Examining the Driving Factors of Urban Sprawl in San Antonio Metropolitan Area
During 1990-2010

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I. Introduction

There are many definitions and methods of measurement of urban sprawl. The Cambridge Dictionary suggests that urban sprawl is the "spread of a city into the area surrounding it, often without planning" (Cambridge Dictionary, n.d.). Other scholars define urban sprawl as fragmented spread of built-up areas over time (Li and Yeh 2001) or the "less compact outgrowth of a core urban area exceeding the population growth rate" (Bhatta 2010). Bhatta (2010) points out that the definition of urban sprawl is a subjective perspective depending on the people. Besides various definitions proposed by the researchers, policy makers and governance institutions like the United States Environmental Protection Agency defines sprawl as "when the rate at which land is converted to non-agricultural or non-natural uses exceeds the rate of population growth" (cited in Barnes et al. 2002). Nevertheless, one must not confuse urban sprawl with urban growth, which means an increase in the concentration of population distribution in towns and cities (Bhatta 2010). Urban growth can happen with or without urban sprawl. However, urban sprawl only occurs during urban growth. However, there are some indicators that could be used to identify sprawl. More specifically, urban sprawl has some characteristics that would distinguish itself from urban growth that are 1) low density development (single family residence) (O'Toole 2008; Glaeser and Kahn 2004), 2) Leapfrog, scattered development at urban edges (Li and Yeh 2001; Glaeser and Kahn 2004), 3) single-family residential (Popenoe 1979).

Urban sprawl is a common problem in the United States (Bhatta 2010). Since industrialization, people in rural areas have been migrating into urban areas because of the pulling factors of the cities (e.g. more jobs and better lifestyle). The total urban population of the United States roughly doubled from around 126 million in 1960 to 265 million in 2016 (The

World Bank 2016). According to the 2010 Decennial Census, the urban population of the U.S. increased from 39.6% in 1900 to 80.7% in 2010 (Census Bureau 2000, 2012). Cities were expanding to accommodate the increasing population and population density. As a result of urban growth, some cities expanded and became great metropolitan areas that combined multiple cities around them such as the great Boston area, Dallas-Fort Worth- Arlington area, Houston-Galveston-Brazoria area, Los Angeles-Riverside-Orange County area, Minneapolis-St. Paul area, etc.

Urban sprawl is often linked to unsustainable urban development and associated problems. For instance, while cities are expanding, the commuting time for people to different destinations is typically becoming longer (Bhatta 2010). Hence, walking is a less desired traveling mode and people drive cars instead. Increasing gas emissions cause air pollution, which adversely affect the health of urban residents (Barnes et al. 2001). Urban sprawl can be characterized by the expansion of impervious area, and thus there is a positive relationship between the land surface temperature and impervious area (Bhatta 2010). In general, the urban heat island effect causes urban areas to be hotter than surrounding areas on warm days because vegetation loss reduces the cooling effect through evapotranspiration (U.S. Environmental Protection Agency 2014). The increasing temperature in urban areas also presents a higher demand for cooling equipment that pollutes the air by emitting carbon dioxide, particulate matter, Sulphur oxides, nitrogen oxides, and air toxics (U.S. Environmental Protection Agency 2014). Another drawback of increasing impervious area is that it allows more stormwater runoff that seriously harms water quality as well as public health (Burchell et al. 2005). Economically, local government typically must provide infrastructure and services to the sprawling area, including building new roads, widening existing ones, building fire stations, trash collection, etc.

(Burchell et al. 2005). Utilities are needed for the sprawling area as well. These will increase the cost of public service and potentially lead to tax increases (Holtzclaw and Leinberger 2010).

Due to the undesirable consequences of urban sprawl, the topic has garnered substantial interest from urban researchers. In particular, many researchers have attempted to measure urban sprawl, despite the absence of any consensus, in order to better understand its causes and consequences (Verzosa and Gonzalez 2010; Zeng et al. 2014; Li and Yeh 2001; Nengroo et al. 2017; Li et al. 2016; Chong 2017). Remote sensing techniques are commonly used for land use and land cover classification through supervised and unsupervised classification techniques. The analysis of land use and land cover change with proper interpretation allows us to identify land cover and land use change, an indicator of urban growth, over time. To quantify the "disorderness" of a process, Shannon's entropy has been utilized as an indicator for measuring urban growth (Verzosa and Gonzalez 2010; Zeng et al. 2014; Li and Yeh 2001). It measures the degree of concentration and dispersion of a geographic variable and tests whether the land development is dispersed or compact to quantify the extent of urban sprawl (Li and Yeh 2001). Besides measuring urban sprawl, a popular approach to examine the driving factors of urban sprawl is to conduct conventional and spatial regression modeling, such as Ordinary Least Square (OLS) regression, Geographically Weighted Regression (GWR), and logistic regression to (Cowell 2011; Noresah and Ruslan 2009; Alsharif and Pradhan 2013; Hamdy et al. 2016; Osman et al. 2016). Identifying the important driving factors to urban sprawl and their relationships is an essential task for understanding and forecasting urban sprawl.

The purpose of this study was to understand how different driving factors affecting urban sprawl and examine their relationship over time for a particular study area: San Antonio, Texas. Knowing the influencing factors behind urban sprawl is critical for building a sustainable city.

The research questions of this study include: 1) Did San Antonio, TX appear to experience urban sprawl from 1990 to 2010? 2) Are there any changes of significance in the driving factors of urban sprawl in San Antonio during this period?

II. Literature Review

This chapter surveys the literature related to the processes of urban sprawl and modeling practices. Urban growth can take place at varying rates depending on a variety of factors, including but not limited to population growth, economic growth, expansion of transportation facilities, housing availability, etc. Since not all urban growth results in sprawling, therefore, not all factors causing the urban growth are necessarily related to urban sprawl. Factors such as population growth, country-living desire, living and property cost, or development and property tax, among others, may have varying degree of relevance and significance on urban sprawl (Bhatta 2010). In general, Bhatta (2010) summarized a series of categorical factors, including economic, sociological, and political, that could cause urban sprawl. Variables important to the process of urban sprawl, how they would be measured and modeled the phenomenon will be discussed next in this section.

Process of Urban Sprawl

The process of urban sprawl generally starts with urban growth characterized by increasing population in urban areas either by local residents' growth or by immigrants from surrounding suburban areas looking for a better life (Tombolini et al. 2015; Beyhan et al. 2012; Rahman 2016). The increasing population stimulates economic growth and attracts more people moving in, which generally leads to a high population density in the urban core. As a result of higher demand for housing in the urban core that drives up housing cost, some residents start moving out to the surrounding suburban areas for more affordable and larger housing options (Tombolini et al. 2015; Rahman 2016; Verzosa and Gonzales 2010; Debbage and Bereitschaft 2016). In the United States, for instance, low density suburban development took place in cities like Providence (RI), Raleigh (NC), and Austin (TX) from 2001-2011 (Debbage and

Bereitscyhaft 2016). In general, the connectivity of road networks, along with the lack of proper urban planning and other driving factors (e.g. lower property tax, topographic limitation, availability of agriculture lands to be converted into urban, etc.) make cities sprawl into different forms (Table 1) (Verzosa and Gonzales 2010; Wassmer 2002; Barrington-Leigh and Millard-Ball 2015; Beyhan et al. 2012; Jat et al. 2007).

Physical constrains like topography and road network geographies limit the form as well as process of urban expansion. For example, Mersin City, Turkey, where mountains in the north limits the expansion of city, which sprawled along the major transportation road from west to east in a linear form (Beyhan et al. 2012). Similar forms manifested in Baguio City, Philippines where the city is surrounding by mountains and can only connect the city with other places through highways (Verzosa and Gonzales 2010). Another example is Ajmer, India where the city expands south-north along highways due to the mountains in west and east (Jat et al. 2007). Since 1980s, distance to major road network is an important variable in modelling urban sprawl (Noresah and Ruslan 2009; Hamdy et al. 2016; Alsharif and Pradhan 2013). Thus, the closer land is to major road network, the more likely that urban sprawl takes place.

As a fiscal factor, property tax affects urban sprawl, such as the metropolitan areas in western United States because developers and residents tend to acquire lands and houses in the suburban areas where lower property tax prevails (Wassmer 2002). Moreover, lower property tax indicates lower cost of housing, which is likely to increase dwelling size, decrease population density, and induce urban sprawl (Brueckner and Kim 2003; Song and Zenou 2006). If a land parcel supports a low population density, more land will be needed. The lack of proper planning during the early stage of urban growth is another factor in the United States that leads to a

Author	Geographic area	Form	Time	Factors	Relationships
Verzosa and Gonzales	Baguio City, Philippines	Concentric	1979-1992	1. Population growth	Positive relationship: population growth causes the sprawl
			1992-2002	2. Topography (surrounding mountains, steep terrain)	Topography limits land available for development
			After 2002		
Wassmer	Western metropolitan areas in the U.S.	Polycentric	1950-1990	1. Country-side living desire	Positive relationship: people moving to suburbs stimulate suburban retail activities
			1977-1997	2. Property tax	Positive relationship: greater property tax pushes out residents and retail activities towards urban fringe
Barrington-Leigh and Millard-Ball	Metropolitan areas in the U.S.	Linear	1920-1990	1. Automobile dependency	Positive relationship: people can travel further
			1990-1994	2. Availability of new roads with poor connectivity	
			1994-2012	3. Increase of road network connectivity	Negative relationship: more road network connectivity will decrease the degree of sprawl
Beyhan et al.	Mersin City, Turkey	Linear	1987-2000	1. Immigration	Positive relationship: immigration coming into city causing expansion, mountains on north limit the northern expansion, and the expansion of city has to follow the major transportation road from west to east.
				2. Topography	
			2000-2009	3. Major transportation road	

Table 1. Process of Different Forms of Urban Sprawl.

transformation of agricultural land around the urban edge into an urban area like Lexington, KY and Raleigh, NC (Phillips 2015).

Cowell (2011) tested some socioeconomic variables, such as median household income, transportation cost, poverty rate and crime rate which he assumes are important factors in urban sprawl. The results show that the median household income is not statistically significant to urban sprawl, even though it has a positive relationship with the amount of urban sprawl. The increasing inner-city crime rate and poverty rate are significant and would serve as a push factor to drive people out of central urban area. The transportation cost, which is statistically significant in the result of his study, shows an inverse relationship with the amount of urban sprawl (Cowell 2011).

Measuring and Modeling Urban Sprawl

In order to examine variables in the process of urban sprawl, researchers are using remote sensing, entropy and statistical techniques for measuring and modeling urban sprawl (Deep and Saklani, 2014; Jat et al. 2007; Shi et al. 2017; Li and Yeh 2001). Remote sensing is a cost-effective technology to monitor and analyze urban sprawl (Jat et al. 2007). In practice, researchers have applied supervised (e.g. Maximum likelihood) and unsupervised (e.g. ISODATA) classification techniques to classify and distinguish built-up areas along with other land cover and land use (LCLU). The resulting maps have been used to conduct change detection to examine how LCLU has been transformed through time (Zeng et al. 2014; Deep and Saklani 2014).

To quantify LCLU change, entropy (e.g. Shannon's entropy) in Information theory is adopted for understanding spatial association (Li and Yeh 2001; Verzosa and Gonzalez 2010;

Rahman 2016). In general, entropy quantifies the degree of randomness or disorder in a system. The higher the value, the higher the randomness in space. In the context of urban sprawl, higher entropy values mean higher disorder or randomness of the distribution of a geographical phenomenon (i.e. density of urban development) (Li and Yeh 2001). Lower entropy values indicate that an area is more homogenous with a compact development. Using the concept of relative entropy, Li and Yeh (2001) quantified urban sprawl on the Pearl River Delta Region of China by creating 48 buffer zones around city center and 24 buffer zones around roads with 250m buffer distance. Rahman (2016) set the buffer distance to 1km and simplifies the creation of buffer zones into creating concentric buffer zones around city center of Riyadh, Saudi Arabia only. Choong (2017) conducted a sensitivity analysis of the relative entropy value for City of Minneapolis and Chicago in the United States. She designed buffer zones around each city center with 1-mile buffer distance and calculate the relative entropy value to measure urban sprawl. Her study also compared the relative entropy value between buffer zones created by five mile/half mile buffer distance around each city center and the result indicates that the relative entropy value is not sensitive to the size of buffer zones (Choong 2017).

In empirical studies, regression techniques (e.g., GWR, logistic regression and OLS) are commonly used to model urban sprawl, (Noresah and Ruslan 2009; Cabral et al. 2011; Cowell 2011; Alsharif and Pradhan 2013; Osman 2016; Hamdy 2016). Logistic regression has been used to model the binary outcome of urban expansion and to investigate the relationship between important factors and urban sprawl based on the regression coefficient of independent variables (Alsharif and Pradhan 2013). Unlike logistic regression using a binary outcome, Cowell (2011) and Cabral et al. (2011) used the amount of urban area as a dependent variable in OLS regression for modeling urban sprawl. OLS is also referred to as “global linear regression” and the variables are typically aggregated into coarse geographic units, e.g. county. Hence, the resulting model may not model the process well for finer geographic units. GWR is another technique in the regression family that is sensitive to spatial variation of modeled variables. By assigning unequal weights customized to each local area, GWR was reported to perform better with a higher goodness-of-fit statistics (i.e. R^2) than OLS (Noresah and Ruslan 2009). This indicates that the myriad relationship between urban sprawl and factors important to the process may vary at the local scale.

Summary

Unlike the process of urban sprawl in European and Asian cities, urban sprawl in North American cities typically experience the spread of low density settlement in suburban areas (Wassmer 2002; Debbage and Bereitschaft 2016). Presence of immigrants, accessibility to major road networks, property tax, etc. are some of the significant driving factors for the urban sprawl in the United States (Cowel 2011; Wassmer 2002; Brueckner and Kim 2003; Song and Zenou 2006; Phillips 2015; Barrington-Leigh and Millard-Ball 2015). Among the literature surveyed, the practice of urban sprawl modeling did not examine the changes in the important factors over time. For instance, as present in Table 2, distance to highway, distance to city center, population density and slope are used in regression models throughout the entire but various time periods (Alsharif and Pradhan 2013; Noresah and Ruslan 2009; Osman 2016; Hamdy 2016). Based on previous research examined urban sprawl in 1970, Cowell (2011) used the same variables (median household income, population, transportation cost and agricultural land rent) but added poverty rate as a new variable for the focus year in 2000. By using relative entropy to identify urban sprawl, this research explores the dynamic change of important variables to urban sprawl over time and space in San Antonio.

Author	Study Period	Distance to highway and city center	Population Density	Slope
Noresah and Ruslan	1990-2000	✓		✓
Osman	2004-2013	✓	✓	
Hamdy	2001-2013	✓		✓
Alsharif and Pradhan	1984-2002	✓	✓	✓

Table 2. Common variables used in different study throughout the time period examined.

III. Methodology

Study Area

In this research, the study area is San Antonio, TX, a major city in south-central Texas (Figure 1). San Antonio is the seventh most populous city in the United States (Census Bureau 2016). It has a long history of Spanish heritage because the city was founded as a Spanish mission and colonial outpost. Early settlers built this city along the San Antonio River Valley where San Antonio is part of the "Hill Country" with rolling hills and rivers. The altitude of San Antonio is 772 feet above sea level, however, there is no significant mountain range that could physically restrict the city from expanding in those areas.

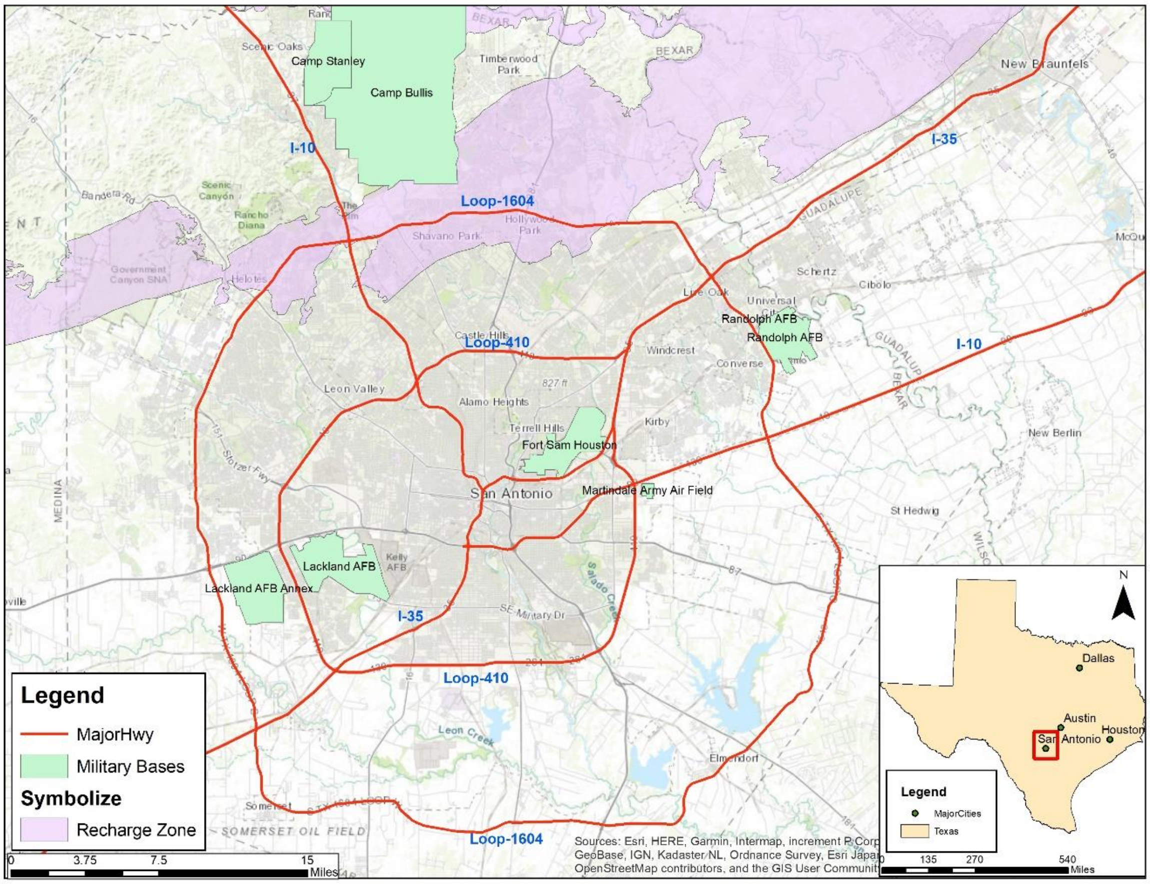
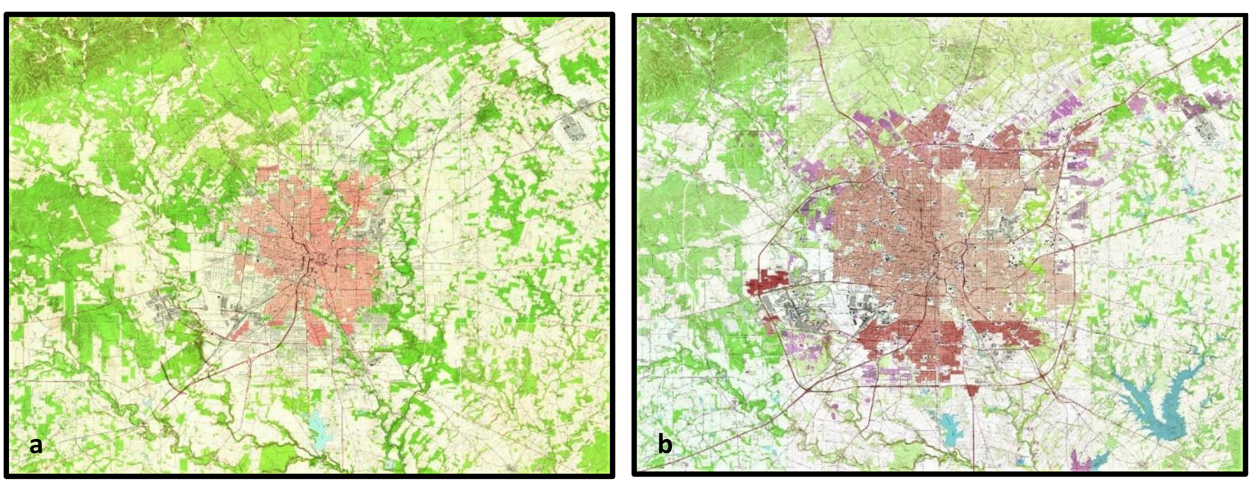


Figure 1. Current Map of San Antonio

There are two intersecting major highways (I-10, I-35) passing through the city and two loops (Loop 410, Loop 1604) encircling it. From Figure 1, most of the city area is within loop 1604 with some areas extend outside to the north of loop 1604. Among the five major military bases in San Antonio (Lackland AFB, Martindale Arcy Air Field, Fort Sam Houston Base, Randolph AFB, CampBulls), two (CampBulls and Randolph AFB) are located outside the Loop 1604 and Lackland AFB is located at the city edge between Loop 1604 and Loop 410.

Starting in the 1950s, San Antonio experienced a dramatic urban expansion (Figure 2). The city was expanding outward between 1953 and 1967, and the Loop 410 was built around the city edge at that time. During 1967 to 1992, the city expanded in the west, north and particularly northeast along Interstate Highway 35. Loop 1604 was built along the northern edge of the city to mitigate traffic congestion. After 1992 until present time, the northern and western expansion caught up to the development along I-35 in the northeast. According to the SA Tomorrow plan, the city is expecting a 1.1 million population increase over the next three decades (Davila 2016). San Antonio ranked 3rd in terms of number of new residents from 2015 to 2016 where there were 24,473 new residents coming into the city (Census Bureau 2016).



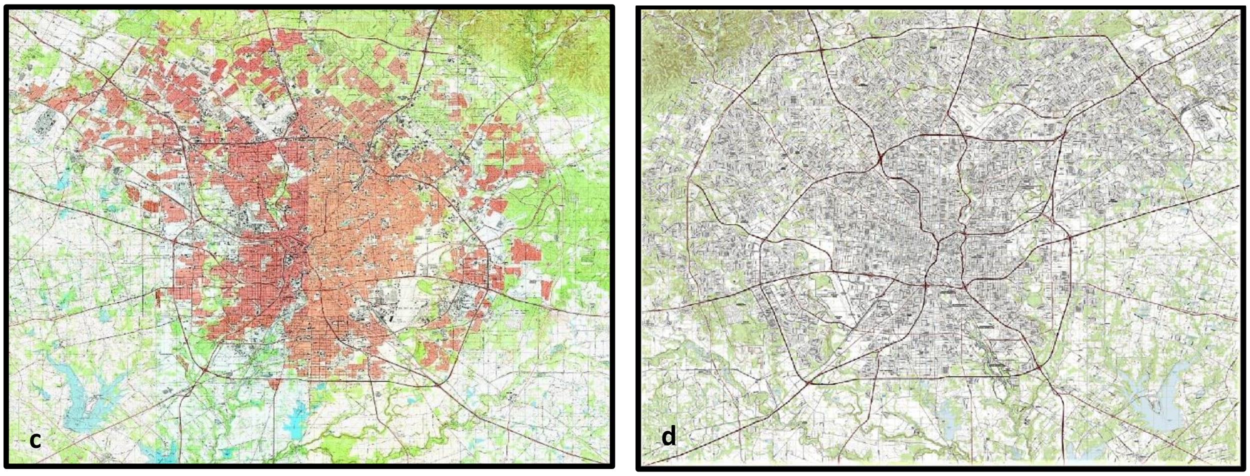


Figure 2. Topographic Maps of San Antonio in 1953 (a), 1967 (b), 1992 (c), and 2016(d).

The Edward Aquifer Recharge Zone lies north of Loop 1604. While the city expands to the north, real estate developments built over the recharge zone and environmental concerns about protecting the Edward Aquifer became a controversial topic in recent years (Rivard 2012; Sharp et al. 2014; AGUA 2005). As discussed earlier, San Antonio also experienced urban sprawl and its associated problems whilst the city is trying to build a smart city sustainably according to the SA Tomorrow Comprehensive Plan (City of San Antonio 2016).

Data

Landsat 5 images for the year of 1991, 2000, 2010 were acquired from the U.S. Geology Survey LandsatLook viewer. All images were Landsat Level-1 Precision and Terrain (L1TP) corrected Tire 1 collection. Landsat L1TP corrected data is suitable for time-series analysis because of its long history and consistency. All images were chosen for the winter time because of less cloud cover and less tree cover over the urbanized area that would make classification process easier and generate more accurate result (Table 2). The format of the images was GeoTIFF and the spatial resolution was 30 meters.

Based on the literature reviewed (Cowell 2011; Wassmer 2002; Barrington-Leigh and Millard-Ball 2015; Alsharif and Pradhan 2013; Noresah and Ruslan 2009; Osman 2016; Hamdy 2016), the following factors were chosen to study variability in urban sprawl for the years of 1990, 2000, and 2010: major highway, median household value, travel time to work, poverty, military bases, Edward Aquifer recharge zone, DEM and single family residential at block group level. Table 3 provides the list of variables and their data sources.

Variables	**Year**	**Source**	**Justification**
Median Home Value	1990, 2000, 2010	U.S. Census Bureau	Representation of Property Tax
Travel Time to Work (Not including work from home)	1990, 2000, 2010	U.S. Census Bureau	Barrington-Leigh and Millard-Ball (2015)
Poverty	1990, 1999, 2010	U.S. Census Bureau	Cowell (2001)
Distance to Major Highways	current	City of San Antonio	Alsharif and Pradhan (2013), Noresah and Ruslan (2009), Osman (2016), Hamdy (2016)
Density of Single Family Residential	1990, 2000, 2010	U.S. Census Bureau	Wassmer (2002), Bhatta (2010)
Distance to military bases		City of San Antonio	The existence of five military bases in San Antonio
Distance to Edward Aquifer Recharge Zone		Edwardaquifer.org	The raising concern of protecting recharge zone
Slope	1990, 2000, 2010	USGS	Alsharif and Pradhan (2013), Noresah and Ruslan (2009), Hamdy (2016)

Table 3. List of Variables

Methods

This study was conducted in two phases. The first phase involved the measurement of urban sprawl in San Antonio, and the second phase examined the relationship between various factors and urban sprawl. In order to examine urban sprawl in San Antonio, Landsat images were classified into urban, non-urban and water classes based on the Anderson Level 1 classification scheme. The Iterative Self-Organizing Data Analysis Technique Algorithm, known as ISODATA, was used to classify images. ISODATA is an unsupervised classification technique that assign pixels to randomly-placed spectral clusters based on the shortest distance method. Then the standard deviation within each cluster, and the distance across cluster centers is calculated. In this iterative process, two clusters are merged if the distance between them is less than the user-defined threshold to form new clusters. The algorithm stops the iteration when: 1) the average inter-center distance reached the user-defined threshold or 2) the average change in the inter-center distance over iterations is less than user-specified tolerance or 3) the maximum number of iterations is reached. In this study, the following parameters were used: the maximum number of clusters was 30; the maximum number of pixels in class was 5; the maximum iteration was 20 times; the maximum class standard deviation was 5; the change threshold was 5%; and the minimum distance between cluster means was 2. The settings of parameters were based on default values.

Shannon's Entropy is a way to measure the degree of concentration and dispersion of a geographic variable, which, in this case, is built-up area among *n* zones in San Antonio. By looking at the map of San Antonio (Figure 1), the city is built around the city center (downtown area). Highways like loop 410 and loop 1604 circulate the city (Figure 2). Therefore, San Antonio is arguably consistent with a concentric urban development pattern. Covering the entire study area, there were 27 buffer zones drawn from the geocentric point of San Antonio with 1-mile buffer distance based on Chong (2017). The classification of remote sensing images provided the built-up area which was used to calculate the amount of built-up area within each zone by the zonal statistics. Then the overall entropy value (*H_n*) was calculated by using the equation below (Li and Yeh 2001):

$$H_n = \sum_i^n p_i \log(\frac{1}{p_i}) \qquad (1)$$

where p_i is the probability of built-up area occur in the *i*-th zone which is given by:

$$p_i = x_i / \sum_i^n x_i \qquad (2)$$

where x_i is the density of built-up area in the *i*-th zone and n is the number of buffer zone created. The entropy value typically ranges from 0 to log N where value close to 0 represents a compact distribution of built-up area and a value close to log N indicates dispersed distribution.

Relative entropy normalizes the entropy value into a range from 0 to 1. The equation is shown below (Li and Yeh 2001):

$$H'_n = \sum_i^n p_i \log\left(\frac{1}{p_i}\right) / \log(n) \qquad (3)$$

The interpretation of the relative entropy value is similar to entropy value that value close to 0 indicates compact development and value close to 1 indicates sprawl development.

In addition to the degree of urban sprawl in San Antonio, another iterative process carried out to test if any buffer zones have compact urban development. To achieve this, the process of calculating entropy value was repeated 26 times and each time a relative entropy value would be calculated starting from the inner buffer zone and expand outward incrementally. Buffer zones with relative entropy values less than 0.5 were considered as compact development and were taken out from this study. The threshold 0.5 was adopted from Dadras et al. (2015)'s work, which aimed to distinguish between sprawl development and compact development. After the first phase, regression models were used to model the urban sprawl. Exploratory regression and OLS were used to examine the overall coefficients and statistical significance of chosen variables. In addition, the Variance Inflation Factors (VIFs) from OLS were examined to identify potentially multicollinearity issues. From the exploratory regression exercise, only statistically significant independent variables with VIF less than 7.5 were used for a subsequent GWR (ESRI 2018). Then the GWR analysis was used to examine the relationships between factors and urban sprawl in 1990, 2000, and 2010 at the census block group level. The dependent variable and independent variables are shown below,

$$Urban = \beta_0+\beta_1(MHV)+\beta_2(DTH)+\beta_3(TTW)+\beta_4(PRATE)+\beta_5(SFHD)$$
$$+\beta_5(DTB)+\beta_5(DTA)+\beta_5(SLOPE)+\varepsilon$$

Where:

Urban = The percentage of the amount of urban area

MHV = Median Home Value

DTH = Distance to highway

TTW = Average travel time to work

PRATE = Poverty rate

SFHD = Single family residential density

DTB = Distance to military bases

DTA = Distance to Edward Aquifer recharge zone

SLOPE = Slope

IV. Results

Image classification and Shannon's Entropy

The overall relative entropy value for each study time was close to 1 which answers the first research question that San Antonio has been experiencing urban sprawl (Figure 3). The overall relative entropy value increased from 0.84 in 1990 to 0.92 in 2010 which indicated that the dispersal of urban development had been increasing throughout time. The inner 5 zones for all three decades had relative entropy values less than 0.5 and were eliminated for later regression model. Starting from the 6^{th} zone, the overall entropy values were all larger than 0.5.

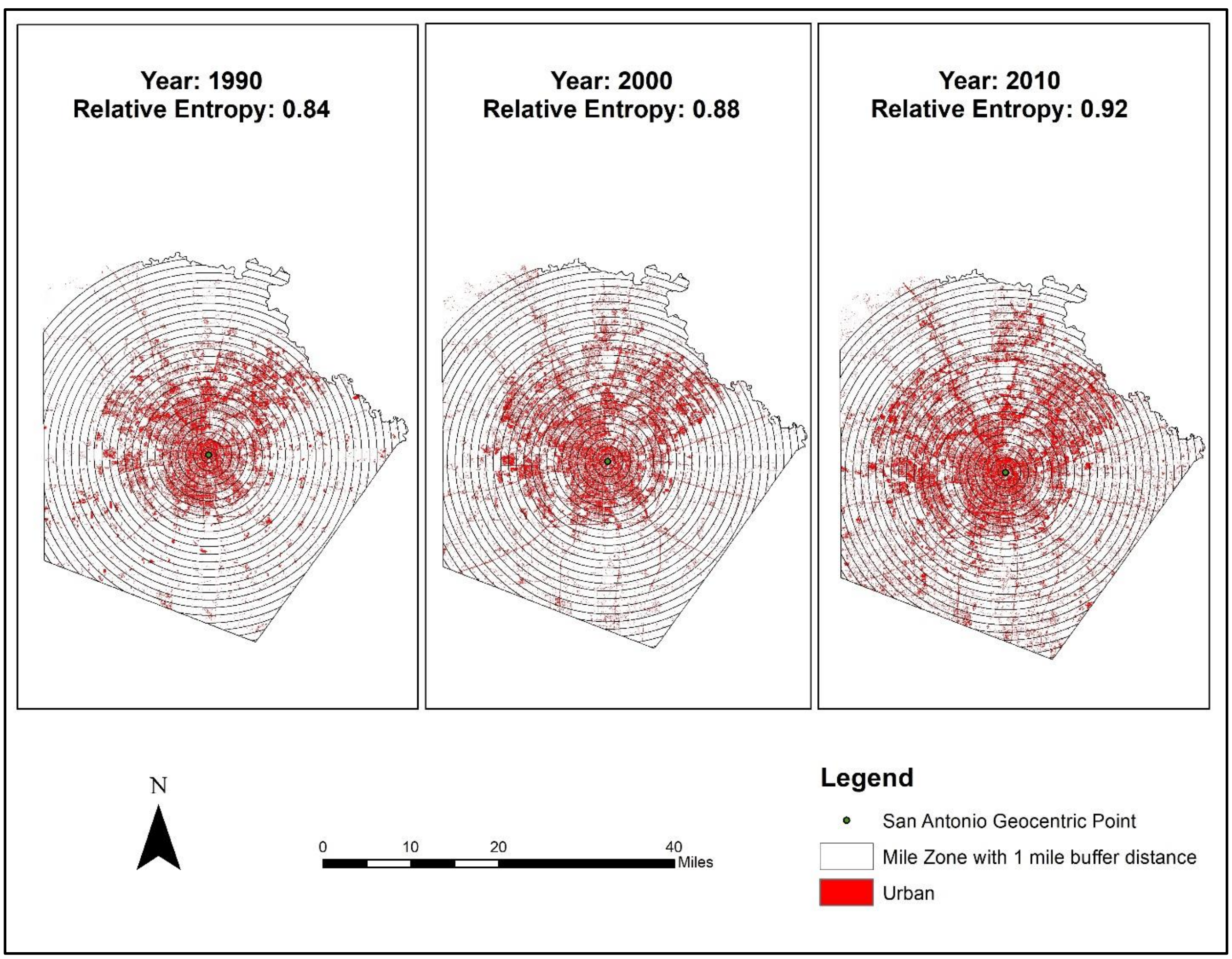


Figure 3. Results of Shannon's Entropy.

OLS and Exploratory Regression

Table 4 presents the results of exploratory regression in details with the percentage of significance, positive and negative relationship for each independent variable. It was found that four variables, including MHV, SFHD, PRATE, and SLOPE were significant in all three decades and hence were chosen for further investigation in OLS. On the other hand, DTH and DTA were not significant at 95%. DTB became significant in 2010 while it was not significant in 1990 and 2000 with 0% significance in 1990 and 4.04% significance in 2000. In addition, some independent variables, such as TTW, DTB, DTH, and DTA had mixed percentage of negative and positive relationships with urban sprawl which showed local differences of relationships within the study area.

	1990	**2000**	**2010**
MHV			
Significant (%)	98.44	100.00	100.00
Negative (%)	100.00	100.00	100.00
Positive (%)	0.00	0.00	0.00
DTH			
Significant (%)	75.00	63.64	87.50
Negative (%)	50.00	68.69	100.00
Positive (%)	50.00	31.31	0.00
TTW			
Significant (%)	50.00	27.27	7.87
Negative (%)	95.31	96.97	88.28
Positive (%)	4.69	3.03	11.72
PRATE			
Significant (%)	93.75	87.88	100.00
Negative (%)	0.00	0.00	0.00
Positive (%)	100.00	100.00	100.00
SFHD			
Significant (%)	100.00	100.00	100.00
Negative (%)	0.00	0.00	0.00
Positive (%)	100.00	100.00	100.00
DTB			
Significant (%)	0.00	4.04	100.00
Negative (%)	32.81	88.89	100.00
Positive (%)	67.19	11.11	0.00

DTA			
Significant (%)	44.53	66.67	64.06
Negative (%)	78.91	75.76	51.56
Positive (%)	21.09	24.24	48.44
SLOPE			
Significant (%)	100.00	100.00	100.00
Negative (%)	100.00	100.00	100.00
Positive (%)	0.00	0.00	0.00

Table 4. Results of Exploratory Regression.

To compare the changing magnitude of coefficient for different independent variables, the same combination of variables was used for the three decades. Based on the results of exploratory regression, TTW, DTA and DTH were excluded from OLS since they were not significant. For comparison through decades, variables needed to be significant for all decades. Even DTB became significant in 2010, it was not included in OLS and GWR. PRATE was not significant in 1990 and 2000 with 93.75% significance in 1990 and 87.88 significance in 2000. However, the level of significance is relatively high, and the relationship is constant at 100% positive through all decades. It was worthy for further testing. Under these criteria, the final combination of independent variables for OLS was MHV, SFHD, PRATE, and SLOPE.

After running the OLS regression, the adjusted R^2 for OLS in 1990 is 0.62, in 2000 is 0.49, and in 2010 is 0.36 (Table 5). All chosen independent variables are statistically significant (p-value <0.01). Moreover, the VIFs for all variables in all study periods were smaller than 7.5 (Table 5). OLS regression also provided the result of Koenker test which indicates if there is a nonstationarity in the variables. If the Koenker test is statistically significant, regional variation occurs and using GWR would improve the model results (ESRI 2018). In this case, the results of Koenker test were 0.02 for 1990, <0.01 for 2000, and 0.03 for 2010 respectively. MHV and SLOPE shoed negative relationship with urban sprawl and others were positive. The standardized coefficients showed that MHV and PRATE affected urban sprawl more from 1990 to 2010 (Table 5). SFHD on the other hand, affected urban sprawl less where standardized coefficient changed from 0.78 in 1990 to 0.43 in 2010 (Table 5). SFHD was the most important variable in 1990 and 2000, but MHV became the most important one instead in 2010. SLOPE remained stable in its affection on urban sprawl (Table 5).

Variables		**1990**	**2000**	**2010**
MHV	**Unstandardized Coefficient**	-0.000452	-0.000941	-0.000667
	Standardized Coefficient	-0.12	-0.37	-0.53
	Standard Error	<0.01	<0.01	<0.01
	p-value	<0.01	<0.01	<0.01
	VIF	1.22	1.38	1.19
SFHD	**Unstandardized Coefficient**	0.000460	0.000333	0.000158
	Standardized Coefficient	0.78	0.67	0.43
	Standard Error	<0.01	<0.01	<0.01
	p-value	<0.01	<0.01	<0.01
	VIF	1.53	1.56	1.53
PRATE	**Unstandardized Coefficient**	0.145213	0.243657	0.869047
	Standardized Coefficient	0.08	0.20	0.39
	Standard Error	0.06	0.05	0.11
	p-value	0.02	<0.01	<0.01
	VIF	1.15	1.33	1.20
SLOPE	**Unstandardized Coefficient**	-0.008855	-0.005361	-0.006044
	Standardized Coefficient	-0.26	-0.19	-0.25
	Standard Error	<0.01	<0.01	<0.01
	p-value	<0.01	<0.01	<0.01
	VIF	1.59	1.64	1.55
Adjusted R^2		0.62	0.49	0.36
AIC		-856.56	-720.12	-757.07

Table 5. Results of OLS Regression.

GWR

The final combination of independent variables was MHV, SFHD, PRATE, DTH, and SLOPE. DTH was added in GWR because literatures showed that it was significant to urban sprawl with a negative relationship (Alsharif and Pradhan 2013; Noresah and Ruslan 2009; Osman 2016; Hamdy 2016). DTH might be non-statistically significant globally, but in some lobal areas it might be significant. It would provide insights in GWR. Table 6 shows the results of the adjusted R^2 from GWR for each time with the combination of five independent variables. The five variables explained more than 60% of the variance of urban sprawl in this model for all decades. However, the R^2 was decreasing from 1990 to 2010. In addition, the standardized coefficients for each variable through all decades were shown in detail (Table 6). The Akaike Information Criterion (AIC) is a value used to compare different models. Model with smaller value performs better (ESRI 2018).

Variables		**1990**	**2000**	**2010**
MHV	**Minimum**	-0.55	-1.10	-2.09
	25% quartile	-0.26	-0.55	-0.79
	50% quartile	-0.08	-0.38	-0.46
	75% quartile	0.16	-0.17	-0.13
	Maximum	0.85	0.48	0.93
SFHD	**Minimum**	0.09	-0.18	-0.62
	25% quartile	0.48	0.22	-0.04
	50% quartile	0.71	0.53	0.21
	75% quartile	0.87	0.71	0.47
	Maximum	1.36	1.21	1.39
PRATE	**Minimum**	-0.27	-0.15	-0.98
	25% quartile	-0.01	0.07	0.10
	50% quartile	0.11	0.17	0.22
	75% quartile	0.21	0.31	0.34
	Maximum	0.67	0.67	0.85
DTH	**Minimum**	-0.92	-1.33	-1.84
	25% quartile	-0.26	-0.25	-0.31
	50% quartile	-0.07	-0.09	-0.14
	75% quartile	0.02	0.02	0.02
	Maximum	0.28	0.27	0.54
SLOPE	**Minimum**	-0.67	-0.69	-1.19
	25% quartile	-0.27	-0.26	-0.31
	50% quartile	-0.17	-0.11	-0.11
	75% quartile	-0.07	0.02	0.00

	Maximum	0.12	0.37	0.62
Adjusted R^2		0.79	0.68	0.63
AICc		-1165.14	-965.46	-1099.93

Table 6. Standardized Coefficients of GWR.

The observed urban map from classified imageries for the three study periods were shown below in Figure 4. Comparing the process of changing percentage of urban area, the northern half of the whole region generally experienced a faster urban development than the southern half. The southern half, especially outside loop 410, barely experienced any significant urban development.

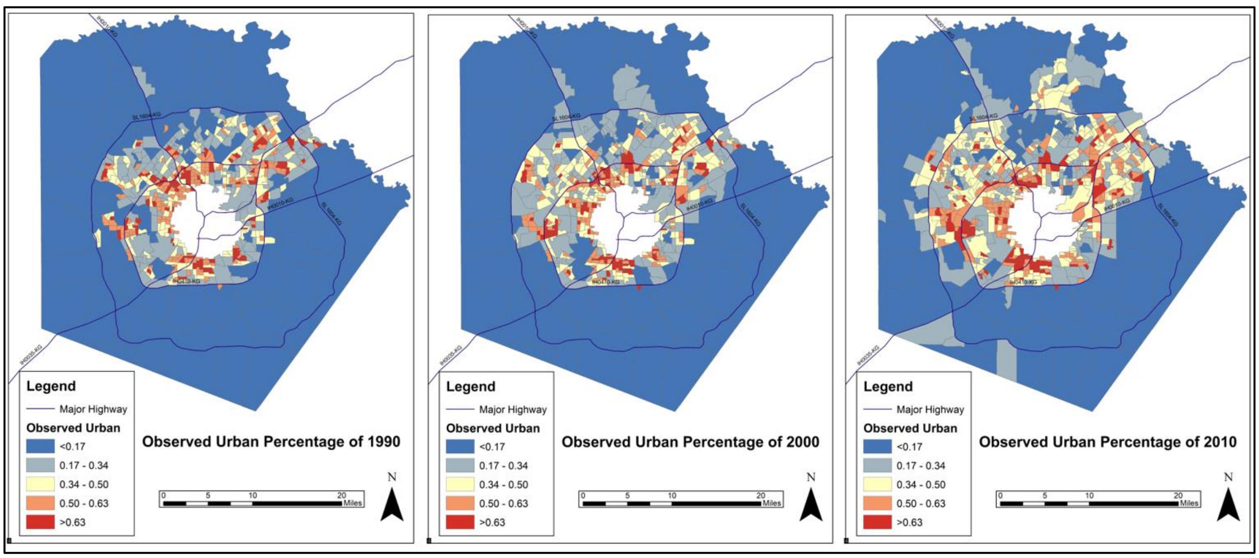


Figure 4. Observed Urban Percentage.

MHV

The GWR results for MHV are shown in Figure 5. From 1990 to 2000, areas with positive relationship reduced from mostly outer edges (i.e. outside loop 1604) to northwestern and eastern edges and western outside downtown. In 2000, areas in southern part with positive relationship changed to negatively related. In 2010, positive relationship areas in the north shifted eastward and some areas reappeared on the southeastern part. Overall the region showed that median home value was negatively related to urban sprawl especially within loop 1604 where some of the strong negative relationship appeared. Based on the standardized coefficients for GWR, MHV was increasingly important to model urban sprawl from 1990 to 2010 for most quartiles except 75% (Table 6).

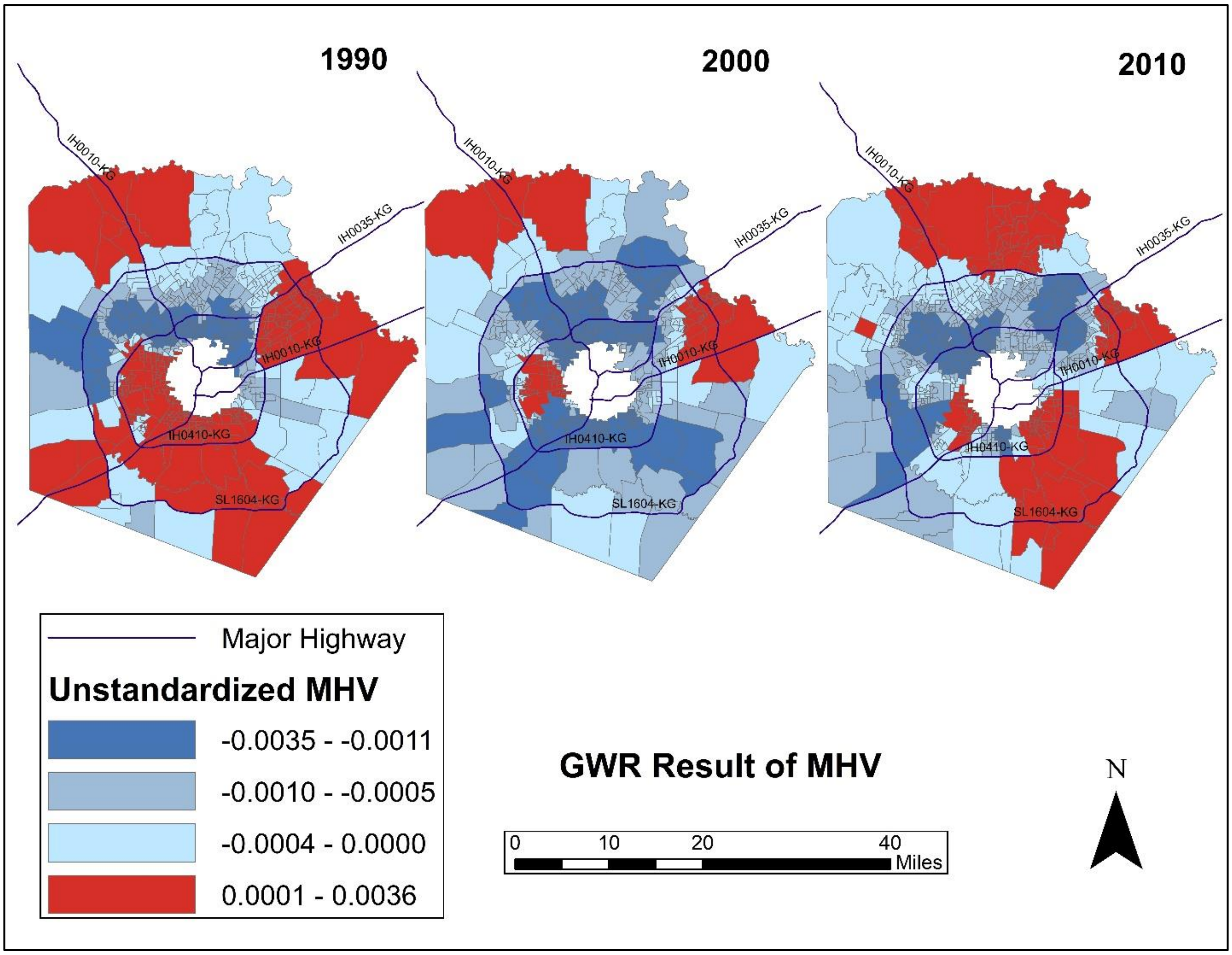


Figure 5. Comparison of regression coefficients of MHV in GWR.

SFHD

The GWR results for SFHD are shown in figure 6. In 1990, the relationship between SFHD and the urban sprawl was positive and showed strong positive relationship. Northern part outside of downtown area represented that the SFHD had relatively weak positive relationship on urban sprawl. In 2000, the areas with the strongest positive relationship were still mostly over outer edges except for central north. The effects of SFHD decreased in the northern downtown area and expanded toward loop 1604. Some areas north of downtown within I-410 started showing negative relationship. In 2010, the negative relationship expanded over the northern and northwestern areas inside loop 1604. However, the outer edges remained a strong positive relationship except for western edges. The SFHD was negatively related to urban sprawl around the medical centers near northwestern area outside loop 410. Overall, the outer edges had stronger positive relationship comparing to the rest of the areas during the three decades. The standardized coefficients in Table 6 showed that except for minimum standardized coefficients which had greater negative affection on urban sprawl, other quartiles showed less affection from 1990 to 2010.

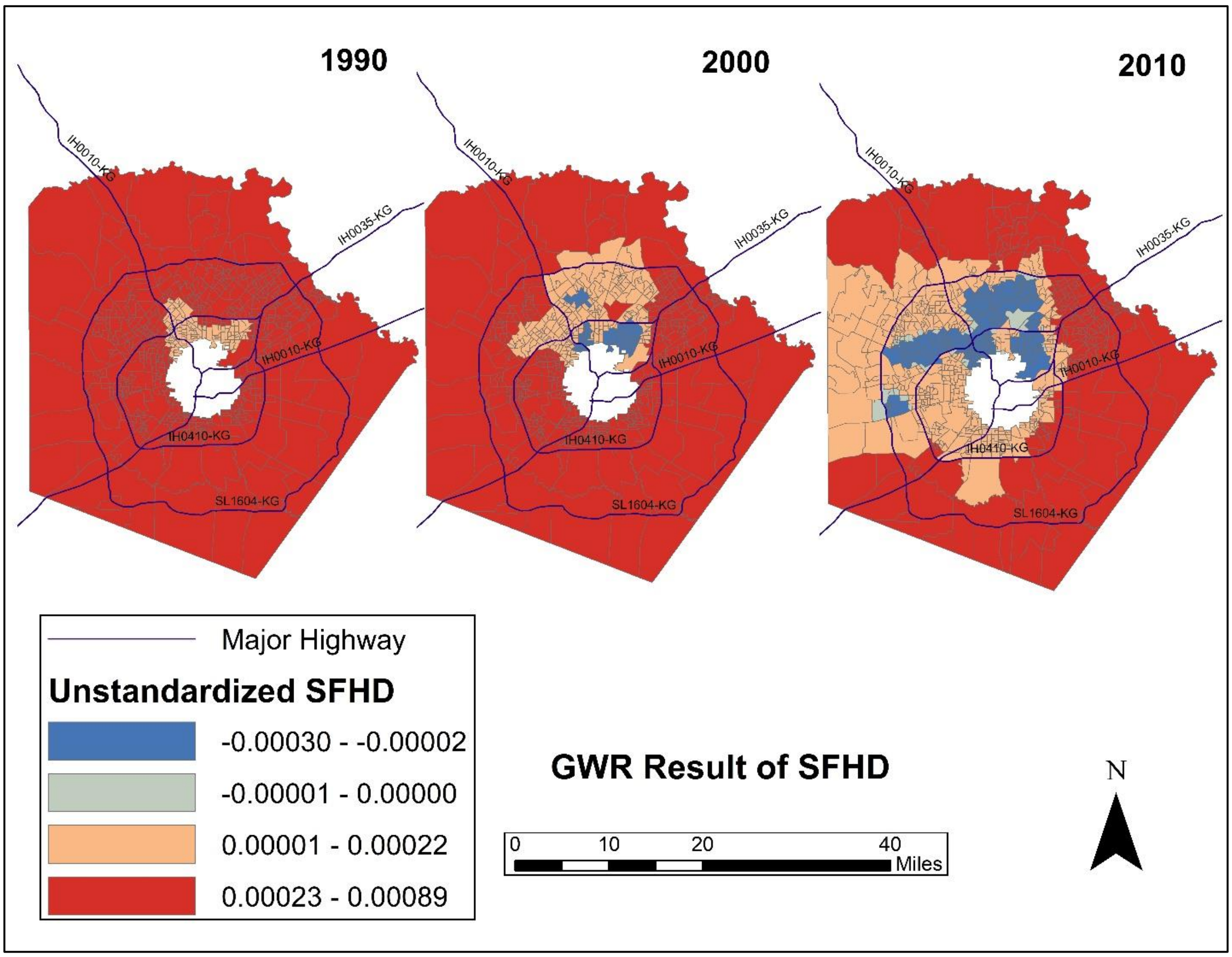


Figure 6. Comparison of regression coefficients of SFHD in GWR.

PRATE

The GWR results for PRATE are shown in Figure 7. In 1990, majority of the whole region showed positive relationship between poverty rate and urban sprawl except for the west side of loop 410 and the southwestern region. In 2000, the relationship between PRATE and urban sprawl showed similar pattern as of 1990. However, some areas in the eastern region along I-10 changed their relationships from positive to negative. The negative relationship weakened over southwestern part. Western part between downtown and loop 410, however, changed from negative relationship to positive relationship. In 2010, overall, areas with positive relationship occupied the majority of the study area. The western edges and southern half of the study area indicated a negative relationship. The same negative relationship pattern also existed in an area over the east where loop 1604 intersected I-10. The standardized coefficients for PRATE for all quartiles showed increasing affection on urban sprawl from 1990 to 2010 in both positive and negative relationships.

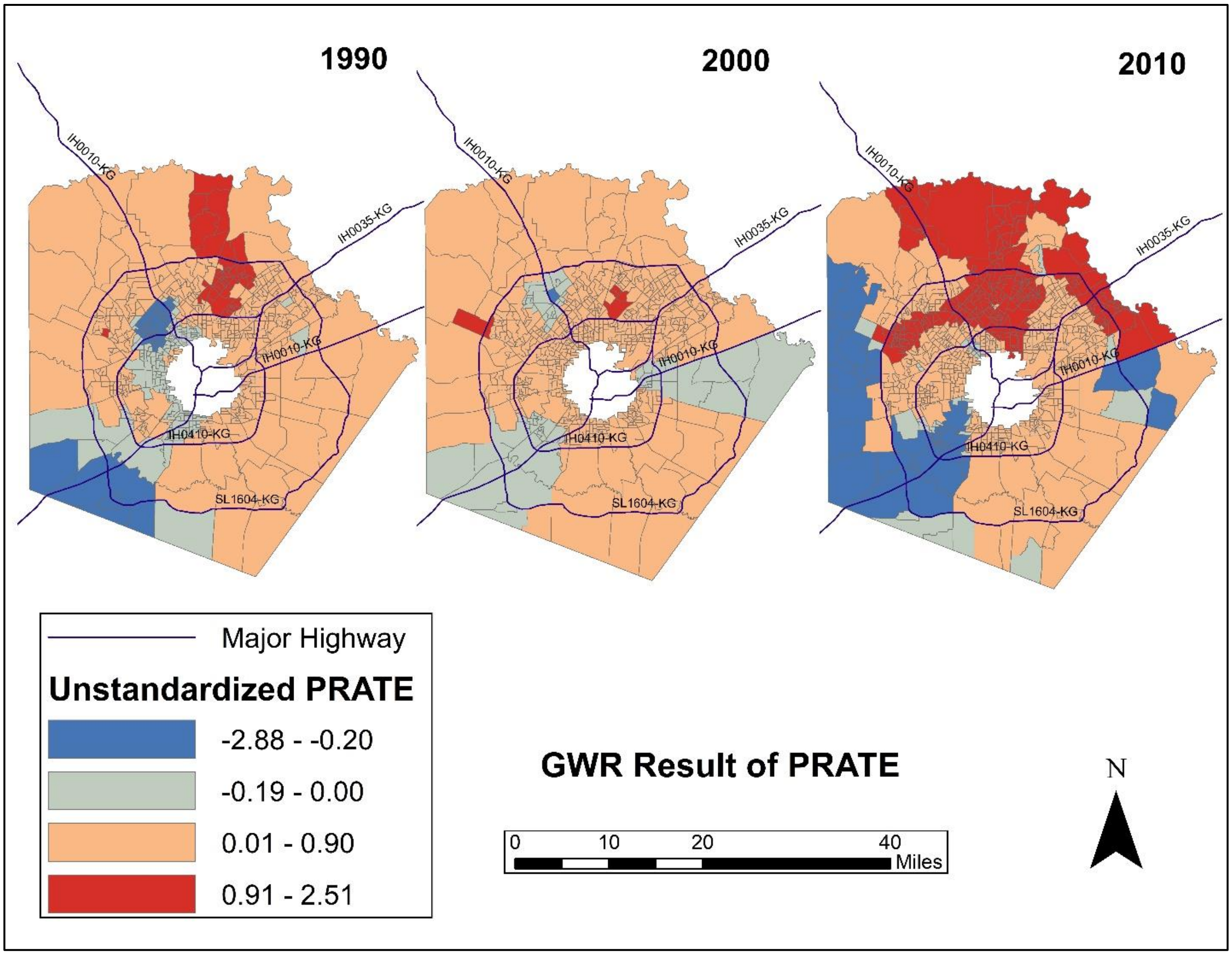


Figure 7. Comparison of regression coefficients of PRATE in GWR.

DTH

The GWR results for DTH are shown in Figure 8 below. In 1990, except for majority of areas in the south and northwest, other areas showed a negative relationship that the closer to highway, the more urban development there would be, vice versa. In 2000, areas over northwestern outer edges changed from a positive relationship between DTH and urban sprawl to negatively related. In addition, there was an inward movement of strong negative relationship in the eastern area from between I-10 and I-35 to the intersection of loop 410 and I-10. In 2010, the significance of negative relationship between DTH and urban sprawl increased mostly at the northwest areas. More areas outside southern loop 1604 changed their relationship from positive to negative. Some southern edges of the study area kept positively related DTH to urban sprawl and the significance of the relationship did not change too much from 2000. Overall, the whole region experienced a changing from positive relationship between DTH to urban sprawl to negative. The strong negative relationship areas became more fragmented which indicated more localized variation over time. The standardized coefficients also indicated the increase of affection for DTH to urban sprawl except for 75% quartile, the affection remained the same through decades (Table 6).

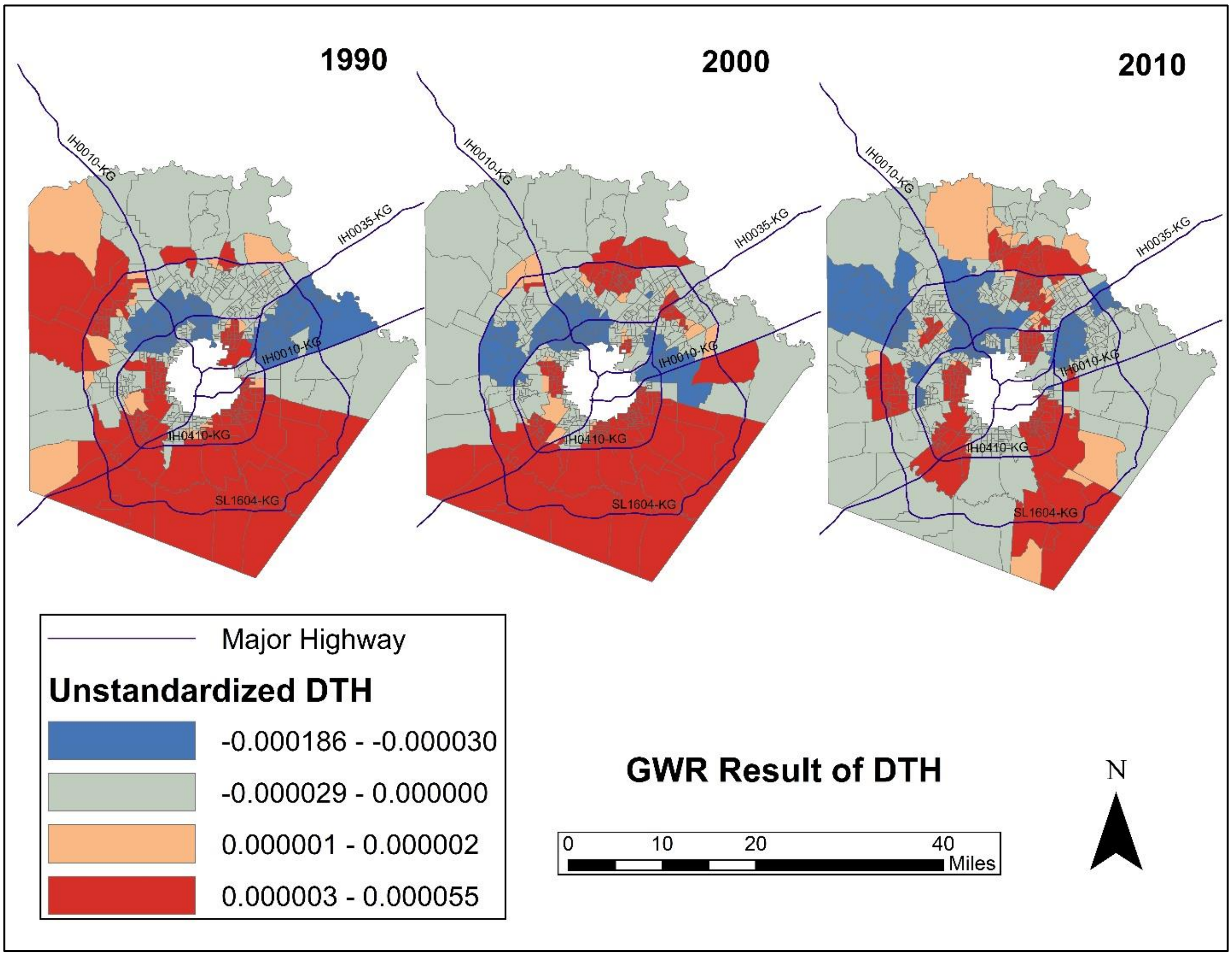


Figure 8. Comparison of regression coefficients of DTH in GWR.

SLOPE

The GWR results for SLOPE are shown in Figure 9. In 1990, nearly the entire study area showed a negative relationship which described more urban development happened in flatter areas. During the latter two decades, especially the central northern part of the study area appeared more urban development even the steepness of slope increased. By examining the standardized coefficient for SLOPE in GWR, the affection was increased except at 50% and 75% quartile (Table 6).

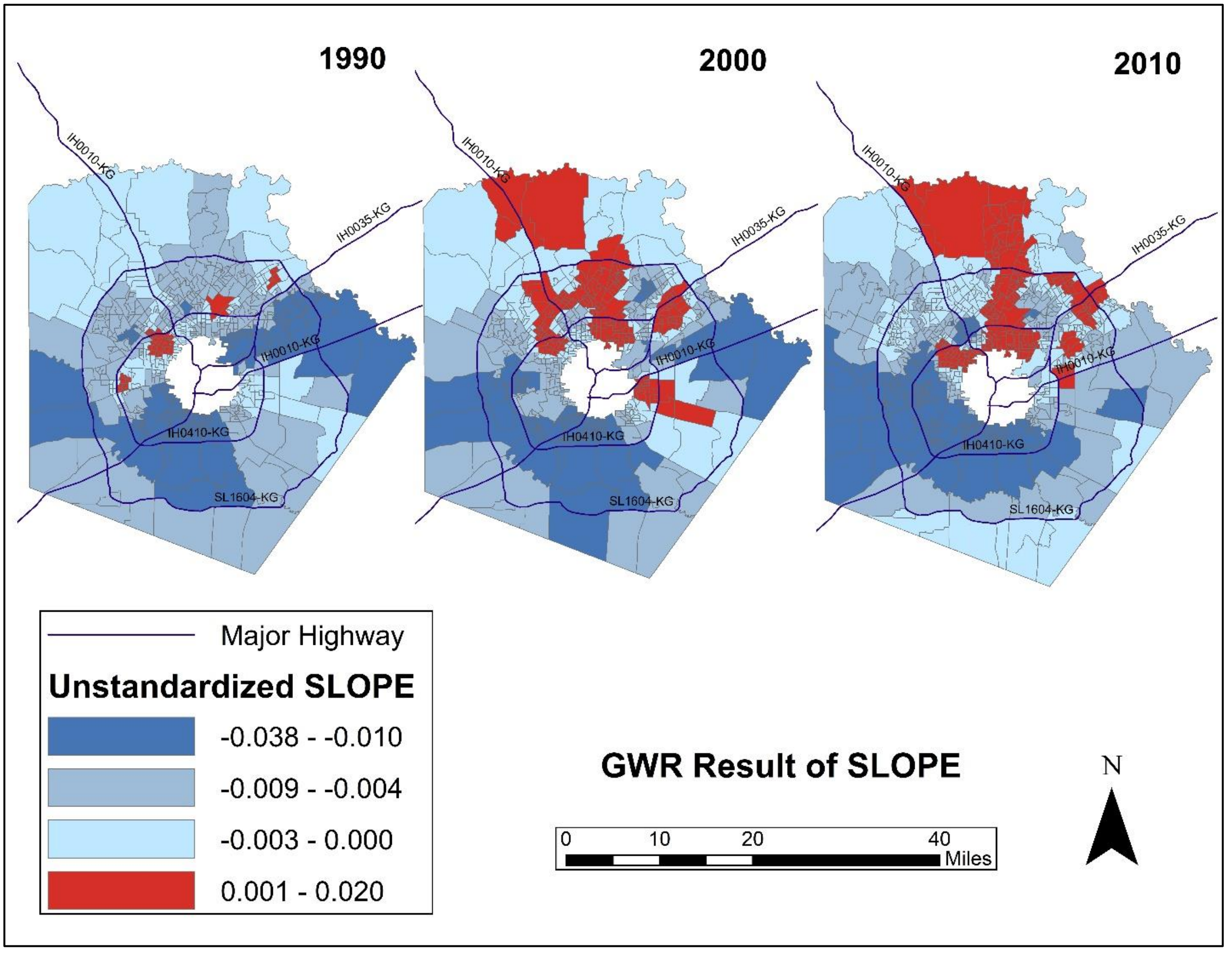


Figure 9. Comparison of regression coefficients of SLOPE in GWR.

V. Findings

Has San Antonio been experiencing urban sprawl from 1990 to 2010?

The entropy values suggest that San Antonio had been experiencing urban sprawl over time and the urban areas became more dispersed where relative entropy value changed from 0.84 in 1990 to 0.92 in 2010 (Figure 3). This answered the first research question. From Figure 3, the urban sprawl tended to be focused on northern part.

Overall performance of models

Comparing the adjusted R^2 and AIC value between OLS and GWR for each decade, GWR worked better for this study with higher adjusted R^2 and lower AIC value. The combination of independent variables in GWR model explained more variances than in OLS. Local R^2 presented that the GWR model worked better over the outer edges (Figure 10). On the other hand, areas along north loop 410 in 1990, the central northern areas in 2000, the circle near loop 410 and along north and west loop 1604 in 2010 had low R^2 in these models. This indicated that there might be some other variables in those areas that were not identified in this study. Outer edges were predicted better in this model, which might be due to little or no urban areas being present in these spaces. Most of the outer edges were under predicted based on the residual (Figure 11). The relationships identified in this study are well-aligned with existing literature (Cowell 2011; Wassmer 2002; Barrington-Leigh and Millard-Ball 2015; Alsharif and Pradhan 2013; Noresah and Ruslan 2009; Osman 2016; Hamdy 2016). However, Cowell (2011) identified a negative relationship of poverty rate as a push factor for people to move outward instead of a positive relationship. Details about the relationships are discussed below.

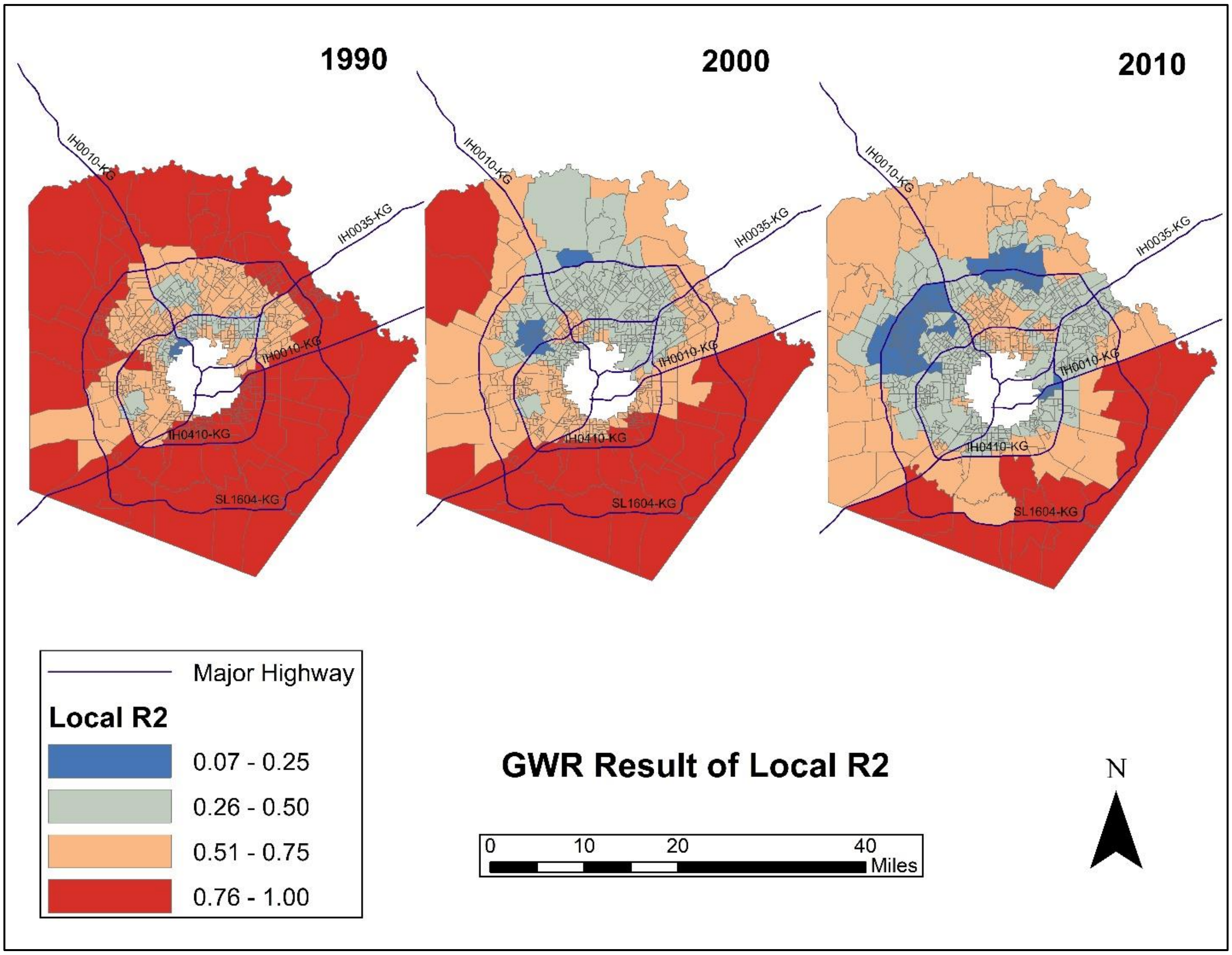


Figure 10. Local R^2 for GWR.

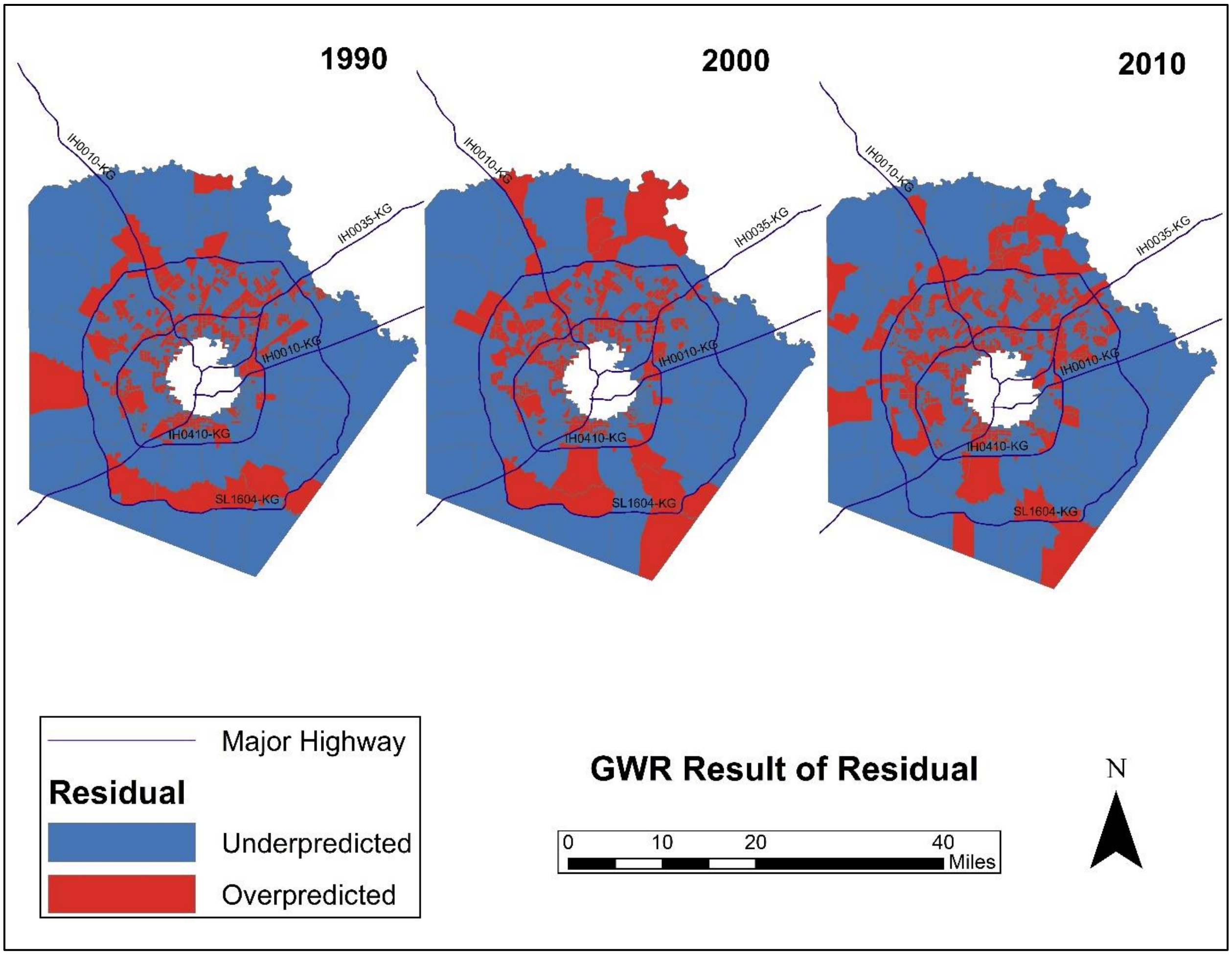


Figure 11. Residual for GWR.

Are there any changes of significance in the driving factors of urban sprawl in San Antonio during this period?

The R^2 from GWR for different study year was decreasing (Table 6). It could be possible that there were new variables affecting urban sprawl in recent years that were not identified in this study. For example, DTB was identified as statistically significant in 2010 but not in 1990 and 2000. If the GWR was conducted for examining 2010 alone, including DTB would possibly increase the performance. Another reason could be one of the identified significant variables became less important in affecting urban sprawl. For example, SFHD had a decreasing standardized coefficient over time. Changes in policies and future development focus (zoning code, city master plan) could lead to the change of significance in some variable.

Breaking down into each identified independent variable, each of them revealed different stories behind it. The changing pattern where positive relationship between MHV and urban sprawl over northern, southern and part of eastern area over time indicated that median home value did not represented the relationship as it was expected (Figure 5). From the observed urban area map (Figure 4), the direction of urban development in San Antonio was going north. This means more urban areas appeared to the north. As home value was increasing in the northern area, the relationship between MHV and urban development should be positive. This observation contradicted the negative relationship resulted from both exploratory regression and OLS (Table 4 and 5). The reason that southern part of the study area showed a positive relationship between MHV and urban sprawl might be due to less urban development in the south with low home value. In this study, the median home value was used as a proxy of property tax. From Figure 5, most of the study area especially for 2000 and 2010 showed that lower MHV was associated with more urban sprawl which aligned with literatures (Wassmer 2002). However, there were some areas on the north, southeast and part of the east showed negative relationship. The reason for southern area could be less urban sprawl with lower MHV. The northern area was where the development trend was heading to, the MHV did not affected too much.

For SFHD, the area between I-10 and I-35 in the north between loop 410 and loop 1604 showed relatively weak positive coefficients in 1990, a negative relationship in 2010 and a transition phase in between (Figure 6). This illustrated a recent trend between single family house density and urban sprawl that higher SFHD was associated with less urban development.

On the other hand, there might be lower SFHD with higher urban areas the model predicted. This brought up a problem during Landsat image classification which is called mixed pixel problem. The spatial resolution of Landsat images in this study was 30 meters. Even though images were collected during the winter time, trees were still green in Texas. Those trees covered a lot of urban development in that specific area. Under the circumstance that the resolution was not fine enough, pixels would be classified as vegetation instead of urban. Therefore, even more single-family houses were built in that area, the true amount of urban development might not be classified accurately. Furthermore, this could explain the clustered higher residuals inside northern part of loop 1604 (Figure 12). The standardized residual map showed that the areas that had negative relationship of SFHD with urban sprawl also had large residuals where red and orange colors clustered. By comparing the standardized coefficients (Table 5 and 6), SFHD impacted urban sprawl less in recent years. Looking at the study area as a whole, SFHD was still a significant variable throughout time especially over urban edges where urban sprawl was associated with low-density development.

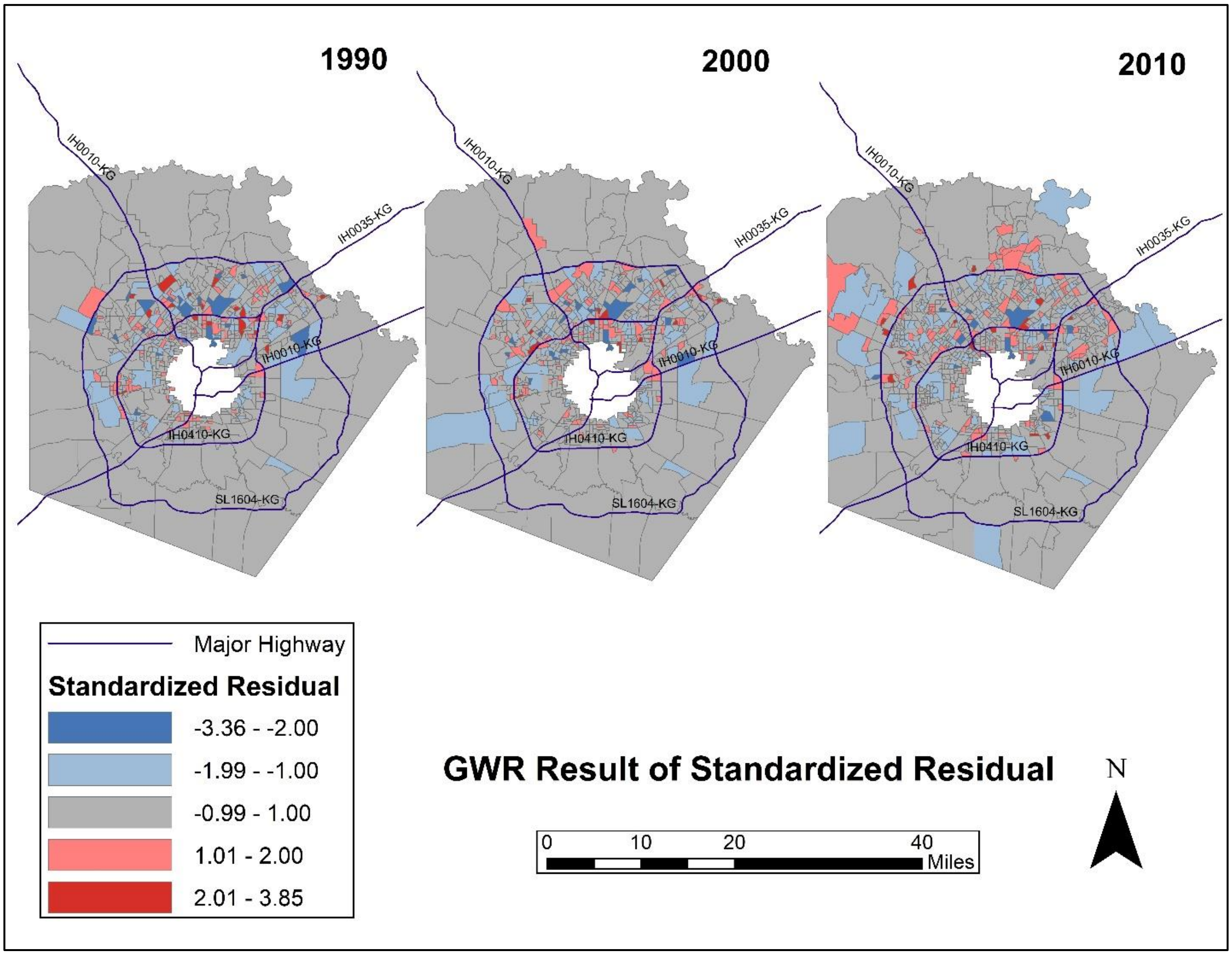


Figure 12. Standardized Residual of GWR.

GWR results with respect to PRATE showed interesting patterns that do not necessarily align with extant literature. It was possible that there might be higher poverty but less urban sprawl over the eastern area that showed negative relationship since those parts had fewer urban areas observed (Figure 4 and 8). The northern part of the study area displayed a positive relationship whereas some western and southern parts were the opposite (Figure 7). Its impact on urban sprawl increased from 1990 to 2010 (Table 5 and 6). From the literature (Cowell 2011), the expected result for this variable should be negatively related to urban sprawl. However, the

GWR in this study showed an opposite relationship for most of the study area. The difference between this study and the literature is that Cowell (2011) combined crime rate with poverty rate. If the crime data at block group level was used, the model might generate a better result which might change some of the positive relationship patterns to negative among outer edges since the regression result in Cowell's (2011) study crime rate was statistically significant to urban sprawl and higher crime rate pushed people "move out of the central city to the suburbs where less crime occurs".

The results of DTH in 1990 showed a positive relationship in areas where closer to highway would yield less urban development except for southern and western part (Figure 8). Combining the observed urban area map back in 1990 (Figure 4), there was not much urban development along loop 1604 yet. While areas along loop 1604 started to be developed after 1992 (Figure 2), the relationship changed from positive to negative. The standardized coefficients also indicated an increase of impact on urban sprawl (Table 6). In global linear regression such as exploratory regression, DTH was not statistically significant to urban sprawl (Table 4). The local variation from GWR showed that more areas at the outer edges and along most part of major highways were showing a negative relationship between DTH and urban sprawl through decades (Figure 8). This indicated that while the city was expanding outwardly, more urban areas appeared close to highways. This result was consistent with what the literature found (Alsharif and Pradhan 2013; Noresah and Ruslan 2009; Osman 2016; Hamdy 2016). In general, the study area had gentle slope with less variations except for northwest part where slightly steep slope occurred (Figure 13). This explained why the study area showed negative relationship between slope and urban sprawl (Table 5). Some northern areas showed a positive relationship between slope and urban sprawl indicated that regardless the increasing of slope, urban sprawl still occurs. One of the reasons could be that slope is not too steep to develop. Another reason could be that people desired to live higher for better aesthetic views. Combining with the standardized coefficients from OLS, slope kept relatively stable impact on urban sprawl overall (Table 5).

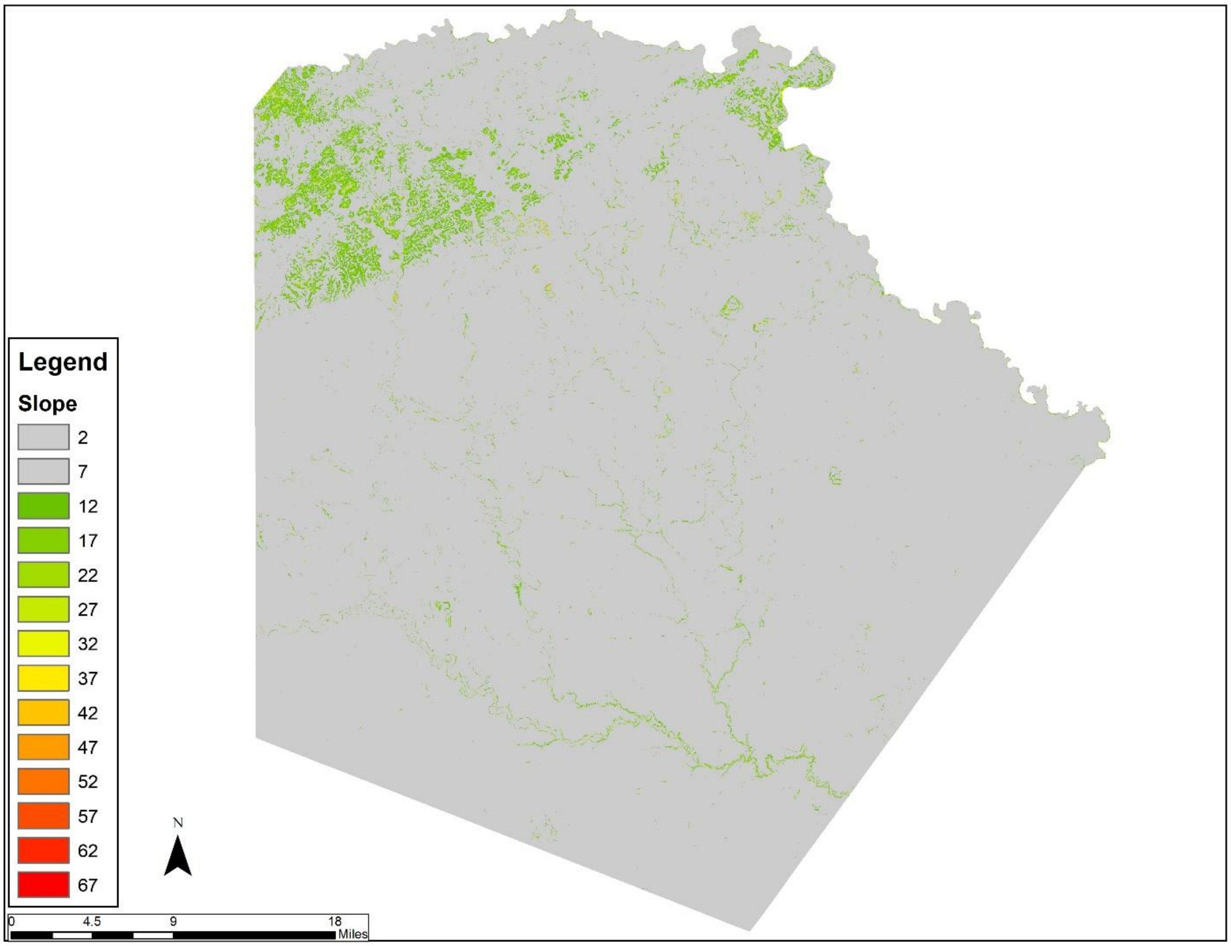


Figure 13. Slope of San Antonio.

Variables not selected in GWR

First of all, results comparing between original variable selection and final selection in Table 7 showed that excluding those insignificant variables in the model did not negatively impact the explanatory power too much. The adjusted R^2 was brought down by 0.02 in 1990 and 2000 and 0.04 in 2010. The AIC value did not increase too much as well.

	8 Variables		5 Variables	
	Adjusted R^2	AIC	Adjusted R^2	AIC
1990	0.65	-892.71	0.63	-856.56
2000	0.51	-741.98	0.49	-720.12
2010	0.40	-801.62	0.36	-757.07

Table 7. Comparison Between Variable Selections in Exploratory Regression.

The change in the degree of significance of TTW in exploratory regression indicated that travel time to work was not significant in determining how much urban development there should be (Table 4). The changing of relationship from negative to positive also suggested that more urban development used to appear where people lived closer to their work back in 1990. However, more recent urban development was taken place where people live far away from their work (Table 4). With the ownership of cars per household increases, people tend to live far from work. They were not generally depending on public transportation in San Antonio. The development of public transportation in San Antonio had not been catching up the outward expansion of the city. Since getting from home to work was not convenient through public transportation, it resulted in dependency of private vehicle for residents. The ability that private vehicle could travel further with more convenience and more efficiency, residents could choose to live further away from work (Table 4). Additional reason that might affect the TTW on the challenge of becoming significant might be the increasing number of people working from home since the data of TTW did not included people work from home.

Results in DTB indicated that there might be more military families moving into the city where more urban areas were developed close to military bases in 2010 (Table 4). This was a unique characteristic for cities having military bases installation like San Antonio. Some bases such as Camp bull, Randolph AFB, and Lackland AFB lied at the outer edge of the city (Figure 1). Therefore, this might become one of the factors that San Antonio was experiencing outward urban development.

Figure 14 presents the GWR results of DTA from the model in combination of all proposed independent variables. The map portrays the coefficients for DTA from the three decades. Selected areas in the maps are over the Edward Aquifer Recharge Zone. From the coefficients for three decades, the overall relationship between distance to recharge zone and urban sprawl over selected areas in 1990 was positive which means overall for those areas with closer to recharge zone experienced less urban development. This was because majority of the areas were outside loop 1604 and there was not much urban development. However, the patterns had been shifted from 1990 to 2010 from northwest to central north where the positive coefficients were getting less. This reflects that from 1990 to 2010, there were more urban developments over recharge zone regardless the distance to it. According to Figure 3, the trend of future urban development in San Antonio was to the northern and western area. The northwestern area showed weaker positive relationship over time between DTA and urban sprawl indicated that distance to recharge zone did not prohibit urban sprawl (Figure 14). The model presented the results that closer to recharge zone over northwestern area predicted to have more urban sprawl. Therefore, the final combination of independent variables in GWR model did not include DTA.

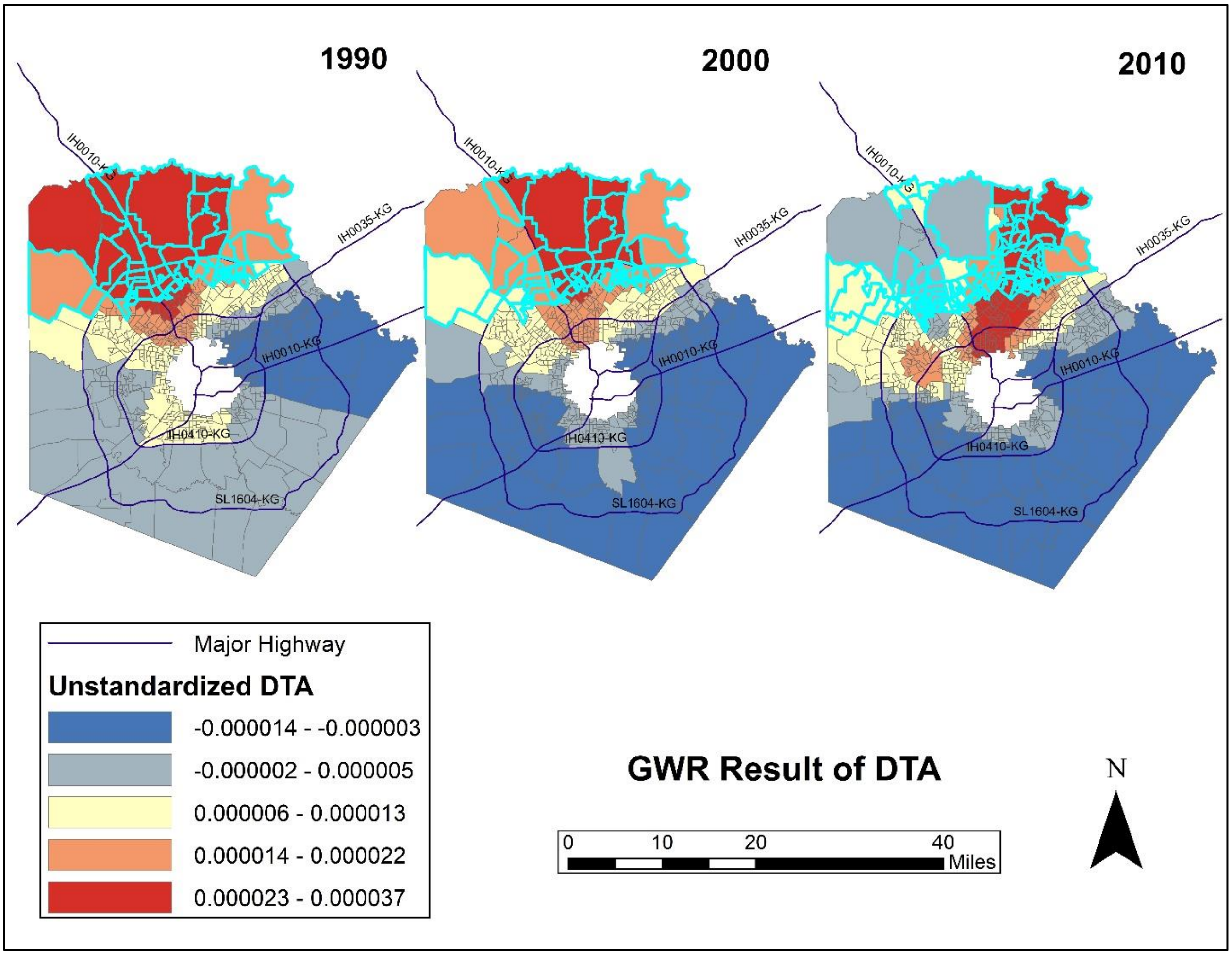


Figure 14. Testing GWR Results for DTA.

Due to data unavailability, historical property tax at block group level could not be found, which was an important factor suggested by Brueckner and Kim (2003) and Song and Zenou (2006). As a pilot study, not all variables were fully examined, such as vegetation area availability, municipal policies and residential occupancy. In particular, there was no dataset available to indicate whether the residential buildings are abandoned, occupied by residents or used as business office over time. With the exception of Dadras et al. (2015), this study and existing literature were limited in defining the appropriate threshold(s) to quantify urban sprawl. As such, the boundary between urban growth and urban sprawl was unclear and fuzzy.

VI. Conclusion and Future Study

As the third largest metropolitan area in Texas, San Antonio has experienced rapid growth—and this research shows that at least some of that growth was horizontal (sprawling) in nature, which can have serious negative consequences. What is more, sprawling urban development appeared to increase from 1990 to 2010, meaning that problems of dispersed urban development could be worsening in San Antonio. Learning the driving factors of urban sprawl in the past is critical to policy makers to build a sustainable city in the future. Although some factors have been established by other researchers as significantly affecting the form and process of urban sprawl (Table 1), less is known about the changes, if any, in the significance of factors through time.

The exploratory regression shows that the degree of significance of travel time to work decreased from 1990 to 2010 (Table 4). Residents in San Antonio are depending more on their private vehicles for commuting. This is due to the development of public transportation service not catching up with the sprawled development in San Antonio. Commuting through private vehicle gives people ability to live far from urban center. If the public transportation is improving, usage of private vehicle will possibly reduce. This will eventually attract people back to urban center where majority of office buildings are at as well as reducing air pollution.

The relationship between distance to military bases and urban sprawl used to be mixing with positive and negative in 1990 and 2000 which also were not statistically significant. However, in 2010, distance to military bases was significant to urban sprawl and closer to military bases, more urban sprawl. News in 2016 showed that San Antonio is famous FOR those joint military bases especially Lackland Air Force Base and this was attracting both new soldiers or veterans (Lawrence 2016). This is a unique situation in San Antonio that urban planners should consider this when they plan the zoning codes and future urban development.

Median home value, single family residential density, and poverty rate are three identified variables that are statistically significant in affecting urban sprawl in all three study decades. Each variable shows different patterns of its magnitude of coefficient. Overall, single family residential density affects urban sprawl along urban edges area. The density of single family residential is a strong indicator whether or not a city is built sustainably. In order to control the urban sprawl, more building with mixed land use could be planned with better community services and better access to different facilities (work, entertainment, shopping) within walking distance. One of the directions of urban sprawl in San Antonio was the areas over Edward Aquifer Recharge Zone (Figure 4). Despite the debate about protecting the recharge zone from urban development, sprawling development still appeared regardless how close to the recharge zone. This implies to urban planner that either additional protections should be needed while building more urban areas over recharge zone or restrictions of development should be applied.

In future research, more variables could be considered if more data is available. For instance, crime incidents could be used instead of poverty rate in future study for urban sprawl. Changes in policies are worth to be investigated further. As mentioned earlier, there is no universal method to measure and define urban sprawl, which could be a future research direction related to this topic. For example, how fast or how much urban development could be considered as urban sprawl. Could different cities be categorized to apply different rules in defining urban sprawl? Relative entropy value based on a multiple ring buffer zones could be a good way to measure urban sprawl. However, considering the complexity of how cities are built into different forms, how to adjust the setting of buffer zones to accommodate different forms would need more future research.

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