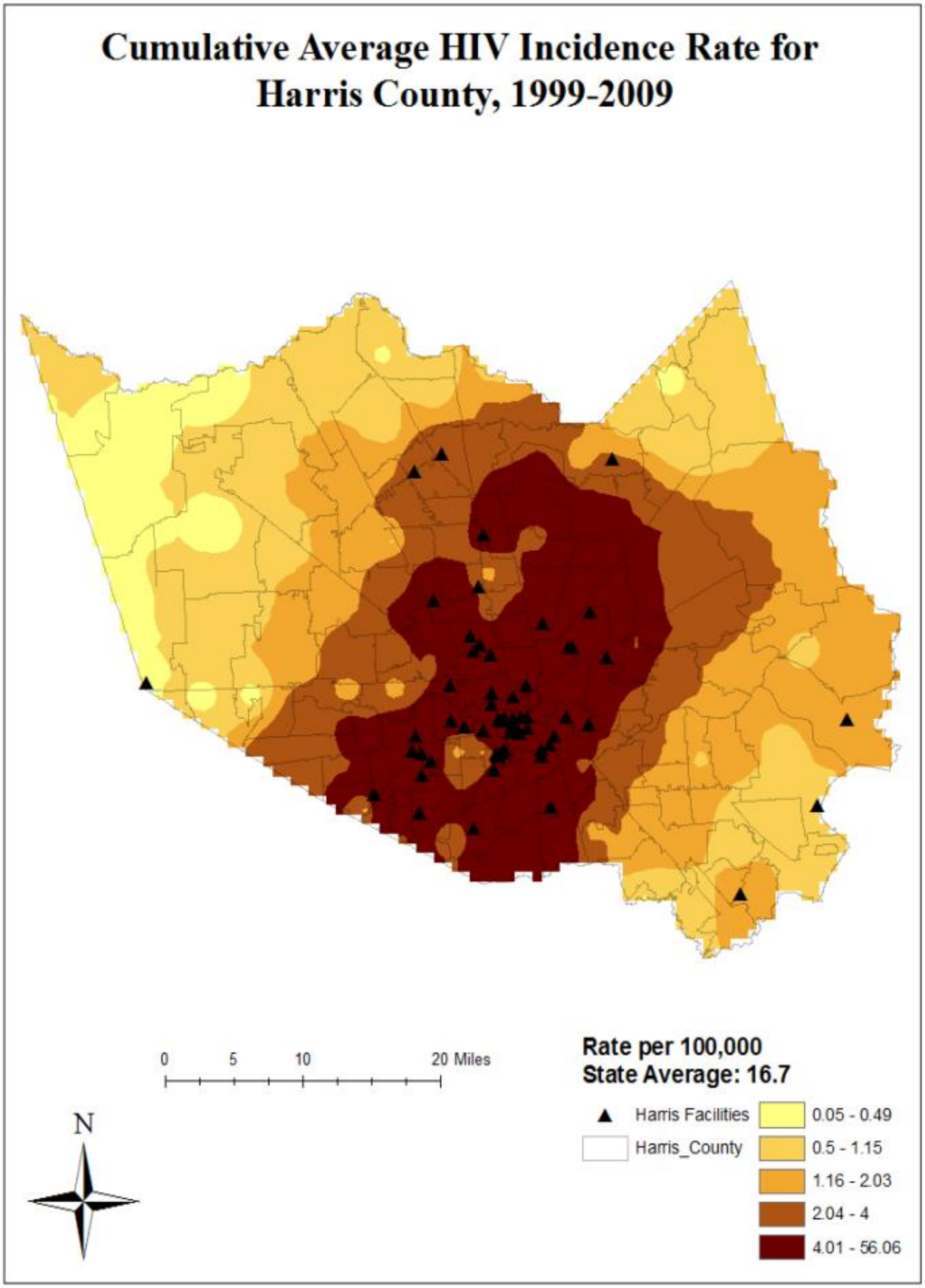

Figure 5 HIV Rates for Harris County, 1999-2009. Source: TDSHS

4.4 Explanatory Variables

Distance was used as a measure for spatial accessibility from the supply center (service facility) to the demand point (population in zip code) and ranged from 0 miles to 19.14 miles. The average distance for the study area was 3.05 miles whilst median distance was 3.68 miles. Euclidean distances were not uniformly distributed in both zip codes and counties of study.

This research uses percent White, percent Black and percent Hispanic populations for race/ethnicity. Previous research has emphasized the fact that HIV disproportionately affects minority populations. The story is especially important in Texas where the state has been identified as a “minority-majority” one. In the study area, Whites constitute 42.90%, Hispanics and Blacks represent 32.34% and 17.60% respectively with state averages of about 39% and 12%. Blacks have high average HIV rates compared to the other race/ethnic groups. For instance, percent of incidence cases for the 3 main race/ethnic groups were 26.1%, 51.5% and 20.7% for Whites, Blacks and Hispanics respectively.

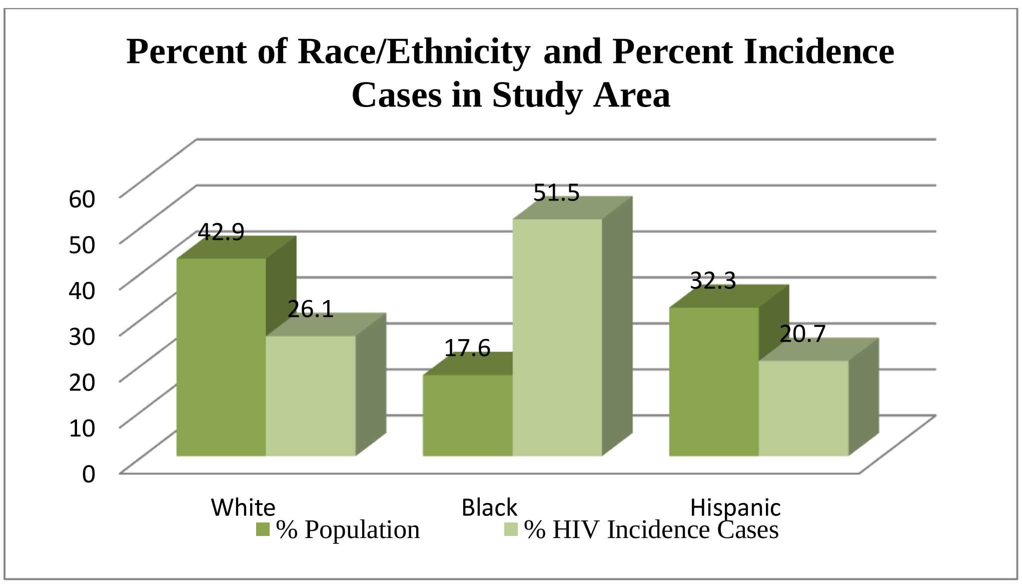

Figure 6 Race/Ethnicity and HIV Cases

Poverty in this research was used as a measure for socioeconomic status. The CDC considers poverty as an important predictor of HIV risk (CDC, 2013). Using the classification model developed by Kneebone et al. (2011), 5 zip codes recorded 48.1% of their total population below poverty level, and all happen to be in Dallas County. These zip codes were: 75247, 75220, 75006, 75039 and 75234. Despite these high poverty rates, only one zip code (75247) had an average HIV rate above the state average, meaning poverty is not the only factor responsible for high HIV rate in the study area. In fact, the Spearman's rho rank correlation between average HIV rate and percent below poverty level was 0.422**. The table below shows the counts of zip codes which lie within the different poverty classifications. Although the state average poverty rate for 2011was 18.7%, about 55% of the zip codes in the study area recorded poverty rates above that.

Table 7 Poverty Classification. Source: ACS: 2007-2011 Estimates

Classification	Counts (Zip Codes)	% Below Poverty
Low	136	< 20
Moderate	190	20-39
Extreme	20	>39

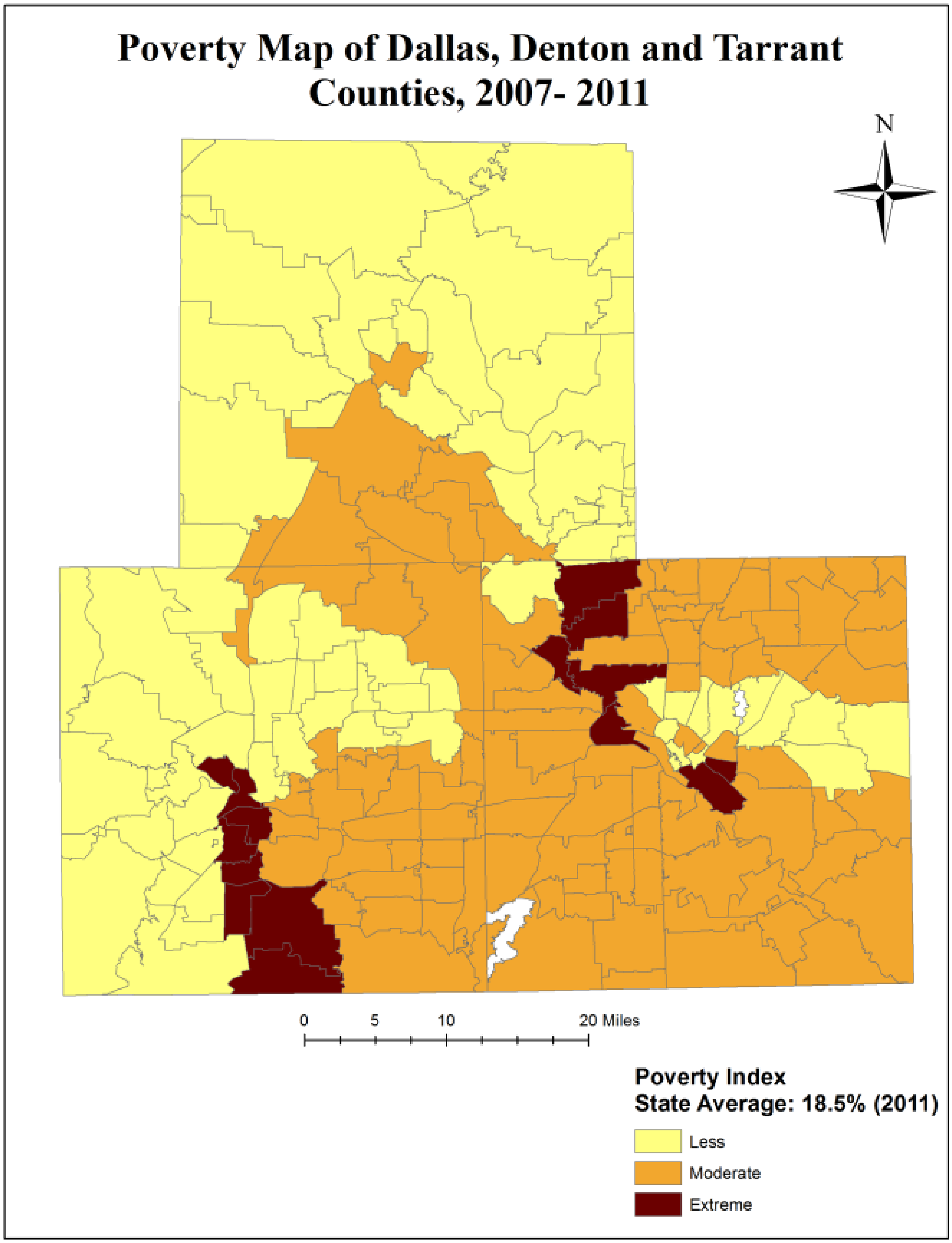

Figure 7 Poverty Map of Study Area. Source: ACS: 2007-2011

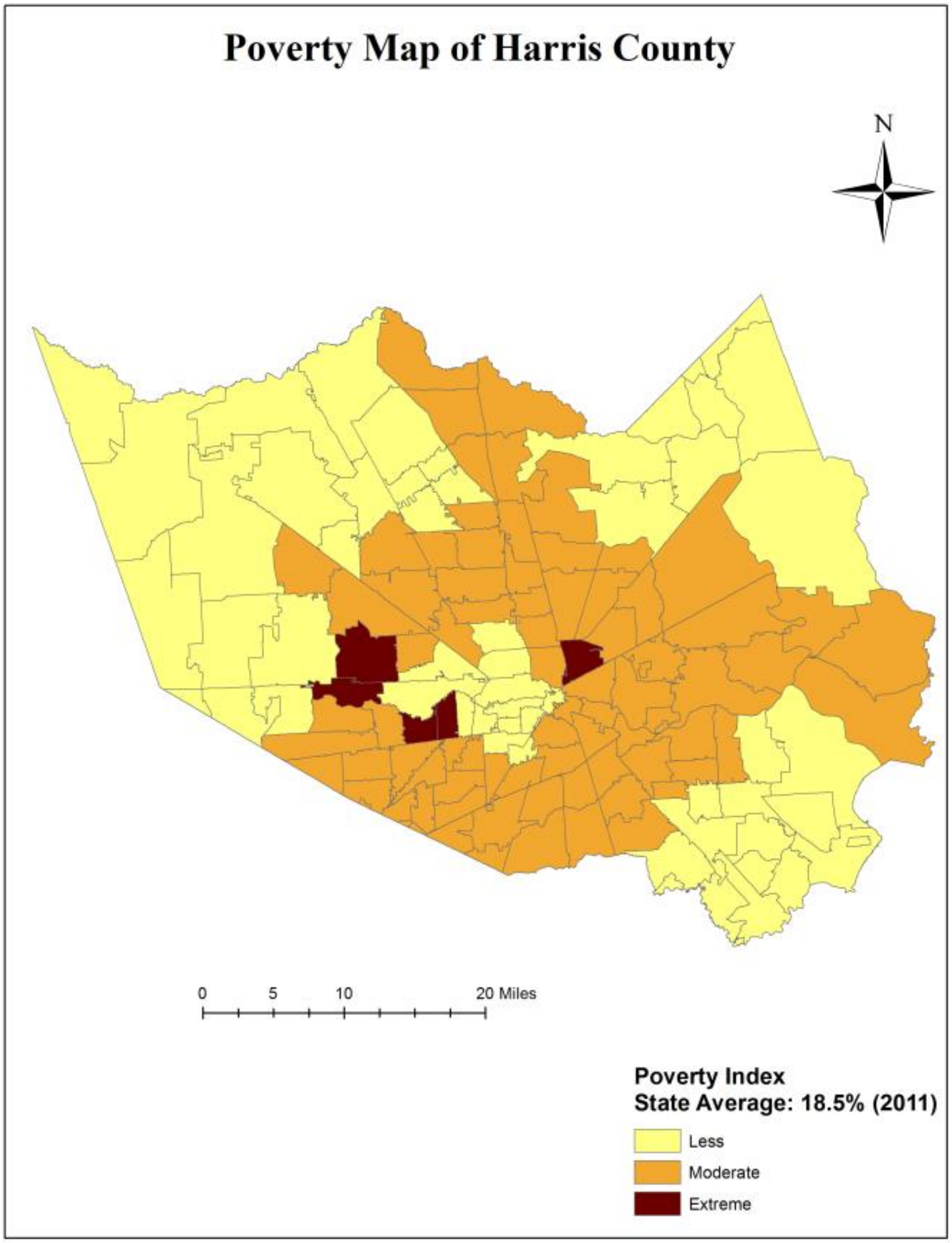

Figure 8 Poverty Map of Harris County. Source: ACS: 2007-2011 Estimates

Median Income for the study area ranged between $15218.00 for zip code 75210 in Dallas County and $183,656.00 for zip code 76092 in Denton County. Average median income for the study area was around $60,255.

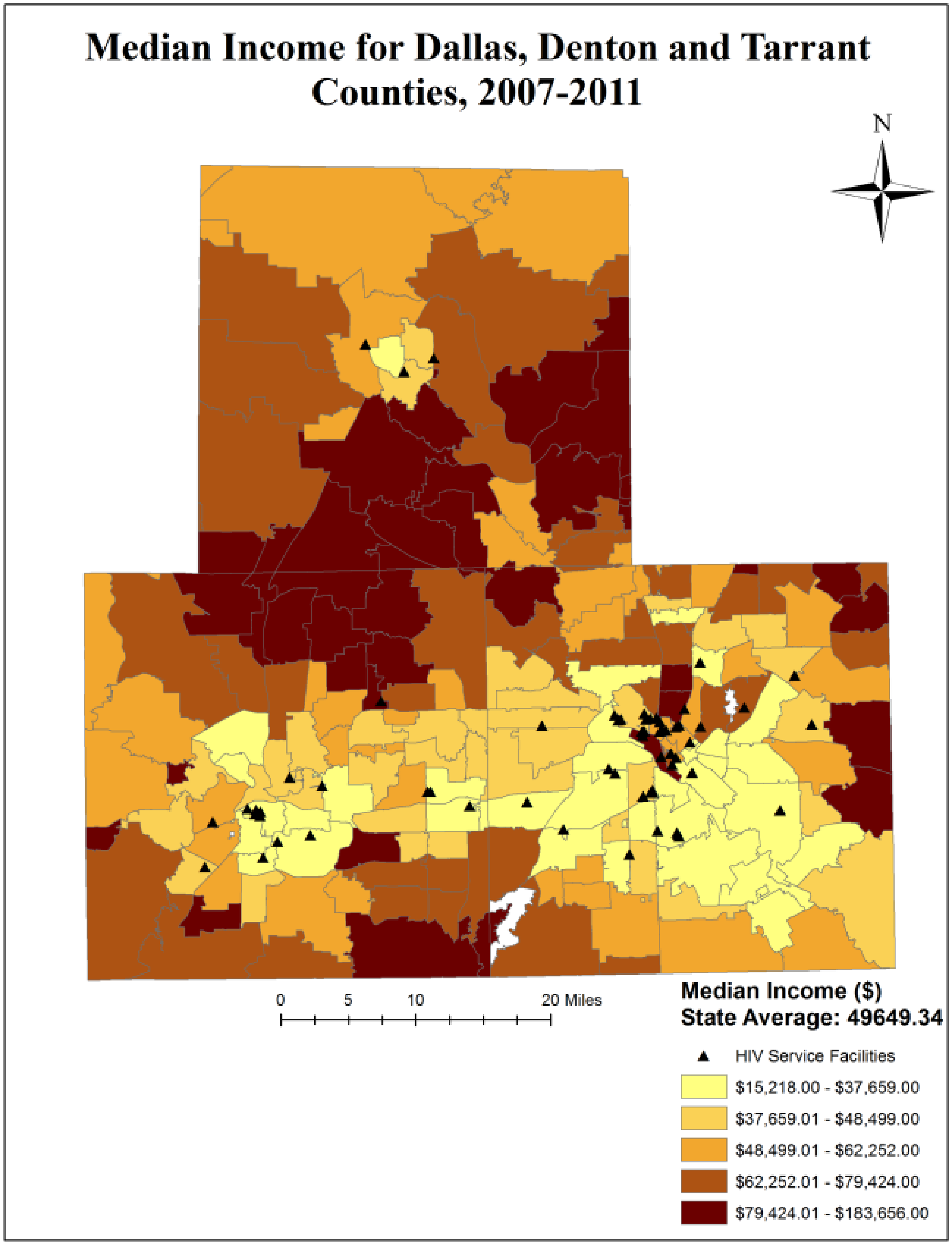

Figure 9 Median Income for Dallas, Denton and Tarrant Counties. Source: ACS, 2007-2011 Estimates

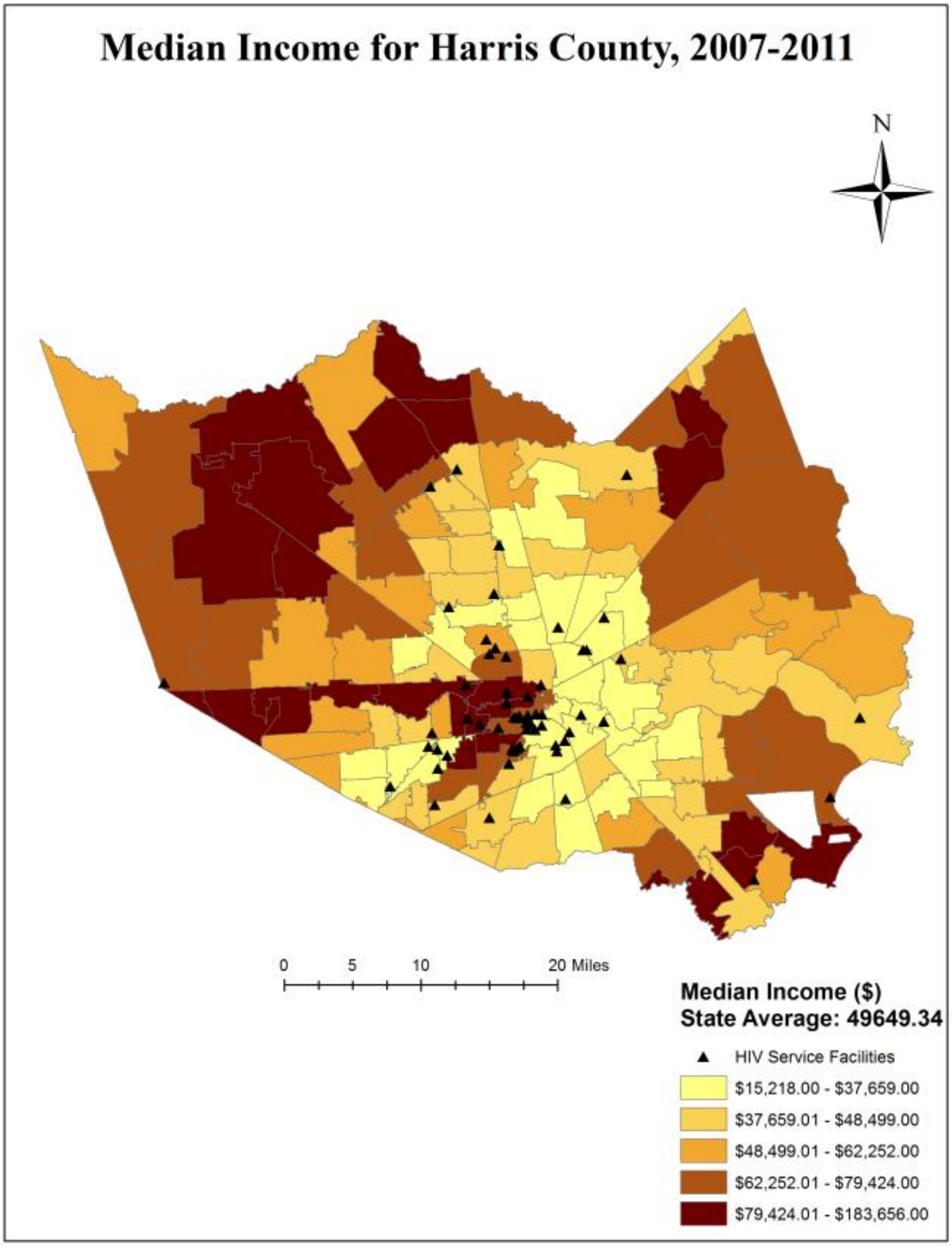

Figure 10 Median Income for Harris County. Source: ACS, 2007-2011 Estimates

We used percent of the population 25 years and older who have less than 9th grade education as a measure of education and proxy for socioeconomic status. Though the state average for this variable in 2010 was about 10%, the study area's average for the 5 year estimate was 9.9%. In addition, percent of the population in zip codes with less than 9th grade education ranged from 0% to 39.3%. Four zip codes reported 0% for this variable in the study area out of which 3 were from Harris County: 77010, 77046 and 77094 whilst the other zip code was 76155 from Tarrant County.

4.5 Normality Test, Correlations and Kruskal-Wallis H Test (k-samples)

We tested the variables in the dataset for normality to determine which statistical tools to apply in the analyses. Table 8 below shows the outcome of the normality test. The results show that all the explanatory variables are not normally distributed.

Table 8 Normality Test Results

Explanatory Variables	**Shapiro-Wilk**
	Significance
Percent Below Poverty Level	.000
Median Household Income	.000
Percent Less than 9th Grade Education	.000
Percent White	.000
Percent Black	.000
Percent Hispanic	.000

Thus, we used a non-parametric Spearman's correlation coefficient to show associations between HIV rates and the explanatory variables. As shown in table 9 below, distance to HIV service facility increases with decreasing HIV rate and increasing median income. These correlations were all significant at 1% though some were weak and moderate.

Table 9 Correlation Matrix

Explanatory Variables	HIV Rate / 100,000	Access		
		Affordability		Accessibility & Availability
		Median Income	Poverty	Distance
HIV Facility Count	.432**	-.266**	Not Sig.	-.717**
% Less than 9th Grade Education	.499**	-.807**	.439**	-.331**
% White	-.630**	.782**	-.587**	.387**
% Black	.567**	-.461**	.447**	-.289**
% Hispanic	.386**	-.690**	.364**	-.269**
Distance (Miles)	-.609**	.467**	-.114**	1
% Below Poverty Level	.422**	-.516**	1	-.114**
% Transport-Walk	.480**	-.409**	.209**	-.404**
% Transport-Cars, Van, Truck	-.447**	.146**	Not Sig.	.321**
% Transport- Public excluding Taxis	.664**	-.455**	.263**	-.515**
% Employed	-.287**	.587**	-.341**	.346**
% Unemployed	.371**	-.770**	.456**	-.313**
% Bachelor's Degree	-.309**	.771**	-.398**	.252**

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

In addition to the above, a Kruskal-Wallis H Test (k-samples) was conducted to see how cumulative average HIV rates varied across different categories of accessibility to service facilities, median income, poverty, education (percent less than 9th grade) and extent of vulnerability. The null hypothesis which we tested states that: distribution of rates (or dependent variable) is same across categories of independent variable.

4.5.1 HIV Rates and Education

We used the k-samples test to test for differences in HIV rates across the diverse categories of education (percent less than 9^{th} grade). Categories of education were obtained from the quantile classification which were: 0-2, 3-5, 6-9, 10-18 and 19-39. A significant result was found ($H(4) = 56.883$, $p<.01$), indicating that HIV rates varied with different categories of education. Zip codes with low percent less than 9^{th} grade education had low rates of HIV compared to those with high percent. For instance, categories 0-2 and 19-39, 0-2 and 6-9, 0-2 and 10-18, 3-5 and 10-18 were significant from each other. A pairwise comparison showed the following:

Table 10 Pairwise Comparison between HIV Rates and Education

Pairwise Comparison (HIV and Education)	
Education Categories (%)	Sample Average at Node
0 -2	105.96
3- 5	110.91
6-9	190.50
10-18	210.85
19-39	189.38

The pairwise comparison above shows a low HIV rank for the zip codes with 0%-5% with less than 9^{th} grade education; however, those with 6%-18% percent recorded very high ranks. It will be good to explore those zip codes to see why this is so especially when their HIV ranks are more than zip codes with 19-39 percent of the population with less than 9^{th} grade education. From the above results, we rejected the null hypothesis.

4.5.2 HIV Rates and Poverty

We further tested for variations within different poverty classes and HIV rates using the k-samples test. Our poverty classifications were as follows: low (< 20%), moderate (20%-39%) and extreme (< 39%). A significant result was found (H (2) = 51.767, p<.01), indicating HIV rates varied significantly between different poverty classes. Zip codes with low poverty had low HIV rates whilst those with extreme poverty had high HIV rates. For instance, low and moderate, and low and extreme were all significant from each other. Below is a pairwise comparison of the samples.

Table 11 Pairwise Comparison between HIV Rates and Poverty Groups

Pairwise Comparison (HIV and Poverty)	
Poverty Classification	Sample Average at Node
Low	120.84
Moderate	196.32
Extreme	216.30

4.5.3 Distance and Poverty

Also, we looked at how different classes of poverty varied with distance to HIV service facility. A significant result was found (H (2) = 6.103, p<.05), meaning that different classes of poverty differed from each other regarding distance. Extreme poverty zip codes had close proximity to HIV service facilities than low poverty zip codes. Our pairwise comparison below shows that increased poverty is associated with shorter distances to HIV service facilities.

Table 12 Pairwise Comparison between Distance and Poverty Groups

Pairwise Comparison (Distance and Poverty)	
Poverty Classification	Sample Average at Node
Low	150.61
Moderate	128.30
Extreme	115.50

4.5.4 HIV Rates and Vulnerability

We further analyzed to see if different categories of vulnerability varied with HIV rates. A significant result was found (H (3) = 50.514, p<.01), indicating that HIV rates varied with levels of vulnerability. More vulnerable zip codes had higher their HIV rates as shown in the pairwise comparison below.

Table 13 Pairwise Comparison between HIV Rates and Vulnerability Groups

Pairwise Comparison (HIV and Vulnerability)	
Categories of Vulnerability	Sample Average at Node
Less	99.36
Average	154.49
High	202.57
Extreme	236.48

4.5.5 Distance and Vulnerability

Different categories in vulnerability were also compared to distance to HIV facilities. A significant result was found (H (3) = 34.594, p<.01), meaning vulnerability varies significantly with distances to HIV service facilities. Distance to HIV service facilities decreases with increasing vulnerability.

Table 14 Pairwise Comparison between Distance and Vulnerability Groups

Pairwise Comparison (Distance and Vulnerability)	
Vulnerability Categories	Sample Average at Node
Less	210.47
Average	171.67
High	149.76
Extreme	87.66

4.5.6 HIV Rates and Median Income

Finally, we compared HIV rate with categories of median income. The results show that HIV rates varied significantly with median income categories ($H (4) = 109.108$, $p < .01$). High income zip codes tend to have low HIV rates compared to low median income zip codes.

Table 15 Pairwise Comparison between HIV Rates and Median Income Groups

Pairwise Comparison (HIV and Median Income)	
Median Income Classification	Sample Average at Node
$15,000-$24,999	297.44
$25,000-$49,999	220.82
$50,000-$99,999	133.47
$100,000-$149,999	69.91
$150,000-$199,999	30.25

4.6 Vulnerability Maps

Vulnerability maps were created to show areas of susceptibility to HIV within the study area. Previous research shows that, vulnerability to HIV is not uniform across space and we expected same for our study area. Areas with high percent minority populations, less education, high unemployment, poor means of transportation, low median income, and high percent below poverty level are most likely to have high risk for HIV rates. Clear vulnerability patterns could be seen in the study area as extreme vulnerability was evident in Harris and Dallas counties whilst less and high vulnerability were predominant in Denton and Tarrant counties. For instance, less vulnerability in Denton County was reported among zip codes in the northern and western parts of the county whilst the southeastern zip codes showed average and above vulnerabilities.

The table below shows comparisons between mean HIV rates and distance at different categories of vulnerability.

Table 16 Vulnerability Groups, HIV Rates and Distance

Categories of Vulnerability	**Mean HIV Rates (per 100,000)**	**Mean Distance (Miles)**
Less	1.63	4.59
Average	3.57	3.36
High	5.53	2.39
Extreme	13.88	1.39

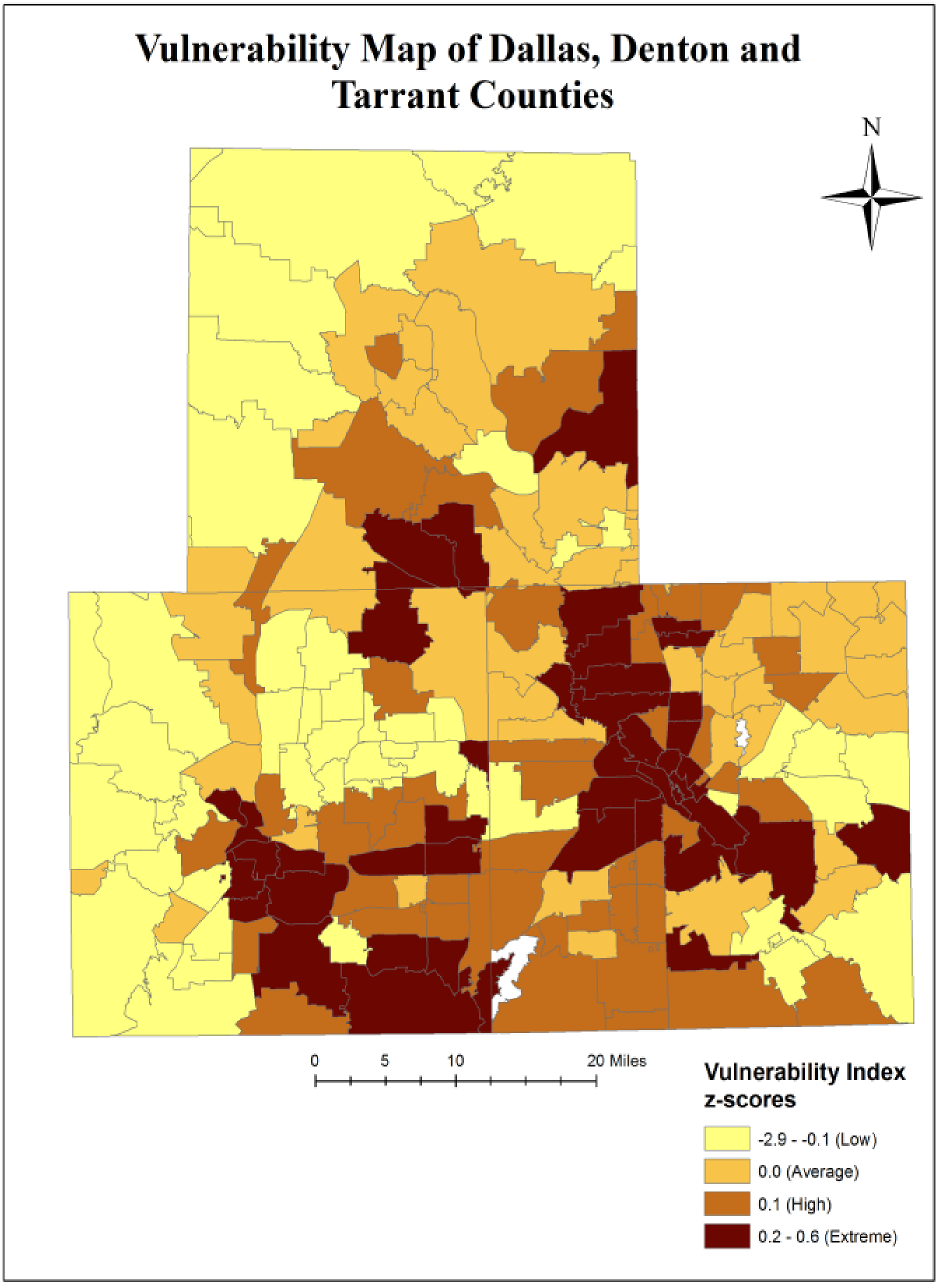

Figure 11 Vulnerability Map of Dallas, Denton and Tarrant Counties

4.7 Regression Analysis

Regression analysis was used to model and examine the relationship between HIV rates and the explanatory variables which were percent Black, HIV service facilities in a zip code, percent who own cars and percent who use public transport except taxi services. Table 16 below shows the results of our regression model built using the Ordinary Least Squares (OLS) tool in ArcMap. The model explained about 70% of variance in HIV rates and could be considered a good model. We created a map using the standard deviation residuals of our explanatory variables and this ranged from < -2.5 to >1.5.

Table 17 OLS Summary Results

Summary of OLS Results				
Variable	Coefficient	Probability	Robust_Pr	VIF
Intercept	53.361919	0.000000*	0.000002*	
Percent Black	0.060994	0.000032*	0.000110*	1.552879
HIV Facilities	1.284450	0.000000*	0.022908*	1.147596
Percent Transport (Cars, Trucks and Vans)	-0.573870	0.000000*	0.000003*	2.767177
Percent Transport (Public except Taxi)	0.481510	0.000173*	0.000868*	3.53900

Table 16 above is one of 2 tables resulting from the OLS analysis in ArcMap. From the above, the coefficients of our explanatory variables are in the direction (either positive or negative) they are expected to be. For instance, as percent Black in the zip code increases, HIV rate also increases as expected. From the table above, we predict that for each increase in HIV rate, percent Black in a zip code increases by 0.06%. Though this is a small number, it is still positively associated with increased HIV rates and zip codes with a high percent Black population will have high rates of the disease. Similarly, for each increase in HIV rate, HIV service facilities increase by 1.3. We also predict that percent transport owners (cars, trucks and vans) decrease by 0.57% for each increase in HIV rate. Again, we predict that percent who use public transport (except taxi) increase by 0.48% for each increase in HIV rate.

Additionally, all probability values were significant, a good indication for a strong model prediction. The last column, variance inflation factor (VIF), checks for variable redundancy.

Ideally, VIF should not be more than 7.5. Once any of the VIF values is more than 7.5, there is a need to scan through our variables to remove those that are redundant to the model. In our case, all variables were below 4 and that was very good.

Table 18 OLS Diagnostics

OLS Diagnostics	
Number of Observations: 335 zip codes	AICc: 1857.834370
Multiple R-Squared: 0.699817	Adjusted R-Squared: 0.696178 (about 70%)
Joint F-Statistic: 192.332054	Prob(>F), (4,330) degrees of freedom: 0.000000*
Joint Wald Statistic: 244.855302	Prob(>chi-squared), (4) degrees of freedom: 0.000000*
Koenker (BP) Statistic: 42.953000	Prob(>chi-squared), (4) degrees of freedom: 0.000000*
Jarque-Bera Statistic: 15551.003180	Prob(>chi-squared), (2) degrees of freedom: 0.000000*

Koenker (BP) statistic measures whether our explanatory variables show a consistent relationship to HIV rate. A significant Koenker test therefore means there is a consistent relationship between the dependent and independent variables. According to ArcGIS help online, when the Koenker (BP) statistic is significant, our model can only trust the Robust_Pr (Table 16) for significance and thus the more reason why both probability columns in table 16 should be statistically significant.

On the other hand, a significant Jarque-Bera statistic result suggests that variables were clustered or dispersed (not random) within the study area which results in biased predictions. Although the result is significant here, we know variables associated with HIV rate in the study area varies with zip code though it is the clustering of vulnerable variables in a place which make that environment highly susceptible to infections including HIV. Since both HIV rate and vulnerability vary across space, zip codes with a concentration of vulnerable populations will have high rates of HIV and that is what the results of our vulnerability map suggest (Figure 11). Also, a non-significant result here suggests our dataset is randomly distributed but a significant result could also be as a result of misspecification.

Both Joint F-statistic and Joint Wald measures the overall model's statistical significance. They measure the effectiveness of the explanatory variables. From the results, both statistics are significant which means the variables we used were good for explaining the relationship between HIV rates in the study area and those variables.

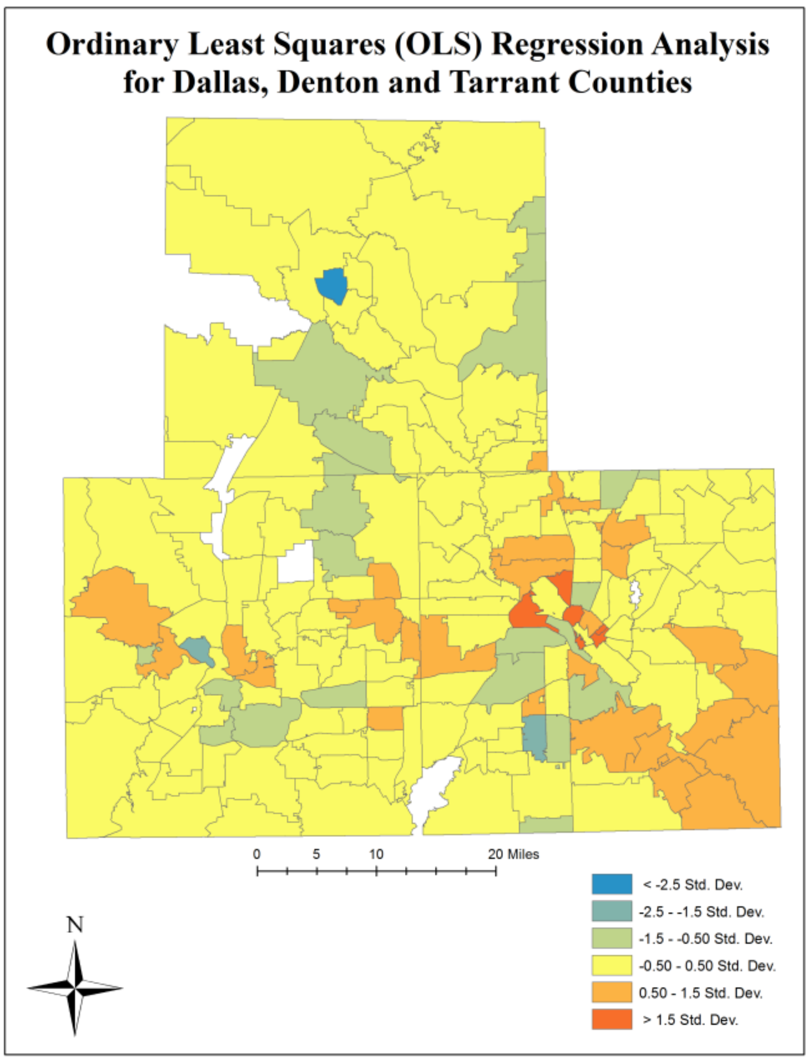

Figure 12 OLS Map of Dallas, Denton and Tarrant Counties

Finally, the Akaike's information criterion (AICc) measures the strength and efficiency of the model. A lower AICc is preferred to a larger one thus the need to run multiple models to find which one has at least an adjusted R-squared of 0.5 or over and a corresponding low AICc. The AICc value was 1857.83. Comparing different models of the same dependent variable, a lower AICc is always preferred to a higher one to show model fit and efficiency. Denton County shows a clear cold spot (blue) in in the area around the city center whilst a number of hot spots (red) are seen in Dallas and Tarrant counties. The blue areas on the map above mean those rates have been over predicted by our model whilst the red areas on the map show zip codes of under prediction. Normally, we would expect to see these colors (red and blue) randomly distributed across space but what we see in our study area are pockets of clusters of either over or under prediction.

After the OLS, we further conducted a geographic weighted regression (GWR) to see the relationship between HIV rates and the independent variables and to further show how they vary spatially across the study area. The independent variables used for this model were percent male, number of HIV facilities in a zip code, percent Black and percent transport (public, except taxis). We excluded percent transportation (cars, trucks and vans because it had no variation across space and was thus unsuitable for the GWR. The table below shows the outcome of the GWR model.

Table 19 Results of GWR

Geographical Weighted Regression Results (GWR)	
Neighbors	12
ResidualSquares	23.957
AICc	180.670
R-Square	0.9914
Adjusted R-Square	0.9622

Using the adaptive kernel type, we selected 12 neighbors as bandwidth method. First, the adaptive kernel type was preferred to the static type because it offers the best means for smoothing model results based on nearest neighbors. Hence, local model estimates are based on the same number of features. ResidualSquares is the sum of squared difference between the observed y values and the estimated values produced by the model. A small ResidualSquares is preferred to a higher one because it suggests a close fit between the model and the observed data. Whereas the AICc for the GWR was lower than that of the OLS, the adjusted R-squared of 0.96 predicted by the GWR was higher than the 0.70 obtained from the OLS. In the figure below, we show the GWR map of the study area showing areas of under-predicting and over-predicting.

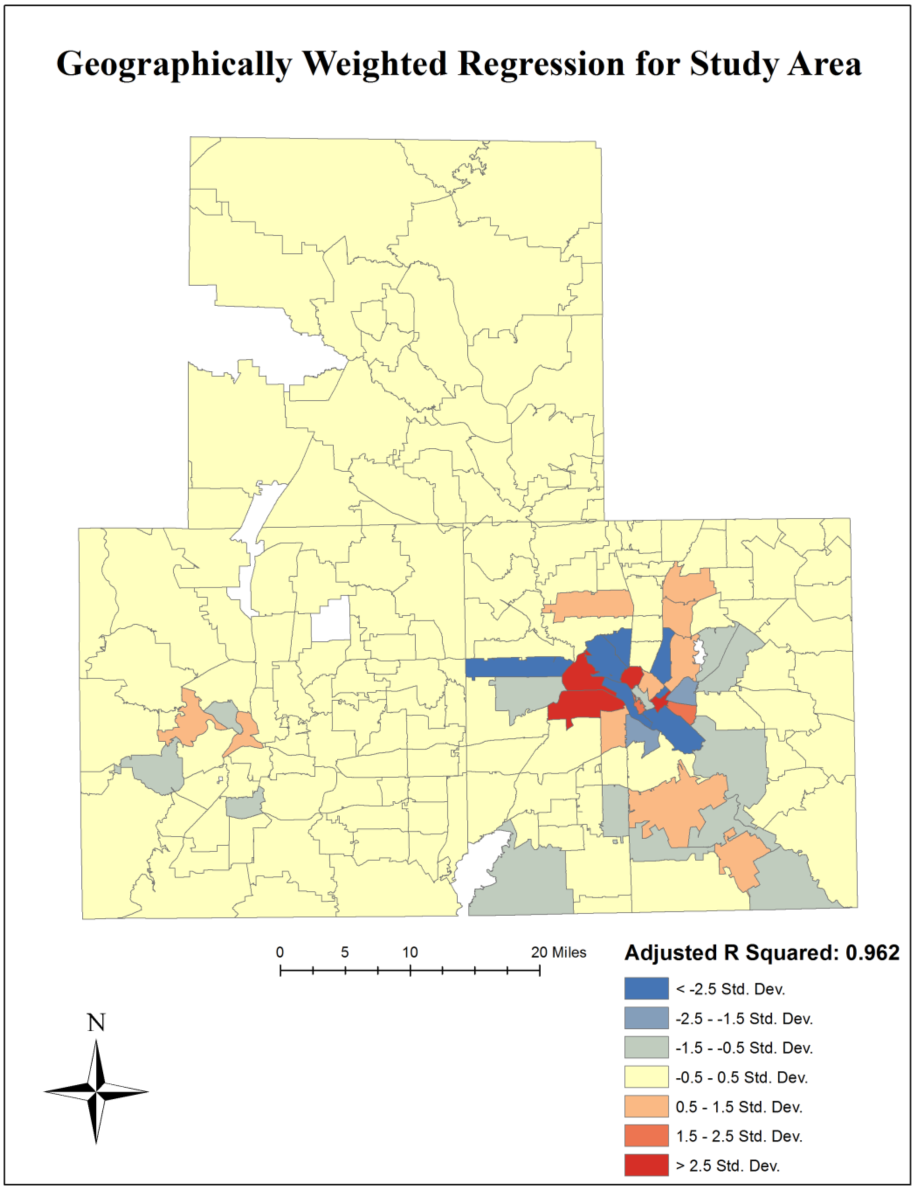

Figure 13 GWR Map of Study Area

We further mapped (figures 14 and 15) the coefficients of the independent variables obtained from the model. The coefficients show areas of under-prediction and over-prediction of specific variables relative to HIV rates.

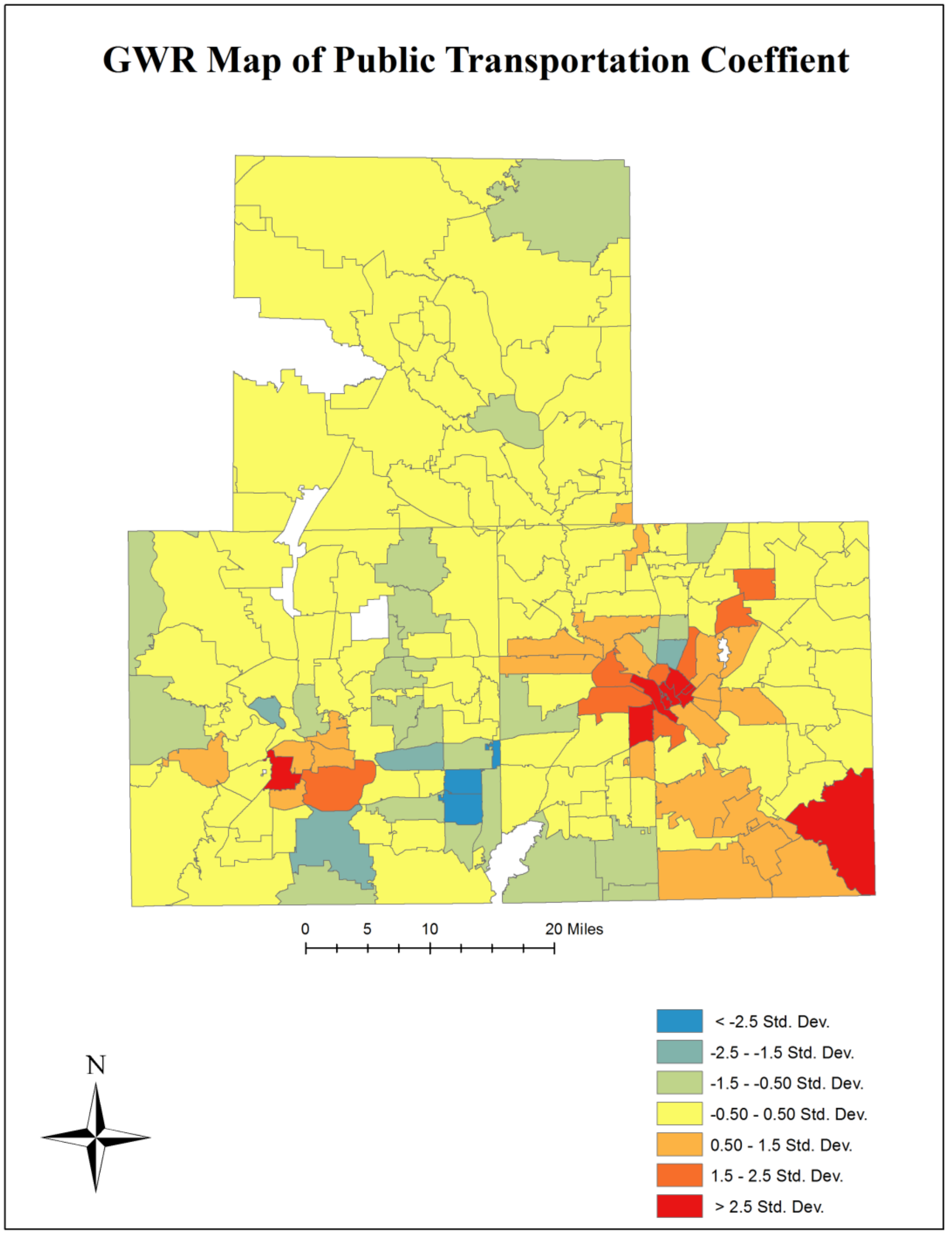

Figure 14 GWR Coefficient Map of Public Transportation (Except Taxis)

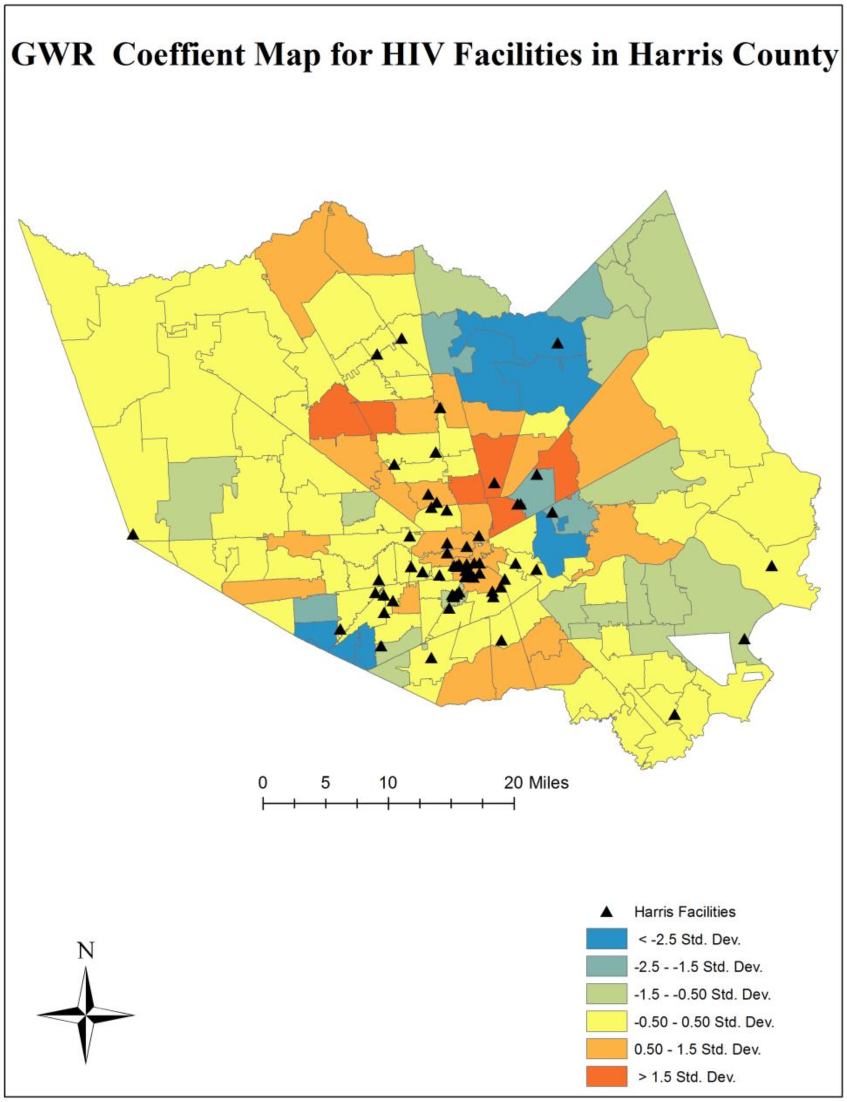

Figure 15 GWR Coefficient Map of HIV Facilities

From the maps above, the red areas show zip codes where public transportation and HIV service facilities are strong predictors of HIV rates whilst the blue areas are areas where they are not strong predictors. These help in decision making regarding allocation of scarce resources. For instance, in figure 14, we realize that public transport is a strong predictor of HIV rates in some zip codes in the central and southeastern corner of Dallas. Improving transportation in these zip codes may significantly reduce HIV rates in those areas.

Using SPSS 20.0, we conducted a simple linear regression predicting HIV rates based on percent Black, HIV service facilities, percent that have cars, trucks or vans, percent who use public transportation but not taxis, percent whose means of transportation is walking, and percent males were the independent variables. A significant regression equation was found ($F (5,329) = 180.938$, $p < .001$), with an R-squared of .729. Hence, average cumulative HIV rate is equal to 31.838 (Constant) -.563 (percent who own cars, vans and trucks) + .526 (percent who use public transport except taxi) + 1.100 (number of HIV facilities) + .415 (percent males) + .083 (percent Black). HIV rates therefore increased with all the explanatory variables except percent who own cars, trucks and vans.

CHAPTER 5

DISCUSSION AND CONCLUSION

The research set out to examine whether there is a spatial mismatch between HIV rates and access to HIV service centers. We found that HIV rates are high in zip codes which have HIV service facilities. Thus, from an accessibility point of view, there is no mismatch between distribution of HIV rates and access to service facilities. Whereas zip codes without service facilities reported a mean rate of 3.34 per 100,000, those with facilities reported 10.04 per 100,000. Since place of diagnosis is not necessarily place of exposure to the infection, it is difficult to identify the exact zip code or place where these PLWH were exposed to the infection. Presence of HIV service centers in a zip code is likely to influence the number of HIV diagnosis and the resultant high rates in those zip codes.

Knowing now that there is no spatial mismatch, we continued to analyze whether people who need HIV care the most (PLWH) have access to service facilities. Using the ICL, our results show that HIV service facilities are located in zip codes where they are needed most. Thus the inverse care law does not apply to HIV service facilities in our study area. Hypothesis 1 is rejected since HIV service facilities are more frequent in zip codes with high HIV rates.

On the question of whether access to HIV service facilities varied with neighborhood characteristics, a number of tests were conducted on percent of the population with less than 9th grade education, median income as well as vulnerability. We found that poverty varied with access to HIV service facilities. The poorest in the study area had the closest proximity to HIV facilities whilst the less poor reported longer distances to HIV facilities. Thus Hypothesis 2 is also rejected. Hypothesis 3 drew a relationship between median income and access to HIV service. Since we looked at the broad concept of access, our finding was in two-folds (accessibility and affordability). In terms of accessibility, low income zip codes recorded closest proximity to HIV service facilities. These populations are likely to be predominantly below poverty level and of minority race/ethnic groups. Adversely, in terms of affordability, low income zip codes had worse access to HIV service facilities since high income populations are able to afford HIV care, and health insurance.

Vulnerability also varied with access to HIV service facilities. More vulnerable zip codes were located in close proximity to the facilities compared to the less vulnerable zip codes. Hence, neighborhood characteristics influence access to HIV service facilities as well as HIV rates. Also, better transport access was found to be negatively associated with HIV rates and vice versa. Zip codes with more people whose main mode of transportation is walking and public transport are likely to have high rates of HIV than those zip codes with private access to transport.

First, we now know the spatial distribution of HIV service facilities in the study area, and can easily inform service providers on resource poor zip codes and further help in allocating services effectively to cater for people who need services. In addition, the vulnerability index created for the study area shows the various levels of vulnerability in the study area. Areas which are more vulnerable and need specific socioeconomic variables can be targeted for improvements. We also realize the needs of the populations with regards to HIV rates are not uniform. This will help the HIV care providers to streamline their approach to specific groups and areas for better results. This also forms the basis for future research especially in the area of the transportation ownership and HIV infection as well as better classifying the HIV service facilities since they are diverse and attend to different groups of people.

The regression model also shows which variables are associated with increasing HIV rates. We can clearly see that apart from percent who own cars and trucks, all other explanatory variables in the regression model relate positively with HIV rates. In an era where billions of US dollars are spent on HIV treatment annually, knowledge of variables associated with HIV will help decision makers take steps to reduce people's susceptibility by putting in place measures to help them drastically reduce risk of contracting the infection. Furthermore, the model provides grounds for more research into why those independent variables are correlated with increased risk for HIV. For example, why do peoples with poor access to transport have high rates of HIV compared to those who have easy access?

Our research was also hampered by a number of factors including mapping methods, missing data, distance measure, category declaration and geocoding errors.

Choropleth maps used to show the geography of dependent and independent variables are affected by the Modifiable Areal Unit Problem (MAUP) and small number problem (Dark and Bram, 2007). Thus, the choropleth map results are influenced by the spatial units used for this study. A census tract or block data would have yielded different results. However, this was the only option since the HIV data for this research was only available at the zip code level. Also, though the research covered an 11 year period (1999-2009), some zip codes still had very low HIV cases which usually results in unstable rate outcomes.

Another important dataset which could not be obtained for our research was health insurance data. Such data could have helped us show who has access to HIV care based on affordability and even get some information on the facility they use. Though we used median income as a proxy for health insurance, data on health insurance at zip code level would have been ideal. In addition, HIV service facilities did not contain capacity data. This data was needed to develop some gravity models to help calculate a more applicable distance measure and further help in conducting some location allocation models in this research.

Accessibility (spatial or geographic access) was difficult to measure. Although the spatial join method is not the best distance measure, we used it anyways because that is what our data could help us with. One limitation of this approach is the inability to account for distances within the same spatial unit.

Finally, the research was also limited by information on where the diagnosed people had lived prior to their current residence. We know from health studies that place of diagnosis is not necessarily the place of exposure. Information on previous places of residence or even work will be helpful in future research as we are currently bound to ascribe the high rates to zip codes where diagnosis took place. It is also likely people will travel to farther distances to get tested because of anonymity.

It will be good to examine how different variables influence HIV rates and access in the individual counties. Since these counties have diverse characteristics, we expect the leading variables associated with HIV rates to be significant from each other. In addition, capacity data on HIV service facilities within the study area will help with some location-allocation models to enhance service provision in the study area. HIV service facilities should also be distinguished into their individual functions for better analysis in future research instead of combining them as one single service provider.

In the study area, accessibility to HIV service facilities is better in zip codes with high rates of HIV, low median income, and high minority population contrary to the ICL. However, affordability is better in zip codes with high median income. Thus, access to HIV services depends on our definition of access. Additional research is needed to determine whether the quality of services offered is acceptable and accommodating within the study area. Improved effective access for all who need HIV services is surely critical for reducing HIV spread.

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