SPATIOTEMPORAL DRIVERS OF MUNICIPAL WATER CONSUMPTION

DISSERTATION

Presented to the Graduate Council of
Texas State University-San Marcos
in Partial Fulfillment
of the Requirements

for the Degree

Doctor of PHILOSOPHY

By

Matthew H. Connolly, B.S., M.A. Geo.

San Marcos, Texas
August 2013

SPATIOTEMPORAL DRIVERS OF MUNICIPAL WATER

CONSUMPTION

Committee Members Approved:

____

Ronald R. Hagelman III, Chair

____

Alberto Giordano

____

Sven Fuhrmann

____

Mark A. Fonstad

Approved:

____

J. Michael Willoughby
Dean of the Graduate College

FAIR USE AND AUTHORS'S PERMISSION STATEMENT

Fair Use

Duplication Permission

ACKNOWLEDGEMENTS

My journey through the labyrinth of graduate school has been both arduous and rewarding, and there were many individuals that contributed to my success. First and foremost, I would like to thank my amazing wife Aimee for her unending support of my decision to pursue a doctoral degree. Aimee helped me find the dream I never knew I had, and encouraged me to follow my newfound spark in the hopes that I would finally understand the intrinsic value of doing something because it makes you happy. This was a difficult lesson, but one for which I am eternally grateful. I would like to thank my dog Charlee for always distracting me with a fuzzy yellow tennis ball and a trip outside when I didn't know I needed a break. I would also like to thank my mother Lois who was always supportive of my path wherever it happened to lead.

Thank you to my advisor Dr. Ron Hagelman who graciously welcomed me into his office during the early days of my master's and doctoral career when he should have sent me away. Thank you for always listening to me, guiding me, and most of all knowing when to take off the training wheels and kick me out of the nest. I would not be the teacher or scholar I am today without you. I must also thank the other members of my doctoral committee, Dr. Alberto Giordano, Dr. Sven Fuhrmann, and Dr. Mark Fonstad. Thank you all for your willingness to help me along the path of my graduate school journey, and for the honest criticisms that ultimately improved my research. Thank you to Dr. Giordano for always making time for quick visit or answering a question in the hallway. Thank you to Dr. Fuhrmann for the bluntly honest criticism of my first maps so many years ago, and the criticisms and encouragement that shaped my cartographic perspective and understanding of the power of maps. Thank you to Dr. Fonstad for sharing your love of rivers, always finding the hole in my logic, and for profoundly altering my understanding of models and science.

In addition to my committee members, my graduate school experience was also strongly influenced by several other faculty members in the Department of Geography. Thank you to Dr. Fred Day for exposing me to the broader world of Geography beyond GIScience. I still credit Dr. Day's Geographical Analysis course with the beginning of my fascination with Geography. Thank you to Dr. David Butler for sharing your love of Physical Geography with me, and for serving as an unofficial sounding board during my GIScience/Environmental Geography academic identity crisis. Thank you to Dr. Richard Dixon for always keeping his door open to answer my random statistics questions. Thank you to Dr. Richard Earl for renewing my interest in water, and whose Applied Water Resources course gave me the foundation to write my dissertation on municipal water consumption. Thank you to Dr. Yongmei Lu for giving me the opportunity to guide students through real world GIS projects and hone my project management skills.

Finally, I would like to thank the staff of the Department of Geography and my colleagues. Without the unofficial counseling of Allison Glass-Smith, I would likely not have survived many of the graduate school pitfalls including self-doubt and momentary lapses of reason. Thank you to Angelika Wahl and Pat Hell-Jones for keeping the Department running smoothly, while the rest of us are absorbed in other pursuits. We couldn't do what we do without you. Thank you to Charles Robinson and Dan Hemenway for keeping the labs and the servers running. My research and I sincerely appreciate your efforts. Thank you to Christi Townsend, Clayton Whitesides, Todd Moore, Matt Patton, and David Parr for being great colleagues and friends. Thank you to Christi for being the best office mate ever and always listening to my rambling stories and other assorted nonsense. You helped take the edge off some of my worst days. Thank you to Clayton for always listening to my rambling anecdotes when you had more important things to do, and thanks for being a great collaborator. I look forward to our future projects.

Thank you to Todd for providing guidance with statistical analysis, and for the great conversations about all things science. I will miss our conversations my friend. Thank you to Matt for the conversations, the music, and the shows that helped keep me sane during the final stages of my dissertation work. You are a great friend and I will miss you terribly. Thank you to David for helping me solve many of the issues with my initial spatial analysis, as well as the cribbage games. Additionally, I would like to thank Kevin Kluge at the Texas Water Development Board for his patience and thoughtful suggestions. Kevin, this research wouldn't have been possible without you! For all those not mentioned here, your contributions have not been forgotten and you have my sincere thanks. Thank you all, because I could not have reached the end of my graduate school journey without you.

This manuscript was submitted on May 14, 2013.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

SPATIOTEMPORAL DRIVERS OF MUNICIPAL WATER

CONSUMPTION

by

Matthew H. Connolly, B.S., M.A. Geo.

Texas State University-San Marcos

August 2013

SUPERVISING PROFESSOR: RONALD R. HAGELMAN III

This study analyzed the individual and joint influences of social, urban, and physical landscape characteristics on patterns of municipal water consumption at the county scale for the state of Texas using a cross-sectional research design on three distinct temporal slices (1990, 2000, and 2010). Global multiple linear regression models and measures of global and local spatial association were combined to determine which landscape characteristics significantly influenced per capita municipal water consumption at the county scale, whether or not the statistically significant landscape characteristics varied over time, and to assess the degree to which the patterns and landscape characteristics of municipal water consumption reflected spatially stationarity. Overall results suggested that the social, urbanized, and physical environments contributed

significantly to the patterns of per capita municipal water consumption to varying degrees in each year. The social and urbanized environments consistently exerted the strongest influences on per capita municipal water consumption, while the physical environment was generally less important. Additionally, the social environment had the greatest cumulative influence in all three years, and the urbanized environment singly accounted for the majority of the variation in per capita municipal water consumption when the joint influences of the other statistically significant landscape characteristics were considered.

Differences in the composites of significant independent variables and the magnitudes of recurring significant variables between years, suggested that time influenced the landscape characteristics of per capita municipal water consumption. The spatial analysis of municipal water consumption patterns and its landscape characteristics suggested that they both exhibited weak to moderate degrees of spatial non-stationarity in each year. Furthermore, the measures of global and local spatial autocorrelation in the residuals of the multiple linear regression models suggested that spatial processes confounded the ability of a global model to adequately explain the significant driving landscape characteristics of per capita municipal water consumption.

CHAPTER I

INTRODUCTION

Fresh water is a spatially dispersed, finite resource. Yet, reliable supplies of fresh water play an integral role in the health, welfare, and development of human communities. Fresh water is not only essential for life itself; it is also an important component of economic activities such as agriculture, industrial processes, power generation, and waste disposal (McCarl 1995; TWDB 2011; Ward 2011). From a development perspective, fresh water is potentially our most important natural resource, as it has strongly influenced the location, function, and growth of both human (Arbues et al. 2003) and ecological (Petersen et al. 2012) communities.

Sociopolitical disputes over access to fresh water resources are common and reflect the degree to which demand often outstrips supply (Arbues et al. 2003). This mismatch is exacerbated by the spatial and temporal variability of fresh water resources and by the fact that, in general, municipal water consumption is not easily reduced through conservation initiatives (Arbues et al. 2003; Dingman 2002; Martinez-Espiniera and Naughes 2004; Petersen et al. 2012). Research also indicates that climate change, along with population growth and urbanization, will continue to alter the quantity, quality, and spatial distribution of global fresh water resources (Bednarek 2001; Dallman and Spongberg 2011; Kundzewicz et al. 2008; Ward 2011), thus further complicating management of this precious resource.

Simple population growth would seem to be the main contributor to increased water use, however previous studies have demonstrated that municipal water consumption is a function of both human and physical landscape factors (House-Peters et al. 2010; Kenney et al. 2008). Furthermore, local differences within the human and physical factors may produce inequalities in municipal water consumption that disrupt the delicate supply and demand relationships of neighboring communities. This interaction between the municipal consumption of one community and the municipal supply of another could potentially trigger political conflict or regional emigration with disastrous economic and environmental consequences (Ward 2011). In addition to the influence of natural and anthropogenic drivers, changing management goals can also influence water use. Water conservation remains unpopular in many communities and further complicates management of municipal water. More often than not, increasing demand results in costly engineering solutions rather than conservation methods, which may, in turn, trigger changes in the physical environment such as the degradation of water quality and the loss of aquatic habitat (Bednarek 2001).

The goal of this research is to discover the degree to which human and physical landscape characteristics significantly influence municipal water consumption. In this research, municipal water consumption is a combination of both residential and commercial water use. Municipal water use managers will benefit from an improved understanding of significant landscape drivers for water consumption, while analytical research into water resource patterns will benefit from further exploration of relevant landscape drivers for municipal water use in an ever changing, rapidly urbanizing world.

Understanding the drivers of municipal water consumption is especially important in arid and semi-arid climatic regions with highly variable precipitation patterns and rapid population growth such as those found throughout the American Southwest. Texas is no exception, with its mosaic of arid, semi-arid, and sub-tropical humid climates (Dixon and Moore 2011; Petersen et al. 2012) and booming urban populations. According to the Texas Water Development Board (TWDB), the population of Texas is expected to grow 80% between 2010 and 2060, and require an additional 8.3 million acre feet of water per year to meet projected demands for all water using groups (e.g. municipal, agriculture, industry, etc.).

Water for Texas, the state's 2011 summary of regional water plans, reported that these additional 8.3 million acre feet will be created from a variety of sources throughout the state including the construction of new reservoirs, increased surface water withdrawals, water re-use, irrigation conservation, and municipal conservation (TWDB 2011). Although the 2060 water consumption projections are based on historical water use, the municipal water use data do not reflect potential changes in the underlying factors that influence human water consumption such as climate and socio-demographic characteristics (House-Peters et al. 2010; Wentz and Gober 2007). Failing to account for changes in these drivers, or influencing factors, of municipal water consumption could severely hamper the implementation of statewide and regional water plans, due to mismatches in demand and available supply.

This potential mismatch between municipal water consumption, and available water supply may be especially important in North Central and East Texas as they are home to four TWDB Planning Regions (Figure 1) that are expected to show a collective 68% increase in water consumption, and an 86% increase in population between 2010 and 2060 (Table 1). Research has shown that municipal water consumption, like the location of fresh water, is also spatially variable (House-Peters et al. 2010; Wentz and Gober 2007), and that municipal water consumption is a function of human and geophysical factors (Carver and Boland 1980; Cochran and Cotton 1985; Kenney et al. 2008). The issue of spatial variability is further confounded by the fact that meeting fresh water demands is often accomplished through the expansion of existing water supplies, which has far-reaching environmental consequences. For example, the construction of new reservoirs may trigger bank erosion and the degradation of water quality a considerable distance downstream from the new impoundment (Bednarek 2001).

The purpose of this research is to improve our understanding of the quantitative synergies among social and physical environmental landscape characteristics relative to municipal water consumption, to characterize spatiotemporal changes among those characteristics, and to assess the degree to which municipal water consumption can be explained by a spatially stationary model. These research purposes were operationalized through the spatiotemporal analysis of municipal water consumption patterns in Texas counties in comparison to social, urban, and physical landscape characteristics at three temporal slices over a twenty-year period. The research questions addressed in this dissertation are:

1) Which social, urban, and physical landscape characteristics contribute significantly to municipal water consumption patterns at the county scale?;

2) Do these driving characteristics vary over time?; and

3) To what degree do municipal water consumption patterns exhibit spatial stationarity?

Answering these questions will serve three purposes. Firstly, this analysis addresses the larger question regarding the degree to which quantitative measures of human environments, physical environments, and the synergies between the two explain patterns of municipal water consumption. Secondly, the increased understanding of human fresh water consumption in water-stressed environments extends the existing body of knowledge addressing interactions between humans and the Earth's fragile fresh water resources. Thirdly, this research extends the literature supporting the application and utility of GIScience in resolving water resource problems. Additionally, this study added the explicit consideration of time to the investigation of municipal water consumption, using temporal slices to identify drivers of consumption that are consistently significant over multiple cross-sections of a period of record. An awareness of significant influences on municipal water consumption that are temporally consistent could help water managers anticipate future needs, and improve the targeting of use-reduction campaigns. A conceptual overview of this research project is provided in Figure 2.

Although the results of this study have the potential to greatly improve the management of municipal water, there are several important limitations that deserve attention. The scale of spatial analysis, the short period of record, the confounding influence of the aggregated measure of municipal water consumption, and the inability of quantitative analysis to fully capture the intangible variables that influence municipal water consumption limit the conclusions that may be drawn from this research. These limitations are developed further in the Data section of the Research Methods chapter. However, the inclusion of both time and spatial stationarity in this analysis offers an advancement over previous quantitative research relating to water consumption that have tended to focus exclusively on a limited number of dimensions driving demand. Understanding the role of space, spatial stationarity, and time in the evolution of municipal water demand will also aid current management and future planning for water resource development and conservation.

CHAPTER II

LITERATURE REVIEW

The high spatial and temporal variability (Dingman 2002; Petersen et al. 2012), and the ability of human use to influence the location, quantity, and quality of fresh water (Dallman and Spongberg 2012), make a compelling case to investigate the drivers of municipal water consumption at multiple temporal cross-sections and locations. The relevant literature for this research will be addressed in three primary categories including previous investigations of municipal water consumption, local indicators of spatial association (LISA), and historical GIS. The previous studies of municipal water consumption will be considered first, and help frame the contributions of this research project. Copious volumes of literature have been dedicated to water consumption patterns and water resource availability, and thus only those studies that apply most directly the present investigation will be reviewed here. The reviews of LISA and historical GIS provide insight into the ways in which these techniques will facilitate the research goal of explaining the drivers of municipal water consumption across multiple temporal periods, as well as the degree to which patterns of municipal water consumption is spatially stationary.

Municipal Water Consumption

The study of municipal water consumption patterns is essential to the health and longevity of human communities everywhere due to the important role that fresh water plays in daily human life. More specifically, reliable fresh water supplies are imperative to meet the direct needs of the human population, as well as, many economic activities such as power generation and industrial processes (McCarl 1995; TWDB 2011; Ward 2011). The importance of reliable municipal water supplies in Texas is especially important in the face of rapid population growth, dwindling supplies of ground and surface water, and highly variable precipitation patterns (TWDB 2011).

Carver and Boland (1980) explored municipal water consumption in the context of demand sensitivities to changes in price, otherwise known as price elasticity of demand. The study investigated the relationship between the price of water and water consumption for thirteen water utilities in Washington D.C. between 1969 and 1974 with a total of 390 observations derived from monthly water production records. The explanatory variables in this study included socio-economic and climatic data such as household income, the average number of residents per water connection, and the price of water and moisture deficit (defined as effective precipitation) respectively. Multiple linear regression was used to assess the relative and combined influence of the independent variables on municipal water consumption with separate models for seasonal and non-seasonal use. Final results suggested that moisture deficit was a statistically significant predictor of water consumption for three out of five cases at the alpha level of 0.05. Additionally, the study showed that the response of water consumption to changes in price (elasticity of demand) was higher over the long-run, defined as periods of one year or more. While this study contributed greatly to the understanding of socio-economic and climatic influences on municipal water demand, the findings were limited by a short temporal period and a single geographic location.

A similar study comparing the municipal water consumptions of Oklahoma City and Tulsa, Oklahoma between 1961 and 1980 was completed by Cochran and Cotton (1985). While price elasticities of water demand were not explicitly explored here, the price of water was included as a variable in several simple linear and logarithmic regression equations along with the number of households per 1000 people, per capita income, rainfall, and temperature. The precipitation and temperature data were monthly averages obtained from the National Oceanic and Atmospheric Administration (NOAA). Cochran and Cotton (1985) ultimately found that the socio-economic variables greatly outweighed the climatic variables in terms of relative importance for both Oklahoma City and Tulsa using simple linear regression techniques. The average price of water, per capita income, and the number of households per 1000 people all yielded R^2 values over 0.80 at a significance level of 0.01. Additionally, temperature and precipitation were found to be largely statistically insignificant in both locations, with the exception of temperature in Tulsa which was significant at the 0.10 alpha level. Final results from both the simple and logarithmic regression analyses suggested that per capita income exerted the strongest overall influence on water consumption in both cities, and that the climatic variables had little to no influence. The authors concede, however, that the weak influence of climatic variables may be an artifact of the inability to remove several commercial and industrial use records from the municipal use data.

Rather than attempting to explain the driving forces behind municipal water consumption, Zhou et al. (2000) focused their efforts specifically on the forecasting urban water demand over a twenty-four hour period for the city of Melbourne, Australia. Despite the difference in purpose, this study highlights the importance of considering temporal and spatial scale when examining municipal water consumption. Zhou et al. (2000) only examined the influence of maximum daily temperature, and daily pan evaporation on per capita water consumption for the entire city of Melbourne. The relative influence of population was controlled for in the use of per capita water consumption as a dependent variable, and other socio-economic variables such as water price and per capita income were deemed unimportant at the daily time step. This omission of socio-economic data was supported by the fact that income and price effects typically change on an annual time scale (Cochran and Cotton 1985).

Operating at the spatial scale of an individual city over a period of seven years (1989-1996), the researchers were also able to disaggregate water consumption into base and seasonal use. Seasonal use was aggregated into the six month periods of summer and winter, and represented the portion of water consumption that was sensitive to climatic variables. Final results suggested that precipitation, antecedent precipitation (the amount of precipitation occurring prior to an individual time step), and pan-evaporation were the strongest predictors of per capita water consumption at daily time steps. Following a series of validation runs, seasonal disaggregation and nonlinear regressions improved overall model fit to an R^2 of 0.896.

The influence of climatic variables on municipal water consumption was also explicitly investigated by Gutzer and Nims (2005). This study examined the inter-annual variability of precipitation, temperature, and humidity on seasonal municipal water use in Albuquerque, New Mexico. Seasonal water use was used in favor of annual per capita consumption due to the fact that Albuquerque's water supply is drawn entirely from groundwater sources, which insulate the city's water supply from short-term climatic variation. Although the influence of population and other socio-economic variables were not explicitly considered, the authors conceded that population growth drives long-term fresh water consumption. Additionally, previous local studies had indicated that the highest water usage is concentrated during the summer months. Forty-nine percent of all residential water use in Albuquerque occurred between June and September for the period of 1980-2001 (Gutzer and Nims 2005).

Simple linear and multiple regression techniques were applied to the summer season data (June through September) with municipal water consumption as the dependent variable, and the climatic data as the independent variables. Separate models were constructed for the periods 1980-1994, and 1995-2001 to capture the effects of pre- and post-water conservation initiatives. Final results of the study found that both precipitation and temperature were strongly correlated with residential water consumption between years, and over the entire study period. Despite the short seven-year period of record for post-conservation data, final results for Albuquerque suggested that conservation measures had no short-term effect on municipal water demand.

Wentz and Gober (2007) solely considered socio-economic variables relative to municipal water consumption in Phoenix, Arizona. This study was one of the first to explore the drivers of residential water consumption at a spatial resolution finer than that of an entire city, and to consider a variation in human land use. Wentz and Gober (2007) used average household size, lot size, the presence of a swimming pool, and landscaping type to explain the variation in average single family household water consumption at the census tract level for the year 2000. These variations were explained using multiple linear (MLR) and geographically weighted regression (GWR) techniques to provide the estimates of relative and combined influences of the independent variables. The GWR model was used to investigate the spatial dependence between water consumption in a given census tract and the corresponding values in neighboring tracts. All dependent and independent variables were used in both models, with census tract centroids supplying the point inputs for the GWR model.

The MLR regression analysis produced and overall R^2 of 0.64 and suggested that lot size and the presence of swimming pools had the greatest influence on water consumption. Landscape type and average household size were statistically significant, but accounted for much less of the overall variance. The GWR model increased the overall model fit to 0.848 (mean R^2 for all individual GWR models), and suggested that the presence of swimming pools, and household size are spatially dependent on neighboring tracts. Aside from confirming the importance of urban land use, and population at the census tract scale, the major contribution of this study was to demonstrate the utility of GWR in municipal water consumption studies.

Kenney et al. (2008) also employed a variant of multiple regression known as a fixed effect model to examine residential water demand for 10000 individual accounts for the City of Aurora Colorado between 1997 and 2005. This study used an expanded array of socioeconomic variables including household income, the median age of the home owner, the percentage of owner occupied homes, the percentage of homes built after

1991, the percentage of homes built prior to 1970, and the median number of bedrooms. The climatic variables were limited to total precipitation per billing period, and average maximum temperature during the billing period. Other variables such as the CPI adjusted price of water, the presence of water restrictions, the length of the billing period, smart water reader use, and participation in rebate programs were also analyzed. Prior to analysis, the authors partitioned the data into two distinct segments to separate the drought and non-drought periods. The data ranging from 1997 to 1999 represented relatively normal conditions, while the period from 2000 to 2005 experienced prolonged sequences of dry weather patterns. Despite the short temporal period of the dataset, the comprehensive nature of the records allowed the research team to explore the relationship between class of user (high, medium, and low) in addition to drought period. While much of the influences of the socio-demographic data are masked by the choice of regression technique, Kenney et al (2008) admit that the stratification of users by volume of use confirmed that the age, income, and housing stock age are related to municipal water consumption. Additionally, the authors found both climatic variables to be strongly related to seasonal water consumption, with the highest demands occurring in the summer.

Continuing the emphasis on the combined power of socio-demographic and physical housing characteristics variables to explain municipal water consumption, House-Peters et al. (2010) conducted a study of census blocks in Hillsboro, Oregon from 2004 to 2007. The researchers were interested principally in determining the significant drivers of municipal water use, the sensitivity of single family households to drought conditions, inter-annual climate variation, the magnitude of response to drought conditions and inter-annual climate variability at the census block scale. The water consumption dataset contained 21800 records at the scale of individual households which were aggregated to the census block scale for the entire city of Hillsboro. These census block water records yielded seven dependent variables including base water use for 2004 and 2006, seasonal water uses for 2004 and 2006, drought sensitivity defined as the ratio of 2006 seasonal use to 2004 seasonal use, and inter-annual climate variability for 2004 and 2006. The socio-demographic variables considered in this study were mean household size, median household income, average education level as a percentage of the population, and median population age. Physical urban landscape variables included outdoor size, average year built, building size, and total property value. Both MLR and spatial regression methods were used to explore the individual and shared contributions of the independent variables to water consumption.

Generally, the study indicated that socio-demographic and physical housing characteristics contributed differently to each dependent variable for both model types. However, the most statistically significant variables were shown to be mean household size, percentage of college education, and outdoor space (e.g. backyard, front yard, etc.). Mean household size was significant for both the MLR and spatial regression models of base use in 2004 and 2006; and the percentage of outdoor space, and the percentage of the population that has a college education were statistically significant for both models of seasonal use in 2004 and 2006. The spatial regressions for the climate sensitivity variables indicated statistically significant spatial variation for all physical housing and socio-demographic variables, while the MLR regressions found that all physical housing variables were significant at the 0.05 level. Likewise, the MLR regressions found that the socio-economic variables were significant at the 0.05 level for inter-annual climate sensitivity in both years. Despite the high spatial resolution of the water consumption dataset, the short temporal period and the two year interval between temporal slices may have masked the actual long-term influences of the socio-demographic variables that were evident in previous studies.

This review of previous municipal water consumption studies suggests that my research is well positioned to contribute to the literature by employing both linear and spatial regression methods at multiple temporal slices over longer periods of record, and by examining the effect of scale on water consumption patterns. Even when spatial interactions were considered in the cases of Wentz and Gober (2007), and House-Peters et al. (2010), the primary spatial unit of analysis was the census tracts, or census blocks for a given city. The importance of this work cannot be understated, as the majority of water resources planning decisions in many regions of the country are made by municipalities (House-Peters et al. 2010; Wentz and Gober 2007). However, I would like to add the consideration that water consumption patterns and water resource supply decisions may have impacts that extend beyond the unit at which they occur. For example, the City of Dallas, Texas is located in the North Central region of the state, but draws a portion of its water supply from reservoirs in East Texas hundreds of miles away (Young 2012). In this way, the consumption patterns of Dallas bleed into, and ultimately affect water availability in other regions of the state (TWDB 2011). Similarly, the water consumption patterns of municipalities may potentially aggregate to affect future planning efforts to meet water needs at different spatial scales. The purpose of this research is to test whether significant drivers of municipal water consumption are consistent across multiple temporal periods at the county scale.

Local Indicators of Spatial Association

Local Indicators of Spatial Association, or LISA, refers to a suite of metrics used to measure the spatial autocorrelation between individual observations within a given dataset. The term was first coined by Anselin (1995) to distinguish a particular subset of local spatial statistics that conform to more stringent requirements than simple local measures of spatial autocorrelation such as the G_i and G_i^* statistics of Getis and Ord (1992). In addition to analyzing the spatial autocorrelation of each individual observation, a LISA must provide an indication of the extent of significant spatial clustering of similar values around an observation, and be proportional to a global measure of spatial association when summed with the local estimate for all other observations (Anselin 1995). These two properties of LISAs permit local indicators of spatial association to be used as inferential statistics with sufficiently large sample sizes, in addition to their primary role as exploratory spatial data analysis tools (Raty and Kangas 2007).

Since their introduction in 1995, LISAs have grown in popularity as a means to account for the smoothing effects of global estimators of spatial autocorrelation, and have appeared in studies analyzing remotely sensed imagery (Wulder and Boots 1998), patterns of crime (Ratcliffe and McCullagh 1999), mine field delineation (Cressie and Collins 2001), regional distributions of European GDP (Le Gallo and Ertur 2003), the height structure of forests (Raty and Kangas 2007), and traffic accidents within transportation networks (Yamada and Thill 2007). Wulder and Boots (1998) used the

Getis statistic to provide information about the spatial interrelationships between individual pixels in LANDSAT TM imagery, and found that LISA techniques were capable of generating fuzzy boundaries around individual image objects. This ability to ascertain approximate boundaries for discrete objects in satellite imagery greatly decreases the ordeal of remotely sensed imagery classification (Jensen 2005).

Ratcliffe and McCullagh (1999) found a modified version of the Getis Ord G_i and G_i^* statistics to aid police officers in the determination of vehicular crime hotspots in the UK where geocoded incident data had been disaggregated from zonal police beats. LISAs were used to separate concentrations of related incidents from background 'noise' created by global spatial autocorrelation measures. The successful identification of these hotspots helped officers manage personnel deployments amidst increasingly scarce police resources. Cressie and Collins (1999) used LISAs to examine simulated clusters of clutter and actual mines in coastal mine fields in remotely sensed imagery collected by UAV drones. LISAs were found to significantly improve the analyst's ability to differentiate between land mines and random clutter in the target area. This particular application of LISA offered naval researchers the opportunity to reduce the mine-related loss of valuable human capital in combat situations.

Le Gallo and Ertur (2003) used local implementations of Moran's I and Moran scatterplots to assess the spatial non-stationarity of regional distributions of GDP throughout Europe between 1980 and 1995. In this study the LISAs were able to successfully highlight the importance of spatial interactions and geographical location relative to GDP growth disparities. LISAs were able to provide additional evidence that the economic growth of an individual region in Europe was dependent on the growth of commercial activity in neighboring regions (Le Gallo and Ertur 2003).

Raty and Kangas (2007) tested four different LISAs including a Local Moran's I, Geary's c_i, and the Getis G_i and G_i^* statistics to localize multiple linear regression models for the heights of individual trees in a southern Finnish forest. Although the LISAs tested in this application failed to improve estimates of spatial non-stationarity amongst the heights of individual trees, the researchers were able to identify potential improvements to the original regression model. Finally, Yamada and Thill (2007) applied LISA techniques to develop a local indicator of spatial association that responds to the analysis constraints imposed by a transportation network. The authors combined LISAs with a local K function and the Geographical Analysis Machine (GAM) to detect hotspots of traffic accidents in Buffalo, New York during 1997. The study ultimately found that the inclusion of LISAs exposed a latent pattern of high spatial variability in highway safety, which could be used to help target future analysis of dangerous areas.

The synthesis of the aforementioned studies suggests that LISAs have a broad base of applications to human and physical environmental problems with moderate to high levels of success. Despite the ability of LISAs to improve estimations of spatial non-stationarity in all cases, the inclusion of local indicators of spatial association consistently generated new insights into existing datasets or research methodologies. Additionally, the use of LISAs was able to successfully highlight the benefits of extending exploratory spatial data analysis beyond global measures of spatial autocorrelation. Thus, local indicators of spatial association will be used to gain insight into the spatial stationarity of municipal water consumption patterns, and the efficacy of global statistical models to explain the driving characteristics of the consumption of municipal water.

Historical GIS

The discussion of Historical GIS given here is brief, as this research draws loosely on the organization of temporal data employed by historical geographers, and extends a recent vein of research that uses GIS to integrate historical human and physical environmental data. In their comprehensive introduction to the emerging field of Historical GIS, Gregory and Ell (2007) describe it as the synthesis of historical research and GIS technology to analyze change over time. They are careful to concede that GIS is not a panacea for all historical research problems, but remain strong advocates of the application of GIS techniques to historical data when the original source data allow. One of the greatest considerations in any Historical GIS project, is the organization of temporal data since GIS was not natively designed to accommodate time. Several primary strategies to account for this temporal deficiency include the temporal slice, base map with overlays, and the space-time composite models.

The temporal slice model is useful for cross-sectional analysis and involves organizing and storing only spatial and attribute data for each specific snapshot of interest. Under this model, the state of the selected variables at each time step, the change in a given variable between snapshots, and the frequency of change in a given variable may be assessed. The temporal slice method is the simplest to implement, but suffers from a lack of temporal topology, and produces large amounts of data redundancy (Gregory and Ell 2007). The base map with overlays model consolidates all of the original data into a single base map, and changes are represented as a cumulative intersection of the data for all interceding periods. This method is capable of assessing longitudinal changes in a given variable, but requires a finer temporal resolution than is often available from historical sources. The space-time composite is essentially a variation on the base map with overlays approach in which the base map becomes a temporal composite built from accumulated geometric changes. The primary advantage of the space-time composite model is that time may be treated atemporally, and space may be treated aspatially allowing both temporal and spatial changes to be analyzed simultaneously (Gregory and Ell 2007). Additionally, this organizational structure can reduce storage requirements by eliminating most data redundancy. The use of date stamps as attributes may also provide an alternative means of organizing temporal data (Gregory and Ell 2007).

Given the nature of my research questions and the TWDB water consumption data, I will use the temporal slice model to organize all attribute and spatial data to conduct a cross-sectional analysis of municipal water consumption's driving landscape characteristics across time at various spatial scales. A more comprehensive longitudinal analysis will be reserved for future research. In addition to borrowing temporal organization strategies from Historical GIS methods, my research will also extend the body of literature using GIS to combine human and physical environmental data over time. Raymond (2011) used GIS to integrate personal accounts of urban change, historical photographs, county tax assessor records, and topographic data to reconstruct the re-grade of Denny Hill in Seattle, Washington. A variety of sources were combined to produce a continuous record of urban morphology between 1893 and 2008 using building footprints. Time stamps were applied to each digital representation of a building's footprint to aggregate all building morphologies into a single GIS feature class that could be disaggregated at the will of the analyst. Historical topographic surveys originally produced during the construction of Seattle's sewer system were digitized and georeferenced to produce records of historical topography prior to the Denny Hill re-grade initiative. The historical topography and building datasets were subsequently combined to construct several three dimensional models of Seattle's urban past. Results of this study provided new insight into the definitive spatial extent of the area once occupied by Denny Hill, as well as the socio-demographic characteristics of the area over time.

An earlier study by Pearson and Collier (1998) also combined historical human and physical environmental data to investigate agricultural landscape changes. The study combined analog historical tithe maps with digital representations of Ordinance Survey maps of land use, soil type, and geology to examine changes in agricultural fields and land improvement practices in Newport, Pembrokeshire, UK. Initial comparisons of historical tithe maps and modern Ordinance Survey data revealed that few boundary changes had occurred between 1845 and the present day, thus eliminating the need for the digitization and georeferencing of the original tithe maps. Instead, field boundaries were digitized from the more recent Ordinance Survey maps using the UK's National Grid at a scale of 1:10000. After reconciling the historical land use definitions with their modern equivalents, the digital agricultural field boundaries were combined with landownership records from the region's wealthy landowning families. This compilation of data was used to recover fertilization and other land improvement strategies. The "new" spatially informed dataset was processed using a Multi-level modeling procedure to further explore the nested influences of owner versus renter occupation of specific agricultural fields. When cross-referenced against available tax records, which were used as a surrogate for agricultural productivity, study results suggested that GIS was an effective means of synthesizing historical landscape change from human and physical environmental data.

Both Raymond (2011) and Pearson and Collier (1998) used GIS to combine human and physical environmental data to provide detailed accounts of interactions between humans and the environment over time at a single spatial scale. Raymond (2011) examined the urban morphology of a Seattle neighborhood, while Pearson and Collier (1998) investigated the effects of land use practices on agricultural productivity for an entire British village. These studies provided internally consistent records of change over periods of more than 100 years for a single geographic scale. This research applied similar standards of internal data consistency for multiple spatial scales over a shorter temporal period. Trading time for space allowed this research to facilitate comparisons between larger numbers of discrete spatial entities (individual counties) and extract more generalized inferences about human-environment interactions from spatial and temporal patterns. Linking the explicit consideration of time to generalizations about human-environment interactions may entice more environmental researchers to employ Historical GIS techniques, and further advance the sub-discipline.

CHAPTER III

RESEARCH METHODS

Conceptual Research Overview

The purpose of this research is to improve our understanding of the quantitative synergies among social and physical environmental landscape characteristics relative to municipal water consumption, to characterize the spatiotemporal changes among those characteristics, and to assess the degree to which the municipal consumption of water can be explained by a spatially stationary model. Figure 2 illustrates the relationship between the variables that were considered and the general analysis procedure. The collective influences of the social, urbanized, and physical environments on municipal water consumption were analyzed at the county scale during three different temporal periods.

The county scale was selected for this analysis because it provided temporally complete and spatially contiguous coverage for the entire state of Texas that includes municipal water consumption estimates for both in-system and private wells (personal communication, Texas Water Development Board Historical Water Use Survey Manager Kevin Kluge, September 24, 2012). The absence of private well data from the other spatial scales of data available from the Texas Water Development Board precluded a multi-scale analysis of municipal water consumption because equivalent comparisons cannot be made between scales. Every county in Texas was used to develop a multiple linear regression model for each temporal slice, while local indicators of spatial association were applied to regression model residuals, statistically significant driving landscape characteristics of municipal water consumption, and the original county scale municipal consumption patterns.

Statistically significant drivers of municipal water consumption were identified by constructing separate models for temporal period (1990, 2000, and 2010) at the county scale. The improved understanding of municipal water consumption drivers were derived from the comparison of the statistically significant drivers from the MLR model for each temporal slice. Following the comparison of the statistically significant drivers in each temporal period, the spatial stationarity of the residuals from each MLR model, the statistically significant drivers of municipal water consumption, and the original municipal water consumption patterns were evaluated with LISA metrics.

Site and Situation

Municipal Water in Texas

While municipal use is estimated to have the sharpest increase of all the water use groups in Texas (TWDB 2011), understanding the spatial drivers of this trend and their synergetic influences on consumption patterns have received limited attention among scholars. The TWDB itself remains focused primarily on providing "leadership, planning, financial assistance, information, and education for the conservation and responsible development of water for Texas (TWDB 2010)." As evidenced in this statement, the focus of the organization is on the responsible development of water resources, rather than management of water resource demand. Conservation also appears in the mission statement, but has a much weaker influence on TWDB activities due to the difficulties associated with implementing conservation policies, and current Texas water law.

Water conservation measures are typically politically unpopular and difficult to enforce (Thompson 1999). However, Texas bears the additional burden of a unique combination of prior appropriation, rule of capture, and riparian water law traditions that do not favor reductions in water consumption. Under prior appropriation doctrine, the most senior surface water rights are served first, and are the most influential during times of drought. The influence of prior appropriation on water conservation stems from the fact that the quantity of water guaranteed by a water right under this system is subject to revision over time (Thompson 1999). A senior right will always be served first, but a failure to use a right's allotted amount of water in its entirety may result in a permanent quantity reduction. Similarly, the rule of capture applies to ground water, and declares that the ownership of water belongs to the party that removed it from the ground regardless of the water's actual source. Under this law, water rights may also be treated as property, allowing ground water to be traded or sold for profit (Thompson 1999). Despite these challenges, conservation initiatives may need to play a larger role in the future water management decisions in Texas due to continued industrialization and resource extraction, pressure from population growth and urbanization, and potential changes in the physical environment.

Industrialization and Resource Extraction

Arranged from highest to lowest, the primary uses of water in Texas, are agriculture, urban populations (municipal), manufacturing, and the generation of electricity (McCarl 1995; TWDB 2011). The competition that currently exists between these four uses will continue to grow in response to changes in the aforementioned impacts on the water resources of Texas, but municipal water supplies may be the most heavily affected due to feedbacks between municipal water and water intensive industries such as electricity generation and hydraulic fracturing. Texas' energy mix is currently dominated by coal (37%) and natural gas (49%) fired power plants, both of which use a technique known as thermoelectric generation (Stillwell et al. 2011). Thermoelectric generation plants require large volumes of water to create high pressure steam that moves turbines, and to re-condense that steam for reuse. The average annual water consumption of thermoelectric generation is 595,000 ML (482,374.35 AF) which is roughly equivalent to the annual municipal consumption of three million people (Stillwell et al. 2011).

The feedback component of thermoelectric generation in Texas is that while electricity creation requires large amounts of water, the purification and treatment of wastewater require large amounts of electricity. The average annual electricity consumption of wastewater treatment plants is approximately 2.1 to 2.7 TWh (Stillwell et al. 2011). Thus, the positive relationship between population growth and climate warming, and electricity consumption (Jones and Ozuna Jr. 1995), could potentially drive water consumption even higher and strengthen competition between electricity generation and municipal use.

Hydraulic fracturing, commonly known as "fracking", also threatens municipal water supplies due to the degradation of large volumes of water. The average fracking operation consumes anywhere from 11.36 ML (9.21 AF) to 18.92 ML (15.34 AF) of water per well (Arthur et al. 2010), where water is combined with sand and chemical solvents prior to borehole injection. The mixture of chemicals, water, and sand is used to release raw petroleum products from underground shale deposits by inducing physical fractures caused by increases in pressure (Arthur et al. 2010). Water is essential to the extraction process because it both increases subterranean pressure within the shale deposit, and lubricates the drill bit. Fracking is threatening municipal water supplies near the Barnett Shale outcrop in North Texas via decreases in both water quality and quantity, as the extraction operation continues to encroach upon human settlements (Wiseman 2009). These reductions in the quantity and quality of fresh water become especially acute during times of low stream flow which increases competition with municipal demand (Arthur et al. 2010). This competition will also be strengthened by increases in population size and the spatial extent of urbanization processes.

Population Growth and Urbanization

Increasing population size and the spatial extent of urbanization increase the human use of water, as well as, altering its quantity, quality, and spatial distribution (Dallman and Spongberg 2012). These expansion processes typically reduce water resource availability by increasing the demand for municipal water, as well as the demand for electricity (Hitchcock 2011; Murdoch et al. 2000). The growth of electricity demand is especially important due to the amount of water that is consumed by the typical thermoelectric power plant, and the amount of energy consumed by water purification in treatment plants (Stillwell at al. 2011). In this way, an increase in municipal water consumption could create a positive feedback loop. Increasing municipal water consumption requires additional electricity which in turn requires additional water consumption. Addressing these potential shortages created by population growth will be complicated by the fact that structural solutions such as the construction of new reservoirs and the use of inter-basin transfers are much more difficult to implement than in the past. In fact, nearly all of the sites in Texas that are amenable to reservoir construction are already in service (Schmandt 1995).

Despite the TWDB's efforts to encourage the inclusion of water conservation and reuse strategies in the recent revision of regional water plans, surface water alone accounts for slightly more than 50% of the anticipated increase (TWDB 2011). At the state level, new reservoir construction and new connections to existing surface water supplies account for 16.7% and 33.9% of the projected 2060 demand respectively. When considered from the scale of individual Planning Regions, however, the contribution of surface water to overall demand is considerably higher in some cases. For example, Planning Regions C, D, H, and I, which collectively cover North Central Texas, all of East Texas, and the northernmost extent of Texas' Gulf Coast (Figure 1) all exceed the 51% state average for total surface water use (Table 2). Given the strong influences of population and urbanization on fresh water demand and the heavy reliance of these regions on surface water, increases in population size are likely to alter the character of fresh water and other aspects of the physical environment.

Physical Environment

In addition to increased demands on sparse and highly variable runoff in these areas (Ulery et al. 1993), the high proportion of additional surface water use via the construction of new reservoirs may have hydrological and geomorphic consequences on the rivers in Planning Regions C, D, H, and I. For example, a sizeable body of literature exists on the hydrologic and geomorphic impacts of large dams on rivers. According to the Texas Administrative Code (State of Texas 2009), a large dam is any dam that impounds 50,000 acre feet of water or more, a definition that is generally consistent with the literature (Graf 2005). Large dams, such as are often built during the construction of reservoirs, can profoundly alter the hydrology and geomorphology of rivers which may cause local or downstream problems due to changes in the timing of peak and minimum discharges, and changes in sediment budgets (Graf 2001).

The shifts in the timing of peak and minimum discharges disrupt the natural hydrological cycle and reduce overall flow variability, which has implications for both river channel form, and riverine habitat (Bednarek 2001; Graf 2001). Changes in the flow regime of river can cause a simplification of river planform such as the straightening of a previously meandering channel. This shift from a meandering to a straight channel can alter the development of riffles and pools which provide vital habitat for fish and other riverine organisms (Bednarek 2001). Potential changes in sediment budget due to impoundment may also drastically alter channel form through increased local or downstream erosion (Schmidt and Wilcock 2008). Furthermore, a study of Livingston Dam in the Lower Trinity River Basin has documented some the aforementioned effects in Texas. The study found that the closure of Livingston Dam, located in Planning Region H (Figure 1), has reduced the natural variability in the planform of the river channel below the dam by approximately 42% (Wellmeyer et al. 2005). Additionally, municipal water supplies in existing reservoirs may be compromised by Texas' natural inter-annual climate variability, and potential climate warming.

Texas is home to four primary climate types according to the Köppen-Geiger classification system including humid subtropical (Cfa), cold mid-latitude desert (BSk), cold mid-latitude steppe (BWk), and hot subtropical steppe (Bsh) (Dixon and Moore

2011). The humid subtropical zone covers most of the state extending from North Central Texas south to the Gulf Coast, and east to the Louisiana border. The cold mid-latitude desert covers the bulk of the Texas panhandle, extending south to the Texas-Mexico border. The hot subtropical steppe lies south of the cold mid-latitude desert and west of the humid subtropical zone, extending both south and west to the Mexican border. The cold mid-latitude steppe begins at the western border of the cold mid-latitude desert in West Texas and extends south and west to the Texas-Mexico border, and north to southern New Mexico. Temperature and precipitation patterns follow north-south and east to west gradients respectively, with temperature increasing from north to south, and precipitation increasing from west to east. In addition to the regional climate differences, Texas climates also experience high inter-annual variability in temperature and precipitation which complicate water planning efforts (North 1995). Given the water management difficulties that exist under current climatic conditions, climate warming would only exacerbate Texas' municipal water predicament.

The Intergovernmental Panel on Climate Change has demonstrated that atmospheric concentrations of greenhouse gasses such as methane and carbon dioxide have increased dramatically since 1750 (IPCC 2007). These increased concentrations of insulating gasses are likely to accelerate the natural component global climate change (IPCC 2007) and produce increased water availability in high, and wet tropical latitudes; and decreased water availability in mid, and dry tropical latitudes by the middle of the twenty-first century (Kundzewicz et al. 2008). Following this global pattern, climate change is also expected to affect the water resources of the conterminous United States. Semi-arid regions such as the American Southwest may experience the greatest departure from baseline levels, either gaining or losing approximately 50% of currently available water resources (Thomson et al. 2005).

Texas is also expected to experience changes in climate that could potentially alter the character and distribution of its water resources. Trend analysis of climate stations from the United States Climatology Network revealed statistically significant cooling, rather than warming temperatures; and increasing, rather than decreasing, precipitation trends for the North Central and East regions of Texas (Dixon and Moore 2011). The temporal coincidence of periodic droughts with these trends of cooling temperatures and increasing precipitation, suggest that a shift towards warmer temperatures and lower precipitation volumes may further complicate existing water supply issues.

The North Texas Municipal Water District, which serves the Dallas-Fort Worth metropolitan area as well as others in the TWDB Planning Region C, struggled to meet both municipal and agricultural demands in 2006 due to extremely low lake levels at Lavon Lake. Over a period of two years, higher than average temperatures and low precipitation volumes decreased the fresh water storage of Lavon Lake to 36% of its conservation pool capacity (Appleton 2009). Longer droughts could exponentially increase water shortages in river basins with ample precipitation. A seven year drought similar to that of the 1950s would seriously impair the Upper Trinity basin (one of the wettest in Texas) under current climate conditions (Schmandt 1995). In addition to periodic drought and potential changes in climate, Texas' water resources will also likely be impacted by future population growth and urbanization processes. The population of TWDB Planning Region C alone, home to Dallas, Tarrant, and Denton Counties among others, is projected to increase by 96% in 2060, and will spawn an 86% increase in municipal water consumption (Table 1), and a corresponding stress on existing water supplies.

Failing to meet the future water needs of Planning Region C alone could translate into an economic loss of approximately $2,336,000,000 (TWDB 2011). Further investigation into the geographic drivers of municipal water consumption can be especially useful in helping water managers develop better conservation campaigns in the face of dwindling supplies. A more thorough understanding of the factors that influence municipal water consumption could also improve the management of fresh water in semi-arid regions due to the spatial linkages and complex process-response relationships that exist between the components of a hydrologic system (Charlton 2008; Giardino et al. 1995).

Furthermore, these linkages and patterns may be reflected in municipal water use patterns. For example, drainage basin boundaries are the principal spatial unit of hydrology, and are rarely contained within a single administrative political boundary (e.g. city, county, etc.). Thus, many different administrative units may share and influence a single source of water. Similarly, the municipal water consumption of a single political unit could span the boundaries of multiple drainage basins, allowing the consumption in one basin to influence water availability in another. The City of Dallas is located in the Trinity River drainage basin, and has been intermittently supplementing its municipal water supply for years with water from the Lake Texoma watershed (Young 2012). In summary, the current scarcity and uneven spatial distribution of fresh water in Texas, coupled with the effects of potential changes in climate, population, energy production, and hydrology make a compelling case to investigate the drivers of municipal water consumption at multiple geographic scales.

Study Area

In addition to the counties in Texas Water Development Board Planning Regions C, D, H, that jointly represent approximately 57% of the Texas population (2010 and 2060) and account for 30% and 42% of the total water demand for the entire state of Texas in the years 2010 and 2060 respectively (Table 1), the study area includes every county in the state of Texas to permit a temporally complete and spatially contiguous analysis (Figure 3). Despite sharing the same Köppen climate type of sub-tropical humid (Cfa), moisture deficits and surpluses have historically varied within the Planning Regions C, D, H, and I (Ulery et al. 1993). Similarly, the strong east-west precipitation and north-south temperature gradients that exist in all regions of Texas are responsible for variations in moisture surpluses and deficits within, as well as, between other Köppen climate types across the state (Muller and Faiers 1995).

The mean precipitation across all planning regions in the study area is approximately 29.5 inches (750 mm) per year, and within region variation is controlled by the proximity to the Gulf of Mexico (Muller and Faiers 1995). The majority of precipitation is delivered via thunderstorms of both the frontal and convective variety, providing infrequent but intense rainfall. This pattern of precipitation contributes to the recurrence of droughts of varying severity. The presence of recurring droughts is relevant to municipal water consumption patterns due largely to the difficulty in detecting drought signals. The lag between the onset of prolonged dry conditions and the response of the physical landscape to the moisture deficit (e.g. crops, lake levels, etc.), can cause delays in human adaptation to reduced water availability. In other words, it is often too late to repair the damage caused by a drought once it has been formally recognized. A deeper understanding of the strongest influences on municipal water demand may help water managers across Texas transition from supply management to demand management strategies by targeting areas for water use reductions more effectively and alleviating some of the drought related water supply shortages that plague arid and semi-arid regions.

Data

The data required for this project were broadly grouped into three conceptual categories of independent variables obtained from various sources listed in Table 3. The conceptual categories drawn from the relevant literature and the unique geographic setting of the study area were the social environment, the urban environment, and the physical environment. The term environment is used here to describe a unique set of characteristics that comprise a specific type of surrounding (Petersen et al. 2012). Each of these individual surroundings represents a component of the larger surrounding or 'environment' that influences the municipal consumption of fresh water. The social environment variables assessed the influence of human characteristics on municipal water consumption, and included the educational attainment, per capita household income, average household size, population age structure, occupancy type, the type of dwellings in a given county, and the work locations for county residents. The urban environment variables accounted for the influence of urbanization processes on municipal water consumption including the level of urbanization, and population density. The physical environment variables incorporated the physical aspects of surface water as they pertain to its geographic distribution and potential use including drought conditions, precipitation, lake evaporation, and water source. The dependent variable in the statistical analysis conducted here was annual per capita municipal water consumption to mitigate the bias of counties with larger population sizes.

Per capita municipal water consumption was obtained from the Texas Water Development Board's Historical Water Use Database for the county scale (TWDB 2009a). Per capita water consumption was selected as a dependent variable in order to partially control for the well documented effects of population growth on municipal water use (Zhou et al. 2000), and its availability as historical data routinely collected by the Texas Water Development Board. The Historic Water Use Database is derived from the results of an annual Water Use Survey administered to all municipal water providers both public and private in the state of Texas. These data have been collected consistently and reliably since 1984 by the TWDB due to the mandatory participation of all municipal water entities (TWDB 2009a). Additionally, the historic water use data has been adjusted for leakages due to broken transmission networks, and clerical errors such as erroneous water meter readings (TWDB 2009a).

Educational Attainment was considered as a surrogate measure for the general awareness of water resource issues due to its demonstrated influence on residential water consumption at the city scale (Guhathakurta and Gober 2007; Syme et al. 2004). The primary assumption underlying the education level variable was that higher levels of education equate to a greater likelihood that the population has been exposed to information addressing human-environment interactions, conservation, and water resources. The National Historical Geographic Information System (NHGIS) produced by the Minnesota Population Center (MPC) provided downloadable access to all available census tables for all previous and recent decennial U.S. censuses, while the U.S. Census Bureau's (USCB) *American Factfinder* data download tool only contained data from the 2000 and 2010 census.

Additionally, in response to feedback from the general public, the 2010 decennial Census used a modified short form survey that captured very limited information to lessen the burden of census participation. The collection of the traditional long form sample data such as educational attainment and household income was also transferred to the U.S. Census Bureau's American Community Survey (ACS) during the 2010 Census. Consequently, the educational attainment of the resident populations was measured using the Educational Attainment tables from the NHGIS for the years 1990 and 2000, and the ACS was used for 2010 due to changes in survey forms and the reporting structure of U.S. Census Bureau in 2010 (USCB 2010). In order to establish a consistent measure of education level over time, the education variables were the percentage of the population that earned a four year college diploma, and the percentage of the population that completed high school for all persons twenty-five years and older. These education data were collected at the county scale for each of the three temporal slices (1990, 2000, and 2010).

Per capita Household Income measured each county's level of affluence because affluence provides a surrogate for access to water saving technologies and consumer response to differences in the cost of municipal water. Household income was selected as a measure of affluence instead of water price due to the short-term inelasticity of municipal water demand in response to changes in price (Martinez-Espiniera and

Naughes 2004). Previous studies also support the inclusion of affluence when considering influences on the residential component of municipal water consumption. House-Peters et al. (2010) and Kenney et al. (2008) both found household income to be statistically significant drivers of residential water use. The per capita income data for 1990 and 2000 was obtained in a similar fashion to the education data; the 1990 and 2000 data was extracted from the NHGIS Household Income tables, and the 2010 data was drawn from the ACS. Actual values for per capita income were derived from household income to ensure consistent data integrity across all temporal periods, and to account for the absence of per capita income tabulations during the 1990 census. The simple procedure for calculating per capita income is described in more detail in the Data Processing section.

Average Household Size was used to partially account for the volume of residential water use that occurs indoors, as well as to acknowledge the relationship between municipal water consumption and population size. The underlying assumption for this variable is that larger households consumed more residential indoor water than smaller households. Although median household size lacks the sensitivity to extreme values that is embedded within the average household size, the average household size was chosen because the inclusion of the extreme values will provide an estimate that aligns more closely with the dependent variable of per capita municipal water consumption. The average household size was obtained directly from the NHGIS Average Household Size tables for all years (1990, 2000, and 2010).

Population Age Structure also considered indoor residential water use by capturing the influence of the amount of time spent inside the home. The age structure variable will be represented by the percentage of the population 65 years and older, and the percentage of the population 18 years and younger. These age categories were selected under the assumption that they spend more time at home than those between 19 years and 64 years old due to minimal external commitments such as formal employment. Additionally, the selection of the 65 years and older and 18 years and younger variables assumes that more time spent at home increases indoor water use. The complete age structures were obtained from the Age tables in the NHGIS for each of the 1990, 2000, and 2010 decennial censuses. The aggregation processes for the 65 years and older, and the 18 years and younger categories are explained in greater detail in the Data Processing section.

Occupancy type was a surrogate for the influence of property ownership on outdoor residential water use, and was operationalized as the percentage of owner occupied dwellings, and the percentage of renter occupied dwellings. Occupancy type has been shown to influence municipal water consumption due to the large proportion of water use that occurs outdoors (lawn irrigation, swimming pool use, etc.) (House-Peters et al. 2010; Wentz and Gober 2007). The logic employed in the present investigation was that owner occupied dwellings were more likely to have higher levels of water consumption resulting from a vested interest in the maintenance of lawns and other outdoor areas. Similarly, *dwelling type* was defined as the percentage of single family homes, and the percentage of multi-family homes based on similar hypothesized influences on water consumption. Single family dwellings were suspected to exhibit higher water consumption rates due to the increased likelihood that an outdoor area such as a lawn or other water based amenities will be present (Wentz and Gober 2007). The occupancy and the dwelling type data were taken from the NHGIS for the years 1990 and 2000, while the 2010 data were extracted from the ACS. The calculations of these measures are explained in greater detail in the Data Processing section.

Work Location was used as a surrogate for the influence of commercial activity on municipal water consumption and account for the non-residential component of municipal water use. The operational equivalents of the work location variable will be the percentage of the population working inside their county of residence, and the percentage of the population working outside their county of residence under the assumption that higher percentages of people working in a given county translates into a higher level of commercial activity. In turn, it was also assumed that increased levels of commercial activity increased municipal water consumption.

While the percentages of people working inside or outside their county of residence fail to directly account for the influx of workers from other counties, these data were selected as the best available estimate of commercial influence on municipal water consumption. The U.S. Census Bureau's *County to County Workflow* files would have offered a more precise estimate of the percentage of people working in a given county, but these data could not be used because they were not available for all three temporal periods (1990, 2000, and 2010) at the time of analysis. The total numbers of workers for the inside and outside county of residence categories were obtained from the *Place of Work* census tables in the NHGIS for the years 1990, 2000, and 2010. The calculation of the percentages of workers in each category will be described in greater detail in the Data Processing section.

The urbanized environment variables were intended to capture the extent of the human footprint on fresh water resources, and included urbanization level, total population, and population density. The urbanization level was included in this analysis as a surrogate for the influence of urbanization processes on municipal water consumption under the assumption that urbanized areas have higher concentrations of population that require more municipal water. Previous research has also suggested that urbanization processes significantly influence the municipal consumption of fresh water (Dallman and Spongberg 2012). The urbanization level was measured as the percentages of urban and rural population for a given county respectively. The percentages of urban and rural population were selected to represent urbanization processes because they have been calculated consistently during all three temporal slices (1990, 2000, and 2010), unlike the physical measurements of 'urbanized areas' provided by the U.S Census Bureau. The total number of people residing in urban and rural areas was obtained from the NHGIS for 1990 and 2000, and the 2010 totals were drawn from the ACS. The calculation of the urban and rural population percentages is discussed in the Data Processing section.

The population variables were included in this study to provide an estimate of population pressure on municipal water consumption. The total population variable was not analyzed directly, but rather it was used to calculate population density. Population density was included in this analysis as an alternative and more direct measure of population concentration in a given county following the assumption that higher concentrations of population use more municipal water than lower concentrations of population. Population density also offered a standardized measure of population concentration that accounts for areal differences between counties. Additional support for the inclusion of population density may be found in the municipal water consumption literature. The effects of population size have been long been recognized as a significant determinant of municipal water consumption (Carver and Boland 1980; Cooley and Gleick 2009; Wentz and Gober 2007), while population density has been relatively unexplored. Total population counts were obtained directly from the MPC's NHGIS (2011) Population Tables for all census years, while the population densities were calculated using the total population and area measurements for each county.

No study of water consumption patterns is complete without a consideration of water availability via the physical environmental variables, as indicated by both common sense and the topical literature (Carver and Boland 1980; Cochran and Cotton 1985; Gutzer and Nims 2005; House-Peters et al. 2010; Wentz and Gober 2007). The present investigation examined water availability using the climatic variables of annual average potential for drought conditions, annual average precipitation, annual average lake evaporation, and water source. The potential for drought conditions was predicated on the assumption that water availability is generally lower during a drought, as well as, the fact that the literature has provided evidence of strong relationships between municipal water consumption and the related variables of temperature and precipitation (Gutzer and Nims 2005; House-Peters et al. 2010; Kenney et al. 2008).

More generally, drought indices have been shown to be useful predictors of available surface water resources (Larsen 2000). This study used the Palmer Hydrological Drought Index (PHDI) from the National Atmospheric and Oceanic Administration's (NOAA) National Climatic Data Center (NCDC) to estimate the potential for drought conditions in each of the three census years (1990, 2000, and 2010) for all ten climate divisions in the state of Texas (NCDC 2012). The advantages of the PHDI over other available indices is that the PHDI is slower to respond to moisture inputs from precipitation events, thus providing a better proxy for stream flow, groundwater, and reservoir response to climatic conditions (NOAA 2012).

Average Annual Precipitation was included in this study as a surrogate for the influence of short-term moisture inputs that may affect the outdoor component of residential municipal water consumption via irrigation requirements. The average annual precipitation for a given county was selected to match the temporal aggregation of all of the other independent variables, and smooth out the seasonal variations in moisture. *Annual Average Lake Evaporation* was used as a substitute for reductions in water availability that results from short-term moisture losses under the assumption that higher moisture losses reduce available water supplies. Lake evaporation was selected because it offers a more direct measure of moisture loss than temperature despite the close association between the two metrics. Additionally, annual lake evaporation closely approximates the pan evaporation; a hydrologic metric which is a generally accepted measure of moisture loss (Dingman 2002).

The precipitation and lake evaporation variables, available from the TWDB for 1990, 2000, and 2010 at a spatial resolution of 1 degree quadrangles, were examined for correlations with the PHDI prior to inclusion in the final analysis to avoid statistically significant multicollinearity of variance. General climatic relationships suggest that there is a strong correlation between precipitation, lake evaporation, and the PHDI despite the PHDI's slower response to moisture inputs. *Water Source* was included as a surrogate measure for influences of geographic water location and source dependence on the consumption of municipal water. In addition to capturing the spatial variability of surface and ground water, the water source variable will also account for the differential susceptibility of the two water sources to the evaporative losses that affect water supply availability. The operational equivalents of the water source variable were the percentage of surface water and the percentage of ground water used by a given county. These data were obtained directly from the TWDB's Historical Water Use Database at the county scale for each temporal slice (1990, 2000, and 2010).

Data Limitations

The limitations of this research are largely associated with the scale of the spatial analysis, the short period of record, the confounding influence of the aggregate measure of municipal water consumption, and the inability of quantitative analysis to capture intangible variables that may influence the consumption of municipal water. The spatial scale of this study was limited to that of individual counties due to the quality of the original municipal water consumption data from the Texas Water Development Board, as well as the intent to analyze consumption patterns for the entire state of Texas. Analyzing the municipal water consumption of Texas required the inclusion of rural water users in addition to urban water users that are more easily measured. The inclusion of rural water consumers dictated that private wells not connected directly to municipal systems be considered in order to provide a complete and spatially contiguous analysis of municipal water consumption patterns. The county scale data available from the Texas Water Development Board was the only spatial scale that had been adjusted to account for the rural, or non-system, municipal water use.

The restrictions imposed by the county scale data include both the Modifiable Areal Unit Problem (MAUP) (Openshaw 1983) and the ecological fallacy problem. The MAUP essentially states that observable spatial patterns are dependent on the scale of the analysis. In the context of this research, the patterns of municipal water consumption, as well as, the driving human and physical landscape characteristics that influence those patterns may be different at a finer spatial scale due to the differences in areal boundaries. Similarly, the ecological fallacy (Piantadosi et al. 1988) describes the inability to draw conclusions about individual behaviors from patterns present at aggregated spatial scales. Thus, the patterns of municipal water consumption and their associated drivers at the county scale may not be entirely representative of the patterns and influences of individual consumers in a given municipality. The advantage of using county boundaries as unit of spatial analysis was that the areas covered by these administrative units have not changed in recent history unlike the boundaries of municipalities that respond to the dual influences of growth and urbanization. The lack of changes in county boundaries over time removes the need to interpolate municipal water consumption estimates and account for areal differences in the spatial unit of analysis over time. Additionally, the county scale is relevant to the analysis of municipal water consumption patterns in Texas because counties are the principal areal and administrative units that comprise the state's water planning regions which are used to assess statewide water availability and future needs.

The short period of record, i.e. the three temporal slices that span a total of twenty years, limit the ability this research to describe the long term relationships that exist between municipal water consumption and components of the human and physical environment. The temporal slices selected for this project were chosen in response to the concurrent availability of municipal water consumption and census data on which the spatial and aspatial analyses relied. Unfortunately, while the Texas Water Development Board's municipal water consumption data are relatively robust in the sense of data quality issues that plague similar datasets such as erroneous meter readings and transmission losses due to system leaks and broken pipes, the consumption data were not consistently collected prior to 1984. Following the 2000 U.S. decennial census, estimates of many demographic variables such as population totals and household income were developed for inter-censual periods, but these data do not exist for previous time periods. Despite these limitations, however, the use of discrete temporal slices provided the opportunity to explicitly examine the influence of time on municipal water consumption patterns and driving characteristics whereas longitudinal analyses typically consider persistent trends and aggregate change during the period of record.

Another limitation of this study relates to the measure of municipal water consumption as an aggregation of residential and commercial use which ultimately confounded the detection of relationships between consumption patterns and their driving human landscape characteristics. For example, the percentage of single family homes in a county may exhibit a moderate to strong association with residential water consumption while only possessing a weak or no association with commercial water use. In this case, the presence of the commercial water component in the municipal consumption metric could mask the true relationship between the dependent and independent variables. Although only considering residential water consumption would likely improve the quality of the consumption signal, an internal unpublished study conducted by the Texas

Water Development Board has suggested the commercial component of municipal water is significant and should not be ignored (personal communication with Kevin Kluge, TWDB Water Survey Manager on September 24, 2012).

Finally, this research is limited by the inability of quantitative methods to completely capture the uniquely human and intangible characteristics that influence the consumption of municipal water such as attitudes toward conservation, political structures, and general awareness of water issues. A deep understanding of the motivations for individual consumption behavior was not one of the goals of this study, but the influence individual decisions must be acknowledged because it may contribute to the residuals in the quantitative models. Thus, the independent variables selected for this study were chosen as surrogates for some of these intangible human traits. For example, educational attainment was selected as a surrogate for exposure to the consequences of environmental problems such as water supply shortages under the assumption that higher levels of education would translate into a greater degree of environmental awareness. Additionally, the use of quantitative rather than qualitative data facilitates the direct comparison of results from previous or future studies that employ a similar methodology across multiple locations.

Data Acquisition

The methods in this study followed the outline provided in Figure 4, and were divided into the general phases of data collection, data cleaning, data processing, regression screening, model building, model evaluation, and the mapping of model results. The data collection phase was separated into distinct veins to reflect the collection of both tabular and spatial datasets. The tabular data collection began with the social and urbanization components of the 1990, 2000, and 2010 decennial censuses. Census data such as total population, household income, educational attainment, owner occupancy, renter occupancy, and dwelling type were downloaded from the NGHIS project hosted by the University of Minnesota (MPC 2011) for 1990 and 2000. For 2010, the total population data were downloaded from the NHGIS (MPC 2011), and the remaining variables were obtained directly from the U.S. Census Bureau's ACS (USCB 2010). All census data were downloaded as comma delimited files at the county level.

Following the acquisition of the tabular census data, the water availability variables were obtained. The Palmer Hydrological Drought Index (PHDI) data were downloaded from the NCDC (2012) for all climate divisions in Texas. The annual lake evaporation and precipitation (TWDB 2012) were downloaded from the Texas Water Development Board. The lake evaporation and precipitation data were available with a spatial resolution of 1 degree quadrangles, and the water source data was available for all counties in Texas.

The spatial data were collected through state or federal government agencies. The county boundaries for 1990, 2000, and 2010 were downloaded as shapefiles from the National Historical Geographic Information System (MPC 2011). The U.S. Climate Division boundaries for the tabular PHDI data were downloaded from the National Climatic Data Center. Texas Water Development Board regional water planning boundaries and the one degree quadrangle grid for the precipitation and lake evaporation data were downloaded directly from the TWDB data warehouse (TWDB 2009b).

Data Cleaning

Tabular Data

Tabular and spatial data sets were cleaned sequentially, with tabular data first and spatial data second. The tabular census data were reorganized into a database friendly format where each geographic unit was a row, and each attribute (total population, per capita income, etc.) were represented as columns. Following the data reorganization, the values for educational attainment, household income, age structure, owner occupancy, renter occupancy, and dwelling type were aggregated into their respective categories. The educational attainment data were aggregated into the binary categories of High School Diploma and Bachelor's Degrees for each year (1990, 2000, and 2010). The High School Diploma category represented individuals that only completed high school and was extracted directly from the census counts without further manipulation, while the Bachelor's Degree category was derived by aggregating counts for holders of bachelor's degrees with persons that obtained advanced degrees (master's degrees and doctorates). This initial aggregation for the Bachelor's Degree category was necessary to provide a complete estimate for all holders of undergraduate degrees. Post-graduate education was not considered separately, due to its relatively low percentage of the overall population statewide. The statewide average percentages of the population with high school diplomas, bachelor's degrees, and graduate degrees are provided in Table 5.

The Household Income data for 1990 and 2000 were initially aggregated to the income classes used by the 2010 ACS to provide a common scale for the measure of total income. These income classes were less than $10000, $10000 to $14999, $15000 to $24999, $25000 to $34999, $35000 to $49999, $50000 to $74999, $75000 to $99999,

$100000 to $149999, and more than $150000. In order to avoid introducing the bias of extreme values associated with averages (Earickson and Harlin 1994), the counts for each class of household income were multiplied by the median value for each class prior to aggregation to a single income value for county (see Equation 1). The median values for each income class are available in Table 4. A potential limitation of using the class medians rather than the averages to represent total income was that income may have been systematically underestimated in all classes except the less than $10000 category.

The final cleaning step for the income data was to adjust the values for 1990 and 2000 to reflect 2010 equivalents using the purchasing power calculation published by the U.S. Bureau Labor Statistics (BLS 2012). The purchasing power equation is simply a ratio of annual Consumer Price Index (CPI) values that expresses the value of a given dollar amount for one year in terms of another. The calculation of purchasing power places the Base Year CPI (the year for which equivalent dollars is desired) in the numerator, and the Original Year CPI (the year for which dollars are being converted) in the denominator. The result of this ratio is then multiplied by the value of interest (See Equation 2 below). This inflation adjustment allowed the income data to be compared across all three temporal periods.

Equation 1. Total Household Income = ∑ (income class count * median class value)

Equation 2. Adjusted Income Value = (Base Year CPI/Original Year CPI) * Original Year Value (Perrins and Nilsen 2007)

The owner and renter occupancy data were collapsed into a single value for the total number of owner and renter occupied dwellings respectively. Data pertaining to dwelling type were separated into two categories in a fashion similar to that of the education data. The Units in Structure census table was used to distinguish single family from multi-family dwellings. Dwellings that had only one unit were classified as single family dwellings, and those that had more than one unit were classified as multi-family dwellings for each county.

Prior to aggregation of annual averages, the physical environmental data were be reorganized into a database friendly format similar to that of the tabular census data. Firstly, the data for PHDI, precipitation, and lake evaporation were rearranged such that the geographic units (e.g. climate divisions) were rows, and the attributes (e.g. PHDI values) were columns. Secondly, the comma delimited files for all three datasets were converted to database (DBF) files that can be read by ESRI's ArcGIS 10. Thirdly, the ArcGIS database engine was used to extract data relevant only to the study area, and create new streamlined data tables. Finally, the monthly values for PDHI, precipitation, and lake evaporation were aggregated to annual averages.

Spatial Data

The first step in the cleaning process for the spatial data was to project all GIS datasets to a common coordinate system to prevent overlay problems such as boundary misalignment. The target coordinate system for all GIS datasets was an adjusted version of the U.S. Contiguous Albers Equal Area Conic projection due to its ability to preserve areas, and apply minimal distortion to the remaining projection properties of distance, direction, and shape (Snyder 1987). The selection of the Albers projection was also supported by the need to maintain consistent areal measurements for the analysis of spatial stationarity that were performed on the regression residuals, the statistically significant driving landscape characteristics of municipal water consumption, and the original municipal water consumption patterns for 1990, 2000, and 2010. The final coordinate system was the Texas Centric Mapping System/Albers Equal Area (State of Texas 2011) which adjusts the central meridian and standard parallels to preserve areas while minimally distorting the map properties of shape, distance, and direction for the entire state of Texas simultaneously. The specific adjustments to the standard U.S. Albers Contiguous Equal Area Projection are stated in Table 6. Following the conversion to a common coordinate system, all GIS data datasets were converted from shapefiles to geodatabase feature classes. The conversion from shapefile to geodatabase feature class was necessary to ensure that attributes such as shape length and shape area are automatically updated during geoprocessing operations (clip, intersect, etc.) (Price 2011).

The second cleaning step for the spatial data was to extract only data relevant to the Texas study area using a series of attribute queries, spatial queries, and spatial overlay operations. The data extraction step was essential to reduce the volume of data that was processed, as well as, to conserve data storage space. After all the GIS data were projected and reduced to reflect the spatial extent of the study area (every county in Texas), the cleaned tabular data was joined to the appropriate feature class using ArcGIS 10's Table Join function. At this stage, attribute queries were used to cull the historical water use dataset, and remove counties that did not have water use records for all three temporal periods (1990, 2000, and 2010). This culling process generated 254 (every county in Texas) temporally and spatially consistent historical water use records at the county scale.

Data Processing

The data processing stage involved the final calculation of tabular data values such as per capita income, the percentage of the population with a bachelor's degree, the percentage of the population with a high school diploma, the percentage of the population 65 years and older, the percentage of the population18 years and younger, the percentage of owner occupied dwellings, the percentage of renter occupied dwellings, the percentage of single family homes, the percentage of multi-family homes, the percentage of the population working inside their county of residence, the percentage of the population working outside their county residence, the percentages of surface and groundwater, and the individual county values for the precipitation, lake evaporation, and PHDI. Per capita income was calculated for each county by dividing the total household income in 2010 dollars by the total population in each county. The percentages of bachelor’s degree holders and high school diploma holders were calculated by dividing the counts in each category by the total population over twenty-five years of age, while the percentages of county residents 65 years and older and county residents 18 years and younger were calculated by dividing the counts in each category by the total population in each county.

The percentages of owner occupancy and renter occupancy were calculated by dividing the counts in each category by the total number of dwellings, and the percentages of single family and multi-family homes were calculated by dividing the total counts for each category by the total number of housing units. Similarly, the percentages of county residents working inside and outside their county of residence were calculated by dividing the total counts in each category by the total working population. The percentages of surface water and groundwater in each county were calculated by dividing the total municipal water consumption in each category by the county's total municipal water consumption. All final tabular calculations were performed with ArcGIS 10's Field Calculator operation to ensure referential integrity.

Calculating the remaining physical environmental variables of average annual precipitation, average annual lake evaporation, and average annual PHDI required several spatial overlay operations along with simple areal interpolation to account for the differences between the scales of data collection and the administrative county boundaries, and naming conventions used by the United States Geological Survey (USGS) and the Texas Water Development Board (TWDB). Simple areal interpolation methods that assume a homogenous distribution of average annual precipitation, average annual lake evaporation, and PHDI were permissible here because all of these measures had been aggregated to their corresponding spatial units using more sophisticated methods such as Delaunay triangulations based on original climate station data (NOAA 2012; TWDB 2012). The steps involved in the calculation of these data are summarized in Figures 5 and 6. Firstly, the Texas County boundaries were intersected with the USGS one degree quadrangles to determine the spatial correspondence between each quadrangle and its corresponding counties. Secondly, the resulting intersection of the quadrangles and the county boundaries was used to reconcile the names of the USGS one degree quadrangles with the quadrangle nomenclature used by the TWDB to provide a means of joining the tabular precipitation and evaporation data to the quadrangle GIS feature class.

Thirdly, the new quadrangle feature class containing the TWDB designations for each quadrangle was joined to the tabular data for average annual precipitation. Fourthly, the quadrangle feature class containing the average annual precipitation data was intersected with the original county boundary feature class to yield the areal contribution of each quadrangle to each individual county. The areas of these new intersection polygons were subsequently used to calculate the areal weights for the interpolation process. The areal weights were calculated by dividing the area shared by each county and a given quadrangle by the county's original area. Fifthly, the areal weights were multiplied by the average annual precipitation values for each quadrangle. These calculations were performed with the Field Calculator in ESRI's ArcGIS 10 to ensure referential integrity. Finally, the individual precipitation values for each intersection polygon were aggregated to their corresponding counties using the Summarize tool in ESRI's ArcGIS 10. All six of these steps were repeated for average annual precipitation and average annual lake evaporation in each year (1990, 2000, and 2010).

The calculation of each county's average annual PHDI values followed a similar series of steps, substituting the NOAA Climate Division feature class for the USGS one degree quadrangles. Firstly, the tabular PHDI data for each year was joined to the climate division feature class using the Table Join function in ESRI's ArcGIS 10. Secondly, the climate division feature class containing the PHDI values for each year was intersected with the administrative boundary feature class to determine the areas of each climate division in each county. Thirdly, the areal weights for each intersection polygon were determined by dividing the area shared by each county and climate division by the original area of the county. Fourthly, the new areal weights were multiplied by the PHDI value of the corresponding climate division to yield the adjusted PHDI value for each intersection polygon. Finally, the PHDI values for each intersection polygon were aggregated to their corresponding counties using ArcGIS 10's Summarize tool.

In preparation for multiple linear regression data screening, ESRI's ArcGIS 10 database engine was used to consolidate all of the analysis variables for each year into a single comma delimited file that could be imported into IBM's SPSS 20. A series of table joins was used to combine the social, urbanized, and physical environmental data for each year to the feature class containing the administrative county boundaries. The join operations were performed separately for each year in order to create temporally discrete data files for statistical screening. After consolidating all of the analysis variables for a given year, the resulting attribute table was exported as a comma delimited file for further data cleaning in Microsoft Excel. Using the Excel spreadsheet software, join artifacts such as redundant attributes and object-ids were removed to create files for direct import into SPSS 20.

Data Screening for Multiple Linear Regression

Multiple linear regression (MLR) was used in this analysis to determine the magnitude of the individual and joint relationships between the dependent variable (municipal water consumption) and the independent variables (the social, urbanized, and physical environments) for each year. The joint consideration of multiple independent variables was essential to represent a close approximation of the real-world relationships between municipal water consumption and its driving characteristics, as well as account for the fact that municipal water consumption is influenced by more than a single factor. The standardized beta weights for each statistically significant independent variable assessed the magnitude of each driving characteristic's influence on municipal water consumption when combined with other independent variables. All of the independent variables listed in Table 3, except Total Population, were entered into multiple linear regression equations, and required data screening procedures to ensure that the basic assumptions of MLR were not violated. All assumptions of MLR were tested with a conservative alpha level of 0.05 to minimize the probability of detecting a relationship that did not actually exist (Type I error).

In the interest of producing the most robust model possible, multiple permutations of the regression model for each year (1990, 2000, and 2010) were constructed with the addition of new independent variables, the substitution of new independent variables for existing independent variables, and a regionalization of counties relative to a climatic divide known as the dry line respectively. A description of each model permutation and its corresponding sample size is available for reference in Table 7. Models 2 and 3 added the *Per Capita Commercial Businesses* variable to the original variables listed in Table 3 to improve the signal strength of commercial municipal water consumption present in the *Percent Worked Inside County of Residence* variable. Models 4 and 5 used only the original variables from Table 3 and were constructed to remove the confounding influence of differences in climate east and west of the dry line respectively. Models 6 and 7 included the *Per Capita Residential Building Permit* variable to improve detection of a residential development signal. Two models were required to accommodate the residential development variable due to a reduction in sample size that reflected the exclusion of counties without building permit data for all three years (1990, 2000, and 2010). Thus, Model 6 represented an adjusted baseline model using only the independent variables listed in Table 3, while Model 7 included both the original independent variables along with the *Per Capita Residential Building Permit* variable. Model 8 combined the all of the original independent variables except *Percent Worked Inside*

County of Residence with the *Percent Lodging* variable to capture the influence of temporary transient increases in population not reflected in decennial census estimates on the consumption of municipal water.

Normality

The assumptions of MLR include normality, homogeneity of variance, linearity, and a lack of collinearity between independent variables. Firstly, all the independent variables were tested for normality, or the idea that each independent variable follows a normal (Gaussian) distribution where the mean is equal to zero, and the standard deviation is equal to one. In addition to evaluating normality with the Shapiro-Wilk test which guarded against the extreme sensitivity to minor deviations from a normal distribution found in the more common F Max test, the skewness and kurotsis threshold of plus or minus one (1.0) was used to provide a more liberal estimate of normality (Meyers et al. 2006).

This decision to use Shapiro-Wilk in concert with a kurtosis and skewness threshold instead of F Max was important because the degree to which data must conform to the normality assumption of linear regression varies according to the application of the technique. Applying MLR techniques to predict quantities or outcomes requires more stringent adherence to the normality criterion than using MLR to determine the magnitude of relationships between dependent and independent variables (Pedhazur 1997). This analysis used MLR to examine the magnitude of the relationships between the independent variables (the social, urbanized, and physical environments) and the dependent variable (municipal water consumption). Furthermore, the extreme sensitivity of the F Max test could have prematurely required transformations for essential independent variables or excluded them altogether.

The results of the Shapiro-Wilk test for the dependent and independent variables in every model permutation for each year are reported in Table 8 (1990), Table 9 (2000), and Table 10 (2010) at a significance level of 0.05. Models 2 and 6 were omitted from Tables 8, 9, and 10 because their Shapiro-Wilk values were identical to those of Models 3 and 7 respectively. The distribution of each variable was tested against the null hypothesis that it was significantly different from a normal, or Gaussian, distribution. A p-value less than 0.05 indicated that a variable was statistically different from the normal distribution, while a p-value greater than or equal to 0.05 indicated that was a variable was not statistically different from the normal distribution. The Shapiro-Wilk test overwhelmingly suggested that the majority of data were not normally distributed. The bolded values in Table 8, Table 9, and Table 10 indicate exceptions to these findings. For the year 1990 *Annual Lake Evaporation*, *Percent 18 Years and Younger,* and *Percent 65 Years and older* were not significantly different from the normal distribution. *Annual Lake Evaporation* was not significantly different from the normal distribution in models 1, 3, 5, and 8. *Percent 18 Years and Younger* was not significantly different from the normal distribution in model 5, and *Percent 65 Years and Older* was not significantly different from the normal distribution in model 4.

In the year 2000, *Average Annual Precipitation*, *Per Capita Income, Percent 18 Years and Younger, Percent 65 Years and Older,* and *Percent High School Diploma* were not significantly different from the normal distribution given a significance level of 0.05. *Average Annual Precipitation* and *Per Capita Income* were not significantly different from the normal distribution in Model 5. *Percent 18 Years and Younger* was not significantly different from the normal distribution in any of the models (1, 3, 4, 5, 7, and 8), while *Percent 65 Years and Older* was not significantly different from the normal distribution in Model 4. The *Percent High School Diploma* variable was significantly different from the normal distribution for all models except Model 5.

For the year 2010, *Per Capita Income*, *Percent 18 Years and Younger, Percent 65 Years and Older,* and *Percent High School Diploma* were not significantly different from the normal distribution. *Per Capita Income* was not significantly different from the normal distribution in any of the models (1, 3, 4, 5, 7, and 8). *Percent 18 Years and Younger* was not significantly different from the normal distribution in Model 7, and *Percent 65 Years and Older* was not significantly different from the normal distribution in Model 4. The *Percent High School Diploma* variable was not significantly different from the normal distribution in Model 7.

The results of the Shapiro-Wilk test required both the normality of the dependent and independent variables to be evaluated further with a skewness and kurtosis threshold of plus or minus 1.0 due to its lower sensitivity to deviations from the normal distribution. Despite its more forgiving nature, the results of the skewness and kurtosis threshold revealed that few of the variables in any given model for each year conformed to the approximate bounds of statistical normality. The skewness and kurtosis values are reported in Tables 11, 12, and 13 for the years 1990, 2000, and 2010 respectively. Bolded values indicate pairs of skewness and kurtosis values where both metrics are within the plus or minus 1.0 threshold.

In 1990, variables that whose distribution was approximately normal included *Average Annual PHDI*, *Average Annual Precipitation, Average Annual Lake Evaporation, Percent 18 Years and Younger, Percent 65 Years and Older, Percent High School Diploma, Percent Urban*, and *Percent Worked Inside County of Residence*. *Average Annual PHDI* was approximately normally distributed in Models 1, 3, 7, and 8. *Average Annual Precipitation* was approximately normally distributed in Models 1, 3, 5, 7, and 8, while *Average Annual Lake Evaporation* followed an approximately normal distribution in all models (1, 3, 4, 5, 7, and 8). *Percent 18 Years and Younger* was approximately normally distributed in Models 1, 3, 5, 7, and 8, while *Percent 65 Years and Older* followed an approximately normal distribution in all models (1, 3, 4, 5, 7, and 8). *Percent High School Diploma* was approximately normally distributed in all models (1, 3, 4, 5, 7, and 8). *Percent Urban* was approximately normally distributed in Models 4 and 7, while *Percent Worked Inside County of Residence* followed an approximately normal distribution in Models 1, 3, 4, and 7. Actual skewness and kurtosis values for all variables in each 1990 model are presented in Table 11.

For the year 2000, *Average Annual PHDI*, *Average Annual Precipitation, Average Annual Lake Evaporation, Per Capita Commercial Businesses*, *Percent 18 Years and Younger*, *Percent 65 Years and Older, Percent High School Diploma*, and *Percent Worked Inside County of Residence* were approximately normally distributed. *Average Annual PHDI* was approximately normally distributed in Models 1, 3, 7, and 8. *Average Annual Precipitation* followed an approximately normal distribution in Models 4 and 5, while *Average Annual Lake Evaporation* was approximately normally distributed in Models 1, 3, 5, 7, and 8. *Per Capita Commercial Businesses* was approximately normally distributed in Model 3 (the only model in which it was actively considered). *Percent 18 and Younger* was approximately normally distributed in Models 1, 3, 5, 7, and 8, while *Percent 65 and Older* followed an approximately normal distribution in all models (1, 3, 4, 5, 7, and 8). *Percent High School Diploma* was also approximately normally distributed in all models. *Percent Worked Inside County of Residence* followed an approximately normal distribution in all models for it was actively considered (Models 1, 3, 4, 5, and 7). Actual skewness and kurtosis values for all variables in each 2000 model are presented in Table 12.

In 2010, the following variables were approximately normally distributed: *Average Annual PHDI*, *Average Annual Precipitation, Average Annual Lake Evaporation*, *Per Capita Commercial Businesses*, *Per Capita Income*, *Percent 18 Years and Younger, Percent 65 Years and Older, Percent Bachelor's Degree, Percent High School Diploma*, and *Percent Worked Inside County of Residence*. *Average Annual PHDI* was approximately normally distributed in Models 1, 3, 4, 7, and 8. *Average Annual Precipitation* was approximately normally distributed in all models (1, 3, 4, 5, 7, and 8), while *Average Annual Lake Evaporation* only followed an approximately normal distribution in Models 4 and 5. *Per Capita Commercial Businesses* was approximately normally distributed in Model 3 (the only model in which it was actively considered). *Per Capita Income* was approximately normally distributed in all models (1, 3, 4, 5, 7, and 8). *Percent 18 Years and Younger* and *Percent 65 Years and Over* were both approximately normally distributed in all models. *Percent Bachelor's Degree* and *Percent High School Diploma* followed an approximately normal distribution in Models 5 and 7 respectively. *Percent Worked Inside County of Residence* was approximately normally distributed in Models 1, 3, 4, 5, and 7. The actual skewness and kurtosis values for all variables in each 2010 model are presented in Table 13.

In summary, the Shapiro-Wilk test and the skewness and kurtosis threshold of plus or minus 1.0 both yielded similar results. Nearly half of the independent variables in each model permutation for every year violated the assumption of normality required by Multiple Linear Regression. These violations suggested that transformations would be necessary in all conceptual variable categories (the social, urbanized, and physical environments) prior to regression analysis. Furthermore, the dependent variable, *Per Capita Municipal Water Consumption*, exhibited severe departures from the normal distribution using both normality metrics for all models in all years.

<u>Homogeneity of Variance</u>

Secondly, the homogeneity of variance for each independent variable and the dependent in each year was assessed with the Levene test. The Levene test was selected in order to avoid increasing the probability of committing a Type II error by failing to detect an existing relationship between the dependent and independent variables. The increased probability of committing a Type II error often results from using the FMax test which requires a more stringent alpha level (Meyers et al. 2006). The homogeneity of variance test was only performed on the data for the original model (Model 1) listed in Table 3 due to the results of the Shapiro-Wilk and skewness and kurtosis threshold normality tests. The extreme departures from normality present in the majority of independent variables in each model for every year had already suggested the necessity of variable transformations. Thus, the results of the Levene test are presented in Table 14 solely in the interest of completeness.

All of the independent variables in Table 3, along with the independent variable were subjected to Levene's test of homogeneity of variance at a significance level of 0.05. The null hypothesis of the Levene Test states that variances between levels of the independent variables are equal, where p-values less than 0.05 indicate that the assumption of equal variances has been met. In this case, the homogeneity of the variables was tested across the years 1990, 2000, and 2010. Surprisingly, only four of the sixteen variables violated the assumption of equal variances. The offending independent variables included *Average Household Size, Percent 18 Years and Younger, Percent Single Family*, and *Population Density*. The values of the Levene statistic and their corresponding p-values are listed in Table 14.

Linearity and Collinearity

Thirdly, the linearity and collinearity of the independent variables was evaluated using non-parametric bivariate correlations and simple bivariate scatterplots. The results of the normality tests suggested that non-parametric measures of association would provide a better approximation of the relationships between variables than Pearson's r. Kendall's Tau was selected over Spearman's Rho for two reasons. Firstly, Kendall's Tau provides an unbiased estimate of the true population parameter, while Spearman's Rho does not. Secondly, the Kendall Tau statistic is better suited to intermediate sample sizes such as those used in this study (e.g. N = 254 for Models 1, 2, 3, and 8) (Daniels 1990). The linearity tests determined whether or not linear relationships existed between the dependent and each independent variable, as well as the strength of the association between independent variables (Draper and Smith 1998; Meyers et al. 2006). Bivariate Kendall's Tau correlations and scatterplots were examined for pairings of each independent variable and the dependent variable, and correlation matrices were used to assess the collinearity among the independent variables. The Kendall Tau correlations between each independent variable and *Per Capita Municipal Water Consumption* for the years 1990, 2000, and 2010 are reported in Tables 15, 16, and 17 respectively. The bivariate correlations for Models 2 and 6 were omitted from the tables to avoid redundancy. The correlations for Model 2 were identical to those of Model 1, and the correlations for Model 6 were identical to those of Model 7 with the exception of the *Per Capita Building Permit* variable which was not considered in Model 6. The two-tailed significance of each independent variable is reported where two asterisks denote correlations that were statistically significant at an alpha level of 0.01, and a single asterisk denotes correlations that were statistically significant at the required alpha level of 0.05. Below, the linearity of the independent variables is summarized for each year with special attention to similarities and differences between model permutations.

In 1990, the strengths of linear association between the independent variables and the dependent variable varied by model in select cases, but the overwhelming majority of independent variables expressed a statistically significant linear relationship with *Per Capita Municipal Water Consumption.* The conceptual variables of social, urbanized, and physical environment displayed statistically significant linear associations for all model permutations, but the strongest associations were not consistently concentrated in a single conceptual variable. The physical and social environmental variables in Models 1, 3, and 8 exhibited the strongest linear associations with *Average Annual Precipitation* ($\tau = -0.306$, $p < 0.001$) and *Percent Owner Occupied* ($\tau = -0.243$, $p < 0.001$) ranking among the highest independent variables. Models 4, 5, and 7 showed the greatest differences in the linear association strength of the conceptual variables with the strongest linear relationships being present in the urbanized and social, the social, and the social and physical environmental variables respectively.

Percent Urban ($\tau = 0.346$, $p < 0.001$) and *Percent High School* ($\tau = -0.328$, $p < 0.001$) had the strongest degree of linearity in Model 4, and *Percent Worked Inside County of Residence* ($\tau = 0.271$, $p < 0.001$) and *Percent Owner Occupied* ($\tau = -0.204$, $p < 0.001$) displayed the greatest degree of linearity in Model 5. Models 4 and 5 also showed weaker yet statistically significant linear relationships between *Per Capita Municipal Water Consumption* and *Percent Surface Water*. Model 7 showed the strongest linear associations in the *Percent Worked Inside County of Residence* ($\tau = 0.352$, $p < 0.001$) and the *Average Annual Precipitation* ($\tau = -0.346$, $p < 0.001$) variables. The new independent variables introduced in Models 3, 7, and 8 exhibited mixed strengths of linear association with the dependent variable. *Per Capita Commercial Businesses* ($\tau = 0.225$, $p < 0.001$) in Model 3 was relatively strong, while *Percent Lodging* ($\tau = 0.097$, $p = 0.023$) in Model 8 was exceptionally weak. Additionally, *Per Capita Income* and *Per Capita Building Permits* were the only independent variables that did not display a statistically significant linear relationship with *Per Capita Municipal Water Consumption* in any of the model permutations for 1990. The Kendall's Tau bivariate correlations and their corresponding significance values (p-values) are given in Table 15.

In 2000, the strengths of linear association between the independent variables and the dependent variable varied by model in select cases, but the overwhelming majority of independent variables expressed a statistically significant linear relationship with *Per*

Capita Municipal Water Consumption. The conceptual variables of social, urbanized, and physical environment displayed statistically significant linear associations for all model permutations, but the strongest associations were not consistently concentrated in a single conceptual variable. The physical and social environmental variables in Models 1, 3, and 8 exhibited the strongest linear associations with *Average Annual Precipitation* ($\tau = -0.274$, $p < 0.001$) and *Percent Owner Occupied* (τ = 0.-0.249, $p < 0.001$) ranking among the highest independent variables. Models 4, 5, and 7 showed the greatest differences in the linear association strength of the conceptual variables with the strongest linear relationships being present in the urbanized and social, and the social and physical environmental variables respectively.

Percent Urban ($\tau = 0.363$, $p < 0.001$), *Percent High School* ($\tau = -0.334$, $p < 0.001$), and *Percent Owner Occupied* ($\tau = -0.334$, $p < 0.001$) had the strongest degree of linearity in Model 4, and *Percent Worked Inside County of Residence* ($\tau = 0.277$, $p < 0.001$) and *Percent Urban* ($\tau = 0.213$, $p < 0.001$) displayed the greatest degree of linearity in Model 5. Models 4 and 5 also showed statistically significant linear relationships between *Per Capita Municipal Water Consumption* and *Percent Surface Water.* The linearity of *Percent Surface Water* was stronger in 2000 than in 1990. Model 7 showed the strongest linear associations in the *Percent Worked Inside County of Residence* ($\tau = 0.358$, $p < 0.001$) and the *Average Annual Precipitation* ($\tau = -0.295$, $p < 0.001$) variables. The new independent variables introduced in Models 3, 7, and 8 exhibited mixed strengths of linear association with the dependent variable. *Per Capita Commercial Businesses* ($\tau = 0.212$, $p < 0.001$) in Model 3 was relatively strong, while) and *Percent Lodging* ($\tau = -0.041$, $p = 0.335$) in Model 8 was exceptionally weak. Additionally, *Average Household Size*, *Annual Average* PHDI, and *Per Capita Building Permits* did not display a statistically significant linear relationship with *Per Capita Municipal Water Consumption* in any of the model permutations for 2000. The Kendall's Tau bivariate correlations and their corresponding significance values (p-values) are given in Table 16.

In 2010, the strengths of linear association between the independent variables and the dependent variable varied by model in select cases, but the overwhelming majority of independent variables did not express a statistically significant linear relationship with *Per Capita Municipal Water Consumption.* The conceptual variables of social, urbanized, and physical environment displayed statistically significant linear associations for all model permutations, but the strongest associations were not consistently concentrated in a single conceptual variable. The physical and social environmental variables in Models 1, 3, and 8 exhibited the strongest linear associations with *Average Annual Precipitation* ($\tau = -0.222$, $p < 0.001$) and *Population Density* ($\tau = -0.178$, $p < 0.001$) ranking among the highest independent variables. Models 4, 5, and 7 showed the greatest differences in the linear association strength of the conceptual variables with the strongest linear relationships being present in the social, the physical, and the physical and social environmental variables respectively.

Percent Worked Inside County of Residence ($\tau = 0.193$, $p < 0.001$), and *Percent High School* ($\tau = -0.153$, $p = 0.013$) had the strongest degree of linearity in Model 4, and *Percent Surface Water* ($\tau = -0.278$, $p < 0.001$) and *Average Annual Precipitation* ($\tau = -0.248$, $p < 0.001$) displayed the greatest degree of linearity in Model 5. The linearity of *Percent Surface Water* in Model 5 was the strongest of any model permutation in all three years (1990, 2000, and 2010). Model 7 showed the strongest linear associations in the *Average Annual Precipitation* ($\tau = -0.255$, $p < 0.001$) and *Percent Worked Inside County of Residence* ($\tau = 0.213$, $p < 0.001$) variables. The new independent variables introduced in Models 3, 7, and 8 exhibited mixed strengths of linear association with the dependent variable. *Per Capita Commercial Businesses* ($\tau = 0.013$, $p = 0.769$) in Model 3 and *Per Capita Building Permits* ($\tau = -0.025$, $p = 0.586$) in Model 7 were not statistically significant, while *Percent Lodging* ($\tau = -0.134$, $p = 0.002$) in Model 8 displayed a weak yet statistically significant linear association with the dependent variable. Additionally, *Average Household Size*, *Per Capita Income, Percent 18 Years and Younger, Percent 65 Years and Older, Percent Bachelor's Degree, Percent Single Family,* and *Percent Urban* did not display a statistically significant linear relationship with *Per Capita Municipal Water Consumption* in any of the model permutations for 2010. The Kendall's Tau bivariate correlations and their corresponding significance values (p-values) are given in Table 17.

A review of the bivariate correlations between the independent variables and the dependent variable for all model permutations in every year resulted in a reduction of the total number of independent variables used in the MLR models. Several variables including *Percent Multi-Family, Percent Renter Occupied Dwellings, Percent Worked Outside County of Residence, Percent Rural,* and *Percent Groundwater* were removed from further consideration to reduce redundancy and multicollinearity in any given model. The relationships of these variables to *Per Capita Municipal Water Consumption* were perfectly symmetrical to those of *Percent Single Family, Percent Owner Occupied Dwellings, Percent Worked Inside County of Residence, Percent Urban,* and *Percent*

Surface Water respectively. Thus, the latter independent variables were retained due to their greater conceptual value and interest.

The collinearity between the independent variables in this analysis was assessed using the full Kendall's Tau correlation matrices that were generated for each set of variables in each model permutation for 1990, 2000, and 2010. A threshold of +/-0.7 was used to identify variables with strong inter-variable associations due to the fact that moderate correlations were expected between certain sets of independent variables in each conceptual category (e.g. Annual Lake Evaporation and Annual Average PHDI, Population Density and Percent Urban, etc.). Furthermore, the omission of a moderately collinear but practically significant variable may have undermined the explanatory goal of this research.

The correlation matrices revealed the majority of the independent variables were well below the +/- 0.7 collinearity threshold for all model permutations in every year. One exception to this finding was the strong linear relationship between *Percent Owner Occupied Dwellings* and *Percent Single Family* in Model 4 for the year 2010 ($\tau = 0.709$, $p < 0.001$). Consequently, this relationship was scrutinized carefully during the MLR model building phase.

The final results of the independent variable screening process yielded several important discoveries. Firstly, the Shapiro-Wilk and skewness and kurtosis threshold tests indicated that more than half of the independent variables in any given model permutation for any given year violated the assumption of normality required by multiple linear regression analysis. Secondly, the Levene test for homogeneity of variance revealed that only four out of the original sixteen independent variables displayed unequal variances across all three years in the study period (1990, 2000, and 2010). The variables whose variances were unequal included *Average Household Size, Percent 18 Years and Younger, Percent Single Family,* and *Population Density.* Thirdly, the majority of independent variables in every model for 1990 and 2000 had at least a weak statistically significant linear association with *Per Capita Municipal Water Consumption*. The number of independent variables with a statistically significant linear relationship to the dependent variable for most of the models in 2010 was much lower than the previous years, with *Average Household Size*, *Per Capita Income, Percent 18 Years and Younger, Percent 65 Years and Older*, *Percent Bachelor's Degree, Percent Single Family,* and *Percent Urban* expressing no statistically significant linearity.

Due to these findings during the screening process, all of the independent variables in every model for each year were transformed to enable subsequent multiple linear regression analysis. The standard square root, logarithm, and natural logarithm transformations were abandoned because they failed to adequately remove the violation of normality from the offending independent variables. Furthermore, it quickly became apparent that using multiple transformations on such a large number of variables would confound the interpretation of the resulting regression model (Draper and Smith 1998; Meyers et al. 2006). Thus, the Rank Transformation (Connover and Iman 1981) was applied uniformly to both the dependent and independent variables in every model permutation for each year prior to building the regression models.

Despite a reduction in statistical power and marginal increases in the probability of falsely rejecting the null hypothesis with small datasets when compared to parametric ordinary least squares regression (Headrick and Rotou 2001), the Rank Transformation can be safely applied to regression analysis under select circumstances. Iman and Connover (1979) conceded that while multiple regression analysis performed on rank transformed variables provides a robust estimation of the strength and direction of relationships between a dependent variable and a set of independent variables, the technique is not appropriate for developing precise predictive mathematical models. This research applied Multiple Linear Regression in the former context as a means to determine the joint influences of the independent variables on *Per Capita Municipal Water Consumption*.

The Rank Transformation assigned the lowest ranks to the lowest values of the original continuous variables and the highest ranks to the largest values of the original continuous variables. This method of ranking the original data was selected for two reasons. Firstly, assigning the highest and lowest ranks to the highest and lowest values of the original data respectively preserves the general direction (positive or negative) and the magnitude of the relationship between the continuous variables as in non-parametric measures of association (Daniel 1990). Secondly, ranking the variables in this manner improves the visual interpretation of bivariate scatterplots by increasing the visual distance between individual observations. Comparisons of the original and rank transformed bivariate scatterplots for each independent variable and *Per Capita Municipal Water Consumption* for Model 1 in 1990 are provided as examples in Figures 7 through 36.

<u>Model Building</u>

Multiple linear regression (MLR) was used to explain the individual and combined influences of the independent variables on per capita municipal water consumption. The technique has been widely applied in similar water resource studies with moderate to high levels of success (Carver and Boland 1980; Cochran and Cotton 1985; Wentz and Gober 2007; Zhou 2000). Eight separate multiple linear regression models were built for each temporal slice using the pre-screened independent variables at the county scale, producing twenty-four equations in all. A stepwise method was used to construct the regression models to ensure that only variables that were statistically significant at the 0.05 level were included (Meyers at al. 2006).

Support for the stepwise method may be found in the weaker inclusion criterion (0.10) of the backward method, and the single entrance criterion (0.05) of the forward method. Backward regression models often produce higher R Square values at the expense of a higher probability of committing a Type I Error, while forward regression models provide lower R Square values with lower Type I Error probabilities. Although a forward model may have guarded against the premature exclusion of practically significant variables with statistically insignificant linear relationships, the inclusion of these statistically weak independent variables may have confounded the explanatory goal of this research. For example, including statistically insignificant independent variables in a multiple linear regression model could potentially artificially reduce the relative influences of variables with stronger statistical relationships (Meyers et al. 2006). In contrast to the forward method, stepwise methods employ an iterative reevaluation procedure where independent variables may be removed as new variables are considered, which reduces the likelihood that independent variables exhibiting exceptionally low associations with the dependent variable will be included in the final regression model.

While MLR permits the individual and joint consideration of relationship magnitudes between the dependent and independent variables under analysis, it may also produce exaggerated estimates of those relationships as a result of multicollinearity. Multicollinearity, a condition that arises when MLR models are constructed from independent variables that are strongly associated with each other, was addressed using the Variance Inflation Factor (VIF). The VIF is a diagnostic that measures the degree of linear association between an independent variable and the remaining independent variables included in the model (Meyers et al. 2006). A VIF threshold of 7.5 was used to determine the presence of significant multicollinearity to account for moderate associations between several pairs of independent variables (e.g. *Percent Bachelor's* and *Degree* and *Per Capita Income* ($\tau = 0.435$, $p < 0.001$); Percent *Single Family* and *Population Density* ($\tau = -0.546$, $p < 0.001$); and *Average Annual Precipitation* and *Average Annual Lake Evaporation* ($\tau = -0.504$, $p < 0.001$)). The choice of 7.5 also reflects a compromise between the respective conservative and liberal bounds of 5.0 and 10.0 that appear in multivariate analysis literature (Meyers et al. 2006; Morrow-Howell 1994). Independent variables that met or exceeded the multicollinearity threshold were systematically removed to achieve the best model fit.

Model Evaluation

Model Comparison

After the models for each temporal slice were adjusted for multicollinearity concerns, the statistically significant independent variables (driving landscape characteristics of municipal water consumption) from the MLR models were compared to test for significant differences between years. The squared semi-partial correlations, which provide the unique contribution of each independent variable to the variation in the dependent variable (Meyers et al. 2006), were used to identify pairs of statistically significant independent variables whose values were statistically different between years (e.g. Average Household Size$_{1990}$ and Average Household Size$_{2000}$). The squared semi-partial correlations were compared for each pair-wise combination of common statistically significant drivers of municipal water consumption for every model in each year to ensure that all comparisons of independent variables were considered in the absence of a non-parametric post-hoc test. This inter-year comparison of statistically significant independent variables helped explain the influence of time on certain drivers of municipal water consumption. A difference between the magnitudes of the squared semi-partial correlations of a given driver in two different time periods suggested that time contributed to the change in that particular driving landscape characteristic. Conversely, the lack of a difference between the magnitudes of the squared semi-partial correlations of a given driver in two different time periods suggested that time did not play a role in the change in that particular driving landscape characteristic.

Evaluation of Spatial Stationarity

Following the comparison of the statistically significant municipal water consumption drivers for each temporal period, the spatial stationarity of municipal water consumption was evaluated using measures of global and local spatial autocorrelation. The global spatial autocorrelation metric served two purposes. Firstly, the presence of global spatial autocorrelation helped assess the efficacy of global statistical models such as MLR to explain the drivers of municipal water consumption at the county scale. A statistically significant high positive global spatial autocorrelation value for the regression residuals in a given year suggested that a global statistical model may not sufficiently explain the contribution of the selected drivers of municipal water consumption at the county scale. The significance level for the global spatial autocorrelation test was set at 0.05 in order to maintain consistency with the entrance criteria for the original MLR models.

Secondly, the presence of global spatial autocorrelation in the regression residuals may indicate misspecification in the original MLR model for a given year (ESRI 2012). The local spatial autocorrelation metric was used to provide insight into potential interactions between the drivers of municipal water consumption in neighboring counties, if high global spatial autocorrelation values had been detected in a given year. These potential interactions between drivers in neighboring counties highlighted areas where formal investigations of physical fresh water resources or municipal water policies may help explain municipal water consumption patterns, and aid the development of demand management strategies.

Global spatial autocorrelation was measured at the county scale using Moran's I due to its longstanding acceptance as a spatial autocorrelation metric, as well as its use of z-scores that provide a standardized output which can be easily compared across multiple variables (Anselin 1995). Likewise, in the presence of positive global autocorrelation Anselin's Local I was used to investigate potential clusters of spatial non-stationarity at the county scale. Anselin's Local I was selected as the local measure of spatial autocorrelation because as a local indicator of spatial association (LISA) it can be statistically aggregated to provide a direct comparison with the results of the Global Moran's I metric (Anselin 1995). Additionally, the global Moran's I and Anselin's Local I will were used to examine spatial stationarity in this research because these metrics do not introduce multicollinearity into multiple regression analyses unlike the increasingly popular technique of geographically weighted regression. Previous research has shown that geographically weighted regression often introduces collinearity and multicollinearity into multivariate regression analyses due to the small sample sizes that are used to analyze individual observations (Paez et al. 2011).

Prior to the implementation of the global and local spatial autocorrelation metrics, the inverse distance weighting conceptualization that was applied in these assessment tools required an appropriate distance threshold. Inverse distance weighting was used to conceptualize the spatial relationship between the drivers and patterns of municipal water consumption to reflect real-world conditions. For example, supplies of surface and groundwater are often consumed at a considerable distance from their source due to inter-basin transfers, and remote water rights (Thompson 1999). Ripley's K function was selected to determine the distance thresholds due to its ability to simultaneously analyze degrees of spatial association for a given point pattern over multiple spatial scales (O'Sullivan and Unwin 2010). These ideas have two embedded implications for the spatial patterns of municipal water consumption and its driving landscape characteristics. Firstly, the presence of inter-basin transfers and remote water rights preclude adjacency as a defining spatial criterion for local municipal water consumption because the origin and destination counties involved in the transfer may not share an administrative boundary. Secondly, the expense of transferring water serves as a defacto limit on the distance over which it is relocated. Thus, the Ripley K function helped ensure that the measures of spatial autocorrelation were not confounded by the spatial distribution of the county centroids that were used in the global Moran’s I and the Anselin’s Local I calculations.

This explicit consideration of scale was necessary to distinguish between the spatial relationships inherent in the county centroids and the patterns in the actual data. Four different distance thresholds were determined to account for differences in spatial coverage and sample size between models. A unique distance threshold was used for Models 1, 2, 3, and 8, Model 4, Model 5, and Models 6 and 7. The results of the Ripley K function are summarized in Table 18 and presented graphically in Figures 37, 38, 39, and 40. The Ripley K graphs provide several sources of important information, including the expected and observed values of the function over multiple distances, and the confidence interval for the given function run.

The relationship between the observed and expected values of the K function at given distance indicates the degree to which a point pattern is clustered or dispersed, while the confidence interval provides an assessment of statistical significance. For example, distances that result in the observed value exceeding the expected value of the K function indicate that level of clustering is greater than the level of clustering present in a completely spatially random distribution. Observed K function values that exceed the expected values and are above the confidence interval threshold are considered to be statistically significant at the given level of significance. Each Ripley K function was configured to produce 100 distance bands with a 99% confidence interval (a significance level of 0.01). In all cases, the maximum difference in K values (observed minus expected) was selected to represent the shortest distance at which spatial processes promoted statistically significant clustering (ESRI 2012b; O’Sullivan and Unwin 2010). These threshold values were chosen deliberately to account for the inherent spatial relationships between the county centroids, as well as to improve the detection of spatial associations between the values of individual variables.

After the distance threshold had been determined using the Ripley K function, the global Moran's I was applied to the MLR residuals for each year (1990, 2000, and 2010), as well as the original patterns and statistically significant driving landscape characteristics of municipal water consumption. MLR residuals that exhibited statistically significant positive spatial autocorrelation were subjected to the Anselin's Local I to examine potential clusters of model performance, i.e. clusters of model fits that were exceptionally weak or exceptionally strong. Anselin's Local I was also applied to the statistically significant driving characteristics and the original patterns of municipal water consumption for each year to examine the degree of spatial association between neighboring counties.

Result Mapping

After testing for statistically significant differences across temporal periods, the original municipal water consumption patterns, and the values of Anselin's Local I (residuals, statistically significant driving landscape characteristics, and original consumption patterns) were mapped to visually assess any inherent spatial patterns. Mapping the original municipal water consumption patterns and the Anselin's Local I values provided insight into the spatial stationarity of municipal water consumption processes, and the potential relationships between the consumption of municipal water in neighboring counties. For example, a simple choropleth map of the original municipal water consumption values for each year permitted a cursory visual inspection for the locations of the highest and lowest consumers of municipal water, the proximity of high and low consumers to each other, and visual clusters of similar values prior to a formal test of spatial autocorrelation. Mapping the Anselin's Local I values for the municipal water consumption values were then used to formalize the relationships visible in the original consumption patterns. Similarly, the Local Anselin's I maps of the statistically significant driving characteristics of municipal water consumption for each year indicated potential clusters of spatial non-stationarity amongst driving characteristics.

Mapping the Anselin's Local I values of the residuals for each MLR model by year exposed potential spatial patterns in model performance. The spatial distribution of the Anselin's Local I values for the MLR residuals in each year highlighted statistically significant zones of exceptionally strong or exceptionally weak model performance, as well as illuminating pockets of spatial non-stationarity in the overall performance of each model. Areas with large over or underestimations indicated either model misspecification or genuine spatial non-stationarity in the per capita consumption of municipal water. Model misspecification typically means that unnecessary independent variables have been included, or that important ones have been omitted (ESRI 2012a; Lavin and Clark 1984), while a lack of spatial stationarity suggests that a global model may not best explain patterns of per capita municipal water consumption or its driving landscape characteristics due to the presence of spatial processes.

CHAPTER IV

RESULTS AND DISCUSSION

The results of this study are discussed in the following manner. Firstly, the original patterns of per capita municipal water consumption for 1990, 2000, and 2010 are presented along with plausible explanations for their genesis and manifestation on the landscape. Secondly, the bivariate Kendall Tau correlations of each independent variable for every year in Model 1 are presented again with special attention to the strength and direction of the relationship of each variable with per capita municipal water consumption, and the implications of these characteristics relative to the original consumption patterns. Thirdly, a summary of the findings of the original multiple regression models (Model 1) is presented, followed by a detailed breakdown of the statistically significant independent variables for each year (1990, 2000, and 2010). Fourthly, the results and interpretations of the tuned multiple regression model permutations are presented by year for each model that improved the original model fit. In all cases, the results of the global and local spatial autocorrelation metrics are presented in concert with their landscape interpretations immediately following their corresponding global multiple regression models. Finally, the results and interpretations for each model permutation in every year are discussed in the context of the original research questions.

Original Patterns of Per Capita Municipal Water Consumption

The original patterns of county scale per capita municipal water consumption in Texas revealed several unexpected anomalies. Firstly, high per capita consumptions of municipal water were not restricted to the urban corridor of Interstate Highway 35 in any of the three years analyzed. In 1990, the traditional population centers of Dallas, Tarrant, Travis, Bexar, and El Paso counties had intermediate consumptions of municipal water ranging from approximately 224762 liters to 370409 liters per capita. However, this same range of consumption values was also evident in west Texas along the Texas-Mexico border and the Texas Panhandle (see Figure 41). The highest municipal water consumptions occurred in the low population counties of Oldham and Jeff Davis. The location of these relatively high municipal consumption values outside well established population centers starkly contrasted the 1990 distributions of total population throughout the state (see Figure 42). A comparison of municipal water consumption patterns for 1990, 2000, and 2010 in Figure 43 showed that while consumption remained high in the primary population centers, the panhandle and the Texas-Mexico border also continued to produce high levels of consumption. These patterns are particularly strong in 2000 and 2010. Detailed maps of per capita municipal water consumption for 2000 and 2010 are provided in Figures 44 and 45 respectively. The corresponding detailed maps of total population are available in Figure 46 for 2000, and Figure 47 for 2010.

While these initial patterns of municipal water consumption clearly support the idea that municipal water consumption is influenced by more than just population size, there are several plausible explanations that may partially account for the high consumption values along the Texas-Mexico border. A series of conversations with employees at the Texas Water Development Board suggested that the official decennial census counts were underestimating the true populations along the Texas-Mexico border due to illegal immigration and the presence of a sizable migratory agricultural workforce. Either of these situations could have potentially generated visible discrepancies, due to the assumption that the population value used in a per capita level measurement accurately reflects true landscape conditions. In other words, if the transient or unofficial consumers of municipal water could be accounted for, the resulting per capita values may align more closely with the influence of population size.

Supporting data from illegal immigration activities were not pursued due to the inherent challenges associated with acquiring and using them, such as the subject's fear of reprisal and self-reporting bias (Fowler Jr. 2009). Estimates of seasonal migrant worker populations often suffer similar problems, but are slightly easier to obtain as a result of the legal migrant worker programs maintained by the U.S. Department of Agriculture, and the Migrant Health Care Program of the U.S. Department of Health and Human Services (Larson 2000). Larson (2000) was contracted by the U.S. Department of Health and Human Services to prepare adjusted estimates of seasonal and migrant farm worker populations between 1994 and 1998. These data were produced by combining existing national farm worker databases with surveys from the National Agricultural Worker Survey (NAWS) and the expert opinions of knowledgeable individuals involved in Texas agricultural operations. The resulting estimates of migrant and seasonal farm worker populations reflect only those farm workers that would not have been recorded by decennial census counts, i.e. they are not permanent residents in their respective worksites. Larson's (2000) estimates of migrant and seasonal populations were not used to adjust the population counts in this research due to the absence of comparable data for all study years. However, a cursory comparison of the influence of migrant and seasonal farm worker populations on per capita municipal water consumption for the year 2000 in border counties was performed. Table 19 suggested that transient populations were capable of influencing per capita municipal water use. Hudspeth (-38.77%), Zavala (-20.14%), and Presidio (-11.22%) counties all showed relatively high percentage changes in per capita municipal water consumption as a result of including transient populations in total population estimates.

The estimates of migrant and seasonal farm workers offered a plausible explanation for the pattern of high municipal water consumption values along the Texas-Mexico border, but similar patterns along the western edge of the Texas Panhandle were better served by an alternate source of unrecorded transient populations. A review of county histories provided by the Texas State Historical Association (2013) revealed that many of the panhandle counties and border counties shared an additional economic characteristic. Between the end of the twentieth and the beginning of the twenty-first century, the contribution of tourism to the local economies of these counties had increased in response to declining incomes from agriculture and fossil fuel extraction. The nebulous nature of tourism creates difficulties in developing an operational measure of the variable, but the County Business Pattern data available from the U.S. Census Bureau (2013a) offered a viable alternative in concert with a simplifying assumption. The county business pattern data was used to develop a *Percent Lodging* variable as a surrogate for tourism activity under the assumption that counties with a higher percentage of commercial businesses dedicated to lodging experienced higher levels of tourism activity.

The county business patterns for Texas were obtained from the U.S. Census Bureau (2013) by industry classification code for 1990, 2000, and 2010. After adjusting for the conversion from Standard Industry Code (SIC) that was used in 1990 to the North American Standard Industry Classification System (NAICS) employed in 2000 and 2010 with a concordance table (USCB 2013b), the total number of hotels, motels, and other lodging establishments were extracted from the total number of commercial businesses. Commercial businesses were defined as the sum of retail and wholesale trade, and services (professional employment establishments, restaurants, entertainment, and lodging). The total number of lodging establishments was divided by the total number of commercial businesses to provide the percentage of commercial businesses dedicated to temporary housing accommodations used by travelers (lodging).

Although not a perfect match, maps of lodging establishments as a percentage of commercial businesses in 1990 (Figure 48), 2000 (Figure 49), and 2010 (Figure 50) illustrate visual agreement with per capita municipal water consumption values in those same years. The percent lodging data mirrored panhandle municipal water consumptions most closely in 2000 and 2010, with visible albeit weaker pattern similarities in 1990. The spatial distribution of lodging percentages in 2000 suggested relatively high concentrations of tourism along the Texas-Mexico border in Culberson, Jeff Davis, Brewster, Val Verde, and Zapata counties which also exhibited high per capita municipal water consumptions. The visual agreement of lodging patterns in the western panhandle was not as strong as those along the border, but both the per capita municipal water consumption and percent lodging values were high in Dallam and Oldham counties. Previously, these high municipal water consumptions defied possible explanation.

The visual match between per capita municipal water consumption (Figure 45) and percent lodging (Figure 50) in 2010 was similar to that of 2000 where the values of both variables were relatively high along the Texas-Mexico border and the western panhandle. High value border counties included Brewster, Culberson, Jeff Davis, Val Verde, and Zapata, while the highest values for the panhandle counties were found in Oldham and Dallam counties. In 1990, the visual agreement between high values of municipal water consumption and percent lodging was weaker, but apparent. The spatial distribution of these variables suggested that tourism activity and its associated transient population most strongly influenced the consumption of municipal water in the border counties of Brewster, Jeff Davis, Terrell, Val Verde, and Zapata, and the panhandle counties Oldham and Dallam. Additionally, the visual agreements between municipal water consumption and percent lodging were loosely supported by the Kendall Tau bivariate correlations for these variables in two of the three years. *Per Capita Municipal Water Consumption* and *Percent Lodging* displayed weak yet statistically significant Kendall Tau correlations in 1990 ($\tau = 0.097$, $p = 0.023$) and 2010 ($\tau = -0.134$, $p = 0.002$). Thus, despite statistically weak explanatory power, it was possible that the temporary increases in population from tourism activity may have contributed to the seemingly erroneous patterns of municipal water consumption along the Texas-Mexico border and the western Texas Panhandle.

Secondly, the consistent differences in municipal water consumption between Dallas and Harris counties were equally puzzling. Despite the fact that Harris County had higher total populations than Dallas County in 1990, 2000, and 2010 (see Figures 42, 46, and 47), Harris County's per capita municipal water consumption was lower than that of Dallas County in each of the same years (Figure 43). While this curious relationship was not explicitly explored in the context of this research, the consumption differences between Harris and Dallas counties may be partially explained through disparities in local water policies. Unlike Dallas County, Harris County was forced to develop comprehensive water conservation measures to combat severe land subsidence problems (USGS 1999). Land subsidence, or the sinking of the land, has plagued Harris, Fort Bend, and Galveston counties for decades due to the removal of incredibly large volumes of groundwater for municipal use and fossil fuel recovery (Gabrysch and Bonnet 1975). The unequal rates of groundwater withdrawal and recharge caused decreases in underground pressure which in turn caused the land surface to sink.

Land subsidence has created multiple problems for Harris, Fort Bend and Galveston counties including decreased water quality resulting from shifts in the 'bad water line' that separates fresh and saline water supplies, and increased susceptibility to inundation during periods of high rainfall due to decreases in land surface elevation. While the water quality issues were important, it was the severity of land subsidence driven flooding events that eventually spurred policy changes. In 1975, the Texas Legislature responded to the property damage concerns of citizens in Houston, and created the Harris-Galveston Coastal Subsidence District which had the power to restrict groundwater withdrawals (USGS 1999). The regulatory power of the agency was strengthened following the destruction of the Brownwood subdivision in Baytown by Hurricane Alicia in 1983, and again in 1992 in response to the rising costs of substituting surface water for groundwater (USGS 1999). These increases in regulatory strength resulted in aggressive water conservation policies that are still in effect today. Recent studies of land subsidence in northwest Houston further demonstrate the need for the continued management of groundwater resources and subsidence which likely reduce the per capita consumption of municipal water. Engelkemeir et al. (2010) found that portions of Jersey Village, a city in northwest Harris County, were still sinking at rates of 45.7 to 56.0 centimeters per year.

Following the previous discussion of land subsidence and its potential influence on active water conservation policies in Harris County, it is safe to conclude that land subsidence may partially account for the consistent disparities between the per capita municipal water consumptions of Harris and Dallas counties. Dallas County has suffered several severe municipal water shortages in recent years that have led to identification of new water supplies (Appleton 2009), but authoritative conservation measures have yet to be implemented. Likewise, evidence has been provided to support the possibility that the per capita municipal consumption patterns along the Texas-Mexico border and the Texas Panhandle may be partially explained by the unrecorded fluxes in transient populations. This research stepped beyond these cursory explanations, and quantitatively explored the human and physical landscape characteristics that individually and jointly to contributed to these same patterns. The results of this quantitative analysis are described and explained in the subsequent sections of this chapter.

Original Bivariate Kendall Tau Correlations

1990

In 1990, the Kendall Tau correlations indicated that independent variables in each of the conceptual categories, i.e. the social, urbanized, and physical environments, exhibited weak but statistically significant linear associations with *Per Capita Municipal Water Consumption*. The set of independent variables in Model 1 (see Table 15) showed that the strongest correlations were present in the social and physical environmental variables. *Percent Worked Inside County of Residence* had the highest degree of association ($\tau = 0.320$, $p < 0.001$) followed by *Average Annual Precipitation* ($\tau = -0.306$, $p < 0.001$). The positive relationship between the percentage of the population that worked inside their county of residence and the per capita municipal water consumption suggested that county municipal water use increased in response to increases in the volume of commercial water consumers. Conceptually, the direction and strength of this relationship suggested that increases in the amount of water used outside the home significantly increase the overall consumption of municipal water.

The negative association between the annual average amount of precipitation that a county received and its per capita municipal water consumption suggested that water use decreased in response to increases in precipitation. Conceptually, the direction and strength of this relationship suggested that short-term increases in available moisture significantly decreased the amount of outdoor municipal water consumption at the county scale. Another possible interpretation of this association is that outdoor areas such as lawns are less likely to require additional water if more water is available from naturally occurring sources. This finding was generally consistent with previous studies conducted at finer spatial scales (Gutzer and Nims 2005; Kenney et al. 2008).

The second highest associations were also present in the social and physical environmental variables with *Percent Owner Occupied* ($\tau = -0.243$, $p < 0.001$) and *Average Annual Lake Evaporation* ($\tau = 0.226$, $p < 0.001$). The negative association between the percentage of the population that lived in a dwelling that they owned and per capita municipal water consumption suggested that the consumption of municipal water decreased in response to increases in the number of people residing in properties that they owned. Conceptually, the strength and direction of this relationship suggested that increases in residential property ownership significantly decreased the residential component of municipal water consumption on a per capita basis. This finding contradicted the supposition that a vested interest in the maintenance of outdoor areas such as lawns would increase water consumption. One potential explanation for the direction of this relationship is that the county scale was obscuring the true association relative to individual consumer behavior which cannot be discerned here. Another possibility is that the *Percent Owner Occupied* variable is reflecting an indoor rather than an outdoor consumption of water. For example, research has shown that owner occupied dwellings are more likely to have energy and water efficient devices than renter occupied dwellings (Davis 2010). In this case the negative relationship could indicate that the presence of more efficient appliances in an owner occupied dwelling decreased per capita indoor municipal water consumption.

The positive association between the annual average amount of lake evaporation and per capita municipal water consumption suggested that the consumption of municipal water increases in response to increases in evaporative processes that likely result from a combination of increases in average annual temperature and decreases in average annual precipitation. Temperature was not considered in this analysis due to collinearity with evaporation, but the association between *Annual Average Lake Evaporation* and *Average Annual Precipitation* was moderately strong ($\tau = -0.504$, $p < 0.001$). Conceptually, the direction and strength of the relationship between *Average Annual Lake Evaporation* and *Per Capita Municipal Water Consumption* suggested that the consumption of municipal water at the county scale significantly increased in response to increases in short-term moisture loss. Short-term moisture losses did not appear to affect the relative mix of municipal water sources at the county scale as evidenced by the exceptionally weak and statistically insignificant association between *Annual Average Lake Evaporation* and *Percent Surface Water* ($\tau = -0.005$, $p = 0.918$).

The statistical significance of the social environment variables continued with the educational attainment variables of *Percent High School Diploma* ($\tau = -0.213$, $p < 0.001$) and *Percent Bachelor's Degree* ($\tau = .194$, $p < 0.001$) displaying moderately weak overall, yet moderately high associations with *Per Capita Municipal Water Consumption* compared to the complete set of independent variables (see Table 15). The negative association between per capita municipal water consumption and the percentage of the population that had completed high school suggested that municipal water consumption at the county scale decreased in response to increases in the completion of secondary education. Conceptually, the strength and direction of this relationship suggested that the consumption of municipal water significantly decreased in response to increases in the cursory exposure to environmental and water resource issues. The positive association between per capita municipal water consumption and the percentage of the population that had completed a Bachelor's degree suggested that municipal water consumption at the county scale increased in response to increases in the attainment of a post-secondary degree. Conceptually, the strength and direction of this relationship suggested that the consumption of municipal water significantly increased in response to increases in the additional exposure to environmental and water resource issues.

The opposite directions of the respective associations between *Per Capita Municipal Water Consumption*, *Percent High School Diploma,* and *Percent Bachelor's Degree* contradict each other under the original assumption that higher levels of educational attainment would reduce municipal water consumption due to an increased awareness of environmental and water resource issues. One possible explanation for this apparent contradiction is that the educational variables are reflecting a latent income effect rather than the influence of exposure to environmental information. Previous studies have documented higher residential municipal water consumptions amongst wealthier and highly educated populations (House-Peters et al. 2010; Kenney et al. 2008). This research further supports the possibility that the education variables are reflecting the influence of income rather than exposure to environmental information in the Kendall Tau correlations between *Per Capita Income* and *Percent High School Diploma* (τ = 0.086, p = 0.041), and *Per Capita Income* and *Percent Bachelor's Degree* (τ = 0.435, p < 0.001). Although per capita income increases in response to both education variables, the attainment of a bachelor's degree clearly has a stronger influence.

The urbanized environment variables displayed statistically significant, but weaker associations with *Per Capita Municipal Water Consumption* where *Percent*

Urban ($\tau = 0.208$, $p < 0.001$) was stronger than *Population Density* ($\tau = -0.128$, $p = 0.002$). The positive association between the percentage of the population living in urban areas and per capita municipal water consumption suggested that the consumption of municipal water increased in response to increases in the size of urban populations. Conceptually, the strength and direction of this relationship suggested that the consumption of municipal water at the county scale significantly increased in response to increases in urbanization processes, or the redistribution of people from agricultural to non-agricultural communities with greater degrees of infrastructure and service availability (Weeks 1996). This finding supports earlier research by Dallman and Spongberg (2012) that found increases in urbanization processes significantly increased fresh water consumption.

The negative association between the density of a county's population and its per capita municipal water consumption suggested that the consumption of municipal water decreased in response to increases in the concentrations of population on the physical landscape. Conceptually, the strength and direction of this relationship suggested that the consumption of municipal water at the county scale significantly decreased in response to increases in the concentration of potential users in a given area. While the opposite directions of the respective associations between *Per Capita Municipal Water Consumption*, *Percent Urban* and *Population Density* may appear initially contradictory, the finding is partially supported by the lower than expected association between the two variables in 1990. The Kendall Tau correlation between *Percent Urban* and *Population Density* was high relative to bivariate correlations present in other variables, but low in an absolute sense ($\tau = 0.336$, $p < 0.001$).

The remaining statistically significant independent variables belonged to the social and physical conceptual categories, and exhibited the weakest of the significant associations with *Per Capita Municipal Water Consumption.* These variables included *Percent 18 Years and Younger* ($\tau = 0.112$, $p = 0.008$), *Percent Single Family* ($\tau = 0.110$, $p = 0.009$), *Annual Average PHDI* ($\tau = -0.093$, $p = 0.028$), and *Percent 65 years and Older* ($\tau = -0.083$, $p = 0.050$). The positive association between the percentage of the population eighteen years of age or less in a county and its per capita municipal water consumption suggested that the consumption of municipal water increased in response to increases in indoor water use by children eighteen years or younger. Conceptually, the strength and direction of this relationship suggested that the consumption of municipal water at the county scale significantly increased in response to an increase in the size of one of the populations that was the most likely to spend the largest amount of time inside the home.

The positive association between the percentage of the population residing in single family homes and per capita municipal water consumption suggested that municipal water consumption increased in response to an increase in the size of the residential population that was more likely to affect the use of both indoor and outdoor water (Wentz and Gober 2007). Conceptually, the strength and direction of this relationship suggested that the consumption of municipal water at the county scale significantly increased in response to an increase in outdoor residential water use resulting from the increased likelihood that a lawn or similar water consuming amenity was present. The true strength of the association between the percentage of single family homes and municipal water consumption may have been muted by the scale of observation or the use of a per capita measurement, as Wentz and Gober (2007) and House-Peters et al. (2010) found stronger relationships between these variables at finer spatial resolutions.

The positive association between the average annual hydrological drought index and per capita municipal water consumption suggested that municipal water consumption increased in response to decreases in moisture deficiencies. The inverse relationship expressed by a positive association is derived from the fact that a positive value of PHDI indicates normal or wet conditions while a negative value of PHDI abnormally dry conditions (NOAA 2012). Examining the Kendall Tau correlations between *Annual Average PHDI* and the precipitation and evaporation variable helped clarify the initially confusing relationship between the long-term drought index and municipal water consumption. For example, *Average Annual Precipitation* ($\tau = 0.320$, $p < 0.001$) was positively associated with *Average Annual PHDI*, and *Average Annual Lake Evaporation* ($\tau = -0.133$, $p = 0.002$) was negatively associated with *Average Annual PHDI.* The direction of these associations means that wetter conditions were present with increases in precipitation, and that drier conditions were present with decreases in available moisture.

Conceptually, the strength and direction of this relationship suggested that the consumption of municipal water at the county scale increased in response to decreases in long-term reductions in available moisture. Although statistically significant, *Average Annual PHDI* exhibited the weakest association of with *Per Capita Municipal Water Consumption* of all of the physical environment variables, as well as the larger group of variables that were statistically significant (see Table 15). While the long-term measure of moisture deficiency very weakly influenced the per capita consumption of municipal water, it had a much stronger relative effect on water sourcing decisions. The Kendall Tau correlation between *Average Annual PHDI* and *Percent Surface Water* ($\tau = 0.266$, $p < 0.001$) suggested that the increased availability of moisture spurred increases in the use of surface water.

This positive relationship between long-term moisture availability and municipal water consumption has not appeared elsewhere in the literature, but it is plausible if the municipal use of water is considered from the perspective of shared or common pool resources. A common pool resource (CPR) is one in which public ownership of the resource accelerates its degradation or depletion due to a lack of individual accountability for the consequences associated with its use (Krause et al. 2003). One problem commonly linked to CPRs, is the insensitivity to the interrelationships that exist between the consumption patterns of individual users, i.e. the decreased availability of the resource to user A that results from the consumption of user B (Krause et al. 2003, Ostrom et al. 1994). Despite the highly private nature of water in Texas, the laws that encourage and protect the privatization of water create resource consumption patterns with CPR characteristics. For example, the Rule of Capture incentivizes higher rather than lower uses of water without regard for the impacts of that use on other water users (Thompson 1999). Under the Rule of Capture, which assigns ownership of water to the party that physically removed it from the ground, a water user whose well runs dry as the result of a neighbor's heavy withdrawals is left without legal recourse (Thompson 1999). Similarly, Prior Appropriation of surface water preserves the seniority of water rights, but not the volume of water. Under this doctrine, water rights that do not use their full allotment may be subject to future reduction (Thompson 1999). Thus, it is possible that an increase in the availability of water could result in increased consumption of surface water.

The negative association between the percentage of the population 65 years and older and per capita municipal water consumption suggested that municipal water consumption decreases in response to increases in indoor water use by adults 65 years or older. Conceptually, the strength and direction of this relationship suggested that the consumption of municipal water at the county scale significantly decreased in response to an increase in the size of one of the populations that was the most likely to spend the largest amount of time inside the home. The negative association between the elderly population and per capita uses of municipal water may be reflecting age-related differences in the attitudes towards water consumption and frequency of common indoor water consuming activities, rather than simply the amount of time spent inside the home (Corbella and Pujol 2009). Naughes and Thomas (2002) found that the percentage of the population 65 years and older tended to use less water for showers, laundry, and dishwashing than other segments of the population, including the percentage of the population that was 18 years of age or younger.

The following independent variables demonstrated very weak associations with *Per Capita Municipal Water Consumption* that were not statistically significant: *Average Household Size* ($\tau = 0.071$, $p = 0.094$), *Per Capita Income* ($\tau = -0.063$, $p = 0.137$), and *Percent Surface Water* ($\tau = -0.018$, $p = 0.684$). The strength of the respective relationships between per capita municipal water consumption and independent variables of average household size and per capita income may be partially attributed to the level of spatial aggregation for each variable. The use of individual consumer records in Aurora, Colorado produced slightly stronger associations for these variables (Kenney et al. 2008). The direction of the relationship between municipal water consumption and average household size was intuitive, as one would assume water consumption to increase with larger household sizes.

The direction of the relationship between per capita income and per capita municipal water use was initially counterintuitive, but this finding was supported by previous studies. House-Peters et al. (2010) and Kenney et al. (2008) both found that average and median household incomes exhibited positive associations with municipal water consumption, while per capita incomes displayed negative associations. The strength and direction of the relationship between the percentage of surface water and per capita municipal water consumption was neither expected nor unexpected since it has not been explored in previous research. The Kendall Tau correlations and their corresponding significance values for all of the independent variables in each model are listed in Table 15.

2000

In 2000, the Kendall Tau correlations indicated that independent variables in each of the conceptual categories, i.e. the social, urbanized, and physical environments, exhibited weak but statistically significant linear associations with *Per Capita Municipal Water Consumption*. The set of independent variables in Model 1 (See Table 16) showed that the strongest correlations were present in the social and physical environmental variables. *Percent Worked Inside County of Residence* had the highest degree of association ($\tau = 0.329$, $p < 0.001$) followed by *Average Annual Precipitation* ($\tau = -0.274$,

$p < 0.001$). The positive relationship between the percentage of the population that worked inside their county of residence and the per capita municipal water consumption suggested that county municipal water use increased in response to increases in the volume of commercial water consumers. Conceptually, the direction and strength of this relationship suggested that increases in the amount of water used outside the home significantly increase the overall consumption of municipal water.

The negative association between the annual average amount of precipitation that a county received and its per capita municipal water consumption suggested that water use decreased in response to increases in precipitation. Conceptually, the direction and strength of this relationship suggested that short-term increases in available moisture significantly decrease the amount of outdoor municipal water consumption at the county scale. Another possible interpretation of this association is that outdoor areas such as lawns are less likely to require additional water if more water is available from naturally occurring sources. This finding was similar to the finding in 1990 and maintained consistency with previous studies conducted at finer spatial scales (Gutzer and Nims 2005; Kenney et al. 2008).

While the levels of statistical significance for *Percent Worked Inside County of Residence* and *Average Annual Precipitation* both remained constant between 1990 and 2000 ($p < 0.001$), the relationship strengths for these variables was different in each year. The strength of the association between per capita municipal water consumption and the percentage of the population working inside their county of residence increased from 0.320 in 1990 to 0.329 in 2000. Conversely, the strength of the association between the per capita municipal water consumption and the average annual amount of precipitation that a county received decreased from -0.306 in 1990 to -0.274 in 2000. These differences in association strength suggest that the relationship between municipal water consumption and non-residential water uses and the relationship between municipal water consumption and short-term moisture inputs are influenced by time.

The second highest associations were also present in the social and physical environmental variables with *Percent Owner Occupied* ($\tau = -0.249$, $p < 0.001$) and *Average Annual Lake Evaporation* ($\tau = 0.245$, $p < 0.001$). The negative association between the percentage of the population that lived in a dwelling that they owned and per capita municipal water consumption suggested that the consumption of municipal water decreased in response to increases in the number of people residing in properties that they owned. Conceptually, the strength and direction of this relationship suggested that increases in residential property ownership significantly decreased the residential component of municipal water consumption on a per capita basis. This finding contradicted the supposition that a vested interest in the maintenance of outdoor areas such as lawns would increase water consumption. One potential explanation for the direction of this relationship is that the county scale was obscuring the true association relative to individual consumer behavior which cannot be discerned here. Another possibility is that the *Percent Owner Occupied* variable is reflecting an indoor rather than an outdoor consumption of water. For example, research has shown that owner occupied dwellings are more likely to have energy and water efficient devices than renter occupied dwellings (Davis 2010). In this case the negative relationship could indicate that the presence of more efficient appliances in an owner occupied dwelling decreased per capita indoor municipal water consumption.

The positive association between the annual average amount of lake evaporation and per capita municipal water consumption suggested that the consumption of municipal water increases in response to increases in evaporative processes that likely result from a combination of increases in average annual temperature and decreases in average annual precipitation. Temperature was not considered in this analysis due to collinearity with evaporation, but the association between *Annual Average Lake Evaporation* and *Average Annual Precipitation* was moderately strong ($\tau = -0.560$, $p < 0.001$). The strength of the association between lake evaporation and precipitation also increased from 1990 when its value was -0.504 at the same level of statistical significance, suggesting that increases in short-term moisture inputs reduced short-term moisture deficits more quickly. Conceptually, the direction and strength of the relationship between *Average Annual Lake Evaporation* and *Per Capita Municipal Water Consumption* suggested that the consumption of municipal water at the county scale significantly increased in response to increases in short-term moisture loss. Short-term moisture losses did not appear to affect the relative mix of municipal water sources at the county scale as evidenced by the exceptionally weak and statistically insignificant association between *Annual Average Lake Evaporation* and *Percent Surface Water* ($\tau = -0.026$, $p = 0.555$).

The strength and direction of the respective relationships between per capita municipal water consumption, the percentage of the population that lived in a dwelling that they owned, and the average annual short-term loss of moisture were identical to those expressed in 1990 (see Tables 15 and 16). The lack of change in the associations of these variables with municipal water consumption suggested that their relationships were not influenced by time between 1990 and 2000. While the direction and statistical insignificance of the association between annual short-term moisture losses and the percentage of surface water used as a source of municipal water remained consistent between 1990 and 2000, the relationship strength increased from -0.005 in 1990 to -0.026 in 2000. This change in association strength suggested that the relationship between these variables was influenced by time between 1990 and 2000.

The third highest associations with *Per Capita Municipal Water Consumption* were found in the social and urbanized environment variables with *Percent High School Diploma* ($\tau = -0.244$, $p < 0.001$) and *Percent Urban* ($\tau = 0.220$, $p < 0.001$) displaying moderately weak overall, yet moderately high associations compared to the complete set of independent variables in Model 1 (see Table 16). The negative association between per capita municipal water consumption and the percentage of the population that had completed high school suggested that municipal water consumption at the county scale decreased in response to increases in the completion of secondary education. Conceptually, the strength and direction of this relationship suggested that the consumption of municipal water significantly decreased in response to increases in the cursory exposure to environmental and water resource issues. The positive association between per capita municipal water consumption and the percentage of the population living in urban areas suggested that municipal water consumption at the county scale increased in response to increases in the size of urban populations. Conceptually, the strength and direction of this relationship suggested that the consumption of municipal water at the county scale significantly increased in response to increases in urbanization processes, or the redistribution of people from agricultural to non-agricultural communities with greater degrees of infrastructure and service availability (Weeks 1996).

This finding closely resembles the relationship between per capita municipal water consumption and the percentage of the population living in urban areas in 1990, and also supports earlier research by Dallman and Spongberg (2012) that found increases in urbanization processes significantly increased fresh water consumption.

The direction of the respective relationships between municipal water consumption and the independent variables of *Percent High School Diploma* and *Percent Urban* was the same as in 1990, but the association strengths increased between 1990 and 2000 in both cases. The strength of the relationship between per capita municipal water consumption and the percentage of the population that had completed high school increased from -0.213 in 1990 to -0.243 in 2000. Similarly, the strength of the relationship between per capita municipal water consumption and the percentage of the population living in urban areas increased from 0.208 in 1990 to 0.220 in 2000. This change in association strength suggested that the relationships between these independent variables and municipal water consumption were influenced by time between 1990 and 2000.

The fourth strongest associations with *Per Capita Municipal Water Consumption* were present in social and urbanized environment variables with *Percent 18 Years and Younger* ($\tau = 0.168$, $p < 0.001$) and *Population Density* ($\tau = -0.164$, $p < 0.001$) displaying weak statistical relationships overall. The positive association between the percentage of the population eighteen years of age or less in a county and its per capita municipal water consumption suggested that the consumption of municipal water increased in response to increases in indoor water use by children eighteen years or younger. Conceptually, the strength and direction of this relationship suggested that the consumption of municipal water at the county scale significantly increased in response to an increase in the size of one of the populations that was the most likely to spend the largest amount of time inside the home.

The negative association between the density of a county's population and its per capita municipal water consumption suggested that the consumption of municipal water decreased in response to increases in the concentrations of population on the physical landscape. Conceptually, the strength and direction of this relationship suggested that the consumption of municipal water at the county scale significantly decreased in response to increases in the concentration of potential users in a given area. Following the pattern established in the first three pairs of independent variables that expressed statistically significant associations with per capita municipal water consumption, the percentage of the population 18 years and younger and population density maintained relationships with the same direction in both 1990 and 2000. Additionally, the association strengths of these relationships were stronger in 2000 than in 1990. The strength of the relationship between *Per Capita Municipal Water Consumption* and *Percent 18 Years and Younger* increased from 0.112 in 1990 to 0.168 in 2000, while the relationship between *Per Capita Municipal Water Consumption* and *Population Density* increased from -0.128 to -0.164 over the same period. The increased strength of these associations between 1990 and 2000 suggested that the respective relationships between the independent variables and the dependent variable were influenced by time.

Once again *Percent Urban* and *Population Density* correlated with *Per Capita Municipal Water Consumption* in opposite directions which appeared contradictory until considering the statistical relationship between the two independent variables. The

Kendall Tau correlation between *Percent Urban* and *Population Density* was high relative to bivariate correlations present in other variables, but low in an absolute sense ($\tau = 0.385$, $p < 0.001$).

The remaining statistically significant independent variables belonged to the social conceptual category, and exhibited the weakest of the significant associations with *Per Capita Municipal Water Consumption.* These variables included *Per Capita Income* ($\tau = -0.135$, $p = 0.001$), *Percent 65 Years and Older* ($\tau = -0.111$, $p = 0.009$), and *Percent Bachelor's Degree* ($\tau = 0.096$, $p = 0.023$). The negative association between the per capita income of a county and its per capita municipal water consumption suggested that municipal water consumption decreased in response to an increase in an equal distribution of total household income across the total population. Conceptually, the strength and direction of this relationship suggested that the consumption of municipal water at the county scale significantly decreased in response to an increase in the affluence level of the county.

This negative relationship between income and municipal water consumption in 2000 may be partially explained in the same manner as the relationship between municipal water consumption and the percentage of owner occupied dwellings in 1990. Counties with high per capita incomes may be more likely to also have high incidences of property owners occupying their own dwellings. In turn, this higher percentage of owner occupied dwellings may reduce the residential component of municipal water consumption through the increased ownership of water efficient appliances such as clothes washing machines, and dishwashers (Davis 2010). The positive statistically significant association between *Per Capita Income* and *Percent Owner Occupied*

Dwellings ($\tau = 0.116$, $p = 0.006$) supported this possible explanation despite a weak relationship strength.

The negative association between the percentage of the population 65 years and older and per capita municipal water consumption suggested that municipal water consumption decreases in response to increases in indoor water use by adults 65 years or older. Conceptually, the strength and direction of this relationship suggested that the consumption of municipal water at the county scale significantly decreased in response to an increase in the size of one of the populations that was the most likely to spend the largest amount of time inside the home. The negative association between the size of the elderly population and the consumption of municipal water in 2000 mirrors the relationship between these two variables in 1999 and may be partially explained in a similar fashion. Despite the increased likelihood that persons aged sixty-five years an older to spend more time inside the home than other segments of the larger population, their attitudes towards resource consumption and water use preferences may result in lower consumptions of municipal water (Corbella and Pujol 2009; Naughes and Thomas 2002).

The positive association between per capita municipal water consumption and the percentage of the population that had completed a Bachelor's degree suggested that municipal water consumption at the county scale increased in response to increases in the attainment of a post-secondary degree. Conceptually, the strength and direction of this relationship suggested that the consumption of municipal water significantly increased in response to increases in the additional exposure to environmental and water resource issues. While the strength of the association between these two variables in 2000 was weaker than in 1990, its direction remained the same. Thus, the positive relationship between *Per Capita Municipal Water Consumption* and *Percent Bachelor's Degree* in 2000 may also be partially attributed to a latent income effect where higher incomes coincide with increased access to water consuming devices such as swimming pools (Wentz and Gober 2007; House-Peters et al. 2010). This potential explanation is supported by the strength and direction of the statistically significant association between *Per Capita Income* and *Percent Bachelor's Degree* ($\tau = 0.474$, $p < 0.001$).

The relationships between *Per Capita Municipal Water Consumption* and the independent variables of *Per Capita Income, Percent 65 Years and Older*, and *Percent Bachelor's Degree* all maintained the same direction in 1990 and 2000, while the strength of each association was different. The strength of the relationship between per capita municipal water consumption and per capita income increased from an insignificant -0.063 in 1990 to a statistically significant -0.135 in 2000 (see Tables 15 and 16). Similarly, the strength of the relationship between per capita municipal water consumption and the percentage of the population aged sixty-five years and older increased from -0.083 in 1990 to -0.111 in 2000. Unlike the previous two independent variables, the strength of the relationship between per capita municipal water consumption and the percentage of the population that earned a bachelor's degree decreased from 0.194 in 1990 to 0.096 in 2000. The differences in the strengths of these associations between years suggested that time influenced the relationships between the dependent variable and the independent variables were influenced by time.

The following independent variables demonstrated very weak associations with *Per Capita Municipal Water Consumption* that were not statistically significant in 2000:

Average Household Size ($\tau = 0.057$, $p = 0.175$), *Percent Single Family* ($\tau = -0.051$, $p = 0.226$), *Percent Surface Water* ($\tau = -0.025$, $p = 0.575$), and *Average Annual PHDI* ($\tau = -0.022$, $p = 0.611$) . The strength of the respective relationships between per capita municipal water consumption and independent variables of average household size and percent single family may be partially attributed to the level of spatial aggregation for each variable just like in 1990. The use of individual consumer records in Aurora, Colorado produced slightly stronger associations for these variables (Kenney et al. 2008). The direction of the relationship between municipal water consumption and average household size was intuitive, as one would assume water consumption to increase with larger household sizes. The direction of the relationship between per capita municipal water consumption and the percentage of single family homes was counterintuitive, but may be partially explained by the likelihood that single family homes share the propensity of owner occupied dwellings to have water efficient appliances (Davis 2010). This potential explanation is also supported by the strength and direction of the association between *Percent Single Family* and *Percent Owner Occupied Dwellings* ($\tau = 0.245$, $p < 0.001$) in 2000.

The strengths of the respective associations between per capita municipal water consumption, the percentage of surface water used to meet municipal water demands, and the average annual long-term loss of moisture were weaker in 2000 than in 1990. These relationships were also statistically significant in 1990 and statistically insignificant in 2000. The directions of these relationships in 2000 were opposite their original directions in 1990. Taken together, the differences in association strength and direction between *Per Capita Municipal Water Consumption* and *Percent Surface Water*, and *Per Capita*

Municipal Water Consumption and *Average Annual PHDI* suggested that these relationships were influenced by time.

The positive association between the average annual hydrological drought index and per capita municipal water consumption suggested that municipal water consumption increased in response to decreases in moisture deficiencies. The inverse relationship expressed by a positive association is derived from the fact that a positive value of PHDI indicates normal or wet conditions while a negative value of PHDI abnormally dry conditions (NOAA 2012). Examining the Kendall Tau correlations between *Annual Average PHDI* and the precipitation and evaporation variable helped clarify the initially confusing relationship between the long-term drought index and municipal water consumption. For example, *Average Annual Precipitation* ($\tau = 0.320$, $p < 0.001$) was positively associated with *Average Annual PHDI*, and *Average Annual Lake Evaporation* ($\tau = -0.133$, $p = 0.002$) was negatively associated with *Average Annual PHDI*. The direction of these associations means that wetter conditions were present with increases in precipitation, and that drier conditions were present with decreases in available moisture.

<u>2010</u>

In 2010, the Kendall Tau correlations indicated that independent variables in each of the conceptual categories, i.e. the social, urbanized, and physical environments, exhibited weak but statistically significant linear associations with *Per Capita Municipal Water Consumption*. The set of independent variables in Model 1 (see Table 17) showed that the strongest correlations were present in the social and physical environmental variables. *Percent Worked Inside County of Residence* had the highest degree of association ($\tau = 0.226$, $p < 0.001$) followed by *Average Annual Precipitation* ($\tau = -0.222$, $p < 0.001$). The positive relationship between the percentage of the population that worked inside their county of residence and the per capita municipal water consumption suggested that county municipal water use increased in response to increases in the volume of commercial water consumers. Conceptually, the direction and strength of this relationship suggested that increases in the amount of water used outside the home significantly increased the overall consumption of municipal water.

The negative association between the annual average amount of precipitation that a county received and its per capita municipal water consumption suggested that water use decreased in response to increases in precipitation. Conceptually, the direction and strength of this relationship suggested that short-term increases in available moisture significantly decreased the amount of outdoor municipal water consumption at the county scale. Another possible interpretation of this association is that outdoor areas such as lawns are less likely to require additional water if more water is available from naturally occurring sources. This finding was similar to the finding in 1990 and 2000 and was consistent with previous studies conducted at finer spatial scales (Gutzer and Nims 2005; Kenney et al. 2008).

While the levels of statistical significance for *Percent Worked Inside County of Residence* and *Average Annual Precipitation* both remained constant between 1990, 2000, and 2010 ($p < 0.001$), the relationship strengths for these variables were different in each year. The strength of the association between per capita municipal water consumption and the percentage of the population working inside their county of residence increased from 0.320 in 1990 to 0.329 in 2000, and decreased to 0.226 in 2010.

Conversely, the strength of the association between the per capita municipal water consumption and the average annual amount of precipitation that a county received consistently decreased from -0.306 in 1990 to -0.274 in 2000, and to -0.222 in 2010. These differences in association strength suggested that the relationship between municipal water consumption and non-residential water uses and the relationship between municipal water consumption and short-term moisture inputs were influenced by time.

The second highest associations were present in the urbanized and physical environmental variables with *Population Density* ($\tau = -0.178$, $p < 0.001$) and *Average Annual Lake Evaporation* ($\tau = 0.146$, $p < 0.001$). The negative association between the density of a county's population and its per capita municipal water consumption suggested that the consumption of municipal water decreased in response to increases in the concentrations of population on the physical landscape. Conceptually, the strength and direction of this relationship suggested that the consumption of municipal water at the county scale significantly decreased in response to increases in the concentration of potential users in a given area.

Given the statistically insignificant association between *Percent Urban* and *Per Capita Municipal Water Consumption* ($\tau = 0.064$, $p = 0.137$) in 2010, a comparison between the size of a county's population living in an urban area and its concentrations of population on the physical landscape was not made for that year. However, the direction of the relationship between population density and per capita municipal water consumption may be partially explained by the fact that urban areas often contain a mixture of both high and low population densities that reflect inverse levels of resource consumption. Wentz and Gober (2007) and House-Peters et al. (2010) found similar relationships between municipal water consumption and population density, although their research did not explicitly consider the concentrations of population on the physical landscape. Both studies linked the highest consumptions of municipal water to lower density urban areas where lot sizes were larger and more outdoor water consuming devices such as swimming pools were present.

The positive association between the annual average amount of lake evaporation and per capita municipal water consumption suggested that the consumption of municipal water increases in response to increases in evaporative processes that likely result from a combination of increases in average annual temperature and decreases in average annual precipitation. Temperature was not considered in this analysis due to collinearity with evaporation, but the association between *Annual Average Lake Evaporation* and *Average Annual Precipitation* was moderately strong (τ = -0.531, $p < 0.001$) in 2010. The strength of the association between lake evaporation and precipitation also increased from 1990 when its value was -0.504, and decreased from 2000 when its value was -0.560 at the same level of statistical significance in all three years. These differences suggested that increases in short-term moisture inputs reduced short-term moisture deficits more quickly in 2000 than in 1990, and that short-term moisture deficits responded more slowly to short-term moisture inputs in 2010 than in 2000.

Conceptually, the direction and strength of the relationship between *Average Annual Lake Evaporation* and *Per Capita Municipal Water Consumption* suggested that the consumption of municipal water at the county scale significantly increased in response to increases in short-term moisture loss. Short-term moisture losses did not appear to affect the relative mix of municipal water sources at the county scale as evidenced by the exceptionally weak and statistically insignificant association between *Annual Average Lake Evaporation* and *Percent Surface Water* in 2010 (τ = -0.071, p = 0.106).

The direction of the respective relationships between per capita municipal water consumption, the concentrations of population in the physical landscape, and the average annual short-term loss of moisture were identical to those expressed in 1990 and 2000 (see Tables 15, 16, and 17). However, the association strength of each relationship was different in every year. The strength of the association between *Per Capita Municipal Water Consumption* and *Population Density* consistently increased from -0.128 in 1990 and -0.164 in 2000, to -0.178 in 2010. The strength of association between *Per Capita Municipal Water Consumption* and *Average Annual Lake Evaporation* increased from 0.226 in 1990 to 0.245 in 2000, but decreased to 0.146 in 2010. These changes in association strength suggested that the relationships between these independent variables and per capita municipal water consumption were influenced by time between 1990, 2000, and 2010.

The remaining statistically significant independent variables belonged to the social conceptual category, and exhibited the weakest of the significant associations with *Per Capita Municipal Water Consumption.* These variables included *Percent High School Diploma* (τ = -0.123, p = 0.003), and *Percent Surface Water* (τ =- 0.117, p = 0.008). The negative association between per capita municipal water consumption and the percentage of the population that had completed high school suggested that municipal water consumption at the county scale decreased in response to increases in the completion of secondary education. Conceptually, the strength and direction of this relationship suggested that the consumption of municipal water significantly decreased in response to increases in the cursory exposure to environmental and water resource issues. Just like in 1990 and 2000, the negative association between per capita municipal water consumption and the percentage of the population that completed high school is likely best explained through a latent income effect embedded in educational attainment rather than exposure to environmental information.

House-Peters et al. (2010) and Kenney et al (2008) both reported that the highest municipal water consumptions occurred amongst the wealthier and more highly educated segments of the population. Despite the negative association the between *Percent High School Diploma* and *Per Capita Income* ($\tau = -0.091$, $p = 0.032$) in 2010, the latent income effect is plausible based on the relationships between *Percent High School* and *Percent Bachelor's Degree* ($\tau = -0.346$, $p < 0.001$), and *Percent Bachelor's Degree* and *Per Capita Income* ($\tau = 0.427$, $p < 0.001$). The negative association between the percentage of the population that only completed high school and the percentage of the population that attained at least a bachelor's degree suggested that the size of the population whose formal education ceased at the secondary level decreased in response to an increase in the size of the population that completed a post-secondary education. Likewise, the positive association between the percentage of the population that attained at least a bachelor's degree and per capita income suggested that per capita income increased in response to an increase in the completion of a post-secondary education. Thus, an application of the transitive property suggested that the segment of the population possessing only a high school education would earn lower incomes and use less water than their more highly educated counterparts.

The negative association between per capita municipal water consumption and the percentage of surface water used for municipal purposes suggested that municipal water consumption increased in response to a decrease in the amount of surface water used to meet county scale municipal water demands. Conceptually, the strength and direction of this relationship suggested that the consumption of municipal water significantly increased in response to a decrease in the surface water component of municipal water sources. One potential explanation for the negative association between per capita municipal water consumption and the percentage of surface water used for municipal purposes may be a reduced consumption of outdoor residential water.

This explanation is plausible based on the statistically significant negative relationship between *Per Capita Municipal Water Consumption* and *Annual Average Precipitation* ($\tau = -0.222$, $p < 0.001$) in 2010, as well as the spatial distribution of average annual PHDI values for the same year. The negative association between precipitation and per capita municipal water consumption suggested that the outdoor residential component of municipal water consumption decreased in response to increases in precipitation. Hence, an increase in precipitation may have reduced the amount of surface water used to satisfy the residential component of outdoor municipal water demands. Similarly, Figure 51 illustrated that despite the presence of regionally varying hydrological drought index values across the state, the average moisture conditions for 2010 were generally wet. East Texas experienced a normal range of moisture; west Texas and the eastern panhandle were mildly wet; the western panhandle along with north and central Texas were moderately wet; the southern Texas-Mexico border was extremely wet; and the northern gulf coast counties experienced the onset or early stages of prevailing wet conditions. This prevalence of normal to wet moisture availabilities may have also contributed to a reduced need for additional surface water.

The direction of the associations between the percentage of the population that only completed high school and per capita municipal water consumption, and per capita municipal water consumption and percent surface water were both consistently negative in 1990, 2000, and 2010. The strengths of the associations between the dependent variable and each independent variable, however, were different in every year. The association strength between *Per Capita Municipal Water Consumption* and *Percent High School Diploma* increased from -0.213 in 1990 to -0.244 in 2000, and decreased to -0.123 in 2010. The association between *Per Capita Municipal Water Consumption* and *Percent Surface Water* was only statistically significant in 2010 (see Tables 15, 16, and 17), but increased in strength from -0.018 in 1990 to -0.025 in 2000, and increased to -0.117 in 2010. These changes in association strength suggested that the relationships between these independent variables and per capita municipal water consumption were influenced by time between 1990, 2000, and 2010.

The majority of independent variables demonstrated very weak associations with *Per Capita Municipal Water Consumption* that were not statistically significant in 2010. The statistically insignificant independent variables included *Per Capita Income* (τ = -0.080, p = 0.058), *Percent Owner Occupied* (τ = -0.064, p = 0.131), *Percent Urban* (τ = 0.064, p = 0.134), *Percent Single Family* (τ = -0.054, p = 0.199), *Percent Bachelor's* Degree (τ = -0.027, p = 0.529), *Percent 18 Years and Younger* (τ = 0.019, p = 0.655), *Percent 65 Years and Older* (τ = -0.014, p = 0.744), *Average Household Size* (τ = - 0.003, p = 0.175), and *Average Annual PHDI* (τ = 0.002, p = 0.968). The negative association between per capita income and municipal water consumption in 2010 may be partially explained in the same manner as the relationship between municipal water consumption and the percentage of owner occupied dwellings in 1990 and 2000. Counties with high per capita incomes may be more likely to also have high incidences of property owners occupying their own dwellings. In turn, this higher percentage of owner occupied dwellings may reduce the residential component of municipal water consumption through the increased ownership of water efficient appliances such as clothes washing machines, and dishwashers (Davis 2010). The positive statistically significant association between *Per Capita Income* and *Percent Owner Occupied Dwellings* ($\tau = 0.141$, $p = 0.001$) supported this possible explanation despite a weak relationship strength.

The strength and direction of the association between per capita municipal water consumption and the percentage of the population living in urban areas were addressed in the previous discussion of population density in 2010, and are not mentioned here. The strength of the respective relationships between per capita municipal water consumption and the independent variables of average household size and percent single family may be partially attributed to the level of spatial aggregation for each variable just like in 1990 and 2000. Kenney et al. (2008) used individual consumer records in Aurora, Colorado which produced slightly stronger associations for these variables. The direction of the relationship between municipal water consumption and average household size was counterintuitive, as one would assume water consumption to increase with larger household sizes.

The negative association of this relationship may be partially explained by an economy of scale effect that surfaces in average households sizes larger than 2.5 (Arbues et al. 2003). In 2010, 160 of Texas' 254 counties (approximately 63%) met this criterion. The direction of the relationship between per capita municipal water consumption and the percentage of single family homes was counterintuitive, but may be partially explained by the likelihood that single family homes share the propensity of owner occupied dwellings to have water efficient appliances (Davis 2010). This potential explanation is also supported by the strength and direction of the association between *Percent Single Family* and *Percent Owner Occupied Dwellings* ($\tau = 0.511$, $p < 0.001$) in 2010.

The direction of the association between per capita municipal water consumption and the percentage of the population that attained a bachelor's degree suggested that municipal water consumption decreased in response to an increase in the completion of a post-secondary degree. Although it is possible that holders of bachelor's degrees possessed an increased awareness of environmental and water resource issues in 2010, it is equally likely that the reversal of the association direction is spurious due to the moderately high probability that the correlation between *Per Capita Municipal Water Consumption* and *Percent Bachelor's Degree* ($p = 0.529$) occurred by random chance in that year. Likewise, the directions of the associations between per capita municipal water consumption, the percentage of the population eighteen years of age and younger, the percentage of the population aged sixty-five years and older, and hydrological drought index are not discussed here due to exceptionally high probabilities that the relationships occurred by random chance. The p-values for *Percent 18 Years and Younger*, *Percent 65 Years and Older,* and *Average Annual PHDI* were 0.655, 0.744, and 0.968 respectively.

Summary

While at least one independent variable in each conceptual category (the social, urbanized, and physical environment) expressed a statistically significant bivariate correlation with per capita municipal water consumption, the highest associations were not consistently concentrated in a single conceptual variable. The following rankings of conceptual variables and their corresponding operational counterparts are listed from highest to lowest strength. In 1990, the strongest statistically significant bivariate relationships with *Per Capita Municipal Water Consumption* were found in the social and physical environmental variables (*Percent Worked Inside County of Residence* and *Annual Average Precipitation* in Table 15). The second strongest statistically significant bivariate relationships were present in the social and physical environmental variables (*Percent Owner Occupied, Average Annual Lake Evaporation* in Table 15). The third strongest bivariate relationships were expressed in the social and urbanized environmental (*Percent High School Diploma*, *Percent Urban,* and *Percent Bachelor's Degree* in Table 15). The weakest statistically significant bivariate relationships were found in the urbanized and social environmental variables (*Population Density*, *Percent 18 Years and Younger,* and *Percent 65 Years and Older* in Table 15).

In 2000, the strongest statistically significant bivariate relationships were identical to the strongest bivariate associations in 1990. The second strongest statistically significant bivariate relationships were expressed in the social and physical environmental variables (*Percent Owner Occupied, Annual Average Lake Evaporation,* and *Percent High School* in Table 16). The third strongest statistically significant bivariate relationships were present in the urbanized and social environmental variables

(*Percent Urban, Percent 18 Years and Younger,* and *Population Density* in Table 16). The weakest statistically significant relationships were confined to the social environmental variables (*Per Capita Income, Percent 65 Years and Older,* and *Percent Bachelor's Degree* in Table 16).

The statistically significant bivariate relationships in 2010 were similar to those in 1990 and 2000 in that all three conceptual variables were represented. The major differences between 2010 and the previous years were that the groupings of strong and weak correlations were larger, and that fewer operational variables expressed statistically significant relationships with per capita municipal water consumption overall. The strongest statistically significant bivariate relationships were found in the social, physical and urban environmental variables (*Percent Worked Inside County of Residence*, *Average Annual Precipitation,* and *Population Density* in Table 17). Conversely the weakest statistically significant bivariate relationships were found in the physical and social environmental variables (*Annual Lake Evaporation, Percent High School,* and *Percent Surface Water* in Table 17). Additionally, the differences in the strength and direction of the statistically significant variables between years suggested that the relationships between the independent variables and per capita municipal water consumption were influenced by time. The bivariate associations discussed in this section reflect the individual relationship between each independent variable and per capita municipal water consumption.

Original Model Results

The results of the stepwise multiple regression models (MLR) are presented here because they produced more robust models than the forward method, and had a lower tendency to include statistically insignificant independent variables in the final model. This decision was made to maintain consistency with the research goal of examining the significant driving human and physical landscape characteristics behind per capita municipal water consumption patterns in 1990, 2000, and 2000. Additionally, the practical significance typically gained through the inclusion of statistically insignificant independent variables in regression models was outweighed by the exceptionally small improvements in overall model fit achieved by leaving these variables in the model.

A limitation of the results presented in the following sections is that the regression models were built using the ranks of the dependent and independent variables rather than the original values themselves. The important implications here are that the ranks of the independent variables are ‘predicting’ the ranks of the dependent variable, and that the units of the standard error of the estimate are ranks rather than the original units of the dependent variable. The use of the Rank Transformation (Connover and Iman 1981) was permissible in this research due to its explanatory rather than predictive goal. Essentially, the Rank Transformation can be used in MLR models under select circumstances because the ranks preserve the strength and direction of the original relationships between variables when assigned appropriately (Iman and Connover 1979). This relationship preserving attribute of the Rank Transformation is also the principle behind non-parametric measures of association such as Spearman’s Rho and Kendall’s Tau (Daniels 1990).

Model 1 considered the entire collection of independent variables list in Table 3 with the exception of *Percent Renter Occupied*, *Percent Multifamily Dwellings, Percent Worked Outside County of Residence*, *Percent Rural* and *Percent Groundwater*. These independent variables were removed during the regression screening stage to alleviate multicollinearity concerns. The Model 1 results are presented by year, and include the overall model fits, and the standardized beta weights and p-values of the statistically significant independent variables. Following the description of the regression model results, the numerical output is discussed and the output from the spatial analysis conducted for each year is presented and discussed. The spatial analysis examined the spatial stationarity of the original patterns of municipal water consumption, each statistically significant independent variable, and the standardized residuals for each model using measures of global spatial autocorrelation (Moran's I) and local indicators of spatial association (Anselin's Local I).

1990 MLR Model 1

The overall MLR model fit was moderately weak in 1990 with an adjusted R-Square value of 0.385 ($F = 40.517$, $p < 0.001$, $Df = 249$). The adjusted R-Square value is reported here because it accounts for inflation of model fit that occurs as an artifact of increasing the number of independent variables in the model (Meyers et al. 2006). Despite a relatively high standard error of the estimate (Std Err = 57.637), which is functionally equivalent to the univariate standard deviation (Earickson and Harlin 1994), the results of Model 1 may be considered robust due to the fact that the adjusted R-Square is statistically significant at the alpha level of 0.05 ($p < 0.001$). The robustness of Model 1 was also supported by the approximately normal distribution of the standardized residuals (Figure 52). The integrity of Model 1 was preserved due to the absence of multicollinearity amongst the independent variables in the final model. The Variance Inflation Factor (VIF) values for *Percent Bachelor's Degree* (1.276), *Average Annual*

Precipitation (1.189), *Percent Worked Inside County of Residence* (1.736), and *Per Capita Income* (1.765) were all well below the previously established 7.5 threshold described in the Research Methods chapter.

Model 1 accounted for 38.5% of the variation in per capita municipal water consumption in 1990 using *Percent Bachelor's Degree, Average Annual Precipitation, Percent Worked Inside County of Residence*, and *Per Capita Income* as predictors. Conversely, Model 1 failed to account for 62.5% of the variation in the 1990 per capita municipal water consumption pattern, suggesting that additional variables besides short-term moisture inputs, income, post-secondary educational attainment, and commercial activity were influencing the consumption of municipal water. The model fit and diagnostics for Model 1 are given in Table 20, and the standardized beta weights and p-values for each statistically significant independent variable are provided in Table 21.

Additional insight into the relative influences of statistically significant independent variables on per capita municipal water consumption was gained by calculating the beta ratio matrix in Table 22. The standardized beta ratio expresses the influence of a stronger independent variable in terms of a weaker one by removing the signs, placing the largest beta weight of the pair in the numerator, and dividing the two values (Meyers et al. 2006). The rows and columns of Table 22 are organized from left to right in descending order from largest to smallest standardized beta weights. The values along the diagonal are similar to the diagonal values in a correlation matrix, i.e. they represent an independent variable's relationship to itself. For example, while the influence of *Percent Bachelor's Degree* is only slightly stronger than *Annual Average Precipitation*, the influence of *Percent Bachelor's Degree* is nearly 1.75 times as strong as *Per Capita Income*. Additionally, Table 20 suggests that the physical environment is an important conceptual variable to consider when investigating drivers of municipal water consumption despite the stronger representation of the social environment (three statistically significant independent social variables compared to one physical variable).

Percent Bachelor's Degree ($\beta = 0.383$, $p < 0.001$) exerted the strongest influence on per capita municipal water consumption in 1990 and expressed a positive association with the dependent variable which suggested that the consumption of municipal water increased in response to increases in the percentage of the population that attained post-secondary education. Conceptually, this relationship suggested that the social environmental variables influenced municipal water consumption the most heavily, as well as that increased levels of education increased water use. The positive relationship between *Percent Bachelor's Degree* and *Per Capita Municipal Water Consumption* was likely the result of a latent income effect rather than an increased exposure to environmental and water resource issues. This explanation was supported by the strength and direction of the association between *Percent Bachelor's Degree* and *Per Capita Income* in 1990 ($\tau = 0.435$, $p = 0.001$). A more detailed discussion is available in the original bivariate correlation section of this chapter, and is not repeated here. Combining the percentage of the population that earned a bachelor's degree with the suite of other statistically significant independent variables also increased the strength of its relationship with per capita municipal water consumption relative to its individual association (see Table 15). This increased relationship strength due to inclusion in the MLR model suggested that the ability of *Percent Bachelor's Degree* to explain increases in the consumption of municipal water was increased by interacting with multiple physical and human landscape characteristics. In other words, the relative influence of postsecondary educational attainment on municipal water consumption became more important than it was individually due to interactions with other driving human and physical landscape characteristics.

Average Annual Precipitation ($\beta = -0.310$, $p < 0.001$) exerted the second strongest influence on per capita municipal water consumption in 1990 and expressed a negative association with the dependent variable which suggested that the consumption of municipal water decreased in response to increases in precipitation. Conceptually, this relationship suggested that the physical environment significantly contributed to municipal water consumption despite being outweighed by the social environment, as well as that the residential component of residential outdoor municipal water consumption decreased in response to increases in short-term moisture inputs. The relative influence of *Average Annual Precipitation* on *Per Capita Municipal Water Consumption* also increased from its bivariate correlation of -0.306 which suggested that the interaction of the independent variables increased the ability of changes in short-term moisture inputs to explain the consumption of municipal water consumption patterns. In other words, the influence of precipitation was slightly stronger under real world conditions where multiple factors combine to drive municipal water consumption than when it was considered individually.

Percent Worked Inside County of Residence ($\beta = 0.267$, $p < 0.001$) exerted a moderately weak influence on per capita municipal water consumption in 1990 and expressed a positive association with the dependent variable which suggested that the consumption of municipal water increased in response to increases in the size of the population consuming water outside the home in a given county. Conceptually, this relationship suggested that municipal water consumption increased in response to increases in commercial activity, as well as that the influence of commercial activity on the consumption of municipal water consumption was less than that of short-term moisture inputs under circumstances where multiple human and physical landscape characteristics interacted with each other. Including the percentage of the population that worked inside their county of their county of residence in the MLR model also decreased its relative influence on municipal water consumptions in 1990 from its bivariate association of 0.320. This decrease in association strength suggested that the interactions that occur between human and physical driving characteristics in the real world decreased the ability of commercial activity to explain increases in municipal water consumption. In simpler terms, non-residential uses of municipal water were less important to overall municipal water consumption patterns when its interaction with other driving characteristics were considered.

Per Capita Income ($\beta = -0.220$, $p = 0.001$) exerted the weakest influence on per capita municipal water consumption in 1990, and expressed a negative association with the dependent variable which suggested that the consumption of municipal water decreased in response to increases in the equal distribution of a county's total income across the total population. Conceptually, this relationship suggested that municipal water consumption decreased in response to increases affluence, as well as that the influence of affluence on the consumption of municipal water was less than that of postsecondary educational attainment, short-term moisture inputs, and commercial activity when multiple human and physical landscape characteristics interacted with each other. The negative association between *Per Capita Income* and *Per Capita Municipal Water Consumption* in the MLR model was consistent with the bivariate correlation between the two variables, and likely reflected the increased presence of water efficient appliances in higher income counties (Davis 2010). A full discussion of this potential explanation is provided in the bivariate correlation section of this chapter.

Including the *Per Capita Income* in the MLR model also dramatically increased its relative influence on municipal water consumptions in 1990 from its statistically insignificant bivariate association of -0.063 ($p = 0.137$). This increase in association strength suggested that the interactions that occur between human and physical driving characteristics in the real world increased the ability of income to explain decreases in municipal water consumption. In other words, income was more important to overall municipal water consumption patterns when its interaction with other driving characteristics were considered. This finding also suggested statistically insignificant bivariate correlations may not completely justify the exclusion of an independent variable from a multivariate model.

<u>2000 MLR Model 1</u>

The overall MLR model fit was moderate in 2000 with an adjusted R-square value of 0.410 ($F = 36.098$, $p < 0.001$, $Df = 248$). The adjusted R-Square value is reported here because it accounts for inflation of model fit that occurs as an artifact of increasing the number of independent variables in the model (Meyers et al. 2006). Despite a relatively high standard error of the estimate (Std Err = 56.453), the results of Model 1 may be considered robust due to the fact that the adjusted R-Square is statistically significant at the alpha level of 0.05 ($p < 0.001$). The robustness of Model 1 was also supported by the approximately normal distribution of the standardized residuals (Figure 53). The integrity of Model 1 was preserved due to the absence of multicollinearity amongst the independent variables in the final model. The Variance Inflation Factor (VIF) values for *Population Density* (1.792), *Percent Urban* (2.465), *Percent Worked Inside County of Residence* (1.556), *Percent Bachelor's Degree* (1.070), and *Percent 65 Years and Older* (1.476) were all well below the previously established 7.5 threshold described in the Research Methods chapter.

Model 1 accounted for 41% of the variation in per capita municipal water consumption in 2000 using *Population Density*, *Percent Urban*, *Percent Worked Inside County of Residence*, *Percent Bachelor's Degree*, and *Percent 65 Years and Older* as predictors. Conversely, Model 1 failed to account for 59% of the variation in the 2000 per capita municipal water consumption pattern, suggesting that additional variables besides the concentration of population on the physical landscape, the size of the population living in urban areas, commercial activity, post-secondary educational attainment, and the size of the elderly population were influencing the consumption of municipal water. The model fit and diagnostics for Model 1 are given in Table 23, and the standardized beta weights and p-values for each statistically significant independent variable are provided in Table 21.

Additional insight into the relative influences of statistically significant independent variables on per capita municipal water consumption was gained by calculating the beta ratio matrix in Table 24. The rows and columns of Table 24 are organized from left to right in descending order from largest to smallest standardized beta weights. The values along the diagonal are similar to the diagonal values in a correlation matrix, i.e. they represent an independent variable's relationship to itself. For example, the dominant influence of the urban environment in 2000 is clear from the relationship between *Population Density* and the remaining independent variables. The influence of *Population Density* on *Per Capita Municipal Water Consumption* was almost 1.5 times as strong as of *Percent Urban*, slightly more than 2 times as strong as *Percent Worked Inside County of Residence*, slightly more than 2.75 times as strong as *Percent Bachelor's Degree,* and 3 times stronger than *Percent 65 Years and Older.* Additionally, Table 23 suggested that the urbanized environment played a more important in driving the municipal water consumption patterns in 2000 than the social environment despite the stronger representation of the social environment (three statistically significant independent social variables compared to two urbanized variables).

Population Density ($\beta = -0.534$, $p < 0.001$) exerted the strongest influence on per capita municipal water consumption in 2000 and expressed a negative association with the dependent variable which suggested that the consumption of municipal water decreased in response to increases in the percentage of the concentration of population on the physical landscape. Conceptually, this relationship suggested that the urbanized environment influenced municipal water consumption the most heavily, as well as that increased concentrations of population in a county decreased municipal water use. The negative relationship between *Population Density* and *Per Capita Municipal Water Consumption* was likely the result of an increased presence of water efficient appliances in owner occupied dwellings (Davis 2010). This explanation was supported by the statistical significance and direction of the association between *Population Density* and *Percent Owner Occupied* in 1990 ($\tau = -0.151$, $p < 0.001$), which suggested low population densities contained higher percentages of the population that lived in a home that owned.

Combining a county's population density with the suite of other statistically significant independent variables also increased the strength of its relationship with per capita municipal water consumption relative to its individual association (see Table 15). This increased relationship strength due to inclusion in the MLR model suggested that the ability of *Population Density* to explain decreases in the consumption of municipal water was increased by interacting with multiple physical and human landscape characteristics. In other words, the relative influence of the concentration of a county's population on the physical landscape on municipal water consumption became more important than it was individually due to interactions with other driving human and physical landscape characteristics.

Percent Urban ($\beta = 0.363$, $p < 0.001$) exerted the second strongest influence on per capita municipal water consumption in 2000 and expressed a positive association with the dependent variable which suggested that the consumption of municipal water increased in response to increases in the size of the population living in urban areas. Conceptually, this relationship provided additional support for the suggestion that the urbanized environment significantly contributed to municipal water consumption despite being outnumber by the social environment, as well as that the residential component of municipal water consumption decreased in response to increases in the size of the county's population that resided in urban areas. The relative influence of *Percent Urban* on *Per Capita Municipal Water Consumption* also increased from its bivariate correlation of 0.220 which suggested that the interaction of the independent variables increased the ability of changes in a county's urban population to explain the municipal water consumption patterns. In other words, the influence of the size of a county's urban population was slightly stronger under real world conditions where multiple factors combine to drive municipal water consumption than when it was considered individually.

Percent Worked Inside County of Residence ($\beta = 0.262$, $p < 0.001$) exerted a moderately weak influence on per capita municipal water consumption in 2000 and expressed a positive association with the dependent variable which suggested that the consumption of municipal water increased in response to increases in the size of the population consuming water outside the home in a given county. Conceptually, this relationship suggested that municipal water consumption increased in response to increases in commercial activity, as well as that the influence of commercial activity on the consumption of municipal water consumption was less than that of concentrations of population on the physical landscape and the size of the urban population in a given county under circumstances where multiple human and physical landscape characteristics interacted with each other. Including the percentage of the population that worked inside their county of residence in the MLR model also decreased its relative influence on municipal water consumptions in 2000 from its bivariate association of 0.329. This decrease in association strength suggested that the interactions that occur between human and physical driving characteristics in the real world decreased the ability of commercial activity to explain increases in municipal water consumption. In simpler terms, non-residential uses of municipal water were less important to overall municipal water consumption patterns when its interaction with other driving characteristics was considered.

Percent Bachelor's Degree ($\beta = 0.193$, $p < 0.001$) exerted a moderately weak influence on per capita municipal water consumption in 2000 and expressed a positive association with the dependent variable which suggested that the consumption of municipal water increased in response to increases in the percentage of the population that attained post-secondary education. Conceptually, this relationship suggested that the social environmental variables influenced municipal water consumption the most heavily, as well as that increased levels of education increased water use. The positive relationship between *Percent Bachelor's Degree* and *Per Capita Municipal Water Consumption* was likely the result of a latent income effect rather than an increased exposure to environmental and water resource issues. This explanation was supported by the strength and direction of the association between *Percent Bachelor's Degree* and *Per Capita Income* in 1990 ($\tau = 0.474$, $p = 0.001$). A more detailed discussion is available in the original bivariate correlation section of this chapter, and is not repeated here.

Combining the percentage of the population that earned a bachelor's degree with the suite of other statistically significant independent variables also decreased the strength of its relationship with per capita municipal water consumption relative to its individual association (see Table 16). This decreased relationship strength due to inclusion in the MLR model suggested that the ability of *Percent Bachelor's Degree* to explain increases in the consumption of municipal water was decreased by interacting with multiple physical and human landscape characteristics. In other words, the relative influence of postsecondary educational attainment on municipal water consumption became less important than it was individually due to interactions with other driving human and physical landscape characteristics.

Percent 65 Years and Older ($\beta = -0.178$, $p < 0.001$) also exerted a moderately weak influence of *Per Capita Municipal Water Consumption* in 2000, and expressed a positive association with the dependent variable which suggested that the consumption of municipal water decreased in response to increases in the size of a county's elderly population. Conceptually, this relationship suggested that municipal water consumption decreased in response to an increase in the residential water consuming activities of the segment of the county's population that was most likely to spend the most time inside the home. The negative relationship between *Percent 65 Years and Older* and *Per Capita Municipal Water Consumption* was likely due to the reduced frequency of indoor water consuming activities such as showers, dish washing, and clothes washing (Corbella and Pujol 2009).

Including the size of the elderly population in the MLR model for 2000 with the suite of other statistically significant independent variables slightly increased the strength of its relationship with per capita municipal water consumption relative to its individual association (see Table 16). This increased relationship strength suggested that the ability of *Percent 65 Years and Older* to explain decreases in the consumption of municipal water was increased by interacting with multiple physical and human landscape characteristics. In other words, the relative influence of the residential water use activities on municipal water consumption became slightly more important than it was individually due to interactions with other driving human and physical landscape characteristics.

<u>2010 MLR Model 1</u>

The overall MLR model fit was weak in 2010 with an adjusted R-Square value of 0.187 ($F = 20.358$, $p < 0.001$, $Df = 250$). The adjusted R-Square value is reported here because it accounts for inflation of model fit that occurs as an artifact of increasing the number of independent variables in the model (Meyers et al. 2006). Despite a relatively high standard error of the estimate (Std Err = 66.256), the results of Model 1 may be considered robust due to the fact that the adjusted r-square is statistically significant at the alpha level of 0.05 ($p < 0.001$). The robustness of Model 1 was also supported by the approximately normal distribution of the standardized residuals (Figure 54). The integrity of Model 1 was preserved due to the absence of multicollinearity amongst the independent variables in the final model. The Variance Inflation Factor (VIF) values for *Population Density* (1.113), *Percent Worked Inside County of Residence* (1.148), and *Percent High School Diploma* (1.207) were all well below the previously established 7.5 threshold described in the Research Methods chapter.

Model 1 accounted for 18.7% of the variation in per capita municipal water consumption in 1990 using *Population Density*, *Percent Worked Inside County of Residence*, and *Percent High School Diploma* as predictors. Conversely, Model 1 failed to account for 82.3% of the variation in the 2010 per capita municipal water consumption pattern, suggesting that additional variables besides concentrations of population commercial activity, and secondary educational attainment, and were strongly influencing the consumption of municipal water. The model fit and diagnostics for Model 1 are given in Table 25, and the standardized beta weights and p-values for each statistically significant independent variable are provided in Table 21.

Additional insight into the relative influences of statistically significant independent variables on per capita municipal water consumption was gained by calculating the standardized beta ratio matrix in Table 26. The rows and columns of Table 26 are organized from left to right in descending order from largest to smallest standardized beta weights. The values along the diagonal are similar to the diagonal values in a correlation matrix, i.e. they represent an independent variable's relationship to itself. For example, while neither the urbanized or social environment dominantly influenced municipal water consumption, the relative strength of the urbanized environment may be discerned from the relationship between *Population Density* and the remaining independent variables. The influence of *Population Density* on *Per Capita Municipal Water Consumption* was only slightly stronger than *Percent Worked Inside County of Residence,* and more than 1.5 times stronger than *Percent High School Diploma.* Additionally, Table 25 suggested that the urbanized environment played a more important in driving the municipal water consumption patterns in 2010 than the social environment despite the stronger representation of the social environment (two statistically significant independent social variables compared to one urbanized variables).

Population Density ($\beta = -0.291$, $p < 0.001$) exerted the strongest influence on per capita municipal water consumption in 2010 and expressed a negative association with the dependent variable which suggested that the consumption of municipal water decreased in response to increases in the percentage of the concentration of population on the physical landscape. Conceptually, this relationship suggested that the urbanized environment influenced municipal water consumption the most heavily, as well as that increased concentrations of population in a county decreased municipal water use. The negative relationship between *Population Density* and *Per Capita Municipal Water Consumption* was likely the result of an increased presence of water efficient appliances in owner occupied dwellings (Davis 2010). This explanation was supported by the statistical significance and direction of the association between *Population Density* and *Percent Owner Occupied* in 2010 ($\tau = -0.141$, $p = 0.001$), which suggested that low population densities contained higher percentages of the population that lived in a home that they owned.

Combining a county's population density with the suite of other statistically significant independent variables also increased the strength of its relationship with per capita municipal water consumption relative to its individual association (see Table 17). This increased relationship strength due to inclusion in the MLR model suggested that the ability of *Population Density* to explain decreases in the consumption of municipal water was increased by interacting with multiple physical and human landscape characteristics. In other words, the relative influence of the concentration of a county's population on the physical landscape on municipal water consumption became more important than it was individually due to interactions with other driving human and physical landscape characteristics.

Percent Worked Inside County of Residence ($\beta = 0.246$, $p < 0.001$) exerted a moderately weak influence on per capita municipal water consumption in 2000 and expressed a positive association with the dependent variable which suggested that the consumption of municipal water increased in response to increases in the size of the population consuming water outside the home in a given county. Conceptually, this relationship suggested that municipal water consumption increased in response to increases in commercial activity, as well as that the influence of commercial activity on the consumption of municipal water was less than that of concentrations of population on the physical landscape in a given county under circumstances where multiple human and physical landscape characteristics interacted with each other.

Including the percentage of the population that worked inside their county of residence in the MLR model also increased its relative influence on municipal water consumptions in 2010 from its bivariate association of 0.226. This increase in association strength suggested that the interactions that occur between human and physical driving characteristics in the real world increased the ability of commercial activity to explain increases in municipal water consumption. In simpler terms, non-residential uses of municipal water were more important to overall municipal water consumption patterns when its interaction with other driving characteristics was considered.

Percent High School Diploma ($\beta = -0.183$, $p = 0.004$) exerted a moderately weak influence on per capita municipal water consumption in 2010 and expressed a negative association with the dependent variable which suggested that the consumption of municipal water decreased in response to increases in the percentage of the population that attained secondary education. Conceptually, this relationship suggested that increases in the size of a county's population that completed high school decreased water use. The negative relationship between *Percent High School Diploma* and *Per Capita Municipal Water Consumption* was likely the result of a latent income effect rather than an increased exposure to environmental and water resource issues. This explanation was supported by the strength and direction of the association between *Percent High School Diploma* and *Per Capita Income* in 2000 ($\tau = -0.091$, $p = 0.032$). A more detailed discussion is available in the original bivariate correlation section of this chapter, and is not repeated here.

Combining the percentage of the population that completed high school with the suite of other statistically significant independent variables also increased the strength of its relationship with per capita municipal water consumption relative to its individual association (see Table 17). This increased relationship strength due to inclusion in the MLR model suggested that the ability of *Percent High School Diploma* to explain decreases in the consumption of municipal water was increased by interacting with multiple physical and human landscape characteristics. In other words, the relative influence of completing a secondary education on municipal water consumption became more important than it was individually due to interactions with other driving human and physical landscape characteristics.

<u>Summary MLR Model 1</u>

The independent variables used in Model 1, otherwise known as the original model, are listed in Table 27, Table 28, and Table 29 for the years 1990, 2000, and 2010 respectively. The gray cells in each table indicate that a given independent variable was deliberately excluded from a model and was not actively considered. For example, in 1990 all of the independent variables except *Per Capita Building Permits, Per Capita Commercial Businesses,* and *Percent Lodging* had an equal chance of being statistically retained in Model 1. The cells marked with an "x" indicate that an independent variable was statistically included, or retained, in a given model while the cells marked with a "0" indicate that an independent variable was statistically excluded from a given model.

There were three operational independent variables that were statistically significant in more than one year for the Model 1 specification. *Percent Bachelor's Degree* was statistically significant in 1990 and 2000, and exerted the strongest influence on *Per Capita Municipal Water Consumption* in 1990 ($\beta = 0.383$, $p < 0.001$). *Percent Worked Inside County of Residence* was statistically significant in 1990, 2000, and 2010, and exerted the strongest influences on *Per Capita Municipal Water Consumption* in 1990 ($\beta = 0.267$, $p < 0.001$) and 2000 ($\beta = 0.262$, $p < 0.001$) respectively. *Population Density* was statistically significant in 2000 and 2010, and exerted the strongest influence on *Per Capita Municipal Water Consumption* in 2000 ($\beta = -0.534$, $p < 0.001$).

Only two of the three conceptual variables were statistically significant in any given year under the Model 1 specification. The social and physical environments were statistically significant in 1990, and the urbanized and social environments were statistically significant in 2000 and 2010. In 1990, the social environmental variables were both the most numerous, and the most helpful in explaining per capita municipal water consumption (Table 22). In 2000, the urbanized environmental variables were the most helpful in explaining per capita municipal water consumption, despite their smaller frequency (Table 24). The urbanized environment was the most helpful conceptual variable in 2010 (Table 26).

The Model 1 MLR specification performed the best in 2000, when it accounted for 41% of the variation in the county scale per capita municipal water consumption patterns (Adjusted R-Square = 0.410, $F = 36.098$, $p < 0.001$, $Df = 248$). Model 1 produced a slightly weaker model fit in 1990 when it accounted for 38.5% of the variation in per capita county scale municipal water consumption (Adjusted R-Square = 0.385, $F = 40.517$, $p < 0.001$, $Df = 249$). The Model 1 specification performed the worst in 2010 and only accounted for a scant 18.7% of the variation in per capita municipal water consumption patterns (Adjusted R-Square = 0.187, $F = 20.358$, $p < 0.001$, $Df = 250$). Full model diagnostics for each year are listed in Tables 20 (1990), 23 (2000), and 25 (2010).

There were several potential explanations for the exceptionally weak performance of Model 1 in 2010. Firstly, the MLR model could have been grossly miss-specified for the per capita municipal water consumption data in 2010, i.e. important explanatory variables may have been excluded or unimportant explanatory variables may have been included (Draper and Smith 1998; Meyers et al. 2006). This explanation is unlikely given the moderate model fits in 1990 and 2000 using the same set of independent variables, as well as the fact that the standardized residuals were approximately normally distributed (see Figure 54).

Secondly, it was possible that an external force was reducing the variation in per capita municipal water consumption at the county scale. Such a reduction in variation would impair the ability of a linear regression model to detect existing relationships between the dependent and independent variables (Draper and Smith 1998). A cursory visual inspection of the per capita municipal water patterns in 2010 (Figure 45), suggested that lack of variation was not a problem, but the coefficient of variation (CV) revealed that there was very little variation between the consumption of municipal water in individual counties. The CV provides a measure of relative variability between datasets where larger values indicate higher degrees of variation and vice versa. The CV is calculated by dividing the standard deviation of a variable by its mean (Earickson and Harlin 1994). The CV for *Per Capita Municipal Water Consumption* declined from 82.977% in 1990 to 28.037% in 2010 (Table 30).

This reduced variation in the 2010 county scale per capita municipal water consumption patterns may be plausibly explained by the changes that occurred in the development of Texas' State Water Plans between 2000 and 2010. The State of Texas has prepared statewide plans to address present water issues and future water needs every five years since 1961 (TWDB 1997). Prior to the 2002 State Water Plan, water allocation and management strategies were developed relative to Texas' fifteen major river basins. While this unit of analysis is intuitive from the hydrologic perspective, using drainage basins to develop water plans created an administrative nightmare for planners charged with balancing the needs of the myriad county and local agencies involved. For example, the Brazos River Basin extends from the western panhandle to the Gulf of Mexico and covers parts of seventy-four counties (TWDB 1990).

In response to this administrative issue, the Texas Water Development Board collaborated with multiple agencies to redesign the unit of analysis for state water plans to better reflect the combined influences of different economic, cultural, climatic, physiographic, and hydrologic characteristics throughout the state. The new administrative units divided the entire state into sixteen Planning Regions that were first implemented in the 2002 Water for Texas plan (see Figure 5). Under the new Planning Region model, each region develops its own suite of solutions to existing problems, and strategies to meet future demands. Approved regional plans are then aggregated to develop the statewide water plan. The connection between the changeover from drainage basins to Planning Regions and the decrease in the 2010 CV proposed here is that the change in the water management strategy contributed to a decrease in the variation of municipal water consumption between individual counties. The plausibility of this explanation is further supported by the fact that the per capita municipal water consumption of 153 out 254 (60.24%) counties decreased between 1990 and 2010.

In an effort to improve the overall fit of the MLR model, seven additional model permutations were built for each year using three new social environment variables, and partitioning the municipal water consumption data east and west of the dry line. A full listing of the variables included in each model permutation is available in Tables 27, 28, and 29 for the years 1990, 2000 and 2010 respectively. The new social environment variables included *Per Capita Commercial Businesses, Per Capita Commercial Building Permits,* and *Percent Lodging. Per Capita Commercial Businesses* and *Per Capita Commercial Building Permits* were included as independent variables to help improve the explanatory power of commercial activity captured by *Percent Worked Inside County of Residence*. These specific variables were selected for two reasons.

Firstly, the commercial component of municipal water consumption was the only independent variable that was statistically significant in all three years. This temporal consistency suggested that improving its relationship with municipal water consumption stood the best chance of improving the model's explanatory power. Secondly, an internal unpublished Texas Water Development Board study revealed that the consumption of municipal water increased sharply in response to the proliferation of low-density shopping establishments such as strip malls (Personal Communication, Kevin Kluge on

February 25, 2013). Counties were partitioned east and west of the dry line to account for the influence of climate, as well as to informally test the spatial stationarity of municipal water consumption patterns in each year. An improvement in the fit of model, east or west, would have suggested that there were underlying spatial relationships in Texas' per capita municipal water consumption patterns. The extent to which the bivariate correlations, overall model fits, statistically significant independent variables, and spatial analysis of each model permutation differ from Model 1 in each year are presented and discussed following the presentation and discussion of Model 1's spatial analysis.

Model 1 Spatial Analysis

The spatial analysis of the Model 1 results examined the spatial stationarity of the initial patterns of per capita municipal water consumption, the statistically significant independent variables, and the standardized residuals in each year using Moran's I as a measure of global spatial autocorrelation, and Anselin's Local I as a local measure of spatial association. A statistically significant value of Moran's I suggested that spatial processes were present across the entire dataset, while a statistically significant value of Anselin's Local I suggested that spatial processes were present between individual counties. Furthermore, a statistically significant value for either spatial metric suggested that the given variable was not spatially stationary. In other words, the variable's value at one location was related to the value at another location. All Moran's and Anselin's Local I statistics for Model 1were calculated with a Euclidean distance threshold of 171966.75 meters to minimize the distance at which statistically significant clustering was detectable. The results and discussion in this section are organized by rather than by year in order to maintain consistency with the existing format of previous sections.

The per capita municipal water consumption patterns for 1990 exhibited weak, yet statistically significant global spatial autocorrelation ($I = 0.028$, $z = 2.409$, $p = 0.016$). The I, z, and p for the global spatial autocorrelation metric represent the value of the Moran's I index, the z-score, and the p-value of a given dataset respectively. The Moran's I results suggested that the per capita municipal water consumption of any county was weakly related to the per capita municipal water consumption of any other county within the established distance threshold. The Anselin's Local I metric indicated that spatial clusters and spatial outliers were present in the 1990 per capita municipal water consumption patterns. The presence of these clusters and outliers suggested that the patterns of per capita municipal water consumption were not completely spatially random. Oldham and Knox counties were identified as high-high clusters, or areas of high municipal water consumption values surrounded by counties that also had high municipal consumption values. Hudspeth County was identified as a low-high spatial outlier, or an area of low municipal water consumption values surrounded by high municipal water consumption values (Figure 55). A visual comparison of the Local Anselin's I output and the original per capita municipal water consumption patterns in Figure 43 suggested that the local spatial association metric was reflecting actual landscape patterns.

In 1990, The *Percent Bachelor's Degree* patterns expressed a weak degree of global spatial autocorrelation that was statistically significant ($I = 0.080$, $z = 4.551$, $p < 0.001$). The strength of the Moran's I value suggested that the patterns of postsecondary educational attainment in any given county were weakly related to postsecondary education patterns in any other county within the established distance threshold. The local spatial association metric corroborated the Moran's I value and further suggested that the spatial processes were influencing the distribution of the more highly educated segment of the population. High concentrations of bachelor's degree holders lived along the Interstate 35 corridor in Central and North Texas in 1990, and spatial outliers (high-low) were found in Jeff Davis, Lubbock, Midland, and Nacogdoches counties Bexar and El Paso counties did not produce statistically significant concentrations of population that had completed a postsecondary education, and several counties along the southern Texas-Mexico border and the Texas-Louisiana border contained low levels of postsecondary education surrounded by high postsecondary education levels (See Figure 56).

The *Average Annual Precipitation* for 1990 was expressed an almost perfect degree of spatial autocorrelation ($I = 0.905$, $z = 48.528$, $p < 0.001$). The extremely high level of global spatial autocorrelation suggested that rainfall in any county was highly dependent on rainfall in another county within the established distance threshold. The local measure of spatial association metric produced very sharp divides between clusters. East Texas from the Oklahoma border in the north, to the Louisiana border in the east, and out the gulf coast in the south was occupied by a large cluster of high average precipitation. The majority of the panhandle, the northern Texas-Mexico border to Hudspeth County, and the southernmost tip of the Texas-Mexico border, formed two large clusters of low precipitation values (Figure 57). The strong spatial relationships between the precipitation patterns in neighboring counties may have reduced the ability of the 1990 MLR model to detect the true strength of the relationship between average annual precipitation and per capita municipal water consumption at the county scale (Earickson and Harlin 1994; O'Sullivan and Unwin 2010).

In 1990, *Percent Worked in County of Residence* expressed a moderate degree of global spatial autocorrelation (I = 0.196, z = 10.695, p < 0.001). The moderate strength of the Moran's I value suggested that the size of the population that worked in their county of residence was dependent on the size of a population with a similar work location in another county. The local measure of spatial association produced a small checkerboard pattern in the lower panhandle with alternating counties of high-high and statistically insignificant Local I values, a concentration of high values surrounded by high values below the checkerboard on the northern Texas-Mexico border, and a row of alternating spatial outliers along the Interstate 35 corridor (Figure 58). The urban population centers e.g. Bexar, Travis, Dallas, etc., were all high value areas surrounded by low value areas. This pattern of outliers likely reflected the commuting patterns of the workforce along the Interstate corridor, where the high-high counties (job centers) received additional workers from the low-high counties (residential areas).

The *Per Capita Income* in 1990 expressed a strong degree of global spatial autocorrelation (I = 0.315, z = 17.154, p < 0.001). The strong Moran's I value suggested that the per capita income in any given county was highly dependent on the per capita income in another county within the established distance threshold. The local measure of spatial association indicated clusters of low (low-low) per capita income values along the southern Texas-Mexico border from stretching from Val Verde County to Hidalgo County with a smaller cluster in Presidio County. Clusters of high per capita incomes were evident in the northern panhandle along the Texas-Oklahoma border, in north Texas extending for several counties in all directions from the Dallas-Fort Worth Metroplex and north to the Oklahoma border, and in the northern gulf coast around Houston. Travis County was also designated as a concentration of high per capita incomes surrounded by other counties with high per capita income values, while Coryell and McMullen counties were low-high and high-low spatial outliers respectively (Figure 59).

The clusters of low per capita incomes may be partially explained by the seasonality of incomes in the border counties that respond to the fluxes in the agriculture and tourism industries on which their economies relied (TSHA 2013). Likewise, the high-low spatial outlier in McMullen County may be reflecting the influence of the natural gas industry that was still played an active role in the local economy in addition to seasonal tourism activity (TSHA 2013). The clusters of high values around Dallas-Fort Worth and Houston likely reflect the more stable incomes generated by the technology and petroleum industries respectively in addition to the large volumes of services that accompany urban populations (Irwin 2004).

The standardized regression residuals for 1990 expressed a weak yet statistically significant degree of global spatial autocorrelation ($I = 0.042$, $z = 2.464$, $p < 0.014$). The low value of Moran's I suggested that the overall model fit for Model 1 in a given county was weakly related to the overall model fit in another county within the distance threshold. In the sense of overall model fit and integrity, the low level of global spatial autocorrelation suggested that the composite of independent variables in Model 1was not strongly confounded by spatial processes. The local measure of spatial association indicated several small high-high clusters where Model 1 strongly over or underestimated per capita municipal water consumption in the northwest corner of the panhandle along the Texas-New Mexico border, along the Texas-Mexico border in Kinney County, and west of Dallas and Denton counties (Figure 60). Conversely, Anselin's Local I indicated low-low clusters where Model 1 weakly over or underestimated per capita municipal water consumption in the southern tip of Texas, and in the central panhandle west of Lubbock County. In other words, the performance of Model 1 was exceptionally weak in the high-high clusters and exceptionally strong in the low-low clusters. Spatial outliers of exceptionally weak model performance surrounded by exceptionally strong model performance (high-low) were identified in the northern panhandle and along the southern gulf coast. Spatial outliers of exceptionally strong model performance surrounded by exceptionally weak model performance (low-high) were detected on the northern Texas-New Mexico border, and the southern Texas-Mexico border south of Kinney County.

In 2000, the per capita municipal water consumption patterns expressed a moderate degree of global spatial autocorrelation ($I = 0.165$, $z = 7.491$, $p < 0.001$) which suggested that the consumption of municipal water in any given county was moderately dependent on the consumption of municipal water in another county. This moderate degree of spatial association between per capita municipal water consumption patterns may have slightly confounded the ability of Model 1 to estimate the contributions of the driving landscape characteristics. The local measure of spatial association identified a large cluster of high per capita municipal water consumption values along the central Texas-Mexico border and west Texas east of Jeff Davis and Brewster counties, and in the northern panhandle along the Texas-New Mexico border. Several isolated high-high clusters were also found in the eastern panhandle in Childress, Motley, King, and Kent counties (Figure 61). The high value clusters along the Texas-Mexico border closely resemble the original patterns of municipal water consumption in 2000, and suggest a north-south spatial relationship between those counties. Similarly, the northwestern panhandle cluster of high per capita municipal values aligned closely aligned with the original municipal water consumption map, and suggested a north-south chain of spatial dependence between counties.

Clusters of low per capita municipal water values surrounded by other low values were located in the northern gulf coast along the Texas-Louisiana border, in the central gulf coast west of Fort Bend County, and west of Tarrant County in north Texas. These concentrations of low values reflected the original map patterns in Figure 42 and suggested that the per capita municipal water consumptions in these counties may influenced by their proximity to the relatively higher consumption patterns in the adjacent more urbanized metropolitan counties. This influence may reflect the commuting flows from the less urbanized residential counties into the more highly urbanized economic centers of Tarrant, Dallas, and Harris counties. The commercial component of municipal water consumption may be lower in the clusters of low values because residents in these counties work in the economic centers rather than their county of residence. The statistically significant driving landscape characteristics supported this potential explanation as *Percent Worked in County of Residence* was the third strongest influence on *Per Capita Municipal Water Consumption* in 2000 (Table 24).

In 2000, *Population Density* expressed a weak, yet statistically significant degree of global spatial auto correlation ($I = 0.079$, $z = 48.351$, $p < 0.001$) which suggested the physical concentrations of population on the landscape in any county were loosely influenced by the physical concentrations of population on the landscape in another county within the distance threshold. The local measure of spatial association identified two distinct clusters of high population densities that mirror the approximate footprints of the Dallas-Fort Worth and Houston metroplexes (Figure 62). Bexar County was identified as a spatial outlier with high population densities surrounded by low population densities.

The global spatial autocorrelation value for *Percent Urban* in 2000 was also weak, yet statistically significant ($I = 0.053$, $z = 3.053$, $p < 0.001$) which suggested that the percentage of the population residing in urban areas in one county was weakly dependent on the percentage of the population residing in urban areas in another county within the distance threshold. The local measure of spatial association indicated clusters of high urban percentages in the southern tip of Texas along the Texas-Mexico border from Webb County south to Hidalgo County, in the southwest corner of the panhandle with Winkler, Ector, and Andrews counties, and in Galveston County in the northern gulf coast (Figure 63). Clusters of low percent urban values were identified in north-south pattern in the eastern panhandle, and along the Texas-Louisiana border. The local measure of spatial association also detected high-low spatial outliers in El Paso County, Sutton, Tom Green and Taylor counties, and adjacent to the large cluster of low values in the panhandle. Low-high clusters were indentified in the vicinity of the southwestern and southern Texas-Mexico border clusters of high values. The absence of the highly urbanized cores of Dallas-Fort Worth and Houston from the local cluster map was due to the fact that the urban percentages of these counties were not statistically similar or different enough from each other to be detected within the bounds of the distance threshold of 171966.75 meters (Anselin 1995; Le Gallo and Ertur 2003).

The concentrations of high urban percentages in the southwestern panhandle suggested that they may be the result of their proximity to the city of Midland and its dominant petroleum industry (TSHA 2013). Likewise, the cluster of high urban percentages in the southern tip of Texas may have reflected the development of infrastructure to accommodate the maquiladoras along the border (TSHA 2013). The concentrations of low urban percentages in the eastern panhandle may likely be the result of exceptionally low resident populations since all the counties are rural counties with urban percentages of zero. This lack of urban population further suggests that dominant land use was agriculture or ranching in 2000 (TSHA 2013). In general, the strong representation of either high or low clusters of urban percentages (68.89%), suggested that local spatial processes were influencing the urban percentages at the county scale in 2000. The implication here for per capita municipal water consumption is that the local spatial relationships present in the percent urban variable may have affected the global MLR model's ability to detect its true influence on municipal water consumption patterns.

In 2000, *Percent Worked Inside County of Residence* expressed a moderate degree of global spatial autocorrelation in ($I = 0.144$, $z = 7.096$, $p < 0.001$). The moderate strength of this spatial association suggested that the percentage of the population that worked inside their county of residence in one county was moderately spatially dependent on the percentage of the population that worked inside their county of residence in another county within the distance threshold. This finding is important because *Percent Worked Inside County of Residence* was the only driving landscape characteristic of *Per Capita Municipal Water Consumption* that was statistically significant in all three years for Model 1 (see Tables 22, 24, and 26). Although the influence of this independent variable fluctuated from one year to the next, its global spatial association likely affected the MLR model's ability to detect its true relationship to per capita municipal water consumption.

The local measure of spatial association for 2000 (Figure 64) produced a pattern very similar to that of 1990 (Figure 58). The distribution of the low clusters and high-low spatial outliers was identical to 1990 and likely reflected the economic draw of Dallas, Travis, Bexar, and Harris counties. The major difference between the two years was the location of the high percentage clusters. Comparing the 1990 and 2000 maps suggested that the relative composition of worker locations remained largely stable in west Texas and along the northern Texas-Mexico border, while the greatest shifts occurred in the northern panhandle. Counties that were previously identified as high clusters were not statistically different from their surrounding counties in 2000, e.g. Hall, Motley, Cottle, King, Kent and Stonewall counties. This shift indicates that the work locations in these counties became less similar, but not different enough to become outliers (high-low, or low-high).

Percent Bachelor's Degree expressed a moderate degree of global spatial autocorrelation ($I = 0.127$, $z = 7.055$, $p < 0.001$) in 2000 which suggested that the size of the population holding bachelor's degrees in one county was moderately dependent on the size of the population holding bachelor's degrees in another county within the established distance threshold. The global spatial association between the percentage of bachelor degree holders in each county increased from its weak value in 1990 ($I = 0.080$,

$z = 4.551$, $p < 0.001$). This increase suggested that on average, the holders of bachelor's degree became more geographically concentrated.

The Local Anselin's I measure of spatial association produced a pattern of clusters that was nearly identical to the 1990 pattern (Figure 65). High clusters of bachelor's degree holders were found along the Interstate 35 corridor in central Texas (Comal County through Williamson County) and north Texas (Dallas, Tarrant, Denton and Collin counties), along the northern gulf coast (Harris County and Fort Bend County), and Brewster County in west Texas. Low clusters of bachelor's degree holders were found in the southern tip of Texas along the Texas-Mexico border, and on the southern Texas-Louisiana border in Newton County. The spatial outliers also occupied the same relative positions as in 1990. The high-low clusters were located in Jeff Davis County (west Texas); Midland County, Lubbock County, and King County (the panhandle), and Nacogdoches County (east Texas).

The differences between the 1990 (Figure 56) and 2000 (Figure 65) patterns of spatial association were the additional increases of high clusters in central Texas in 2000. The central Texas cluster expanded to include Blanco, Llano, and Bexar counties which suggested that the influence of the existing 1990 cluster may have diffused into these adjacent counties. The low clusters in the southern tip of Texas also expanded slightly to include La Salle, Jig Hogg, and Brooks counties which suggested that the strength of spatial processes driving the concentration of low values in south Texas increased. Overall, the results of the Local Anselin's I suggested that local spatial processes strongly influenced the distribution of bachelor's degree holders in 2000. Twenty-six out of thirty-one counties that produced statistically significant values of Anselin's Local I were clusters of either high or low values (83.87%) which suggested that these spatial association were likely undermined the global linear relationship between *Percent Bachelor's Degree* and *Per Capita Municipal Water Consumption.*

In 2000 *Percent 65 Years and Older* expressed a moderate degree of global spatial autocorrelation ($I = 0.144$, $z = 7.096$, $p < 0.001$), which suggested that the size of the elderly population in one county was moderately influenced by the size of the elderly population in another county within the distance threshold. The local measure of spatial association identified a large cluster of high elderly population values stretching from the northeastern panhandle along the Texas-Oklahoma border south into central Texas just west of the Interstate 35 corridor (Figure 66). Clusters of low elderly population values were found in the north Texas metroplex of Dallas, Tarrant, Denton, and Collin counties, along the northern gulf coast in the vicinity of the Houston metro area including Harris, Fort Bend, Brazoria, Galveston, Chambers, Liberty, and Montgomery counties, and along the southern Texas-Mexico border.

These patterns of high clusters of elderly citizens in predominantly rural counties and low clusters near the highly urbanized cores of Dallas and Houston may reflect a labor migration pattern to some degree. The younger age structure around the economic centers of Dallas and Houston are likely due to the employment migrations of the more youthful working population, while the elderly concentrations in the panhandle may represent either family members left behind in family homesteads or retirees seeking to escape the influence of the city (Weeks 1996). The low clusters of elderly populations along the southern Texas-Mexico border may be due an increased presence of young families with small children, or a lack of amenities that older segments of the population typically require, such as advanced medical care and a reliable public transportation infrastructure (Weeks 1996). In any case, the pronounced north-south cluster that extends from the panhandle into central Texas is likely to have influenced the contribution of the elderly population to per capita municipal water consumption in the original MLR model. Additionally, the influence of spatial processes on the distribution of the size of the elderly population was relatively strong given that 91.23% (fifty-two out of fifty-seven) of all counties with statistically significant Local Anselin I values were clusters of either high or low elderly populations.

The *Standardized Residuals* for the 2000 Model 1 MLR specification expressed a weak, yet statistically significant degree of global spatial autocorrelation ($I = 0.054$, $z = 3.108$, $p < 0.001$), which suggested that the model fits in one county were weakly spatially associated with the model fits in another county within the distance threshold. The Anselin's Local I results indicated clusters of high standardized residual values in the northwestern corner of the panhandle, the western base of the panhandle in west Texas (Winkler, Ector, and Ward counties), and in the northeastern corner of the state near the Texas-Louisiana border (Figure 67). Clusters of low standardized residual values were identified in north central Texas west of Denton and Dallas counties (Jack, Young, Stephens, and Erath counties), and southwest of Fort Bend County (Wharton, Matagorda, Jackson, Victoria, Calhoun, and Goliad counties). The clusters of high and low residuals suggested that the performance of the Model 1 MLR specification was exceptionally weak or exceptionally strong in these areas respectively.

The high-low clusters were located west of the north central Texas low cluster (Shackleford and Taylor counties), and on the northern, eastern, and southwestern flanks of the gulf coast low cluster (Fort Bend, Gonzales, and Jim Wells counties). The low-high clusters were located west and southwest of Collingsworth County (Donley County and Floyd County), and east of the west Texas cluster of high values (Martin County and Glasscock County). The high percentage of counties with statistically significant Local Anselin's I values that were clusters of either high or low standardized residuals (71.88%, 23 out of 32) suggested that local spatial relationships between county model fits may have been strong enough to influence the overall MLR model fit for the Model 1 specification. Additionally, the distribution of clusters in Figure 67 suggested a southeasterly north-south gradient of model fits, with weak model performances in the northern portion of the state transitioning to strong model performances along the gulf coast. This apparent gradient further suggested a potentially strengthened influence of local climatic conditions on per capita municipal water consumption in 2000.

The per capita municipal water consumption patterns in 2010 expressed a moderate degree of global spatial autocorrelation ($I = 0.144$, $z = 7.096$, $p < 0.001$), which suggested that the consumption of municipal water in one county was moderately influenced by the consumption of municipal water in another county within the distance threshold. The degree of global spatial association between the municipal water consumption patterns in neighboring counties was slightly lower than 2000 ($I = 0.165$, $z = 9.159$, $p < 0.001$), and much higher than 1990 ($I = 0.028$, $z = 2.409$, $p = 0.016$). This decrease in the Moran's I index suggested that on average, the influence of spatial processes on municipal water consumption became weaker between 2000 and 2010. Conversely, the increased Moran's I index suggested that on average, the influence of spatial processes on municipal water consumption dramatically increased between 1990 and 2010.

The local measure of spatial association identified clusters of high per capita municipal water consumption values along the northern Texas-Mexico border extending east to include Winkler, Ward, Crane, and Upton counties, and in the northern panhandle in the vicinity of Amarillo. Clusters of low per capita municipal water consumption values were found east and southeast of Tarrant County, and along the northeastern Texas-Louisiana border north of Gregg County (Figure 68). The clusters of high values reflect the original 2010 per capita municipal water consumption patterns in Figure 45 to varying degrees, with the northern panhandle exhibiting a nearly perfect visual match. The high cluster in west Texas and the northern Texas-Mexico border did not visually match the original pattern of consumption values quite as closely, but it clearly illustrated that the spatial relationships between western and northern border counties exerted a considerable influence on the performance of the Model 1 MLR specification in 2010.

The greatest change in cluster locations and volume were evident in comparisons between 1990 and 2000, and 1990 and 2010. Comparing the number of clusters in each year to the total number of counties that produced a statistically significant value of Anselin's Local I, the relative influences of local spatial processes on per capita municipal water consumption increased over time. The percentage of clusters increased from 66.67% (two out of three) in 1990, to 86.96% (forty out of forty-six) in 2000, and again to 92.11% (35 out of 38) in 2010. One potential explanation for these increased spatial influences is that they may partially reflect the transition of the primary planning unit from major drainage basins to planning regions implemented by the Texas Water

Development Board in the 2002 state water plan (TWDB 1997). If further research demonstrated that this change in administrative planning units was partially responsible for the intensification of spatial relationships between counties and the reductions in per capita municipal water consumption that occurred between 2000 and 2010 (Figure 69), it would suggest that changes in water management influenced the municipal water consumption patterns.

In 2010, *Population Density* expressed a weak, yet statistically significant degree of global spatial autocorrelation ($I = 0.095$, $z = 48.351$, $p < 0.001$), which suggested that the physical concentration of population on the landscape in one county was weakly associated with the physical concentration of population on the landscape in another county within the distance threshold. The local measure of spatial association detected clusters of high population densities in north Texas that encompassed the Dallas-Fort Worth metro area, and along the northern gulf coast in the vicinity of the Houston metroplex (Figure 70). These clusters of high population densities clearly reflect the physical footprint of the major metropolitan areas that they contain. The only difference between the population density clusters in 2000 and 2010 is the statistical insignificance of Bexar County in 2010. This change is more closely related to population density changes in the counties that surround Bexar County, rather than population density changes in Bexar County itself. The statistical insignificant Anselin's Local I value for Bexar County in 2010 suggested that the differences in population density between Bexar County and those counties surrounding it were not statistically different. In other words, the population densities in the immediate vicinity of Bexar County became more homogenous between 2000 and 2010. Additionally, the presence of only two clusters of high population densities suggested that these contributed exclusively to the global spatial autocorrelation in the *Population Density* variable for 2010.

Percent Worked Inside County of Residence expressed a moderate degree of global spatial autocorrelation in 2010 (I = 0.154, z = 8.4162, $p < 0.001$), which suggested that the size of the population that worked in their own county in one county was moderately dependent on the size of the population that worked in their own county in another county within the distance threshold. The degree of global spatial association in 2010 was stronger than in 2000 (I = 0.144, z = 7.906, $p < 0.001$), but weaker than in 1990 (I = 0.196, z = 10.694, $p < 0.001$). This comparison of results between years suggested that on average the commercial component of per capita municipal water consumption may have confounded the Model 1 MLR specification in all three years to varying degrees with the strongest influences occurring in 1990 and 2010. This relevance of this observation lies in the fact that *Percent Worked Inside County of Residence* was the only driving landscape characteristic of per capita municipal water consumption that was statistically significant in all three years.

The local measure of spatial association produced a pattern of clusters and spatial outliers similar to that of 2000 (Figure 71). The patterns of high-low spatial outliers matched 2000 pattern, but there were several small changes to the distribution of low value clusters. The low clusters gained Fannin, Red River, and Brazoria counties, and lost Hood and Coryell counties. The low-low spatial outliers lost the northern panhandle counties of Roberts, Randall, and Jones, and gained Martin County. The high clusters remained concentrated in west Texas along the northern Texas-Mexico border, and gained Webb, Zavala, Starr, and Hidalgo counties in the southern tip of Texas. The high clusters also experienced a mild shift in the panhandle, gaining Dickens and King Counties, and losing Dawson, Scurry, Howard, Lubbock, Childress, and Ector Counties.

The general pattern of both clusters (high and low) and outliers was generally consistent with the original per capita municipal water consumption in Figure 45, and the greatest influences on the global spatial autocorrelation of *Percent Worked Inside County of Residence* were located along the Texas-Mexico border, and along the urban corridors of central and northern coastal Texas. The percentage of counties with statistically significant values of Anselin's Local I that were identified as high or low clusters (76.32%, 58 out of 76) also suggested that the spatial relationships between counties may have influenced the ability of the Model 1 MLR specification to detect the true strength of the relationship between *Percent Worked Inside County of Residence* and *Per Capita Municipal Water Consumption*.

In 2010, *Percent High School Diploma* expressed a moderate degree of spatial autocorrelation ($I = 0.133$, $z = 11.727$, $p < 0.001$), which suggested that the size of the population with a high school diploma was moderately dependent on the size of the population with a high school diploma in another county within the distance threshold. The local measure of spatial association indicated clusters of high percentages of high school diploma holders in the southeast corner of the Texas-Louisiana border, and approaching the panhandle in the northwestern portion of the state (Figure 72). Clusters of low values were identified along the urban corridor between Bexar County and Travis County, and the along northern, central, and southern Texas-Mexico border. The cluster of high values on the Texas-Louisiana border extends both north-south and east-west, and likely reflected the employment opportunities available in these counties (natural resource extraction, tourism, and retail), as well as the fact that greater than 60% of residents work inside their counties of residence in seven out of fourteen (50%) of the counties in the cluster (TSHA 2013).

The cluster of low values along the Bexar County-Travis County urban corridor was probably a response to the concentration of higher education institutions (The University of Texas at San Antonio, Texas State University-San Marcos, and The University of Texas at Austin, etc.) rather than a low percentage of high school graduates in the area. The percentage of bachelor's degree holders for Bexar, Comal, Hays, and Travis Counties were 25.3%, 32.6%, 35%, and 43.5% respectively. The cluster of low values along the Texas-Mexico border was likely the result of the available job opportunities (tourism, retail, and agriculture), and high percentages of residents working in their own counties (TSHA 2013). All of the counties in the border cluster of low values recorded at least 60% of residents working inside their own counties. Overall, the high percentage of counties with statistically significant Local Anselin I values that were identified as either high or low clusters (88.10%, 37 out of 42) suggested that the distribution of high school diploma holders was influenced by local spatial processes. These spatial processes, in turn, may have confounded the MLR Model 1 specification.

The *Standardized Residuals* for the 2010 Model 1 MLR specification expressed a weak yet statistically significant degree of global spatial autocorrelation ($I = 0.085$, $z = 4.752$, $p < 0.001$), which suggested the model fit in a given county was weakly influenced by the model fit in another county within the distance threshold. The local measure of spatial association indicated clusters of high standardized residuals in the northern panhandle along the Texas-Oklahoma border, in west Texas northwest of Pecos County, northeast of Williamson County in central Texas (Milam and Falls Counties), and in east Texas approaching the Texas-Louisiana border (Figure 73). The clusters of low values formed a ring around Lubbock County, and extended eastwardly towards north central Texas. Spatial outliers were detected in Coke County (high-low) and Angelina County (low-high). These spatial distributions of clusters and outliers suggested that the performance of the MLR Model 1 specification was exceptionally weak in high consumption locations such as the northwestern panhandle, and exceptionally strong in low consumption locations such as the peripheral counties of Lubbock County (see Figure 45). Additionally, the high percentage of counties with statistically significant values of Local Anselin's I that were identified as high or low clusters (92.31%, 36 out of 39) suggested that spatial processes may have contributed to the poor fit of the global MLR Model 1 specification.

<u>Summary Spatial Analysis of MLR Model 1</u>

The original per municipal water consumption patterns in each of the three years in this study expressed at least a weak statistically significant of degree global spatial autocorrelation at the county scale. The strongest global, or average, spatial autocorrelation value was present in the spatial distribution of per capita municipal water consumption for 2000 ($I = 0.165$, $z = 9.159$, $p < 0.001$), and the weakest global spatial association occurred in 1990 ($I = 0.028$ $z = 2.409$, $p = 0.016$). The statistical significance of these Moran's I values ($p < 0.050$) strongly suggested that the spatial associations were not detected by random chance. Each of the statistically significant driving landscape characteristics of per capita municipal water consumption also expressed at least a weak statistically significant degree of global spatial autocorrelation.

The most noteworthy driving landscape characteristic was *Percent Worked Inside County of Residence* which belonged to the social environmental conceptual variable, and represented the commercial component of municipal water consumption. This variable expressed a moderate degree of statistically significant global spatial autocorrelation, and was the only independent variable that exerted a temporally consistent influence on per capita municipal water consumption despite variations in relationship strength (see Table 20), and spatial association. The degree of statistically significant global spatial autocorrelation for *Percent Worked Inside County of Residence* was the strongest in 1990 ($I = 0.196$, $z = 10.694$, $p < 0.001$), the second strongest in 2010 ($I = 0.154$, $z = 8.416$, $p < 0.001$), and the weakest in 2000 ($I = 0.144$, $z = 7.906$, $p < 0.001$). The implication here is that the driving landscape characteristic that should likely be considered in all county scale global models of per capita municipal water consumption patterns is also likely to seriously confound the model results.

Weak yet statistically significant degrees of global spatial autocorrelation were also present in the standardized residuals of the Model 1 MLR specification for each year. The global spatial associations of the regression residuals increased steadily from 1990 ($I = 0.042$, $z = 2.465$, $p = 0.014$), to 2000 ($I = 0.054$, $z = 3.108$, $p = 0.002$), and through 2010 ($I = 0.085$, $z = 4.753$, $p < 0.001$). This increase in spatial association over time suggested that the ability of the global MLR model to explain the statistically significant driving landscape characteristics of consistently degraded every year between 1990 and 2010. Additionally, local measures of spatial association revealed influential locations that contributed the most strongly to the global spatial association of each per capita municipal water consumption pattern, each statistically significant driving landscape characteristic of municipal water consumption, and each model fit for all three years. Overall, the relatively high percentages of spatial clusters of high or low values suggested that while the degree to which spatial processes influenced varied over time in the Model 1 specification, the patterns and driving landscape characteristics of per capita municipal water consumption are largely spatially non-stationary.

MLR Model Tuning and Adjustments

The weak to moderate model fits for the original MLR Model 1 specification in 1990, 2000, and 2010 resulted in the development of seven additional models for each year. Models 2, 3, 7, and 8 experimented with additional independent variables to improve the strength of the relationship between commercial water use and per capita municipal water consumption at the county scale, while Models 4 and 5 explored the effects of regionalizing the original dataset based on a physiographic and climatic divide. The decision to improve the relationship strength of the commercial component of municipal water consumption was made because *Percent Worked Inside County of Residence* (the commercial water variable), was the only driving landscape characteristic that was statistically significant in all three years. Similarly the decision to explore the effects of a regionalization was a dual attempt to improve overall model fit, as well as to informally test the spatial stationarity of per capita municipal water consumption patterns at the county scale. A complete list of every model permutation is available in Table 7.

Model 2 added the *Per Capita Commercial Businesses* independent variable to the original suite of independent variables in Model 1 (Table 3) to capture commercial water use more directly. The underlying assumption with the addition of this independent variable was that a greater number of commercial businesses would translate into a higher consumption of municipal water. Model 3 retained all of the independent variables from Model 1 except *Percent Worked Inside County of Residence,* which was replaced by *Per Capita Commercial Businesses*. Models 4 and 5 used the original set of independent variables from Model 1, but divided all of the counties in Texas into regions east and west of the dry line respectively. Interstate 35 was used to approximate the average position of dry line, due to the freeway's north-south orientation through the entire state of Texas and its location along the Balcones Escarpment which serves an approximate climatic divide.

Model 6 also used the original variables from Model 1, and provided a baseline of municipal water consumption patterns for comparison with Model 7 which introduced the *Per Capita Building Permits* variable. This baseline was required to account for the removal of twenty-five counties that did not collect data on residential building permits during the study period. Model 8 substituted *Percent Lodging* for the *Percent Worked Inside County of Residence* and retained all of the other independent variables from Model 1. The *Percent Lodging* independent variable attempted to capture the influence of transient tourism activity on per capita municipal water consumption, where the number of businesses dedicated to accommodations was expressed as a percentage of the total number of commercial businesses. In the following sections, the overall performance of each model permutation and its influence on the statistically significant landscape characteristics that drive per capita municipal water consumption are briefly discussed by year. Special attention is given to the models that improved the fit of the original Model 1 specification. The spatial analyses of model residuals are presented following the discussion of the global MLR results for each model.

1990

In 1990, Model 2 left the overall model fit of the original specification unchanged (Table 20). The strength of the original bivariate correlations between *Per Capita Municipal Water Consumption* and *Percent Worked Inside County of Residence* (τ = 0.320, $p < 0.001$), and between *Per Capita Municipal Water Consumption* and *Per Capita Commercial Businesses* (τ = 0.225, $p < 0.001$) suggested that the influence of the latter variable may have been masked by the former. This suggestion proved correct when the substitution of per capita commercial businesses for the percentage of the population working in their own county increased the overall global model fit in Model 3 (Adjusted R-Square = 0.411, F = 26.191, $p < 0.001$, Df = 246). Model 3 accounted for 41.1% of the variation in per capita municipal consumption, while Model 1 only accounted for 38.5%. Additionally, this substitution of independent variables altered the character of the statistically significant driving landscape characteristics, as well as the relative importance of the conceptual variables.

Model 3 suggested that *Population Density* (β = -0.346, $p < 0.001$) exerted the greatest influence on per capita municipal water consumption, followed by, *Percent Bachelor's Degree* (β = 0.339, $p < 0.001$), *Average Annual Precipitation* (β = -0.246, $p < 0.001$) and *Per Capita Income* (β = -0.224, $p < 0.001$). In addition to the physical concentration of population on the landscape, the Model 3 specification also identified three other driving characteristics that were not previously statistically significant in 1990 including *Percent Single Family* (β = -0.222, p = 0.017), *Percent Urban* (β = 0.164, p = 0.026), and *Per Capita Commercial Businesses* (β = 0.155, p = 0.004). The directions of the relationship between each of the statistically significant independent variables in

Model 3 and per capita municipal water consumption were consistent with Model 1 despite changes in relationship strength between models. The standardized beta weights and significance values for each statistically significant driving landscape characteristic for Models 1 and 3 may be directly compared in Table 21.

All three conceptual variables (the social, urbanized, and physical environments) demonstrated statistically significant influences on municipal water consumption in Model 3 unlike the exclusion of the urbanized environment from Model 1. Model 3 also altered the relative influence of each conceptual variable. The urbanized and social environment were the most the important influences on municipal water when considered from the perspective of magnitude, but the social environment was most important by quantity (57.14%, 4 out of 7 variables). Model 1 suggested that the social and physical environments (Table 22) were the most influential by magnitude, but the social environment dominated in terms of quantity.

The standardized residuals for Model 3 expressed a moderate degree of global spatial autocorrelation ($I = 0.247$, $z = 13.429$, $p < 0.001$), which suggested that the fit of Model 3 in one county was moderately dependent on the fit of Model 3 in another county within the distance threshold. This moderate value of Moran's I was more than five times higher than that of Model 1 (($I = 0.042$, $z = 2.465$, $p = 0.014$), which suggested that the increased model fit may have resulted from a small amount of collinearity between some of the variables in the model. An inspection of the Variance Inflation Factor (VIF) for the independent variables in Model 3 suggested that while collinearity was stronger than in Model 1, all values were well below the minimum 5.0 value of concern (Meyers et al. 2006; Pedhazur 1997). The highest VIF was 3.627 for *Percent Single Family*.

The local measure of spatial association indicated clusters of high standardized residuals (weak model performance) in north Texas east of Denton County (Collin, Rockwall, Hunt, Rains, and Franklin Counties), and along the central Texas-Mexico border in Kinney County (Figure 74). Clusters of low standardized residual values (strong model performance) were detected in the central panhandle south of Lubbock County (Lynn County), in the southern tip of Texas oriented east-west between Zapata and Willacy Counties (Jim Hogg, Brooks, and Kennedy Counties), and southwest of Tarrant County (Erath and Hood Counties). Spatial outliers of low residual values (strong model performance) surrounded by high residual values were found along the northern Texas-New Mexico border in Loving County, in the northern panhandle northeast of Amarillo (Hutchinson County), and in north Texas northeast and southeast of Dallas County (Delta and Hutchinson Counties). Spatial outliers of high residual values (weak model performance) surrounded by low residual values were identified in central Texas north sandwiched between San Saba and Lampasas Counties (Mills County), along the southern gulf coast in Calhoun, Nueces, and Willacy Counties, and along the southern Texas-Mexico border in Zapata County. The moderate percentage of counties with statistically significant values of Local Anselin's I that were identified as clusters of exceptionally strong or weak model performance (54.55%, 12 out of 22) suggested that the influence of local spatial processes were weaker than in Model 1 which supported the increased fit of Model 3.

Models 4 (32.0%) and 5 (36.4%) explained less of the variation in per capita municipal water consumption patterns than Model 1 (38.5%) in 1990, and are not discussed in detail here. However, Models 4 and 5 did produce useful insights in 1990.

Regionalizing the original dataset into segments east and west of the dry line, suggested that the original Model 1 specification performed better in drier climates than in wetter climates for 1990. The different model fits produced by the data regionalization also suggested that per capita municipal water consumption patterns in 1990 were not spatially stationary across multiple scales. Table 20 provides the actual Adjusted R-Square values, values of F, significance values, and degrees of freedom for Models 4 and 5.

Models 6 and 7 improved the amount of variation accounted for from 38.5% in Model 1 to 44.0%. This improvement, however, was due to the removal of outliers rather than the inclusion of a more powerful explanatory variable. The twenty-five counties that were removed from the model due to the absence of residential building permit data were scattered throughout the state and shared several common characteristics. Seventy-six percent of these counties had population densities of less than one person per square kilometer, and 80% had a percent urban value of zero.

A review of the bivariate correlations in Table 15 suggested the removal of these twenty-five counties improved the strength of the relationships between *Per Capita Municipal Water Consumption, Population Density,* and *Percent Urban* respectively. The strength of the association between *Per Capita Municipal Water Consumption* and *Population Density* increased from -0.128 ($p = 0.002$) in Model 1 to -0.148 ($p = 0.001$) in Model 7. Likewise, the association strength between *Per Capita Municipal Water Consumption* and *Percent Urban* increased from 0.208 ($p < 0.001$) in Model 1 to 0.243 ($p < 0.001$) in Model 7. The values for Model 6 were identical to those of Model and are not reported. These increases in the strength of the bivariate association may have contributed to the statistical significance of *Population Density* in Model 7 which helped increase the overall model fit.

Model 7 suggested that *Population Density* ($\beta = -0.318$, $p < 0.001$), *Average Annual Precipitation* ($\beta = -0.313$, $p < 0.001$), and *Percent Single Family* ($\beta = -0.281$, $p = 0.001$) were the most influential statistically significant driving landscape characteristics of *Per Capita Municipal Water Consumption.* The slightly weaker statistically significant influences included *Percent Worked In County of Residence* ($\beta = 0.238$, $p < 0.001$), and *Percent Bachelor's Bachelor Degree* ($\beta = 0.186$, $p = 0.002$). These results further suggested that the importance of consumption reducing drivers was greater than that of consumption increasing drivers.

The relative influences of the conceptual variables were also altered by the exclusion of the counties without building permit data. The urbanized and physical environments were the most important influences on per capita municipal water consumption by magnitude, but the social environment provided the greatest quantity of statistically significant driving landscape characteristics. Model 1 shared Model 7's dominance of the social environment as gauged by the quantity of its significant variables, as well as the high relative importance of the physical environment (Table 21).

The standardized residuals for Model 7 expressed no statistically significant global spatial autocorrelation ($I = 0.023$, $z = 1.337$, $p = 0.181$) which suggested that the spatial associations that may exist between the model fits in any county were not statistically different from a random pattern within the distance threshold. The local measure of spatial association detected clusters of exceptionally weak model performance along a northeasterly diagonal stretching from Dallas County to Lamar County on the northeastern border of Texas and Oklahoma, and a short northeasterly diagonal from Dimmit County to Frio County on the southern Texas-Mexico border (Figure 75). Clusters of exceptionally strong model performance were located in the central panhandle south and southwest of Lubbock County, and in Erath County. Spatial outliers of model weak model performance surrounded by strong model performance were found west and north of the Dimmit-Frio cluster of weak model fits, and northeast of the Dallas-Lamar cluster of strong model fits. A single spatial outlier of weak model performance was found in Shackleford County. The moderate percentage of counties with statistically significant values of Anselin's Local I that were identified as clusters of weak or strong model performances (63.16%, 12 out of 19) suggested that local spatial processes were confounding Model 7's ability to explain the consumption patterns of municipal water in 1990. This moderate percentage of clusters may also be combined with the suggestion of complete spatial randomness provided by the Moran's I metric to clearly illustrate that the modifiable areal unit problem may impact global MLR models.

Model 8 improved the overall model fit from 0.385 ($F = 40.517$, $p < 0.001$, $Df = 249$) to 0.393 ($F = 36.806$, $p < 0.001$, $Df = 223$). Although the increased explanatory power of Model 8 was marginal (0.8%) and the *Percent Lodging* variable was not statistically significant, the model did shift the relative importance of both the operational and conceptual landscape characteristics that drive municipal water consumption. Model 8 suggested that *Population Density* ($\beta = -0.384$, $p < 0.001$), *Percent Bachelor's Degree* ($\beta = 0.358$, $p < 0.001$), and *Average Annual Precipitation* ($\beta = -0.260$, $p < 0.001$) were the most influential statistically significant explanatory variables for per capita municipal water consumption. *Percent Urban* ($\beta = 0.197$, $p = 0.008$) and *Per Capita Income* ($\beta = -$

0.192, p = 0.005) were also statistically significant driving landscape characteristics with weaker influences (Table 20). Conceptually, Model 8 suggested that the urbanized and social environments held the greatest degree of influence over per capita municipal water consumption from the perspectives of both magnitude and quantity. The importance of the physical environment was greatly reduced as the contribution of *Annual Average Precipitation* decreased from -0.310 ($p < 0.001$) in Model 1 to -0.260 ($p < 0.001$) in Model 8. However, the fact that the contribution of *Average Annual Precipitation* remained statistically significant despite this explanatory loss suggested that its influence on the patterns of municipal water consumption should not be ignored. In other words, the persistence of precipitation in multiple model permutations for 1990 suggested that it was a relatively robust indicator of per capita municipal water consumption.

The standardized residuals for Model 8 expressed an exceptionally weak degree of global spatial autocorrelation that was not statistically significant (I = 0.023, z = 1.430, p = 0.153), which suggested that the model fit in one county was not significantly influenced by the model fit of any other county within the distance threshold. In other words, the global spatial distribution of the standardized residuals was not statistically different from a random pattern. The local measure of spatial association indicated clusters of exceptionally weak model performance (high residuals) along a northeasterly diagonal stretching from Rockwall County east of Dallas County to Lamar County on the Texas-Oklahoma border (Figure 76). Clusters of exceptionally strong model performance (low residuals) were detected in Lynn County south of Lubbock County, in Erath County southwest of Tarrant County, and along an east-west transect in the southern tip of Texas from the Texas-Mexico border to the Gulf of Mexico. Spatial outliers of weak model performance surrounded by strong model performance were located along the southern gulf coast, and on the western and southern edges of the southern Texas cluster of model overestimates. Spatial outliers of strong model performance were found in the northern panhandle (Hutchison and Wheeler Counties), in west Texas west of Midland County (Loving County), and in the vicinity of the cluster of weak model performance in northeast Texas.

The percentage of counties with a statistically significant value of Anselin's Local I that were clusters of weak or strong model performance (high-high or low-low) was 52.38% (11 out of 21). This moderate percentage of statistically significant clusters supported the weak spatial relationships detected by the Moran's I global spatial autocorrelation, but also reinforced the importance of scale in spatial analysis. The moderate percentage of high-high and low-low clusters suggested that the standardized residuals were influenced by local spatial processes, and that the clustered counties may share a group of characteristics that produced similar model performances.

<u>2000</u>

Models 2 and 3 did not enhance the overall performance of the Model 1 specification in 2000 and are not discussed further. The model fit and diagnostics for all model permutations in 2000 are available in Table 23. Model 4, which contained only the counties east of the dry line, increased the overall model fit from Model 1's 0.410 ($F = 34.059$, $p < 0.001$, $Df = 248$) to 0.422 ($F = 18.380$, $p < 0.001$, $Df = 114$). This increase in model fit suggested that per capita municipal water consumption estimates in 2000 were sensitive to broad climatic differences, and provided further support for the spatial non-stationarity of municipal water consumption patterns. The three-way differences between Models 1, 4, and 5 (Adjusted R-Square = 0.360, F = 14.641, $p < 0.001$, Df = 129), also suggested that changing the scale of analysis altered the ability of a global model to explain the variation in per capita municipal water consumption as well as the which driving landscape characteristics were the most influential.

Model 4 suggested that the greatest influence on the 2000 patterns of per capita municipal water consumption east of the dry line were *Population Density* (β = 0-.557, $p < 0.001$), *Percent Urban* ($\beta = 0.495$, $p < 0.001$), and *Percent Bachelor's Degree* ($\beta = 0.421$, $p < 0.001$). *Percent Surface Water* ($\beta = 0.226$, $p = 0.001$) and *Percent Worked Inside County of Residence* ($\beta = 0.152$, $p = 0.077$) also played important but weaker roles in explaining the consumption patterns of municipal water. Despite, being statistically insignificant at $\alpha = 0.05$, the *Percent Worked Inside County of Residence* variable was included in Model 4 due to the 0.100 significance of the removal threshold in the stepwise regression algorithm. Similarly, the independent variable was not manually removed from the model because its temporal consistency suggested that it may contain practical significance to the consumption of municipal water.

A noteworthy anomaly present in the 2000 version of Model 4 was the statistical significance of *Percent Surface Water* and the reversal of direction from its 2000 bivariate correlation with *Per Capita Municipal Water Consumption* in Model 1 (Table 16). The initial associations suggested, albeit weakly and without statistical significance, that the per capita consumption of municipal water decreased in response to increases in the percentage of surface water used in municipal water supplies. However, the regionalization of the 2000 per capita municipal water consumption patterns suggested that counties east of the dry line increased their consumption of municipal water in response to using a greater proportion of surface water to meet municipal demands. Explaining this relationship in detail required further research that was beyond the scope of this study, but it generally resembled the depletion problems associated with common pool resources or public resources with shared access (CPR).

Depletion becomes a problem with CPR resources due to the prevailing attitude towards conservation, which asserts that reduced resource consumption by one party in the present results in resource hoarding by another party in the future (Krause et al. 2003; Ostrum et al. 1994). Under the most extreme case of this scenario, the hoarding party may continue to accumulate resources to the exclusion of the conserving party. Texas water laws such a Prior Appropriation could unintentionally create this type of situation if holders of surface water rights were supremely interested in maintaining their present allotment in perpetuity (Thompson 1999).

All three conceptual variables (the social, urbanized, and physical environments) were represented in Model 4, but the urbanized and social environment variables were clearly the most influential by magnitude of association. When viewed from the perspective of quantity, the urbanized and physical environments exerted approximately equal influences on the consumption of municipal water. The physical environment was among the lowest in terms of both magnitude and quantity.

The standardized residuals for Model 4 in 2000 expressed a weak degree of global spatial autocorrelation ($I = 0.060$, $z = 1.750$, $p = 0.080$), which suggested that over or underestimates of per capita municipal water consumption in one county were weakly influenced by over or underestimations of per capita municipal water consumption in another county within the distance threshold. This weak degree of global or average, spatial association between the standardized residuals of individual counties may have confounded the Model 4 MLR specification's ability to detect the true relationships between per capita municipal water consumption and its statistically significant driving landscape characteristics due to a lack of independence between observations.

The local measure of spatial association indicated clusters of high standardized residual values (exceptionally weak model performance) east of the Texas-Mexico border and north of Webb County (La Salle and McMullen Counties) (Figure 77). Clusters of low residuals (exceptionally strong model performance) were identified in a north-south strip along the central gulf coast in between Fort Bend County and Nueces County. A lone high-low spatial outlier (weak model performances surrounded by strong model performances) was detected north of the low clusters on the gulf coast (Fort Bend County). Low-high spatial outliers (strong model performances surrounded by weak model performances) were found approaching east Texas north of Harris County (Leon County), and on the northern gulf coast southeast of Harris County (Galveston County). The high percentage of counties with statistically significant values of Anselin's Local I that were identified as clusters of either weak or strong model performance (76.92%, 10 out of 13) supported the presence of global spatial influences, and suggested that local spatial processes were influencing the distribution of model performances.

Model 5 decreased the overall model fit from 0.410 ($F = 34.059$, $p < 0.001$, $Df = 248$) to 0.360 ($F = 14.641$, $p < 0.001$, $Df = 129$), and thus is mentioned only as further evidence that spatial and geographic processes contribute to and influence the per capita consumption of municipal water. Models 6 and 7 increased the overall model fit from Model 1 to 0.424 ($F = 42.933$, $p < 0.001$, $Df = 224$). As in 1990, this increase in model fit was due largely to the exclusion of the twenty-five counties without residential building permit data during the study period (1990, 2000, and 2010), because the experimental independent variable was not statistically significant.

Models 6 and 7 suggested that *Population Density* ($\beta = -0.417$, $p < 0.001$), and *Percent Urban* ($\beta = 0.332$, $p < 0.001$) were the most influential driving landscape characteristics of *Per Capita Municipal Water Consumption* in 2000. *Percent Worked Inside County of Residence* ($\beta = 0.234$, $p < 0.001$) and *Percent High School Diploma* ($\beta = -0.219$, $p < 0.001$) were also important to lesser degrees. The directions of association for the driving landscape characteristics were evenly represented with two characteristics that increased per capita municipal water consumption and two characteristics that decreased per capita municipal water consumption, which was a rare occurrence between years or models.

Only two out the three conceptual variables were included in Model 7, and the physical environment was not among them. The urbanized environment was the most important explanatory conceptual variable for Model 7 in 2000 in the sense of magnitude, but was evenly matched from the perspective of the quantity of operational variables. As evidenced in Table 23, the 2000 version of Model 8 did not increase the overall model fit of Model 1 (Adjusted R-Square = 0.410, $F = 26.107$, $p < 0.001$, Df = 246), and its experimental independent variable was not statistically significant. Therefore, the statistically significant variables are not discussed here.

The standardized residuals for Model 7 in 2000 expressed a weak degree of global spatial autocorrelation ($I = 0.072$, $z = 3.713$, $p < 0.001$), which suggested that over or underestimates of per capita municipal water consumption in one county were weakly influenced by over or underestimations of per capita municipal water consumption in another county within the distance threshold. This weak degree of global or average, spatial association between the standardized residuals of individual counties may have confounded the Model 7 MLR specification's ability to detect the true relationships between per capita municipal water consumption and its statistically significant driving landscape characteristics due to a lack of independence between observations.

The local measure of spatial association indicated clusters of high standardized residual values (exceptionally weak model performance) in the northern panhandle stretching eastward from the northern Texas-New Mexico border towards the eastern Texas-Oklahoma border, south and southeast of Midland County, and north of Dallas County stretching eastward towards the eastern Texas-Louisiana border (Figure 78). Clusters of low residuals (exceptionally strong model performance) were identified in a north-south strip along the central gulf coast in between Fort Bend County and Nueces County, on the southern Texas-Mexico border sandwiched between Starr and Cameron Counties, and a north-south column west of Tarrant County and east of Shackleford County. High-low spatial outliers (weak model performances surrounded by strong model performances) were detected on the northern Texas-Oklahoma border in Wichita County, west of the high cluster that was west of Tarrant County (Shackleford, Taylor, and Kent Counties), and Gonzales County in central Texas. Low-high spatial outliers (strong model performances surrounded by weak model performances) were found north of Midland County (Martin County), and in the northern panhandle southeast of the panhandle high cluster (Donley County). The high percentage of counties with statistically significant values of Anselin's Local I that were identified as clusters of either weak or strong model performance (74.36%, 29 out of 39) supported the presence of global spatial influences, and suggested that local spatial processes were influencing the distribution of model performances.

2010

The especially poor overall fit of Model 1 in 2010 (Adjusted R-Square =0.187, F = 20.358, $p < 0.001$, Df = 250) provided much of the impetus for the subsequent development of the eight model permutations explored in this section of the present chapter. As in both 1990 and 2000, the addition of *Per Capita Commercial Businesses* to the existing suite of independent variables Model 2 did not improve the Model 1 results. Hence, the model fit and diagnostics for Model 2 are available in Table 25, and the standardized beta and significance values for each statistically significant driving landscape characteristic are provided in Table 21 without further explanation here. Model 3 decreased the overall model fit of Model 1 from 0.187 to 0.186 (F = 20.358, $p < 0.001$, Df = 249) and is not discussed here.

Model 4 also failed to improve the Model 1 results, and only accounted for 7.6% (Adjusted R-Square = 0.076, F =10.775, $p < 0.001$, Df = 118) of the variation in per capita municipal water consumption in 2010 compared to 18.7% in Model 1. This exceptionally low fit for Model 4 suggested that the original suite of independent variables from Model 1 poorly explained the variation in per capita municipal consumption in relatively wet or humid climates in 2010. Model 5 provided the best model fit of any model in 2010 and accounted for 37.6% of the variation of per capita municipal water consumption (Adjusted R-Square = 0.376, F = 14.352, $p < 0.001$, Df = 127).

Model 5 suggested that *Population Density* (β = -0.458, $p < 0.001$), and *Percent Single Family* (β = -0.421, $p < 0.001$), were the most influential explanatory variables for per capita municipal water consumption in 2010, followed by *Percent Owner Occupied* (β = 0.367, $p < 0.001$), and *Percent Surface Water* (β = -0.328, $p < 0.001$). *Percent Urban* (β = 0.266, $p < 0.001$) and *Percent Worked Inside County of Residence* (β = -0.176, $p < 0.053$) also contributed to per capita municipal water consumption to a lesser degree. Although in violation of the required significance level of this study (α = 0.05), the commercial component of municipal water consumption was retained in the model because it was the only independent variable that was statistically or very near statistically significant (α = 0.05) in all three years for every model permutation in which it was included.

Model 5's statistically significant driving landscape characteristics behaved similarly to those of most other models with several notable exceptions. The association directions of *Percent Owner Occupied,* and *Percent Worked Inside County of Residence* were opposite of the directions of these variables in all other model permutations. Model 5 displayed a positive association between *Per Capita Municipal Water Consumption* and *Percent Owner Occupied,* which suggested that per capita municipal water consumption at the county scale increased in response to increases in the size of the population that lived in a home that they owned. The direction and strength of this relationship suggested that the *Percent Owner Occupied* variable may have been reflecting an increased use of residential outdoor water to maintain lawns and other outdoor areas. This explanation is plausible based on the strength and direction of the association between *Average Annual Precipitation* and *Per Capita Municipal Water Consumption* in

2010 ($\tau = -0.248$, $p < 0.001$) which suggested that reductions in the short-term moisture supply increased the consumption of municipal water.

Model 5 also displayed a negative association between *Per Capita Municipal Water Consumption* and *Percent Worked Inside County of Residence* which suggested that per capita municipal water consumption at the county scale increased in response to decreases in the size of the population that worked in their own county. This reversal of association direction cannot be reasonably explained via currently available data and requires further research. Conceptually, Model 5 suggested that all three conceptual variables (the social, urbanized, and physical environments) contributed to the patterns of per capita municipal water consumption in counties west of the dry line in 2010. The urbanized and social environments were the most influential explanatory variables in terms of magnitude and quantity. As in previous years, the differences in model performance that occurred as a result of dividing the original dataset into groups of counties east and west of the dry line suggested that patterns of per capita municipal water consumption were not spatially stationary at the county scale.

The standardized residuals for Model 5 in 2010 expressed a moderately weak degree of global spatial autocorrelation ($I = 0.087$, $z = 4.426$, $p < 0.001$), which suggested that the model performances in one county were moderately dependent the model performances in another county within the distance threshold. This moderately weak degree of global or average, spatial association between the standardized residuals of individual counties may have confounded the Model 5 MLR specification's ability to detect the true relationships between per capita municipal water consumption and its statistically significant driving landscape characteristics due to a lack of independence between observations.

The local measure of spatial association indicated clusters of high standardized residual values (exceptionally weak model performance) in the northern panhandle northeast of Amarillo (Hutchison, Carson, and Wheeler Counties), in west Texas along northern Texas-New Mexico border (Reeves and Ward Counties), and a triangle in north Texas including Dallas, McLennan, and Anderson Counties (Figure 79). Clusters of low residuals (exceptionally strong model performance) were identified in an east-west diagonal stretching from the western Texas-New Mexico border towards north central Texas. This low cluster completely enclosed Lubbock County, which suggested that the Model 5 estimate for Lubbock County was close to its actual value, while Model 5 significantly overestimated or underestimated the counties on Lubbock County's periphery. High-low spatial outliers (weak model performances surrounded by strong model performances) were detected on the western Texas-New Mexico border west of Lubbock County, and in central Texas north of Bexar County (Comal County). Low-high spatial outliers (strong model performances surrounded by weak model performances) were found in east Texas east of the southern edge of the high cluster triangle (Angelina County), and on the southern gulf coast (Kennedy County). The high percentage of counties with statistically significant values of Anselin's Local I that were identified as clusters of either weak or strong model performance (87.1%, 27 out of 31) supported the presence of global spatial influences, and suggested that local spatial processes were influencing the distribution of model performances.

Models 6 and 7 both increased the overall model fit of Model 1 from 0.187 ($F = 20.358$, $p < 0.001$, $Df = 250$) to 0.205 ($F = 20.557$, $p < 0.001$, $Df = 225$) and 0.210 ($F = 16.128$, $p < 0.001$, $Df = 224$) respectively. The removal of the twenty-five counties without residential building permit data in Model 6 increased the percentage of explained per capita municipal water consumption variation by 2.3%, while the addition of the *Per Capita Business Permit* independent variable produced a net explanatory power increase 0.5% (the difference between Model 6 baseline 20.5% and Model 7 21.0%). Despite the marginal increase in model fit and explanatory power, the statistically significant driving landscape characteristics for Model 7 are presented here rather than those of Model 6.

Model 7 suggested that Population *Density* ($\beta = -0.317$, $p < 0.001$) was the most important explanatory variable for per capita municipal water consumption at the county scale in 2010, followed by *Percent High School Diploma* ($\beta = -0.219$, $p < 0.001$) and *Percent Worked Inside County of Residence* ($\beta = 0.212$, $p = 0.001$). *Per Capita Building Permits* ($\beta = 0.182$, $p < 0.016$) and *Annual Average Precipitation* ($\beta = -0.169$, $p < 0.030$) were also important to a lesser degree. The directions of the associations between the driving landscape characteristics of per capita municipal water consumption were consistent across time periods, as well as with all other model permutations that considered every county in the dataset. The positive association between *Per Capita Municipal Water Consumption* and Per *Capita Building Permits* suggested that the consumption of municipal water increased in response to an increase in the average number of residential building permits per county resident. Another interpretation of this relationship is that growth in residential development increased the residential component of municipal water consumption.

The social, urbanized, and physical environments were all statistically significant driving landscape characteristics of per capita municipal water consumption in 2010. The urbanized environment was the most important explanatory conceptual variable in terms of magnitude, but the social environment accounted for most of the explanatory power in terms of quantity of variables. The physical environment was the weakest conceptual explanatory variable in 2010 for Model 7. Model 8 decreased the overall model fit of Model 1from 0.187 ($F = 20.358$, $p < 0.001$, $Df = 250$) to 0.186 ($F = 15.456$, $p < 0.001$, $Df = 249$), and thus its statistically significant driving landscape characteristics are not discussed here. Model 8's experimental variable, *Percent Lodging*, failed to significantly contribute to per capita municipal water consumption, which suggested that the transient population fluxes associated with tourism activities did not influence the consumption of municipal water in 2010.

The standardized residuals for Model 7 in 2010 expressed a moderate degree of global spatial autocorrelation ($I = 0.103$, $z = 3.060$, $p = 0.002$), which suggested that over or underestimates of per capita municipal water consumption in one county were moderately dependent on over or underestimations of per capita municipal water consumption in another county within the distance threshold. This moderate degree of global, or average, spatial association between the standardized residuals of individual counties may have confounded the Model 7 MLR specification's ability to detect the true relationships between per capita municipal water consumption and its statistically significant driving landscape characteristics due to a lack of independence between observations.

The local measure of spatial association indicated clusters of high standardized residual values (weak model performance) in the northwestern panhandle along the Texas borders with New Mexico and Oklahoma, a group of north-south clusters along the eastern panhandle border with Oklahoma, and a lone cluster in Coryell County (Figure 80). Clusters of low residuals (strong model performance) were identified in the central panhandle north of Lubbock County (Hale), east of Midland County (Howard, Nolan, and Irion Counties), and El Paso County in west Texas. A lone high-low spatial outlier (weak model performances surrounded by strong model performances) was detected towards the edge of the study area in Palo Pinto County, and low-high spatial outliers (strong model performances surrounded by weak model performances) were found at the center of the northern panhandle cluster of model underestimates and on the southern border northern Texas-New Mexico border. The high percentage of counties with statistically significant values of Anselin's Local I that were identified as clusters of either weak or strong model performance (85%, 17 out of 20) supported the presence of global spatial influences, and suggested that local spatial processes were influencing the distribution of model performances.

Summary: MLR Model Tuning and Adjustments

The results of the model tuning process suggested that the greatest improvements in model performance were achieved through the regionalization of the original Model 1 specification into counties east and west of the dry line, or the exclusion of outliers. The regionalization of the original Model 1 specification suggested that controlling for climatic differences within a region often improved the overall fit of the global model, and altered the relative importance of the driving landscape characteristics. The results of the regionalization (Models 4 and 5) also suggested that the analysis of per capita municipal water consumption patterns was sensitive to changes in scale.

The influence of scale was loosely supported by the fact that the counties east and west of the dry line produced different model fits within the same year, and altered the statistical significance and relative importance of the driving landscape characteristics. The model improvements that occurred as a result of outlier removal were not surprising as the effects of outliers on global models such as multiple linear regression have been extensively documented (Earickson and Harlin 1994; Draper and Smith 1998; Kleinbaum et al. 1988; Meyers et al. 2006). However, the removal of outliers may be problematic in geographical analysis because the excluded entities often have important practical significance or represent real world locations. For example, while excluding specific counties from a per capita municipal water consumption model may improve the global model fit, it may also complicate spatial analysis by creating artificial gaps between observations.

The differences in model fit and statistical significance of driving landscape characteristics within years as a result of changes in scale, and the improvements gained from the removal of outliers suggested that patterns of municipal water consumption were not spatially stationary. Exploratory spatial analysis of the standardized residuals for each global model permutation that improved the overall model fit of the original Model 1 specification further supported the spatial non-stationarity of per capita municipal water consumption. All models that improved the original Model 1 specification in each year expressed at least a weak degree of global spatial autocorrelation as estimated by Moran's I. The Local Anselin's I values for these same models suggested that model fits in each model in each year were influenced by local spatial processes. A brief summary of specific model improvements is given below.

In 1990, Models 3, 8, and 7 improved the overall model fit of the original Model 1 specification. Models 3 and 7 increased the amount of explained variation in the pattern of per capita municipal water consumption by 2.6%, 0.8%, and 5.5% respectively. The improvements of Models 3 and 8 were the attained through changes in the independent variables, while the improvements of Model 7 resulted from the removal outliers. The model improvements in 2000 were attributed to the regionalization of the original per capita municipal water consumption dataset in Model 4, and the removal of outliers in Model 7. Model 4 improved the amount of explained variation in the pattern of per capita municipal water consumption by 1.2%, and Model 7 increased the explained variation by 2.4%.   Regionalization of the original dataset in Model 5 made the greatest improvement to the original Model 1 specification in 2010, increasing the amount of explained variation in the pattern of per capita municipal water consumption by 18.9%.

Overall Summary of Results

Research Question 1

The first research question in this study aimed to determine which social, urbanized, and physical environmental landscape characteristics significantly contributed to municipal water consumption patterns at the county scale. The results indicated that the social and urbanized environment exerted a greater degree of influence on the consumption of municipal water than the physical environment in all three years. The original model specification (Model 1) suggested that the social environment was the most important explanatory variable in 1990, while the urbanized environment was the most important explanatory variable in 2000 and 2010. Detailed information on the relative influences of each statistically significant driving landscape characteristic is in Table 22 (1990), Table 24 (2000), and Table 26 (2010).

The significant landscape characteristics varied by year and included *Percent Bachelor's Degree, Average Annual Precipitation, Percent Worked Inside County of Residence*, *Per Capita Income*, *Population Density*, *Percent Urban*, *Percent 65 Years and Older,* and *Percent High School.* In 1990, municipal water consumption was best explained by the combination of *Percent Bachelor's Degree, Average Annual Precipitation*, *Percent Worked Inside County of Residence,* and *Per Capita Income*. The landscape characteristics for 2000 included *Population Density*, *Percent Urban, Percent Worked Inside County of Residence, Percent Bachelor's Degree*, and *Percent 65 Years and Older*. In 2010, the following landscape characteristics significantly influenced per capita municipal water consumption: *Population Density*, *Percent Worked Inside County of Residence*, *Percent High School Diploma.*

Permutations of the original model specification suggested that the *Per Capita Commercial Businesses* (Model 3) variable was a statistically significant driving landscape characteristic in 1990 and 2010, and that *Percent Surface Water* (Model 4) was an important explanatory variable in 1990 and 2000. Model 5 also suggested that *Percent Surface Water* was a significant landscape characteristic in 2000 and 2010. Model 7 suggested that *Per Capita Building Permits* was an important contributor to per capita municipal water consumption in 2010. Overall, the experimental independent variables introduced in Models 3, 7, and 8 marginally improved the explanatory power of the commercial component of per capita municipal water consumption.

Research Question 2

The second research question in this study aimed to determine whether or not any of the significant driving landscape characteristics varied over time. This study found that the significant driving characteristics were not temporally static between years despite the presence of several recurring significant independent variables. This finding suggested that given adequate data, cross-sectional or temporal slice methodologies would make useful companions to longitudinal studies which examine aggregate change over time but ignore the factors responsible for the genesis of an individual observation. Furthermore, the examination of temporal slices added the ability to identify changes in the influence of specific driving landscape characteristics in different periods, as well as identify independent variables that were significant in more than one time period.

The identification of recurring significant driving landscape characteristics of per capita municipal water consumption suggested that these operational independent variables should be considered in future explanatory models or water planning efforts. Similarly, the lack of temporal stability in the annual composites of statistically significant independent variables suggested that the influences on municipal water consumption shift over time. Thus, pending available data, frequent cross-sectional analyses of municipal water consumption patterns and their driving landscape characteristics may aid long-range water planning efforts by providing a larger pool of empirical relationships from which to generalize consistent influences on municipal water.

The importance of time was formally examined by comparing the squared semi-partial correlations of each pair of common statistically significant driving landscape characteristics between years. Comparisons between the squared semi-partial correlations of a pair of independent variables is analogous to comparing the bivariate coefficients of determination for a pair of independent variables, i.e. the measures of association have been standardized to facilitate direct comparison (Meyers et al. 2006). Thus, any difference between the squared semi-partial correlations of a pair of statistically significant independent variables may be considered statistically significant itself. Following this logic, a difference of any magnitude between a pair of statistically significant driving landscape characteristics suggested that time played a role in of the change in values between years.

This study found that the commercial component of municipal water consumption, represented by *Percent Worked Inside County of Residence*, was a statistically significant driving landscape characteristic in all three years for sixteen out eighteen (88.89%) of the model permutations that used it. The relative importance of the commercial component of municipal water varied over time in response to its individual association with the consumption of municipal water in each period, as well as the other independent variables in the composite for a given year. The amount of variation accounted for by squared semi-partial correlations for 1990 (5.59%), 2000 (4.38%), and 2010 (5.29%) in Model 1 suggested that time influenced the magnitude of the contribution of *Percent Worked Inside County of Residence* to per capita municipal water consumption.

Although *Percent Worked Inside County of Residence* was the only driving landscape characteristic that was statistically significant in all three years, there were several other recurring independent variables that were statistically significant in more than one year including *Average Annual Precipitation, Percent Single Family, Percent Bachelor's Degree, Per Capita Income, and Per Capita Commercial Businesses*. *Average Annual Precipitation* was a statistically significant driving landscape characteristic in 1990 and 2010 for Models 1 and 8. The Model 1 results suggested that precipitation was more important in 1990 when it accounted for 8.06% of the variation in per capita municipal water consumption than in 2010 when it only accounted for 1.57% of the variation. The Model 8 results agreed with the relative importance of *Average Annual Precipitation* and suggested that precipitation was more important in 1990 when it accounted for 3.93% of the variation in per capita municipal water consumption, than in 2010 when it only accounted for 1.67% of the variation.

Model 8 suggested that *Percent Single Family* was more important in 2010 when it accounted for 3.90% of the total variation in per capita municipal water consumption, than in 1990 it only accounted for 1.17% of the total variation. *Percent Bachelor's Degree* was a statistically significant driver of per capita municipal water consumption in Models 1 and 8. Model 1 suggested that *Percent Bachelor's Degree* was more important in 2000 when it accounted for 3.48% of the total variation in per capita municipal water consumption, than when it accounted for only 2.74% of the variation in 1990. Model 8 reported slightly higher squared semi-partial correlations for *Percent Bachelor's Degree* than Model 1 in both years, and suggested that post-secondary education was more important in 1990 when it accounted for 6.10% of the total variation in per capita municipal water consumption, than in 2000 when it only accounted for 4.04% of the variation.

Per Capita Income and *Per Capita Commercial Businesses* were each statistically significant driving landscape characteristics of *Per Capita Municipal Water Consumption* in two different years for a single model. Model 8 suggested that *Per Capita Income* was more important in 2000 when it accounted for 2.08% of the total variation in per capita municipal water consumption, than in 1990 when it accounted for 1.93% of the variation. Similarly, Model 3 suggested that *Per Capita Commercial Businesses* was more important in 2000 when it accounted for 2.04% of the total variation in per capita municipal water consumption, than in 1990 when it only accounted for 1.96%.

The differences between the contributions of these driving landscape characteristics to per capita municipal water consumption for the years in which they were statistically significant suggested that time influenced which landscape characteristics were important, as well as the magnitude of their contribution. These findings also supported the idea that time should explicitly considered in the analysis of per capita municipal consumption in order to improve long-range water planning projects. Additionally, a Kruskal-Wallis one-way ANOVA performed on the original per capita municipal water consumption values suggested that time also influenced the patterns of municipal water consumption themselves. The Kruskal-Wallis ANOVA suggested that differences between the consumption of municipal water at the county scale were statistically significant at $\alpha = 0.05$ between 1990 and 2000 ($\chi^2 = 6.053$, $p = 0.014$, $N = 508$, $Df = 1$), 1990 and 2010 ($\chi^2 = 4.375$, $p = 0.036$, $N = 508$, $Df = 1$), and 2000 and 2010 ($\chi^2 = 19.044$, $p < 0.001$, $N = 508$, $Df = 1$).

Research Question 3

The third research question in this study investigated the degree to which patterns of per capita municipal water consumption were spatially stationary. Spatial analysis of the original per capita municipal water consumption patterns for all 254 counties in each year (1990, 2000, and 2010) suggested that spatial processes actively influenced the consumption of municipal water both globally and locally at the county scale. Formal tests of global spatial autocorrelation with Moran's I suggested that the consumption of municipal water in one county was weakly to moderately dependent on the consumption of municipal water in neighboring counties within the established distance threshold of 171996.75 meters. This distance threshold was determined using the Ripley's K function to ensure that statistically significant spatial processes were detected with a minimal degree of bias from the spatial relationships inherent in the spatial distribution of the county centroids. Additionally, this distance represented the smallest distance over which statistically significant global spatial autocorrelation was maximized. Anselin's Local I was used to identify the locations that exerted the strongest influence on the measure of global spatial autocorrelation, as well as to identify counties for more detailed analysis of local water policies and consumer scale per capita consumptions of municipal water.

The per capita municipal water consumption patterns for 1990 expressed a weak degree of global spatial autocorrelation ($I = 0.028$, $z = 2.409$, $p = 0.016$), which suggested that the per capita municipal water consumption in one county was weakly influenced by the consumption of municipal water in another county within the distance threshold. Local measures of spatial association identified clusters of high (high-high) per capita municipal water consumption in the northwest panhandle on the western Texas-New Mexico border (Oldham County), and approaching north central Texas east of Lubbock County and northwest of Denton County (Figure 55). A lone spatial outlier of low per capita municipal water consumption surrounded by high municipal water consumptions was identified in on the northern Texas-Mexico border east of El Paso County (Hudspeth County). The high percentage of counties with a statistically significant value of Anselin's Local I that were identified as clusters of high values (66.67%, 2 out of 3) suggested that local spatial processes were actively influencing municipal water consumption patterns, albeit weakly.

Both the clusters of high values and the spatial outlier of low values surrounded by high values also reflected the original 1990 consumption patterns in Figure 39, where Oldham and Knox counties had relatively high per capita consumptions of municipal water, and Hudspeth County had a relatively low per capita consumption of municipal water. The local measure of spatial association also suggested that Oldham and Knox Counties were the locations that most strongly influenced the global (average) measure of spatial auto correlation (Anselin 1995; Le Gallo and Ertur 2003). In other words, these counties uniquely influenced the overall per capita consumption of municipal water at the county scale which would have made them good candidates for a formal study of local water policies and consumer scale water consumption patterns.

In 2000, the per capita municipal water consumption patterns expressed a moderate degree of global spatial autocorrelation ($I = 0.165$, $z = 9.159$, $p < 0.001$), which suggested that the municipal water consumption of one county was moderately dependent on the municipal water consumption of another county within the established distance threshold. Local measures of spatial association indicated clusters of high per capita municipal water consumption (high-high) in a northeast-southeast track along the Texas-Mexico border stretching from Reeves County in the north to Kinney County in the south, on the southern Texas-Mexico border in an east-west configuration (Dimmit and La Salle Counties), a north-south three county column in the northern panhandle along the Texas borders with New Mexico and Oklahoma (Dallam, Hartley, and Oldham Counties), and a parallel diagonal in the eastern panhandle beginning on the southeastern Texas-Oklahoma border and stretching south toward the large cluster of high values along the Texas-Mexico border (Figure 61). Clusters of low per capita municipal water consumption were identified in a northwest-southeast diagonal west of Tarrant County in north Texas (Jack and Wise Counties), east of Dallas County (Van Zandt County), northeast of Harris County reaching from the Harris county border east to the Texas-Louisiana border, east of the large cluster reaching the Texas-Louisiana border and north of Harris County (Leon County),on the western border of Harris County (Waller County), and on the northern gulf coast southwest of Fort Bend County (Wharton, Jackson, and Calhoun Counties).

Spatial outliers of high per capita municipal water consumption surrounded by low per capita municipal water consumption were located east of the large Texas-Mexico border cluster of high values (McCulloch County), on the eastern border of the Texas-Mexico high cluster north of Webb County (McMullen County), and in the northeastern corner of the state on the Texas borders with Oklahoma and Louisiana (Bowie County). Spatial outliers of low per capita municipal water consumption values surrounded by high municipal consumption values were identified along a northwest-southeast diagonal along the eastern border of the large high consumption cluster along the Texas-Mexico border (Martin, Glasscock, and Irion Counties). The very high percentage of counties with statistically significant values of Local Anselin's I that were identified as clusters of either high or low per capita municipal water consumption (86.96%, 40 out of 46) supported the moderate degree of global spatial autocorrelation at the county scale and suggested that local spatial processes were influencing per capita municipal water consumption patterns. The spatial distribution of high and low clusters reflected the original 2000 municipal water consumption patterns in Figure 44, and suggested that these counties were worthy of a more detailed formal investigation of local water policies and consumer scale municipal water consumption patterns.

The 2010 per capita municipal water consumption patterns expressed a moderate degree of global spatial autocorrelation that was slightly weaker than that of 2000 ($I = 0.133$, $z = 7.409$, $p < 0.001$), which suggested that the per capita municipal water consumptions in one county were moderately dependent on the per capita consumption of municipal water in another county within the distance threshold. The local measure of spatial association indicated clusters of high per capita municipal water consumption in a northwest-southeast track along the northern Texas-Mexico border stretching from Culberson County south to Kinney County, in an east-west transect in the northern panhandle stretching eastward from the Texas borders with New Mexico and Oklahoma (Dallam and Sherman Counties), in a northeast-southwest diagonal southeast of the New Mexico and Oklahoma border cluster (Hutchison and Olchitree Counties), in an east-west transect in the northern panhandle northeast of Amarillo stretching from Carson County east to the Texas-Oklahoma border, in the northern panhandle northwest of Amarillo

(Oldham County), and in a north panhandle north-south column stretching from Collingsworth County to Mottle Motley County (Figure 68). Clusters of low per capita municipal water consumption were identified in north Texas west of Tarrant County (Jack, Parker, Erath, Comanche, and Callahan Counties), in an east-west transect north of Gregg County stretching east from Upshur County to the Texas-Louisiana border, and on the central gulf coast southeast of Harris County (Jackson County).

A lone spatial outlier of high per capita municipal consumption surrounded by low per capita municipal water consumptions was found in central Texas northwest of Blanco County. Spatial outliers of low per capita municipal water consumptions surrounded by high per capita municipal water consumptions were located in west Texas on the northern Texas-New Mexico border, and in the southern tip of Texas (Jim Hogg County). The spatial distribution of high and low clusters of per capita municipal water consumption reflected the original map patterns in Figure 45, and suggested that these counties exerted the strongest influence on the global measure of spatial autocorrelation. In other words, these locations of these high and low clusters contributed to the moderate degree of spatial autocorrelation suggested by the Moran's I value. The very high percentage of counties with statistically significant values of Anselin's Local I that were identified as clusters of either high or low per capita municipal water consumption (92.11%, 35 out of 38), suggested that local spatial processes influenced the county scale per capita municipal water consumptions in 2010.

The presence of at least weak global spatial autocorrelation combined with the large percentages of high and low clusters of per capita municipal water consumption in all three years strongly suggested that the consumption of municipal water was not spatially stationary at the county scale. The spatial distribution of the high and low clusters of per capita municipal water consumption reflected the original map patterns in all three years, and identified locations that most strongly influenced the global spatial autocorrelation metric. Additionally, the local measure of spatial association identified locations where formal investigations of local water policies may inform regional and state water plans. Understanding the connections between municipal water consumption in neighboring spatial units are likely to become more important in the future as fresh water supplies continue to dwindle in response to depletion and changes in climate.

CHAPTER V

CONCLUSIONS AND FUTURE RESEARCH

Conclusions

This study analyzed the relationships between per capita municipal water consumption and its social, urban, and physical environmental landscape characteristics in Texas at the county scale. Global multiple linear regression models and measures of global and local spatial association were combined to determine which landscape characteristics significantly influenced county scale per capita municipal water consumption patterns, to determine whether or not the statistically significant landscape characteristics varied over time, and to assess the degree to which the consumption of municipal water was spatially stationary. The unique contribution of this research was the simultaneous consideration of spatial and temporal patterns of municipal water consumption, as well as the analysis of municipal water's landscape characteristics at a small spatial scale with temporally stable units of analysis.

Previous research by House-Peters et al. (2010) and Wentz and Gober (2007) analyzed patterns and drivers of residential water consumption at very fine spatial scales such as census blocks and census tracts for a single city or metropolitan area respectively. These studies demonstrated that spatial analysis techniques such as spatial regression specifications and geographically weighted regression could be successfully applied to understand residential water consumption patterns in concert with high resolution water consumption data such as individual consumer records at relatively fine spatial scales and longitudinal or single cross-section research designs. In contrast, this research used a cross-sectional research design with multiple temporal slices at a relatively coarse spatial scale to examine the statistically significant driving landscape characteristics of the residential and commercial components of municipal water consumption both within and between temporal periods for an entire state. While large scale high resolution studies enable a detailed understanding of individual consumer behavior, they may inadvertently overlook interactions that occur at smaller scales which may influence coordinated water planning decisions. Similarly, understanding how the significant driving landscape characteristics of municipal water consumption vary over time may help improve long-range water planning and the development of demand management strategies that are likely to become necessary in the future as reliable fresh water supplies continue to dwindle (Kundzewicz et al. 2008).

The results of this research suggested that each of the conceptual environmental variables (social, urbanized and physical) contributed significantly to the per capita consumption of municipal water to varying degrees. The urbanized and social environments consistently exerted the strongest influences on per capita municipal water consumption, while the physical environment largely played a supporting role. The social environmental variables had the greatest cumulative influence in all three years as evidenced by the quantity of statistically significant operational variables in each of the three years. However, the urbanized environmental variables singly accounted for the majority of the variation in per capita municipal water consumption when the joint influences of other independent variables were considered. The commercial component of municipal water consumption, measured by the *Percent Worked Inside County of Residence* variable, was the most temporally consistent driving landscape characteristic of per capita municipal water consumption as it was statistically significant in at least two of the three years in the study period for any model in which it was considered. This finding suggested that the commercial component of municipal should not be ignored in county scale water planning efforts. The frequent statistical significance of Population Density in multiple years and model permutations, also suggested that it exerted a temporally consistent influence on county scale per capita municipal water consumption.

Despite the presence of several temporally consistent conceptual and operational variables, the standardized beta ratios and squared semi-partial correlations generated by the MLR models suggested the statistically significant driving landscape characteristics varied significantly over time. This temporal variation was highlighted by both changes in a driving landscape characteristic's magnitude of influence and the composite of drivers that were statistically significant in any model permutation in any given year. The implication of this temporal variability in significance is that single cross-sectional studies or longitudinal studies with short periods of record may not adequately reflect the long-term influences on municipal water consumption patterns. Additionally, the temporal variability in statistically significant drivers suggested that the best understanding of county scale municipal water patterns may be obtained by combining multiple cross-sectional and longitudinal analyses pending available data.

The regionalization of counties east and west of the dry line in Models 4 and 5, and the moderate degree of global spatial autocorrelation present in the standardized residuals of the majority of model permutations for 2000 and 2010, suggested that global models such as multiple linear regression may not be the best tools to explain the driving landscape characteristics and patterns of municipal water consumption at the county scale. The regionalization results (Models 4 and 5) suggested that county level municipal water consumption patterns were sensitive to changes in scale due to differences between the eastern and western regions, and the differences between the regional and original model specifications. These differences included significant differences in the magnitude of influence for a statistically significant driving landscape characteristic, and the overall fit of the model. Similarly, the moderate degree of global spatial association between the standardized residuals in 2000 and 2010 for nearly all model permutations suggested that the per capita municipal water consumptions were influences by spatial processes. These spatial associations between the consumption patterns of neighboring counties may have confounded the ability of the MLR model to detect the true relationships between municipal water consumption and its driving landscape characteristics.

In summary, this study generated several important contributions to inform municipal water consumption research. Firstly, the tendency of county municipal water consumption patterns and its driving landscape characteristics to exhibit spatial non-stationarity suggested that global models may not adequately capture or explain the variability in the consumption of municipal water. Spatially informed regression methods that do not induce multicollinearity may prove more useful in explaining these patterns and uncovering more precise spatial relationships between the municipal water consumptions of neighboring administrative entities. Secondly, the temporal variation in the significant human and physical influences on municipal water consumption suggested that the best understandings of residential and commercial water use may be gained from a combination of multiple cross-sectional and longitudinal analyses for a given location. Combining these research designs may aid the development of demand management strategies for municipal water by identifying temporally consistent influences in concert with aggregate change in overall consumption patterns.

Thirdly, this study suggested that commercial water use significantly influenced overall municipal water consumption patterns at the county scale, which further suggested it should be actively considered in municipal water planning efforts. Fourthly, the regionalization of spatially coarse municipal water consumptions suggested that the significant influences on the use of municipal water was sensitive to changes in scale. In turn, this sensitivity to scale suggested that analyses of municipal water consumption should match the scale at which water planning decisions are made to ensure adequate representation of interactions between the municipal water consumptions of neighboring administrative units. Additionally, it may be useful to investigate patterns and driving landscape characteristics of municipal water consumption at a variety of different scales to determine whether or not scale invariant influences on municipal water exist. The identification of scale invariant influences on municipal water consumption would suggest that they should be included in all municipal water models for a given study area.

Future Research

This study spawned several new research avenues related to the consumption of municipal water. Firstly, the investigation of small scale municipal water consumption patterns should be performed for other arid and semi-arid locations using a similar methodology to compare results. Comparing the results of this research to another location with similar climatic characteristics would help determine which human or physical factors were consistently important across multiple geographies. Secondly, the influence of scale on the patterns and drivers of municipal water consumption should be investigated more thoroughly to determine the degree to which scale affects conclusions drawn from municipal water research. Such an investigation could also be used to compare the scales of municipal water management against various scales of consumption. This study suggested that changes in the scale of fresh water management may have influenced the consumption patterns of municipal water. Finally, these investigations of municipal water consumption over multiple scales and geographies should combine quantitative and qualitative analysis to enhance the understanding of actual influences on municipal water use. The addition of qualitative data may provide insight into intangible yet influential water consumption drivers such as attitudes toward conservation and the water requirements of natural systems.

Table 1. Changes in Population and Water Demand in the Study Area Between 2010 and 2060. Water demands are expressed in acre feet (AF). Source: TWDB (2011).

	2010		2060		Percent Change	
Region	Population	Water Demand	Population	Water Demand	Population	Water Demand
C	6670493	1761352	13045592	3272460	96%	86%
D	772163	561076	1073570	838977	39%	50%
H	6020078	2376414	11346082	3524666	88%	48%
I	1090382	730911	1482448	1490596	36%	104%
Total	14553116	5429753	26947692	9126699	85%	68%
Texas	25388403	18010599	46924167	21952198	85%	22%
Percent of Texas	57%	30%	57%	42%	0%	38%

Table 2. Relative Contribution of Surface Water to 2060 Water Requirements for Selected TWDB Planning Regions. Source: TWDB (2011).

Region	Other Surface Water	New Major Reservoir	Total Surface Water
C	45.1%	30.8%	75.9%
D	93.1%	0.0%	93.1%
H	38.7%	16.5%	55.2%
I	73.0%	15.4%	85.4%

Table 3. List of Conceptual and Operational Variables with Primary Data Sources.

Conceptual Variable	Operational Equivalents	Primary Data Source
Social Environment		
	Educational Level: 1. Percentage of Population with a bachelor's degree * 2. Percentage of Population with a high school diploma* * 25 Years and older	1. National Historic Geographic Information System (NHGIS) 2. U.S. Census Bureau American Community Survey (ACS)
	Income: 1. Per Capita Income	1. NHGIS 2. U.S. Census Bureau ACS
	Average Household Size: 1. County Scale	1. NHGIS
	Population Age Structure: 1. Percentage of Population 18 years and younger 2. Percentage of Population 65 years and older	1. NHGIS 2. U.S. Census Bureau ACS
	Occupancy: 1. Percentage of Owner Occupied dwellings 2. Percentage of Renter Occupied dwellings	1. NHGIS 2. U.S. Census Bureau ACS
	Dwelling Type: 1. Percentage Single Family dwellings 2. Percentage Multi-Family dwellings	1. NHGIS 2. U.S. Census Bureau ACS
	Work Location: 1. Percentage of Population working inside county of residence 2. Percentage of Population working outside county of residence	1. NHGIS
Urbanized Environment		
	Total Population	1. NHGIS
	Population Density: 1. County level	1. Derived from Total Population and County area
	Urbanization Level: 1. Percentage of Urban Population 2. Percentage of Rural Population	1. NHGIS
Physical Environment		
	Drought Conditions: 1. Palmer Hydrological Drought Index (PHDI)	1. U.S. National Climatic Data Center (NCDC)
	Precipitation: 1. Annual Precipitation	1. Texas Water Development Board (TWDB)
	Lake Evaporation: 1. Annual Lake Evaporation	1. TWDB
	Water Source: 1. Percentage Surface Water 2. Percentage Groundwater	1. TWDB

Table 4. Median Values for Income Classes in 1990, 2000, and 2010

Income Class	**Median Value**
Less than $10000	$5500
$10000 to $14999	$12500
$15000 to $24999	$20000
$25000 to $34999	$30000
$35000 to $49999	$42500
$50000 to $74999	$62500
$75000 to $99999	$87500
$100000 to $149000	$125000
More than $150000	$175000

Table 5. Statewide Average Percentages for Educational Attainment in 1990, 2000, and 2010. (Source: U.S. Census Bureau)

Education Level	**Year**		
	1990	*2000*	*2010*
High School Diploma	29.46	30.66	32.66
Bachelor's Degree	12.87	15.34	12.23
Graduate Degree	4.06	5.94	5.19

Table 6. Projection Parameters for the Texas Centric Mapping System/Albers Equal Area Projection. Longitude and Standard Parallels are given in decimal degrees, and Eastings and Northings are provided in meters (Source: State of Texas 2011).

Projection Parameter	**Value**
Longitude of Origin	-100
Latitude of Origin	18
Lower Standard Parallel	27.5
Upper Standard Parallel	35
False Easting	1500000
False Northing	6000000
Datum	North American Datum of 1983
Linear Unit of Measure	Meters

Table 7. Description of Regression Model Permutations for All Years. Model 1 is considered to be the original model and includes only the independent variables listed in Table 3.

Model	**Description**	**N**
1	Original Model for All Years	254
2	Per Capita Commercial Businesses Added to Original Model	254
3	Per Capita Commercial Businesses Replacing Percent Worked Inside County of Residence	254
4	Counties East of the Dry Line	120
5	Counties West of the Dry Line	134
6	Original Model for All Years with Counties Missing Building Permit Data Removed	229
7	Building Permit Data Added to Original Model	229
8	Percent Lodging Replacing Percent Worked In County of Residence	254

Table 8. Results of the Shapiro-Wilk Test for Normality for 1990. The SW column contains the value of the test statistic, and the P column contains the P Value. All variables were tested against the null hypothesis that the distribution of a given variable was statistically different from a normal distribution ($\alpha = 0.05$). Variables with P Values greater than 0.05 are highlighted in bold, and are considered to follow a normal distribution. Gray cells indicate that a variable was excluded from a given model.

	Model											
Variable	*1*		*3*		*4*		*5*		*7*		*8*	
	SW	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*
Annual Average PHDI	0.897	0.000	0.897	0.000	0.841	0.000	0.801	0.000	0.891	0.000	0.897	0.000
Annual Average Precipitation (mm)	0.964	0.000	0.964	0.000	0.960	0.001	0.968	0.003	0.967	0.000	0.964	0.000
Average Annual Lake Evaporation (mm)	**0.990**	**0.065**	**0.990**	**0.065**	0.961	0.001	**0.984**	**0.120**	0.988	0.048	**0.990**	**0.065**
Average Household Size	0.907	0.000	0.907	0.000	0.856	0.000	0.924	0.000	0.898	0.000	0.907	0.000
Per Capita Building Permits									0.535	0.000		
Per Capita Commercial Businesses			0.528	0.000								
Per Capita Income (2010 Dollars)	0.955	0.000	0.955	0.000	0.944	0.000	0.973	0.010	0.944	0.000	0.955	0.000

Table 8 Continued

Variable	Model											
	1		*3*		*4*		*5*		*7*		*8*	
	SW	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*
Per Capita Municipal Water Consumption (L)	0.270	0.000	0.270	0.000	0.873	0.000	0.293	0.000	0.448	0.000	0.270	0.000
Percent 18 Years and Younger	0.979	0.001	0.979	0.001	0.952	0.000	**0.981**	**0.063**	0.975	0.000	0.979	0.001
Percent 65 Years and Older	0.980	0.001	0.980	0.001	**0.982**	**0.118**	0.962	0.001	0.978	0.001	0.980	0.001
Percent Bachelor's Degree	0.802	0.000	0.802	0.000	0.779	0.000	0.856	0.000	0.778	0.000	0.802	0.000
Percent High School Diploma	0.968	0.000	0.968	0.000	0.965	0.003	0.967	0.003	0.957	0.000	0.968	0.000
Percent Lodging											0.573	0.000
Percent Owner Occupied	0.853	0.000	0.853	0.000	0.846	0.000	0.881	0.000	0.925	0.000	0.853	0.000
Percent Single Family Dwellings	0.829	0.000	0.829	0.000	0.839	0.000	0.859	0.000	0.825	0.000	0.829	0.000
Percent Surface Water	0.831	0.000	0.831	0.000	0.850	0.000	0.811	0.000	0.846	0.000	0.831	0.000
Percent Urban	0.930	0.000	0.930	0.000	0.969	0.007	0.863	0.000	0.952	0.000	0.930	0.000

Table 8 Continued												
	Model											
Variable	*1*		*3*		*4*		*5*		*7*		*8*	
	SW	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*
Percent Worked Inside County of Residence	0.909	0.000	0.909	0.000	0.970	0.009	0.811	0.000	0.913	0.000		
Population Density (Square km)	0.310	0.000	0.310	0.000	0.391	0.000	0.334	0.000	0.323	0.000	0.310	0.000

Table 9. Results of the Shapiro-Wilk Test for Normality for 2000. The SW column contains the value of the test statistic, and the P column contains the P Value. All variables were tested against the null hypothesis that the distribution of a given variable was statistically different from a normal distribution ($\alpha = 0.05$). Variables with P Values greater than 0.05 are highlighted in bold, and are considered to follow a normal distribution. Gray cells indicate that a variable was excluded from a given model.

	Model											
Variable	*1*		*3*		*4*		*5*		*7*		*8*	
	SW	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*
Annual Average PHDI	0.887	0.000	0.887	0.000	0.801	0.000	0.830	0.000	0.887	0.000	0.887	0.000
Annual Average Precipitation (mm)	0.957	0.000	0.957	0.000	0.904	0.000	**0.982**	**0.079**	0.960	0.000	0.957	0.000
Average Annual Lake Evaporation (mm)	0.953	0.000	0.953	0.000	0.931	0.000	0.926	0.000	0.943	0.000	0.953	0.000
Average Household Size	0.908	0.000	0.908	0.000	0.836	0.000	0.944	0.000	0.896	0.000	0.908	0.000
Per Capita Building Permits									0.612	0.000		
Per Capita Commercial Businesses			0.983	0.005								
Per Capita Income (2010 Dollars)	0.960	0.000	0.960	0.000	0.944	0.000	**0.981**	**0.056**	0.953	0.000	0.960	0.000

Table 9 Continued

Variable	**Model**											
	1		*3*		*4*		*5*		*7*		*8*	
	SW	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*
Per Capita Municipal Water Consumption (L)	0.803	0.000	0.803	0.000	0.680	0.000	0.871	0.000	0.842	0.000	0.803	0.000
Percent 18 Years and Younger	**0.989**	**0.052**	**0.989**	**0.052**	0.967	0.005	**0.983**	**0.084**	**0.990**	**0.119**	**0.989**	**0.052**
Percent 65 Years and Older	0.983	0.005	0.983	0.005	**0.993**	**0.826**	0.955	0.000	0.983	0.009	0.983	0.005
Percent Bachelor's Degree	0.849	0.000	0.849	0.000	0.797	0.000	0.934	0.000	0.827	0.000	0.849	0.000
Percent High School Diploma	0.986	0.013	0.986	0.013	0.971	0.011	**0.988**	**0.307**	0.984	0.013	0.986	0.013
Percent Lodging											0.663	0.000
Percent Owner Occupied	0.877	0.000	0.877	0.000	0.892	0.000	0.858	0.000	0.940	0.000	0.877	0.000
Percent Single Family Dwellings	0.680	0.000	0.680	0.000	0.869	0.000	0.540	0.000	0.669	0.000	0.680	0.000
Percent Surface Water	0.828	0.000	0.828	0.000	0.854	0.000	0.799	0.000	0.844	0.000	0.828	0.000
Percent Urban	0.920	0.000	0.920	0.000	0.965	0.004	0.857	0.000	0.940	0.000	0.920	0.000
Percent Worked Inside County of Residence	0.957	0.000	0.957	0.000	0.975	0.025	0.923	0.000	0.954	0.000		

Table 9 Continued												
	Model											
Variable	*1*		*3*		*4*		*5*		*7*		*8*	
	SW	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*
Population Density (Square km)	0.320	0.000	0.320	0.000	0.411	0.000	0.333	0.000	0.335	0.000	0.320	0.000

Table 10. Results of the Shapiro-Wilk Test for Normality for 2010. The SW column contains the value of the test statistic, and the P column contains the P Value. All variables were tested against the null hypothesis that the distribution of a given variable was not statistically different from a normal distribution ($\alpha = 0.05$). Variables with P Values greater than 0.05 are highlighted in bold, and are considered to follow a normal distribution. Gray cells indicate that a variable was excluded from a given model.

	Model											
Variable	*1*		*3*		*4*		*5*		*7*		*8*	
	SW	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*
Annual Average PHDI	0.879	0.000	0.879	0.000	0.844	0.000	0.750	0.000	0.869	0.000	0.879	0.000
Annual Average Precipitation (mm)	0.966	0.000	0.966	0.000	0.972	0.014	0.976	0.020	0.962	0.000	0.966	0.000
Average Annual Lake Evaporation (mm)	0.954	0.000	0.954	0.000	0.968	0.006	0.928	0.000	0.947	0.000	0.954	0.000
Average Household Size	0.942	0.000	0.942	0.000	0.869	0.000	0.974	0.013	0.933	0.000	0.942	0.000
Per Capita Building Permits									0.691	0.000		
Per Capita Commercial Businesses			0.983	0.004								
Per Capita Income (2010 Dollars)	**0.996**	**0.671**	**0.996**	**0.671**	**0.987**	**0.337**	**0.994**	**0.861**	**0.995**	**0.621**	**0.996**	**0.671**

Table 10 Continued

Variable	**Model**											
	1		*3*		*4*		*5*		*7*		*8*	
	SW	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*
Per Capita Municipal Water Consumption (L)	0.909	0.000	0.909	0.000	0.948	0.000	0.922	0.000	0.849	0.000	0.909	0.000
Percent 18 Years and Younger	0.988	0.037	0.988	0.037	0.973	0.017	0.980	0.042	**0.991**	**0.148**	0.988	0.037
Percent 65 Years and Older	0.973	0.000	0.973	0.000	**0.980**	**0.067**	0.958	0.000	0.973	0.000	0.973	0.000
Percent Bachelor's Degree	0.883	0.000	0.883	0.000	0.832	0.000	0.938	0.000	0.879	0.000	0.883	0.000
Percent High School Diploma	0.937	0.000	0.937	0.000	0.967	0.005	0.867	0.000	**0.991**	**0.188**	0.937	0.000
Percent Lodging											0.672	0.000
Percent Owner Occupied	0.905	0.000	0.905	0.000	0.907	0.000	0.911	0.000	0.951	0.000	0.905	0.000
Percent Single Family Dwellings	0.908	0.000	0.908	0.000	0.870	0.000	0.962	0.001	0.896	0.000	0.908	0.000
Percent Surface Water	0.833	0.000	0.833	0.000	0.867	0.000	0.795	0.000	0.849	0.000	0.833	0.000
Percent Urban	0.920	0.000	0.920	0.000	0.959	0.001	0.849	0.000	0.939	0.000	0.920	0.000
Percent Worked Inside County of Residence	0.961	0.000	0.961	0.000	0.974	0.019	0.944	0.000	0.958	0.000		

Table 10 Continued												
	Model											
Variable	*1*		*3*		*4*		*5*		*7*		*8*	
	SW	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*	*SW*	*P*
Population Density (Square km)	0.337	0.000	0.337	0.000	0.442	0.000	0.320	0.000	0.354	0.000	0.337	0.000

Table 11. Skewness and Kurtosis for All Models 1990. The Skew column contains the skewness value, and the K column contains the kurtosis value. Variables with both Skew and K values that are below the +/-1.0 threshold are highlighted in bold, and are considered to follow a normal distribution. Gray cells indicate that a variable was deliberately excluded from a given model.

	Model											
Variable	*1*		*3*		*4*		*5*		*7*		*8*	
	Skew	*K*	*Skew*	*K*	*Skew*	*K*	*Skew*	*K*	*Skew*	*K*	*Skew*	*K*
Annual Average PHDI	**-0.481**	**-0.563**	**-0.481**	**-0.563**	-0.489	-1.224	0.483	-1.489	**-0.523**	**-0.641**	**-0.481**	**-0.563**
Annual Average Precipitation (mm)	**0.449**	**-0.474**	**0.449**	**-0.474**	0.008	-1.091	**-0.034**	**-0.777**	**0.359**	**-0.582**	**0.449**	**-0.474**
Average Annual Lake Evaporation (mm)	**0.039**	**-0.320**	**0.039**	**-0.320**	**0.395**	**0.041**	**-0.135**	**0.418**	**0.161**	**-0.232**	**0.039**	**-0.320**
Average Household Size	1.344	2.433	1.344	2.433	1.663	3.318	1.173	1.827	1.411	2.612	1.344	2.433
Per Capita Building Permits									5.229	41.255		
Per Capita Commercial Businesses			6.236	53.794								
Per Capita Income (2010 Dollars)	0.645	2.743	0.645	2.743	0.850	2.602	0.070	1.550	0.707	3.322	0.645	2.743
Per Capita Municipal Water Consumption (L)	10.505	130.013	10.505	130.013	1.950	7.748	7.986	72.883	7.757	79.947	10.505	130.013

Table 11 Continued												
	Model											
Variable	*1*		*3*		*4*		*5*		*7*		*8*	
	Skew	*K*	*Skew*	*K*	*Skew*	*K*	*Skew*	*K*	*Skew*	*K*	*Skew*	*K*
Percent 18 Years and Younger	**0.493**	**0.456**	**0.493**	**0.456**	0.858	1.301	**0.279**	**0.001**	**0.537**	**0.638**	**0.493**	**0.456**
Percent 65 Years and Older	**0.373**	**-0.386**	**0.373**	**-0.386**	**0.053**	**-0.812**	**0.410**	**-0.585**	**0.381**	**-0.371**	**0.373**	**-0.386**
Percent Bachelor's Degree	2.090	5.432	2.090	5.432	2.012	4.197	1.598	3.208	2.215	5.885	2.090	5.432
Percent High School Diploma	**-0.645**	**0.447**	**-0.645**	**0.447**	**-0.574**	**0.133**	**-0.707**	**0.851**	**-0.745**	**0.542**	**-0.645**	**0.447**
Percent Lodging											4.214	22.546
Percent Owner Occupied	-2.138	8.645	-2.138	8.645	-2.042	7.084	-1.899	7.665	-1.194	1.999	-2.138	8.645
Percent Single Family Dwellings	-1.803	3.745	-1.803	3.745	-1.569	2.252	-1.550	2.551	-1.787	3.552	-1.803	3.745
Percent Surface Water	0.387	-1.442	0.387	-1.442	0.413	-1.338	0.371	-1.533	0.285	-1.494	0.387	-1.442
Percent Urban	-0.082	-1.125	-0.082	-1.125	**0.133**	**-0.605**	-0.091	-1.510	**-0.167**	**-0.906**	-0.082	-1.125
Percent Worked Inside County of Residence	**-0.904**	**-0.077**	**-0.904**	**-0.077**	**-0.376**	**-0.644**	-1.647	2.240	**-0.850**	**-0.217**		
Population Density (Square km)	6.795	53.600	6.795	53.600	4.924	26.879	6.995	59.764	6.471	48.440	6.795	53.600

Table 12. Skewness and Kurtosis for All Models 2000. The Skew column contains the skewness value, and the K column contains the kurtosis value. Variables with both Skew and K values that are below the +/-1.0 threshold are highlighted in bold, and are considered to follow a normal distribution. Gray cells indicate that a variable was deliberately excluded from a given model.

	Model											
Variable	*1*		*3*		*4*		*5*		*7*		*8*	
	Skew	*K*	*Skew*	*K*	*Skew*	*K*	*Skew*	*K*	*Skew*	*K*	*Skew*	*K*
Annual Average PHDI	**-0.482**	**-0.817**	**-0.482**	**-0.817**	-1.075	0.306	-0.265	-1.437	**-0.552**	**-0.668**	**-0.482**	**-0.817**
Annual Average Precipitation (mm)	0.141	-1.121	0.141	-1.121	**-0.937**	**0.118**	**0.000**	**-0.517**	0.022	-1.126	0.141	-1.121
Average Annual Lake Evaporation (mm)	**0.574**	**-0.206**	**0.574**	**-0.206**	0.838	2.650	**0.506**	**-0.993**	**0.680**	**0.008**	**0.574**	**-0.206**
Average Household Size	1.433	3.588	1.433	3.588	1.935	5.118	0.991	1.617	1.538	3.988	1.433	3.588
Per Capita Building Permits									2.756	8.307		
Per Capita Commercial Businesses			**0.134**	**0.756**								
Per Capita Income (2010 Dollars)	0.687	2.372	0.687	2.372	0.735	2.405	0.318	0.929	0.732	2.765	0.687	2.372
Per Capita Municipal Water Consumption (L)	2.364	8.370	2.364	8.370	3.900	22.588	1.800	5.321	2.082	7.437	2.364	8.370

Table 12 Continued

Variable	Model											
	1		*3*		*4*		*5*		*7*		*8*	
	Skew	*K*	*Skew*	*K*	*Skew*	*K*	*Skew*	*K*	*Skew*	*K*	*Skew*	*K*
Percent 18 Years and Younger	**0.199**	**0.435**	**0.199**	**0.435**	0.677	1.167	**-0.055**	**0.024**	**0.226**	**0.416**	**0.199**	**0.435**
Percent 65 Years and Older	**0.446**	**0.096**	**0.446**	**0.096**	**0.060**	**-0.391**	**0.608**	**-0.192**	**0.452**	**0.145**	**0.446**	**0.096**
Percent Bachelor's Degree	1.856	4.800	1.856	4.800	1.983	4.371	1.118	1.764	2.008	5.453	1.856	4.800
Percent High School Diploma	**-0.379**	**0.167**	**-0.379**	**0.167**	**-0.505**	**0.058**	**-0.284**	**0.044**	**-0.400**	**0.244**	**-0.379**	**0.167**
Percent Lodging											3.535	18.261
Percent Owner Occupied	-1.801	5.746	-1.801	5.746	-1.542	3.596	-2.162	9.640	-1.055	1.529	-1.801	5.746
Percent Single Family Dwellings	-4.455	35.549	-4.455	35.549	-1.594	3.108	-5.842	47.979	-4.506	35.256	-4.455	35.549
Percent Surface Water	0.371	-1.459	0.371	-1.459	0.202	-1.500	0.535	-1.362	0.245	-1.523	0.371	-1.459
Percent Urban	-0.096	-1.227	-0.096	-1.227	0.006	-0.849	-0.048	-1.545	-0.203	-1.042	-0.096	-1.227
Percent Worked Inside County of Residence	**-0.499**	**-0.656**	**-0.499**	**-0.656**	**-0.046**	**-0.925**	**-0.971**	**0.464**	**-0.477**	**-0.750**		
Population Density (Square km)	6.577	50.570	6.577	50.570	4.728	25.020	7.136	62.396	6.261	45.678	6.577	50.570

Table 13. Skewness and Kurtosis for All Models 2010. The Skew column contains the skewness value, and the K column contains the kurtosis value. Variables with both Skew and K values that are below the +/-1.0 threshold are highlighted in bold, and are considered to follow a normal distribution. Gray cells indicate that a variable was deliberately excluded from a given model

	Model											
Variable	*1*		*3*		*4*		*5*		*7*		*8*	
	Skew	*K*	*Skew*	*K*	*Skew*	*K*	*Skew*	*K*	*Skew*	*K*	*Skew*	*K*
Annual Average PHDI	**0.146**	**0.529**	**0.146**	**0.529**	**0.450**	**-0.811**	2.030	9.062	**0.003**	**0.397**	**0.146**	**0.529**
Annual Average Precipitation (mm)	**-0.667**	**0.409**	**-0.667**	**0.409**	**0.261**	**0.047**	**-0.536**	**0.468**	**-0.735**	**0.706**	**-0.667**	**0.409**
Average Annual Lake Evaporation (mm)	-0.066	-1.219	-0.066	-1.219	**0.292**	**-0.778**	**-0.876**	**0.194**	0.000	-1.286	-0.066	-1.219
Average Household Size	1.096	2.630	1.096	2.630	1.702	4.393	0.614	0.462	1.189	2.989	1.096	2.630
Per Capita Building Permits									2.350	6.733		
Per Capita Commercial Businesses			**0.273**	**0.386**								
Per Capita Income (2010 Dollars)	**-0.038**	**0.219**	**-0.038**	**0.219**	**-0.172**	**0.465**	**0.097**	**0.006**	**0.036**	**0.271**	**-0.038**	**0.219**
Per Capita Municipal Water Consumption (L)	1.410	4.868	1.410	4.868	0.301	1.790	1.310	3.468	1.131	2.238	1.410	4.868

Table 13 Continued

Variable	Model											
	1		*3*		*4*		*5*		*7*		*8*	
	Skew	*K*	*Skew*	*K*	*Skew*	*P*	*Skew*	*P*	*Skew*	*P*	*Skew*	*P*
Percent 18 Years and Younger	**0.015**	**0.805**	**0.015**	**0.805**	**0.423**	**0.962**	**-0.163**	**0.547**	**0.303**	**-0.026**	**0.015**	**0.805**
Percent 65 Years and Older	**0.550**	**-0.141**	**0.550**	**-0.141**	**0.435**	**-0.100**	**0.571**	**-0.420**	**0.589**	**0.053**	**0.550**	**-0.141**
Percent Bachelor's Degree	1.487	2.687	1.487	2.687	1.714	3.033	**0.963**	**0.791**	1.540	3.027	1.487	2.687
Percent High School Diploma	0.673	6.828	0.673	6.828	-0.750	1.007	2.034	12.965	**-0.317**	**0.021**	0.673	6.828
Percent Lodging											3.593	18.909
Percent Owner Occupied	-1.514	4.244	-1.514	4.244	-1.430	3.342	-1.513	5.026	-0.929	1.262	-1.514	4.244
Percent Single Family Dwellings	-1.355	2.699	-1.355	2.699	-1.432	2.061	-0.604	-0.034	-1.445	2.919	-1.355	2.699
Percent Surface Water	0.436	-1.375	0.436	-1.375	0.296	-1.394	0.578	-1.309	0.354	-1.418	0.436	-1.375
Percent Urban	-0.064	-1.258	-0.064	-1.258	0.080	-0.883	-0.025	-1.596	-0.174	-1.090	-0.064	-1.258
Percent Worked Inside County of Residence	**-0.441**	**-0.716**	**-0.441**	**-0.716**	**-0.054**	**-0.968**	**-0.792**	**0.122**	**-0.426**	**-0.783**		
Population Density (Square km)	5.953	40.937	5.953	40.937	4.228	19.713	7.382	66.304	5.660	36.871	5.953	40.937

Table 14. Results for Levene's Homogeneity of Variance Test. The Levene column contains the value of the test statistic. The P-Value column contains the probability that the value of the test statistic occurred by chance. Bolded values indicate variables whose variances are approximately equal.

	Model	
	1	
Variable	*Levene*	*P Value*
Annual Average PHDI	27.080	0.000
Annual Average Precipitation (mm)	44.209	0.000
Average Annual Lake Evaporation (mm)	46.881	0.000
Average Household Size	**2.218**	**0.084**
Per Capita Building Permits		
Per Capita Commercial Businesses		
Per Capita Income (2010 Dollars)	215.119	0.000
Per Capita Municipal Water Consumption (L)	21.929	0.000
Percent 18 Years and Younger	**0.406**	**0.748**
Percent 65 Years and Older	4.859	0.002
Percent Bachelor's Degree	213.089	0.000
Percent High School Diploma	7.953	0.000
Percent Lodging		

Table 14 Continued		
	Model	
Variable	*1*	
	Levene	*P Value*
Percent Owner Occupied	274.485	0.000
Percent Single Family Dwellings	**0.403**	**0.751**
Percent Surface Water	282.517	0.000
Percent Urban	80.938	0.000
Percent Worked Inside County of Residence	139.863	0.000
Population Density (Square km)	**2.238**	**0.082**

Table 15. Bivariate Kendall Tau Correlations for All Models 1990. The P Value column contains the probability that the correlation value (τ) occurred by random chance. A single asterisk denotes statistical significance at $\alpha = 0.05$. A double asterisk denotes statistical significance at $\alpha = 0.01$. Gray cells indicate that a variable was deliberately excluded from a given model Models 2 and 6 are not reported here due to redundancy with other models.

	Model											
Independent Variable	*1*		*3*		*4*		*5*		*7*		*8*	
	Kendall τ	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*
Annual Average PHDI	-.093*	0.028	-.093*	0.028	-0.071	0.252	-.136*	0.021	-.115*	0.010	-.093*	0.028
Annual Average Precipitation (mm)	-.306**	0.000	-.306**	0.000	-.263**	0.000	-.187**	0.001	-.346**	0.000	-.306**	0.000
Average Annual Lake Evaporation (mm)	.226**	0.000	.226**	0.000	.211**	0.001	.117*	0.044	.265**	0.000	.226**	0.000
Average Household Size	0.071	0.094	0.071	0.094	.203**	0.001	0.045	0.445	.094*	0.035	0.071	0.094
Per Capita Building Permits									0.038	0.398		
Per Capita Commercial Businesses			.225**	0.000								
Per Capita Income (2010 Dollars)	-0.063	0.137	-0.063	0.137	0.016	0.792	-0.094	0.107	-0.075	0.090	-0.063	0.137
Percent 18 Years and Younger	.112**	0.008	.112**	0.008	0.105	0.091	0.095	0.103	.147**	0.001	.112**	0.008
Percent 65 Years and Older	-.083*	0.050	-.083*	0.050	-.180**	0.004	-0.089	0.128	-.117**	0.008	-.083*	0.050

Table 15 Continued												
	Model											
Independent Variable	*1*		*3*		*4*		*5*		*7*		*8*	
	Kendall τ	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*
Percent Bachelor's Degree	.194**	0.000	.194**	0.000	.214**	0.001	.176**	0.003	.171**	0.000	.194**	0.000
Percent High School Diploma	-.213**	0.000	-.213**	0.000	-.328**	0.000	-.161**	0.006	-.232**	0.000	-.213**	0.000
Percent Lodging											.097*	0.023
Percent Owner Occupied	-.243**	0.000	-.243**	0.000	-.307**	0.000	-.204**	0.000	-.262**	0.000	-.243**	0.000
Percent Single Family Dwellings	-.110**	0.009	-.110**	0.009	-.305**	0.000	-.118*	0.042	-.125**	0.005	-.110**	0.009
Percent Surface Water	-0.018	0.684	-0.018	0.684	.175**	0.006	-.179**	0.003	-0.030	0.508	-0.018	0.684
Percent Urban	.208**	0.000	.208**	0.000	.346**	0.000	.148*	0.014	.243**	0.000	.208**	0.000
Percent Worked Inside County of Residence	.320**	0.000			.234**	0.000	.271**	0.000	.352**	0.000		
Population Density (Square km)	-.128**	0.002	-.128**	0.002	.156*	0.011	-.140*	0.017	-.148**	0.001	-.128**	0.002

Table 16. Bivariate Kendall Tau Correlations for All Models 2000. The P Value column contains the probability that the correlation value (τ) occurred by random chance. A single asterisk denotes statistical significance at $\alpha = 0.05$. A double asterisk denotes statistical significance at $\alpha = 0.01$. Gray cells indicate that a variable was deliberately excluded from a given model Models 2 and 6 are not reported here due to redundancy with other models.

	Model											
Independent Variable	*1*		*3*		*4*		*5*		*7*		*8*	
	Kendall τ	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*
Annual Average PHDI	-0.022	0.611	-0.022	0.611	-0.031	0.617	-0.041	0.488	-0.018	0.682	-0.022	0.611
Annual Average Precipitation (mm)	-.274**	0.000	-.274**	0.000	-.139*	0.025	-.202**	0.001	-.295**	0.000	-.274**	0.000
Average Annual Lake Evaporation (mm)	.245**	0.000	.245**	0.000	.129*	0.037	.163**	0.005	.269**	0.000	.245**	0.000
Average Household Size	0.057	0.175	0.057	0.175	0.120	0.053	0.114	0.051	0.073	0.101	0.057	0.175
Per Capita Building Permits									-0.055	0.224		
Per Capita Commercial Businesses			.212**	0.000								
Per Capita Income (2010 Dollars)	-.135**	0.001	-.135**	0.001	0.011	0.852	-.175**	0.003	-.149**	0.001	-.135**	0.001
Percent 18 Years and Younger	.168**	0.000	.168**	0.000	.165**	0.007	.187**	0.001	.178**	0.000	.168**	0.000
Percent 65 Years and Older	-.111**	0.009	-.111**	0.009	-.207**	0.001	-.178**	0.002	-.103*	0.021	-.111**	0.009

Table 16 Continued												
	Model											
Independent Variable	*1*		*3*		*4*		*5*		*7*		*8*	
	Kendall τ	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*
Percent Bachelor's Degree	.096*	0.023	.096*	0.023	.245**	0.000	-0.041	0.480	0.077	0.084	.096*	0.023
Percent High School Diploma	-.244**	0.000	-.244**	0.000	-.334**	0.000	-.172**	0.003	-.268**	0.000	-.244**	0.000
Percent Lodging											-0.041	0.335
Percent Owner Occupied	-.249**	0.000	-.249**	0.000	-.334**	0.000	-.201**	0.001	-.253**	0.000	-.249**	0.000
Percent Single Family Dwellings	-0.051	0.226	-0.051	0.226	-.139*	0.025	-0.073	0.212	-0.066	0.139	-0.051	0.226
Percent Surface Water	-0.025	0.575	-0.025	0.575	.236**	0.000	-.201**	0.001	-0.010	0.831	-0.025	0.575
Percent Urban	.220**	0.000	.220**	0.000	.363**	0.000	.213**	0.000	.263**	0.000	.220**	0.000
Percent Worked Inside County of Residence	.329**	0.000			.316**	0.000	.277**	0.000	.358**	0.000		
Population Density (Square km)	-.164**	0.000	-.164**	0.000	.126*	0.041	-.137*	0.019	-.165**	0.000	-.164**	0.000

Table 17. Bivariate Kendall Tau Correlations for All Models 2010. The P Value column contains the probability that the correlation value (τ) occurred by random chance. A single asterisk denotes statistical significance at $\alpha = 0.05$. A double asterisk denotes statistical significance at $\alpha = 0.01$. Gray cells indicate that a variable was deliberately excluded from a given model Models 2 and 6 are not reported here due to redundancy with other models.

	Model											
Independent Variable	*1*		*3*		*4*		*5*		*7*		*8*	
	Kendall τ	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*
Annual Average PHDI	0.002	0.968	0.002	0.968	0.026	0.673	-.136*	0.021	-0.005	0.902	0.002	0.968
Annual Average Precipitation (mm)	-.222**	0.000	-.222**	0.000	-0.112	0.070	-.248**	0.000	-.255**	0.000	-.222**	0.000
Average Annual Lake Evaporation (mm)	.146**	0.001	.146**	0.001	.129*	0.037	0.013	0.819	.166**	0.000	.146**	0.001
Average Household Size	-0.003	0.952	-0.003	0.952	-0.008	0.895	0.033	0.569	-0.006	0.889	-0.003	0.952
Per Capita Building Permits									-0.025	0.586		
Per Capita Commercial Businesses			0.013	0.769								
Per Capita Income (2010 Dollars)	-0.080	0.058	-0.080	0.058	-0.117	0.057	-0.044	0.447	-.099*	0.026	-0.080	0.058
Percent 18 Years and Younger	0.019	0.655	0.019	0.655	-0.075	0.225	0.105	0.072	0.030	0.502	0.019	0.655
Percent 65 Years and Older	-0.014	0.744	-0.014	0.744	-0.066	0.288	-0.031	0.594	-0.019	0.674	-0.014	0.744

Table 17 Continued												
	Model											
Independent Variable	*1*		*3*		*4*		*5*		*7*		*8*	
	Kendall τ	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*	*Kendall τ*	*P Value*
Percent Bachelor's Degree	-0.027	0.529	-0.027	0.529	-0.040	0.514	-0.036	0.533	-0.053	0.229	-0.027	0.529
Percent High School Diploma	-.123**	0.003	-.123**	0.003	-.137*	0.027	-0.108	0.065	-.094*	0.035	-.123**	0.003
Percent Lodging											-.134**	0.002
Percent Owner Occupied	-0.064	0.131	-0.064	0.131	-.153*	0.013	0.020	0.735	-0.058	0.194	-0.064	0.131
Percent Single Family Dwellings	-0.054	0.199	-0.054	0.199	-0.114	0.064	-0.080	0.170	-0.049	0.271	-0.054	0.199
Percent Surface Water	-.117**	0.008	-.117**	0.008	.130*	0.040	-.278**	0.000	-.125**	0.007	-.117**	0.008
Percent Urban	0.064	0.137	0.064	0.137	0.083	0.180	0.086	0.156	0.070	0.120	0.064	0.137
Percent Worked Inside County of Residence	.226**	0.000			.193**	0.002	.223**	0.000	.213**	0.000		
Population Density (Square km)	-.178**	0.000	-.178**	0.000	-0.033	0.592	-.179**	0.002	-.203**	0.000	-.178**	0.000

Table 18. Ripley's K Distance Thresholds for All Model Permutations. The distance threshold represents the distance in meters at which clustering is maximized for the county centroids in the study area covered by each model.

Model(s)	**N**	**Distance Threshold (m)**
1, 2, 3, 8	254	171996.75
4	120	107962.05
5	134	132336.78
7	229	175482.88

Table 19. Migrant and Seasonal Farm Worker Populations and Per Capita Municipal Water. The MFW Estimate column reflects the adjusted population estimates of transient agricultural workers, and the Census Population column contains official population counts from the 2000 U.S. Decennial Census. MWC and PC MWC denote Municipal Water Consumption and Per Capita Municipal Water Consumption respectively. Water consumption values are given in liters. (Sources: MFW Estimate: Larson (2000), Census Population: U.S. Census Bureau, Total MWC: Texas Water Development Board).

County	MFW Estimate	Census Population	Adjusted Population	Total MWC (L)	Adjusted PC MWC (L)	Original PC MWC (L)	Difference in PC MWC (L)	Percent Change PC MWC
Brewster	56	8866	8922	2790132800	312725.04	314700.29	1975.25	-0.63
Cameron	9219	335227	344446	83963014892	243762.49	250466.15	6703.66	-2.68
Culberson	83	2975	3058	688282097	225075.90	231355.33	6279.43	-2.71
Dimmit	769	10248	11017	3863260800	350663.59	376977.05	26313.46	-6.98
Hidalgo	40500	569463	609963	103073327654	168982.92	181000.92	12018.00	-6.64
Hudspeth	2117	3344	5461	463788653	84927.42	138692.78	53765.36	-38.77
Kinney	52	3379	3431	1683700827	490731.81	498283.76	7551.95	-1.52
Maverick	2859	47297	50156	9892513287	197234.89	209157.31	11922.42	-5.70
Presidio	923	7304	8227	2050044524	249184.94	280674.22	31489.28	-11.22
Reeves	842	13137	13979	4599648634	329039.89	350129.30	21089.41	-6.02
Starr	5045	53597	58642	11211103898	191178.74	209174.09	17995.35	-8.60
Val Verde	2221	44856	47077	20214277774	429387.55	450648.25	21260.70	-4.72
Webb	944	193117	194061	51439835611	265070.44	266366.17	1295.73	-0.49
Zapata	122	12182	12304	2529868423	205613.49	207672.67	2059.18	-0.99
Zavala	2925	11600	14525	3601762942	247969.91	310496.81	62526.90	-20.14

Table 20. Model Fit and Diagnostics for All Models 1990. All models were statistically significant at α = 0.05 as seen below in the P Values of F. The Degrees of Freedom (Df) listed in this table are the residual degrees of freedom.

Model Diagnostic	**Model**							
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
R Square	0.394	0.394	0.427	0.320	0.364	0.452	0.452	0.407
Adjusted R Square	0.385	0.385	0.411	0.303	0.339	0.440	0.440	0.393
Std. Error	57.637	57.637	56.397	29.049	31.567	49.584	49.584	57.239
F	40.517	40.517	26.191	18.211	14.641	36.806	36.806	28.300
P Value of F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Df	249	249	246	116	128	223	224	247

Table 21. Standardized Beta Coefficients and P-Values for all Models in All Years. The Beta column contains the standardized contribution of each independent variable to its respective model. The P column contains the p-value which represents the probability that a given standardized beta coefficient occurred by random chance. Independent variables with a p-value less than 0.05 were considered to be statistically significant.

		Model															
Independent Variable		*1*		*2*		*3*		*4*		*5*		*6*		*7*		*8*	
	Year	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*
Annual Average Precipitation (mm)	*1990*	-0.310	0.000	-0.310	0.000	-0.246	0.000	-0.275	0.002	-0.177	0.032	-0.313	0.000	-0.313	0.000	-0.260	0.000
	2000	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
	2010	X	X	X	X	-0.162	0.028	X	X	X	X	-0.239	0.001	-0.169	0.030	-0.162	0.028
Average Household Size	*1990*	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
	2000	X	X	X	X	X	X	X	X	X	X	X	X	X	X	-0.375	0.000
	2010	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Per Capita Building Permits	*1990*													X	X		
	2000													X	X		
	2010													0.182	0.016		
Per Capita Commercial Businesses	*1990*			X	X	0.155	0.004							X	X	X	X
	2000			X	X	0.237	0.000							X	X	X	X
	2010			X	X	X	X							X	X	X	X

Table 21 Continued																	
		Model															
Independent Variable		*1*		*2*		*3*		*4*		*5*		*6*		*7*		*8*	
	Year	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*
Per Capita Income (2010 Dollars)	*1990*	-0.220	0.001	-0.220	0.001	-0.224	0.001	X	X	-0.287	0.001	X	X	X	X	-0.192	0.005
	2000	X	X	X	X	X	X	X	X	X	X	X	X	X	X	-0.215	0.003
	2010	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Percent 18 Years and Younger	*1990*	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
	2000	X	X	X	X	X	X	X	X	X	X	X	X	X	X	0.263	0.002
	2010	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Percent 65 Years and Older	*1990*	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
	2000	-0.178	0.003	-0.178	0.003	-0.250	0.000	X	X	X	X	X	X	X	X	-0.209	0.014
	2010	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Percent Bachelor's Degree	*1990*	0.383	0.000	0.383	0.000	0.339	0.000	X	X	0.411	0.000	0.186	0.002	0.186	0.002	0.358	0.000
	2000	0.193	0.000	0.193	0.000	X	X	0.421	0.000	X	X	X	X	X	X	0.275	0.000
	2010	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X

Table 21 Continued																	
		Model															
Independent Variable		*1*		*2*		*3*		*4*		*5*		*6*		*7*		*8*	
	Year	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*
Percent High School Diploma	*1990*	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
	2000	X	X	X	X	X	X	X	X	X	X	-0.219	0.000	-0.219	0.000	X	X
	2010	-0.183	0.004	-0.183	0.004	-0.139	0.038	X	X	X	X	X	X	X	X	-0.139	0.038
Percent Lodging	*1990*															X	X
	2000															X	X
	2010															X	X
Percent Owner Occupied	*1990*	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
	2000	X	X	X	X	-0.138	0.027	X	X	X	X	X	X	X	X	X	X
	2010	X	X	X	X	X	X	X	X	0.367	0.000	X	X	X	X	X	X
Percent Single Family Dwellings	*1990*	X	X	X	X	-0.222	0.017	X	X	X	X	-0.281	0.001	-0.281	0.001	-0.248	0.008
	2000	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
	2010	X	X	X	X	-0.258	0.001	X	X	-0.421	0.000	-0.271	0.000	X	X	-0.258	0.001

Table 21 Continued																	
		Model															
Independent Variable		*1*		*2*		*3*		*4*		*5*		*6*		*7*		*8*	
	Year	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*	*Beta*	*P*
Percent Surface Water	*1990*	X	X	X	X	X	X	0.197	0.022	-0.193	0.017	X	X	X	X	X	X
	2000	X	X	X	X	X	X	0.266	0.001	-0.184	0.022	X	X	X	X	X	X
	2010	X	X	X	X	X	X	X	X	-0.328	0.000	X	X	X	X	X	X
Percent Urban	*1990*	X	X	X	X	0.164	0.026	0.340	0.000	X	X	X	X	X	X	0.197	0.008
	2000	0.363	0.000	0.363	0.000	0.346	0.000	0.495	0.000	0.533	0.000	0.332	0.000	0.332	0.000	0.512	0.000
	2010	X	X	X	X	X	X	X	X	0.266	0.013	X	X	X	X	X	X
Percent Worked Inside County of Residence	*1990*	0.267	0.000	0.267	0.000			X	X	-0.287	0.001	0.238	0.000	0.238	0.000		
	2000	0.262	0.000	0.262	0.000			0.152	0.077	0.179	0.036	0.234	0.000	0.234	0.000		
	2010	0.246	0.000	0.246	0.000			0.289	0.001	0.176	0.053	X	X	0.212	0.001		
Population Density (Square km)	*1990*	X	X	X	X	-0.346	0.000	X	X	X	X	-0.318	0.000	-0.318	0.000	-0.384	0.000
	2000	-0.534	0.000	-0.534	0.000	-0.572	0.000	-0.557	0.000	-0.462	0.000	-0.417	0.000	-0.417	0.000	-0.504	0.000
	2010	-0.291	0.000	-0.291	0.000	-0.365	0.000	X	X	-0.458	0.000	-0.332	0.000	-0.317	0.000	-0.365	0.000

Table 22. Standardized Beta Ratio Matrix for Model 1 1990. The rows and columns are organized in descending order of relationship strength from left to right and top to bottom respectively. The values are expressed in terms of the stronger variable. For example, the value in the second column of the first row indicates that *Percent Bachelor's Degree* was 1.235 times stronger than *Average Annual Precipitation.*

Independent Variable		*Percent Bachelor's Degree*	*Average Annual Precipitation (mm)*	*Percent Worked In County of Residence*	*Per Capita Income (2010 Dollars)*
	Conceptual Variable (Environment)	*Social*	*Physical*	*Social*	*Social*
		Standardized Beta Ratio			
Percent Bachelor's Degree	*Social*	1.000	1.235	1.434	1.741
Average Annual Precipitation (mm)	*Physical*	1.235	1.000	1.161	1.409
Percent Worked In County of Residence	*Social*	1.434	1.161	1.000	1.214
Per Capita Income (2010 Dollars)	*Social*	1.741	1.409	1.214	1.000

Table 23. Model Fit and Diagnostics for All Models 2000. All models were statistically significant at $\alpha = 0.05$ as seen below in the P Values of F. The Degrees of Freedom (Df) listed in this table are the residual degrees of freedom.

Model Diagnostic	**Model**							
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
R Square	0.421	0.421	0.407	0.446	0.379	0.434	0.434	0.426
Adjusted R Square	0.410	0.410	0.395	0.422	0.360	0.424	0.424	0.410
Std. Error	56.453	56.453	57.137	26.445	31.068	50.287	50.287	56.436
F	36.098	36.098	34.059	18.380	14.641	42.933	42.933	26.107
P Value of F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Df	248	248	248	114	129	224	224	246

Table 24. Standardized Beta Ratio Matrix for Model 1 2000. The rows and columns are organized in descending order of relationship strength from left to right and top to bottom respectively. The values are expressed in terms of the stronger variable. For example, the value in the second column of the first row indicates that *Population Density* was 1.471 times stronger than *Percent Urban.*

Independent Variable		*Population Density (Sq Km)*	*Percent Urban*	*Percent Worked In County of Residence*	*Percent Bachelor's Degree*	*Percent 65 Years and Older*
	Conceptual Variable (Environment)	*Urbanized*	*Urbanized*	*Social*	*Social*	*Social*
		Standardized Beta Ratio				
Population Density (Sq Km)	*Urbanized*	1.000	1.471	2.427	2.767	3.000
Percent Urban	*Urbanized*	1.471	1.000	1.385	1.881	2.039
Percent Worked In County of Residence	*Social*	2.038	1.385	1.000	1.358	1.472
Percent Bachelor's Degree	*Social*	2.767	1.881	1.358	1.000	1.084
Percent 65 Years and Older	*Social*	3.000	2.039	1.472	1.084	1.000

Table 25. Model Fit and Diagnostics for All Models 2010. All models were statistically significant at α = 0.05 as seen below in the P Values of F. The Degrees of Freedom (Df) listed in this table are the residual degrees of freedom.

Model Diagnostic	**Model**							
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
R Square	0.196	0.196	0.199	0.084	0.404	0.215	0.224	0.199
Adjusted R Square	0.187	0.187	0.186	0.076	0.376	0.205	0.210	0.186
Std. Error	66.256	66.256	66.283	33.439	30.673	59.084	58.895	66.283
F	20.358	20.358	15.456	10.775	14.352	20.557	16.128	15.456
P Value of F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Df	250	250	249	118	127	225	224	249

Table 26. Standardized Beta Ratio Matrix for Model 1 2010. The rows and columns are organized in descending order of relationship strength from left to right and top to bottom respectively. The values are expressed in terms of the stronger variable. For example, the value in the second column of the first row indicates that *Population Density* was 1.183 times stronger than *Percent Worked In County of Residence*

Independent Variable		*Population Density (Sq Km)*	*Percent Worked In County of Residence*	*Percent High School Diploma*
	Conceptual Variable (Environment)	*Urbanized*	*Social*	*Social*
		Standardized Beta Ratio		
Population Density (Sq Km)	*Urbanized*	1.000	1.183	1.635
Percent Worked In County of Residence	*Social*	1.183	1.000	1.382
Percent High School Diploma	*Social*	1.635	1.382	1.000

Table 27. Statistically Significant Independent Variables by Model 1990. Cells marked with a '0' indicate that a variable was statistically excluded from a model. Cells marked with an 'x' indicate that a variable was statistically included in a model. Gray cells indicate that a variable was excluded from a model by the analyst.

	Model							
Independent Variable	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
Annual Average PHDI	0	0	0	0	0	0	0	0
Annual Average Precipitation (mm)	x	x	x	x	x	x	x	x
Average Annual Lake Evaporation (mm)	0	0	0	0	0	0	0	0
Average Household Size	0	0	0	0	0	0	0	0
Per Capita Building Permits							x	
Per Capita Commercial Businesses		0	x					
Per Capita Income (2010 Dollars)	x	x	x	0	x	0	x	x
Percent 18 Years and Younger	0	0	0	0	0	0	0	0
Percent 65 Years and Older	0	0	0	0	0	0	0	0
Percent Bachelor's Degree	x	x	x	0	x	x	x	x
Percent High School Diploma	0	0	0	0	0	0	0	0
Percent Lodging								0
Percent Owner Occupied	0	0	0	0	0	0	0	0
Percent Single Family Dwellings	0	0	x	0	0	x	x	x
Percent Surface Water	0	0	0	x	0	0	0	0
Percent Urban	0	0	x	x	0	0	0	x
Percent Worked Inside County of Residence	x	x		0	x	x	x	
Population Density (Square km)	0	0	x	0	0	0	0	x

Table 28. Statistically Significant Independent Variables by Model 2000. Cells marked with a '0' indicate that a variable was statistically excluded from a model. Cells marked with an 'x' indicate that a variable was statistically included in a model. Gray cells indicate that a variable was excluded from a model by the analyst.

	Model							
Independent Variable	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
Annual Average PHDI	0	0	0	0	0	0	0	0
Annual Average Precipitation (mm)	0	0	0	0	0	0	0	0
Average Annual Lake Evaporation (mm)	0	0	0	0	0	0	0	0
Average Household Size	0	0	0	0	0	0	0	x
Per Capita Building Permits							0	
Per Capita Commercial Businesses		0	x					
Per Capita Income (2010 Dollars)	0	0	0	0	0	0	0	x
Percent 18 Years and Younger	0	0	0	0	0	0	0	x
Percent 65 Years and Older	x	x	x	0	0	0	0	x
Percent Bachelor's Degree	x	x	0	x	0	0	0	x
Percent High School Diploma	0	0	0	0	0	x	x	0
Percent Lodging								0
Percent Owner Occupied	0	0	x	0	0	0	0	0
Percent Single Family Dwellings	0	0	0	0	0	0	0	0
Percent Surface Water	0	0	0	x	x	0	0	0
Percent Urban	x	x	x	x	x	x	x	x
Percent Worked Inside County of Residence	x	x		x	x	x	x	
Population Density (Square km)	x	x	x	x	x	x	x	x

Table 29. Statistically Significant Independent Variables by Model 2010. Cells marked with a ‘0’ indicate that a variable was statistically excluded from a model. Cells marked with an ‘x’ indicate that a variable was statistically included in a model. Gray cells indicate that a variable was excluded from a model by the analyst.

	Model							
Independent Variable	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
Annual Average PHDI	0	0	0	0	0	0	0	0
Annual Average Precipitation (mm)	0	0	x	0	0	x	x	x
Average Annual Lake Evaporation (mm)	0	0	0	0	0	0	0	0
Average Household Size	0	0	0	0	0	0	0	0
Per Capita Building Permits							x	
Per Capita Commercial Businesses		0	0					
Per Capita Income (2010 Dollars)	0	0	0	0	0	0	0	0
Percent 18 Years and Younger	0	0	0	0	0	0	0	0
Percent 65 Years and Older	0	0	0	0	0	0	0	0
Percent Bachelor's Degree	0	0	0	0	0	0	0	0
Percent High School Diploma	x	x	x	0	0	0	0	x
Percent Lodging								0
Percent Owner Occupied	0	0	0	0	x	0	0	0
Percent Single Family Dwellings	0	0	x	0	x	0	0	x
Percent Surface Water	0	0	0	0	x	x	0	0
Percent Urban	0	0	0	0	x	0	0	0
Percent Worked Inside County of Residence	x	x		x	x	0	x	
Population Density (Square km)	x	x	x	0	x	x	x	x

Table 30. Coefficients of Variation for Selected Variables All Years.

Variable	**Year**		
	1990	*2000*	*2010*
Population Density (Sq Km)	295.951	294.567	290.617
Percent 18 Years and Younger	13.279	13.042	14.754
Percent 65 Years and Older	34.783	29.901	28.037
Average Household Size	10.305	9.386	9.419
Percent Surface Water	100.588	100.374	102.332
Per Capita Municipal Water Consumption	82.977	35.264	28.037
Percent Single Family	8.492	10.303	7.903
Percent Worked Inside County Of Residence	21.192	23.602	24.169
Percent High School Diploma	15.168	17.076	7.903
Percent Bachelor's Degree	41.172	40.515	40.222
Per Capita Income (2010 Dollars)	19.763	20.835	20.326
Percent Owner Occupied	11.107	0.102	0.100
Percent Urban	69.687	71.029	71.726
Average Annual Precipitation (mm)	42.096	44.674	26.450
Average Annual Lake Evaporation (mm)	9.719	17.762	13.363

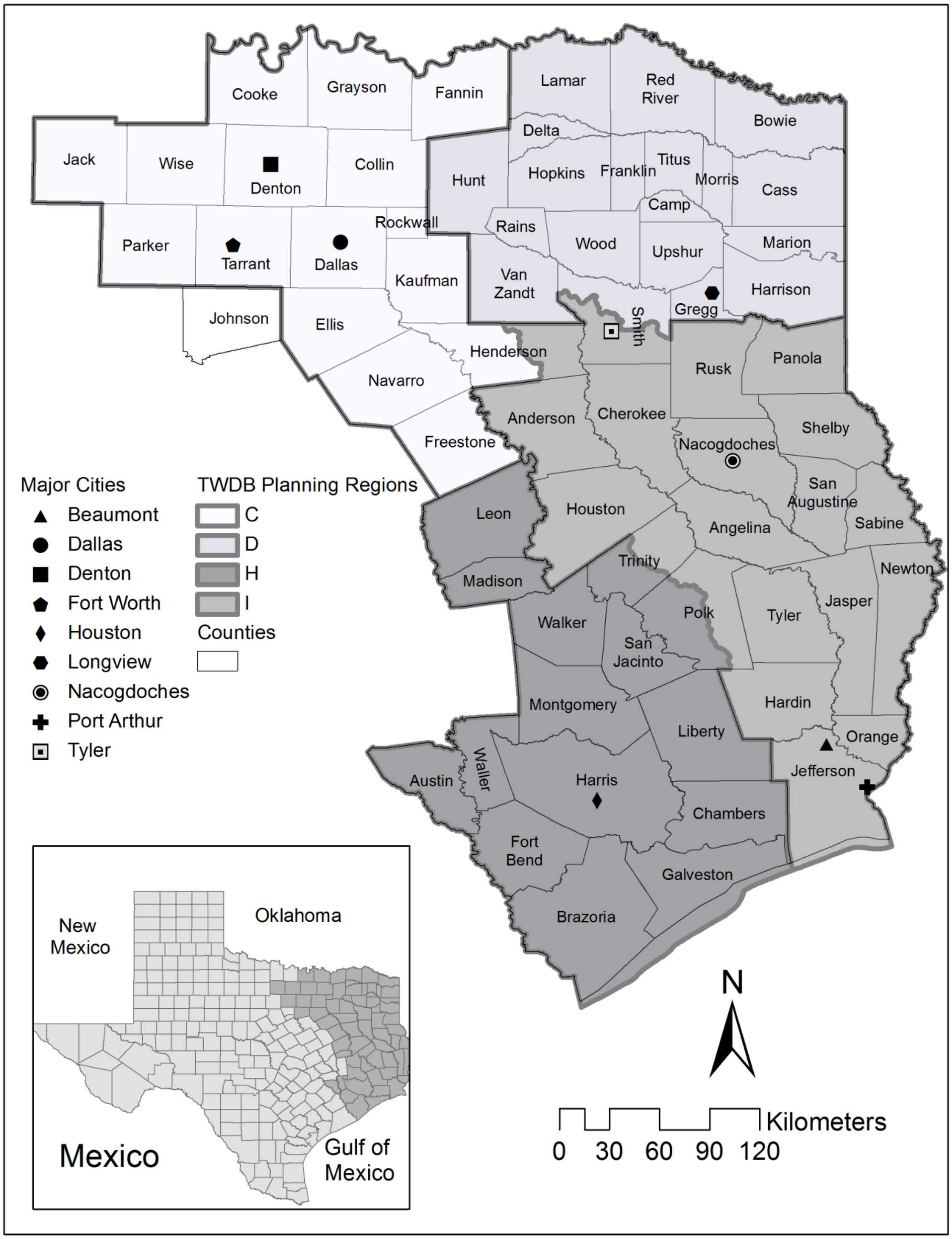

Figure 1. TDWB Planning Regions C, D, H, and I. Collectively these regions expect a 68% increase in water consumption, and an 86% increase in population between 2010 and 2060.

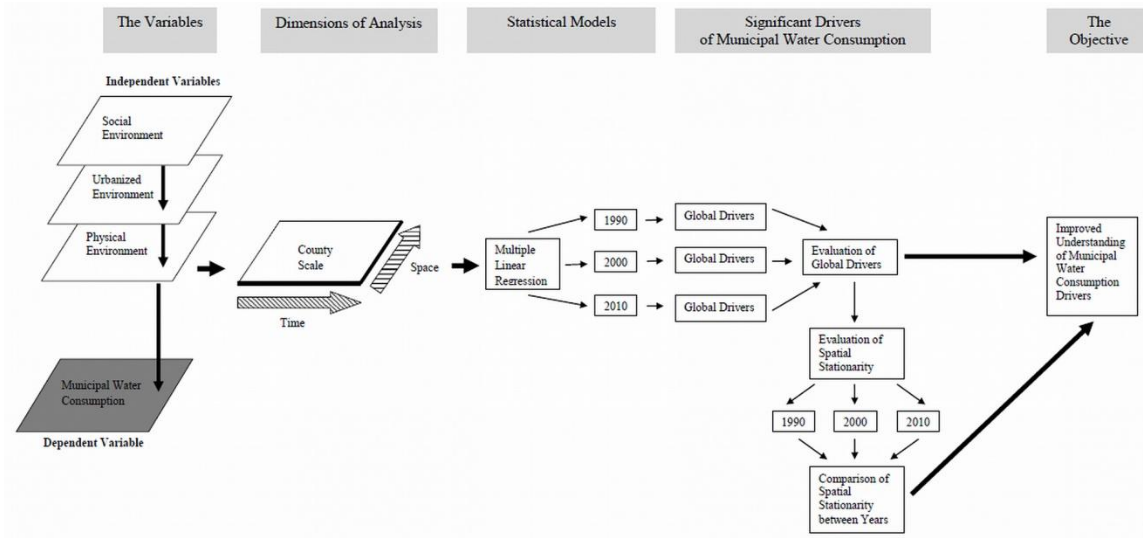

Figure 2. Conceptual Research Overview. Note that the Global designation refers to the mechanics of the multiple linear regression model. A *global* driver refers to a variable whose significance applies to all locations used to produce the model.

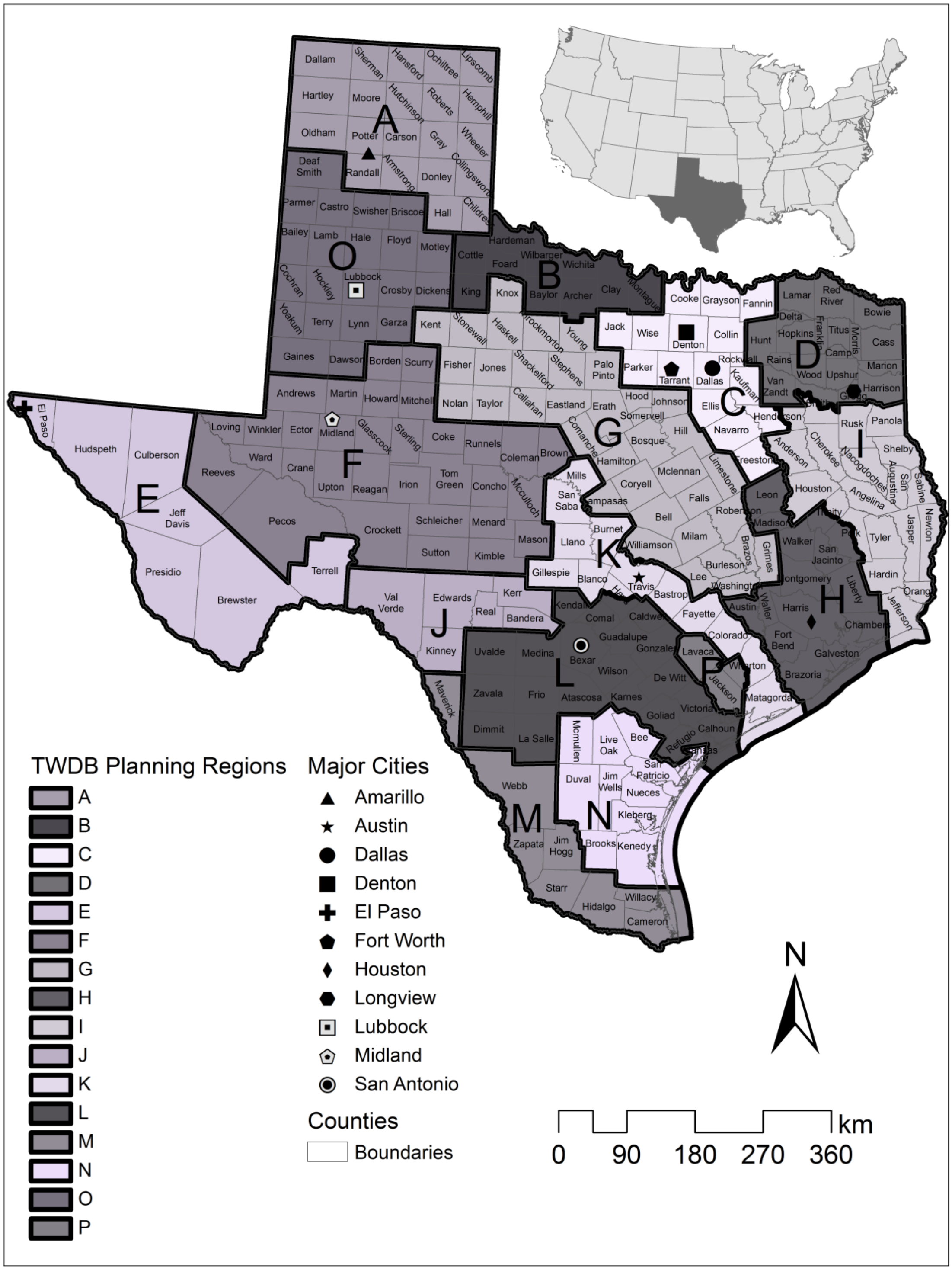

Figure 3. Study Area with TWDB Planning Regions and selected Major Cities.

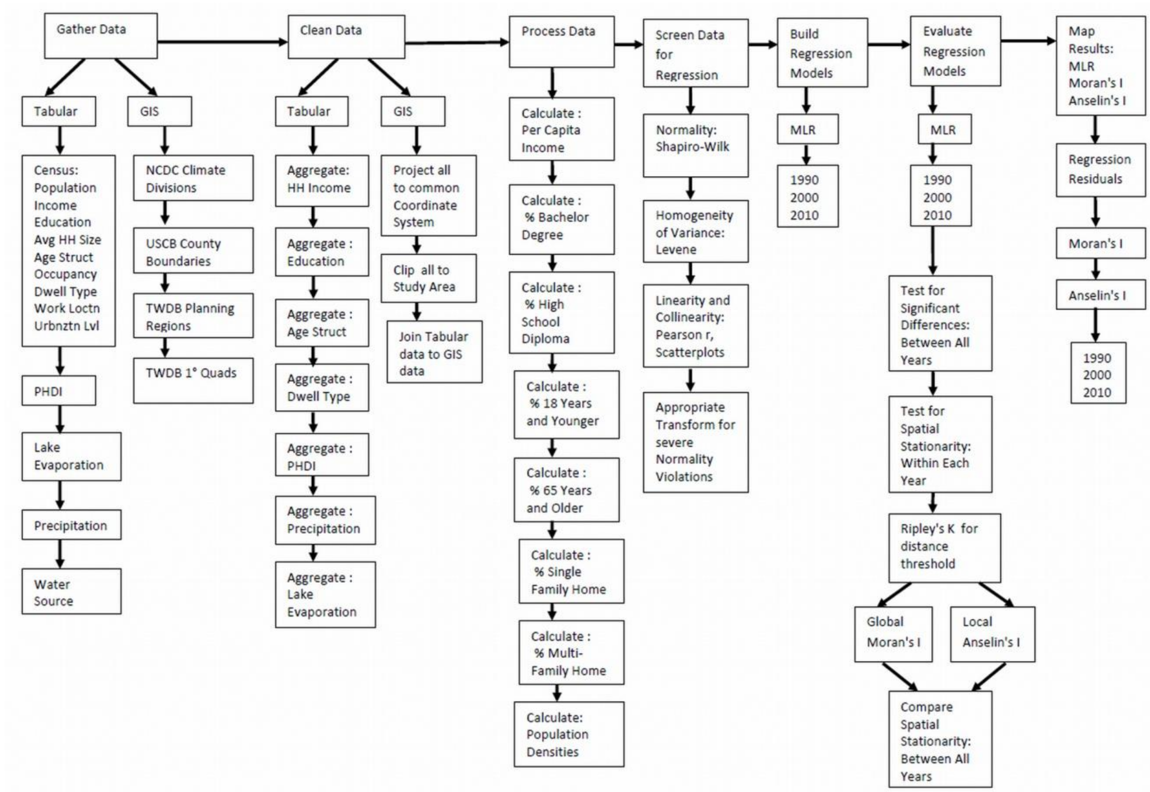

Figure 4. Dissertation Workflow.

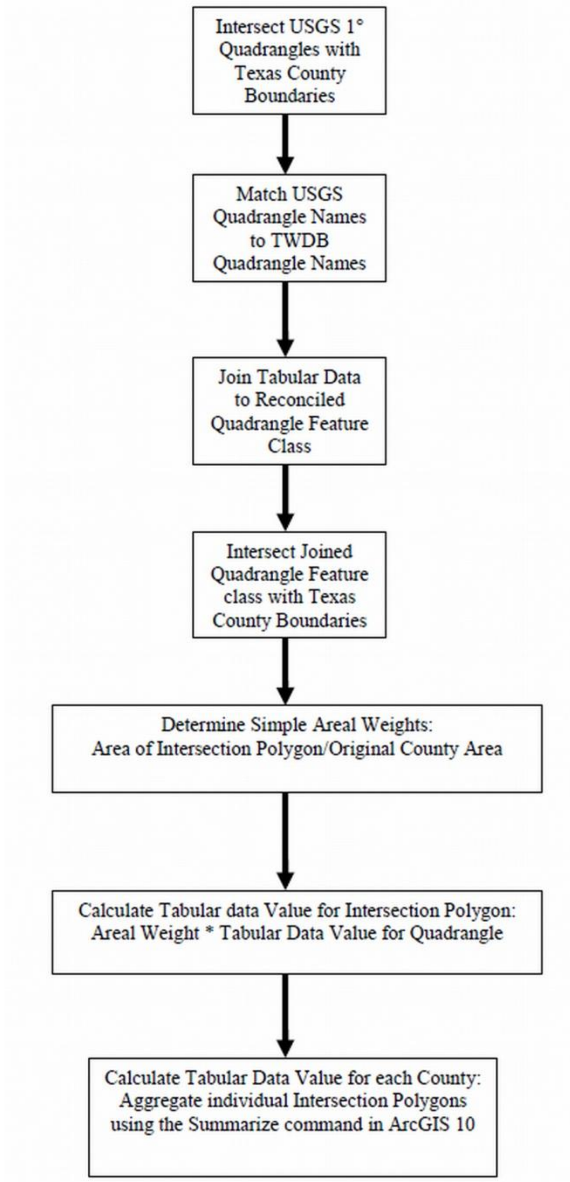

Figure 5. Calculation Workflow for Average Annual Precipitation and Average Annual Lake Evaporation.

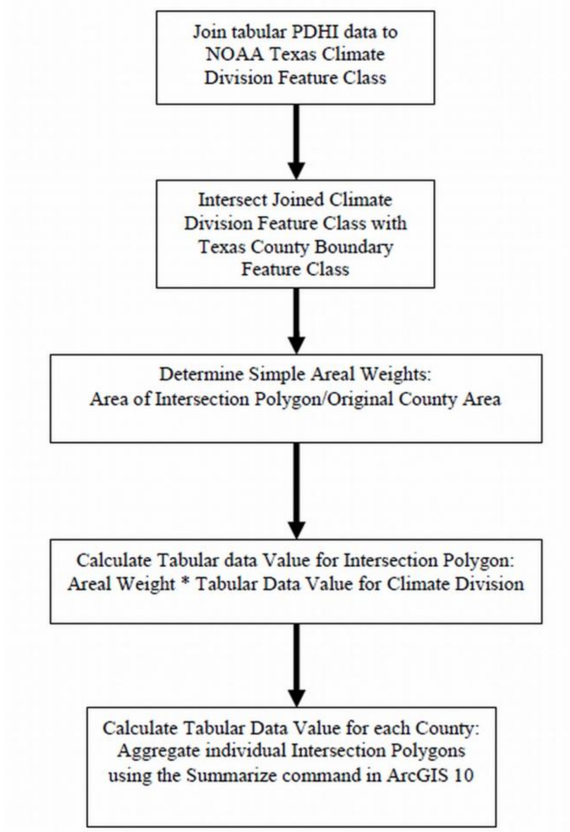

Figure 6. Calculation Workflow for Average Annual PHDI.

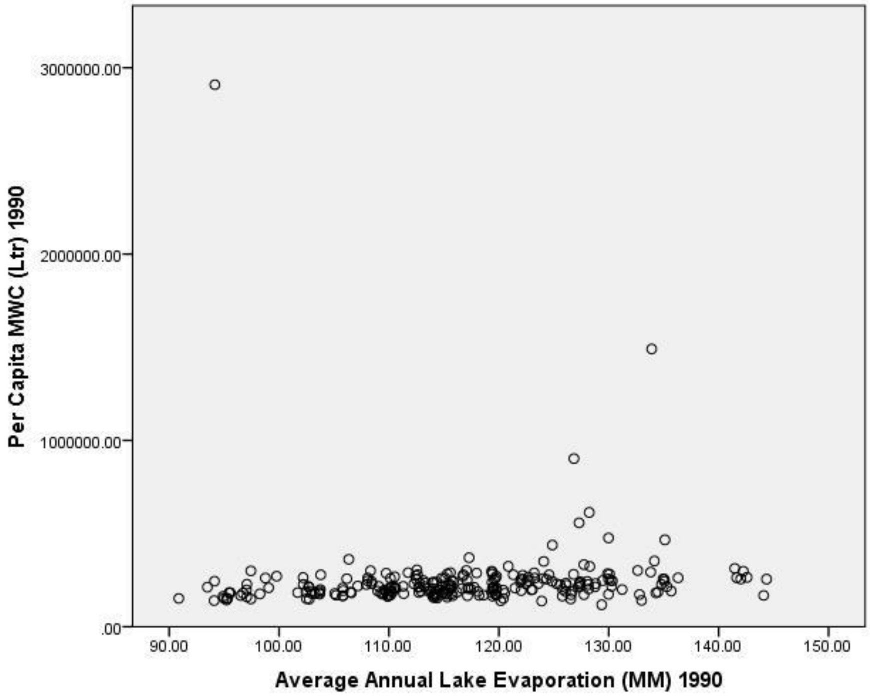

Figure 7. Original Scatterplot for Per Capita Municipal Water Consumption and Annual Lake Evaporation 1990.

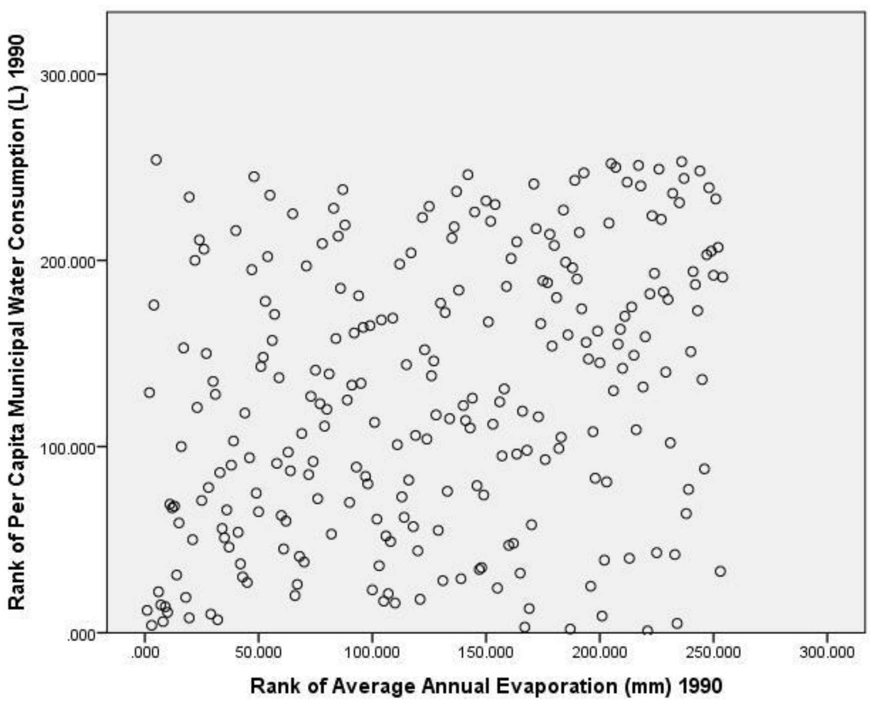

Figure 8. Rank Transformed Scatterplot for Per Capita Municipal Water Consumption and Annual Lake Evaporation 1990.

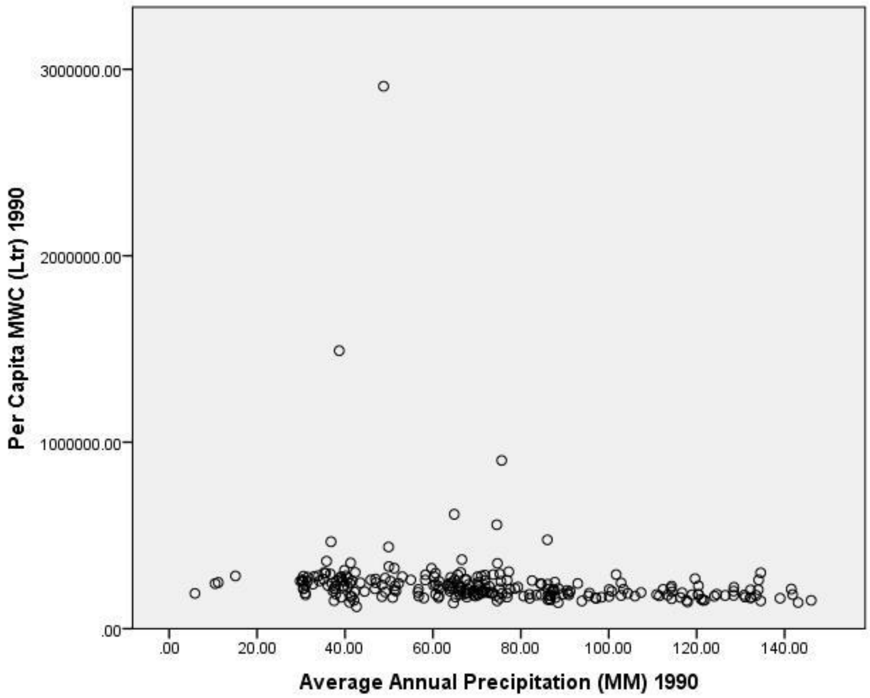

Figure 9.Original Scatterplot for Per Capita Municipal Water Consumption and Average Annual Precipitation 1990.

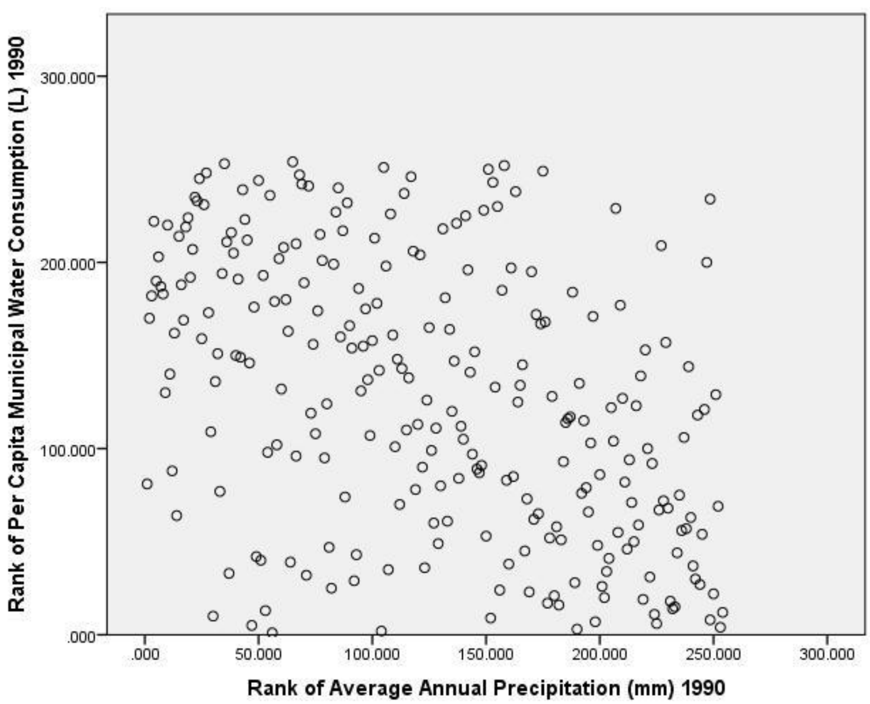

Figure 10.Rank Transformed Scatterplot for Per Capita Municipal Water Consumption and Average Annual Precipitation 1990.

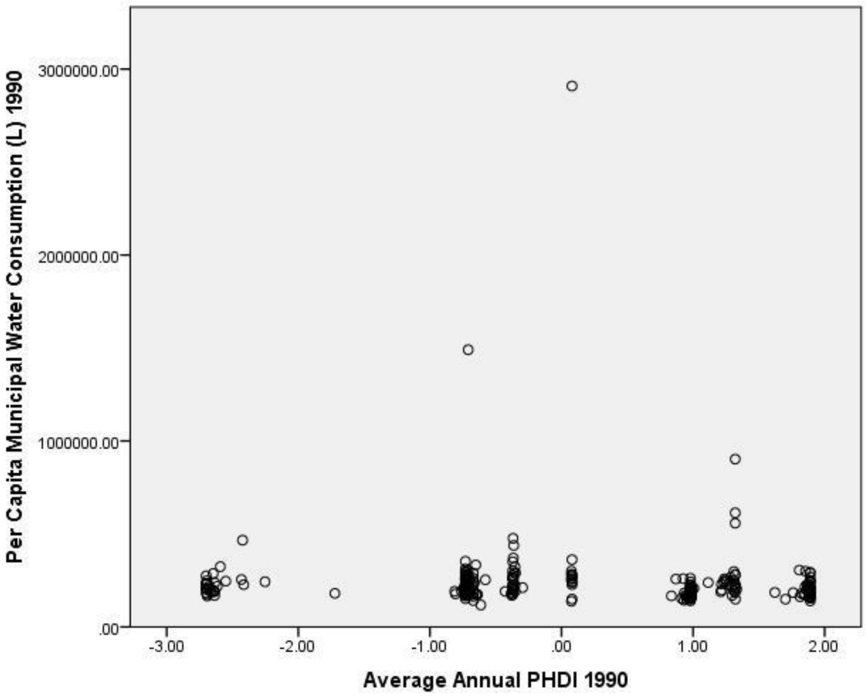

Figure 11. Original Scatterplot for Per Capita Municipal Water Consumption and Average Annual PHDI 1990.

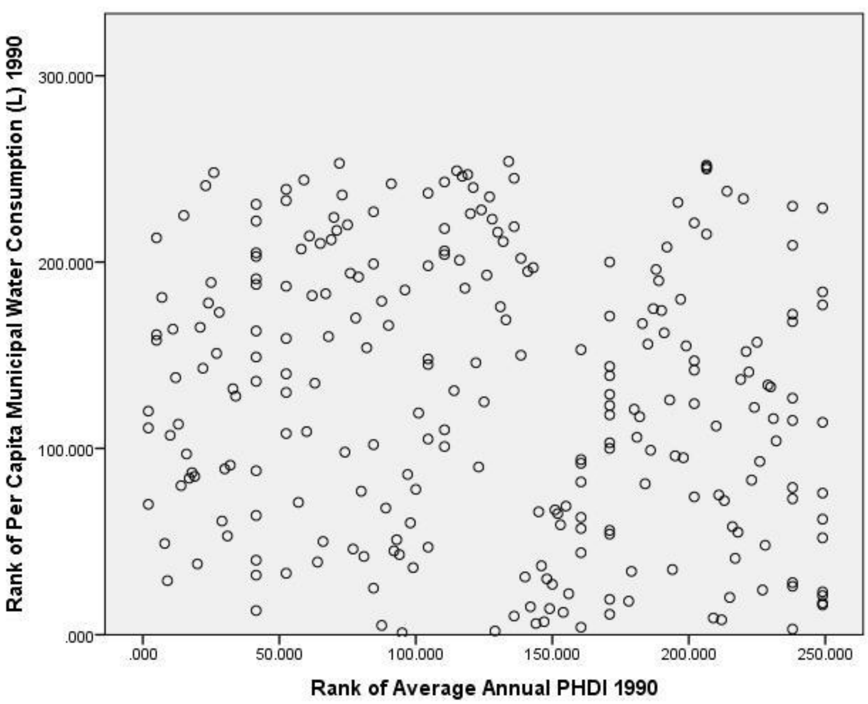

Figure 12. Rank Transformed Scatterplot for Per Capita Municipal Water Consumption and Average Annual PHDI 1990.

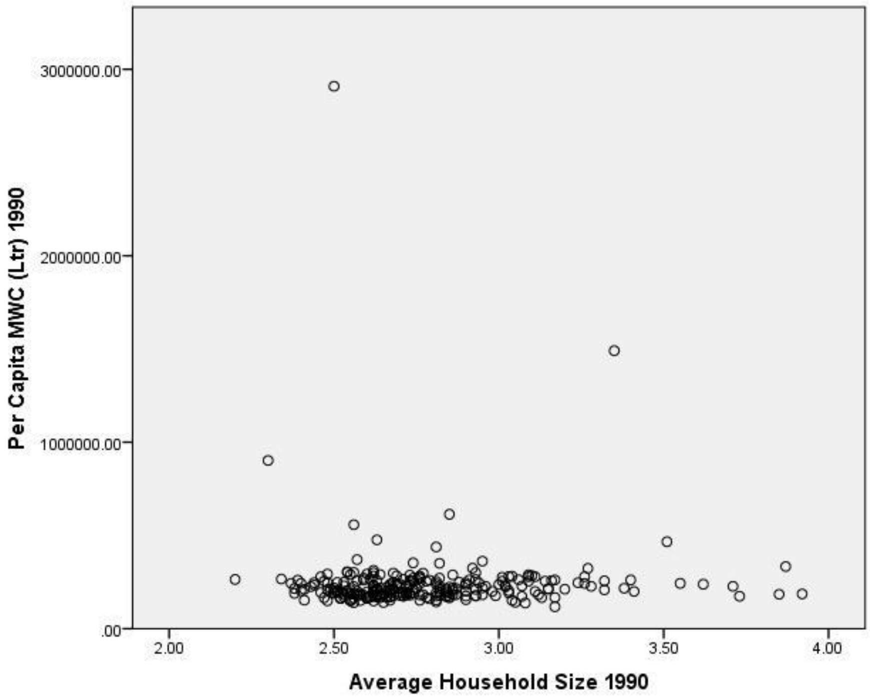

Figure 13. Original Scatterplot for Per Capita Municipal Water Consumption and Average Household Size 1990.

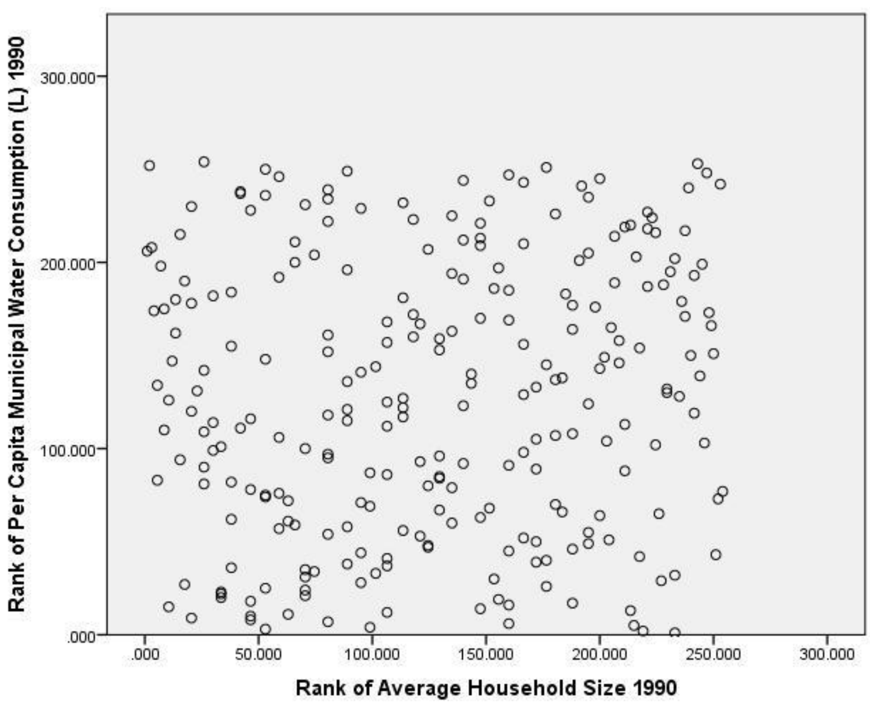

Figure 14. Rank Transformed Scatterplot for Per Capita Municipal Water Consumption and Average Household Size 1990.

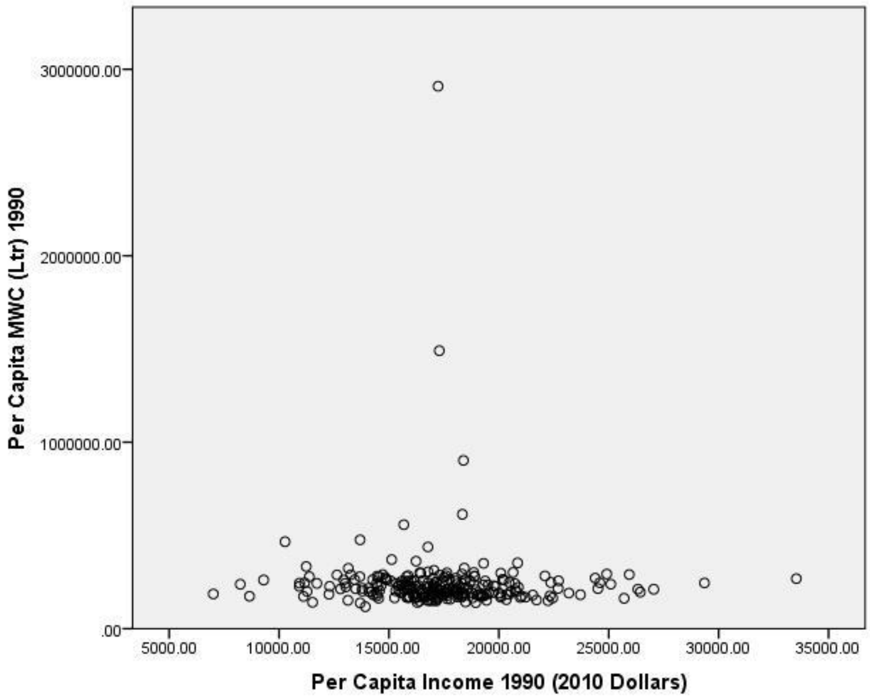

Figure 15. Original Scatterplot for Per Capita Municipal Water Consumption and Per Capita Income 1990.

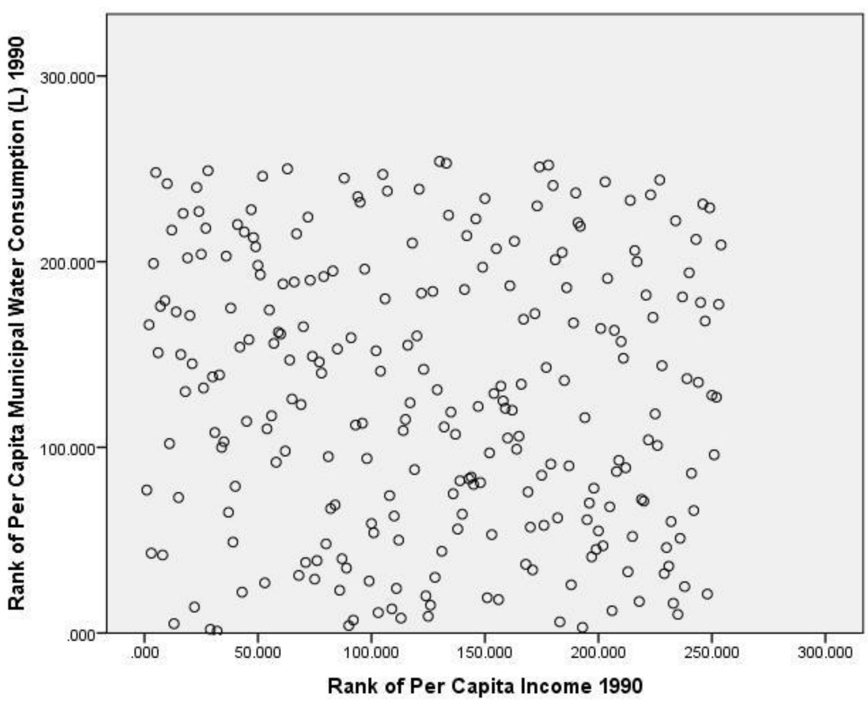

Figure 16. Rank Transformed Scatterplot for Per Capita Municipal Water Consumption and Per Capita Income 1990.

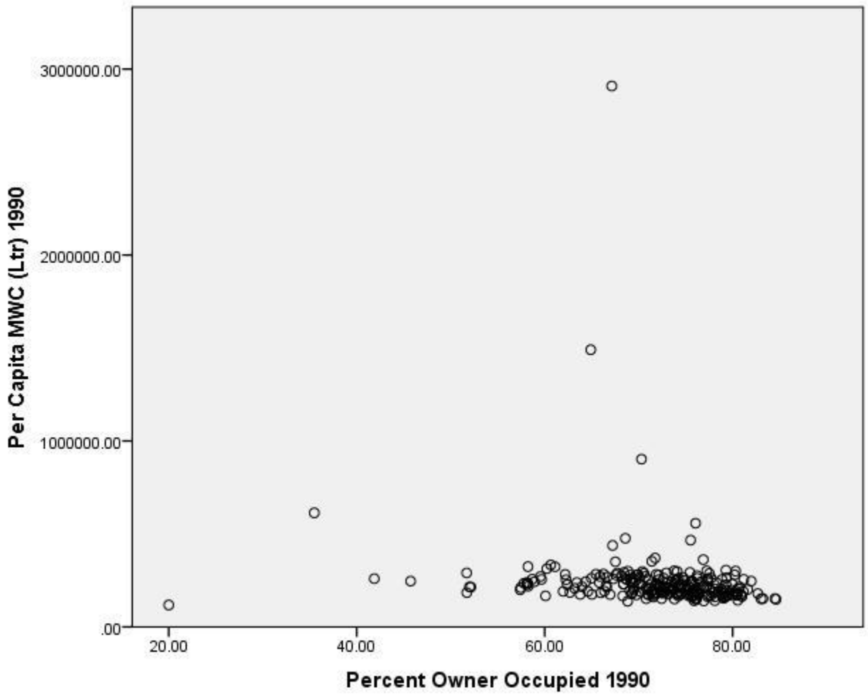

Figure 17. Original Scatterplot for Per Capita Municipal Water Consumption and Percent Owner Occupied 1990.

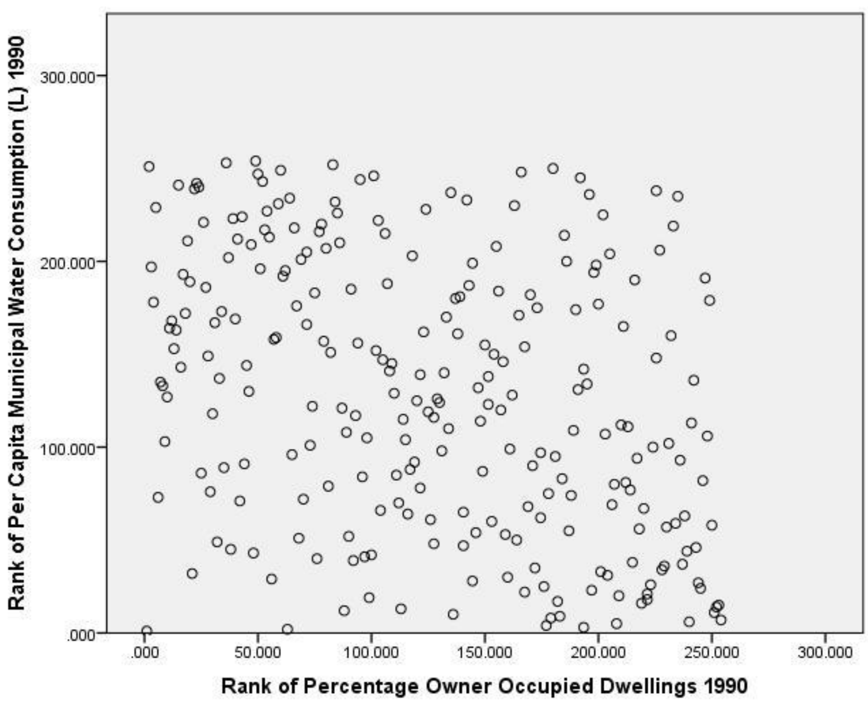

Figure 18. Rank Transformed Scatterplot for Per Capita Municipal Water Consumption and Percent Owner Occupied 1990.

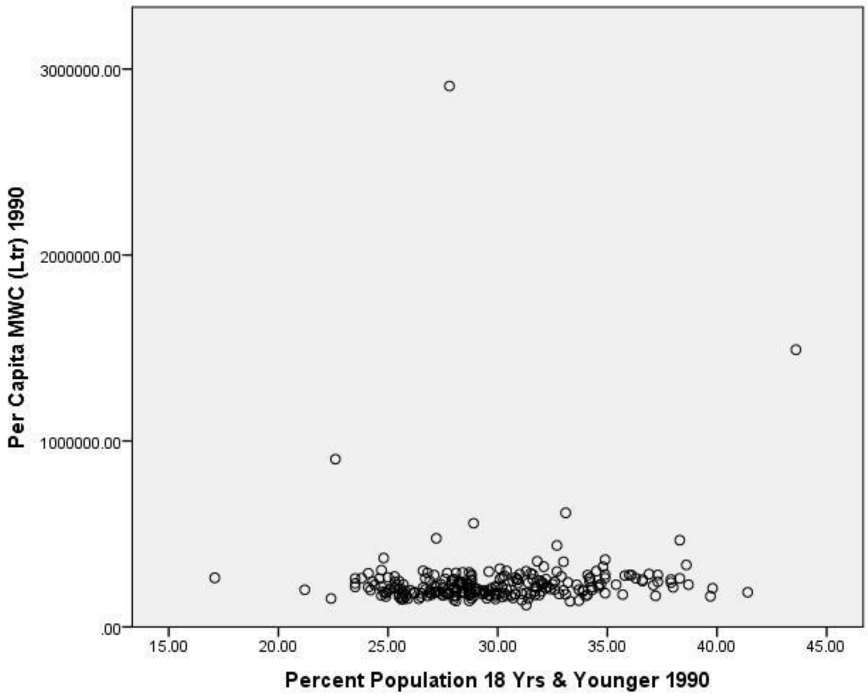

Figure 19. Original Scatterplot for Per Capita Municipal Water Consumption and Percent 18 Years and Younger 1990.

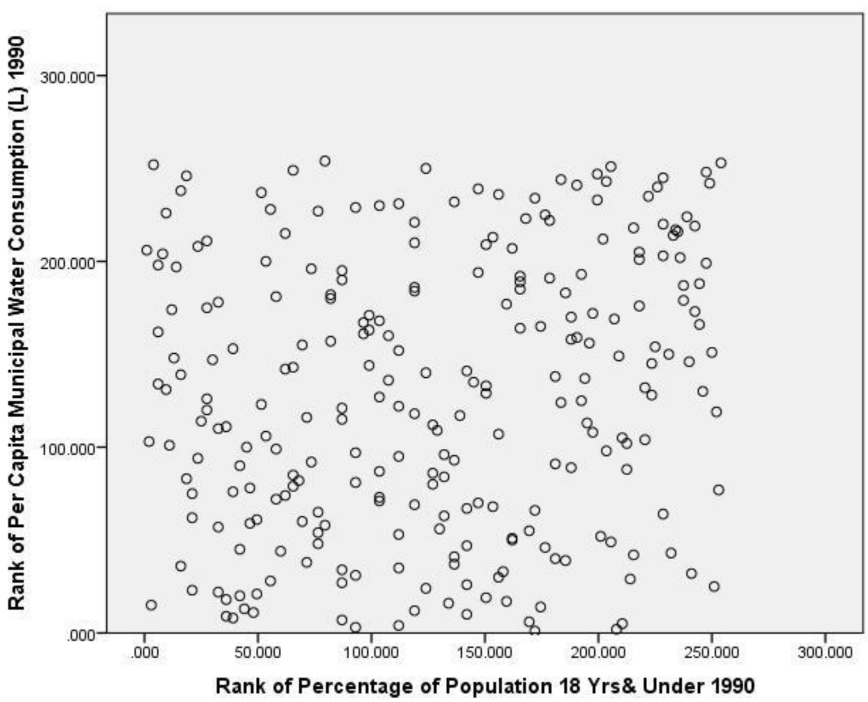

Figure 20. Rank Transformed Scatterplot for Per Capita Municipal Water Consumption and Percent 18 Years and Younger 1990.

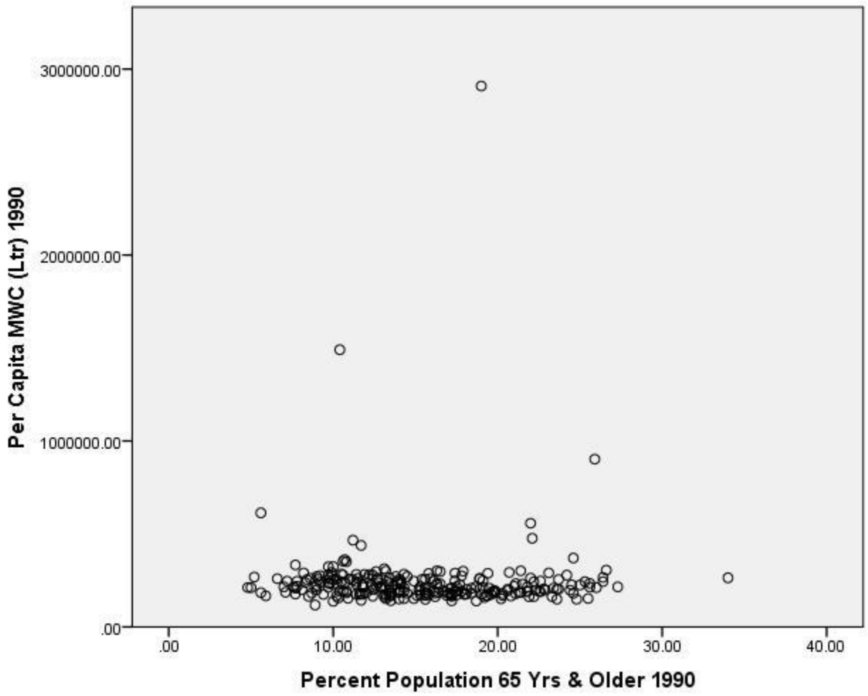

Figure 21. Original Scatterplot for Per Capita Municipal Water Consumption and Percent 65 Years and Older 1990.

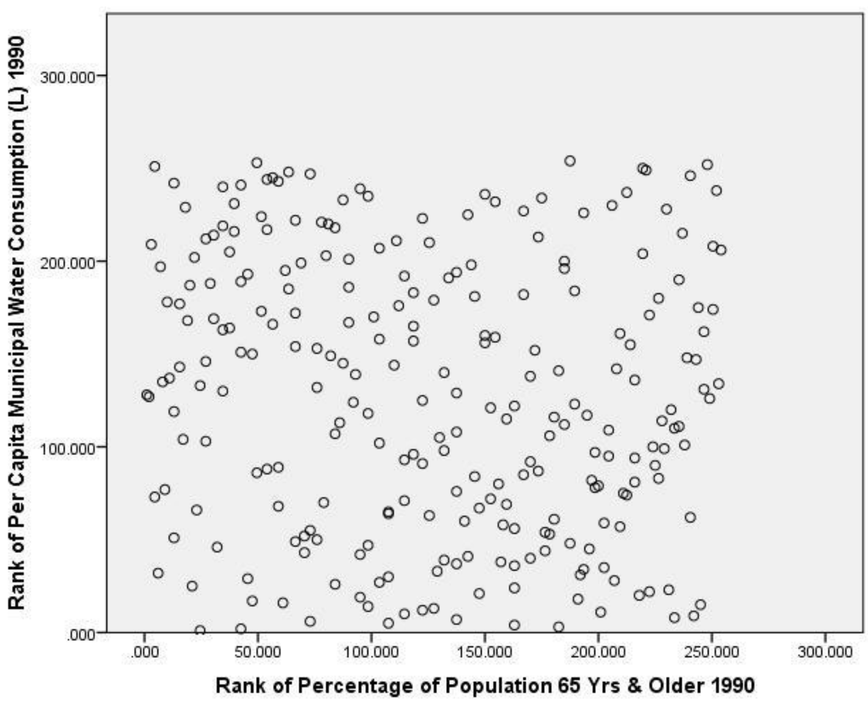

Figure 22. Rank Transformed Scatterplot for Per Capita Municipal Water Consumption and Percent 65 Years and Older 1990.

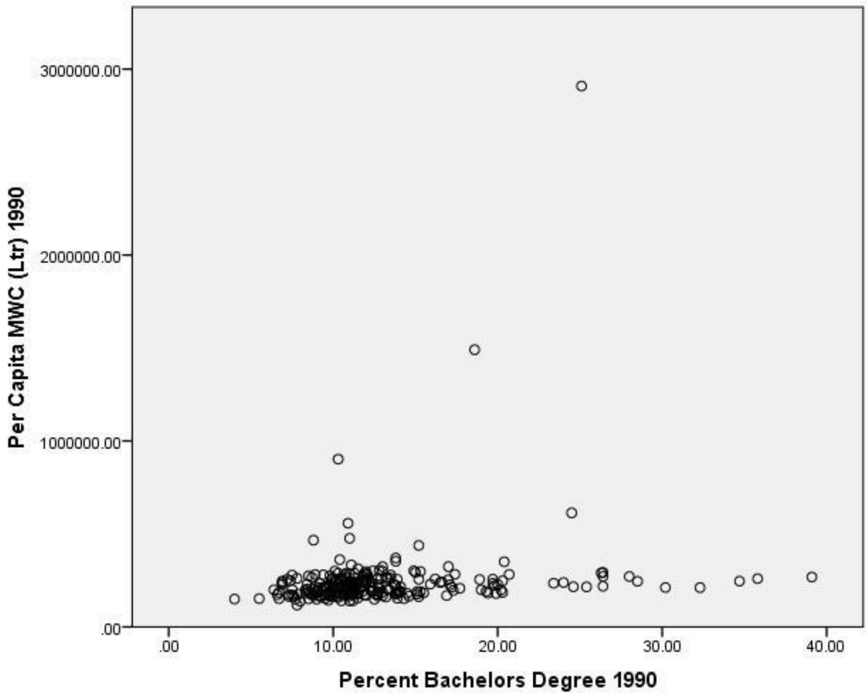

Figure 23. Original Scatterplot for Per Capita Municipal Water Consumption and Percent Bachelor's Degree 1990.

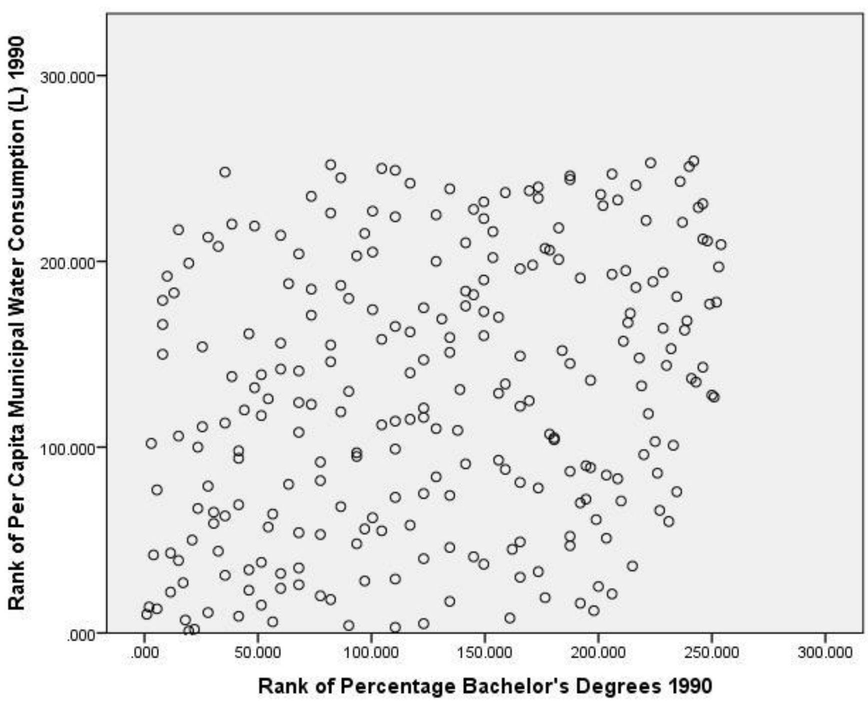

Figure 24. Rank Transformed Scatterplot for Per Capita Municipal Water Consumption and Percent Bachelor's Degree 1990.

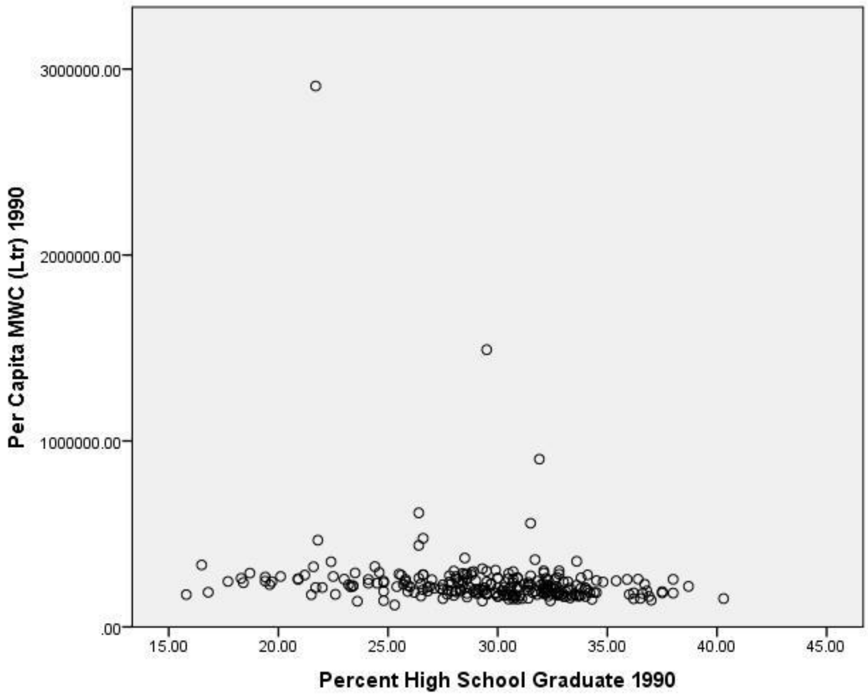

Figure 25. Original Scatterplot for Per Capita Municipal Water Consumption and Percent High School Graduate 1990.

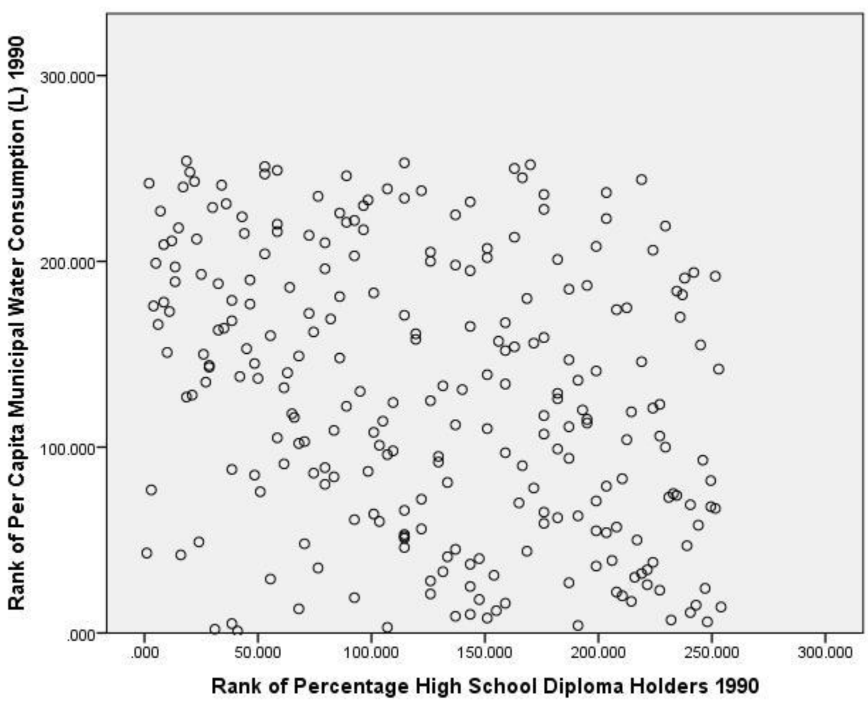

Figure 26. Rank Transformed Scatterplot for Per Capita Municipal Water Consumption and Percent High School Graduate 1990.

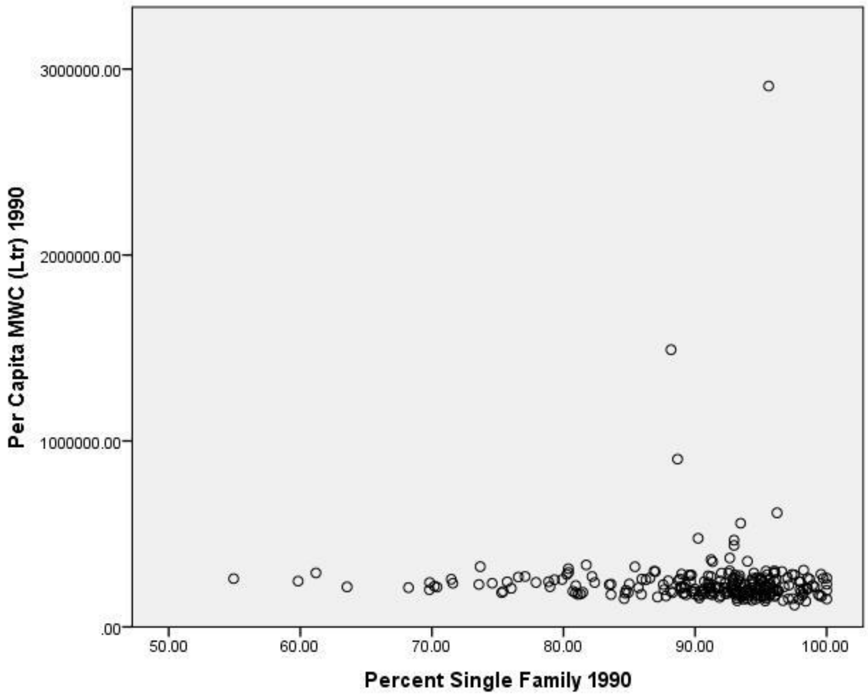

Figure 27. Original Scatterplot for Per Capita Municipal Water Consumption and Percent Single Family 1990.

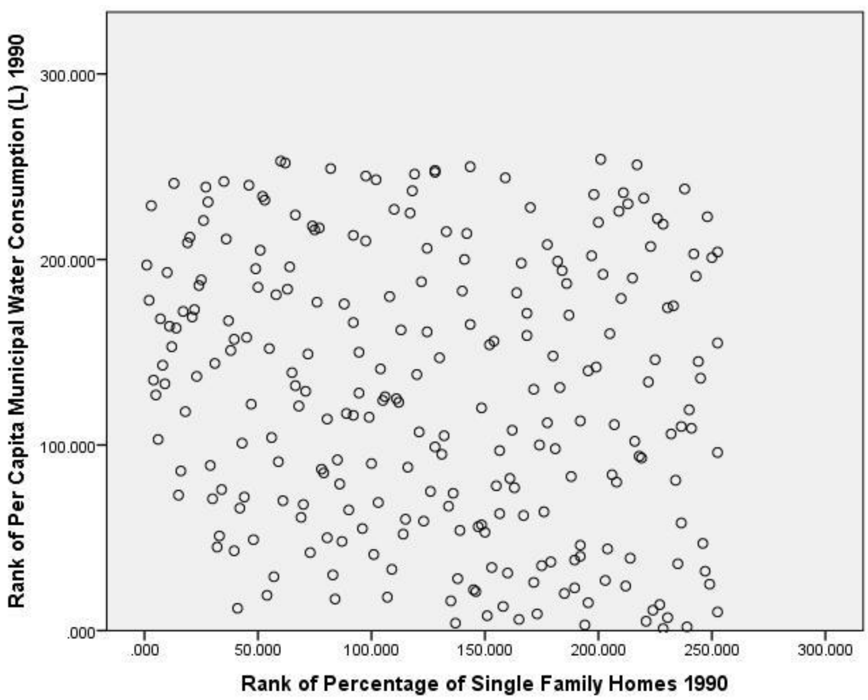

Figure 28. Rank Transformed Scatterplot for Per Capita Municipal Water Consumption and Percent Single Family 1990.

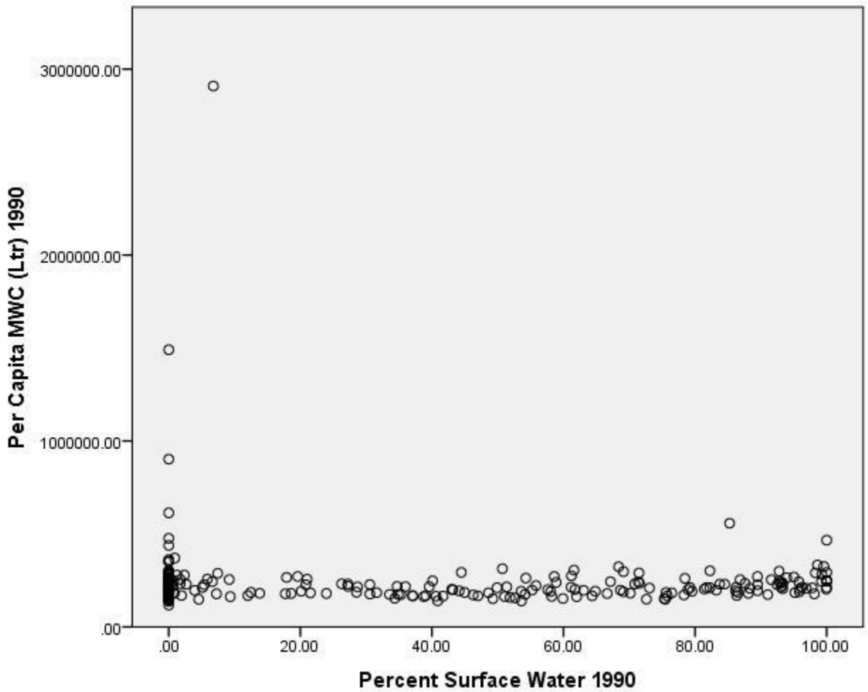

Figure 29. Original Scatterplot for Per Capita Municipal Water Consumption and Percent Surface Water 1990.

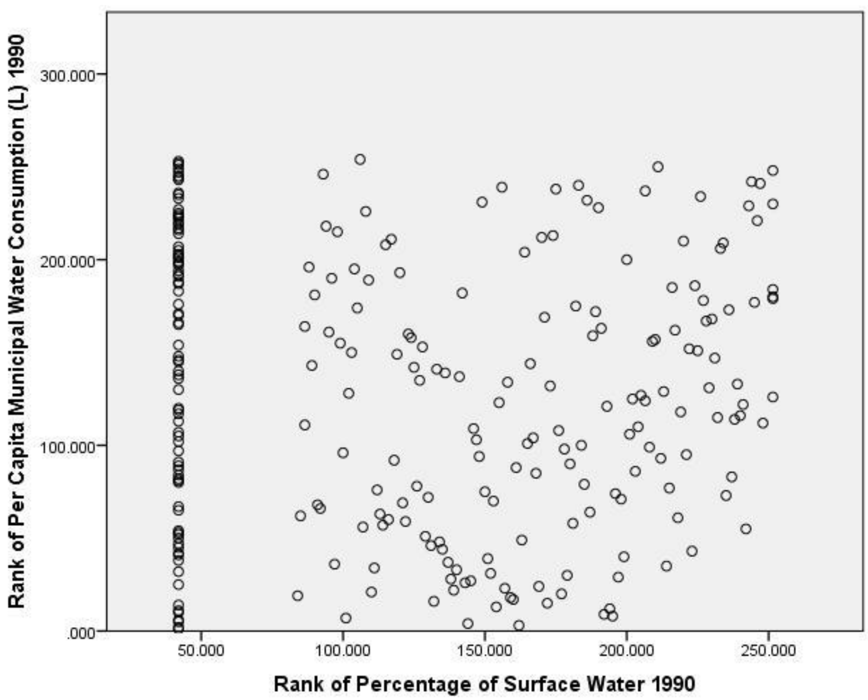

Figure 30. Rank Transformed Scatterplot for Per Capita Municipal Water Consumption and Percent Surface Water 1990.

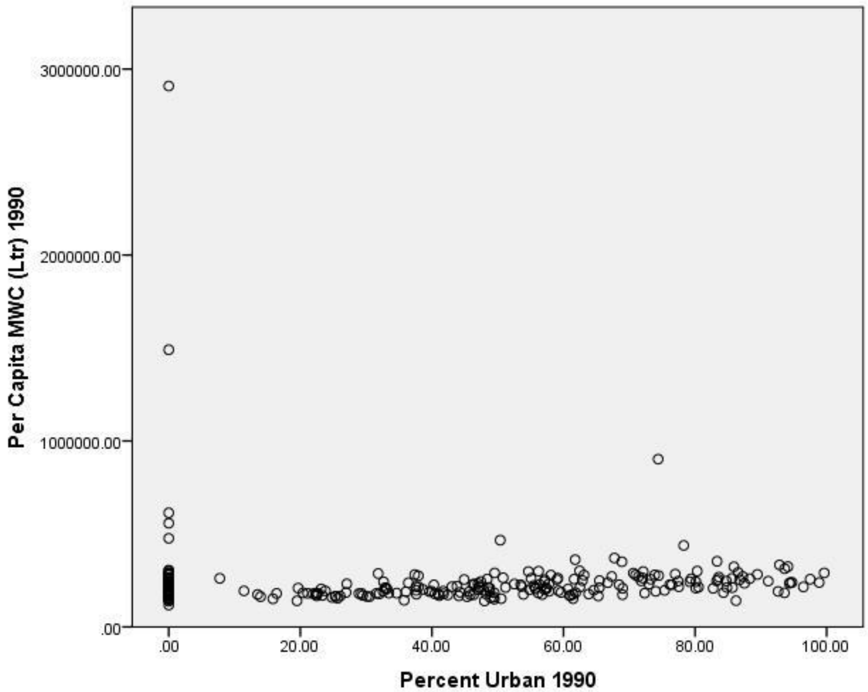

Figure 31. Original Scatterplot for Per Capita Municipal Water Consumption and Percent Urban 1990.

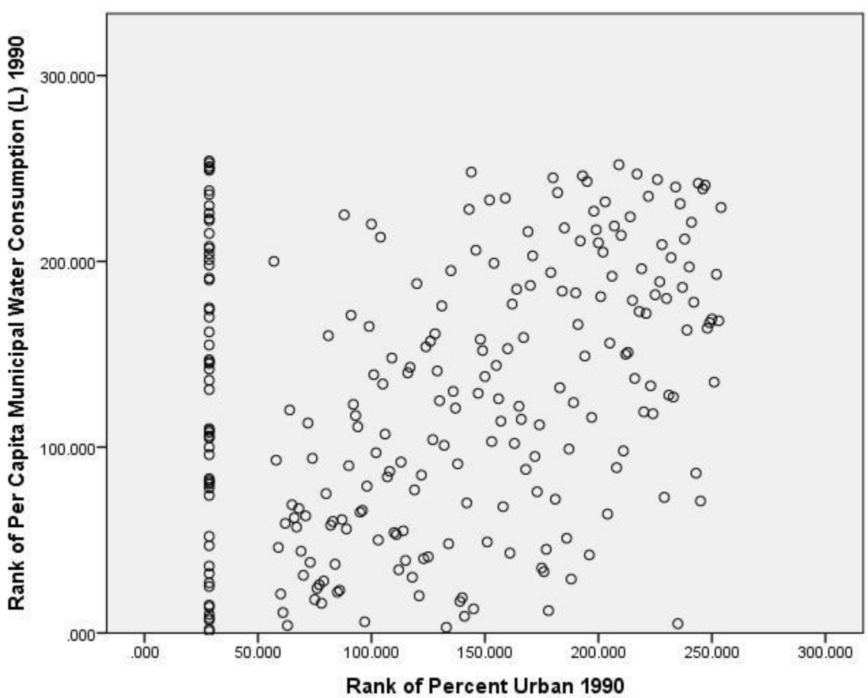

Figure 32. Rank Transformed Scatterplot for Per Capita Municipal Water Consumption and Percent Urban 1990.

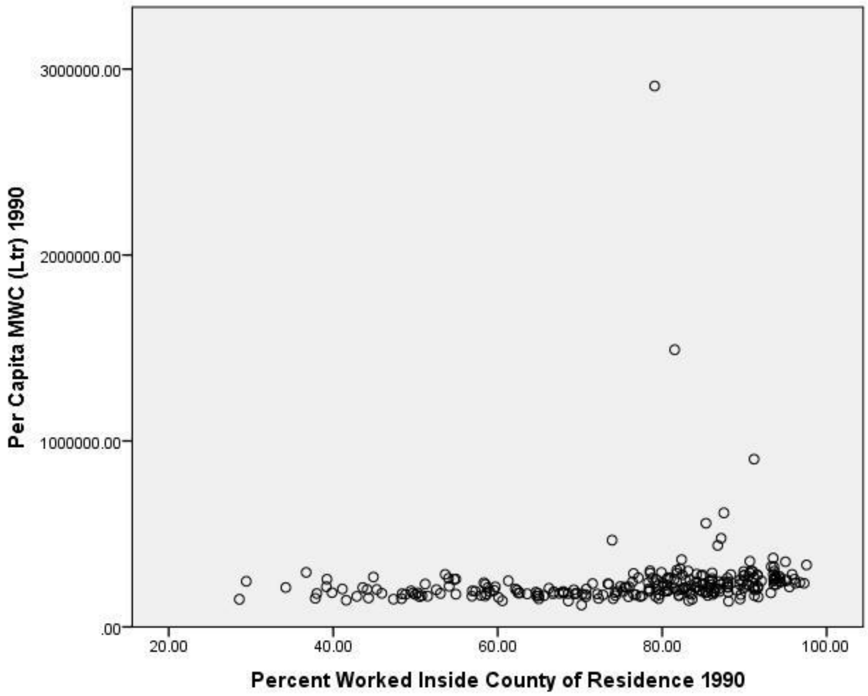

Figure 33. Original Scatterplot for Per Capita Municipal Water Consumption and Percent Worked Inside County of Residence 1990.

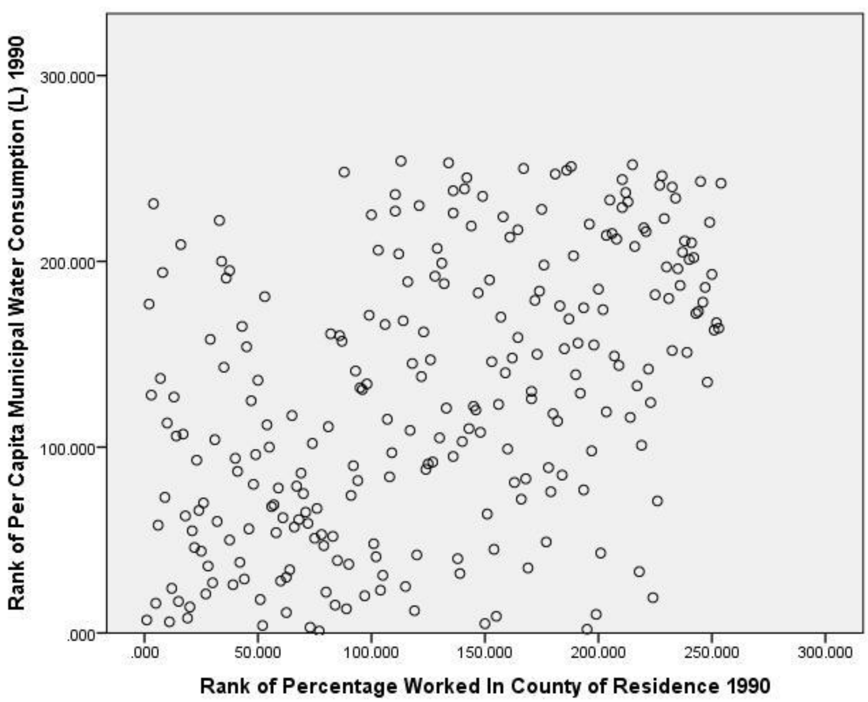

Figure 34. Rank Transformed Scatterplot for Per Capita Municipal Water Consumption and Percent Worked Inside County of Residence 1990.

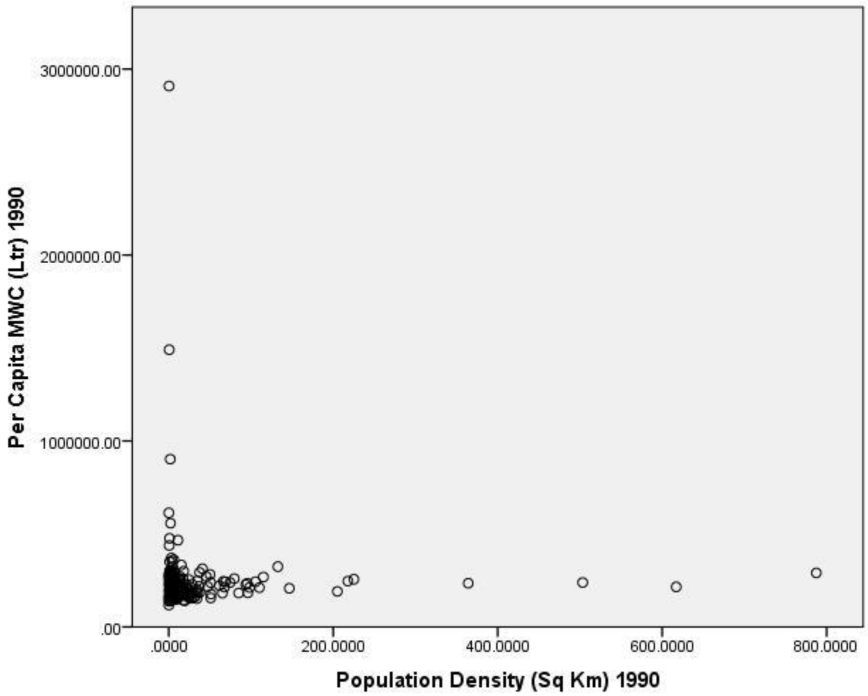

Figure 35. Original Scatterplot for Per Capita Municipal Water Consumption and Population Density 1990.

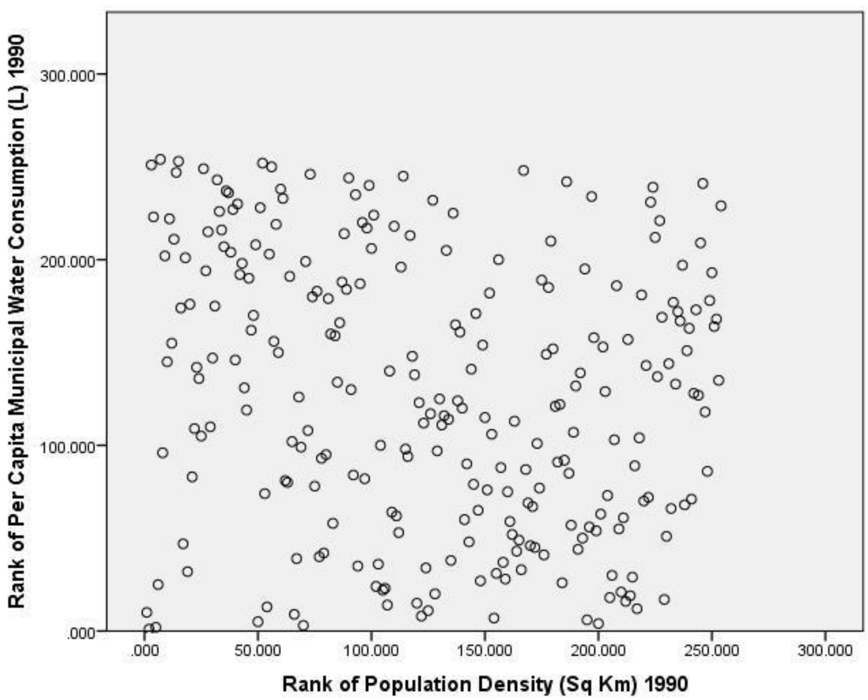

Figure 36. Rank Transformed Scatterplot for Per Capita Municipal Water Consumption and Population Density 1990.

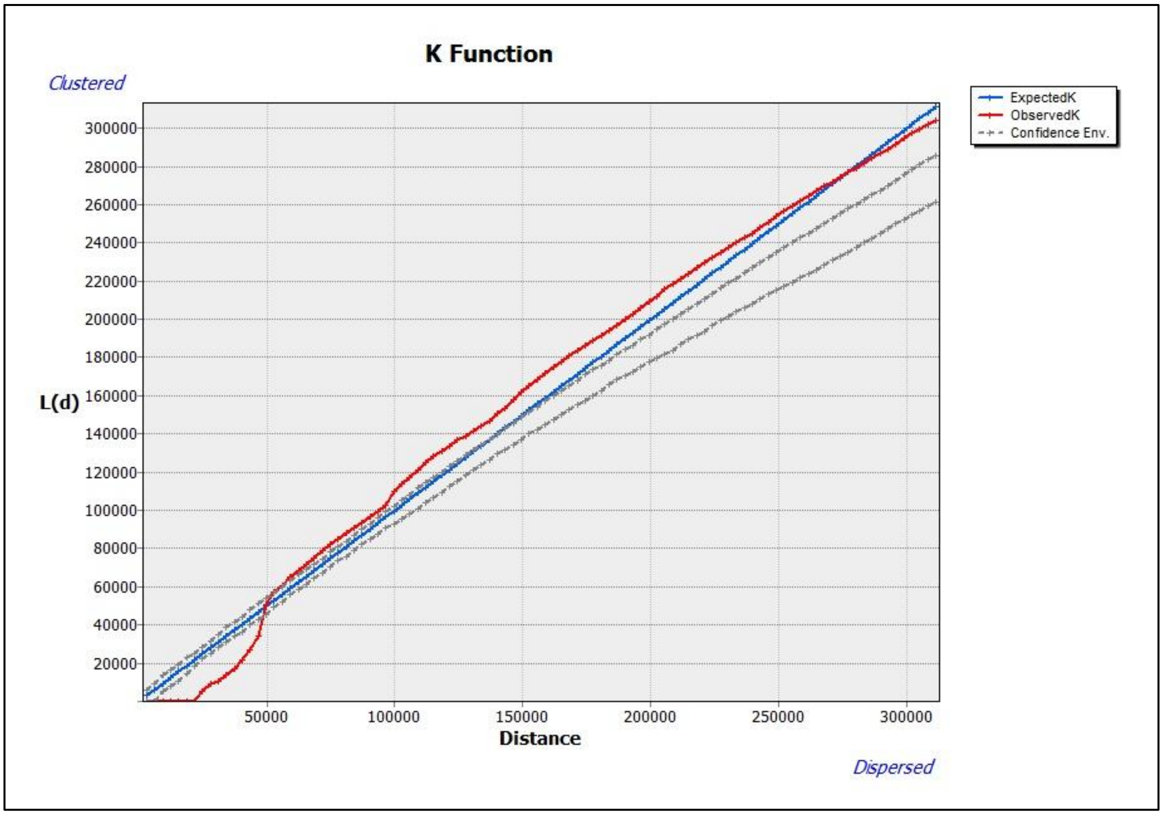

Figure 37. Ripley's K Graph for Models 1, 2, 3, and 8. This graph shows the results of the Ripley K Function for all 254 Texas county centroids based on the generation of 100 distance bands and 99 permutations of the K Function. The confidence envelope represents the 99% confidence interval or $\alpha = 0.01$. Outside the confidence interval, clustering is statistically significant when the observed value of K exceeds the expected value of K. The maximum difference for this function was 171996.75 meters which represented the shortest distance over which spatial processes maximized clustering in the original point pattern.

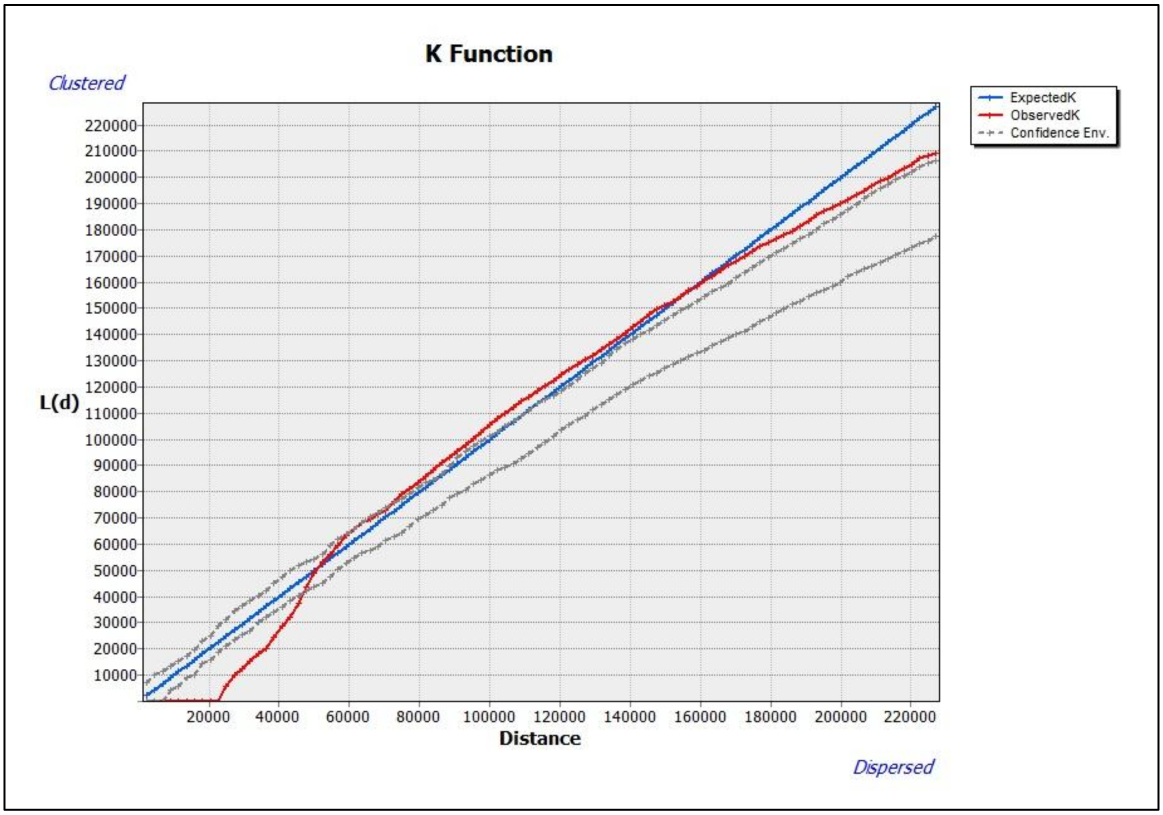

Figure 38. Ripley's K Graph for Model 4.. This graph shows the results of the Ripley K Function for all 120 Texas county centroids east of the dry line based on the generation of 100 distance bands and 99 permutations of the K Function. The confidence envelope represents the 99% confidence interval or $\alpha = 0.01$. Outside the confidence interval, clustering is statistically significant when the observed value of K exceeds the expected value of K. The maximum difference for this function was 107962.05 meters which represented the shortest distance over which spatial processes maximized clustering in the original point pattern

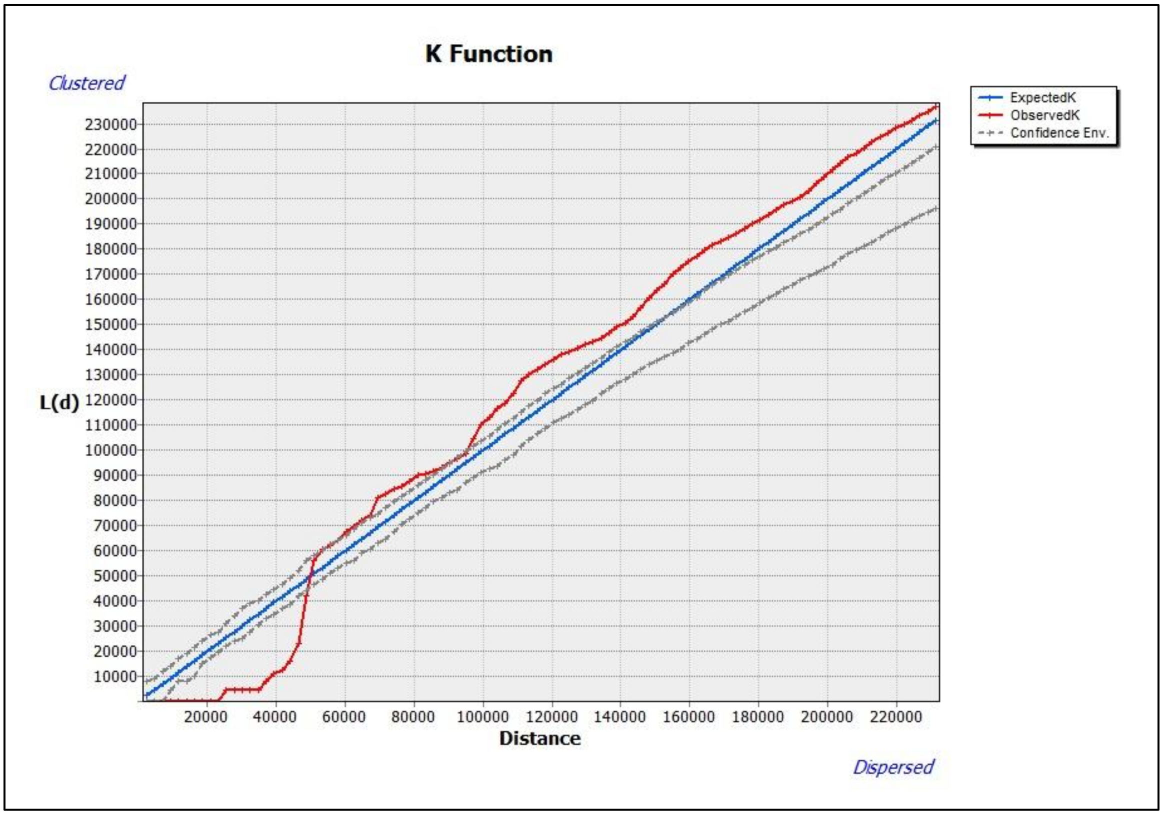

Figure 39. Ripley's K Graph for Models 5. This graph shows the results of the Ripley K Function for all 134 Texas county centroids west of the dry line based on the generation of 100 distance bands and 99 permutations of the K Function. The confidence envelope represents the 99% confidence interval or $\alpha = 0.01$. Outside the confidence interval, clustering is statistically significant when the observed value of K exceeds the expected value of K. The maximum difference for this function was 132336.78 meters which represented the shortest distance over which spatial processes maximized clustering in the original point pattern

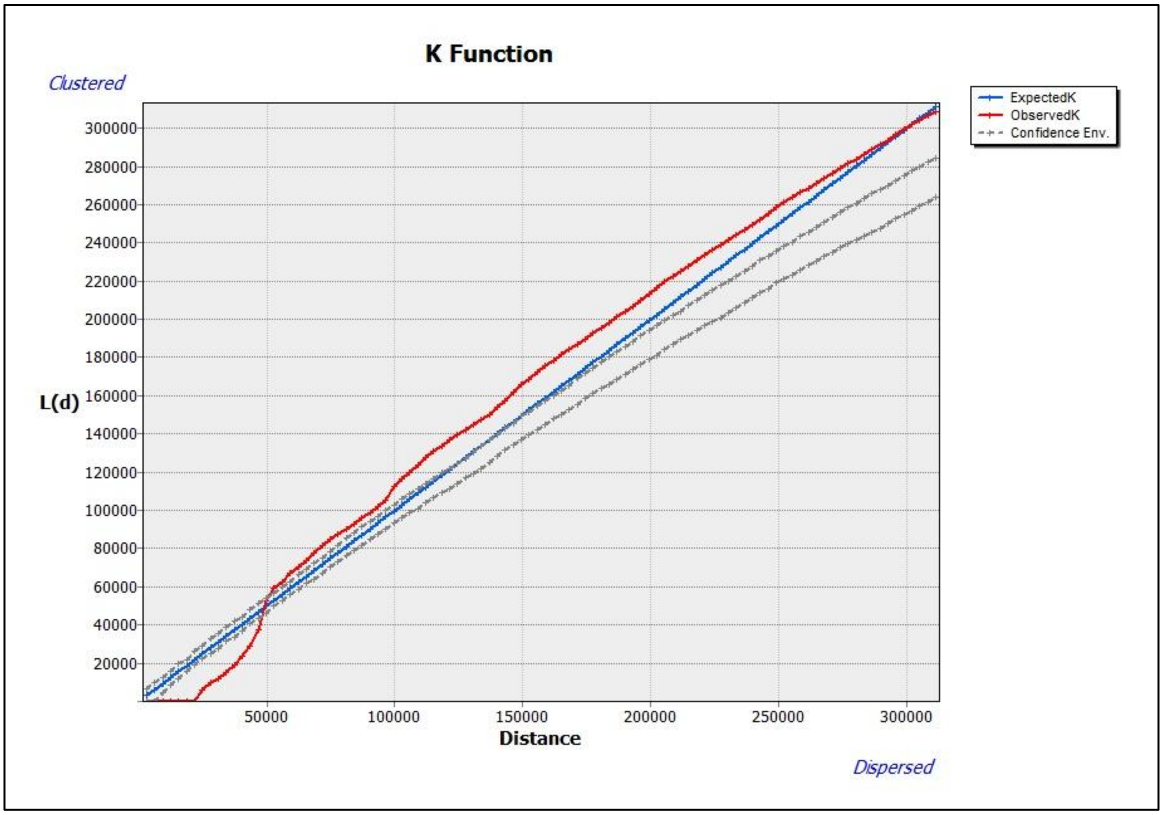

Figure 40. Ripley's K Graph for Models 6 and 7. This graph shows the results of the Ripley K Function for all 229Texas county centroids with residential building permit data for 1990, 2000, and 2010 based on the generation of 100 distance bands and 99 permutations of the K Function. The confidence envelope represents the 99% confidence interval or $\alpha = 0.01$. Outside the confidence interval, clustering is statistically significant when the observed value of K exceeds the expected value of K. The maximum difference for this function was 175482.88 meters which represented the shortest distance over which spatial processes maximized clustering in the original point pattern

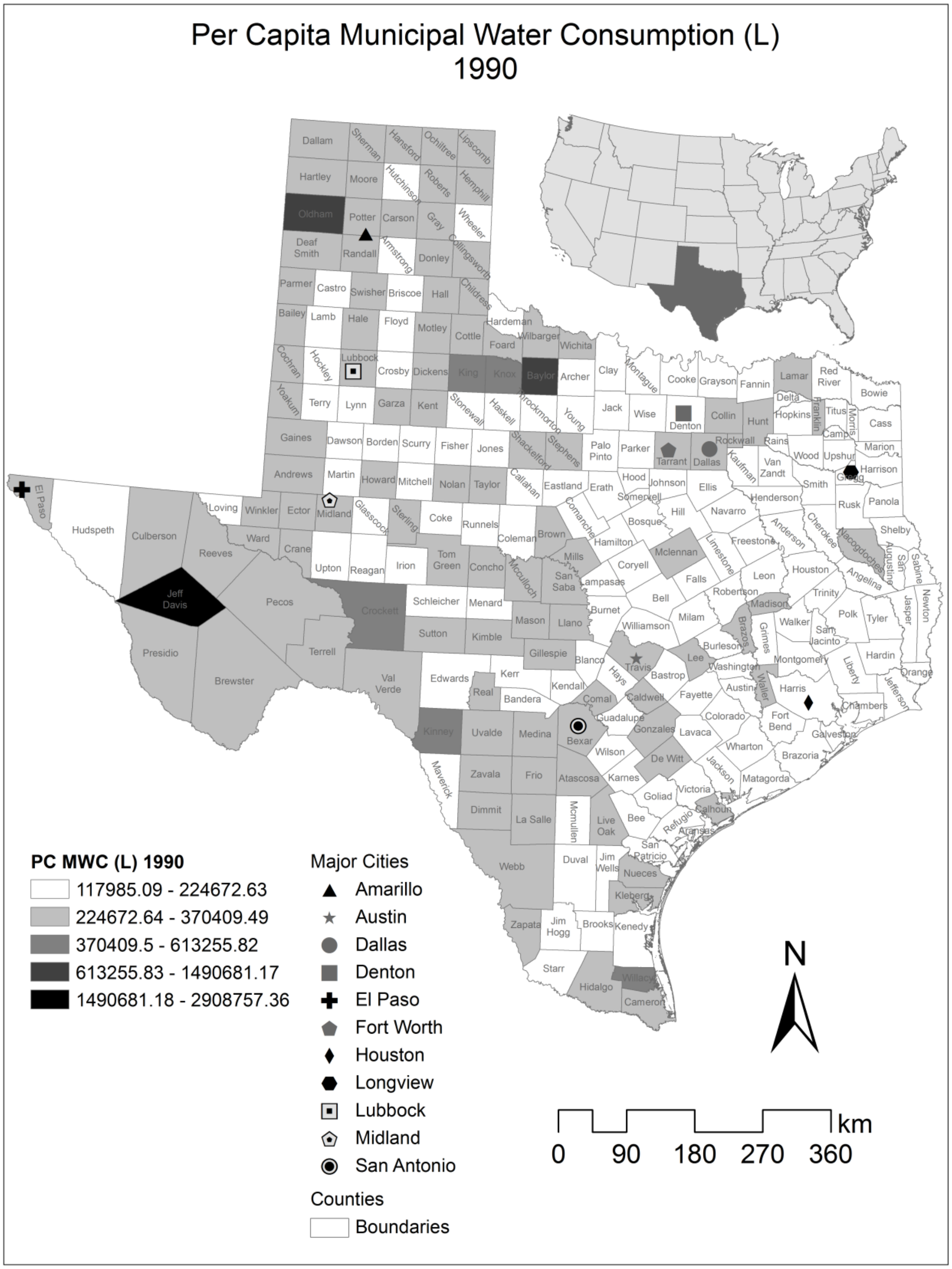

Figure 41. 1990 Per Capita Municipal Water Consumption Patterns. Note that the highest levels of per capita consumption are not confined to the established population centers of El Paso, Bexar, Travis, Dallas and Tarrant Counties. The highest per capita consumptions are in the panhandle and along the Texas-Mexico border.

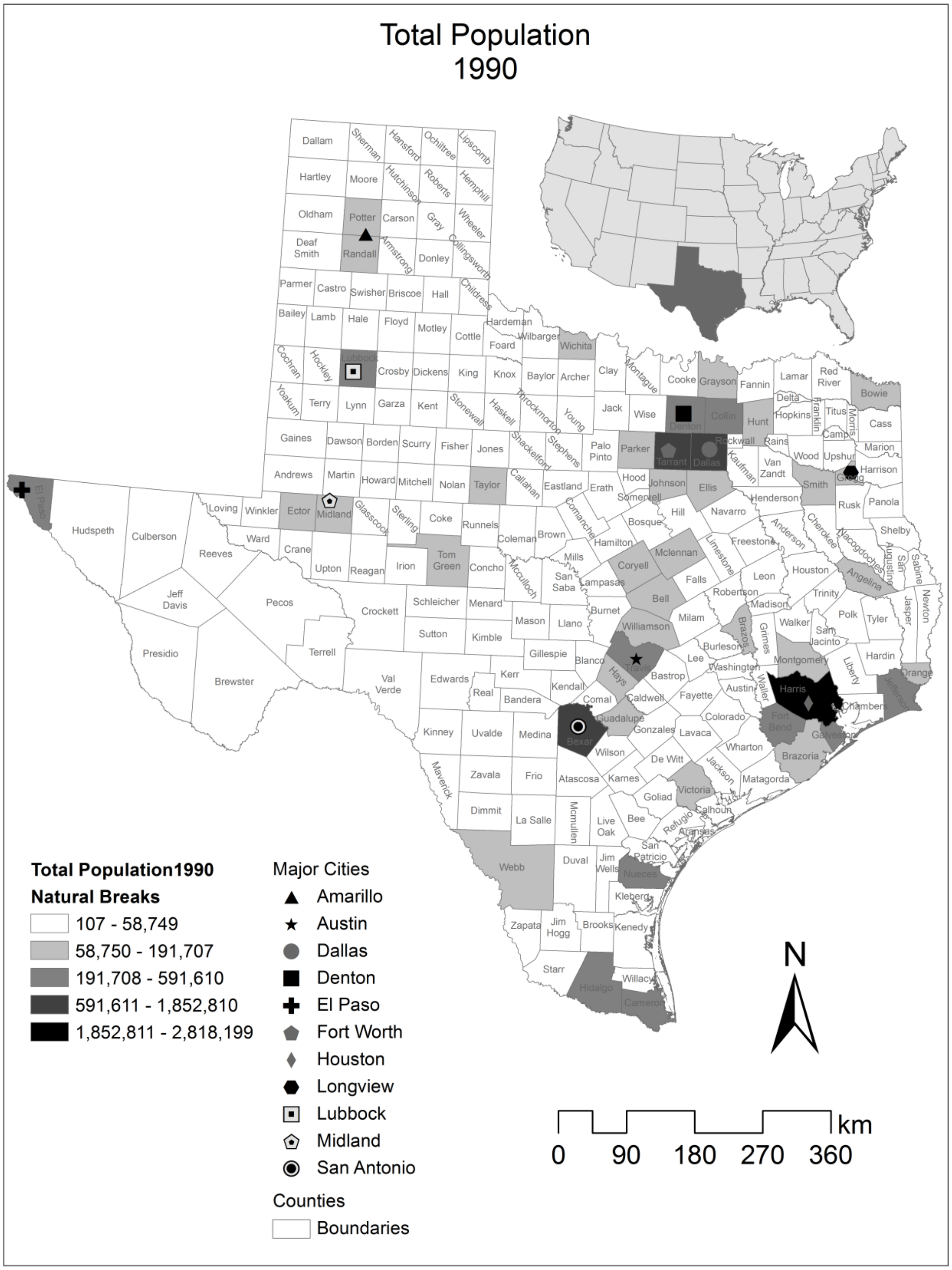

Figure 42. 1990 Total Population with Natural Breaks Classification. Note that the established population centers of El Paso, Bexar, Harris, Tarrant, and Dallas Counties are clearly visible. Additionally, Harris County has the highest population of all Counties.

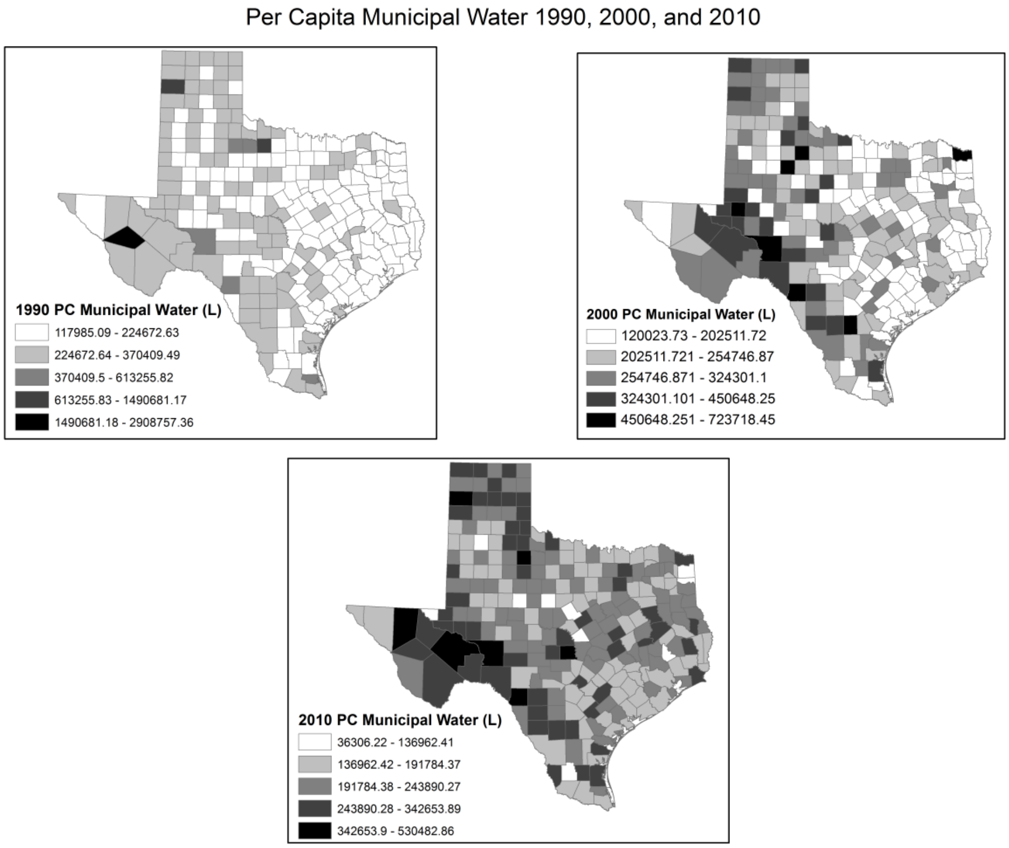

Figure 43. Comparison of Per Capita Municipal Water Patterns in 1990, 2000, and 2010. Note the consistently high consumption values in the panhandle and along the Texas-Mexico border.

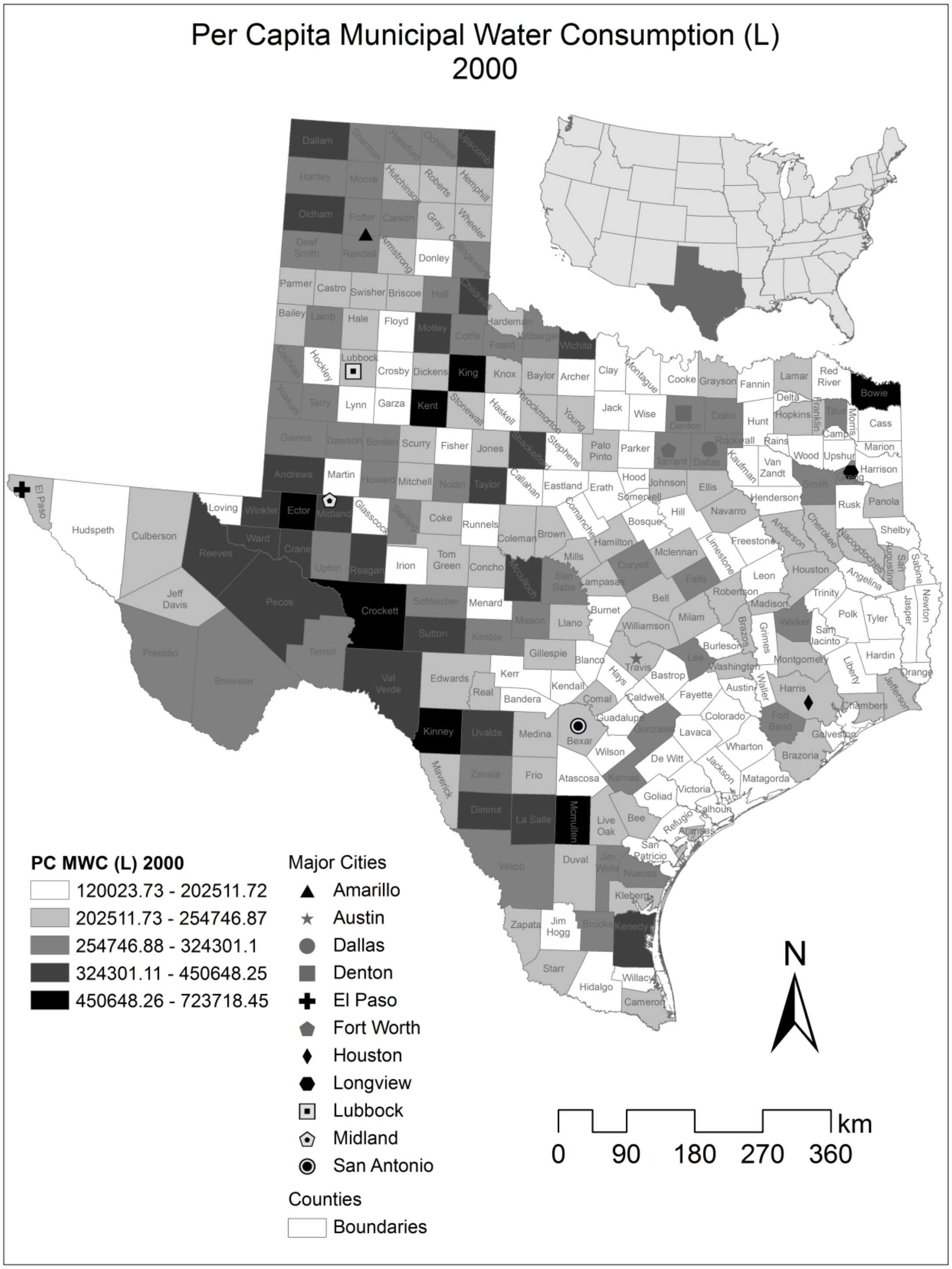

Figure 44. 2000 Per Capita Municipal Water Consumption Patterns. The highest consumption levels were in the panhandle and along the Texas-Mexico border rather than the established population centers. Per capita consumption levels are also higher in Dallas, Tarrant, Denton, and Collin Counties than in Harris County.

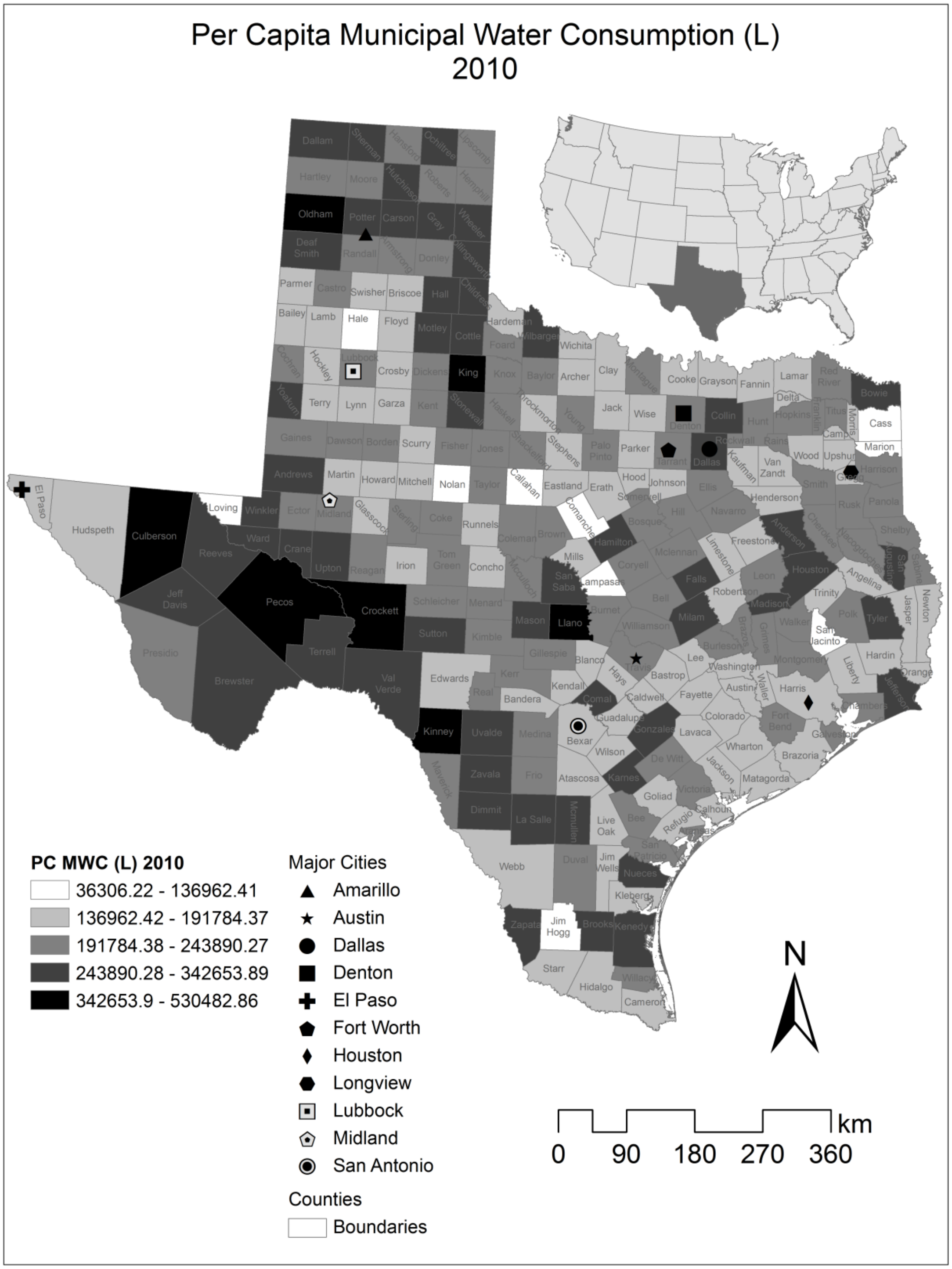

Figure 45. 2010 Per Capita Municipal Water Consumption Patterns. The high consumption levels in the panhandle and along the Texas-Mexico border persisted from 1990 and 2000. Consumption levels in Dallas, Tarrant, Denton, and Collin Counties also remained higher than Harris County.

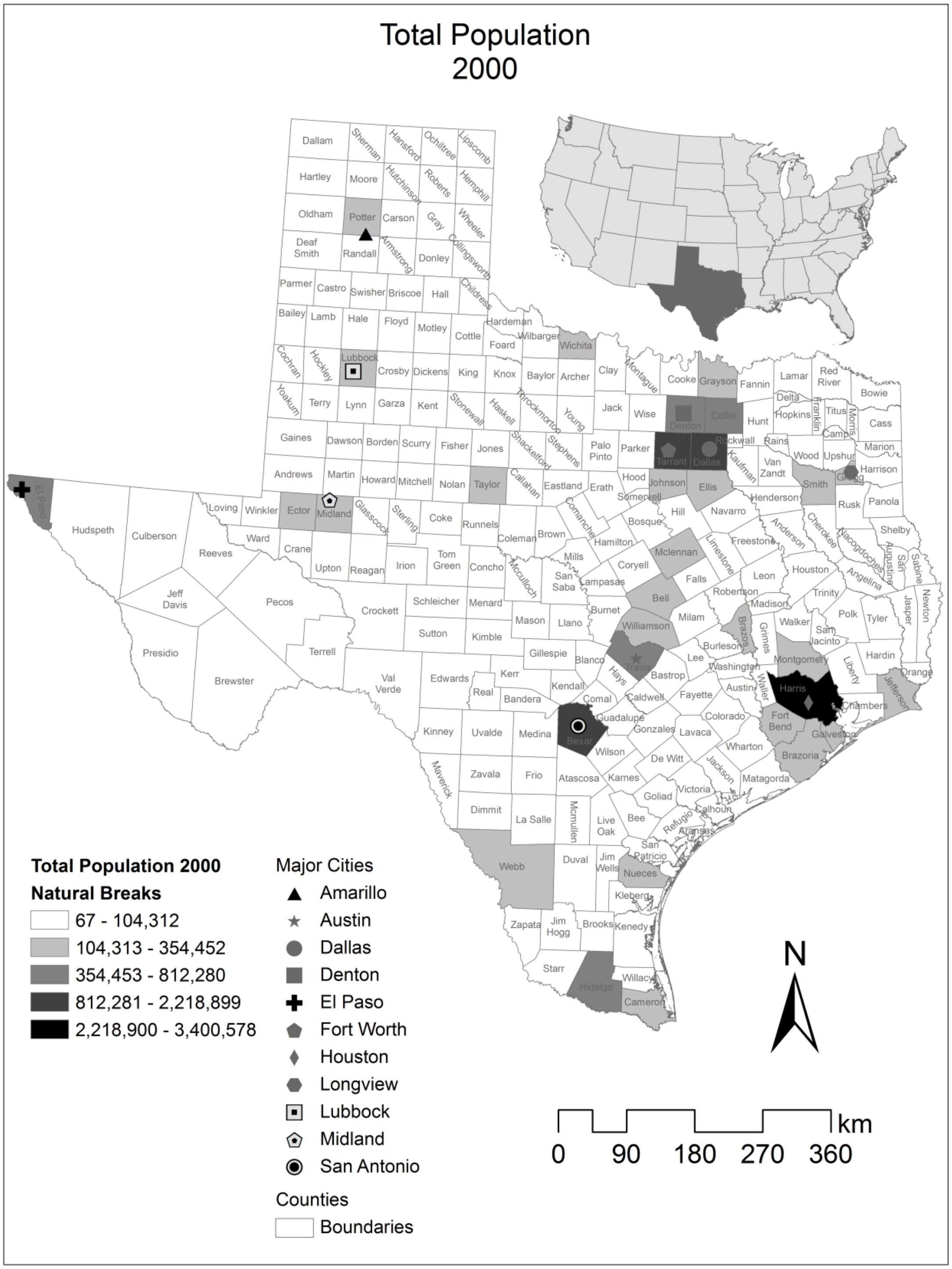

Figure 46. Total 2000 Population with a Natural Breaks Classification. Note that the general concentrations of population remain concentrated in the established population centers, rather than the locations of highest per capita municipal water consumption in Figure 42. Harris County also continued to exceed the population of the north Texas metroplex.

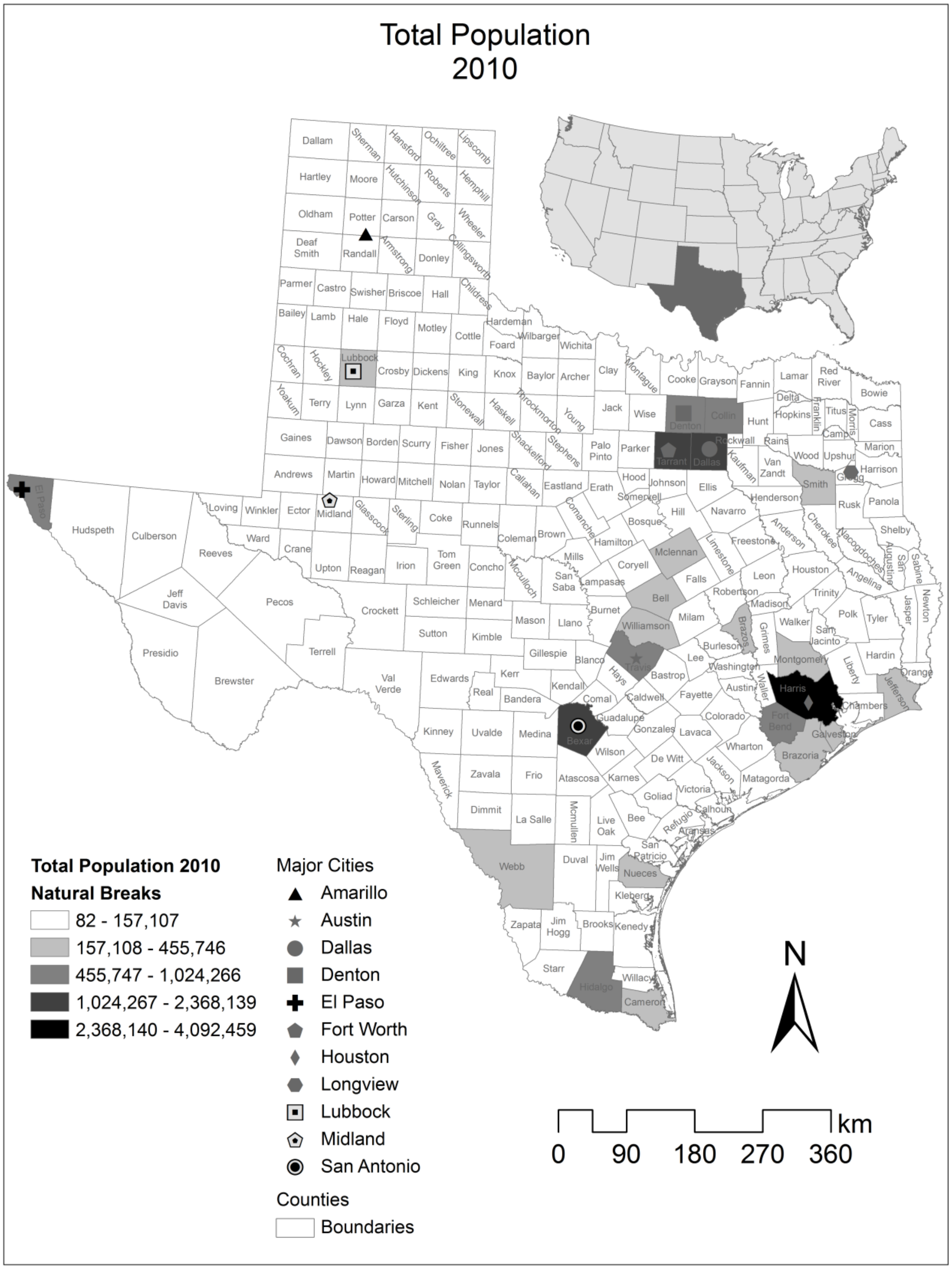

Figure 47. Total 2010 Population with Natural Breaks Classification. The general concentrations of population remained relatively consistent between 2000 and 2010, with the highest total populations in established population centers. Again, Harris County's population exceeded the north Texas core of Dallas, Denton, Tarrant and Collin Counties.

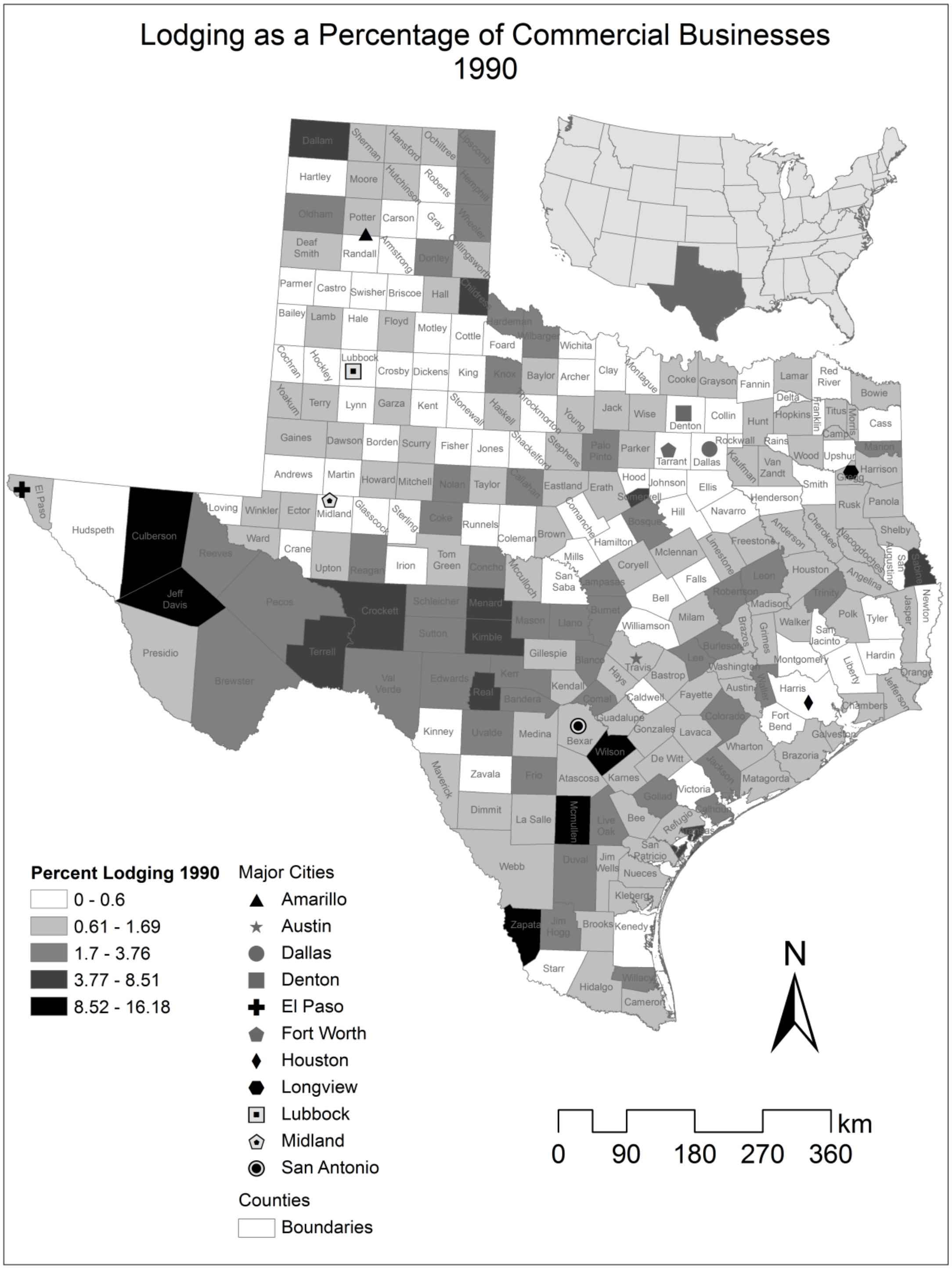

Figure 48. 1990 Lodging as a Percentage of Commercial Businesses. The counties with the highest percentages of lodging shared the same approximate locations as the counties with the highest per capita municipal water consumptions in 1990 (see Figure 41).

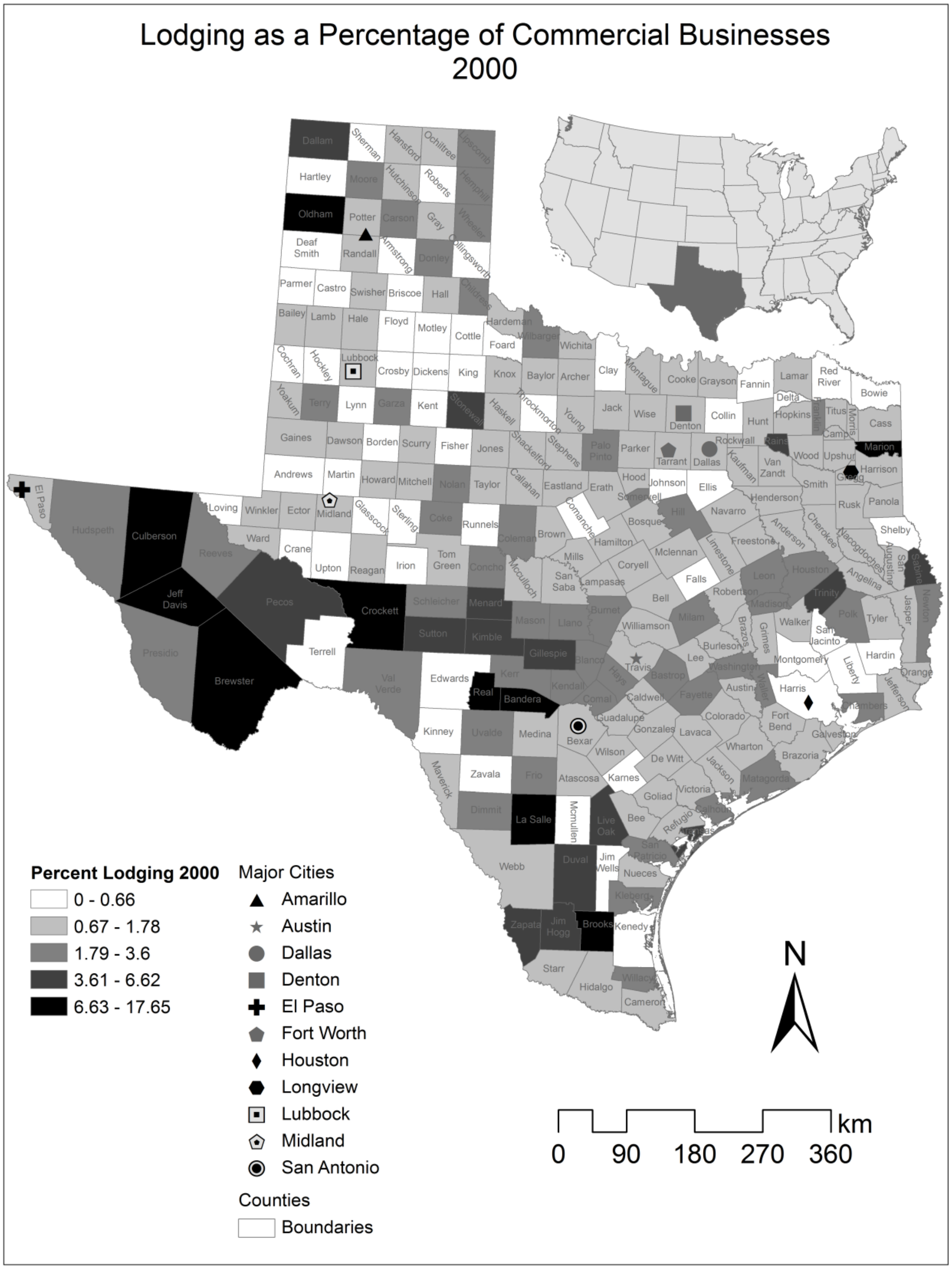

Figure 49. 2000 Lodging as a Percentage of Commercial Businesses. The counties with the highest percentages of lodging shared the same approximate locations as the counties with the highest per capita municipal water consumptions in 2000 (see Figure 44).

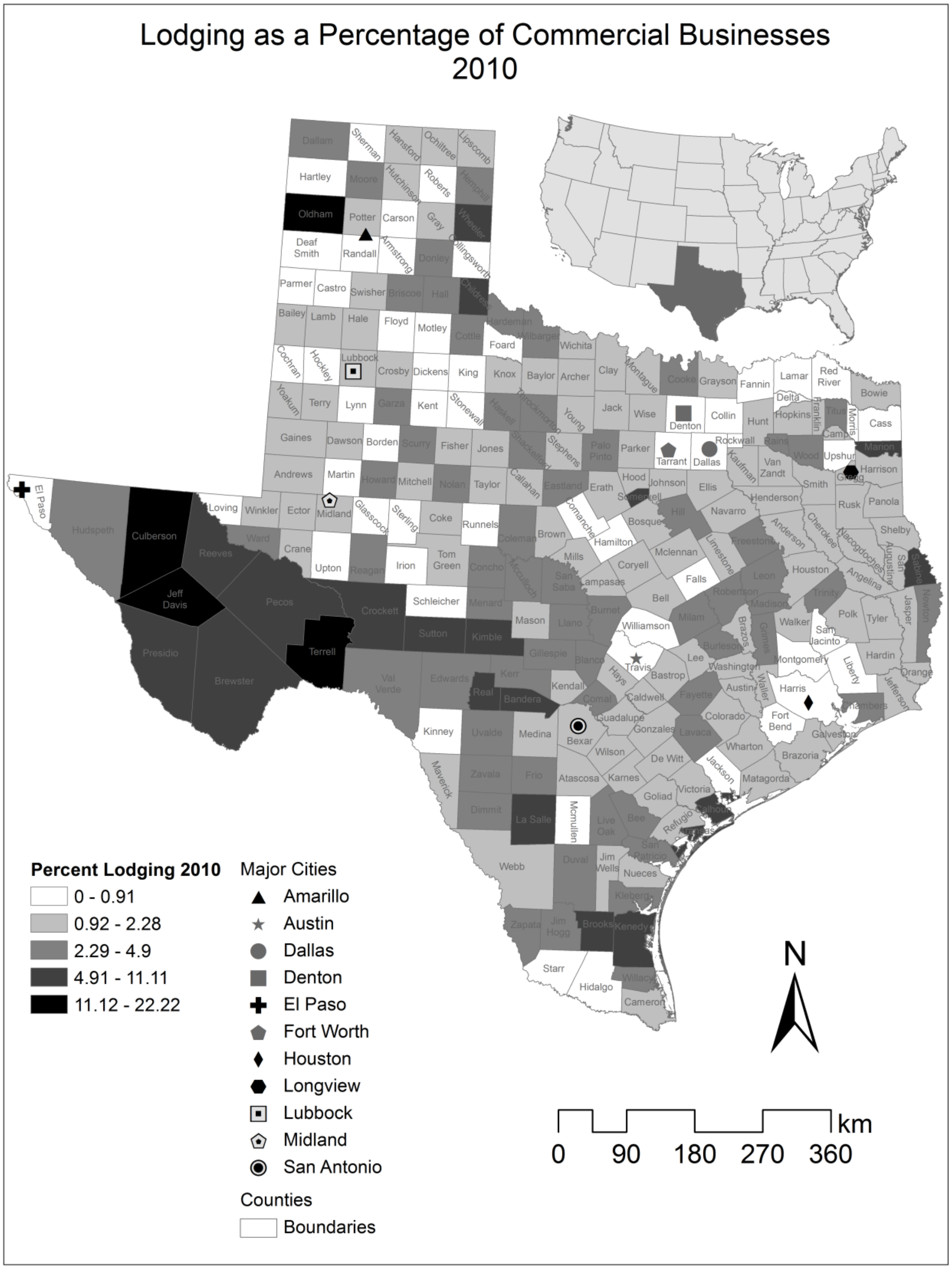

Figure 50. 2010 Lodging as a Percentage of Commercial Businesses. The counties with the highest percentages of lodging shared the same approximate locations as the counties with the highest per capita municipal water consumptions in 2010 (see Figure 45).

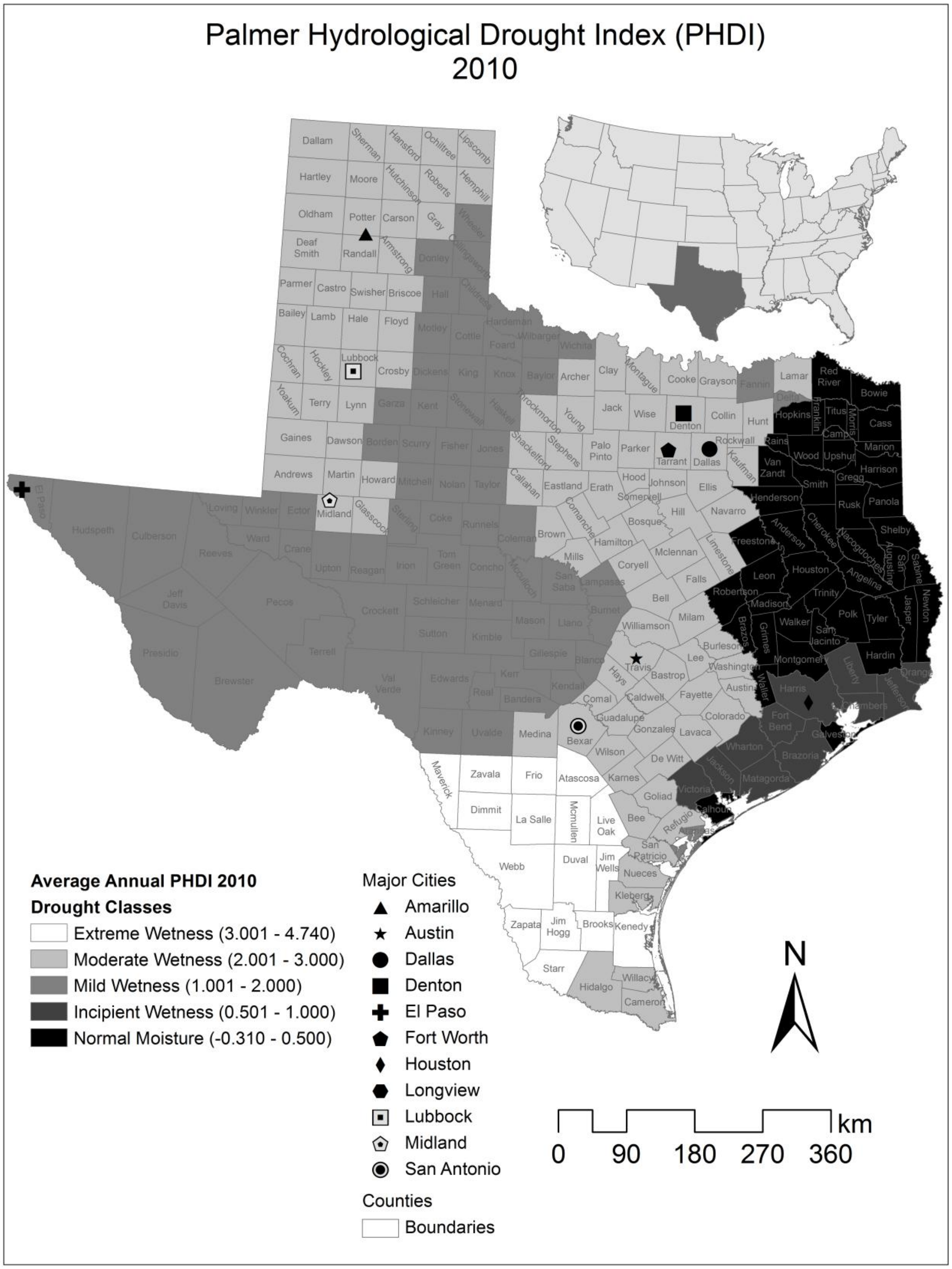

Figure 51. 2010 Palmer Hydrological Drought Index. Despite variation in the map pattern, all counties in Texas were generally wet in 2010 which may have reduced the variation in the residential outdoor component of per capita municipal water consumption.

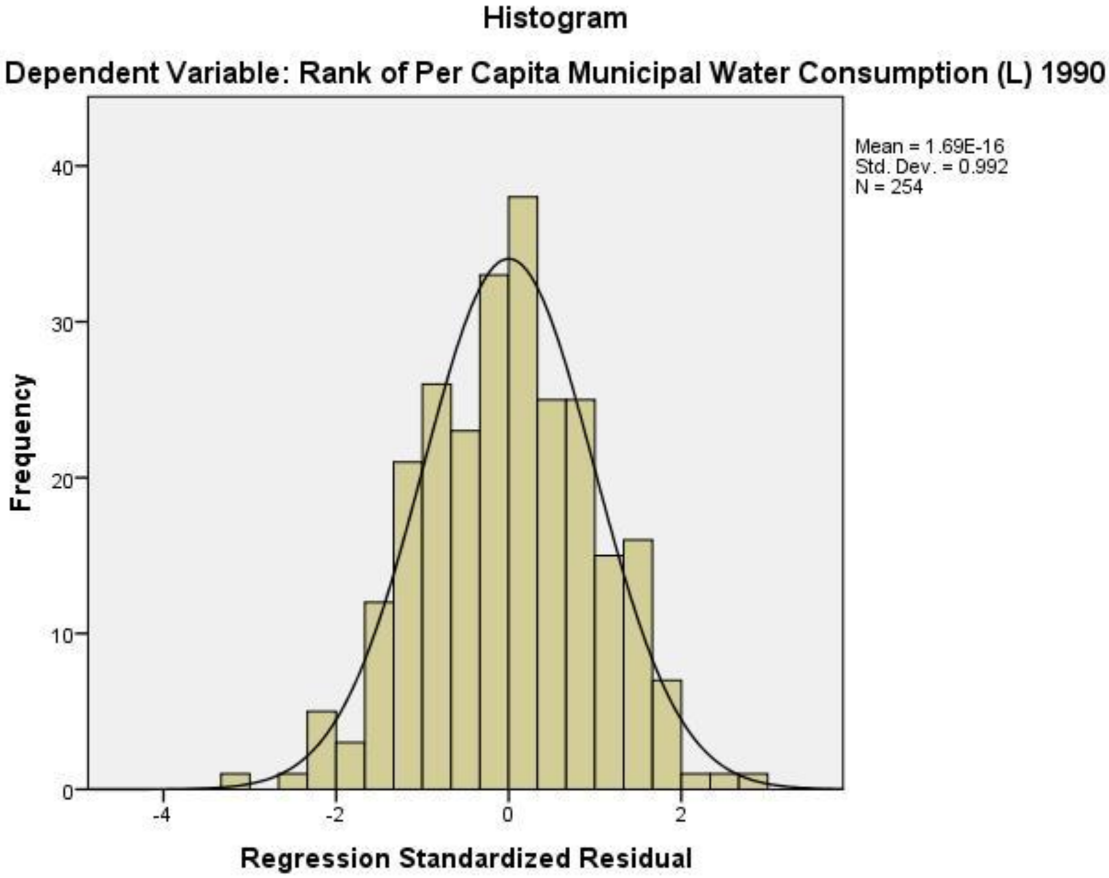

Figure 52. 1990 Model 1Distribution of Standardized Residuals. Note that the Model 1 standardized residuals follow an approximately normal distribution.

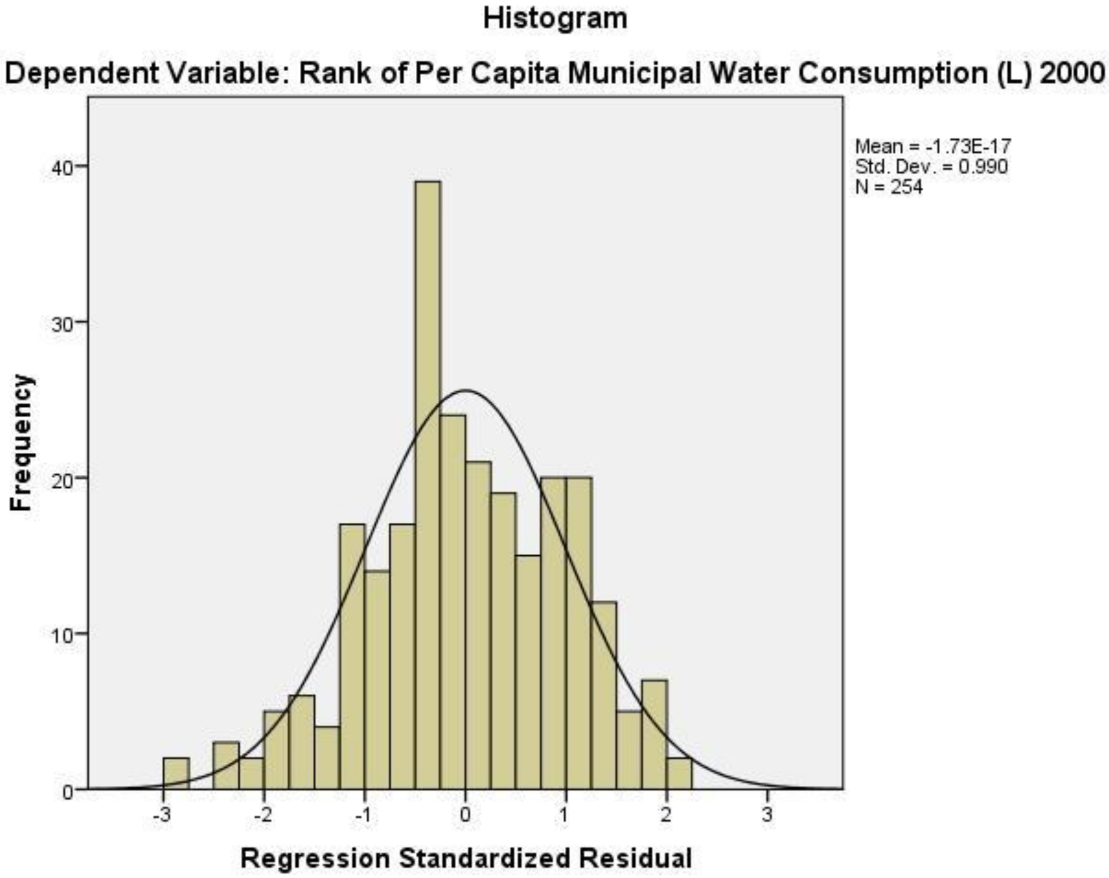

Figure 53. 2000 Model 1Distribution of Standardized Residuals. Note that the Model 1 standardized residuals follow an approximately normal distribution.

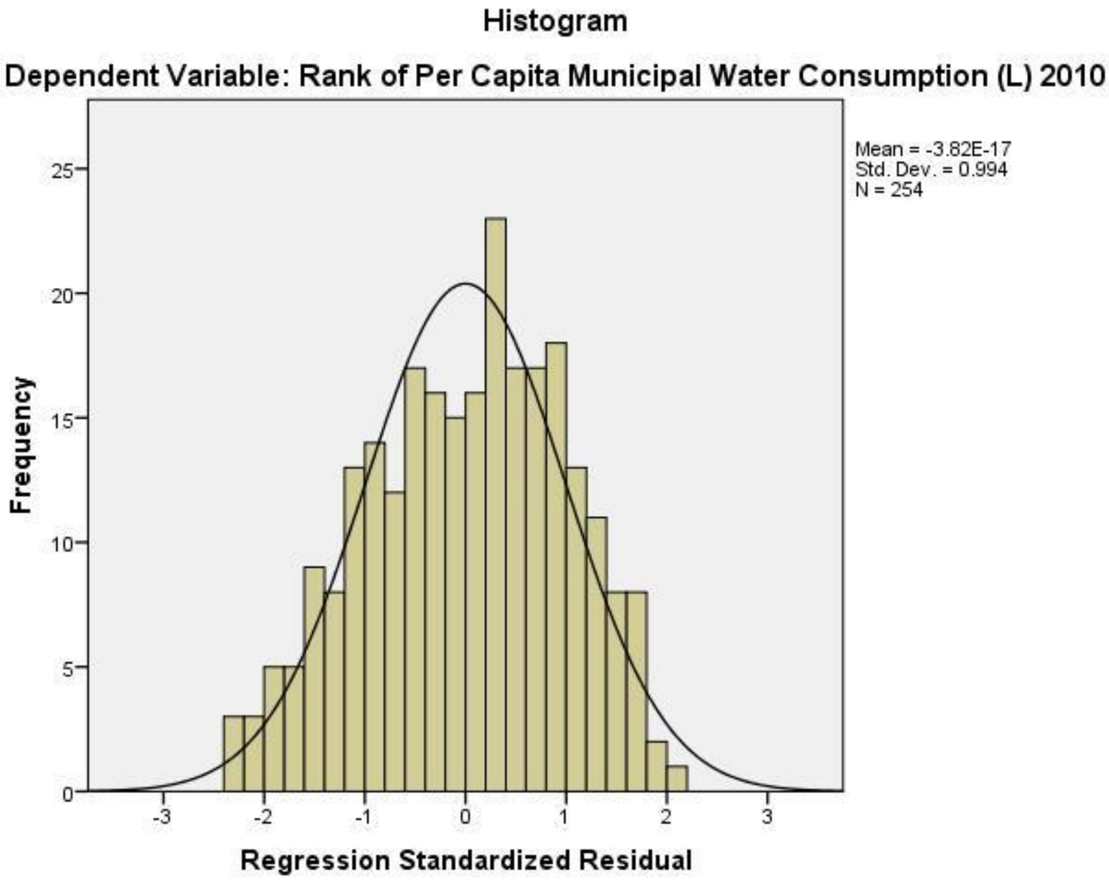

Figure 54. 2010 Model 1Distribution of Standardized Residuals. Note that the Model 1 standardized residuals follow an approximately normal distribution.

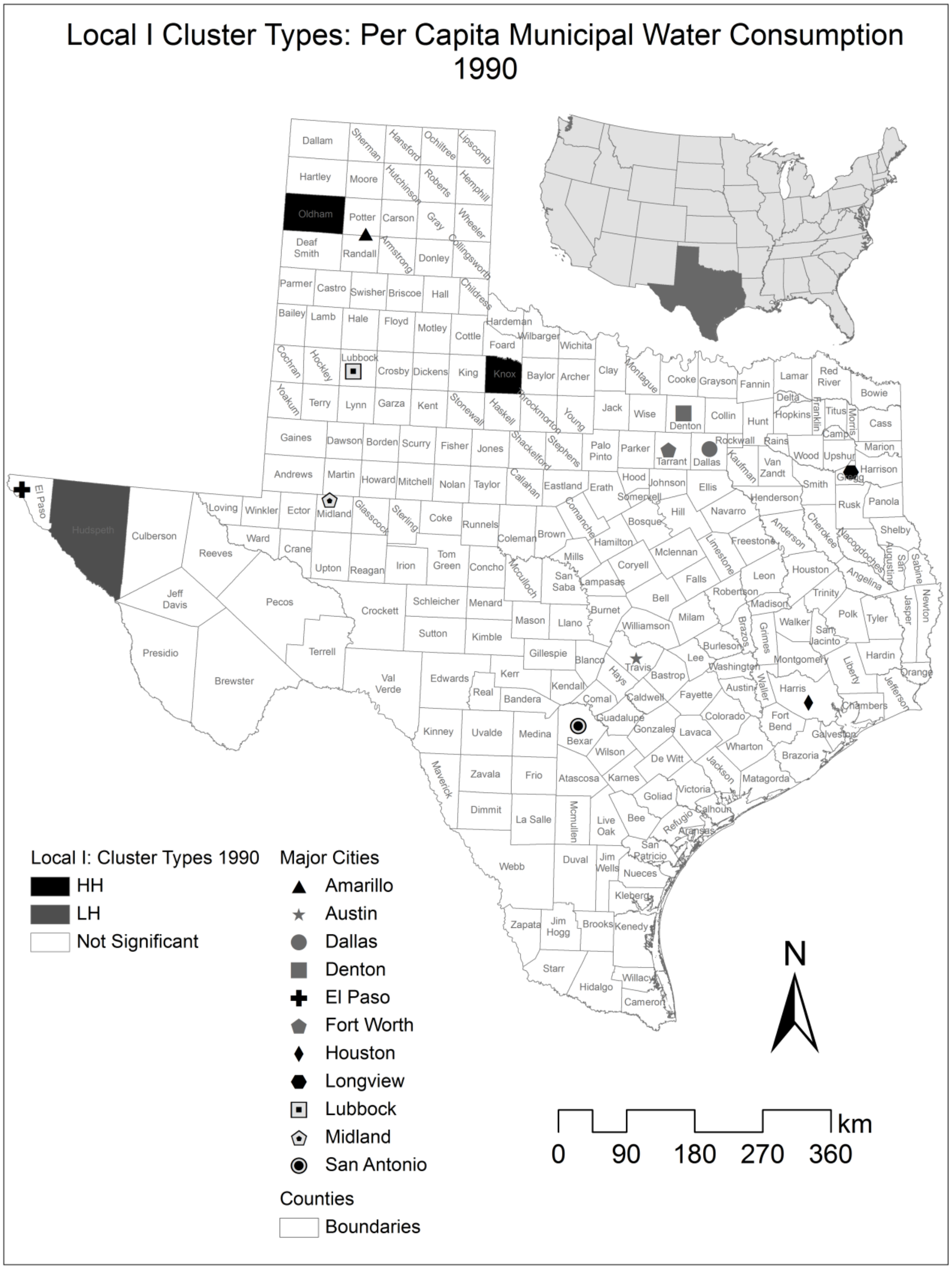

Figure 55. 1990 Local Anselin's I Clusters for Per Capita Municipal Water Consumption. The HH counties represent statistically significant clusters of high per capita municipal water consumption. The LH counties represent spatial outliers where low municipal water consumptions are surrounded by high municipal water consumptions.

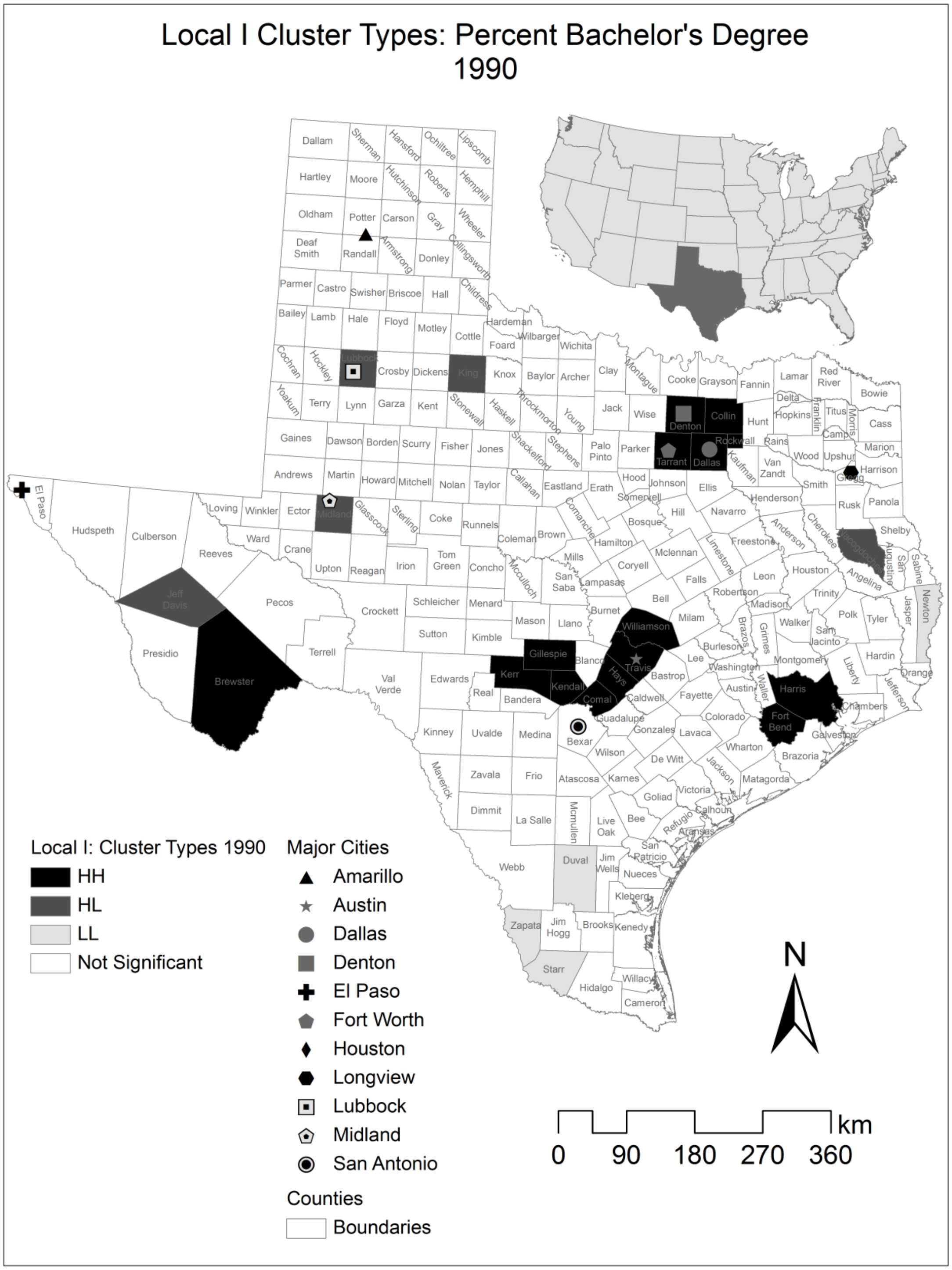

Figure 56. 1990 Local Anselin's I Clusters for Percent Bachelor's Degree. The HH and LL counties represent clusters with statistically significant high and low percentages of bachelor's degree holders respectively. The HL counties represent spatial outliers.

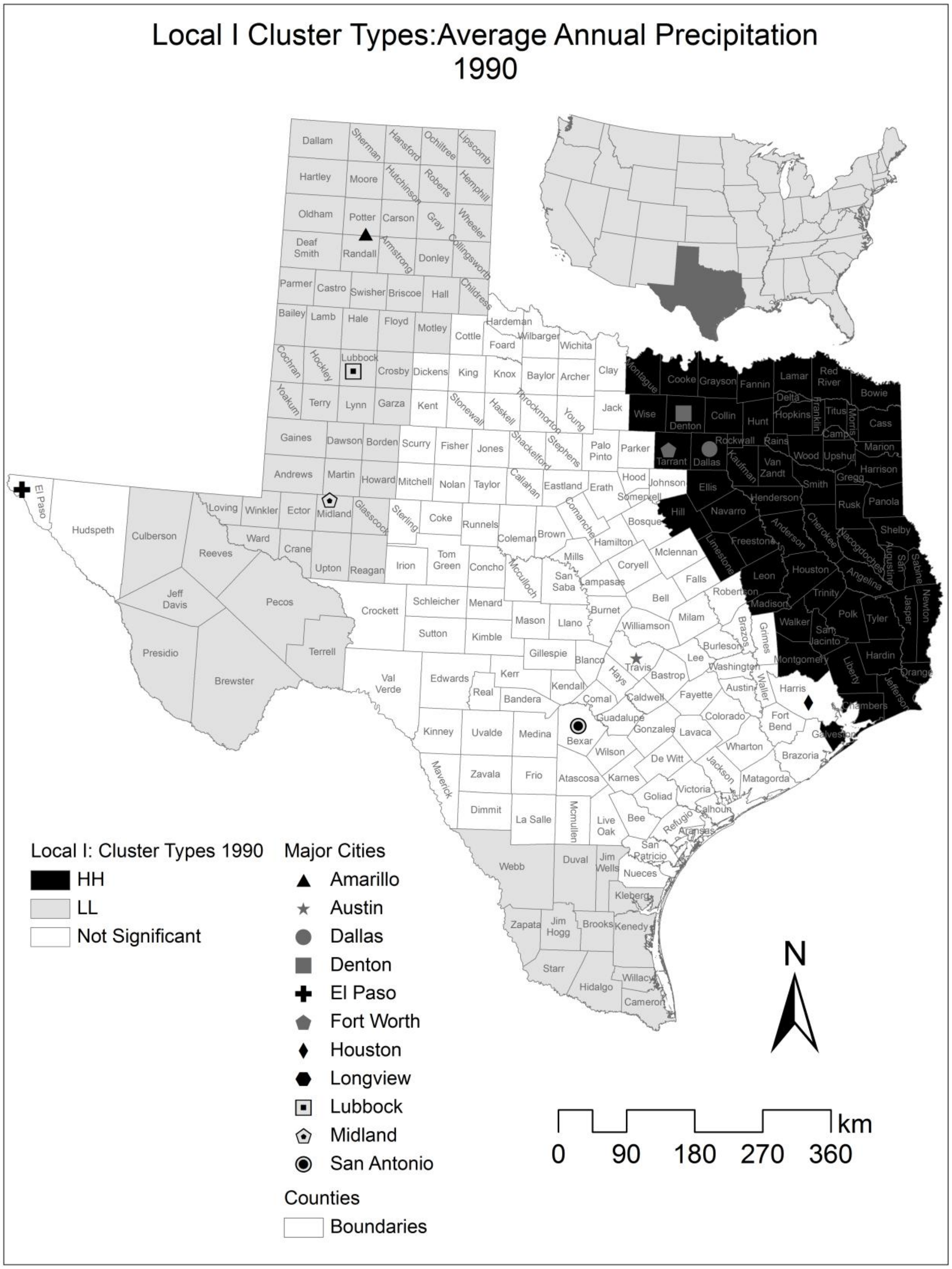

Figure 57. 1990 Local Anselin's I Clusters for Average Annual Precipitation. The HH and LL counties represent clusters with statistically significant high and low precipitation amounts respectively.

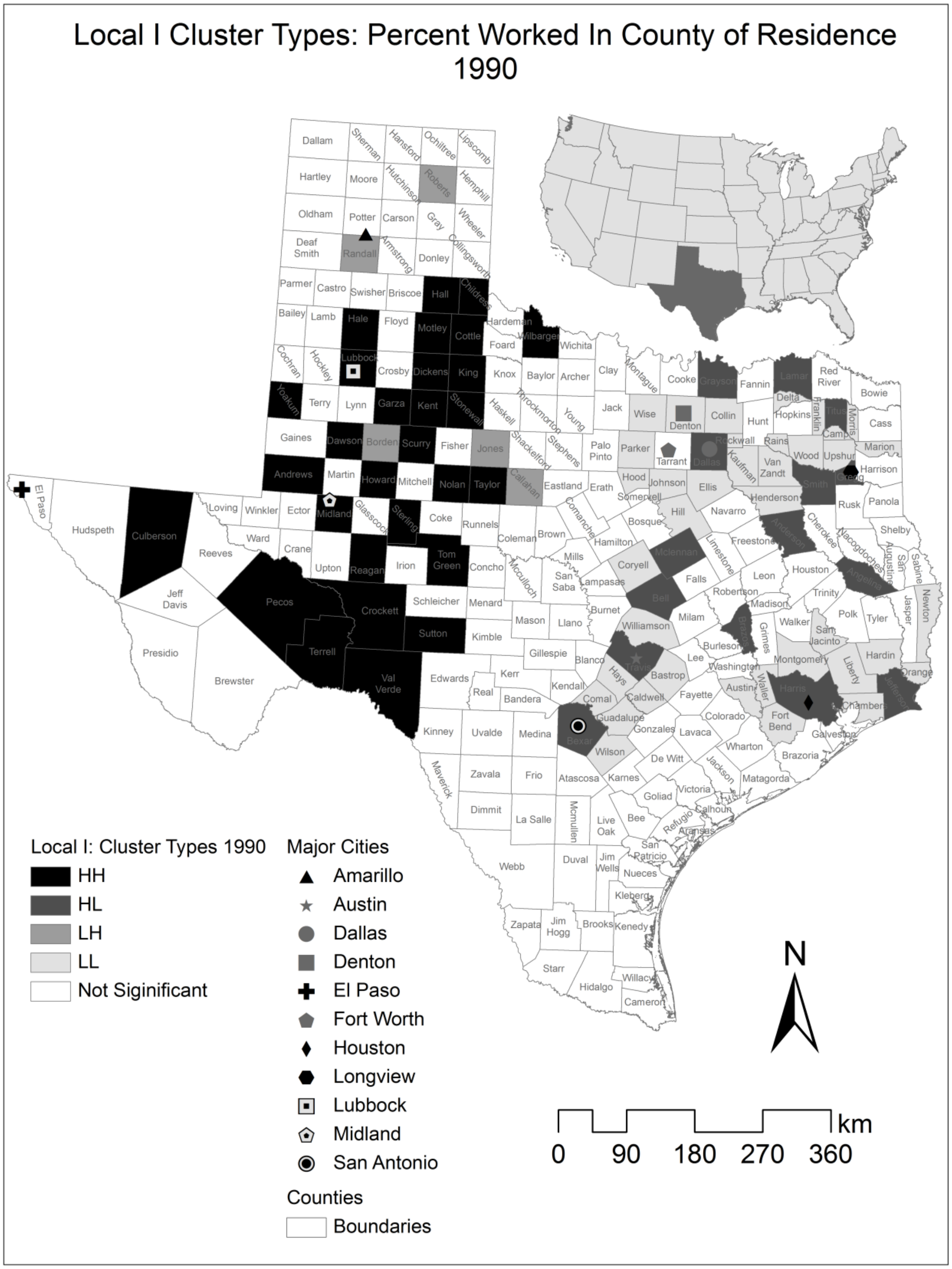

Figure 58. 1990 Local Anselin's I Clusters for Percent Worked In County of Residence. The HH and LL counties represent clusters with statistically significant high and low percentages of the population that worked in their own county respectively. Likewise, the HL and LH counties represent spatial outliers.

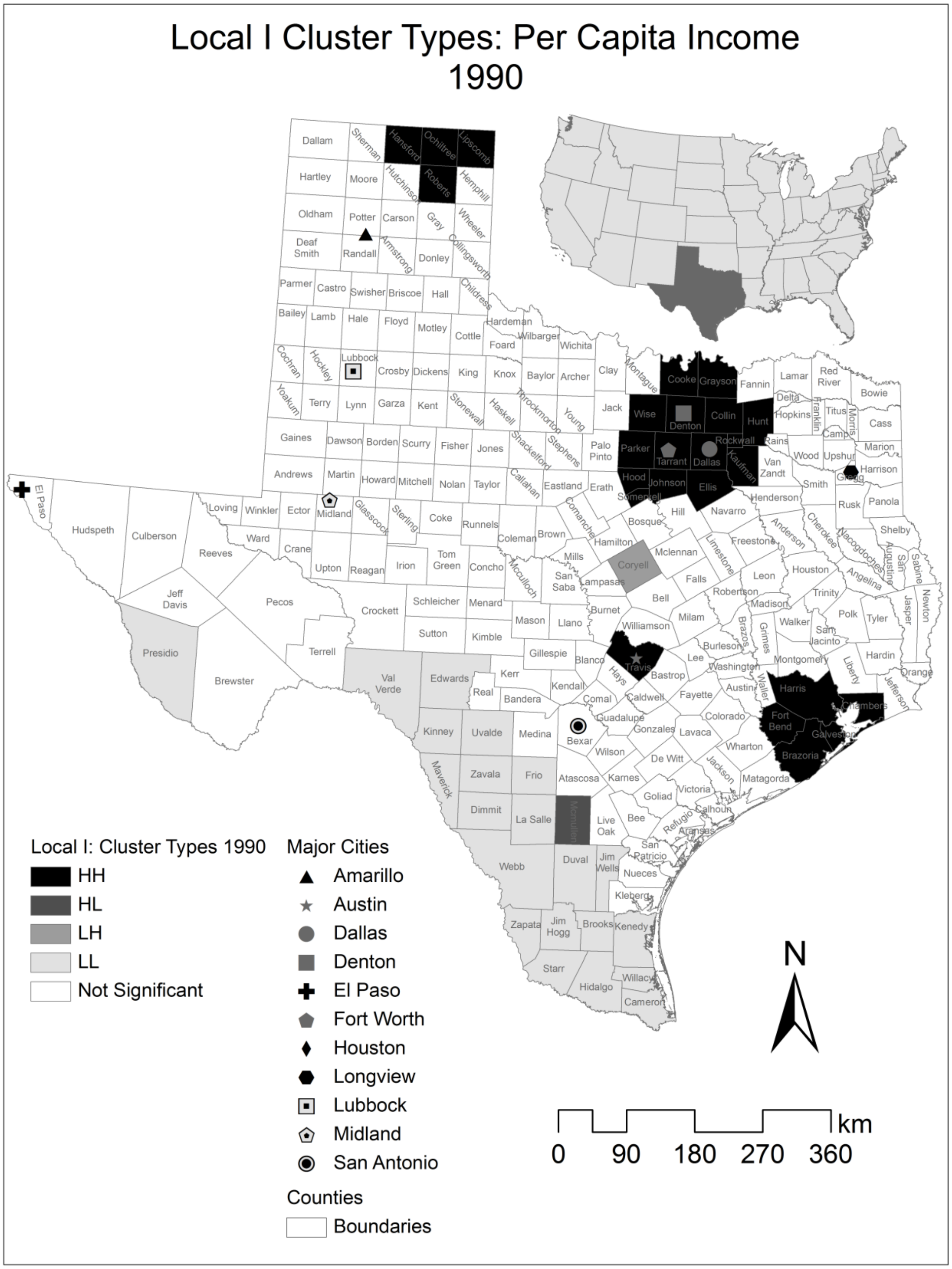

Figure 59. 1990 Local Anselin's I Clusters for Per Capita Income. The HH and LL counties represent clusters with statistically significant high and low per capita incomes respectively. Likewise, the HL and LH counties represent spatial outliers.

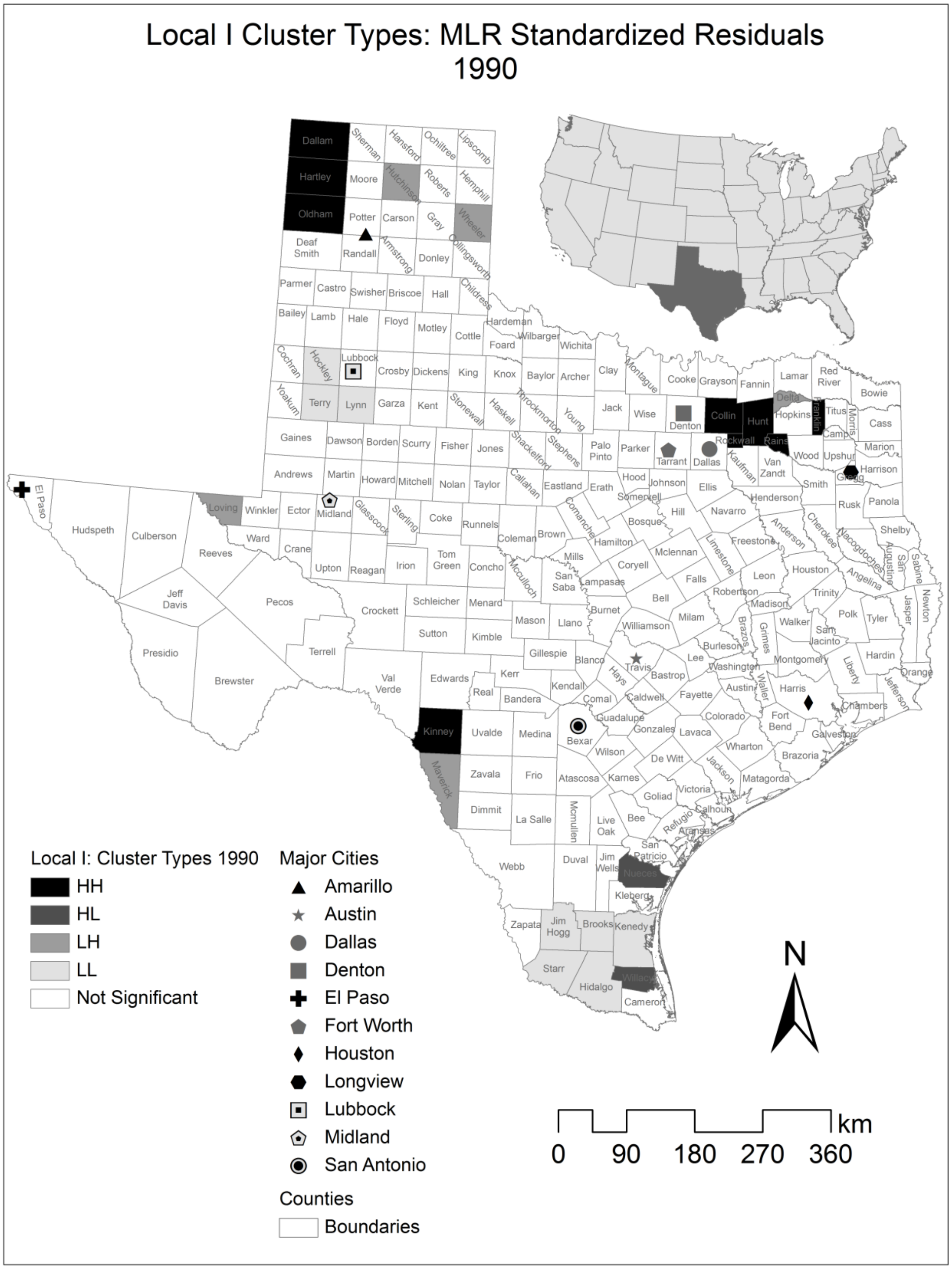

Figure 60. 1990 Local Anselin's I Clusters for Model 1's Standardized Residuals. The HH and LL counties represent clusters with statistically significant under and overestimations of per capita municipal water consumption respectively. Likewise, the HL and LH counties represent spatial outliers.

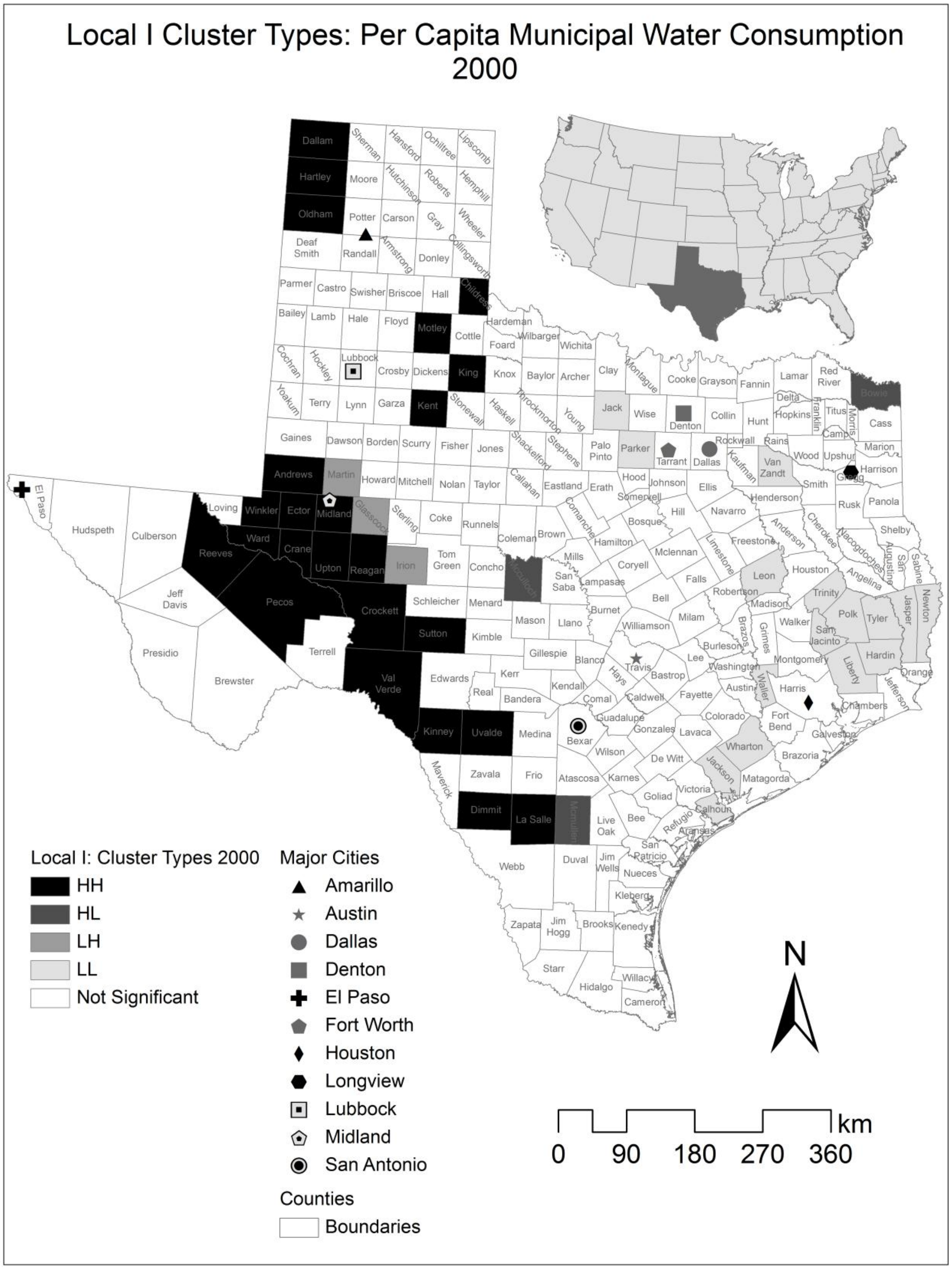

Figure 61. 2000 Local Anselin's I Clusters for Per Capita Municipal Water Consumption. The HH and LL counties represent statistically significant clusters of high and low per capita municipal water consumption respectively. The LH and HL counties represent spatial outliers relative to surrounding municipal water consumptions.

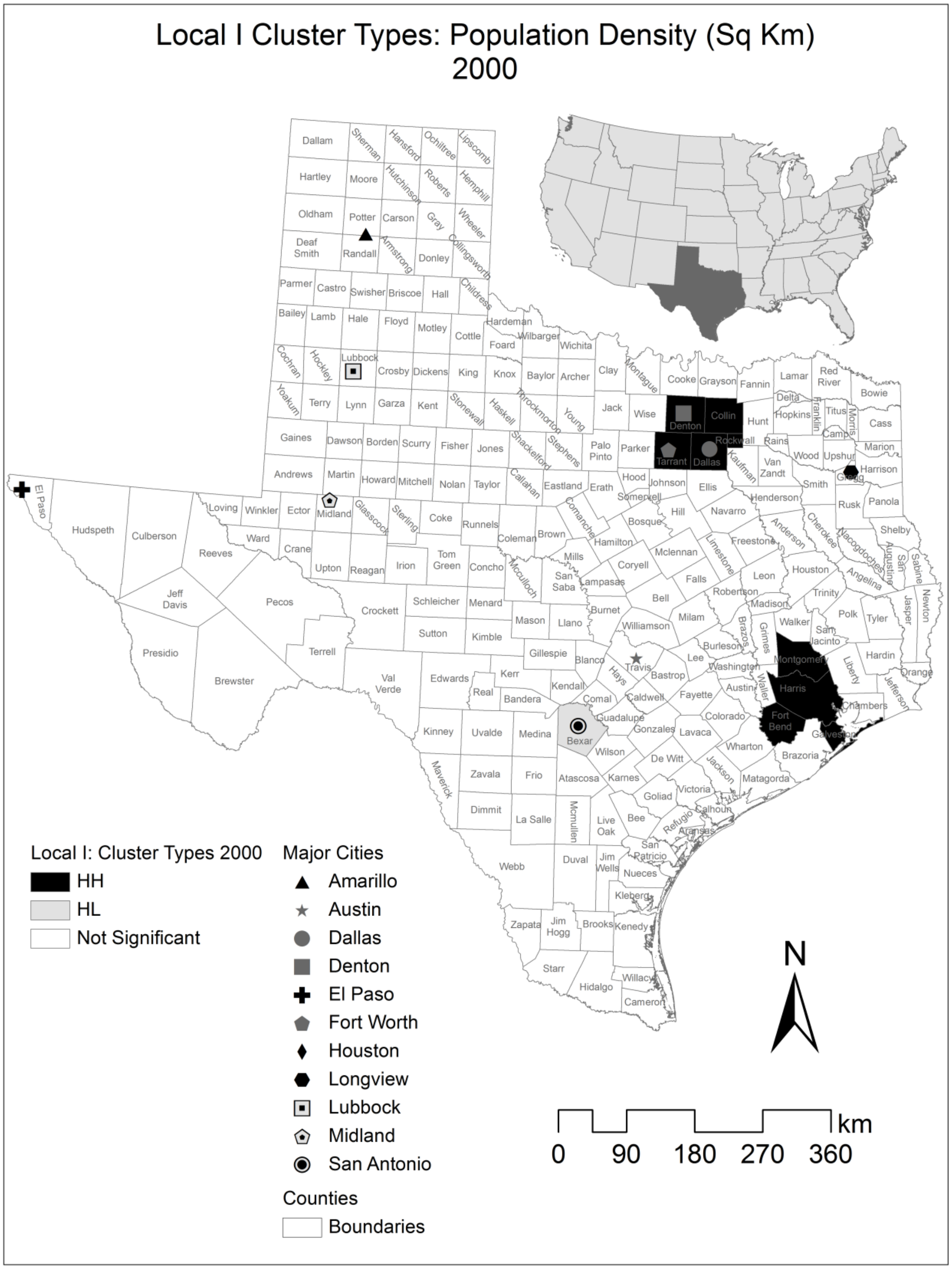

Figure 62. 2000 Local Anselin's I Clusters for Population Density. The HH counties represent statistically significant clusters of high population density. The LH and HL counties represent spatial outliers relative to surrounding population densities.

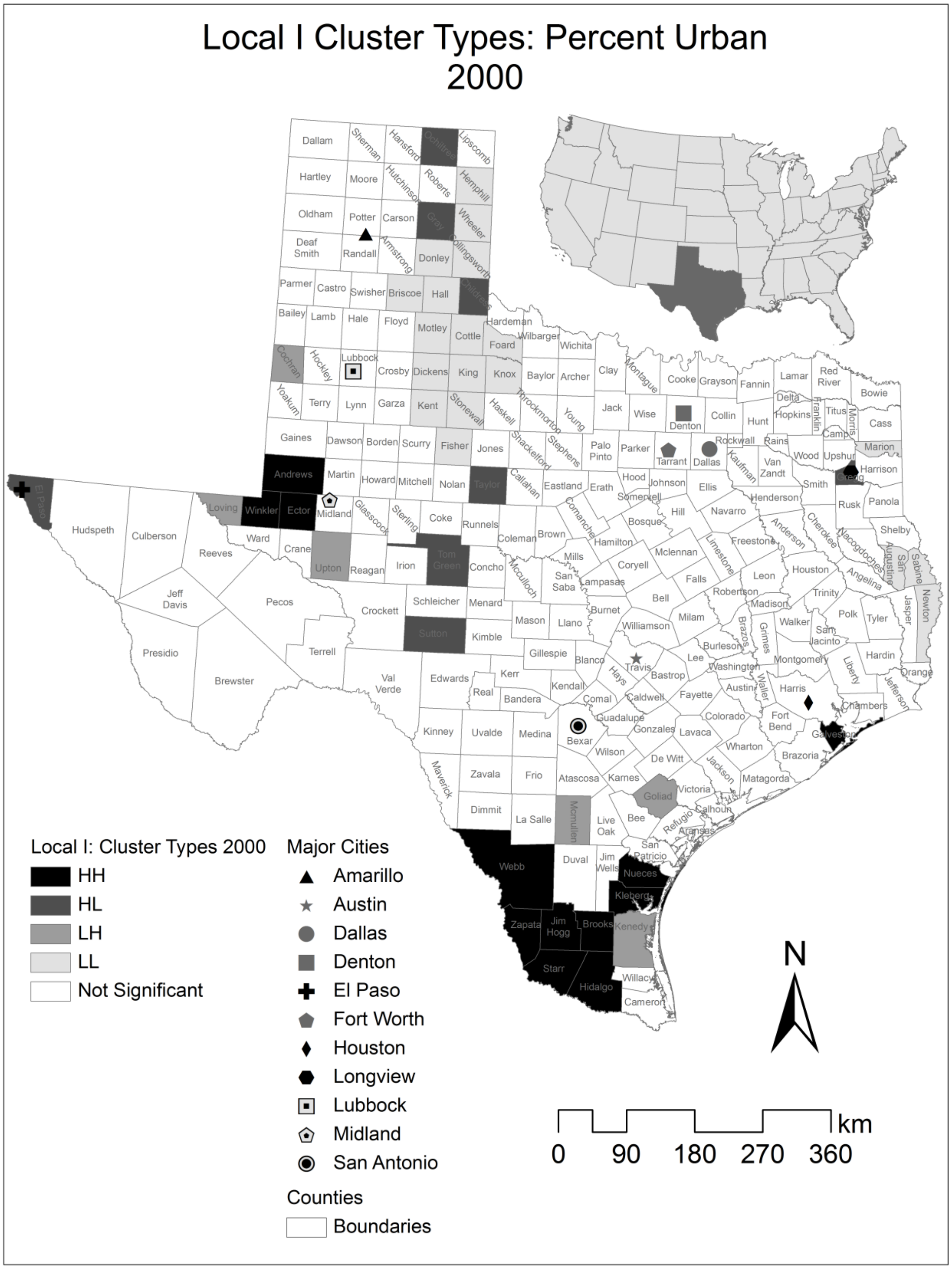

Figure 63. 2000 Local Anselin's I Clusters for Percent Urban. The HH and LL counties represent statistically significant clusters of high and low percentages of urban population respectively. The LH and HL counties represent spatial outliers relative to surrounding percentages of urban populations.

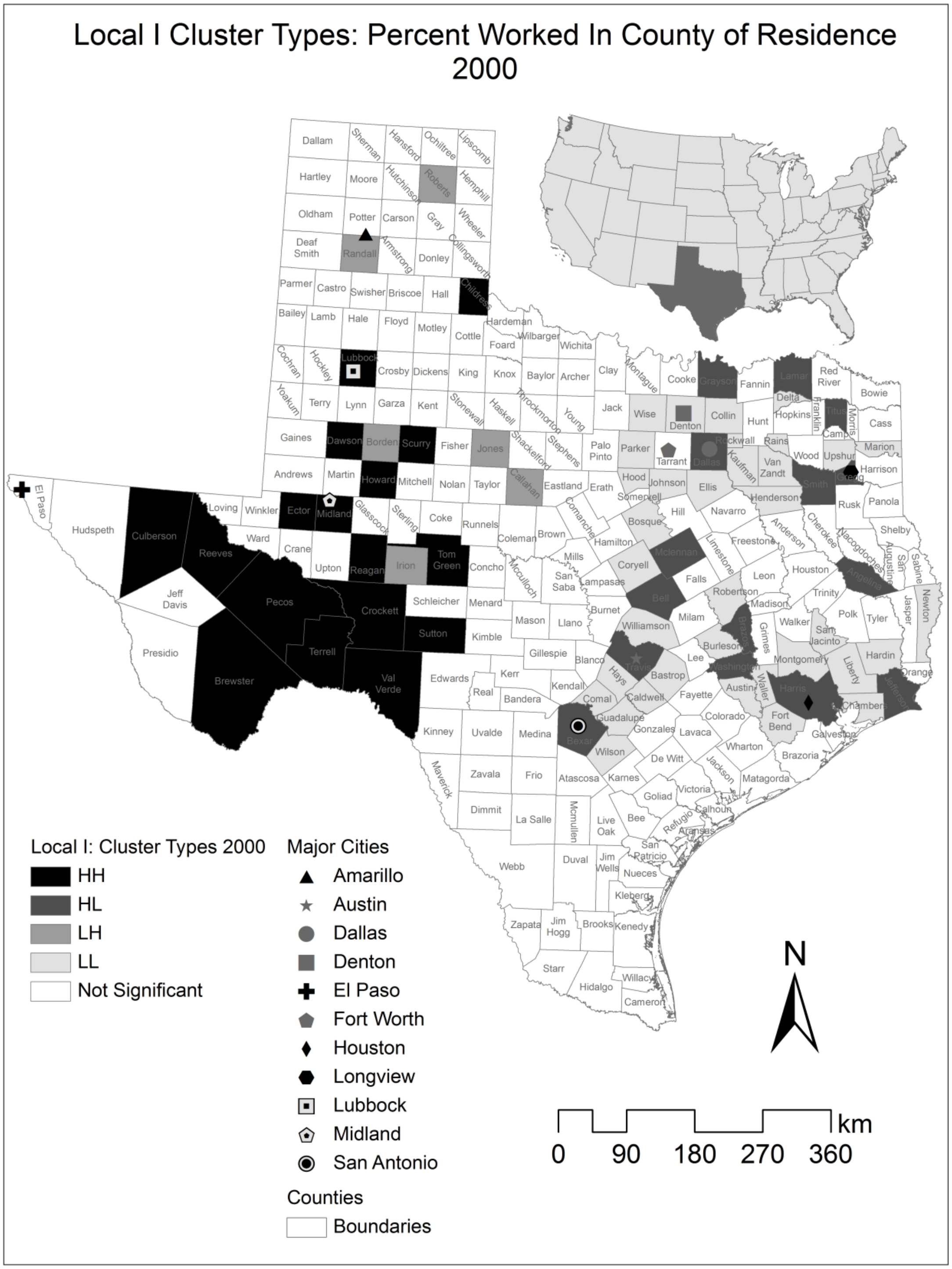

Figure 64. 2000 Local Anselin's I Clusters for Percent Worked In County of Residence. The HH and LL counties represent clusters with statistically significant high and low percentages of the population that worked in their own county respectively. Likewise, the HL and LH counties represent spatial outliers.

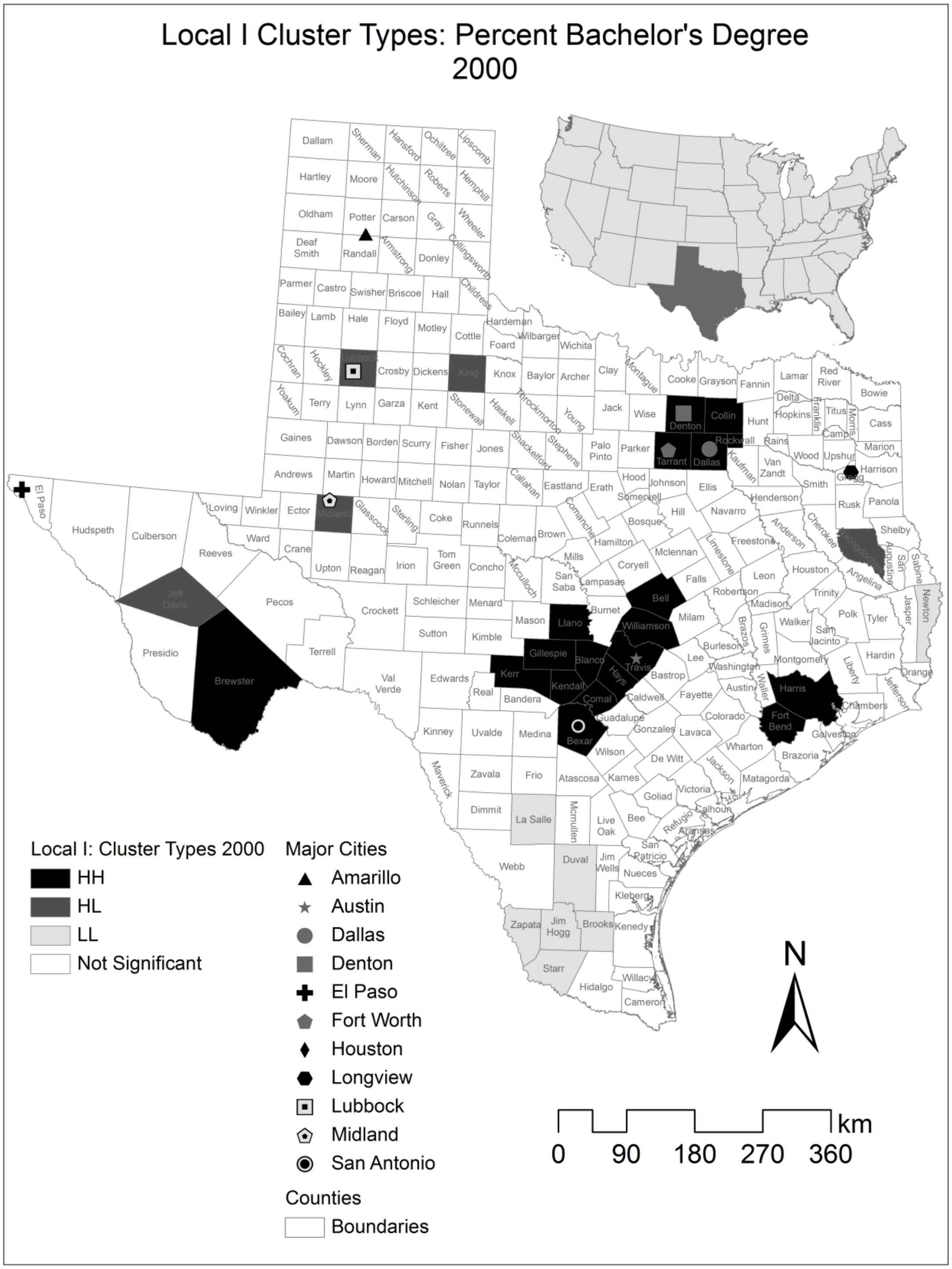

Figure 65. 2000 Local Anselin's I Clusters for Percent Bachelor's Degree.. The HH and LL counties represent clusters with statistically significant high and low percentages of bachelor's degree holders respectively. The HL counties represent spatial outliers.

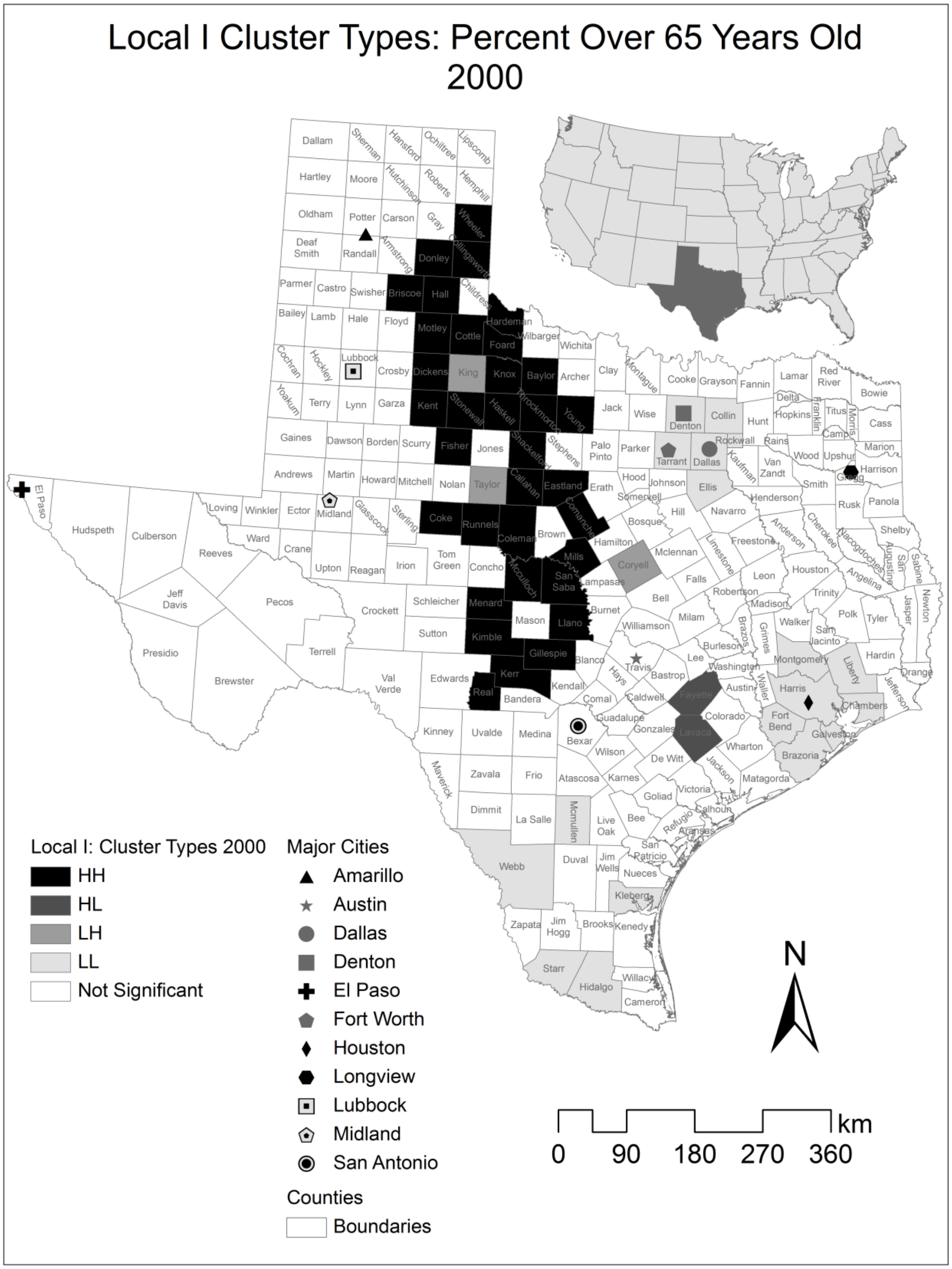

Figure 66. 2000 Local Anselin's I Clusters for Percent 65 Years and Older.. The HH and LL counties represent clusters with statistically significant high and low percentages of elderly populations respectively. The HL and LH counties represent spatial outliers.

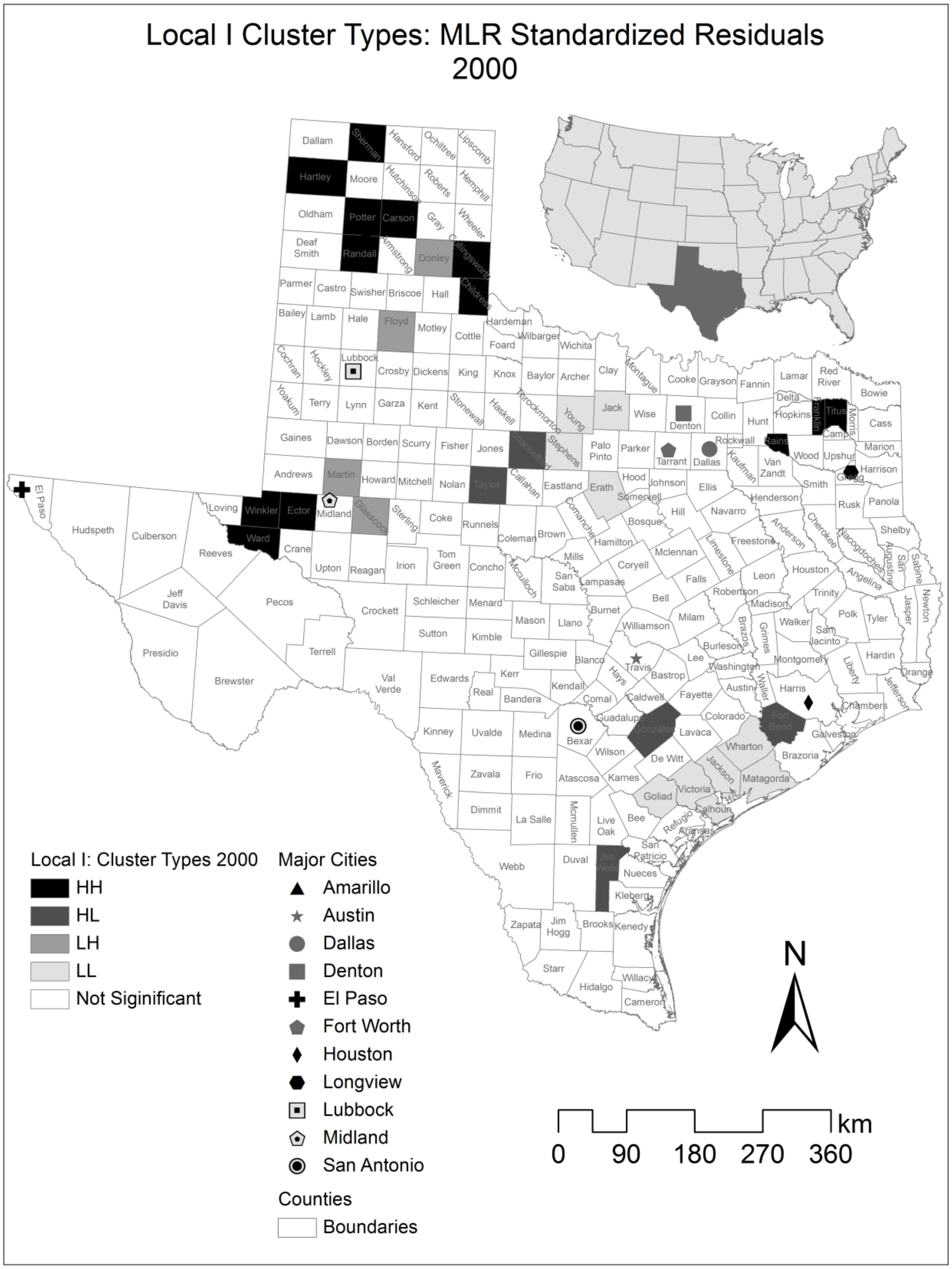

Figure 67. 2000 Local Anselin’s I Clusters for Model 1Standardized Residuals. The HH and LL counties represent clusters with statistically significant under and overestimations of per capita municipal water consumption respectively. Likewise, the HL and LH counties represent spatial outliers.

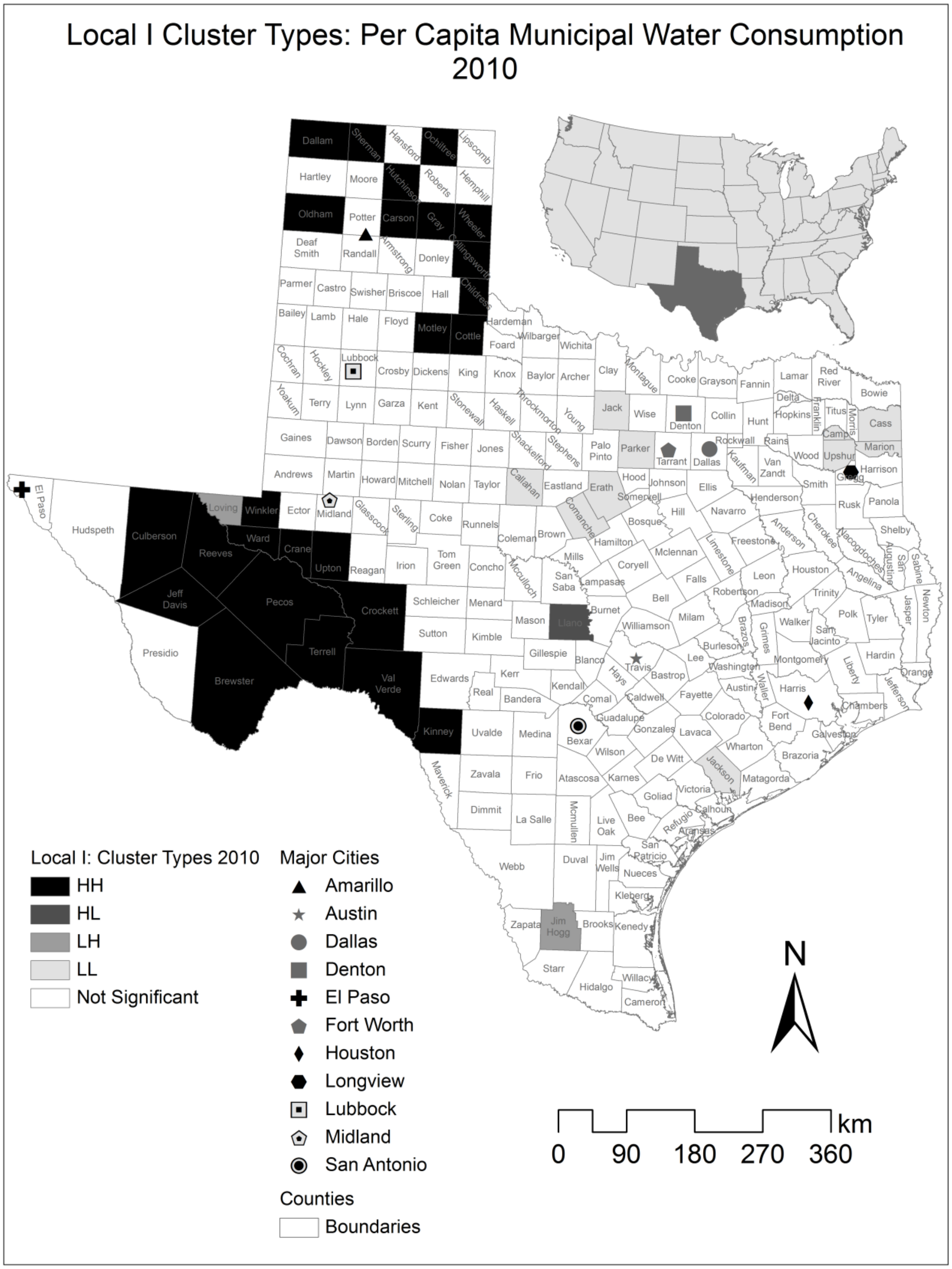

Figure 68. 2010 Local Anselin's I Clusters for Per Capita Municipal Water Consumption. The HH and LL counties represent statistically significant clusters of high and low per capita municipal water consumption respectively. The LH and HL counties represent spatial outliers relative to surrounding municipal water consumptions.

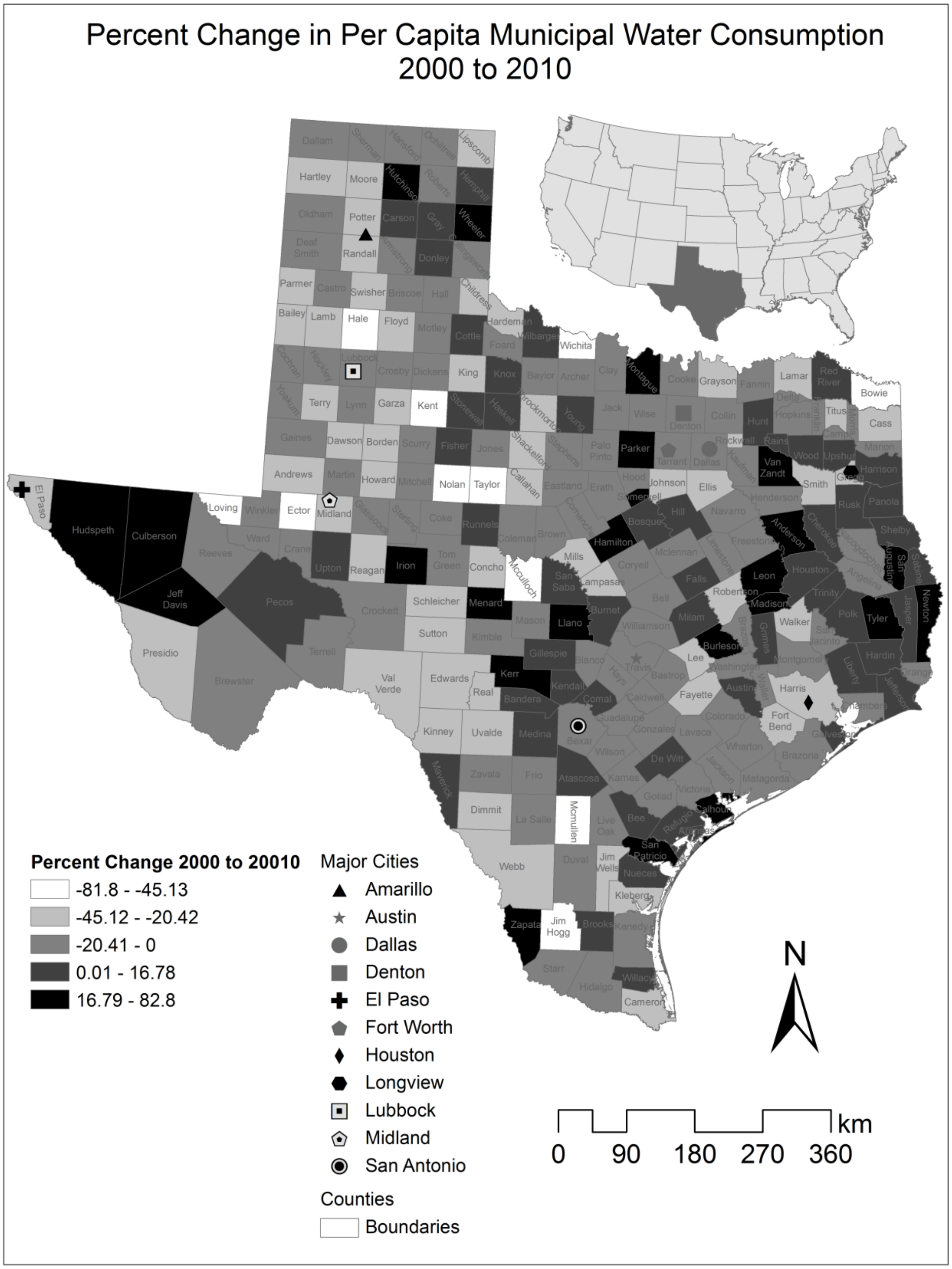

Figure 69. Percent Change in Per Capita Municipal Water Consumption 2000 to 2010. The overwhelming majority of per capita municipal water consumptions either decreased or remained similar to 2000 levels, which suggested than an external forcing was reducing per capita municipal water consumption at the county scale in 2010.

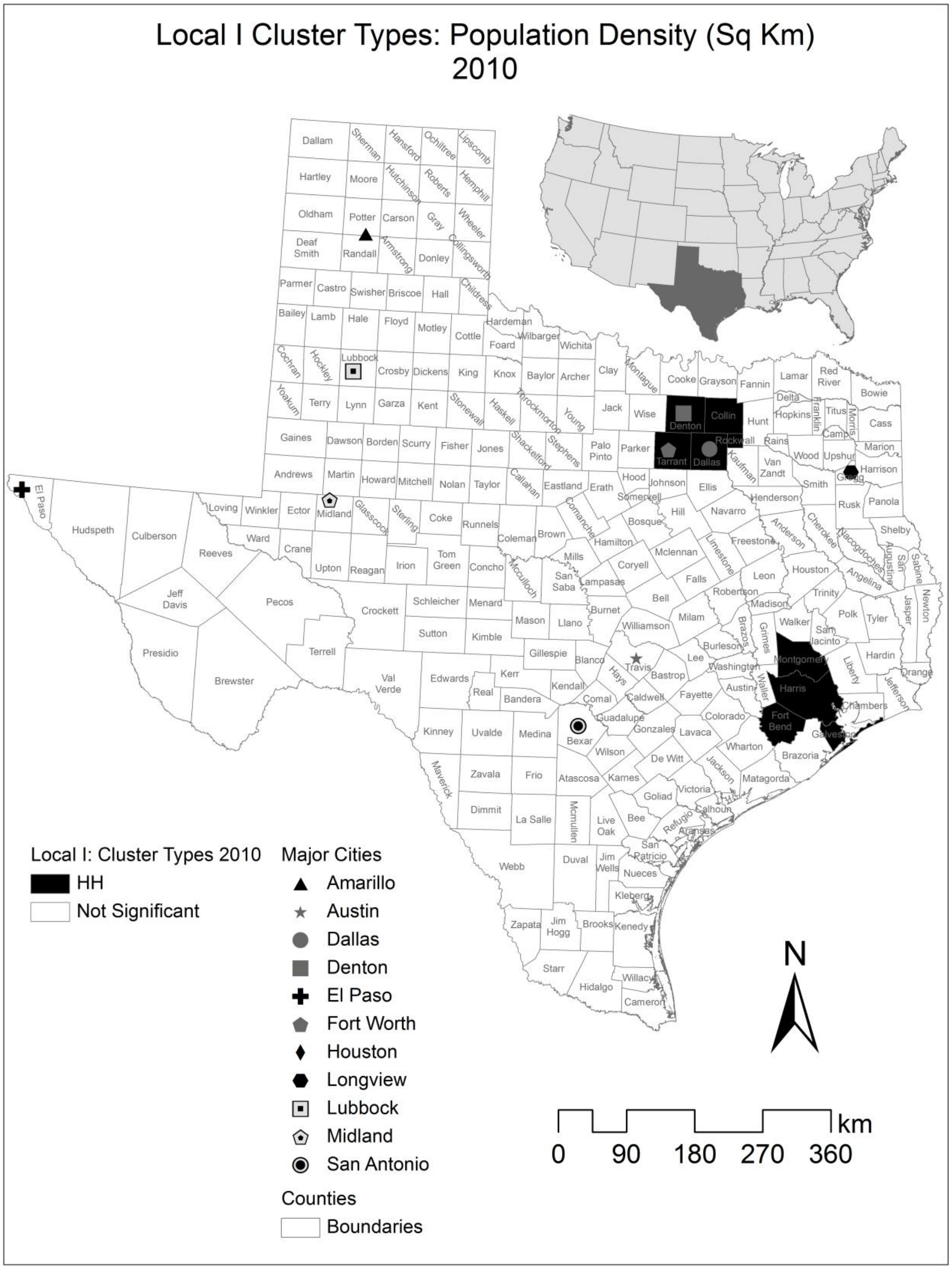

Figure 70. 2010 Local Anselin's I Clusters for Population Density. The HH counties represent statistically significant clusters of high population density.

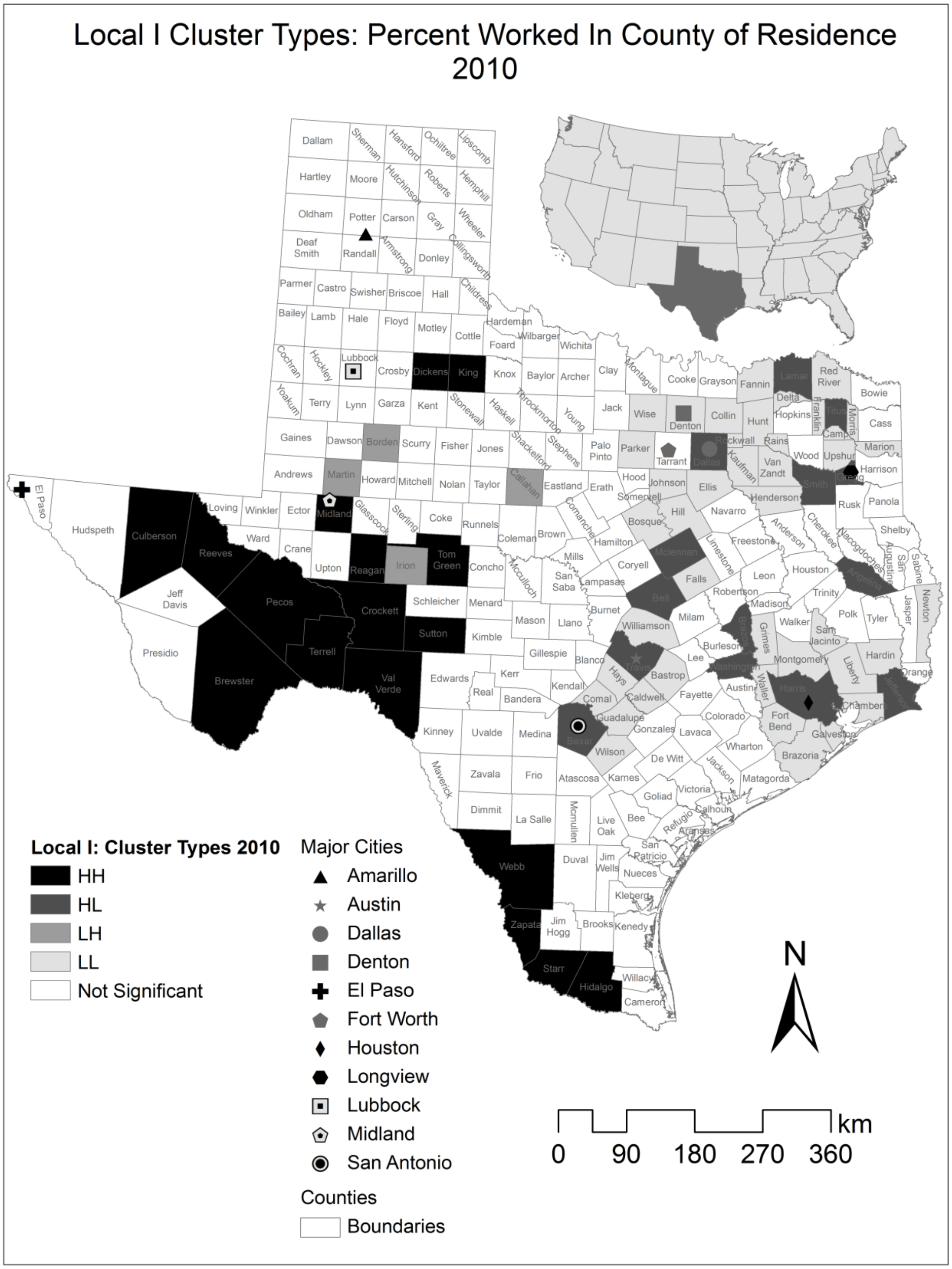

Figure 71. 2010 Local Anselin's I Clusters for Percent Worked In County of Residence. The HH and LL counties represent clusters with statistically significant high and low percentages of the population that worked in their own county respectively. Likewise, the HL and LH counties represent spatial outliers

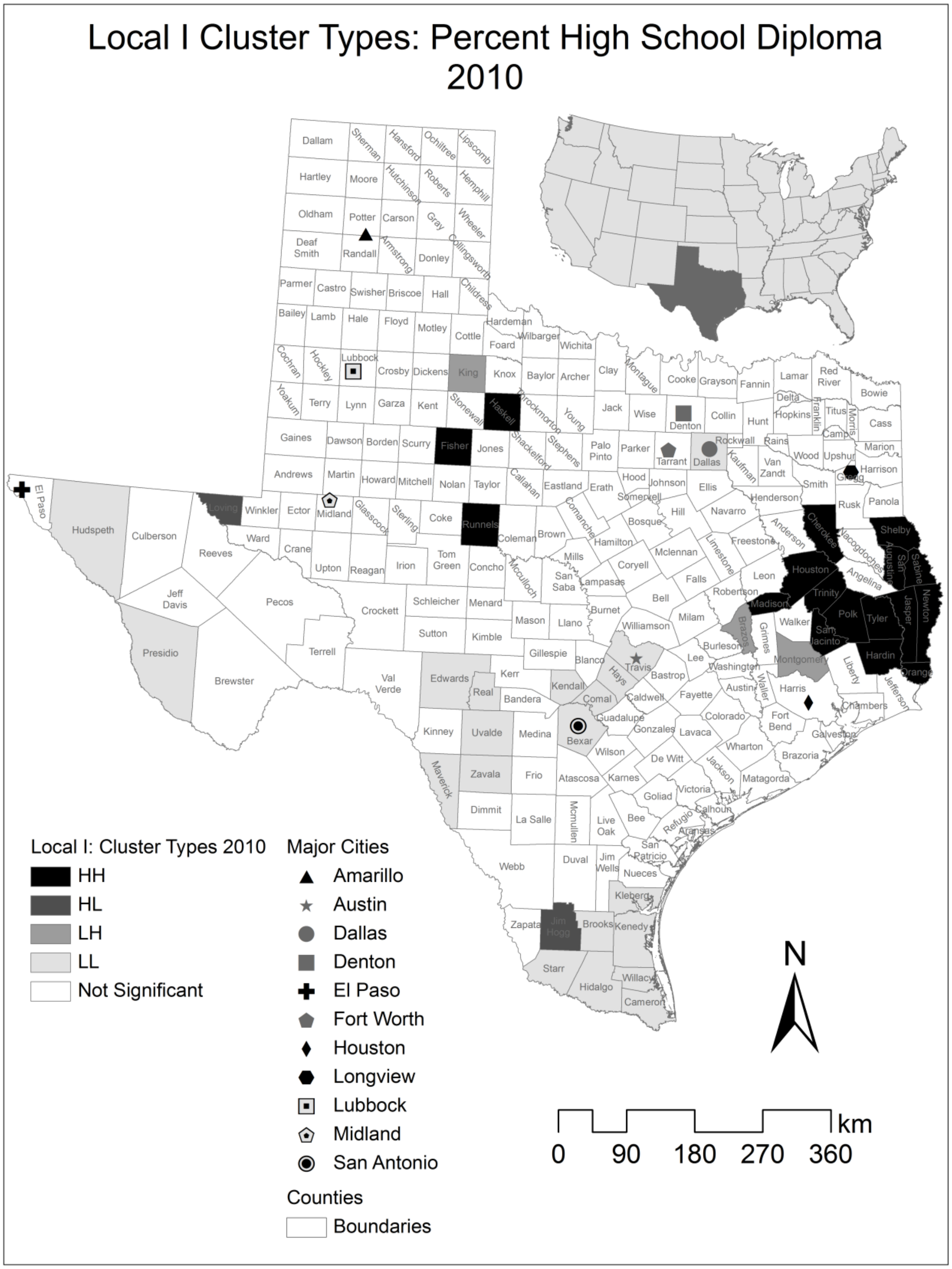

Figure 72. 2010 Local Anselin's I Clusters for Percent High School Diploma. The HH and LL counties represent clusters with statistically significant high and low percentages of high school diploma holders respectively. The HL and LH counties represent spatial outliers.

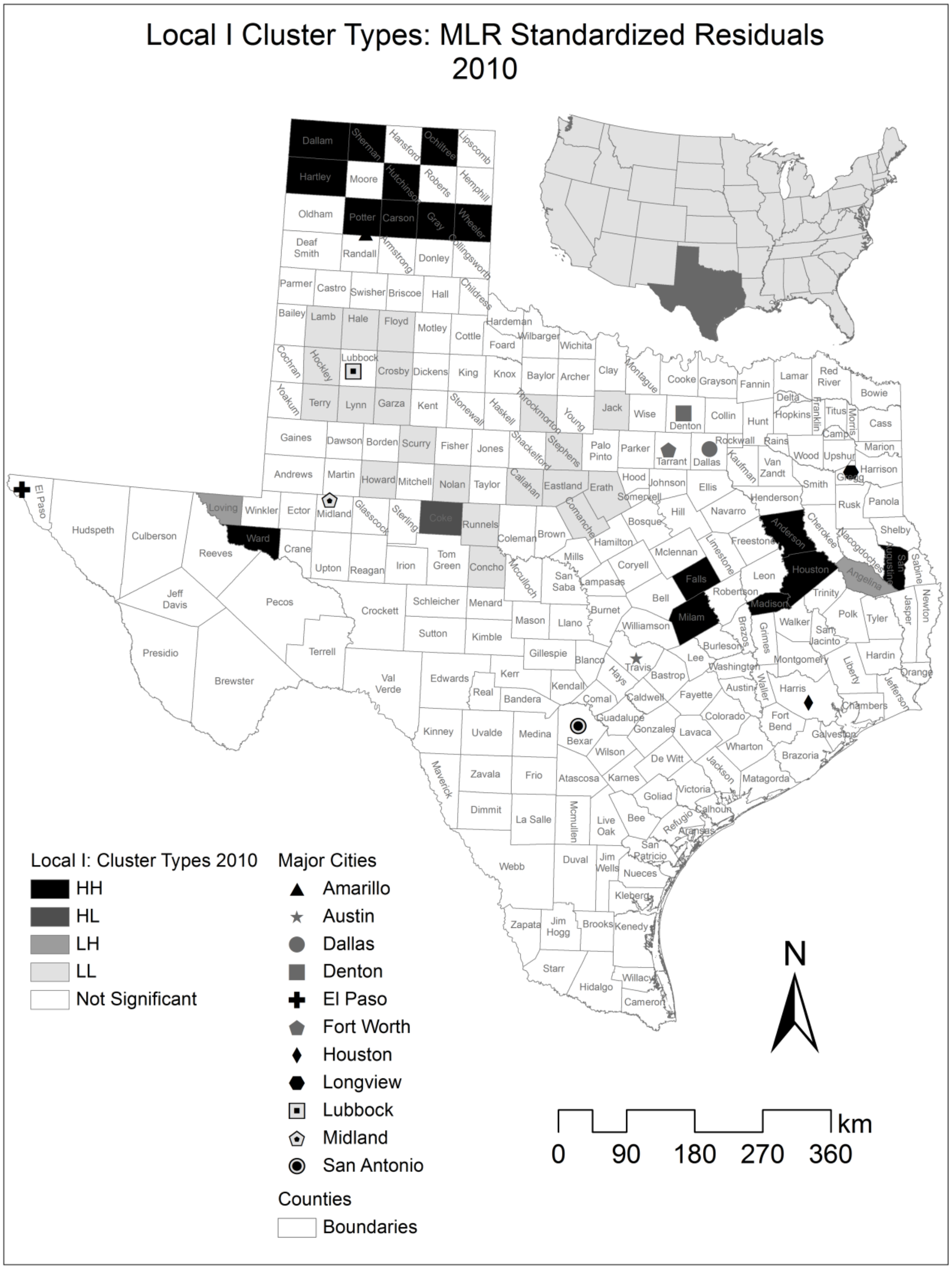

Figure 73. 2010 Local Anselin's I Clusters for Model 1's Standardized Residuals. The HH and LL counties represent clusters with statistically significant under and overestimations of per capita municipal water consumption respectively. Likewise, the HL and LH counties represent spatial outliers.

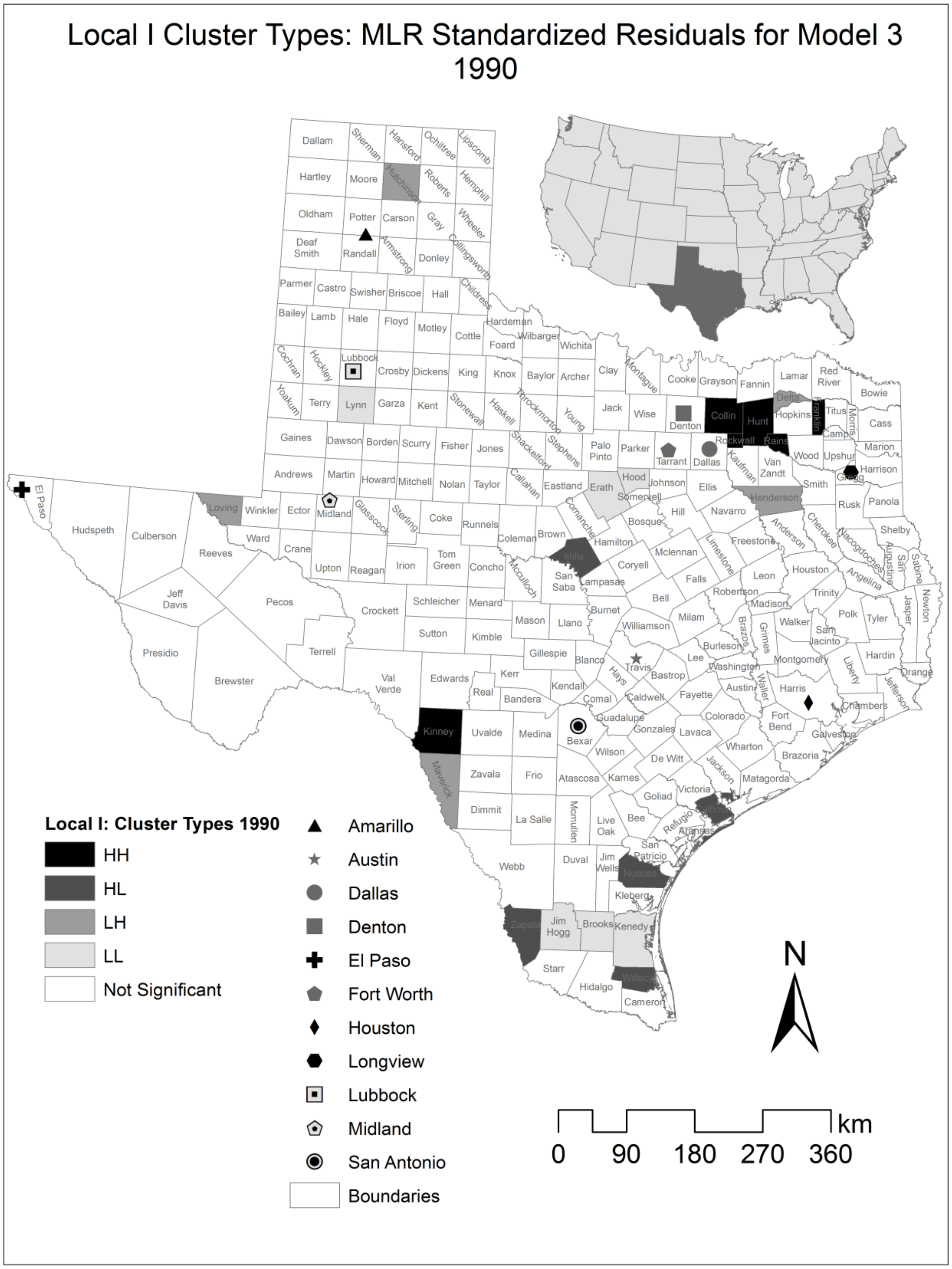

Figure 74. 1990 Local Anselin’s I Clusters for Model 3 Standardized Residuals. The HH and LL counties represent clusters with statistically significant under and overestimations of per capita municipal water consumption respectively. Likewise, the HL and LH counties represent spatial outliers.

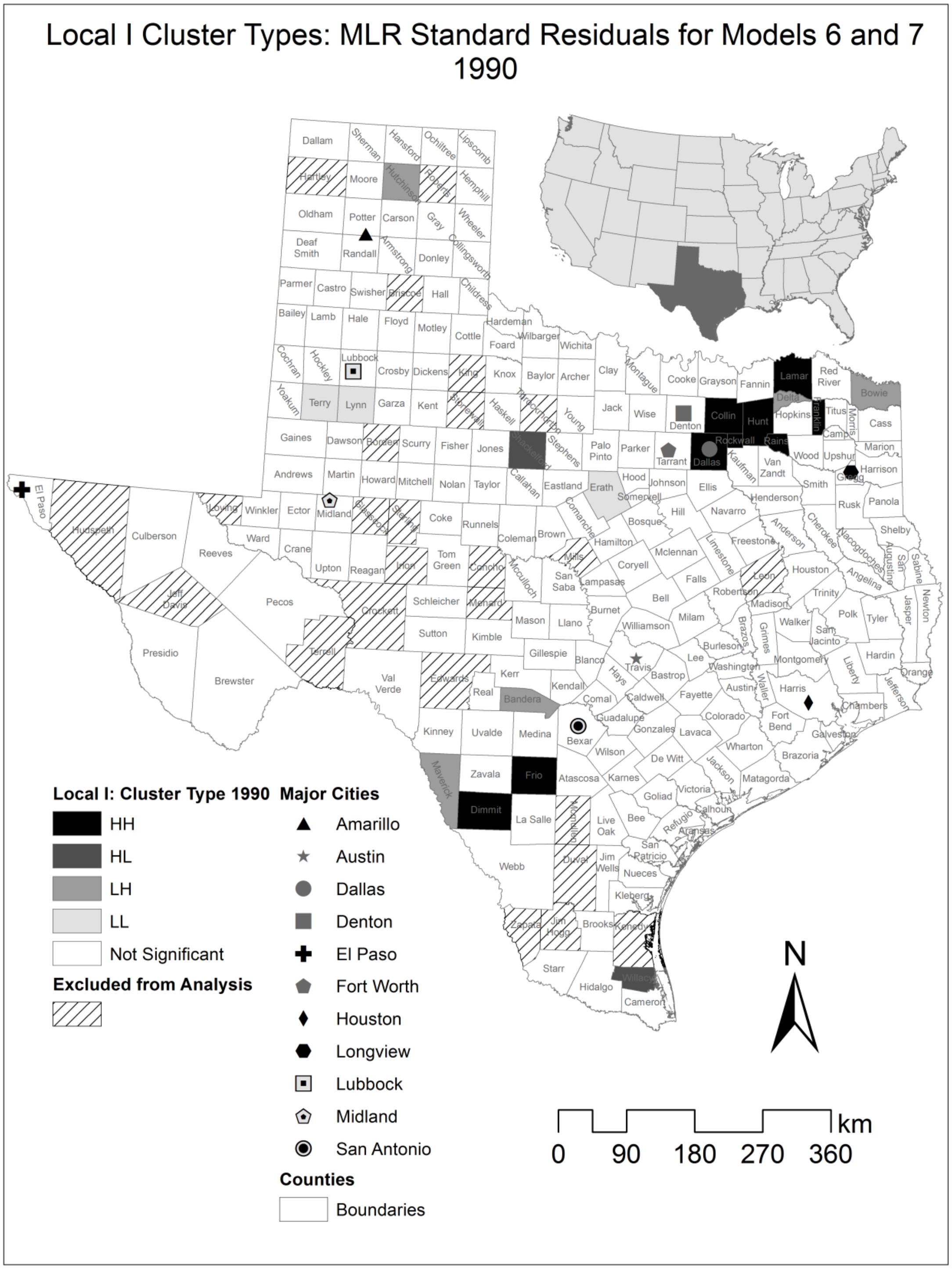

Figure 75. 1990 Local Anselin's I Clusters for Model s 6 and 7 Standardized Residuals. The HH and LL counties represent clusters with statistically significant under and overestimations of per capita municipal water consumption respectively. Likewise, the HL and LH counties represent spatial outliers.

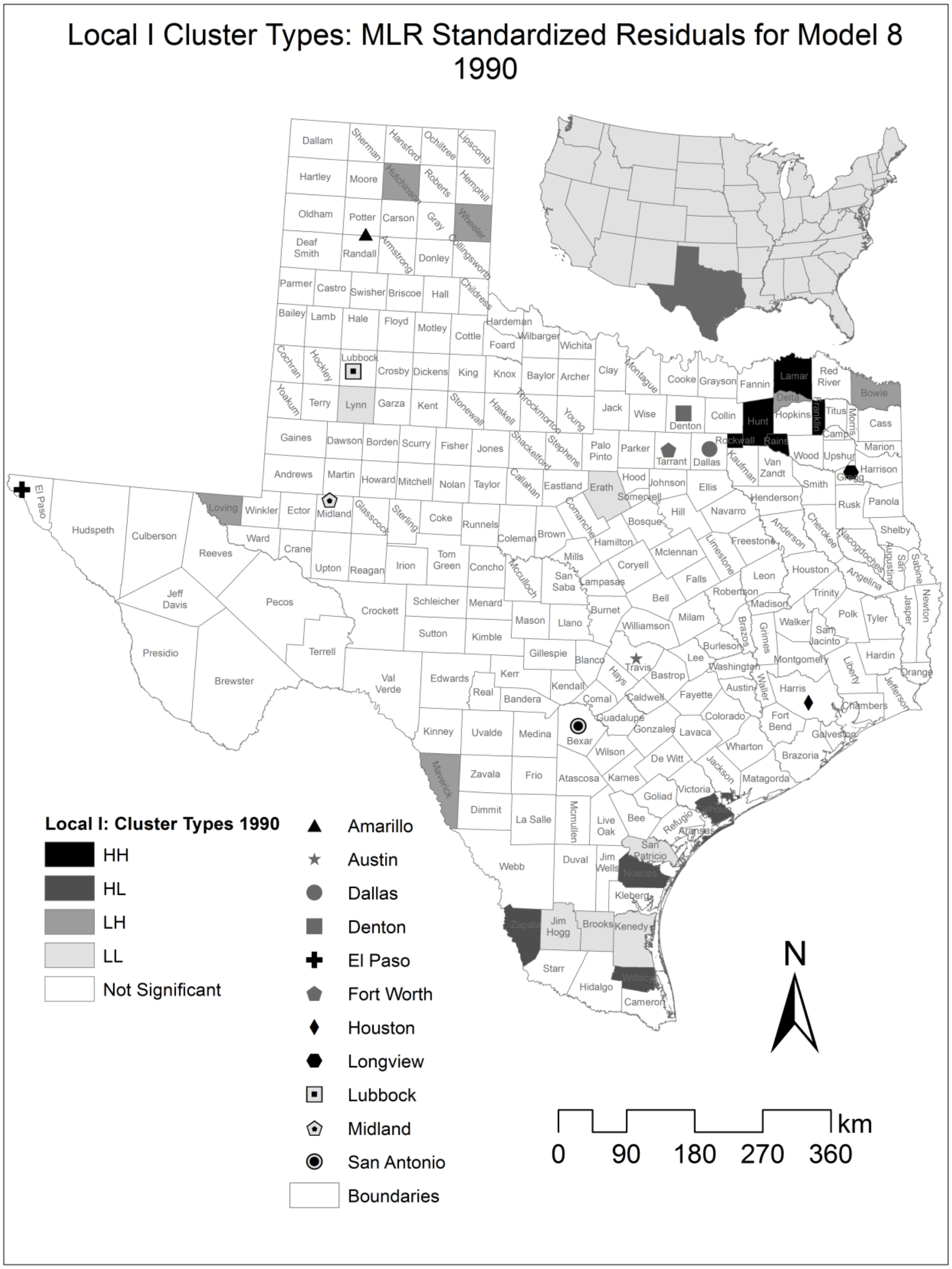

Figure 76. 1990 Local Anselin's I Clusters for Model 8 Standardized Residuals. The HH and LL counties represent clusters with statistically significant under and overestimations of per capita municipal water consumption respectively. Likewise, the HL and LH counties represent spatial outliers

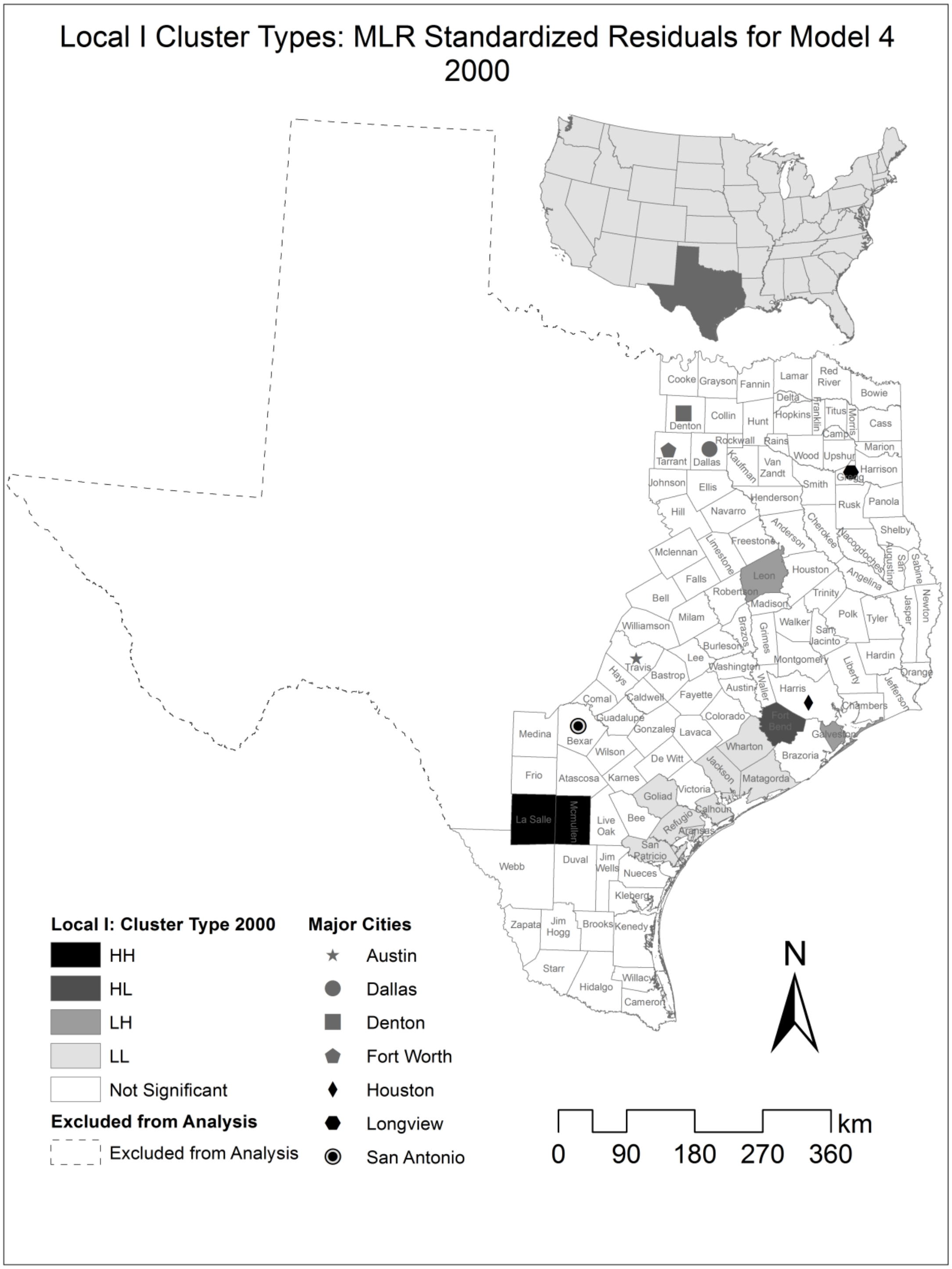

Figure 77. 2000 Local Anselin’s I Clusters for Model 4 Standardized Residuals. The HH and LL counties represent clusters with statistically significant under and overestimations of per capita municipal water consumption respectively. Likewise, the HL and LH counties represent spatial outliers

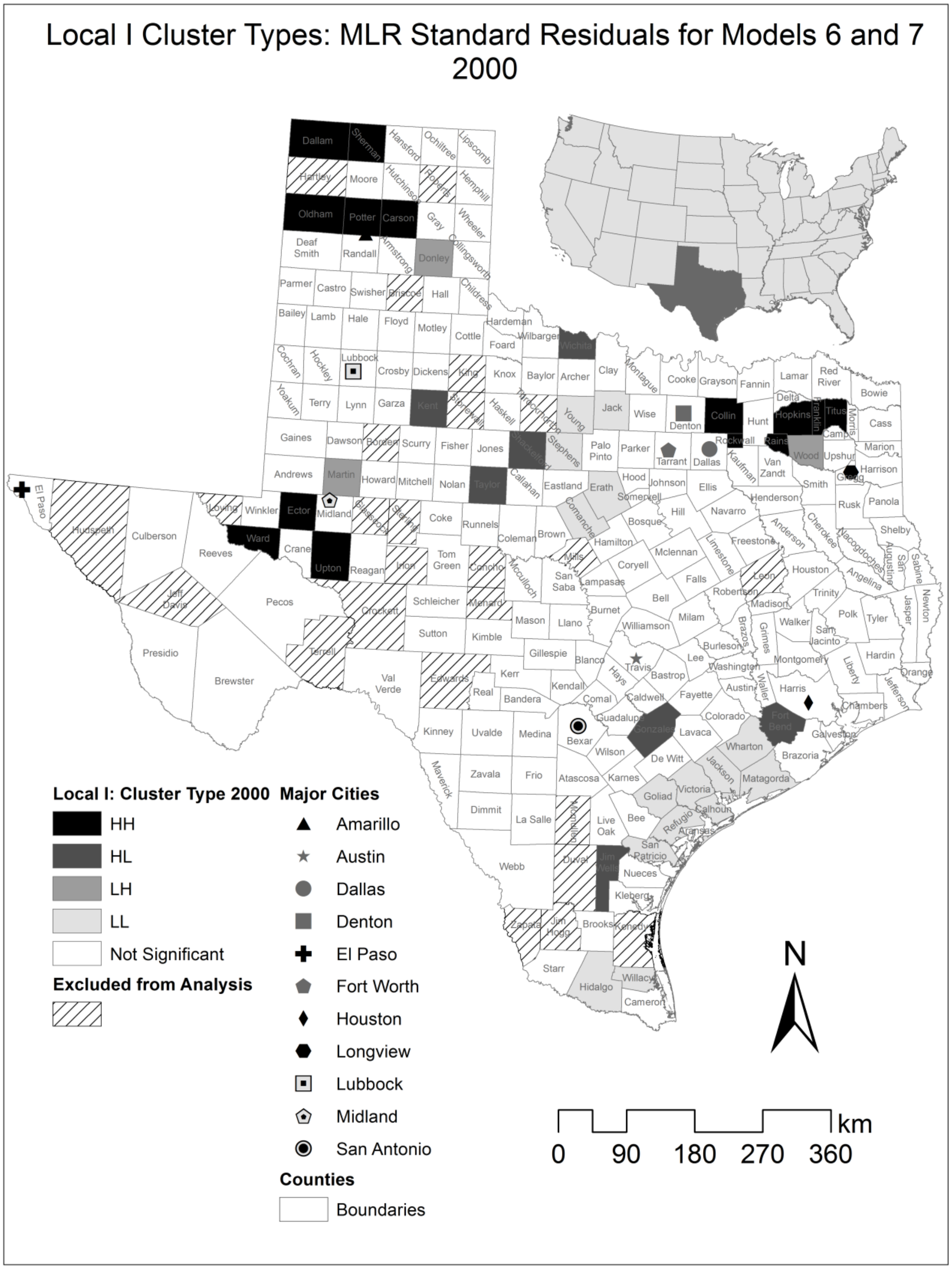

Figure 78. 2000 Local Anselin's I Clusters for Models 6 and 7 Standardized Residuals. The HH and LL counties represent clusters with statistically significant under and overestimations of per capita municipal water consumption respectively. Likewise, the HL and LH counties represent spatial outliers

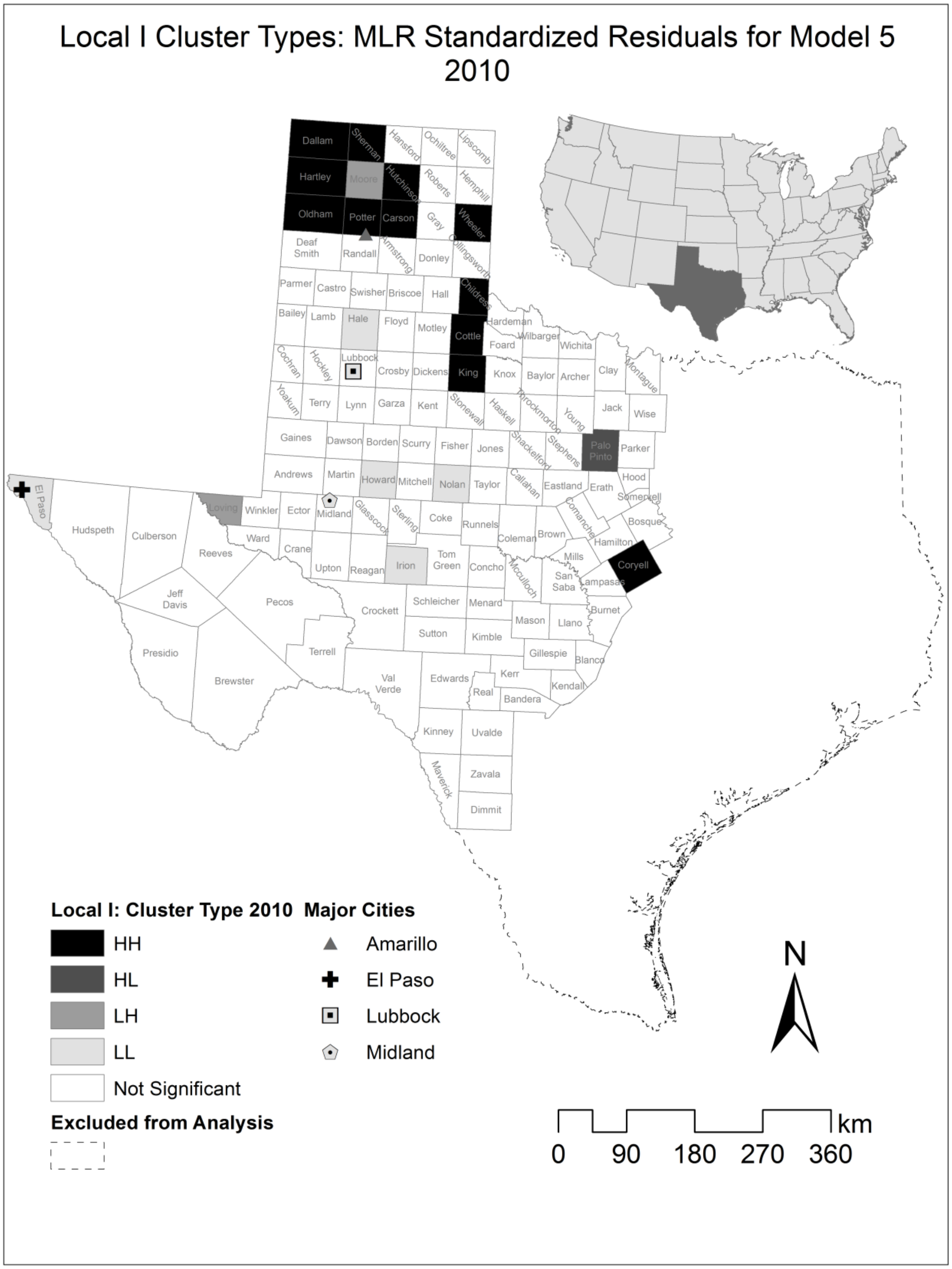

Figure 79. 2010 Local Anselin's I Clusters for Model 5 Standardized Residuals. The HH and LL counties represent clusters with statistically significant under and overestimations of per capita municipal water consumption respectively. Likewise, the HL and LH counties represent spatial outliers

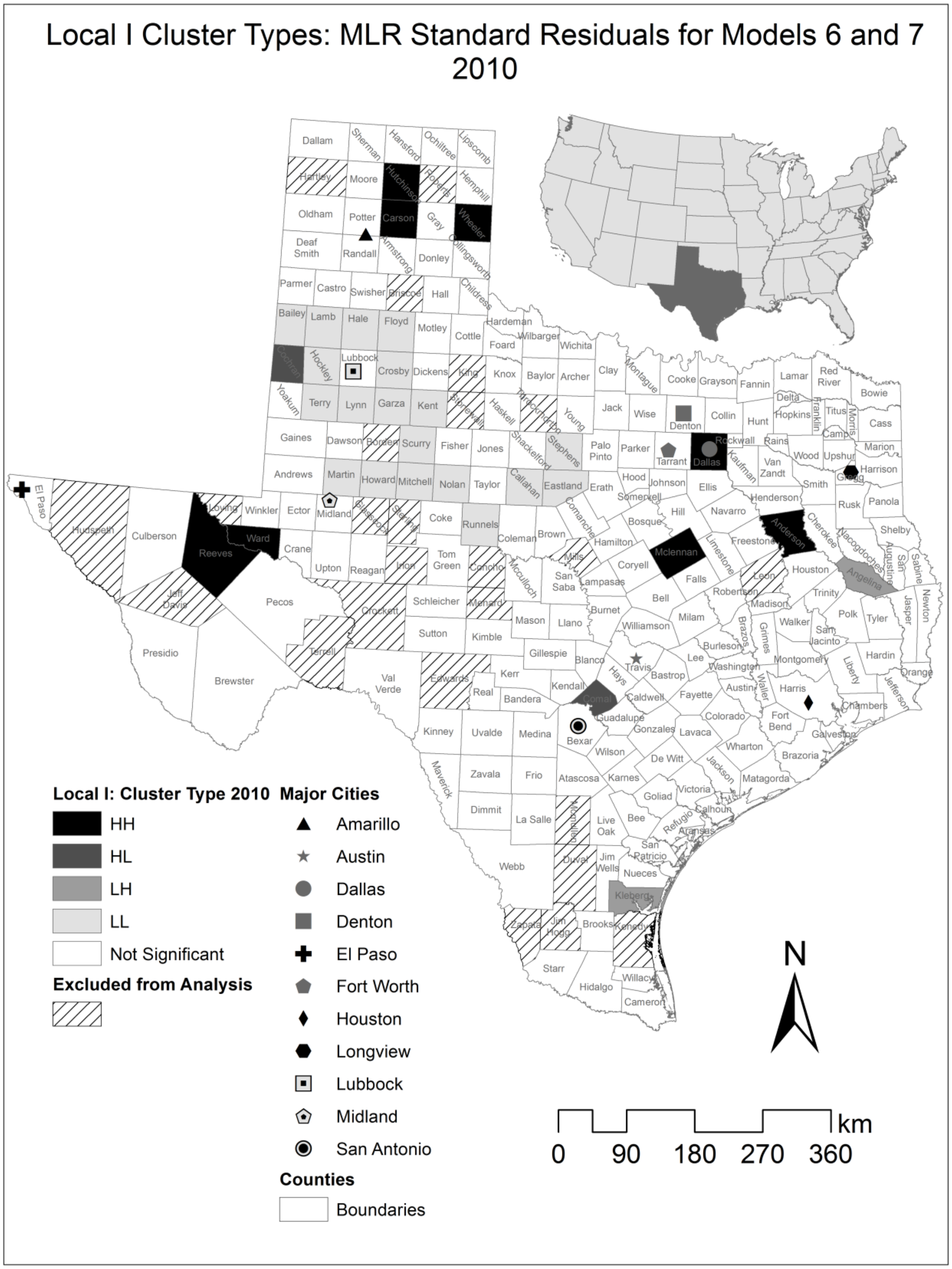

Figure 80. 2010 Local Anselin's I Clusters for Models 6 and 7 Standardized Residuals. The HH and LL counties represent clusters with statistically significant under and overestimations of per capita municipal water consumption respectively. Likewise, the HL and LH counties represent spatial outliers

LITERATURE CITED

Anselin, L. 1995. Local indicators of spatial association-LISA. *Geographical Analysis* 27(2): 93-115.

Appleton, R. 2009. "Texas on its way to new drought as La Niña sits - Official figures show impact greatest in south-central area" *The Dallas Morning News*, February 8, 2009.

Arbues, F., M.A. Garcia-Valinas, and R. Martinez-Espineira. 2003. Estimation of residential water demand: A state-of-the-art review. *The Journal of Socio-Economics* 32(2003): 81-102.

Arthur, D.J., M. Uretsky, and P. Wilson. 2010. *Water resources and use for hydraulic fracturing in the Marcellus Shale Region.* Houston, TX: ALL Consulting.

Bednarek, A.T. 2001. Undamming rivers: A review of the ecological impacts of dam removal. *Environmental Management* 27(6): 803-814.

Bureau of Labor Statistics (BLS). 2012. Consumer Price Index: CPI Tables. http://www.bls.gov/cpi/tables.htm. (last accessed 10 June 2013).

Carver, P.H., and J.J. Boland. 1980. Short- and long-run effects of price on municipal water use. *Water Resources Research* 16(4): 609-616.

Charlton, R. 2008. *Fundamentals of Fluvial Geomorphology*. New York, NY: Routledge.

Cochran, R., and A.W. Cotton. 1985. Municipal water demand study, Oklahoma City and Tulsa, Oklahoma. *Water Resources Research* 21(7): 941-943.

Connover, W.J., and R.L. Iman. 1981. Rank transformations as a bridge between parametric and nonparametric statistics. *The American Statistician* 35(3): 124-129.

Cooley, H., and P.H. Gleick. 2009. Urban water-use efficiencies: Lessons from United States Cities. In: *The World's Water 2008-2009: The Biennial Report on Freshwater Resources,* edited by P.H. Gleick, 101-126. Washington, D.C.: Island Press.

Corbella, H.M., and D.S. Pujol. 2009. What lies behind domestic water use? A review essay on the drivers of domestic water consumption. *Boletin de la A.G.E. N.°* 50(2009): 297-314.

Cressie, N., and L.B. Collins. 2001. Patterns in spatial point locations: Local indicators of spatial association in a minefield with clutter. *Naval Research and Logistics* 48(2001): 333-347.

Dallman, S., and M. Spongberg. 2012. Expanding local water supplies: Assessing the impacts of stormwater infiltration on groundwater quality. *The Professional Geographer* 64(2): 232-249.

Daniel, W.W. 1990. *Applied Nonparametric Statistics.* Pacific Grove, CA: Brooks/Cole.

Davis, L.W. 2010. *Evaluating the slow adoption of energy efficient investments: Are renters less likely to have energy efficient appliances?* Energy Institute at HAAS Working Paper Series: WP 205. Berkeley, CA: University of California at Berkeley.

Dingman, S. L. 2002. *Physical Hydrology*. Long Grove, IL: Waveland Press Inc.

Dixon, R.W., and T.W. Moore. 2011. Trend detection in Texas temperature and precipitation. *Southwestern Geographer* 15(2011): 80-103.

Draper, N.R., and H. Smith. 1998. *Applied Regression Analysis 3rd Edition*. New York, NY: John Wiley and Sons Inc.

Earickson, R.J., and J.M. Harlin. 1994. *Geographic Measurement and Quantitative Analysis*. New York, NY: Macmillan College Publishing Company.

Engelkemeir, R., S.D. Khan, and K. Burke. 2010. Surface deformation in Houston, Texas using GPS. *Tectonophysics* 490(2010): 47-54.

Environmental Research Systems Institute (ESRI). 2012a. Regression Analysis Basics. http://resources.esri.com/help/9.3/arcgisdesktop/com/gp_toolref/spatial_statistics_toolbox/regression_analysis_basics.htm. (last accessed 10 June 2013).

---. 2012b. Multi-Distance Spatial Cluster Analysis (Ripley's K Function) (Spatial Statistics). http://resources.arcgis.com/en/help/main/10.1/index.html#//005p0000000m000000. (last accessed 10 June 2013).

Fowler Jr., F J. 2009. *Survey Research Methods*. Thousand Oaks, CA: SAGE Publications Inc.

Gabrysch, R.K., and C.W. Bonnet. 1975. *Report 188: Land-Surface Subsidence in the Houston-Galveston Region, Texas.* Austin, TX: The Texas Water Development Board.

Getis, A., and K. Ord. 1992. The analysis of spatial association by use of distance statistics. *Geographical Analysis* 24(1992): 189-206.

Giardino, J.R., K.M. Lynch, and D.O. Jennings. 1995. Coupling the fluvial coastal system with rising sea-level: The Texas Gulf Coast paradigm. In: *The Changing Climate of Texas*, edited by J. Norwine, J.R. Giardano, G.R. North, and J.B. Valdes. College Station, TX: Texas A&M University.

Graf, W.L. 2005. Geomorphology and American dams: The scientific, social, and economic context. *Geomorphology* 71(2005): 3-26.

Graf, W.L. 2001. Damage control: Restoring the physical integrity of America's rivers. *Annals of the Association of American Geographers* 91(1): 1-27.

Gregory, I.N., and P.S. Ell. 2007. *Historical GIS Technologies, Methods, and Scholarship*. New York, NY: Cambridge University Press.

Guhathakurta, S., and P. Gober. 2007. The impact of the Phoenix urban heat island on residential urban water use. *Journal of the American Planning Association* 73(3): 317-329.

Gutzer, D.S., and J.S. Nims. 2005. Interannual variability of water demand and summer climate in Albuquerque, New Mexico. *Journal of Applied Meteorology* 44(December 2005): 1777-1787.

Headrick, T.C., and O. Rotou. 2001. An investigation of the rank transformation in multiple regression. *Computational Statistics & Data Analysis* 38(2): 203-215.

Hitchcock, D. 2011. Urban areas. In: *The Impact of Global Warming on Texas Second Edition*, edited by J. Schmandt, J. Clarkson, and G. R. North. Austin, TX: University of Texas Press.

House-Peters, L., B. Pratt, and H. Chang. 2010. Effects of urban structure, sociodemographics, and climate on residential water consumption in Hillsboro, Oregon. *Journal of the American Water Resources Association* 46(3): 461-472.

Iman, R.L., and W.J. Connover. 1979. The use of the rank transform in regression. *Technometrics* 21(4): 499-509.

Intergovernmental Panel on Climate Change (IPCC). 2007. *Climate Change 2007: Synthesis Report.* Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Irwin, E. 2004. Market forces and urban expansion. Paper presented at The Urban Expansion: The Environmental and Health Dimensions PERN Cyberseminar, November 29, 2004.

Jensen, J.R. 2005. *Introductory Digital Image Processing: A Remote Sensing Perspective 3rd edition.* Upper Saddle River, NJ: Pearson Prentice Hall.

Jones, L.L, and T. Ozuna Jr. 1995. Global climate impacts on the Texas economy. In: *The Changing Climate of Texas,* edited by J. Norwine, J.R. Giardano, G.R. North, and J.B. Valdes. College Station, TX: Texas A&M University.

Kenney, D.S., C. Goemans, R. Klein, J. Lowery, and K. Reidy. 2008. Residential water demand management: Lessons from Aurora, Colorado. *Journal of the American Water Resources Association* 44(1): 192-207.

Kleinbaum, D.G., L.L. Kupper, K.E. Muller. 1988. *Applied Regression Analysis and other Multivariable Methods.* Belmont, CA: Duxbury Press.

Krause, K, J.M. Chermak, and D.S. Brookshire. 2003. The demand for water: Consumer response to scarcity. *Journal of Regulatory Economics* 23(2): 167-191.

Kundzewicz, Z.W., L.J. Mata, N.W. Arnell, P. Döll, B. Jimenez, K. Miller, T. Oki, Z. Sen, and I. Shiklomanov. 2008. The implications of projected climate change for freshwater resources and their management. *Hydrological Sciences Journal* 53(1): 3-10.

Larsen, M. 2000. Analysis of 20th century rainfall and streamflow to characterize drought and water resources in Puerto Rico. *Physical Geography* 21(6): 494-521.

Larson, A.C. 2000. *Migrant and Seasonal Farmworker Enumeration Profiles Study Texas.* Vashon Island, WA: Larson Assistance Services Inc.

Lavin, S., and A.J. Clark. 1984. Computer-produced unclassed bivariate choropleth maps. *Cartography and Geographic Information Science* 11(1): 49-57.

Le Gallo, J., and C. Ertur. 2003. Exploratory spatial data analysis of the distribution of regional per capita GDP in Europe, 1980-1995. *Papers in Regional Science* 82(2003): 175-201.

Martinez-Espineira, R., and C. Naughes. 2004. Is all domestic water consumption sensitive to price control? *Applied Economics* 2004(36): 1697-1703.

McCarl, B.A. 1995. Agricultural sensitivity to climate change. In: *The Changing Climate of Texas,* edited by J. Norwine, J.R. Giardano, G.R. North, and J.B. Valdes. College Station, TX: Texas A&M University.

Meyers, L.S., G. Gamst., and A.J. Guarino. 2006. *Applied Multivariate Research Design and Interpretation.* Thousand Oaks, CA: Sage Publications Inc.

Minnesota Population Center (MPC). 2011. National Historical Geographic Information System, Version 2.0. https://www.nhgis.org/. (last accessed 10 June 2013).

Morrow-Howell, N. 1994. The M word: Multicollinearity in multiple regression. *Social Work Research* 18(4): 247-251.

Muller, R.A., and G.E. Faiers. 1995. Water budget of Texas. In: *The Changing Climate of Texas*, edited by J. Norwine, J.R. Giardano, G.R. North, and J.B. Valdes. College Station, TX: Texas A&M University.

Murdoch, P.S., J.S. Baron, and T.L. Miller. 2000. Potential effects of climate change on surface-water quality in North America. *Journal of the American Water Resources Association* 36(2): 347-366.

National Atmospheric and Oceanic Administration (NOAA). 2012. Historical Palmer Drought Indices. http://www.ncdc.noaa.gov/temp-and-precip/drought/historical-palmers.php. (last accessed 10 June 2013).

National Climatic Data Center (NCDC). 2012. http://www1.ncdc.noaa.gov/pub/data/cirs/. (last accessed 10 June 2013).

Naughes, C., and A. Thomas. 2002. Long-run study of residential water consumption. In: *Current Issues in the Economic of Water Resources Management. Theory, Applications, and Policy,* edited by P. Pashardes, T.M. Swanson, and A. Xepapadeas. New York, NY: Springer and Kluwer Academic Publishers.

North, G.R. 1995.Climate change and Texas. In: *The Changing Climate of Texas*, edited by J. Norwine, J.R. Giardano, G.R. North, and J.B. Valdes. College Station, TX: Texas A&M University.

Openshaw, S. 1983. The modifiable areal unit problem. In: *Concepts and Techniques in Modern Geography, Volume 38.* Norwich, UK: Geobooks.

Ostrum, E., R. Gardner, and J. Walker. 1994. *Rules, Games, and Common Pool Resources.* Ann Arbor, MI: Michigan University Press.

O'Sullivan, D., and D.J. Unwin. 2010. *Geographic Information Analysis Second Edition.* Hoboken, NJ: John Wiley and Sons Inc.

Paez, A., S. Farber, and D. Wheeler. 2011. A simulation-based study of geographically weighted regression as a method for investigating spatially varying relationships. *Environmental Planning A* 2011(43): 2992-3010.

Palmer, W.C. 1965. *Meteorological Drought*. Washington, D.C.: United States Department of Commerce.

Pearson, A., and P. Collier. 1998. The integration and analysis of historical and environmental data using a geographical information system: Landownership and agricultural productivity in Pembrokeshire c 1850. *The Agricultural History Review* 46(2): 162-176.

Pedhazur, E.J. 1997. *Multiple Regression in Behavioral Research*. Orlando, FL: Harcourt Brace.

Perrins, G., and D. Nilsen. 2007. *Math calculations to better utilize CPI data*. Washington, D.C.: U.S. Department of Labor, Bureau of Labor Statistics.

Petersen, J.P., D. Sack, and R. Gabler. 2012. *Physical Geography 10th Edition*. Belmont, CA: Brooks Cole Cengage Publishing.

Piantadosi, S,. D.P. Byar, and S.B. Green. 1988. The ecological fallacy. *American Journal of Epidemiology* 127(5): 893-904.

Price, M.H. 2012. *Mastering ArcGIS 5th Edition.* New York, NY: McGraw-Hill Inc.

Ratcliffe, J.H., and M.J. McCullagh. 1999. Hotbeds of crime and the search for spatial accuracy. *Journal of Geographical Systems* 1(1999): 385-398.

Raty, M., and A. Kangas. 2007. Localizing general models on local indices of spatial association. *European Journal of Forest Research* 126(2007): 279-289.

Raymond, A. 2011. Denny regrade, 1893-2008: A case study in historical GIS. *Social Science History* 35(4): 571-597.

Schmandt, J. 1995. Policy implications for Texas of a warmer world. In: *The Changing Climate of Texas*, edited by J. Norwine, J.R. Giardano, G.R. North, and J.B. Valdes. College Station, TX: Texas A&M University.

Schmidt, J.C., and P.R. Wilcock. 2008. Metrics for assessing the downstream effects of dams. *Water Resources Research* 44 DOI:10.1029/2006WR005092.

Snyder, J.P. 1987. Map Projections-A working Manual. *USGS Professional Paper 1395*. Washington D.C: United States Government Printing Office.

State of Texas. 2011. Texas Administrative Code: State Agency Geographic Information Standards. http://info.sos.state.tx.us/pls/pub/readtac$ext.TacPage?sl=R&app=9&p_dir=&p_rloc=&p_tloc=&p_ploc=&pg=1&p_tac=&ti=1&pt=10&ch=205&rl=10. (last accessed 10 June 2013).

----------------. 2009. Texas Administrative Code §299.13. http://info.sos.state.tx.us/fids/200806468-1.html. (last accessed 10 June 2013).

Stillwell, A.S., C.W. King, M.E. Webber, I.J. Duncan, and A. Hardberger. 2011. The energy-water nexus in Texas. *Ecology and Society* 16(1): http://www.ecologyandsociety.org/vol16/iss1/art2.

Syme, G., Q. Shoa, M. Po, and E. Campbell. 2004. Predicting and understanding home garden water use. *Landscape and Urban Planning* 68:121-128.

Texas State Historical Association (TSHA). 2013. The Handbook of Texas Online. http://www.tshaonline.org/handbook/online (last accessed 10 June 2013).

Texas Water Development Board (TWDB). 2012. Precipitation and Lake Evaporation Data for Texas. https://www.twdb.state.tx.us/surfacewater/conditions/evaporation/index.asp. (last accessed 10 June 2013).

--. 2011. Water for Texas: Summary of the 2011 Regional Water Plans. Austin, TX: Texas Water Development Board.

---. 2010. About Texas Water Development Board. http://www.twdb.state.tx.us/about/index.asp. (last accessed 10 June 2013).

--. 2009a. Historical Water Use Database. http://www.twdb.state.tx.us/wushistorical/. (last accessed 10 June 2013).

---. 2009b. Texas Water Development Board: GIS Data. http://www.twdb.state.tx.us/mapping/gisdata.asp. (last accessed 10 June 2013).

---. 1997. 1997 State Water Plan. http://www.twdb.state.tx.us/waterplanning/swp/1997/index.asp. (last accessed 10 June 2013).

---. 1990. Water for Texas: Today and Tomorrow. Austin, TX: Texas Water Development Board.

Thomson, A.M., R.A. Brown, N.J. Rosenberg, R. Srinivasan, and C. Izaurralde. 2005. Climate change impacts for the conterminous USA: An integrated assessment. *Climate Change* 69(2005): 67-88.

Thompson, S. 1999. Water Use, Management, and Planning in the United States. San Diego, CA: Academic Press.

United States Army Corps of Engineers (USACE). 2010. Corps Maps: National Inventory of Dams. http://geo.usace.army.mil/pgis/f?p=397:1:1289153258977233. (last accessed 10 June 2013).

United States Census Bureau (USCB). 2013a. *County Business Patterns.* http://www.census.gov/econ/cbp/index.html. (last accessed 10 June 2013).

---. 2013b. *North American Industry Classification System*. http://www.census.gov/eos/www/naics/concordances/concordances.html. (last accessed 10 June 2013).

---. 2012. 2010 *Census Urban Area FAQs*. http://www.census.gov/geo/reference/urban-rural.html. (last accessed 10 June 2013).

---. 2010. American Community Survey. http://www.census.gov/acs/www/. (last accessed 10 June 2013).

United States Geological Survey (USGS). 1999. *Land Subsidence in the United States, Circular 1182*. Washington, D.C.: U.S. Department of The Interior, United States Geological Survey.

Ulery, R.L., P.C. Van Metre, and A.S. Crossfield. 1993. Trinity River Basin. *Journal of the American Water Resources Association* 29(4): 685-711.

Ward, G.H. 2011. Water resources and water supply. In: *The Impact of Global Warming on Texas Second Edition*, edited by J. Schmandt, J. Clarkson, and G. R. North. Austin, TX: University of Texas Press.

Weeks, J.R. 1996. *Population: An Introduction to Concepts and Issues*. Belmont, CA: Wadsworth Publishing Company.

Wellmeyer, J.L., M.C. Slattery, and J.D. Phillips. 2005. Quantifying downstream impacts of impoundment on flow regime and channel planform, lower Trinity River, Texas. *Geomorphology* 69(2005): 1-13.

Wentz, E.A., and P. Gober. 2007. Determinants of small-area water consumption for the City of Phoenix, Arizona. *Water Resource Management* 2007(21): 1849-1863.

Wiseman, H. 2009. Untested waters: The rise of hydraulic fracturing in oil and gas production and the need to revisit regulation. *Fordham Environmental Law Review* 20(2009): 115-183.

Wulder, M., and B. Boots. 1998. Local spatial autocorrelation characteristics of remotely sensed imagery assessed with the Getis statistic. *International Journal of Remote Sensing* 19(11): 2223-2231.

Yamada, I., and J. Thill. 2007. Local indicators of network-constrained clusters in spatial point patterns. *Geographical Analysis* 39(2007): 268-292.

Young, Michael E. 2012. "Water worries high despite ease in drought", *The Dallas Morning News*, March 28, 2012.

Zhou, S.L., T.A. McMahon, A. Walton, and J. Lewis. 2000. Forecasting daily urban water demand: a case study of Melbourne. *Journal of Hydrology* 236(2000): 153-164.

VITA

Matthew H. Connolly's path to Geography began during his two and a half year stint on the South Rim of the Grand Canyon in the mid 1990s. Matt was captivated by the physical geography of the Canyon and northern Arizona, and spent the majority of his free time hiking and exploring the region's semi-arid landscapes. Over the next several years, he worked in the culinary industry and spent time living in Northern California and Colorado, before enrolling in the Business School at the University of Colorado at Denver in 2004 to study Information Systems. Matt graduated Magna Cum Laude from the University of Colorado at Denver in 2006 with a Bachelor of Science in Business Administration. During his undergraduate studies, Matt rediscovered Geography via GIS, and decided to pursue a graduate degree in Geography at Texas State University-San Marcos in 2007. Thanks to the thoughtful insights of his wife and the faculty at Texas State, he realized that teaching was the vocation that made him happiest. Following the completion of Matt's master's degree in Geographic Information Science in 2009, he enrolled in the Ph.D. Program in the Department of Geography at Texas State where he expanded his studies of Geographic Information Science to include Environmental Geography and Water Resources.

Permanent Address: connolly.matthewh@gmail.com

This dissertation was typed by Matthew H. Connolly.