# USING CENSUS DATA, URBAN LAND-COVER CLASSIFICATION, AND DASYMETRIC MAPPING TO MEASURE URBAN GROWTH OF THE LOWER RIO GRANDE VALLEY, TEXAS

by

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# Abstract

The objective of this thesis is to design and perform an experimental study to demonstrate how census data, urban land-cover classifications, and dasymetric mapping may be combined together to map and measure urban growth. The experiment explored urban growth using 1990, 2000, and 2010 census population data and satellite-derived urban land-cover data. The premise of this thesis was that if the combination of these techniques is found to provide an effective method of measuring urban growth, then urban planners and city managers should be advised to use them together when measuring development patterns and forecasting growth scenarios of urban areas. Census tract population data for 1990, 2000, and 2010 and satellite-derived urban land-cover data were used for the analysis. The study areas included the Lower Rio Grande Valley, TX (LRGV) region and the Hidalgo County Metropolitan Planning Organization (MPO) planning area. Census tract relationships were established across census years to account for changes in tract boundaries. Population counts from 2000 and 2010 were adjusted to 1990 census tract boundaries. Population change, growth rate, and the share of regional growth were calculated for each census tract to identify areas that have experienced substantial growth. Results showed that four census tracts within the Hidalgo County MPO planning area contributed to nearly 25% of the growth of the entire region. Additionally, the Hidalgo County MPO planning area accounted for nearly 70% of the growth of the entire region. Landsat 5 Thematic Mapper (TM) imagery was acquired to coincide with each census year. Landsat images where classified using a 30-class ISO Cluster unsupervised classification. Results from these classifications where used to create training samples for high, medium, and low density urban land-covers. Supervised classification was performed for each year resulting in three

urban land-cover classes and one uninhabited class. Classification results were explored and plotted for each year to determine land-cover changes by urban density type. Results showed that the Hidalgo County MPO planning area has seen an increase in medium density development and a decline in low density development in the past decade. Multi-class weighted dasymetric mapping was performed using the aforementioned census tract data and urban land-cover classifications. The Dasymetric Mapping Extension (DME) for ArcMap 10 was utilized. Dasymetric population density maps were compared to choropleth population density maps. Dasymetric results where explored further for the four census tracts that contributed most to the region's population growth. Results indicate that the majority of the population resided in medium density developments by 2010, however, the areas that contributed most to population growth were still composed largely of low density urban development.

# Introduction

## Statement of the Problem

Decennial census data provides aggregated population counts at various scales. Population change and population density change analysis based on census counts is a ubiquitous technique in planning disciplines that use geographic information systems (GIS). Analysis of population and population density change from the state level down to the census block level can readily be performed using thematic mapping techniques on census layers with most GIS software packages. Resulting thematic maps are also known as choropleth maps. Although widely useful, this method of analysis and the resulting maps have two major limitations.

First, census designated boundaries, often decided arbitrarily, represent aggregated population as "a continuous variable across the entire land area" and do not take into account the spatial configuration of population within the census area (Holt *et al.*, 2004, p. 103). Changes in the orientation and scale of these boundaries (i.e., changes in the arrangement of aggregation) add statistical variation to non-modifiable entities such as individual and household census counts. This effect has been well researched and coined as the Modifiable Areal Unit Problem (MAUP) by Openshaw (1994). Holt *et al.* (2004, p. 104) state that areal-based analysis often results in "overestimates of population density in unpopulated and sparsely populated areas", and it "underestimates population density in more-densely populated areas."

Second, widely used definitions for urban areas and urban growth, such as the U.S. Census Bureau's urban-rural designations and the Urban Sprawl Index (Ewing *et al.,* 2002), rely heavily on population density statistics and other areal-based variables without taking into account the built environment. Social environments and built environments are not mutually exclusive though. Social changes (e.g., rural to urban migration, sprawl) influence the built environment, and in turn, the built environment is an indicator of social elements such as population density. Weeks *et al.* (2005, p. 2) simply state it as, "humans transform the environment, and are then transformed by the new environment." Weeks *et al.* (2005, p. 4) further suggest that "a relatively narrow range of combined values of the built and social environments would describe a unique set of urban populations." For this reason urban measures and urban growth estimates should combine measures from both the social environment (i.e., census data) and the built environment.

## Research Questions

The purpose of this study is to test the utility of census data, satellite-derived land-cover classifications, and dasymetric mapping techniques to measure urban growth over time. By comparison to choropleth maps, dasymetric maps greatly reduce statistical variability by mapping areas of inherent homogeneity in the data (Kimerling *et al.*, 2009; Sleeter and Gould, 2007). Additionally, it is not sufficient to simply consider natural-to-urban land-cover changes as sprawl. Dasymetric population densities are needed to understand both the social and landscape changes that are occurring over time. The use of ancillary data such as remotely sensed land-cover classifications may more accurately map and quantify population density by distributing population only into areas that can be inferred as populated (i.e., residential, medium density land-cover). This study addresses the following two main questions:

1. How do census data and satellite-derived urban land-cover classifications measure urban growth?

2. To what extent does the combination of these datasets through dasymetric mapping enhance the mapping and measurement of population density and urban growth?

The conclusion is that measures of both the social and built environments are needed for accurate measurements of urban growth.

## Research Objective

The objective of this thesis is to design and perform an experimental study to demonstrate how census data, urban land-cover classifications, and dasymetric mapping may be combined to measure and map urban growth. The experiment will explore urban growth using 1990, 2000, and 2010 census population data and satellite-derived urban land-cover data. The premise of this thesis is that the combination of these techniques provides an effective method of measuring urban growth, and planners and managers should use them together when measuring development patterns and forecasting growth scenarios of urban areas. The more accurate these measurements are, the better the job planners will do in estimating housing needs, preparing regional transportation plans, assessing the potential impact to the environment, and designing effective growth strategies.

The study area used for this experiment is the Lower Rio Grande Valley (LRGV) of Texas, a four county region that has seen substantial growth over the last 20 years. LRGV encompasses Starr, Hidalgo, Willacy, and Cameron counties, sharing its southern border with Mexico along the Rio Grande. LRGV is a delta region with agribusiness as the primary economic industry for the last 100 years (Vigness and Odintz, 2011). In the latter half of the 20$^{th}$ century the region has witnessed a merging of separate rural communities into larger metropolitan areas as many agricultural fields have been subdivided into neighborhoods and master planned communities.

A near ten-fold increase in population over the last 80 years in Hidalgo County alone indicates a shift from a rural to a more urban environment. More recently, seasonal tourism from the north (i.e. winter Texans, snowbirds), relaxed trade with Mexico, and an influx of migrant workers and immigrants has led to substantial industrial, commercial, and residential growth. LRGV provides an ideal region to conduct the experiment because its growth is manifested by both land-cover and demographic changes.

# Background

## Defining Urban Areas and Urban Growth

Urban environments often consist of numerous municipalities and census designated areas, but their urban extent cannot simply be defined by their political and administrative boundaries. In many cases, urban environments extend beyond municipal limits leading to more subjective definitions of what is urban and what is rural. In other cases, substantial amounts of undeveloped land (e.g., farmland, ranchland, floodplains) may exist within areas deemed urban. An accurate definition of urban areas is essential to map, quantify, and model urban growth.

Weeks *et al.* (2005) suggest that "urbanness" should be viewed more as a continuum rather than a dichotomy of urban and rural distinctions. Nevertheless, in the United States common definitions for urban and rural areas are provided by the U.S. Census Bureau's urban-rural classification scheme (U.S. Census Bureau, 2011). The White House Office of Management and Budget (2010) defines an urban area as either an urban cluster with a population between 10,000 and 50,000, or an urbanized area with a population greater than 50,000. Urban clusters and urbanized areas in turn serve as the urban cores to micropolitan and metropolitan statistical areas respectively (Office of Management and Budget, 2010). Population density is also used by the U.S. Census Bureau to determine urban areas. All territory, population, and housing units located within census blocks that have a population density of at least 390 people per $km^2$, plus surrounding census blocks that have an overall density of at least 195 people per $km^2$, are considered urban areas (Bhatta, 2010). Although useful for population, demographic, and socio-economic analysis, these census designated urban areas are limited in their usefulness for detecting and quantifying urban growth.

Bhatta (2010) argues that the problem lies in the various ways that one can define what is urban cover (i.e., the physical properties of the ground surface) and what is part of an urban area (e.g., lake, park, floodplain). It is this distinction between urban land-cover and urban land-use that is essential to remotely sensing the urban environments. On the one hand, urban land-cover (i.e. built-up land) is readily detected by remote sensors as buildings, concrete, asphalt, and man-made structures, otherwise known as impervious surfaces. On the other hand, urban areas (e.g., zoned land-use, urban clusters, urbanized areas) may include various land-cover types including natural and undeveloped land making it difficult to quantify urban growth through areal means (Bhatta, 2010). For this reason, the terms urban area and urban areas will be considered synonymous with terms such as developed land, urban land-cover, built-up land, or urban cover for the remainder of this study. Additionaly, the term urban area will be inclusive of residential, commercial, industrial, and transportation land-covers.

Urban growth in the strictest sense can be defined as the sum of increase in developed land. Other concise descriptions define urban growth as “land coversion over time” or “the change in the spatial structure of cities over time” (Hardin *et al.*, 2007, p. 142; Bhatta, 2010, p. 14). Three classes of urban growth include infill, expansion, and outlying growth. Infill growth involves the development of small tracts of land that are surrounded by urban cover. Expansion growth involves the exapansion of existing urban cover. Outlying growth is described as development "beyond the urban fringe" that exhibits isolated, linear branch, or clustered branch growth (Figure 1) (Wilson *et al.*, 2003, p. 277).

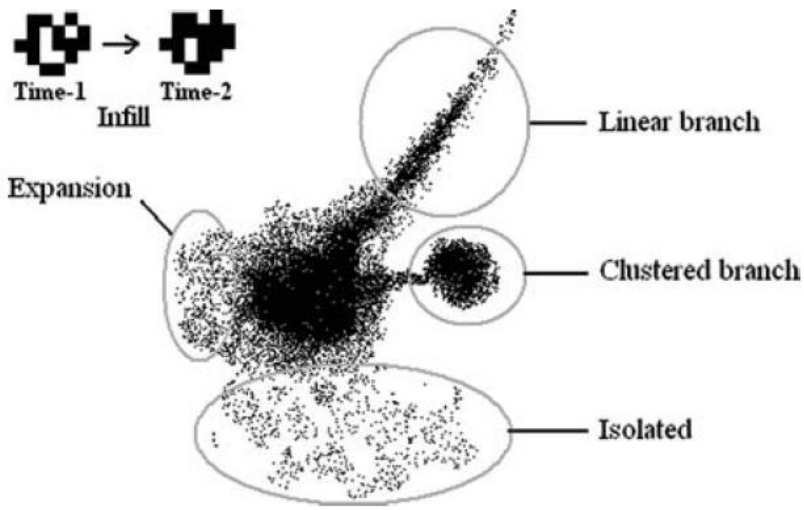



**Figure 1. Urban growth categories (adapted from Bhatta, 2010)**

The term urban growth is at times used interchangably with urban sprawl, a term that may carry with it a negative connotation. In some cases, particularly in undeveloped (i.e., third world) countries, urban sprawl is defined as unmanaged urban growth with negative economic, social, and environmental impacts (Hardin *et al.*, 2007). In developed countries, urban sprawl may be synonymous with suburban sprawl where suburbs expand into rural land at the fringe of urban areas. Wilson *et al.* (2003) argue that urban sprawl lacks a universal definition and can be misleading as not all urban growth, such as infill, is unhealthy or unwanted. Burchell *et al.* (2005) identify three common traits of urban sprawl including; unlimited outward expansion into undeveloped areas, low density development, and leapfrog development. In addition, urban sprawl tends to segregate residential and commercial development. This tendency for less mixed use land-use can be attributed to standardized and predictable (i.e., less risky) types of development, automobile dependence, and a lack of regional authoritative land-use planning (Burchell *et al.*, 2005).

An in-depth review of the causes and effects of sprawl is beyond the scope of this study, but the crux of the problem is that land development outpaces infrastructure. Rapid development beyond the urban fringe can overwhelm local governments' ability to provide services such as basic utilities, transportation, and housing infrastructure (Hardin *et al.*, 2007). Additional public services such as police, fire protection, and education add to the burden of government as well as cost to tax payers. Burchell *et al.* (2005, p. 6) argue that in the United States cost is the primary concern of sprawl, as "the majority of the American public is not unhappy with current pattern of development in metropolitan areas." By virtue of its existence sprawl does provide benefits which are hard to ignore such as reduced housing cost, increased home ownership, increased home and lot size, lower crime rates, greater school choice, and greater consumer choice (Burchell *et al.*, 2005). So the question is not whether urban growth will occur, but rather how has it grown, how will it grow, and ultimately how much will it cost? Studies such as this research that seek to find optimal ways to map, measure, and quantify urban growth can enhance our understanding of this phenomenon to help answer these questions.

## Using Census Data to Measure Urban Growth

The ability to measure urban growth directly from census data is highly limited due to the aforementioned MAUP and broad census urban area designations. Measuring population change and population density change may be a useful proxy for measuring urban growth though. Census enumeration units (e.g. blocks, block groups, tracts) can be analyzed across census years to calculate population change, population density change, and growth rate. A problem that invariably arises is the change of enumeration unit boundaries from one census to the next due to splitting, merging, or boundary adjustments. To account for these boundary changes, the U.S. Census Bureau provides relationship files that allow for population comparisons between census years.

Taking a 2010 census tract relationship file for example, each record in the relationship file represents a polygon that is formed when the 2010 census tracts overlay the 2000 tracts. Relationships may include no change between censuses, boundary revisions, the merging of several tracts, or the splitting of a tract. Once relationships are established, population statistics from 2010 census tracts may be assigned to 2000 tracts and change statistics may be calculated.

Population change and population density change statistics per enumeration unit may be performed by simple subtraction. The growth rate may also be calculated and is defined as the percent change between successive censuses and is expressed simply as:

$$GR = \frac{(Ppresent - Ppast)}{Ppast} \; X \; 100$$ Equation 1 (Parker, 2002)

Where:
$GR$ = Percent growth rate
$Ppresent$ = Present or more recent population
$Ppast$ = Past population

In addition, population projections, and subsequent change statistics, may easily be performed in a GIS using a table calculator or in a spreadsheet software program such as Microsoft Excel. Thematic mapping of these change statistics in a GIS can highlight census units that have experienced large population increase, high growth rates, and population density changes. These maps can be useful, albeit limited, indicators of urban growth.

## Using Satellite Remote Sensing Data to Measure Urban Growth

Although satellite sensor systems are generally lower in spatial and spectral resolution compared to airborne imaging and hyperspectral technology, they are well suited for regional urban analysis as they are more stable and cost effective, with high revisit rates and a wealth of archived data. In addition, satellite images provide complete regional coverage without the problem of imagery stopping at political boundaries (Wilson *et al.*, 2003). de Paul (2007, p. 2267) states that with advances in technology, satellite sensors have "found more applications in the analysis and planning of urban environments," and "are producing data with high potential for use in scientific and technological investigations." Landsat in particular has been invaluable for its longevity and resulting image library. Campbell (2007, p. 180), states that over the last 30 years, Landsats 1 through 7 (excluding Landsat 6 which was lost at launch) have maintained "consistent spectral definitions, resolutions, and scene characteristics, while taking advantage of improved technology, calibration, and efficiency of data transmission." This data collection consistency is vital to monitoring long-term land-cover changes in studies such as this that span decades.

Over 30 years of Landsat imagery archives provide a unique resource for analyzing and measuring urban growth. Essential to this analysis is the ability to detect urban land-cover change over the span of years and even decades. The most common approach to assess urban growth is to classify and detect change from natural-cover to impermeable surfaces such as rooftops, roads, and parking lots, as these "have been proven to be key indicators for identifying the spatial extent and intensity of urbanization and urban sprawl" (Xian and Crane, 2005, p.204). Urban areas are inherently difficult to classify though, due to the variety of spectral signatures (i.e., surface reflectance) in urban environments. The mixed pixel problem exists due to the high heterogeneity per pixel that exists in most urban scenes. This is a significant problem when classifying imagery from medium to low resolution satellite remote sensors such as Landsat (i.e., 30 meter resolution). In urban environments in particular, the spectral signature of a pixel may be a composite of several land-cover classes such as vegetation and asphalt. Spectral confusion can also make urban classification difficult due to reflectance similarites among land-covers such as 1) water, dark impervious surfaces, and shadows, 2) dry soil, commercial / industrial land, and dense residential land, and 3) forests and low density residential land (Lu and Weng, 2006). One can conclude that there are unavoidable trade-offs between the high temporal resolution and platform stability of satellite remote sensors and the high spectral and spatial resolution of airborne systems.

Taking the aforementioned caveats into consideration, urban growth can readily be measured from satellite derived classified images by performing change detection. Jensen and Im (2007) outline the required steps involved in most, if not all, change detection studies. These include, 1) specify the nature of the change detection problem, 2) identify environmental considerations and select the remote sensing system to be used, 3) process data by applying change detection techniques, and 4) evaluate the results. The two primary types of change detection are image based (i.e., image-to-image) and classification based (i.e., map-to-map) (Xian and Crane, 2005). The most commonly used change detection methods include image overlay, post-classification comparison, spectral-temporal classification, image differencing, image ratioing, image regression, and principal component analysis. Additional innovative methods include change vector analysis, artificial neural networks, decision trees, and intensity-hue-saturation transform (Hardin *et al.*, 2007).

## Dasymetric Mapping

Dasymetric mapping displays areas of homogeneity in data and is based on the idea that mapped areas “will have small internal magnitude variations, while there will be larger magnitude variations between mapped areas” (Kimerling *et al.*, 2009, p. 163). More over, the extent of populated areas serve as the denominator for dasymetric population density computations (Holt *et al.*, 2004). The redistribution of population from source zones (i.e., census boundaries) to target zones (i.e., populated land-cover) is known as areal interpolation. Areal interpolation functions are said to preserve the pycnophylactic property (i.e., volume preserving) in that “no data is lost or created during the transformation” (Sleeter and Gould, 2007, p. 1; Tobler, 1979). Furthermore, all error is limited to variations within each original areal unit (e.g. census block, block group, tract) since population is preserved through the transformation (Mennis, 2003). Sleeter and Gould (2007) argue that even though the nature of a population distribution is more realistically represented through dasymetric mapping, its complexity and ancillary data requirements often deter cartographers from using this technique.

The simplest form of dasymetric mapping is the binary “populated” or “unpopulated” approach where population totals are uniformly reassigned to populated areas. The primary advantage of this technique is that features such as lakes, rivers, agriculture, and uninhabited lands are excluded from the interpolation providing a more accurate representation of populatation distribution. An advanced form of the binary techniqe is the multi-class weighted dasymetric techique (Ming-Dawa *et al.*, 2010). This technique is based on the knowledge that populated areas consist of unique areas with different population densities such as multi-family developments versus single family neighborhoods. Weighting factors are assigned to each class according to its characteristic population density. Additional information is required for this technique that may include prior or expert knowledge, emperical sampling, or geo-statistical modeling (Ming-Dawa *et al.*, 2010). Figure 2 displays the binary and multi-class weighted techniques.

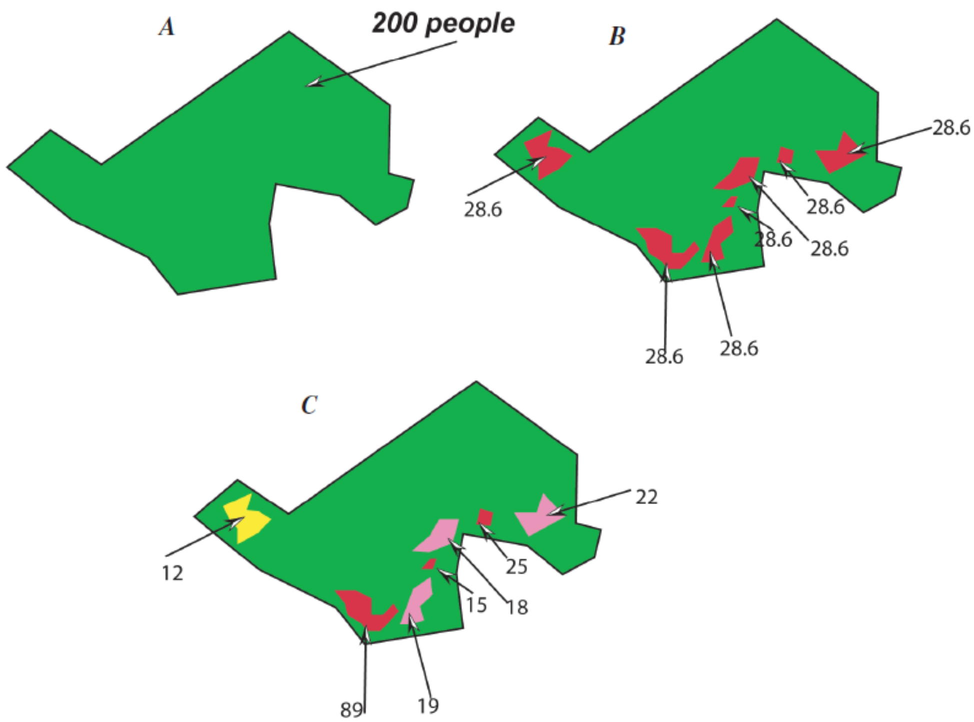



**Figure 2. Three population distribution techniques including A, aggregated population by census enumeration unit, B, binary even distribution into "inhabited" land-use, and C, multi-class weighted distribution into 3 urban density classes (adapted from Sleeter and Gould, 2007).**

Percentage based dasymetric mapping is yet another technique that may be employed by assigning a fixed proportion of the population to each mapped land-cover class. For example, an urban class may receive 80% of the population, open land 15%, and agriculture 5%. Sleeter and Gould (2007) state that the drawback to this technique is that the area of the land-cover class is not considered, leading to the problem where a very small urban area may still be assigned 80% of the population of a census unit.

Regardless of the dasymetric mapping approach used, the quality of the areal interpolation is dependent on quality data. In some cases parcel data may provide more accurate and reliable land-use and land-cover data than is possible with remotely sensed imagery. In addition to land-use attributes, parcel databases may provide information on building types and density parameters that may be useful for population density classifications. A study by Sleeter and Gould (2007) used parcel land-use attributes rather than remotely sensed land-cover classification to define high density, medium density, low density, and uninhabited density classes. A land-use/land-cover raster layer was created from the parcel data density classes to successfully redistribute population for Clatsop County, Oregon. In studies where parcel data is not availiable or historical data is required, the use of land-cover classification from satellite imagery may be the next viable approach. In these cases, the quaility and accuracy of the dasymetric map has a direct correlation with the quality and accuracy of the land-cover classification (Sleeter and Gould, 2007).

A study by Mennis (2003) demonstrates the use of a remotely sensed urban land-cover dataset to define categories of urbanization as high, low, and non-urban. The author suggests that urbanization data derived from satellite imagery provides a “predictable positive relationship between population density and the degree of urban development as indicated by satellite imagery” (Mennis, 2003, p. 35). However, the author admits that with this approach industrial areas that are highly urbanized and sparsely populated must be acknowleged as anomolies that result in error. The author further states that although “satellite remote sensing cannot indicate population density directly” it can describe the urban morphology of built-up and nondeveloped areas, and as such, is a useful data source for dasymetric mapping (Mennis, 2003, p. 34). The approach that was taken for this study was to use land-cover classification maps derived from satellite data to redistribute population to high, medium, and low density classes using a multi-class weighted distribution technique.

Two factors must be considered when using a multi-class weighted distribution technique. First, the relative difference in population densities among the three urban classes must be determined. The DME performs an empirical sampling process that samples population density values for each urban class. The sampling is performed by selecting all census tracts that meet or exceed a "percent cover" declared by a user-defined threshold. The resulting value is the population density fraction, indicating the percentage of a census tract's total population that should be assigned to a specific urban class within the census tract. The population density fraction is expressed as:

$$d_u = \frac{P_u}{(P_h + P_m + P_l)}$$ Equation 2 (Mennis, 2003)

Where:
$d_u$ = population density fraction of urban class $u$,
$P_u$ = population density of urban class $u$,
$P_h$ = population density of urban class $h$ (high),
$P_m$ = population density of urban class $m$ (medium), and
$P_l$ = population density of urban class $l$ (low)

The second factor to consider is the difference in census tract area occupied by each urban class. The aforementioned population density fraction assumes that the census tracts are equally divided in area by the three urban classes. In reality census tracts rarely, if ever, exhibit an even spatial distribution of urban classes (i.e., 33.3% high, 33.3% medium, and 33.3% low). The DME calculates the area ratio to adjust the population density fraction for each individual census tract according to the difference in area occupied by each urban class. The area ratio of a specific census tract can be found by dividing the area of the urban class within the census tract by the total area of the census tract, and dividing this number by the expected percentage (i.e., 33%) (Mennis, 2003). Area in this case is synonymous with number of raster grid cells. The area ratio is expressed as:

$$a_{ut} = \frac{(n_{ut}/n_t)}{0.33}$$ Equation 3 (Mennis, 2003)

Where:
$a_{ut}$ = area ratio of urban class $u$ in census tract $t$,
$n_{ut}$ = number of grid cells of urban class $u$ in census tract $t$, and
$n_t$ = number of grid cells in census tract $t$

The DME combines the population density fraction and area ratio to compute the total fraction. The total fraction indicates the amount of a census tract's total population that should be assigned to a specific urban class within that census tract. The total fraction is expressed as:

$$f_{ut} = \frac{(d_u \times a_{ut})}{[(d_h \times a_{ht})+(d_m \times a_{mt})+(d_l \times a_{lt})]}$$ Equation 4 (Mennis, 2003)

Where:
$f_{ut}$ = total fraction of urban class $u$ in census tract $t$,
$d_u$ = population density fraction of urban class $u$,
$a_{ut}$ = area ratio of urban class $u$ in census tract $t$,
$d_h$ = population density fraction of urban class $h$ (high),
$d_m$ = population density fraction of urban class $m$ (medium),
$d_l$ = population density fraction of urban class $l$ (low),
$a_{ht}$ = area ratio of urban class $h$ (high) in census tract $t$,
$a_{mt}$ = area ratio of urban class $m$ (medium) in census tract $t$, and
$a_{lt}$ = area ratio of urban class $l$ (low) in census tract $t$

Census tract population is finally interpolated (i.e., assigned) to grid cells by equally dividing population among the respective urban class grid cells within the census tract. The "population assignment" to a grid cell within a census tract is expressed as:

$$pop_{ut} = \frac{(f_{ut} \times pop_t)}{n_{ut}}$$ Equation 5 (Mennis, 2003)

Where:
$pop_{ut}$ = population assigned to one grid cell of urban class $u$ in census tract $t$,
$f_{ut}$ = total fraction for urban class $u$ in census tract $t$,
$pop_t$ = population of census tract $t$, and
$n_{ut}$ = number of grid cells of urban class $u$ in census tract $t$

## Study Area

The study area lies along the Texas – Mexico border and includes Starr, Hidalgo, Willacy, and Cameron counties also commonly known as the Lower Rio Grande Valley (LRGV). LRGV has an area of approximately 4,870 square miles and encompasses 47 cities/towns and 191 unincorporated settlements (i.e., census designated places). The 2010 census population was 1,264,091 with over 92% of the population residing within urban areas. The U.S. Census Bureau has designated eight areas within the region as either urbanized area or urban cluster. The largest urbanized areas are the McAllen-Edinburg-Mission and Brownsville-Harlingen metropolitan statistical areas (MSA). As of the 2010 census, the McAllen-Edinburg-Mission and Brownsville-Harlingen MSAs accounted for 93% of the total population of LRGV. The more rural counties of Starr and Willacy are designated as micropolitan statistical areas (U.S. Census Bureau, 2011). Figure 3 displays the study area and census designations as of 2010.

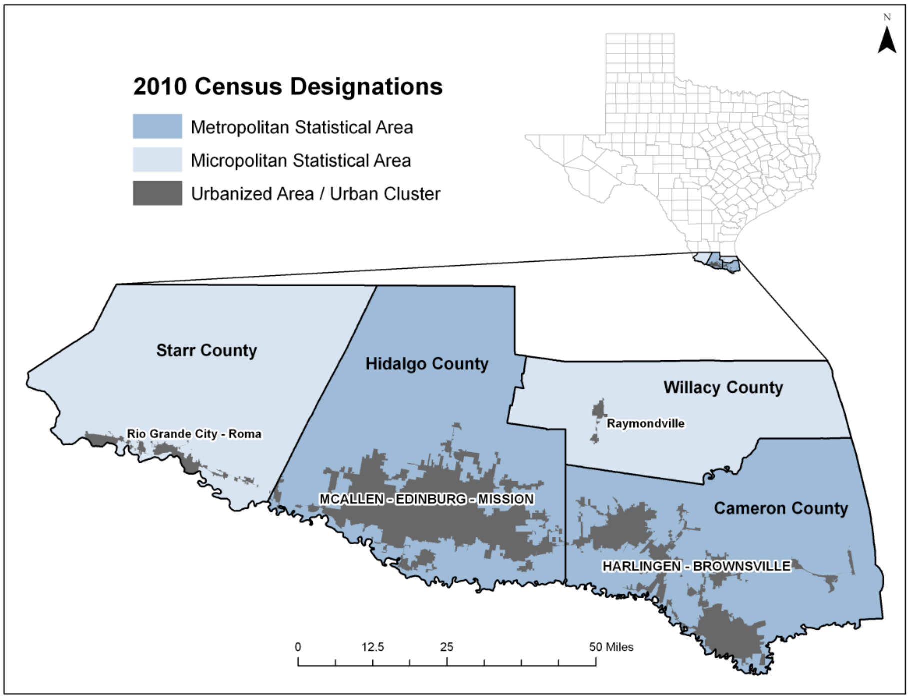



**Figure 3. LRGV counties, metropolitan and micropolitan statistical areas, and urban census designations (adapated from U.S. Census Bureau, 2011).**

The LRGV region has experienced substantial growth over the last 20 years. From 1990 to 2000, the region witnessed a 39% growth rate, increasing in population by 276,494 people. From 2000 to 2010 the growth rate was 29% with a population increase of 285,722 residents. Conservative projections for 2020 project growth rates as low as 8%, while projections based on historic migration rates project growth rates as high as 39% (Texas State Data Center, 2012) (Figure 4). This amounts to possible increases in population ranging from nearly 100,000 to just under 500,000 new residents over the next 10 years.

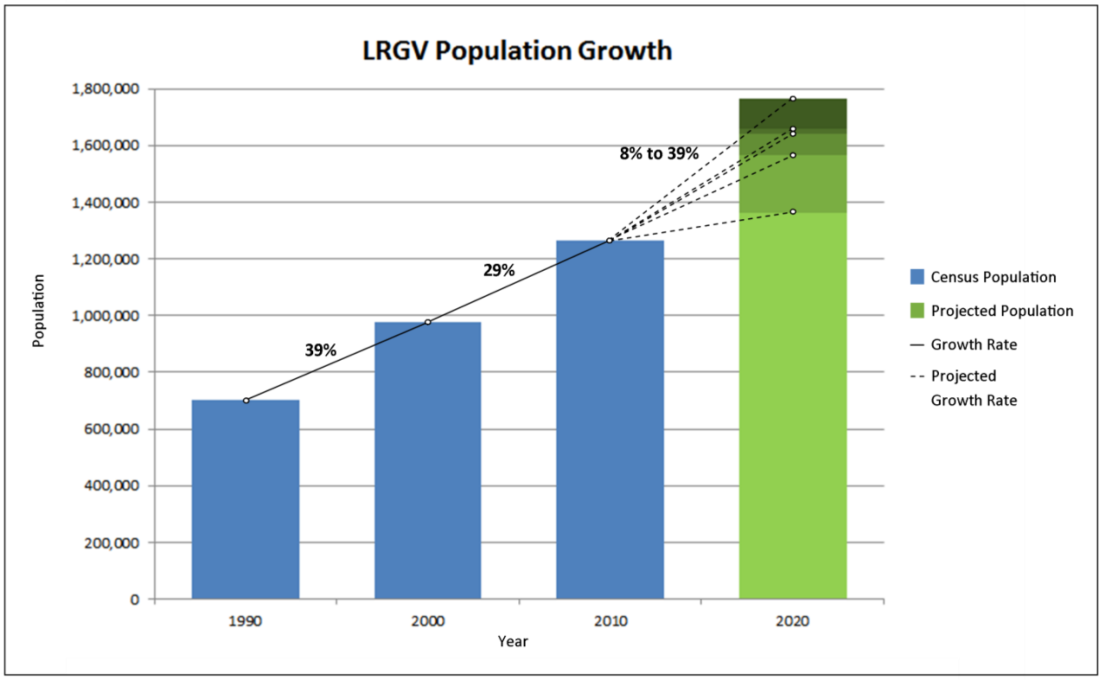



**Figure 4. LRGV 20 year population growth and 10 year projections (adapated from Texas State Data Center, 2012).**

# Data Collection and Data Preparation

## Population Data

Census tract boundary files for 1990, 2000, and 2010 were acquired in shapefile format from the U.S. Census Bureau website. Summary File 1 (SF1) 100% Data population tables were downloaded and joined to their respective census tract shapefiles. SF1 100% Data is based on 100% sampling that is compiled from surveys of all people and most housing units (U.S. Census Bureau, 2001). After reviewing the data, it was apparent that there were significant differences in census tract boundaries between 1990, 2000, and 2010. Census tract relationship files for 2000 and 2010 were acquired from the U.S. Census Bureau website. Tract relationships were established between 1990 and 2000, and 2000 population counts were adjusted to 1990 census tract boundaries. Tract relationships between 2000 and 2010 where then established, and 2010 population counts were applied to 2000 census tract boundary tables.

It is important to note that for sequential census year comparisons, the census relationship tables provide direct relationships and population distributions. In order to place 2010 population counts into 1990 census tracts, 2000 to 1990 tract relationships and population distribution proportions were used to assign 2010 population counts into 1990 tracts. Figure 5 provides an example of this approach. The resulting shapefile provided 1990 census tract boundaries with corresponding population counts for each subsequent decennial census year.

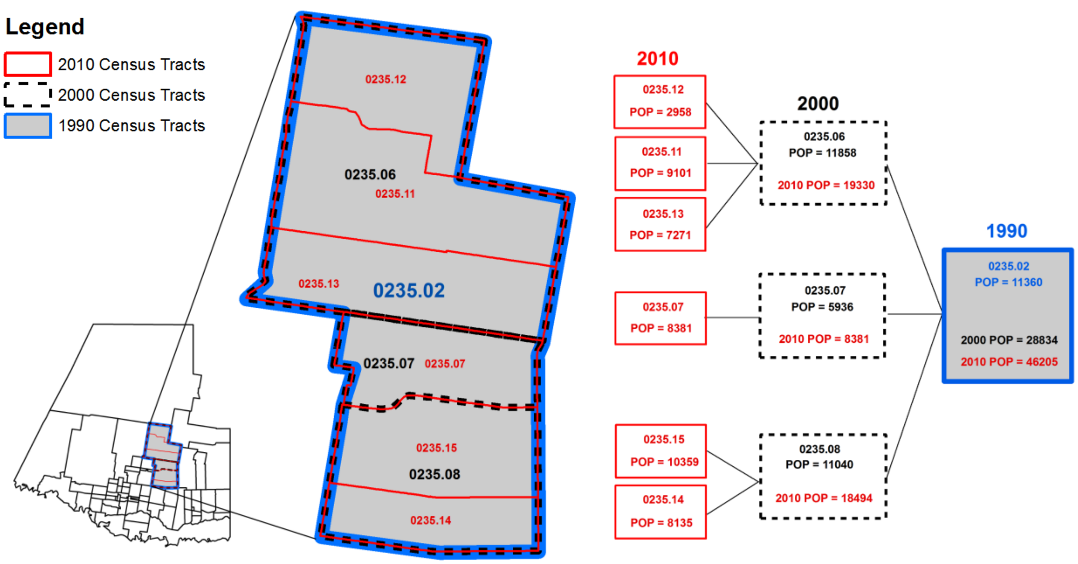



**Figure 5. Method of relating census tract population across census years. Census population counts from 2010 were adjusted to 2000 tract boundaries. 2010 and 2000 census population counts were then adjusted to 1990 tract boundaries.**

Population change and growth rates from 1990 to 2000 and 2000 to 2010 were calculated for each census tract using Field Calculator in Esri ArcMap (Equation 1). Population change, growth rate, and share of regional growth across census years where mapped in ArcMap to provide insight into where population growth has occurred. Thematic maps were created to explore the data and identify tracts that have experienced the highest population change and growth rates over the last 20 years (see Figures 10 and 11 in Results).

## Satellite Imagery

Satellite imagery was acquired for 1990, 2000, and 2010 to coincide with census years. Landsat 4 and 5 Thematic Mapper (TM) scene archives were searched using the online Global Visualization Viewer (GloVis) hosted by the U.S. Geological Survey (USGS) Earth Resources Observation and Science Center (EROS). The study area coincides with three Worldwide Reference System 2 (WRS-2) Path/Row extents, including 26/42, 27/41, and 27/42 (Figure 6).

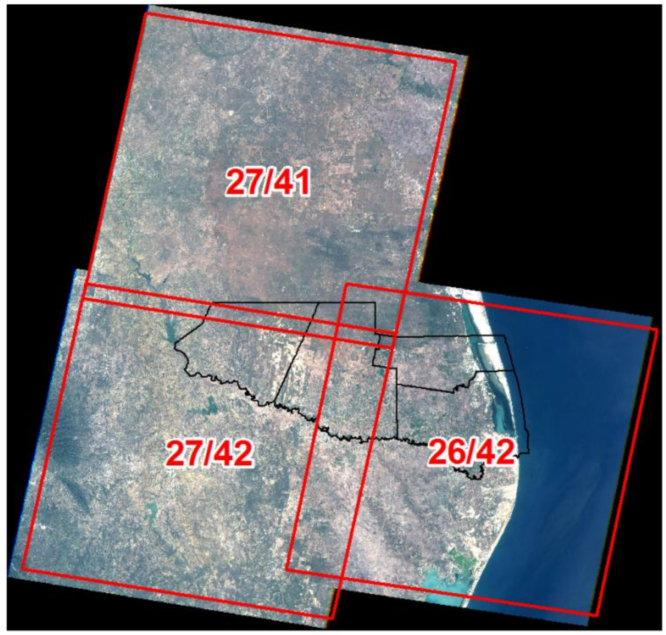


**Figure 6. WRS-2 Path/Row tiles that coincide with the study area.**

The general search criteria used included minimum cloud cover, high image quality, and a similar time frame between scenes. In addition, only "Downloadable" Level 1T scenes were considered as they have already been corrected for radiometric, geometric, and topographic accuracy (U.S. Geological Survey, 2012). GloVis provides the ability to request processing of uncorrected archive images, but processing was not requested due to the availability of Level 1T images and the remaining time frame for the study. Table 1 outlines the Landsat 5 TM scenes that were acquired for each year. Each downloaded scene was of 30 meters spatial resolution and included six spectral bands and one thermal band resampled from 120 meter spatial resolution. Table 2 provides Landsat 5 TM band descriptions and spectral ranges. The thermal band was excluded from further analysis due to the differences in spatial resolution and electromagnetic properties.

The existence of multiple scenes across the study area required that raster mosaics be created for each band, for each year. The ArcMap Mosaic tool was used to merge multiple scenes for each band using the default settings. The band mosaics where then stacked into composite images using the Composite Bands tool. The resulting files included three 6-band composite images for each year. The composite bands where then clipped to the LRGV study area feature class. Three commonly used band combinations where created for each year, including natural color (RGB=321), false color near-infrared (NIR) (RGB=432), and false color short-wave infrared (SWIR) (RGB=742). Urban areas are typically displayed as white to light blue in natural color composites, blue to grey in NIR composites, and lavender in SWIR composites (NASA, 2012). The intention was to visually explore and evaluate the imagery in these combinations to best differentiate urban areas of varying density.

**Table 1. Landsat 5 TM scenes used for the study.**

| Year | Scene ID | Cloud Cover | Date | Quality | Product/Level | Path/Row |
|---|---|---|---|---|---|---|
| 1990 | LT50260421991224AAA03 | 0% | 8/12/1991 | 9 | TM/L1T | 26/42 |
| | LT50270411987268AAA02 | 0% | 9/25/1987 | 9 | TM/L1T | 27/41 |
| | LT50270421991199AAA03 | 0% | 7/18/1991 | 9 | TM/L1T | 27/42 |
| 2000 | LT50260422000249XXX02 | 0% | 9/5/2000 | 9 | TM/L1T | 26/42 |
| | LT50270412003296LGS01 | 0% | 10/23/2003 | 9 | TM/L1T | 27/41 |
| | LT50270422000352XXX02 | 0% | 12/17/2000 | 9 | TM/L1T | 27/42 |
| 2010 | LT50260422010116EDC00 | 0% | 4/26/2010 | 9 | TM/L1T | 26/42 |
| | LT50270412010123EDC00 | 0% | 5/3/2010 | 9 | TM/L1T | 27/41 |
| | LT50270422010123EDC00 | 0% | 5/3/2010 | 9 | TM/L1T | 27/42 |

**Table 2. Landsat 5 TM spectral bands (adapted from U.S. Geological Survey, 2010).**

| Band | Spectral Range | Ground Sampling Interval (pixel size) |
|---|---|---|
| 1 - Visible Blue | 0.45 – 0.52 µm | 30 meter |
| 2 - Visible Green | 0.52 – 0.60 µm | 30 meter |
| 3 - Visible Red | 0.63 – 0.69 µm | 30 meter |
| 4 - Near-Infrared | 0.76 – 0.90 µm | 30 meter |
| 5 - Near-Infrared | 1.55 – 1.75 µm | 30 meter |
| 6 - Thermal | 10.40 – 12.50 µm | 120 meter |
| 7 - Mid-Infrared | 2.08 – 2.35 µm | 30 meter |

# Methodology

## Assumptions and Limitations

Assumptions and limitations inherent in this study must be noted in order to properly assess the results. The choice to use census tracts as enumeration units was made to increase the contrast between choropleth and dasymetric population density results, and to reduce the amount of processing involved in establishing relationships across census years. It can be argued that smaller census enumeration units such as block groups or blocks may reduce MAUP effects and even reduce the need for dasymetric techniques in certain areas. This may be true for densely built up areas, but census block groups and even blocks can be relatively large in more rural areas that are generally not homogeneous. It is also important to note that dasymetric population density results do not eliminate the MAUP effect, although they greatly reduce it relative to the spatial resolution of the ancillary raster data used (i.e., 30 meter resolution in the case of this study).

Census tract relationships were established in order to compare population change from one decennial census to the next. This was accomplished using census tract relationship files. Relationship files relating 1990 to 2000 and 2000 to 2010 were available from the U.S. Census Bureau website, but no relationship file was available to relate 2010 to 1990. In order to relate 2010 to 1990 it was assumed that population distribution proportions from 2010 to 1990 would be the same as those that existed between 2000 and 1990. In other words, 2000 to 1990 relationships were used to carry over 2010 population counts into 1990 census boundaries. This was required to compare multi-decade census population counts and dasymetric population distributions.

The methodology used to produce the three-class urban raster classifications was limited in that urban density classes were defined arbitrarily through visual interpretation and personal knowledge of the study area. This approach, which may be described as “you know it when you see it,” is not a consistent, reproducible method for urban land-cover classification. The use of percent imperviousness to categorize urban density classes would be much more useful in a study such as this, although this approach was not taken largely due time constraints. Additionally, at the outset of the study it was decided that urban areas would be inclusive of residential, commercial, industrial, and transportation land-covers. This is problematic, particularly for high density urban areas that inevitably include commercial and industrial development. Population was interpolated into these highly urbanized and sparsely populated areas that must be acknowledged as anomolies that result in error (Mennis, 2003).

The classification method used is the maximum likelihood supervised classification which requires a set of predefined spectral signatures, derived either from user defined training samples or iteratively defined classes (i.e., clusters). One should ideally experiment with different classifiers to assess the sensitivity of results to the classification method used. Due to time constraints and limitations in user experience, maximum likelihood was chosen for its straightforward application and well documented use. Additionally, a quantitative accuracy assessment of the urban raster classifications would have benefited this study. Acquiring high resolution reference imagery from 10 and 20 years ago that coincided directly with the Landsat data proved to be difficult. Furthermore, in situ ground truthing was not feasible for this study that spanned two decades. That said, attempts where made to thoroughly review and correct classification errors that were identified through visual assessments.

# Analysis

## Urban Land-Cover Classification

A prerequisite to the multi-class dasymetric mapping technique used for this study was the creation of a three-class raster representing high, medium, and low density urban land-covers, as well as an uninhabited class. All classification tasks were performed in ArcMap using the Spatial Analyst Image Classification toolbar. Following work done by Hammann (2012), a 30 class ISO Cluster unsupervised classification was run for each year to define a set of spectral signatures for subsequent supervised classifications. The resulting unsupervised classifications were evaluated to identify areas of rural land that may spectrally resemble urban land-covers.

In order to account for phenological factors that influence spectral signatures, training samples and spectral signatures were created for each year. Google Earth's time slider tool was used to explore historic high-resolution imagery that coincided with census years to verify training samples. Imagery was available as far back as 1995, and up to 2010. Using personal knowledge of the study area and the historic imagery in Google Earth, training samples were collected visually with a focus on capturing signatures for high, medium, and low urban density land-covers. High density urban land-cover was defined as downtown areas and central business/commercial districts. Medium density urban land-cover included residential areas (i.e., subdivisions) in close proximity to downtown areas and within their respective city limits. Low density urban land-cover included residential development outside of city limits that generally exhibited isolated development patterns. To maintain consistency, an attempt was made to collect the same number of training samples and pixels for each urban density type. Table 3 identifies the number of training samples and pixels collected for each urban density type for each year. Unsupervised classification rasters were also used to verify urban training samples as well as to help identify uninhabited land-covers that may be confused for urban land-cover. Additional training samples were collected to identify uninhabited land-cover signatures for agriculture, water, natural areas, and cleared/vacant land. Figure 7 demonstrates the type of training samples that were collected by land cover class using visual cues and first-hand knowledge. Color composite images were used for training sample collection as many surface features are known to exhibit a characteristic appearance based on the spectral band combination used. Signature files for each year were created using the Create Signatures tool in the Image Classification toolbar.

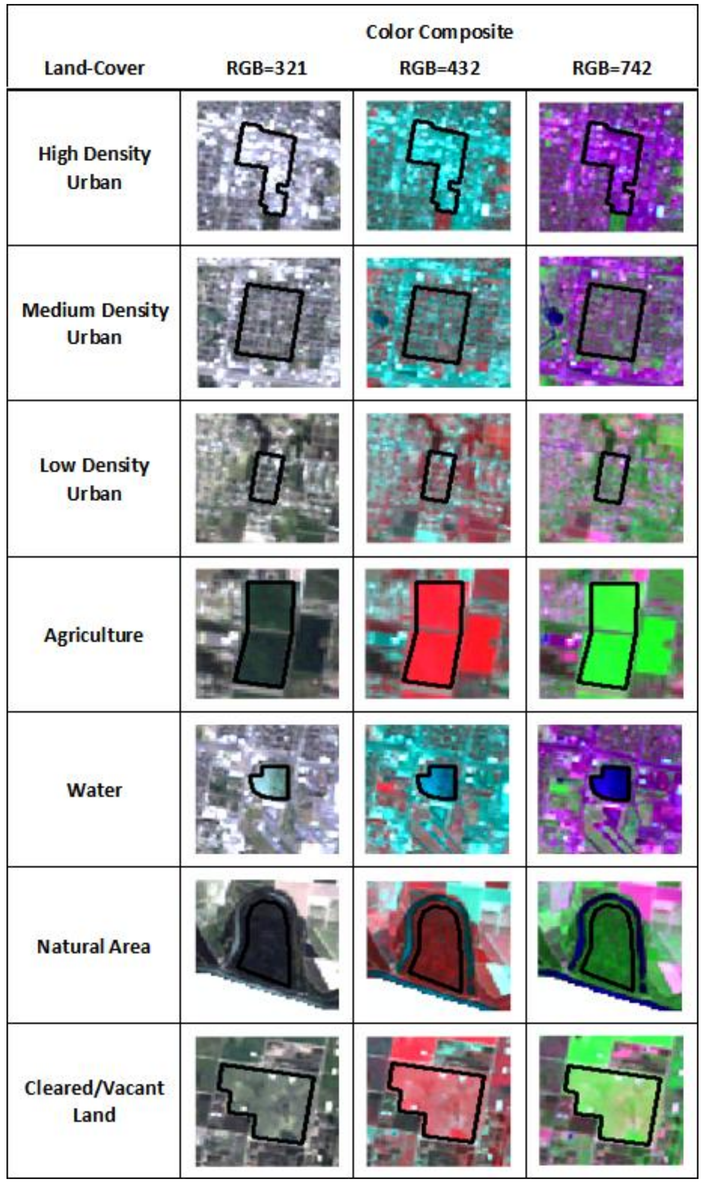



**Figure 7. Example of the type of training samples collected by land-cover type and color composite band combination.**

**Table 3. Supervised classification training samples for each urban density type for each year.**

| Year | Urban Land-Cover Class | Number of Training Samples | Pixel Count |
|---|---|---|---|
| 1990 | High Density | 7 | 2066 |
| | Medium Density | 8 | 4118 |
| | Low Density | 8 | 2074 |
| 2000 | High Density | 7 | 2302 |
| | Medium Density | 8 | 4006 |
| | Low Density | 8 | 2050 |
| 2010 | High Density | 7 | 2126 |
| | Medium Density | 8 | 4019 |
| | Low Density | 8 | 2132 |

Maximum likelihood supervised classification was performed for each year. All non-urban land-covers where merged into one class to represent uninhabited areas. Accuracy assessments were limited due to the lack of high resolution reference imagery that coincided directly with the Landsat data. Instead, simple qualitative accuracy assessments were performed using personal knowledge of the study area and historic Google Earth imagery. Landsat classifications for 2000 and 2010 where compared with Google Earth historic imagery to visually assess their accuracy. The 1990 classification was not assessed for accuracy as no high resolution reference imagery was available. Figure 8 outlines the steps take to perform the urban land-cover classifications.

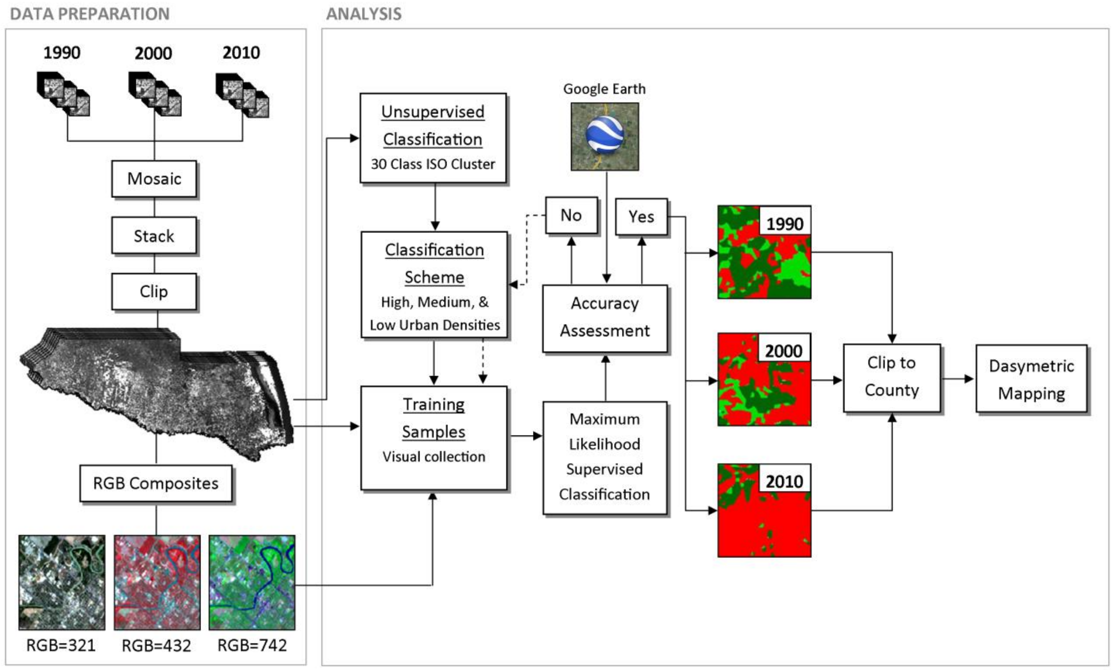



**Figure 8. Urban land-cover classification methodology.**

## Dasymetric Mapping

Dasymetric mapping was performed in order to capture the spatial variation in population density and population density change. As previously discussed, this technique involves areal interpolation of census data into urban land-cover classes. The Dasymetric-Mapping Extension (DME) for ArcMap 10 developed by USGS was used for this task. The objective of the DME is to "automate the process of taking population data from census enumeration units and transferring the data values to overlaying homogeneous zones while (1) maintaining volume preserving properties and (2) using an empirical sampling method for determining relative densities for each homogeneous zone" (Sleeter and Gould, 2007, p. 4). The underlying mathematics of the software is based on the methods developed by Mennis (2003) as described in the Background.

The DME tool was run separately for each county to account for the relative difference in urban class population density from one county to the next. For example, the population density of high urban density areas in Hidalgo County (i.e., the largest metropolitan statistical area) will likely be different than high density urban areas in Willacy County (i.e., a mostly rural micropolitan statistical area). Mennis (2003, p. 36) states that “the actual population density values are not of concern,” but “what is important is the within-county relative difference in population density among the urbanization classes.” Population density sampling and aerial interpolation was performed by county using the DME interface. Census tract shapefiles and three-class urban rasters where used as input for their respective county and year. The resulting output files are described in Table 4.

**Table 4. DME output files.**

| DME Output File Names | Format | Description |
|---|---|---|
| dasy_rast | ESRI GRID | GRID file of intersection of inputs (Urban Land-Cover and Census) with pixel counts and unique ID |
| popraster | ESRI GRID | conversion of vector census file to raster GRID file |
| info | ESRI GRID - support files | support file for ESRI GRID - must be kept in the same location as GRID file |
| dasytable | .dbf | summary table of all results per grid cell (population per grid cell) |
| Dasymetric_Stats | .dbf | run-time summary for DME |

# Results

## Population Growth Based on Census Estimates

A review of regional census population over the last 20 years revealed that the region experienced an 80% growth rate by adding 562,216 new residents. The growth rate for the region declined by 10% from the 1990s to 2000s, but the amount of new residents increased slightly from one decade to the next. County level statistics show that the population increase in Hidalgo County drove much of this growth. Hidalgo County's population doubled and accounted for nearly 70% of the region's growth. Cameron County provided a substantial share of the growth with approximately 25%, while Starr and Willacy Counties combined for just under 5% of the growth for the region. All counties except for Hidalgo saw the majority of their growth happen in the decade of the 1990s with a decline in growth rate and new residents through the 2000 years. Like the region, the growth rate for Hidalgo County dropped from the first decade to the second, but the number of new residents increased over the same time period. Table 5 provides a summary of the population growth for each county within the region.

**Table 5. LRGV county population growth characteristics.**

| Period | Cameron County | | Hidalgo County | | Starr County | | Willacy County | |
|---|---|---|---|---|---|---|---|---|
| 1990 to 2000 | New Residents | 75,120 | New Residents | 185,918 | New Residents | 13,079 | New Residents | 2,377 |
| | Growth Rate | 28.88% | Growth Rate | 48.47% | Growth Rate | 32.28% | Growth Rate | 13.43% |
| | Share of Region | 27.17% | Share of Region | 67.24% | Share of Region | 4.73% | Share of Region | 0.86% |
| 2000 to 2010 | New Residents | 70,993 | New Residents | 205,306 | New Residents | 7,371 | New Residents | 2,052 |
| | Growth Rate | 21.18% | Growth Rate | 36.05% | Growth Rate | 13.75% | Growth Rate | 10.22% |
| | Share of Region | 24.85% | Share of Region | 71.86% | Share of Region | 2.58% | Share of Region | 0.72% |
| Overall (1990 to 2010) | New Residents | 146,113 | New Residents | 391,224 | New Residents | 20,450 | New Residents | 4,429 |
| | Growth Rate | 56.17% | Growth Rate | 102% | Growth Rate | 50.47% | Growth Rate | 25.02% |
| | Share of Region | 25.99% | Share of Region | 69.59% | Share of Region | 3.64% | Share of Region | 0.79% |

Of the 137 census tracts within LRGV, 108 tracts gained new residents while 29 experienced population decline. It is worth noting that the 29 census tracts that experienced population decline lie within urbanized areas or urban clusters. Moreover, these declining census tracts generally coincide with city centers within the region (Figure 9). The rate of decline of these tracts ranged from approximately 1% to 22%.

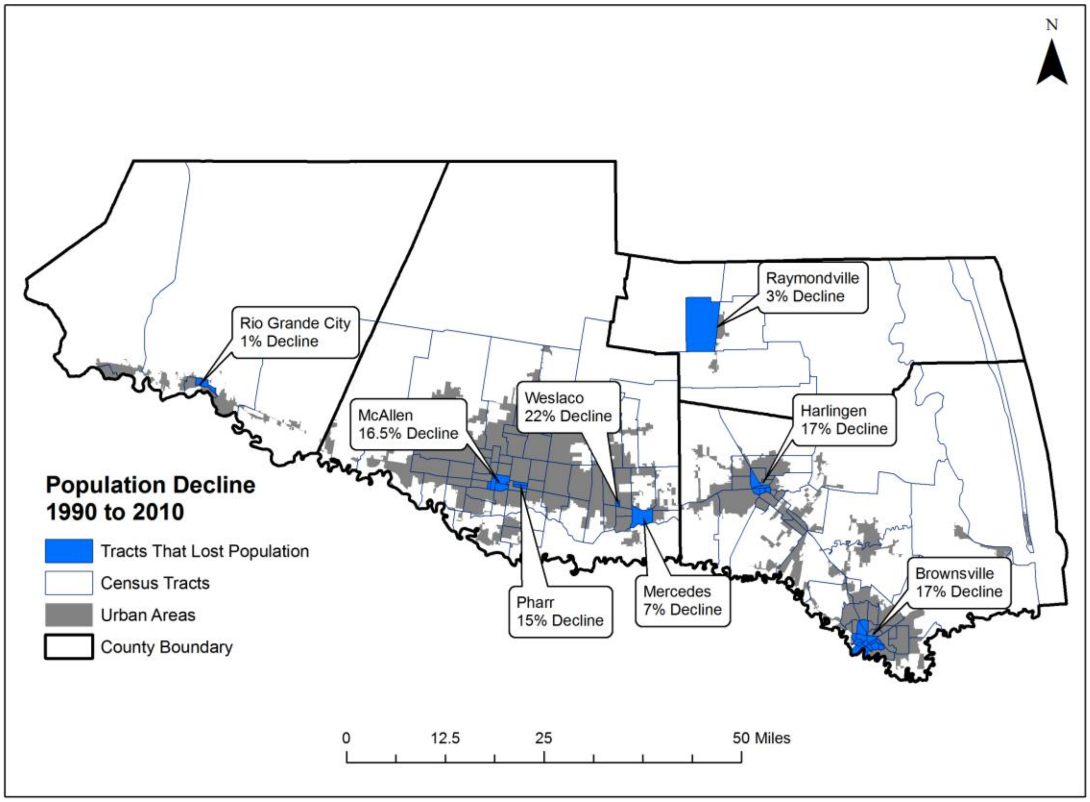



**Figure 9. Census tracts with a negative growth rate from 1990 to 2010. Note that population counts were adjusted to 1990 census boundaries.**

The majority of the census tracts experienced population growth at varying rates from 1990 to 2000. 65 census tracts (approximately 47%) experienced a growth rate greater than 50%. 38 census tracts (approximately 28%) had population more than double in number with a growth rate greater than 100%. A handful of census tracts experienced very high growth rates with population growing three, four, and even five times over. These tracts lie exclusively in Hidalgo and Cameron counties. Figure 10 displays the growth rate by census tract from 1990 to 2010.

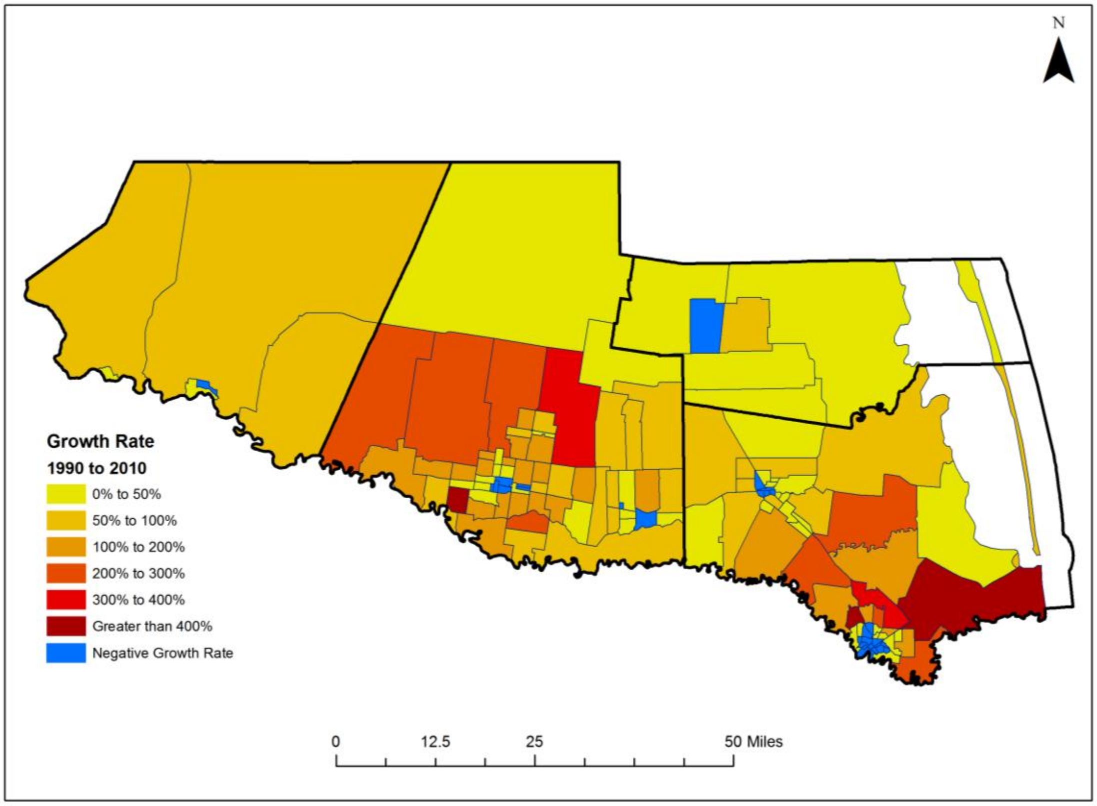



**Figure 10. Population growth rate by census tract from 1990 to 2010.**

Although growth rate may be used to measure the amount of growth that has occurred per census tract, it is a relative measurement and does not indicate where the majority of growth has occurred. Measuring census tracts' share of regional growth reveals how much each tract has contributed to the region's growth and provides a better picture of where the majority of growth has occurred. Mapping the growth of each census tract normalized by the total growth for the region identifies areas that have contributed most to the region's growth (Figure 11). Four tracts in central Hidalgo County including tracts 48215202, 48215235.01, 48215235.02, and 48215241 account for nearly one fourth (23.56%) of the growth of the entire LRGV region. Furthermore, the tracts within the Hidalgo County Metropolitan Planning Organization (MPO) boundary account for nearly 70% of the growth for the entire region. For this reason, the remainder of the study focuses on the growth within the Hidalgo County MPO boundary (Figure 11).

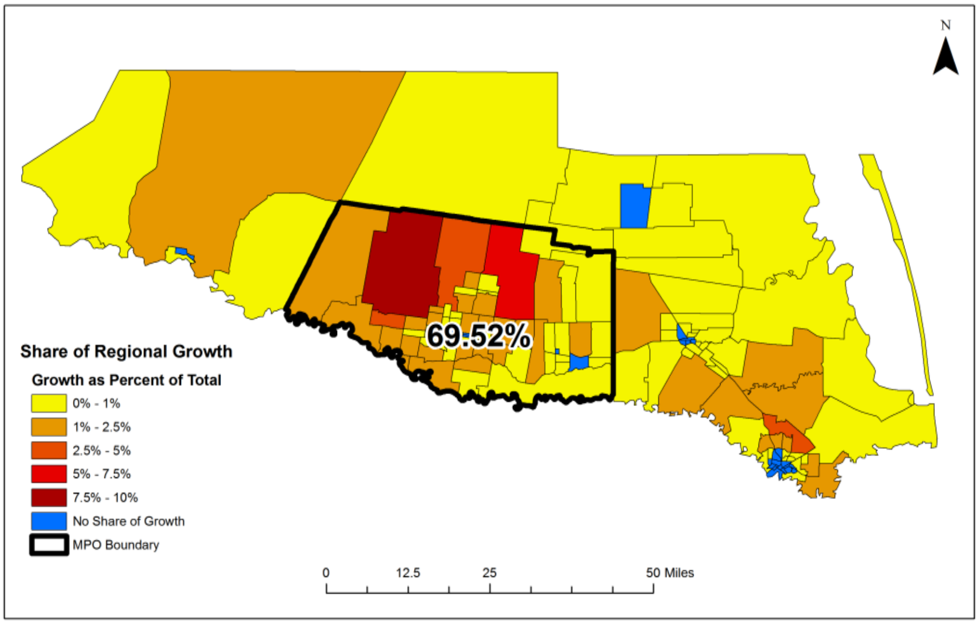



**Figure 11. Share of regional growth by census tract from 1990 to 2010.**

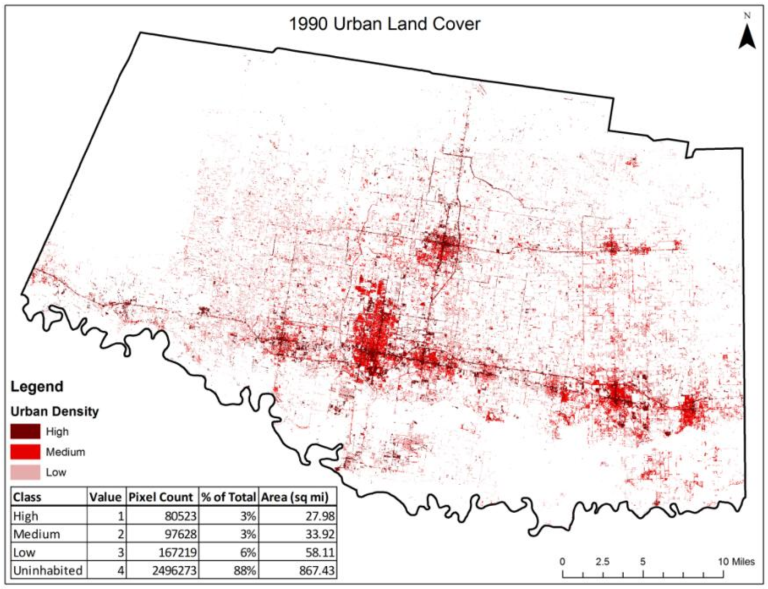
Over the last 20 years, the population within the Hidalgo County MPO planning boundary has more than doubled, increasing by 390,864 new residents. Table 6 outlines the population characteristics and growth rates for each census year within the Hidalgo County MPO planning area. It is apparent that population increased at a fairly constant pace from one decade to the next.

**Table 6. Hidalgo County MPO planning area census population and growth rate.**

| Year | Pop | Growth Rate |
|---|---|---|
| 1990 | 382310 | |
| 2000 | 567857 | 48.5% |
| 2010 | 773174 | 36.2% |

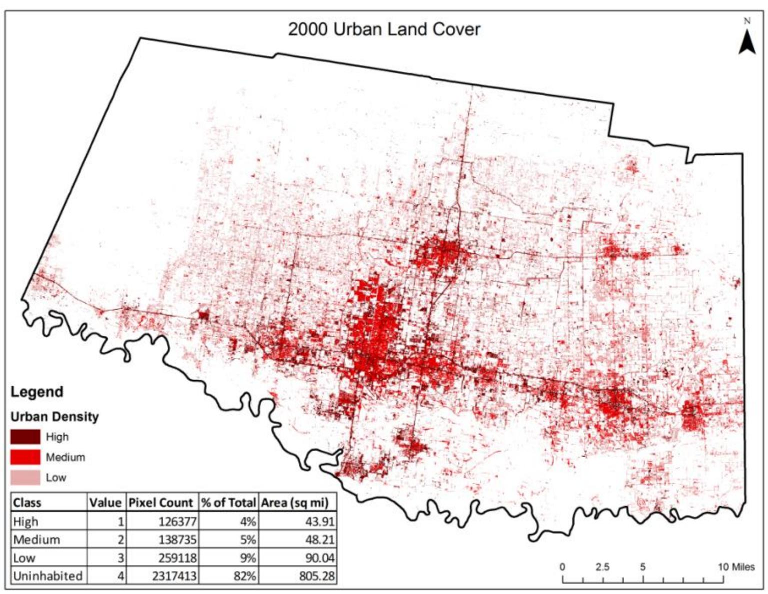
## Land-Cover Classifications

Land-cover classification results for each year are shown in Figures 12 through 14. As previously stated, accuracy assessments were only performed subjectively by visual comparison with available Google Earth imagery.




| Class | Value | Pixel Count | % of Total | Area (sq mi) |
|---|---|---|---|---|
| High | 1 | 80523 | 3% | 27.98 |
| Medium | 2 | 97628 | 3% | 33.92 |
| Low | 3 | 167219 | 6% | 58.11 |
| Uninhabited | 4 | 2496273 | 88% | 867.43 |

**Figure 12. 1990 urban land-cover classification.**




| Class | Value | Pixel Count | % of Total | Area (sq mi) |
|---|---|---|---|---|
| High | 1 | 126377 | 4% | 43.91 |
| Medium | 2 | 138735 | 5% | 48.21 |
| Low | 3 | 259118 | 9% | 90.04 |
| Uninhabited | 4 | 2317413 | 82% | 805.28 |

**Figure 13. 2000 urban land-cover classification.**

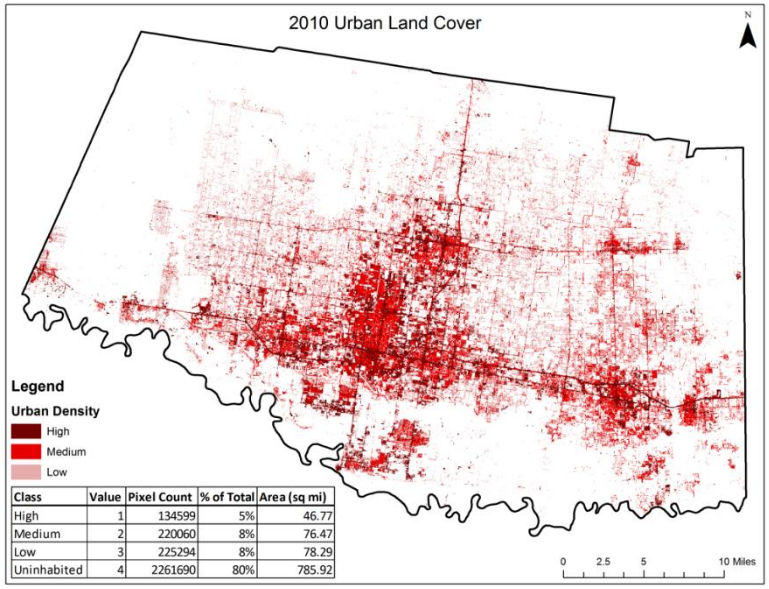



**Figure 14. 2010 urban land-cover classification.**

## Urban Land-Cover Changes

Comparison of the results of the urban land-cover classifications for each decade provides a measure of the land-cover changes that coincide with the census results. Visual results show a definite increase in urban land-cover from one decade to the next throughout the most of the MPO planning area (see Figures 12 through 14). Urban growth types that can be visually interpreted include expansion in much of the northern part of the planning area and some clustered branch growth in the western and southern areas. In addition, a linear development pattern is apparent in all years due to medium-to-high density development along transportation corridors.

Figure 15 displays land-cover change by urban density over time for the City of Mission. The growth that is visually apparent for Mission, TX is indicative of urban growth in many of the cities in the region.

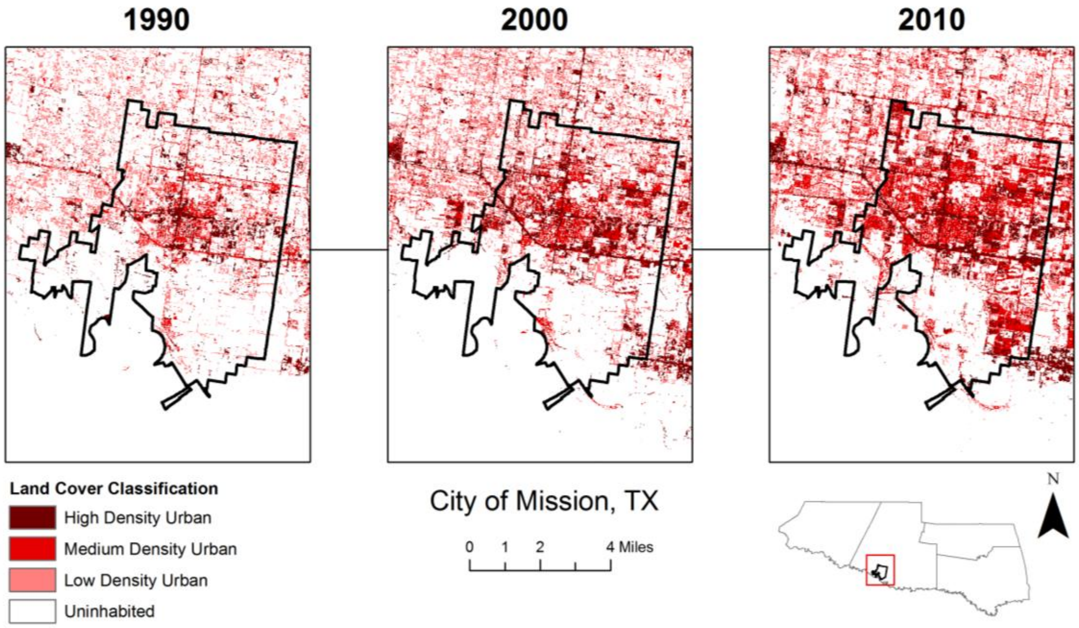



**Figure 15. 3-class urban land-cover showing decadal changes from 1990 to 2010 for the City of Mission, TX.**

The overall rate of increase of urban land-cover within the MPO planning area was 52% for the decade of 1990 and 10.6% during the decade of 2000. High density urban land-cover increased by 57% (15.93 square miles) from 1990 to 2000 and by 6.5% (2.86 square miles) from 2000 to 2010. Medium density urban land-cover increased by 42% (14.28 square miles) from 1990 to 2000 and by 58% (28.26 square miles) from 2000 to 2010. Low density urban land-cover increased by 55% (31.93 square miles) from 1990 to 2000 but decreased by 13% (11.75 square miles) from 2000 to 2010. Figure 16 outlines the urban land-cover characteristics and population for each census year. Results show that the planning area has more recently seen an increase in medium density development and a decline in low density development. This may indicate a type of infill growth where medium density development essentially “catches up to” areas of low density development.

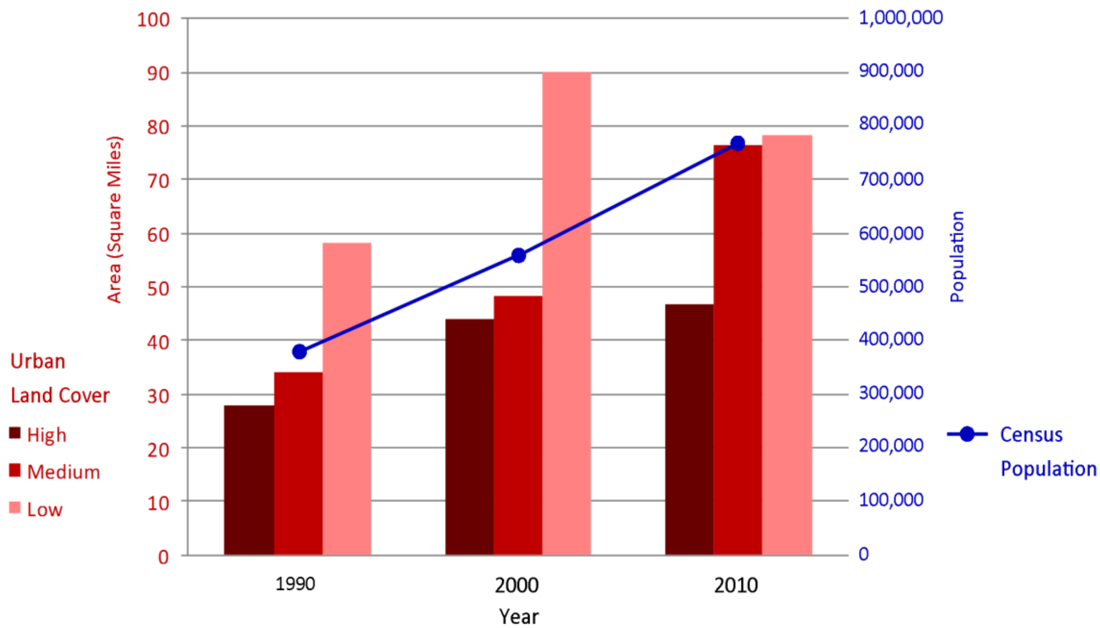



**Figure 16. 1990, 2000, and 2010 urban land-cover area and total population counts for the Hidalgo County MPO planning area.**

## Dasymetric Population Distribution

Output from the DME tool provided a population density raster layer for each year. Population and population density attributes where assigned to each land-cover class within each census tract using weighted aerial interpolation. Figure 17 shows the usefulness of dasymetric mapping to more accurately map population density compared to choropleth mapping. Visual comparison clearly shows that dasymetric mapping provides a better representation of the spatial orientation of population density, particularly in outlying census tracts that encompass much uninhabited land. Within urban centers, the population density distribution is relatively homogeneous and coincides well with the choropleth maps. In the outlying census tracts though, it is more apparent that population distribution is not always homogeneous and is often concentrated in smaller areas within census tracts. For example, Figure 18 displays a relatively dense population concentration within census tract 48215213.02

that is otherwise indistinguishable in the choropleth map. Visual decadal comparison of this tract using the dasymetric maps reveals that population density has in fact increased, but population distribution has remained in the western part of the census tract primarily because much of the northern and eastern areas of the tract are floodplain, limiting development to the west.

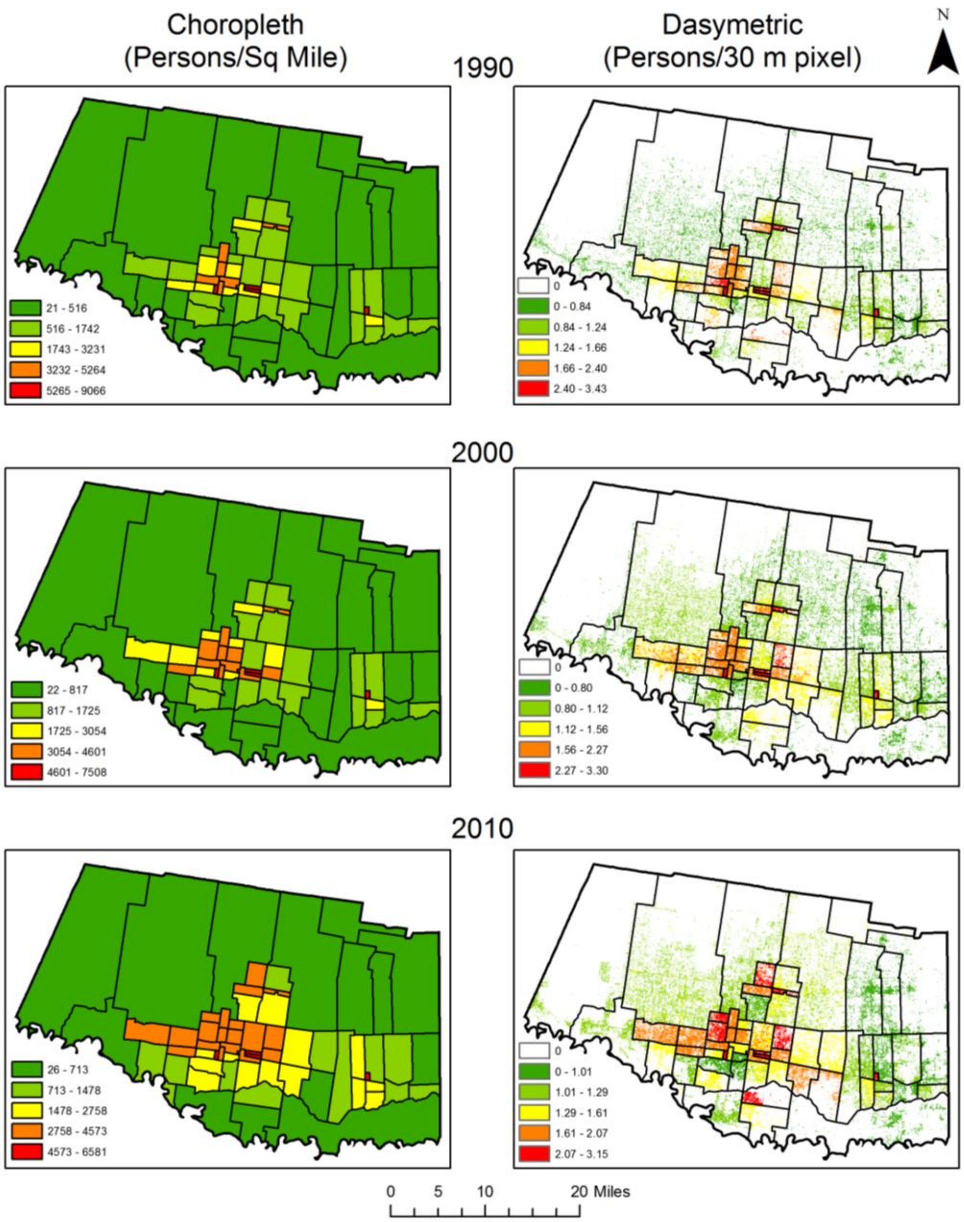



**Figure 17. Comparison between choropleth and dasymetric population density maps for 1990, 2000, and 2010.**

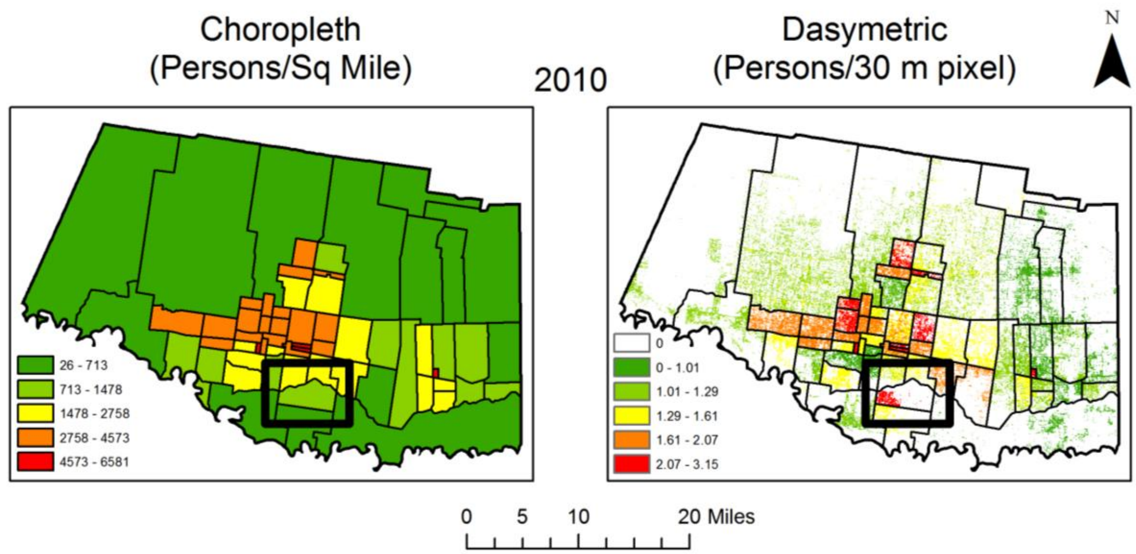



**Figure 18. Comparison of 2010 choropleth and dasymetric population density results for census tract 48215213.02. The dasymetric population density that is highlighted represents the northern population of the town of Las Milpas, TX.**

In addition to a more accurate depiction of the spatial distribution of population density for each year, the results from the dasymetric mapping processes provided quantitative measures of urban population distribution over time. Comparing the aerial interpolation of population for each year provides further insight into what type of urban growth has occurred throughout the planning area. Table 7 provides the overall results of the aerial interpolation for each urban class for each year. Results indicate that more recently, the majority of the population in the planning area lived in medium density urban developments, but this was not always the case. In the years 1990 and 2000, low density developments housed the majority of the population compared with high and medium density developments. Furthermore, although low density urban development declined relative to more dense development by 2010, the absolute population increased steadily for all urban densities over the same time period.

**Table 7. Dasymetic population distribution totals for each urban land-cover type for 1990, 2000, and 2010.**

| Year | High Density | Medium Density | Low Density | Total |
|---|---|---|---|---|
| 1990 | 102,027 (26.9%) | 126,100 (33.2%) | 151,183 (39.9%) | 379,310 |
| 2000 | 155,622 (27.4%) | 182,383 (32.1%) | 229,852 (40.5%) | 567,857 |
| 2010 | 197,735(25.6%) | 303,921 (39.3%) | 271,518 (35.1%) | 773,174 |

Additionally, dasymetric results were evaluated for the four census tracts in central Hidalgo County that contributed to nearly one fourth (23.56%) of the growth of the entire LRGV region. Within the Hidalgo County MPO planning area, census tracts 48215202, 48215235.01, 48215235.02, and 48215241 accounted for 33.9% of the total population growth over the last 20 years. Comparing dasymetric results for each census tract, at each census year, revealed the urban growth and population change that has occurred within each of these census tracts. Figures 19 through 22 show the urban population growth characteristics for each of the aforementioned census tracts. Results indicate that census tracts 48215202 and 48215235.01 have seen a marked increase in medium density population over the last 10 years. Census tracts 48215235.01, 48215235.02, and 48215241 have seen a constant rise in low density population growth over the last 20 years. Census tract 48215202, which is smallest in area and closest to the urban core, has seen a drop in low density urban development and a marked increase in medium density development over the last 10 years. Overall, results indicate that although the majority of the population now resides in medium density developments (Table 7), those areas that are contributing most to population growth are still composed largely of low density urban development.

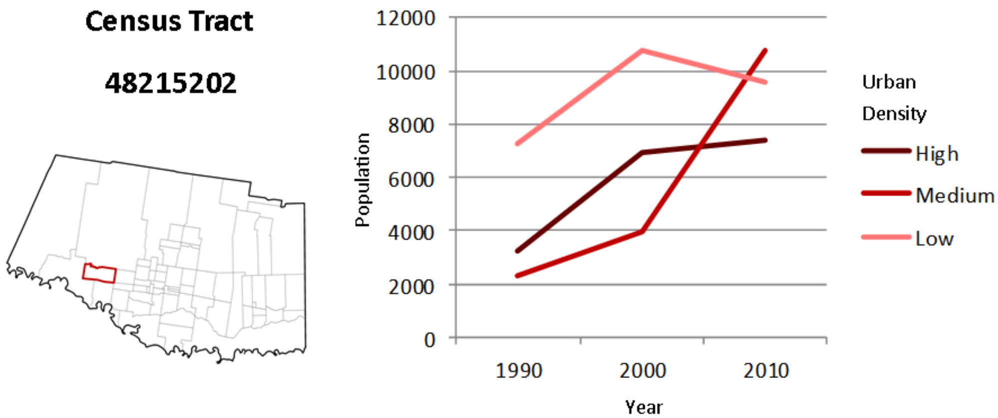



**Figure 19. Census tract 48215202 urban population distribution by year. Population growth rates were 68.9% and 27.9% from 1990 to 2000 and 2000 to 2010 respectively.**

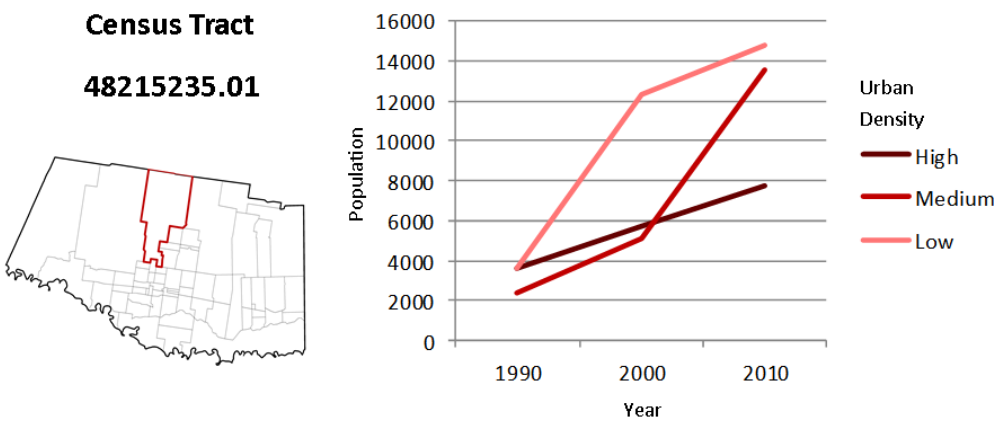



**Figure 20. Census tract 48215235.01 urban population distribution by year. Population growth rates were 142.3% and 56.4% from 1990 to 2000 and 2000 to 2010 respectively.**

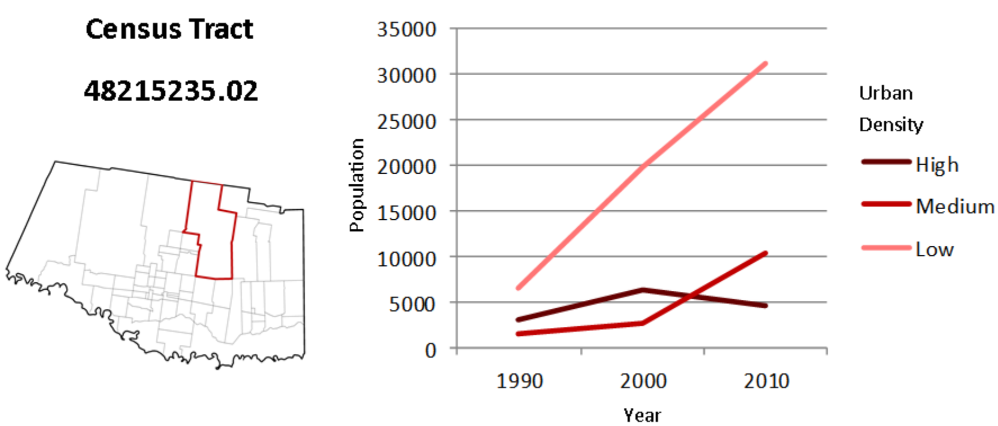



**Figure 21. Census tract 48215235.02 urban population distribution by year. Population growth rates were 153.8% and 60.2% from 1990 to 2000 and 2000 to 2010 respectively.**

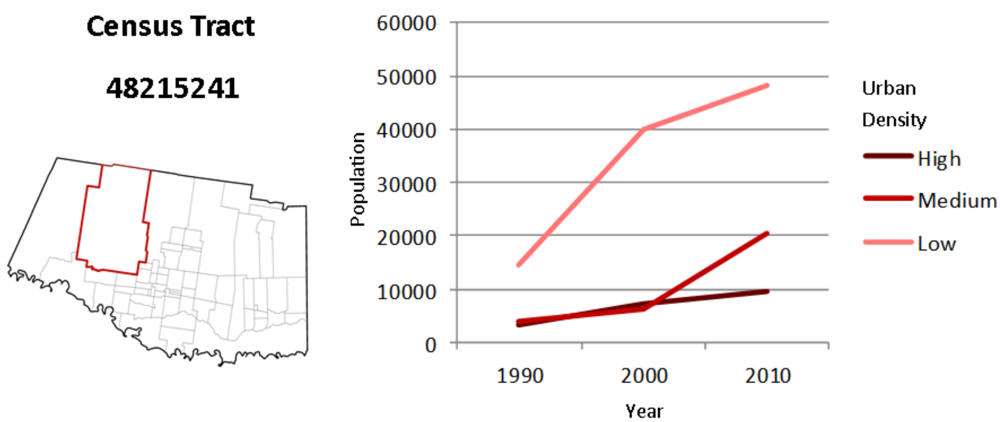



**Figure 22. Census tract 48215241 urban population distribution by year. Population growth rates were 143.2% and 45.8% from 1990 to 2000 and 2000 to 2010 respectively.**

# Discussion and Conclusions

## Summary of the Work

This study has demonstrated the utility of census data, satellite remote sensing data, and dasymetric mapping techniques for measuring urban growth. Decennial censuses provide aggregated population counts within enumeration units that can be spatially related across census years. Population statistics can easily be calculated and mapped using attribute table calculations and thematic mapping functions found in most GIS software packages. Satellite platforms such as Landsat provide a wealth of imagery archives dating back more than 30 years. Urban land-cover classifications that coincide with censuses can be used to provide quantitative measures of change in the built environment. Furthermore, changes in multi-class urban land-cover classifications provide insight into what type of urban growth has occurred. Dasymetric mapping provides a method of combining census data and urban land-cover data to more accurately map population density through aerial interpolation. Comparison of dasymetric population density maps across census years provides a more accurate view than choropleth maps of population density change. In addition, population distributions per enumeration unit can be viewed to understand urban growth in those areas that have experienced the highest population growth rates and contributed most to the region's growth.

## Future Work

This study only looked at a subset of the population and urban land-cover within the study area. Future work should expand to the entire study area, looking at regional population, urban land-cover changes, and individual census tract population distributions over time. The methodology outlined in this study may also be used measure urban growth within specific city boundaries and extraterritorial jurisdictions (ETJ) which may aid in local planning initiatives. Additional measures that may indicate sprawl should also be explored. This may include identifying tracts where low density land-cover has outpaced population growth, or where a decline in high and medium density population coincides with a rise in low density population. Further research is needed to understand how dasymetric results may be used to indicate urban sprawl.

Population and land-cover projections may also be used as dasymetric inputs to project population density and population distributions for future dates. Population projections can be calculated using methods ranging from simple extrapolation to the cohort component technique used by the U.S. Census Bureau. Results from land-use/land-cover change models may be used in conjunction with these population projections to predict future population density and urban population distribution. This would arguably be the most useful information for planners by providing simulations of future urban growth that would influence present day planning initiatives.

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