Whiskey is for Drinking; Water is for Fighting Over:

Population Growth, Infrastructure Change, and Conservation Policy as Drivers of Residential Water Demand

by

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A Dissertation Presented in Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy

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August 2014

ABSTRACT

As urban populations grow, water managers are becoming increasingly concerned about water scarcity. Water managers once relied on developing new sources of water supply to manage scarcity but economically feasible sources of unclaimed water are now rare, leading to an increased interest in demand side management. Water managers in Las Vegas, Nevada have developed innovative demand side management strategies due to the cities rapid urbanization and limited water supply. Three questions are addressed. First, in the developed areas of the Las Vegas Valley Water District service areas, how did vegetation area change? To quantify changes in vegetation area, the Matched Filter Vegetation Index (MFVI) is developed from Mixture Tuned Match Filtering estimates of vegetation area calibrated against vegetation area estimates from high-resolution aerial photography. In the established city core, there was a small but significant decline in vegetation area. Second, how much of the observed decline in per capita consumption can be explained by Las Vegas land cover and physical infrastructure change that resulted from extensive new construction and new use of water conserving technology, and how much can be attributed to water conservation policy choices? A regression analysis is performed, followed by an analysis of three counter-factual scenarios to decompose reductions in household water into its constituent parts. The largest citywide drivers of change in water consumption were increased water efficiency associated with new construction and rapid population growth. In the established urban core, the most significant driver was declining vegetation area. Third, water savings generated by a conservation program that provides incentives for homeowners to convert grass into desert landscaping are estimated. In the city core, 82 gallons of water are saved in June for each square meter of landscape converted in the first year after conversion, but the savings attenuate to 33 gallons per meter converted as the landscape

ages. Voluntary landscape conversion programs can generate substantial water savings. The most significant result is that the most effective way to ensure long term, sustainable reductions in water consumption in a growing city without changing water prices is to support the construction of water efficient infrastructure.

ACKNOWLEDGEMENTS

Thanks first to Josh Abbott for his ideas, consistent expectations, and continued support during the various interruptions I've had over the course of this dissertation. I also thank my other committee members, Abby York, Michael Hanemann, and Tim McPherson for their suggestions and feedback. Thanks also to Soe Myint and James Thieler, whose advice was instrumental in developing the remote sensing work in Chapter 3. The DSA-4 staff at the Los Alamos National Lab, especially Brian Edwards, Dave Judi, and Lisa Inkret provided important sounding boards for ideas, technical assistance, and writing help. Thank you to Kent Sovocool, Chris Meenan, Morgan Bennett, Erik Anderson and other staff members at the Southern Nevada Water Authority, the Las Vegas Valley Water District, and the Clark County Assessors Office for providing the data that is the foundation of this dissertation.

My father, Taylor Brelsford, has used his life and career to demonstrate the value of using careful thought to do good in the world, and more than anyone else, has shaped the intellectual questions I find important. Elizabeth Johnson and Sarah Kelly, my Team Tiny cofounders, were my first and best climbing partners in Arizona. Sandra Rodegher, Emily Freeman, Lauren Gentile and Megan Rowton also provided invaluable friendships, conversation, and moral support. Without Julian Brelsford, Wenson George, Gerald Lumarque, Sujith Kulasekara, and many other helping hands on January 12th, 2010 I would not be here today. I am forever grateful.

Finally, thanks to Ethan Coon for holding my hand.

TABLE OF CONTENTS

CHAPTER Page

APPENDIX Page

LIST OF TABLES

Table | Page

LIST OF FIGURES

Figure Page

Figure Page

Figure Page

Figure Page

Figure Page

Figure Page

LIST OF ABBREVIATIONS

ENVI	Environment for Visualizing Images
FD	First Differences
FE	Fixed Effects
K-S	Kolmogorov-Smirnov
LVVWD	Las Vegas Valley Water District
MF	Matched Filtering
MNF	Minimum Noise Fraction
MT	Mixed Tuning
MTMF	Mixture Tuned Match Filtering
MFVI	Match Filtering Vegetation Index
NDVI	Normalized Difference Vegetation Index
PRISM	Parameter-elevation Relationships on Independent Slopes Model
SNWA	Southern Nevada Water Authority
USBR	United States Bureau of Reclamation
USGS	U.S. Geological Survey
WSL	Water Smart Landscapes

1 INTRODUCTION

The quote “Whiskey is for drinking; water is for fighting over”, often misattributed to Mark Twain[1], emphasizes the way people think about water in the western United States. As urban populations grow, water managers are becoming increasingly concerned about water scarcity. Historically, water managers relied on developing new sources of water supply to manage scarcity but economically feasible sources of unclaimed water are now rare, leading to conflict over existing supplies and an increased interest in demand side management. Las Vegas local and regional governments and area water management agencies have developed many innovative demand side management strategies due to their rapid urbanization and limited water supply. Newspapers and water managers alike have touted their dramatic reduction in per capita residential water use (Southern Nevada Water Authority 2009; “Editorial: Drought Plan Saving More than Water” 2004), but without careful analysis it is unclear what actually drove the change. This dissertation quantifies the impact of population growth, new technology, infrastructure change, and several innovative demand side management strategies played in reducing Las Vegas’s average household water demand between 1996 and 2007. Understanding drivers of the citywide decline in household demand and different contributions of population growth and conservation policy will provide a better theoretical understanding of interactions between the built environment and economic, technological, and political drivers of water consumption in addition to providing information to policymakers and water managers charged with drafting effective, innovative demand side management tools.

[1] This quote has been widely attributed to Mark Twain, but no substantial evidence exists linking him to the quote. It does not appear in any of the major books of American quotations (Shapiro 2006; Knowles 2009; Bartlett 2012). The first time the quote has been identified in print is April 1983, in the Aberdeen American News, when it is attributed to Warren Neufeld, secretary of the South Dakota Department of Water and Natural Resources (O’Toole 2013).

This dissertation is separated into five chapters. This introductory chapter summarizes key results and scope for future research, then describes the problem background, the development of the Southern Nevada Water Authority (SNWA), and outlines SNWA's major strategies for encouraging water conservation, especially the Water Smart Landscapes (WSL) program. The WSL program provides incentives for residents to convert grassy, water intense landscaping to less water intensive desert landscapes. The second chapter reviews the academic literature related to residential water consumption. I consider major trends in North American water use, the substantial literature on the price elasticity of water, literature on non-price based drivers of water consumption, non-price based conservation policy generally, and finally, I review the literature on water conservation programs that provide incentives for landscape change. The literature notes that in desert cities, one of the largest drivers of household water consumption is water used to irrigate residential landscapes. In Las Vegas, there were dramatic changes in vegetation area within both old and new neighborhoods. In order to tease out the impact of policies that incentivize vegetation change, I need to understand how vegetation area was changing, in areas that are strongly influenced by landscape change policy and also areas that were not.

In Chapter 3, I answer the question *how did vegetation area in Las Vegas change between 1996 and 2007?* I estimate the area of vegetation in each Las Vegas census tract in June of each year between 1999 and 2007 from images taken by the Landsat 5 satellite. I find that a common technique for detecting vegetation from satellite images, Mixture Tuned Match Filtering (MTMF), produces biased estimates of vegetation area. I find that it is possible estimate changes in vegetation area in Las Vegas, Nevada by utilizing a unique calibration technique applied to the vegetation area estimates produced by MTMF. To generate a ground truth estimate, I use hand-calibrated data drawn from high-resolution photography taken by the Clark County Assessors Office. I achieve this calibration by determining the mean shift that minimized the Kolmogorov–Smirnov distance between the hand measured dataset and the automated MTMF dataset. Additionally, I reduce the effect of noise by randomly averaging MTMF pixels and utilizing concepts from information theory to ensure that this averaging provides a distribution of calibrated MTMF data for each year that matches the distribution of hand measured data and preserves the higher order moments of the dataset.

This chapter is the first to show the feasibility of using an MTMF dataset in combination with a large ground truth dataset to quantify subpixel changes in vegetation area, and demonstrates a viable path forward to for using MTMF to quantify other trends of interest in Landsat imagery. I show that in the Las Vegas city core, there is a small but meaningful decline in vegetation area in these years, which is suggestive of the importance of Las Vegas' landscape conversion programs. Quantifying vegetation change at the sub-pixel level is critical to examining turf removal policies and their impacts.

In Chapter 4, I answer the question *how much of the observed decline in per capita consumption can be explained by Las Vegas land use, land cover, and physical infrastructure change that resulted from extensive new construction and installation of newer water conserving technology, and how much can be attributed to water conservation policy choices?* I use the results of the vegetation estimate developed in Chapter 3 to estimate changes in household water consumption using a unique dataset that combines estimates of household water consumption, household infrastructure, vegetation area, and weather data, each estimated for all 348 census tracts in the study area over a period of 11 years. Broad panel datasets of residential water consumption have only recently become available from water suppliers, and are necessary to separately determine the effect of infrastructure changes, vegetation change, and weather change on household consumption. In addition to performing a formal regression analysis to determine the marginal effect that changes in our right hand side variables played in influencing water consumption and to decompose the reduction in household water demand into its constituent parts, I also perform a scenario analysis to estimate the total effect that the changes that actually occurred in our right hand side variables played in Las Vegas' decline in household water consumption.

I find that the largest drivers of Las Vegas' decline in average household water consumption are changes in the average age of homes and changes in population location, both driven by substantial population growth. The growth driven changes only influenced average household consumption in the city periphery, but the share of population in the periphery grew to nearly 70% of the total population, so the citywide effect is also large. Within established neighborhoods, vegetation change has a demonstrated impact on household water consumption. When taking the city as a whole, these changes are small compared to the changes associated with new development and urban growth.

Chapters 3 and 4 developed a measure of sub-pixel vegetation area and then used these data to develop a model of the impact of vegetation change on household water demand. In Chapter 5 I link changing residential water demand to the WSL program, and answer the question *how much water was saved by the WSL program*? WSL can potentially influence water consumption through its effect on the area and composition of vegetation, and can also directly influence water consumption by causing household behavioral change and changes in the water intensity of existing vegetation. I find that in the first year of a WSL conversion, each square meter of landscaping converted under the WSL program reduces the measured vegetation area by about 0.38 m^2, and reduces residential water consumption by about 82 gallons per month in June. Of this 82 gallons, about one third of the reduction in consumption is attributable to WSL's effect on measured vegetation area, while the remainder is due to the programs effect on the water intensity of the remaining vegetation and changes in behavior. In comparison, Sovocool, Morgan and Bennett (2006) use household level data to estimate that June water savings are around 95 gallons per square meter of turf removed under the WSL program.

The single most important factor influencing Las Vegas' decline in household consumption was the effect of much more water efficient new construction in conjunction with substantial population growth. The combination of these two factors lead to a large increase in the share of newly constructed, water efficient homes with respect to the total housing stock, and was the primary driver of the observed decline in the citywide average household water consumption. Nevertheless, the success of the WSL program in established areas of the city demonstrates that even for cities with slow population growth, there is substantial scope for reducing household water conservation through changes to existing infrastructure.

These policies create incentives for the use of infrastructure that naturally leads people to consume less water without constraining the choices existing residents may make about their lifestyles and homes. Thus, they are relatively invisible to the end water consumer, which may make them more effective than traditional conservation policies focused on education to motivate altruistic modification of consumption behavior. The most significant result that water policy makers should take from this dissertation is that the most effective way to ensure long term, sustainable reductions in water consumption in a growing city without resorting to politically risky water price increases is to support and incentivize the construction of water efficient infrastructure. In this way, water efficiency can be built into the infrastructure of the city as it grows, rather than requiring expensive retrofits to existing infrastructure.

These results broadly decompose the drivers of residential water consumption from infrastructure change, population growth, and vegetation change. I focus on Las Vegas' most widely known conservation policy, but the largest measureable driver of change in residential water consumption was due to changes in the water consumed by new construction. Within the residential water demand literature, there is little agreement in the role that structural characteristics play in influencing household consumption. Further research could examine the role that changes in municipal building code and incentives for water efficient new construction played in the lower consumption associated with new construction, which would further address this the gap in the literature. Additionally, the attenuation I observe in the water savings generated by the WSL program is inconsistent with the Sovocool, Morgan and Bennett (2006) study, and merits further study. Using a difference in differences approach on household level data would provide a more rigorous estimate of the long term water savings generated through the WSL program. Finally, I would like to consider the role that institutional change, like the creation of SNWA and the implementation of the WSL pilot program played in supporting the strong conservation policy that followed.

1.1 Southern Nevada Water Authority History

Ninety percent of Clark County's water supply is pumped out of Lake Mead, on the Colorado River (Southern Nevada Water Authority 2009). The rest comes from groundwater aquifers with very little natural recharge. In the late 1980s, Las Vegas consumed three-quarters of its total Colorado River allocation, and consumption rates were increasing by 17% to 22% per year (Mulroy 2005).

Prior to the creation of the Southern Nevada Water Authority (SNWA), water allocation within Nevada followed the principle of "first in time, first in right," which also underlies the doctrine of prior appropriation used throughout the Colorado River basin and much of the western United States. As Nevada's unallocated supply from the Colorado River decreased, the five water districts in the Las Vegas area realized that their future share of Nevada's Colorado River allocation depended on their consumption in the present. In 1990, Boulder City began opening fire hydrants at night in order to increase their 1990 consumption, and, thus, their future share of the Colorado River allocation (Mulroy 2005). Around this time, Las Vegas Valley Water District (LVVWD) water managers began an analysis of unallocated supply and realized that more water had been promised to developers for potential projects than was available (Mulroy 2005). LVVWD issued a temporary moratorium on new water commitments, halting new land development (Hynes 1991a). Enough water permits had been issued to support planned construction for a short time. However, if the moratorium had not been resolved quickly, the construction industry would have been almost entirely stopped. For Las Vegas's growth-driven economy, the potential consequences were enormous.

Within six months, the five water districts in the Las Vegas area had agreed on a new allocation system that dramatically changed property rights to water for the agencies, created a system for distribution of rights to developers and created the SNWA, a new water super agency ("Agencies to Create Joint Authority for Colorado River Water" 1991; Gallant 1991). SNWA is responsible for coordinating water issues among the seven agencies, seeking new water supplies, and managing conservation programs (*Executive Summary of Cooperative Agreement Establishing the Southern Nevada Water Authority* 1991, 2). The five districts also shifted from generally conflict-based relationships to cooperative relationships. Property rights to water switched to a fixed allocation for each agency, rather than the previous consumption-based allocation. Developers, in partnership with the water agencies, chose a new water permitting system, which is consistent across the entire county and issues permits very late in the planning process in order to minimize water permits held in speculation (Hynes 1991b). These changes in the formal institutional structure for water allocation and the informal relationships between members are a unique case study of apparently successful institutional adaptation to water scarcity.

SNWA is responsible for water services in all of Clark County. Table 1-1 shows the population served by each of the regional water providers in 1990 and 2010, illustrating the region's rapid growth. The LVVWD is the water provider for the City of Las Vegas and all of unincorporated Clark County. Henderson, North Las Vegas, and Boulder City provide water to their respective cities, and Big Bend Water District serves the town of Laughlin. Water consumption and economic activity are closely correlated with population in each region. The final two members of the SNWA are the city of Las Vegas and the Clark County Sanitation District. The City of Las Vegas owns the rights to sanitary sewage produced in the city, and the Clark County Sanitation District provides sewage treatment for the entire county. Both agencies are SNWA board members, but have limited voting rights (*Executive Summary of Cooperative Agreement Establishing the Southern Nevada Water Authority* 1991).

Table 1-1: Populations served by regional water providers (U.S. Census 1990; U.S. Census 2010).

Regional Water Provider	1990 Population Served	2010 Population Served
Las Vegas Valley Water District	611,452	1,409,233
Henderson	64,942	257,729
North Las Vegas	47,707	216,961
Boulder City	12,567	15,023
Big Bend (Laughlin)	4,791	7,323

Initially, SNWA sought to manage water scarcity through supply augmentation efforts. As available sources of additional water supply were consumed, SNWA shifted its focus to encompass both supply augmentation and demand side management. Household-level water consumption in Las Vegas has declined by 55% since the inception of SNWA, which was enough of a per capita decline in consumption that total water consumption in the city actually declined by a small amount, in spite of Las Vegas's rapid population growth. Total Las Vegas consumption was less than the amount permitted by the Colorado River Compact in 19 of the last 21 years. In popular discussions, this has been used as sufficient evidence that SNWA succeeded in solving Las Vegas's water scarcity problem. However, Las Vegas also grew rapidly, leading to a decline in the average age of water infrastructure and rapid rise in the use of new technology. Large declines in household-level water consumption have been observed in most cities in the United States since the 1980s (Rockaway et al. 2011), although very few studies have attempted to quantify the different factors influencing the decline in urban household water consumption. There are no academic studies on Las Vegas that measure the effects of infrastructure change through new construction, land use and land cover changes, and water conservation policy implemented by SNWA on household water consumption.

1.2 SNWA Conservation Policies

Once SNWA shifted their primary focus to include water demand management, they implemented a wide variety of water conservation programs across the city. Under the conditions of the return flow credit, Nevada receives credit for 100% of water returned to Lake Mead after treatment through the Las Vegas sewer system. Functionally, this means that water used indoors is not counted against Nevada's total

Colorado River allocation, while nearly all outdoor water use does count. As a result, all of SNWA's major conservation programs focused primarily on outdoor water consumption. Some of the conservation policies aimed to influence developer and homeowner water infrastructure choices, while others were aimed at influencing residential water consumption behavior.

Three major policy categories targeted infrastructure change: limits on the amount of turf in new construction, increasingly strict prohibitions on water features, and a turf removal incentive program called Water Smart Landscapes (WSL). The policy choice that permitted the water district to enforce water waste citations directly likely had the largest influence on resident behavior. Other programs that influenced resident behavior included water conservation ad campaigns, incentives and rebates for better irrigation clocks, pool covers, and more water-efficient car washing procedures.

The primary source of information on the different SNWA conservation programs are conversations with SNWA and LVVWD staff members via email and telephone. Conversations with SNWA staff members (emails, telephone calls, etc). Other sources of information include transcripts of interviews performed by Hal Rothman, SNWA and LVVWD promotional materials, and the Las Vegas and Clark County municipal code.

1.2.1 Water Smart Landscapes Program

SNWA began the WSL, a cash-for-grass water conservation program, in 1996. Figure 1-1 shows the square footage of new turf conversions for each month of the program's history. It began as a small pilot program in 1996, increased in scope slightly in the early 2000s, and became a widespread and important aspect of SNWA's water supply security plan during the 2004 drought. The program paid landowners between $0.50 and $2.00 per square foot of grass to remove turf and replace it with xeric landscaping. About 3,300 acres of grass have been removed under the program so far, a little less than 1% of the total land area in the Las Vegas metro area. Homeowners in single-family residential properties have removed 930 acres.

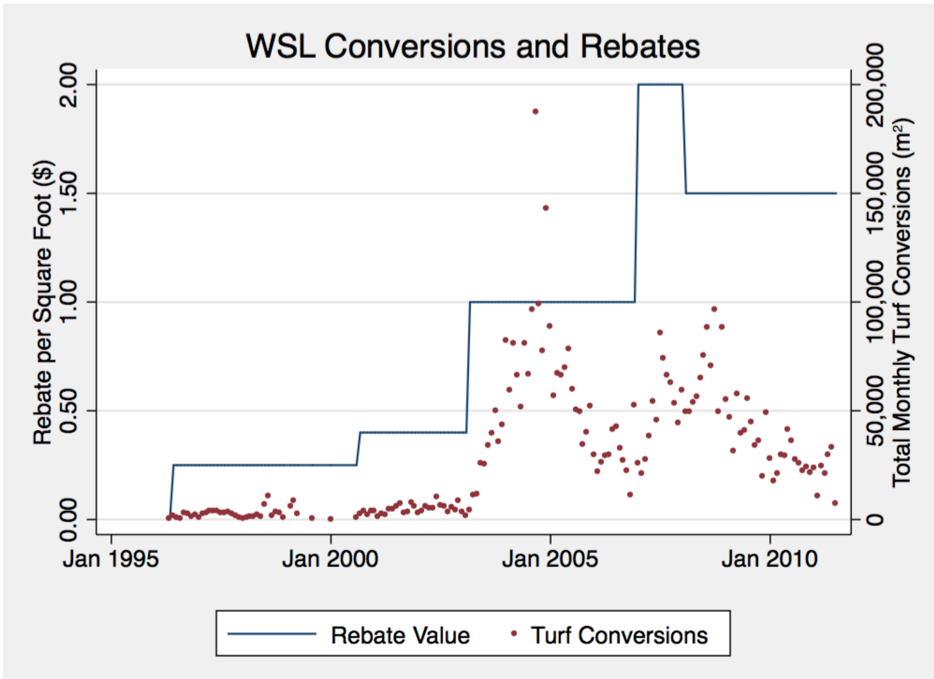

Figure 1-1. Water Smart Landscaping Program Implementation. The pilot program began in 1996, and the scope was significantly increased in 2004.

There have been no significant changes in the post-conversion landscaping requirements over the history of the WSL program. Over the entire history of the WSL program, the post-conversion landscape required at least 50% living ground cover at maturity. The only major change in the program implementation is that, initially, there were no restrictions on the length of time owners were required to maintain the conversion. In February 2003, the terms of the WSL program were changed so that property owners were required to maintain the converted landscape for 5 years. In March 2004, the restrictions on landscaping were altered to last for 10 years, or until the property was sold. SNWA staff members have no recollection of any active efforts to ensure long-term compliance for converted landscapes (Kent Sovocool, Morgan Mitchell and Toby Bickmore in conference call with the author, April 22nd, 2014). In June 2009, the program was again changed, so that a restrictive covenant is now attached to the property title, and the xeric landscape must be maintained in perpetuity, even when the property is sold.

In a newly converted landscape, not all plants are fully mature, so at the post-conversion site review, SNWA calculates a coverage area at maturity based on plants that are installed.

1.2.2 Turf and Water Feature Restrictions

Las Vegas's first major effort to reduce outdoor water consumption was passed in Ordinance 1386 §1 (*Clark County, Nevada* 1993) in January 1993. Due to this ordinance, any homeowners association or similar group that received a permit after July 1, 1992 is not permitted to prohibit the use of xeric landscaping. Thus, the owner of any parcel constructed after July 1992 is permitted to install xeric landscaping in their property, regardless of the preferences of their neighborhood association.

In November 2000, Ordinance 2481 (*Clark County, Nevada* 2000) was passed, prohibiting the area of turf in a front yard from exceeding 50% of the net area of the front yard for new construction, and requiring some sort of water conserving irrigation system for all landscaping. Sprinklers are only permitted for turf, while all other vegetation must use drip irrigation.

In October 2003, Ordinance 2934 (*Clark County, Nevada* 2003) added a host of restrictions for the use of water features and the installation of new vegetation under drought conditions. Under drought watch conditions, planting cool season grasses during the warm season is prohibited. Under drought alert conditions, no new turf may be installed in residential front yards, and any turf installed in side or back yards must be less than 50% of the yard area. Additionally, only fountains and decorative water features with less than 200 square feet of surface area may be operated under drought watch or drought alert conditions. In January 2004, the water feature restrictions were amended to clarify that each residential parcel may operate only one water feature of the permitted size, and the maximum permitted size under drought alert was reduced from 200 square feet to 25 square feet. Operating existing water features larger than the permitted size is prohibited. Swimming pools are not considered decorative water features, and so are not included under these restrictions.

Las Vegas has been under a drought alert since June 2003, so the conditions on turf restrictions implemented in 2003 have always been in effect. Nonetheless, in 2009 (after the end of the formal study period), the Clark County municipal code was changed so that the turf restrictions under drought watch and alert were made permanent for new construction. Thus, the current code shows that for new construction, turf is prohibited in front yards, and can only be 50% of the area of back and side yards. Additionally, no measurement of the turf area can be less than 10 feet across. This restriction limits overspray from irrigation and the use of turf that is solely decorative so that existing turf is a size that is useful for recreation. Changes to the municipal code that are intended to reduce water consumption apply only to new construction, and so must be built into the city as it grows.

Thus, the biggest salient changes in acceptable use and construction of turf grass occurred in November 2000, when the area of turf in new front yards was restricted, and in October 2003, when there were many new restrictions placed on the area of turf, type of turf, and water feature use.

1.2.3 Water Smart Homes

Water Smart Homes is a voluntary program for developers run by SNWA in partnership with a developers association, the Southern Nevada Home Builders

Association that began in 2005. Developers pay an annual participation fee and agree to construct homes and neighborhoods that meet minimum water efficiency standards in the indoor appliances and fixtures, household level landscaping choices, and common area landscapes. They may then use the Water Smart Homes logo and promotional materials in their advertising materials (Southern Nevada Water Authority 2014).

The standards for the Water Smart Homes are generally low cost when implemented during construction, but retrofits to achieve the same end can be costly to implement and incentivize(Deoreo et al. 2001). For example, the Water Smart Homes program prohibits turf in front lawns, any type of ornamental water feature, and limits the turf in backyards to the largest of 50% of the backyard area or 1,000 square feet. These landscaping standards in the Water Smart Homes program reiterate changes in the municipal building code that were implemented about the same time. The cost of installing a xeric landscape is is similar to the cost of installing a mesic landscape in the initial installation, but retrofits can cost between 50 cents and several dollars per square foot of landscape converted (Sovocool, Morgan, and Bennett 2006). Additionally, there are strong standards on the design of the landscape's irrigation system and water efficiency for indoor plumbing fixtures and water consuming appliances. These require careful system design, but otherwise introduce little additional cost.

1.2.4 Water Price Changes

The LVVWD changed the pricing structure only twice during the study period, first in September 2003, and then in February 2007. Data on historical water prices was obtained through email communications with JC Davis at the Las Vegas Valley Water District between 5/9/2013 and 5/13/2013. Las Vegas has used a fixed service charge with block rate billing system since 1990. The 2003 price change kept the fixed service charge the same, and both lowered the thresholds and increased the price for the consumption blocks above 5,000 gallons of consumption. Before the 2003 price change, the first block includes between 0 and 5,000 of water consumed, the second from 5,000 to 15,000, the third from 15,000 to 40,000, and the fourth includes above 40,000 gallons of consumption. After the 2003 price change, the first block was kept the same. The second was lowered to end at 10,000 gallons, down from 15,000; the third includes consumption from 10,000 to 20,000; and the fourth includes above 20,000 gallons of consumption. The bill for a household with consumption at the then-current citywide mean of 21,480 gallons per month in June increased from $35.21 to $45.94, about 23%.

The price change implemented in 2007 increased the fixed service charge by 37 cents, and maintained the same block rate structure and thresholds as the 2003 price change. The cost at each block increased by a few percentage points, leading to an increase from $40.02 to $43.59, about 8%, for a household at the then current citywide mean of 19,390 gallons per month in June.

1.2.5 Behavior Change Policies

SNWA created a number of different programs aimed at changing outdoor water consumption behavior. They included both penalties for over consumption and conservation incentives. The penalty based programs included fines for water running off the property and restrictions on the day of week and time of day that automated irrigation systems are permitted to run. SNWA also implemented a number of behavioral conservation incentive programs, including a car wash coupon program, a pool cover rebate program, and irrigation clock rebate programs. The information on broad SNWA conservation programs was obtained from an informal document written by Kent Sovocool, and return to the author on 8/1/2011. Finally, an award winning ad campaign was created to inform homeowners of current watering restrictions (Brean 2008).

Both the city of Las Vegas and Clark County first issued day of week lawn watering restrictions and water waste restrictions in the summer of 1991 (*City of Las Vegas, Nevada* 1991; *Clark County, Nevada* 1991b; *Clark County, Nevada* 1991a). In October 1991, the City of Las Vegas gave the LVVWD the authority to issue citations for watering outside the permitted day of week and for water running into city streets (*1991 Statutes of Nevada* 1991). The LVVWD took over most oversight of water waste enforcement, but any unpaid citations were processed through small claims court and so, functionally, the formal legal permission had little power and was not widely used. The first citations by LVVWD for water waste occurred in 1994, and the actual payment rate on these citations was very low until 2002 (Sovocool 2011).

In June 2002, LVVWD transitioned account holders to a "Condition of Service" approach to water provision, meaning that LVVWD has the authority to refuse or terminate water service in the event of unpaid fines for water waste (Southern Nevada Water Authority 2002). Fines were initially set at 100 times the daily water service charge, or $14 for most residential uses, increasing up to 1,000 times the daily water service charge for multiple unaddressed citations. This is the regime that was in effect in June 2003. Between June 2003 and June 2004, a large suite of additional waste water reduction measures were implemented and fines were increased (Southern Nevada Water Authority 2003). Most importantly, parcels were assigned to day of week watering groups based on address, which made enforcement of the day of week watering restrictions much more feasible. Additionally, pool-draining rules were created, the time of day restrictions for spray irrigation rules were tightened, and car washing and policies around acceptable water features were revised. Water waste violation fines were increased from $14 to $25 for the first violation and from $140 to $400 for the maximum fine. Between June 2004 and June 2005, water waste fines were increased again to $40 for the first violation and $640 for the maximum fine (Southern Nevada Water Authority 2004). Las Vegas water managers recall an increase in the rate of levying water waste violations around the 2004 drought, but no data are available on the number of citations issued (Sovocool 2011). While LVVWD had the formal legal authority to enforce their water conservation policies beginning in October 1991, this authority only became functionally effective beginning in June 2003, and was further strengthened in June 2004.

One of Las Vegas's most widely publically known conservation programs is the "Don't Make Us Ask You Again" ad series. It was produced by R & R Partners, the same agency that created the "What Happens Here, Stays Here" ad series for the Las Vegas Convention and Visitors Authority. In the most talked about water conservation ad, an elderly woman rings the doorbell at a house with the irrigation sprinklers running. When a middle-aged man answers the door, she kicks him in the groin. The ad ends with the tag line "Don't make us ask you again. It's a desert out there." This ad won silver in the "Government, Institutional & Recruitment" 2008 Effies. It first aired on November 1, 2006, and was timed to coincide with seasonal changes in how many days per week lawn watering is permitted (Brean 2008). It has been aired each fall since, in order to remind homeowners to change their systems from watering seven days per week, down to three (Shine 2013). Despite the ad's salience and widespread recognition, its effect on June water consumption is expected to be very limited, because the ad is aired only in the fall, and encourages homeowners to reduce weekly watering events for the winter season. By the following June, daily watering is again permitted, and seasonal weather changes force almost all homeowners to increase their automated watering schedules from the restricted winter schedule.

The behavior change incentive programs were smaller in scale than the infrastructure change programs, and SNWA staff members believe they have had less of an impact on household water consumption. An irrigation clock rebate program began in 1999. Under various iterations, about 2,000 irrigation clocks were purchased between 1999 and 2007 through this program. A program to provide coupons for the purchase of pool covers was started in April 2005. Between April 2005 and June 2007, about 10,000 coupons were issued, with a total savings to residents of about $580,000. Finally, a program to encourage residents to use commercial car washes, rather than washing cars in their driveway, was launched in December 2004, and gave residents a $2.00 off coupon to use at any carwash in the city.

There is no spatially available data on uptake of these behavior change programs, and so their effect will primarily be observable in temporal effects, or will influence the average consumption of houses of a particular age if the policy is associated with new construction. The key years in which major changes first went into effect were in 2002, when LVVWD first got functional permission to levy fines for water waste, 2004 when they stepped up the enforcement rate, fine size, and types of citable water waste violations, and potentially in 2005, when fines were increased again.

1.3 Study Area

Our study area includes the developed parts of the LVVWD service area, as shown in purple in Figure 1-2. It includes areas within the urban parts of the Las Vegas metro area that are served by the LVVWD. The North Las Vegas Water District serves the developed areas north of the study area, while the Henderson water district serves the developed areas in the southeast part of the city. Note that in large tracts, only small portions of the tract have ever been developed. The few tracts in the middle of the city that are excluded from the study area cover commercial areas in the Las Vegas strip and have no single family residential structures.

I use a study period from 1996 to 2007. The study period begins in 1996 to coincide with the beginning of the Water Smart Landscaping program, an important water conservation program. The study period ends in 2007 in order to avoid including any effects of the 2008 recession, which hit Las Vegas particularly hard and had a large effect on the city's economy, demographics, construction industry, and home vacancy rates. This study period occurs as part of a longer time trend of generally declining household water consumption in the water district service area**.**

High summer temperatures are the major driver of outdoor water use, and on average, June was the driest month during this time period, so this study considers June household consumption only.

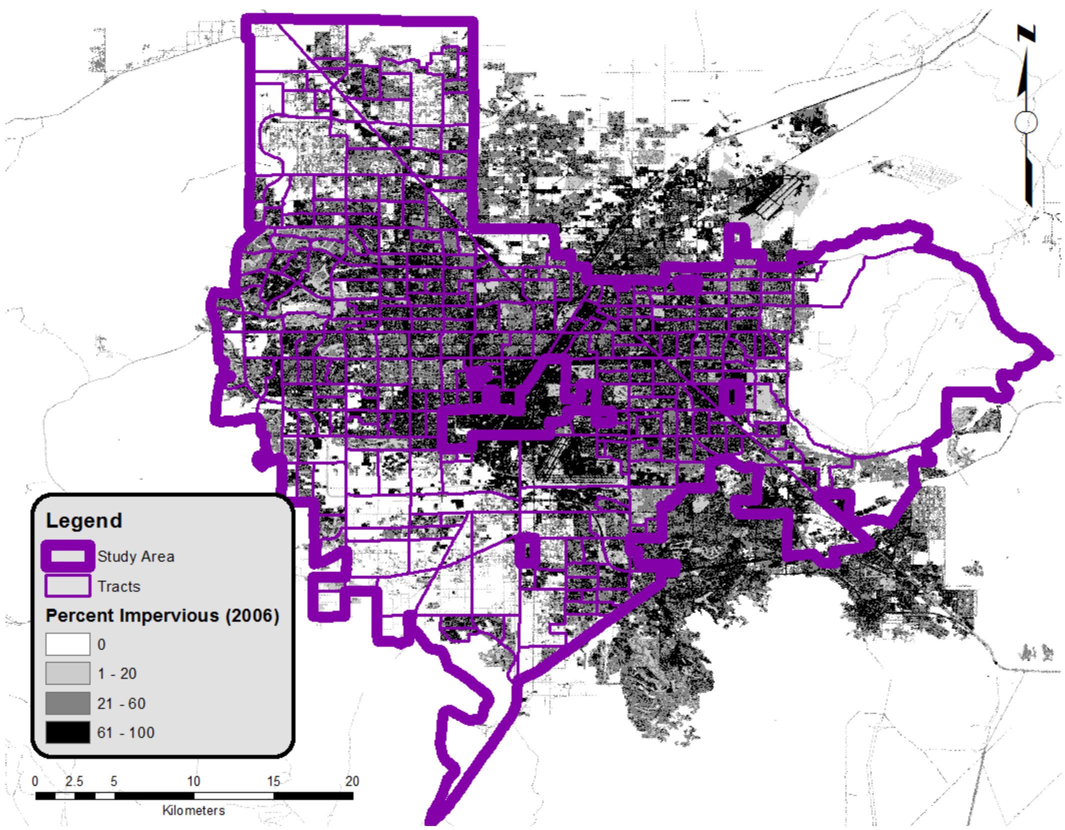

Figure 1-2. The full study area is outlined in purple.

2 LITERATURE REVIEW

There is a broad literature on residential water demand. I first review the academic literature that describes the causes of national or regional trends in per capita residential water consumption. The extensive literature on the elasticity of water demand provides context for the much smaller literature on the effect of non-price based conservation policy tools on residential water consumption. Finally, I review the very narrow literature on the influence of landscape-based conservation incentive programs on residential water demand.

2.1 Trends in North American Water Use

The U.S. Geological Survey (USGS) has performed a comprehensive survey of water withdrawals in the United States every five years since 1950. The long-term trend in municipal water use is shown in Figure 2-1, based on data from USGS Circulars (MacKichan 1951; MacKichan 1957; MacKichan and Kammerer 1961; Murray 1968; Murray and Reeves 1972; Murray and Reeves 1977; Solley, Chase, and Mann 1983; Solley, Merk, and Pierce 1988; Solley, Pierce, and Perlman 1993; Solley, Pierce, and Perlman 1998; Hutson et al. 2004; Kenny et al. 2009). Data are collected from a wide variety of sources at the state and local level. Each of the USGS Circulars cited above describes the authors efforts to ensure consistency across the datasets, but the accuracy of the data relies on the quality of the individual agencies recording the information. Per capita municipal water consumption rose between 1950 and around 1980, and began to decline in the 1990s and 2000s. I have not yet found any studies that look at the drivers of long-term trends in per capita water consumption in the United States prior to the 1990s, so there are few discussions of why the trend in per capita consumption changed direction.

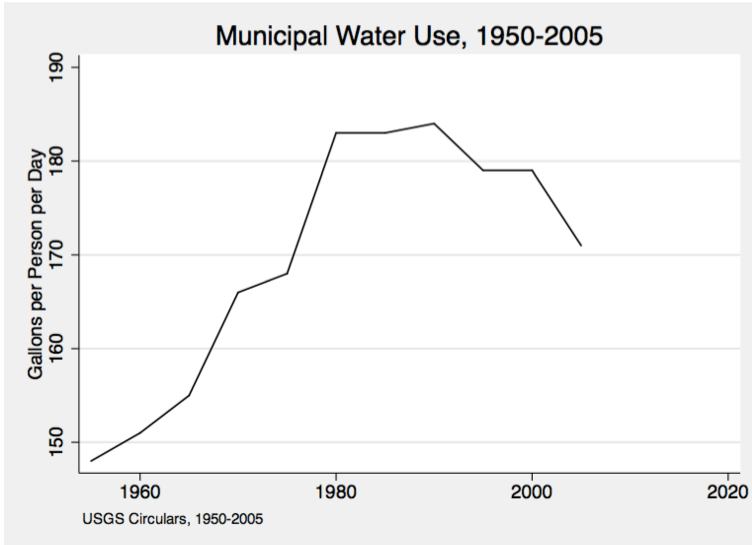

Figure 2-1. Per capita municipal water consumption between 1950 and 2005. The national trend in declining per capita water consumption began in about 1990, and is generally consistent across different city sizes and climates.

Obtaining small spatial scale water consumption data before water agencies began using digital records is challenging, so there are few discussions of the causes of the 1990's era decline in household water consumption. Additionally, many regional-level studies are performed by consulting agencies directly for a specific water district, for example "Post Drought Changes in Residential Water Use," written by the water engineering and management firm Aquacraft for Denver Water. These studies are rarely published in the peer reviewed literature, and are challenging to find, but may provide valuable insights on trends in urban water use in North America.

The USGS studies use population data from the U.S. census and other sources, and report municipal water demand. Municipal water demand includes all water delivered by a water provider with more than 15 connections, and includes supplies delivered to residential, commercial, and industrial uses. The population data includes all people whose residence is served by a municipal water source, so the per capita value reported is a per person average and includes non-residential water consumption. Most peer reviewed studies (e.g. Agthe and Billings 1987; Renwick and Archibald 1998) report per household water demand, because the base data source is meter level data provided by the water district. Decreasing household size has been hypothesized as a contributor to the decline in household level water consumption, but many other factors may also play a role.

The decline in per capita consumption after the 1980s has been widely noted in the literature and appears to be a general trend across the United States (Cooley and Gleick 2009). A large survey of municipal water use from 1992 to 2009 showed statistically significant declines in household level consumption across 43 municipal water providers in the U.S. and Canada (Rockaway et al. 2011). There was broad variation in population served, climate, and institutional form for the different water providers. In an OLS fixed effects regression that controlled for utility size, water source, ownership, and several drought and climate related variables, the time coefficient was negative and highly significant for data between 1992 and the present. An associated study (Coomes et al. 2010) performed in Kentucky at the local level found that the primary explanations for differences in per capita household consumption were varying demographic and economic characteristics, housing age, and low flow appliances. A similar household level study in Denver CO (Aquacraft 2006) concluded that about two-thirds of the observed decline in per capita indoor consumption was due to low flow appliance penetration, and most of the rest was due to changes in household size. In Denver, outdoor water use declined due to drought restrictions, pricing measures, and changing weather patterns.

2.2 Drivers of Residential Water Demand

The first goal of water managers is to ensure a safe and reliable water supply, regardless of changes in weather, climate, characteristic demand patterns, demographics, pricing systems, or any adverse event that may influence the water supply infrastructure. This is noted in the contracting documents that created the SNWA and also the mission statement of the board of commissioners for Denver Water. Secondarily, although still importantly, managers work to ensure that available supply and actual demand are consistent with each other at the least cost. Implicitly, the primary goal of most of the academic literature considering residential water demand is to provide information for water managers as they seek to meet their service objectives (e. g. Renwick and Green 2000; Olmstead and Stavins 2009; Castledine et al. 2014).

The strategies water managers use to meet their service objectives are influenced by their background and training, and have also changed as the physical and social context of water use has changed. Managers of urban water districts in the western US were often hired out of the United States Bureau of Reclamation (USBR), the federal agency that builds and manages the water supply infrastructure system for the entire Colorado River. These managers, nearly all men, are sometimes referred to as water buffaloes for their propensity to focus only on the supply side of water management (E. Green 2008). This traditional focus on the dams, pumps and pipes based infrastructure that is necessary to supply water to cities encourages thinking of household level water consuming infrastructure as a "fixed effect" (Tinker et al. 2005), and is not limited to United States water management. In 1997 the managing director of a UK water provider stated "We are in the water supply business, not the water restriction business . . . .We know what my customers want and I believe we are in the business to give them what they need, whenever they need it (Howarth 1999, 21)." Thus, collaborations between water mangers and urban planners to consider the role that effective planning and municipal code choices can play in shaping future water demand as a city grows are a major departure from the mindset of traditional water managers. As the management strategies of water management professionals have changed, the focus of the academic literature around residential water demand has also shifted from a focus on the price-elasticity of residential water demand to weather, climate, demographic, or infrastructure determinants of demand.

A major focus of early water demand literature, especially that focused on US cities, was to determine the price elasticity of water or more generally, the optimal pricing mechanism for water (e.g. Howe and Linaweaver 1967; Gottlieb 1963). Four more recent widely cited meta-analyses that are focused on broad themes within the literature are Espey, Espey & Shaw (1997), Arbues, Garcia-Valinas & Martinez-Espineira (2003), Dalhuisen, Florax, de Groot, & Nijkamp (2003) and Worthington & Hoffman (2008b). The consensus from these meta-analyses shows that the major determinants of residential water demand and the price-elasticity of residential water demand are: price & price mechanisms, income, weather variables like temperature and precipitation, and demographic characteristics like household size or population density. These analyses largely ignore the effect that non-price based conservation policy changes can have on water consumption.

More recently, a substantial segment of the literature has focused on predicting and mitigating the role that changes in climate or weather (Balling and Gober 2007; Balling, Gober, and Jones 2008; Balling and Cubaque 2009; Billings and Agthe 1998; Michelsen, McGuckin, and Stumpf 1999; Breyer, Chang, and Parandvash 2012; Campbell, Johnson, and Larson 2004), and the local micro-climate (Aggarwal et al. 2012; Guhathakurta and Gober 2007; Guhathakurta and Gober 2010) play in determining household water demand. Some newer literature also considers the interactions between vegetation, local temperature, and water consumption (Middel et al. 2014; Gober et al. 2012; Farag et al. 2011). Generally, these papers find that higher temperatures, operating locally through the urban heat island, or more broadly from weather variation or different climates are associated with higher water consumption. The role of precipitation is less consistent- cities in hot, arid location have much higher outdoor water consumption than cities in more temperate climates, but unusually high precipitation is not always shown to reduce residential water consumption.

Most studies that deal with residential water demand include some characteristics of the built environment as a control variable (e.g. Nauges and Thomas 2000; Dalhuisen et al. 2003; Balling, Gober, and Jones 2008; Grafton et al. 2011; Aggarwal et al. 2012; Fielding et al. 2012; Gober et al. 2012). There is a small but growing branch of the literature whose specific focus is to understand the role that the built environment plays in determining residential water demand, whether that includes landscaping choices, outdoor infrastructure characteristics, or indoor infrastructure characteristics (Tinker et al. 2005; Wentz and Gober 2007; Fox, McIntosh, and Jeffrey 2009; Chang, Parandvash, and Shandas 2010; March and Saurí 2010; House-Peters, Pratt, and Chang 2010; Farag et al. 2011; Rosenberg, Howitt, and Lund 2008). Broadly speaking, these infrastructure based papers aim to support effect urban planning around water demand.

The specific variables used to control for physical infrastructure vary widely, and depend on the level of aggregation in analysis, from the household to multi-city regions, the data available, and whether the analysis is of cross-sectional, time series, or panel data. In general, housing density, vegetation type and extent and some metric of the size of the house like bathrooms, rooms, or indoor area, are typically thought of as the most important characteristics of the built environment necessary to explain household water consumption. The age of the infrastructure, swimming pool characteristics and water efficiency of technology in use are also occasionally included, as summarized from the literature by Chang, Parandvash, and Shandas (2010) and Inman and Jeffrey (2006).

An additional challenge in estimating the role that the built environment plays in determining household water consumption is access to data of spatial scale that matches the water data available. For very broad scale studies, citywide summary statistics can be used (March and Saurí 2010), while for narrowly focused studies, field observations are an option (Fox, McIntosh, and Jeffrey 2009). Recent developments in remote sensing permit use of satellite imagery for metrics like vegetation extent or urban density (Farag et al. 2011; Gober et al. 2012). The highest quality sources of infrastructure data are "insiders" like building developers (Tinker et al. 2005) and tax assessor records (Wentz and Gober 2007; Chang, Parandvash, and Shandas 2010; House-Peters, Pratt, and Chang 2010).

These studies find that more pools, more outdoor area, more vegetation, and a larger indoor areas or more bathrooms are all associated with higher consumption, while the effect of structure age on water consumption is less consistent, and may depend upon patterns in development in each individual city.

While social and demographic characteristics do not present a viable policy lever for water demand management, understanding the role that these characteristics play in determining residential water demand can be important for predicting demand changes as cities grow and change. Like with the literature on the built environment, most empirical studies aimed at understanding some aspect of residential water consumption include some type of variable to control for social, economic, or demographic characteristics of the water users (e.g. Bruvold and Smith 1988; Céline Nauges and Thomas 2000; Renwick and Green 2000; Wentz and Gober 2007). Fewer papers focus specifically on the role that these social factors play in determining residential household consumption (Harlan et al. 2009; Arbues, Villanua, and Barberan 2010; Fielding et al. 2012). The social and demographic variables most commonly used as control variables are household size, and some measure of the age distribution of the population or household, in addition to economic variables like household income. These studies find that larger households and wealthier households are likely to consume more water although the relationship is probably not linear.

Traditionally, water management has focused on supply augmentation. As available but unused supplies become scarcer and urban populations grow, meeting a city's growing demand for water by augmenting the water supply has become more challenging. Current laws and water allocation policies are not conducive to the establishment of markets for water, and so price changes are a regulatory decision that can cause both significant revenue instability and political risk for the water agency. The widespread hesitance for water managers to encourage conservation by raising the price of water is widely noted (Howarth 1999; Dziegielewski 1999; Olmstead and Stavins 2009). Nonetheless, demand side management is becoming an increasingly important tool to prevent water shortages (Howarth and Butler 2004), and there is a growing body of literature examining the role that non-price based water conservation policy can play.

Nearly universally, this demand side management conservation literature notes that volumetric water pricing and the steps necessary to implement it (including installing household meters) are the most economically efficient policy tools for managing water demand (Grafton et al. 2011; Kenney et al. 2008; Inman and Jeffrey 2006; Renwick and Green 2000; Bruvold and Smith 1988). Nonetheless, in situations where changes in the volumetric price of water are technologically impractical or politically infeasible, a wide range of potential non-price based conservation policies exist, with significant variation in their estimated cost per volume of water saved. Major strategies include mandatory policies like building code changes, outdoor watering restrictions, or mandates on technology use, especially related to irrigation systems. Voluntary demand side management strategies include education programs, subsidies for indoor appliances like low flow showerheads, faucets, and toilets, and incentives for changes in outdoor water consuming infrastructure.

The literature finds that mandatory policies have much larger effects (in either direction) than voluntary ones (Kenney, Klein, and Clark 2004; Grafton et al. 2011; Campbell, Johnson, and Larson 2004; Renwick and Green 2000; Castledine et al. 2014). Most mandatory policies do have the expected effect of reducing household water consumption, but Castledine et al. find that compliance with outdoor watering restrictions actually increases household water consumption. The evidence on the effectiveness of voluntary conversions to low flow toilets is strong (Grafton et al. 2011; Tsai, Cohen, and Vogel 2011; Renwick and Archibald 1998), while the evidence for effectiveness of other indoor appliances is weaker, with some studies showing zero or negative effects (Grafton et al. 2011; Campbell, Johnson, and Larson 2004), and others showing positive effects on water conservation (Rosenberg, Howitt, and Lund 2008; Renwick and Archibald 1998).

Finally, landscape conversion incentive programs are growing in their importance as a tool for water demand management. In the late 1990's, the USBR funded a multi-year multi-city research program within water providing agencies to quantify water savings from conversions to xeriscaping. The cities studied were Phoenix, Arizona; Austin, Texas (Gregg et al. 1994); Fargo, North Dakota (Medina and Lee 2006); Las Vegas, Nevada (Sovocool 2005); and the Colorado Front Range (Medina and Gumper 2004). The resulting reports have some useful conclusions, but each also had significant methodological challenges. For example, the Austin study regressed water consumption on the percentage of a lot with turf, but did not control for lot size. The Fargo study is not able to distinguish between the effects of several hours of educational seminars on the benefits of water conservation and actual landscape conversion because the treatment group received both and the control group received neither. Medina and Lee (2006) compared means of water consumption in the treatment different groups in Fargo North Dakota, but did not use any kind of regression analysis to systematically control for annual variation in temperature, precipitation, or other factors. The broad USBR study funded important xeriscape conversion program pilot studies. However, the assessments of the programs are not sufficient to provide reliable estimates about the effect of future xeriscape conversion programs on water demand, and no cross-site analysis was ever attempted.

Despite the growing importance of landscape conversion programs in water conservation policy, in the peer reviewed literature there has been only one attempt to quantify water savings that result from programs that encourage homeowners to convert from turf grass to xeriscaping (Sovocool, Morgan, and Bennett 2006). The Sovocool, Morgan and Bennett study sub-metered 739 homes and performed a careful analysis of the differences between homes that were participants in the WSL program and those that were not, including assessing indoor and outdoor water use separately. Sovocool, Morgan and Bennett estimated that each square meter of grass removed saved about 95 gallons of water each June, about 590 gallons per year. This is a direct measure of the changes in outdoor water consumption before and after the program was implemented, something that is not possible without sub-metering. The method provides a very accurate estimate of savings for households in the study.

The key challenge in relying solely on the Sovocool, Morgan and Bennett study is that it was performed as part of the pilot program. There could be systematic differences between the kinds of homeowners who were early adopters for the turf conversion program, and those who respond after a long period of public messaging, growing acceptance of xeric landscapes, and a much larger financial incentive. The households who were willing to perform a landscape conversion so early on in the program may be the kinds of people who were already conscious of their water consumption and environmental impact, and so have less "wasted" water to conserve through landscape changes. Alternatively, the early adopters might have been more conscientious about water conservation post conversion, by installing extremely low water use landscapes and working to use the absolute minimum amount of landscaping water on the new xeric landscape. In addition to systematic differences between residents who self-select into a new pilot program compared to an established and widely known conservation program, early adopters may have been subject to a different monitoring and enforcement environment, older more established vegetation may have had different water intensities, and there may have been systematic differences in the irrigation system technology that was removed under the old landscape or installed with the new landscape, as the program aged.

Across the broad water demand literature, there are few studies that focus on the influence of landscape water conservation incentive programs on water consumption, and no peer reviewed studies that include an assessment of the relationship between vegetation intensity and water demand. This assessment using spatial and temporal variation in non-price based water conservation policy contributes to a gap in the literature quantifying savings for a policy tool of growing importance and will provide information to policy makers about the different role exogenous and endogenous factors have played in reducing household consumption.

3 USING MIXTURE TUNED MATCH FILTERING TO MEASURE CHANGES IN SUBPIXEL VEGETATION AREA IN LAS VEGAS, NEVADA[2]

3.1 Introduction

In arid urban environments, securing sufficient water supply for the needs of the existing population and also future growth is a complex problem with few easy solutions. Historically, most water supply security programs have focused on developing new water supplies, rather than lowering water demand (Baumann, Boland, and Hanemann 1998). As the number of undeveloped water supply sources has fallen, cities have shifted their focus to include demand side management, especially through conservation incentive programs. In Las Vegas, Nevada, if no major new sources of water are found and water consumption rates remain constant, the only method to ensure the security of the water supply for existing residents would be to strictly limit future population growth and housing development. In Las Vegas's growth driven economy, the potential economic consequences of limiting population growth are enormous.

In single family residential homes in arid environments, water used outdoors makes up 50% to 60% of total residential water consumption (Denver Water 2013; Southern Nevada Water Authority 2013) and is a major target of conservation efforts. To measure the effect of the WSL program on vegetation area and the role that vegetation area had on per capita water consumption, an accurate measure of changes in vegetation area across Las Vegas and over the course of the WSL program is necessary.

The objective of this study is to develop a method to determine the fractional area of vegetation in residential land across Las Vegas, Nevada, each year between 1999 and

[2] This chapter is published in the Journal of Applied Remote Sensing, coauthored with Doug Shepherd (Brelsford and Shepherd 2014). I planned the study and performed the remote sensing analysis and digitization, while Dr. Shepherd performed the information theory analysis.

2007. This will allow an accurate estimate of the causes of the decline in per household water consumption in Las Vegas, the role that changes in vegetation area played in Las Vegas's declining water consumption, and the role that the WSL program played in the general drying trend observed in the Las Vegas area.

In a complex urban environment, when using coarse to medium scale imagery like the Landsat TM images, estimating the sub-pixel fraction of vegetation is necessary to get a useful measure of vegetation area and changes in vegetation area. Many techniques have been used to estimate sub-pixel percentages of a target land cover. Linear Mixture models (Wu and Murray 2003; Rashed et al. 2003) assume that the spectral signature for each pixel is a linear mixture of the spectral signatures for all land covers contained in the pixel, while nonlinear models (Keshava and Mustard 2002) relax the assumption of strictly linear interactions. Background removal spectral mixture analysis techniques (Myint 2006) compare each potential end-member to a composite background spectra. The excellent review paper by Somers et al (2011) notes the challenges associated with end-member selection in nearly all spectral mixture analysis approaches, and covers the wide variety of approaches that have been used to estimate sub-pixel fractions of the relevant end-members in the image. These Spectral Mixture Analysis techniques completely unmix each image and report the fractions of all materials present in each pixel. Thus, they require a spectrum for all major background materials in the image, which can be challenging to obtain in a complex and heterogeneous urban environment.

Matched Filtering (MF) (Harsanyi and Chang 1994) filters an image for spectral matches to a single target spectra and suppresses the response of all other unknown background spectra. Thus, MF performs a partial unmixing of the spectra in each pixel from the analysis image. It distinguishes the target spectra from the background, but does not perform any further analysis on the content of the background materials. As a result of the partial unmixing, MF requires only the target spectra, rather than a spectrum for all land cover materials in the image, which is one of the major advantages of the MF approach. The Mixture Tuning (MT) filter has been developed to address cases where MF generates false positive results; the combined method is called Mixture Tuned Match Filtering (MTMF) (Boardman 1998; Boardman and Kruse 2011).

MTMF has three primary analytical steps. First, the Minimum Noise Fraction (MNF) transformation (A. A. Green et al. 1988) is applied to minimize and decorrelate noise in the images across all spectral bands. Second, the MF is applied for abundance estimation (Chen and Reed 1987; Harsanyi and Chang 1994) as described by Mundt, Strueker, and Glenn (2007). Final MF scores are normally distributed and have a mean of zero. The magnitude of the MF score is the projection of the target spectra onto the original image after both have been transformed into MNF space, so that a perfect match will have a score of one. MF scores are not bounded between zero and one, but the correct abundance interpretation outside of that window is not as clear. Finally, MT is used to separate false positive MF detections from valid detections (Boardman and Kruse 2011; Boardman 1998). The MT step generates an infeasibility score that is related to the expected feasible mixing range as a function of the MF score, as shown geometrically in DiPietro, Manolakis, Lockwood, Cooley, and Jacobson (2012). The complete MTMF procedure is implemented in the "Environment for Visualizing Images" (ENVI), a commercially available image analysis software package (*ENVI User's Guide* 2009).

MF and MTMF both return an MF score for each pixel, which, based on the theory of linear mixing, can be interpreted as the fraction of that pixel with the target land cover (Boardman and Kruse 2011). Although the algorithm yields a quantitative estimate of the abundance of the target material in each pixel, most users of the technique interpret the results for target detection only. MTMF has been applied to mineral detection (Boardman and Kruse 2011), leafy spurge detection (Mundt, Streutker, and Glenn 2007; Parker Williams and Hunt 2002; Parker Williams and Hunt 2004), salt cedar infestation detection(Yang, Everitt, and Fletcher 2013), and explosives residue detection (Bernacki and Phillips 2010). MTMF has been used alone and in combination with other techniques for leafy spurge abundance estimation (Mitchell and Glenn 2009; Sankey and Glenn 2011), forest fire fuel source abundance (Ha et al. 2006), and post fire burn severity estimation (Robichaud et al. 2007). When MTMF results are used for target detection, the results have been consistent and broadly reliable. When MTMF abundance estimations have been compared to field estimates of target abundance, the results show clear positive correlations between the MF score and the field estimate, but the R^2 values are low. The low R^2 values show that MF score is a poor predictor of true target abundance; this is the primary reason that MTMF has rarely been used for abundance estimation.

Of the seven papers identified above that compare field estimates of target abundance to MF scores (Robichaud et al. 2007; Mundt, Streutker, and Glenn 2007; Sankey and Glenn 2011; Mitchell and Glenn 2009; Ha et al. 2006; Parker, Williams, and Hunt 2002; Im et al. 2012), the relationship between the two is generally quite noisy, and analysis is limited by the small number of available data points; no paper has more than 80 validation points. In the regressions shown in these papers, R^2 values range from 0.80 (Sankey and Glenn 2011) to 0.08 (Mundt, Streutker, and Glenn 2007), with most values between 0.2 and 0.6. The low R^2 values and challenges in collecting validation data have discouraged rigorous analysis of systematic errors in MTMF scores, and have also led to low confidence in the accuracy of the abundance estimation scores generated by MTMF.

3.2 Study Area

Las Vegas, Nevada, covers approximately 360 km^2; it is the major population center in Clark County, Nevada. Clark County had a population of approximately 1.3 million in 1999 (United States Census Bureau 2012a) and 1.9 million in 2007 (United States Census Bureau 2012b), making the area one of the fastest growing metropolitan regions in the United States. This rapid population growth meant that the residential land area in Las Vegas and the surrounding metropolitan area grew from 209 km^2 to 320 km^2 between 1999 and 2007, causing substantial changes in average infrastructure age and characteristics. Median lot size in Las Vegas declined from 560 m^2 in 1996 to 450 m^2 in 2007, smaller than the 900 m^2 Landsat pixel. A typical lot includes structures, paved surfaces, soils, and vegetation, so this heterogeneous mixture of land covers in each pixel requires sub-pixel analysis in order to accurately measure target abundance.

Las Vegas is located in the Mojave Desert, and receives an average of 10.6 cm of precipitation per year, and average summer high temperatures peak at 40.1 °C (Las Vegas Weather Forecast Office 2006) creating a substantial need for summer irrigation for any plant from a temperate climate, including any turf grass used as a lawn covering.

The region also faces substantial constraints in access to water. Lake Mead, created in 1935 by the construction of the Hoover Dam, supplies 90% of Las Vegas's water (Southern Nevada Water Authority 2009). The other 10% comes from various groundwater sources and small surface water streams. There is little potential to develop new surface or groundwater sources. Water use from Lake Mead is subject to the Colorado River Compact and the Boulder Canyon Project Act (*Boulder Canyon Project Act* 1928; "Colorado River Compact" 1922), which permits Nevada to withdraw and consume 300,000 acre-feet (370 million cubic meters) of water per year from Lake Mead. This allocation is a political constraint, rather than a physical one, on water availability but it is unlikely to be increased because there is intense competition for the Colorado River's water among all states in the Colorado River Basin (Mulroy 2008).

3.3 Data

In each year between 1999 and 2007, the Landsat TM 5 satellite image closest to mid-June that is also free of cloud cover is used as the base image for this analysis (NASA Landsat Program 2012a; NASA Landsat Program 2012b; NASA Landsat Program 2012c; NASA Landsat Program 2012d; NASA Landsat Program 2012e; NASA Landsat Program 2012f; NASA Landsat Program 2012g; NASA Landsat Program 2012h; NASA Landsat Program 2012i). In Las Vegas, June is the driest month, so nearly all vegetation is irrigated. This is expected to minimize the influence of weather on vegetation area and intensity. For this study, selecting images to minimize variation in vegetation intensity across the different images will permit measurement of a clearer signal of vegetation area.

All processed Landsat images have been geo-rectified within three meters so that pixels represent the same point in space across all images and the solar irradiance has been normalized across all images. In addition to the Landsat images, one-foot per pixel aerial photography taken by the Las Vegas Assessor's Office each spring is available for calibration. These images have been geo-rectified by the Assessor's Office to within approximately five meters.

When the high-resolution photography is overlaid with the geo-referenced pixels from the Landsat images, I am able to visually determine areas of vegetation in Landsat pixels from the Assessor's Office photographs. After the areas of vegetation in each pixel have been drawn, the total vegetated area per pixel is calculated and used to determine the percentage of each pixel that has vegetation. The calibration dataset obtained from my hand estimate is used to check the validity of the MF scores.

3.4 Methods

3.4.1 Target Spectra Selection

A unique target spectrum was created for each annual image in order to control for atmospheric variation and other image specific effects. Target pixels were selected from the center of the green from several of Las Vegas's major golf courses. In Las Vegas, golf courses are easily distinguishable in raw Landsat images and have a very high percentage of turf grass. With only six spectral bands in the Landsat images, small variations in vegetation type are not expected to have any measureable impact on MF vegetation estimates. Ten pixels were selected from different golf courses present in each image, and the spectra were averaged to create single composite target spectra for each image. Figure 3-1 shows one of the ten pixels used to generate the target spectra for the 2004 image. The pixel was selected from the middle of a golf course, and the background image from the Assessor's Office photography demonstrates that over 97% of this pixel is grass. This is very close to a pure target pixel, and is typical of all of the pixels used to generate the target spectra used for the MTMF analysis. There is little variance in the target spectra across the 10 pixels used for each year or across the nine annual images, but averaging many pixels may give a more robust estimate of a pure target spectra.

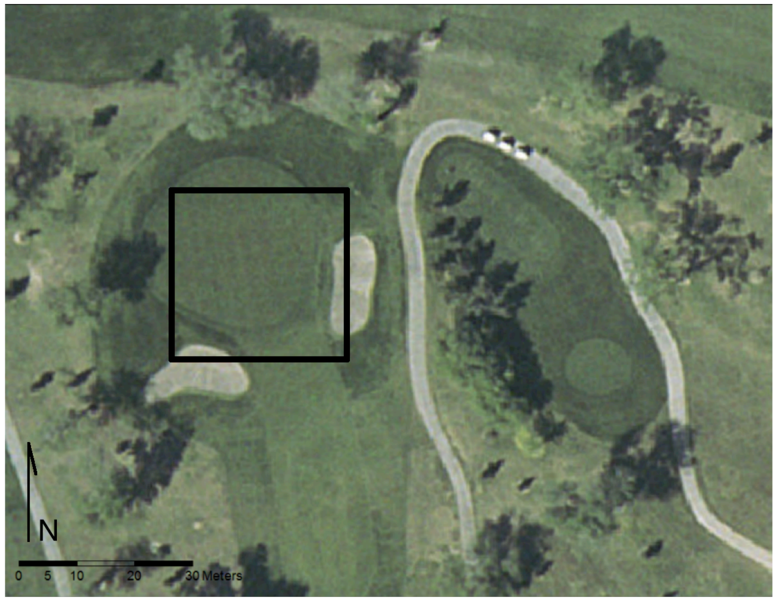

Figure 3-1. One of the ten pixels used to create the 2004 target spectra. The pixel was selected from the middle of a golf course, and the background image from the Assessor's Office photography demonstrates that over 97% of this pixel is grass. This is very close to a pure target pixel, and is typical of all of the pixels used to generate the target spectra used for the mixture-tuned match filtering (MTMF) analysis

3.4.2 Validation Data Collection

In order to test the accuracy of the MTMF results, a validation dataset is needed. This is gathered by estimating the sub-pixel area of vegetation from the high-resolution photography taken by the Las Vegas Assessors Office. 995 pixels were randomly selected across all images. Validation pixels were selected from the pool of all pixels in the images that intersect with a parcel coded for residential land use and a construction date prior to the image date. Validation pixels were also selected to ensure that each pixel is fully covered by aerial photography and is not water. Las Vegas's residential area grew from 270 km^2 in 1999 to 405 km^2 in 2007 and the density of validation pixels in residential areas was held consistent across all images. As a result, there are about 50% more validation pixels in the 2007 image than in the 1999 image.

Figure 3-2 shows all calibration points, colored by year, across Las Vegas. The light pink background shows land that was being used for residences in 1999. The light purple background shows residential land that came into use between 1999 and 2007. For each annual image, calibration pixels were drawn from residential land area that had been constructed at that time. Magenta colored calibration pixels compare the MF score from the 1999 Landsat image to the hand estimated area of vegetation based on the 1999 Assessors Office photography. Similarly, purple pixels compare the 2007 Landsat based MF score to the 2007 Assessors Office photography. Each pixel in each year had an equal probability of being selected as a calibration pixel. The background image is the aerial photography from 2007. After all calibration pixels were selected, pixel outlines were displayed over the high-resolution photography, and based on the photography; the area of vegetation within each pixel was hand drawn. In future discussions, *mtmf* refers to pixel level estimates from ENVI's automated MTMF algorithm, and *hand* refers to the area of vegetation in the Assessor's Office photographs corresponding to MTMF results.

There are at least four potential sources of differences between the *hand* and *mtmf* data. First, the MF score has no method to control for differences in vegetation intensity. Changes in vegetation intensity do appear to influence the MF score, but are not related to changes in vegetation area. Second, there are small geo-rectification errors between the *hand* and the *mtmf* datasets. Third, the dates on which the satellite images were captured do not align with the dates of the aerial photography. Finally, there are significant areas of shadow in the residential landscape, which make it challenging to determine the land cover. There are shadows in both the satellite images and the aerial photography images. Because the two sets of images were not taken at the same time, shadowed areas are not consistent between the two data-sources and for the aerial photography, and they are also not consistent across years.

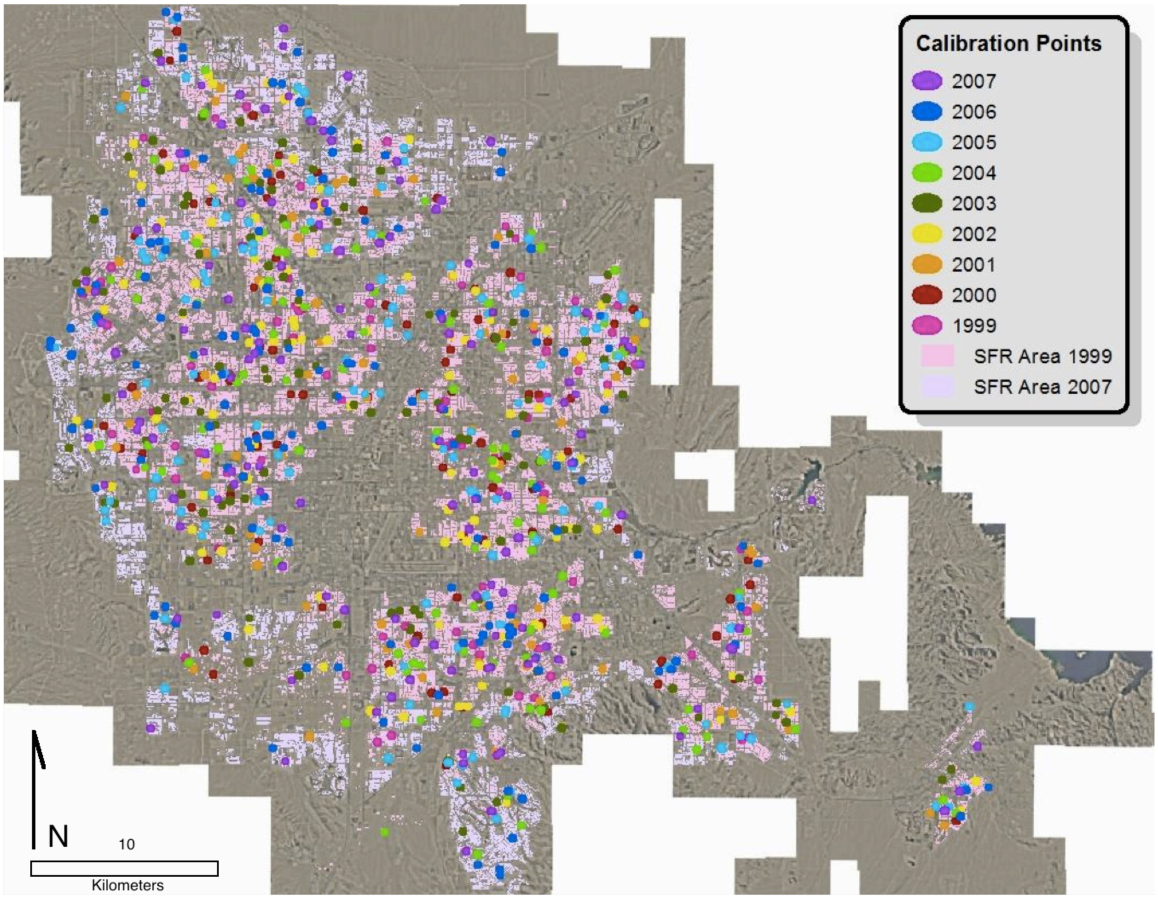

Figure 3-2. All validation points, colored by year, across Las Vegas. Validation pixels were selected from the pool of all pixels in the images that intersect with a parcel that is coded for residential land use and has a construction date prior to the image date.

Figure 3-3 shows a single Landsat pixel overlaid on the Assessor's Office high-resolution photography in 2002, 2003, 2004, and 2005. In all four years, the pixel is fully covered with turf grass in between two ball fields. The *hand* measurement is the area of vegetation; thus for each image, the selected pixel was coded as 100% vegetation. However, these photographs show that there is significant variation in vegetation intensity across the four years. Additionally, the photographic images in Figure 3-3 were captured in March and April, while the Landsat images used were taken in mid-June. As a result, there were always at least 75 days between the capture date of the two images, a mean of 86 days, and at most, 98 days between when the two images were taken.

Seasonal changes in weather and irrigation patterns may cause a systematic bias in the relationship between the *hand* and *mtmf* data, but the direction is unclear.

Figure 3-3. A Landsat pixel overlaid on the Assessor's Office photography in 2002, 2003, 2004, and 2005. Based on the aerial photography, the health of the vegetation varies through these years, and so the intensity of the vegetation signal picked up by the Landsat sensors is expected to vary across the different years. This difference between area and intensity of vegetation may be one source of errors between the *hand* and *mtmf* datasets.

Although the Clark County Assessor's Office has geo-referenced the aerial photography, it is not possible to calibrate it to the Landsat images. There are small variations by year across the images and because each annual image is a composite of hundreds of photographs, there are variations within each image as well. The photography has been geo-referenced to itself within about 3 meters in the east-west direction and 1.5 meters in the north-south direction. This means that up to 15% of the area of one pixel could be coded against land area in a different pixel. In the very heterogeneous environment of Las Vegas residential areas, this could induce classical measurement error(Greene 2003) in the *hand* classification but should not cause any systematic bias in the relationship between *hand* and *mtmf*. Figure 3-4 shows the hand-estimated area of vegetation and the MTMF score for this pixel in each year. The mtmf scores are lower than the hand scores because, although the pixel is 100% covered in grass, the intensity of the vegetation varies considerably in the different years.

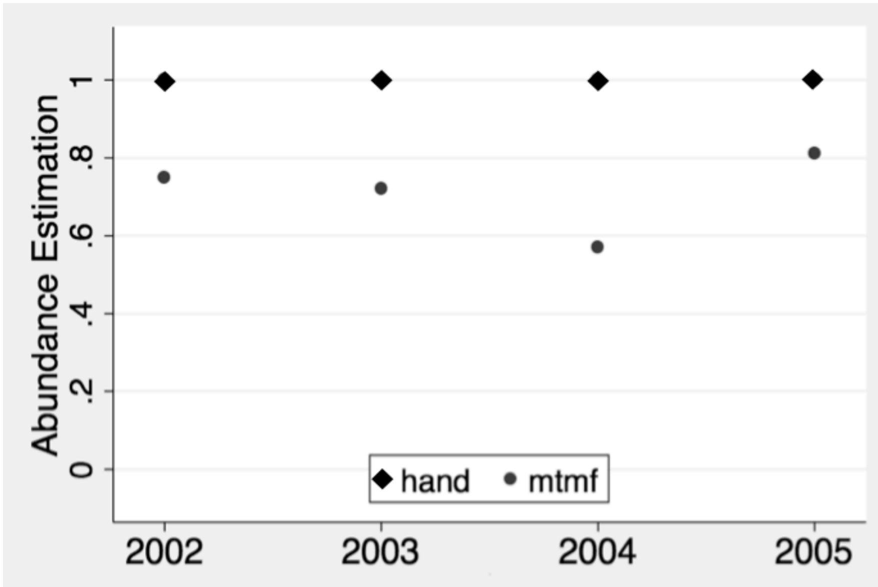

Figure 3-4. MF scores and hand scores for the pixel shown in Figure 3-3 in 2002, 2003, 2004, and 2005.

Finally, the Assessor's Office photography underlying a calibration pixel can be up to 25% shadow, and it is generally not possible to accurately determine the land cover in shaded areas from these images. To create the *hand* estimate, the classifier made a best guess estimate for land cover in shadows based on surrounding land cover and typical vegetation patterns in the region. The direction and magnitude of the bias introduced by this procedure is unknown.

3.4.3 Infeasibility Scores

The infeasibility score selected as a cutoff to exclude pixels from the dataset does not have a large effect on the MF score mean or MF score distribution. Figure 3-5 plots the infeasibility score against the MF score for all pixels with an infeasibility score of less than 20. Figure 3-6 shows the effect of different MF score bins on the infeasibility score distributions. An infeasibility score between about 2 and 7 will preferentially select pixels with a lower MF score than pixels with higher MF scores, and so could have an influence on MF distributions in the full dataset. The infeasibility score has a very small dependence on the MF score. Higher MF scores are slightly more likely to have high infeasibility scores, as demonstrated in Figure 3-6. For example, 88% of pixels with an MF score above 0.8 have an infeasibility score of 5 or below, while 99% pixels with an MF score of below 0.2 have an infeasibility score of below 5. Even this small selective effect vanishes for an infeasibility score cutoff greater than 10, and so any choice of infeasibility cutoff greater than 10 will not have a meaningful effect on the distribution of MF scores in either the validation dataset or the full dataset. Using a cutoff of an infeasibility score of greater than 10, which excludes 945 of all pixels, changes the mean MF score by 3* 10^{-3} %. The dependence of the MF score distribution on the infeasibility score is low, and so the effect of the MT aspect of the MTMF algorithm on my results is very small. Pixels with an infeasibility score above 20 are excluded from the validation dataset. In the full analysis, pixels with an infeasibility score greater than 20 are assumed to have the same MF score as the mean MF score for the tract that they lie within.

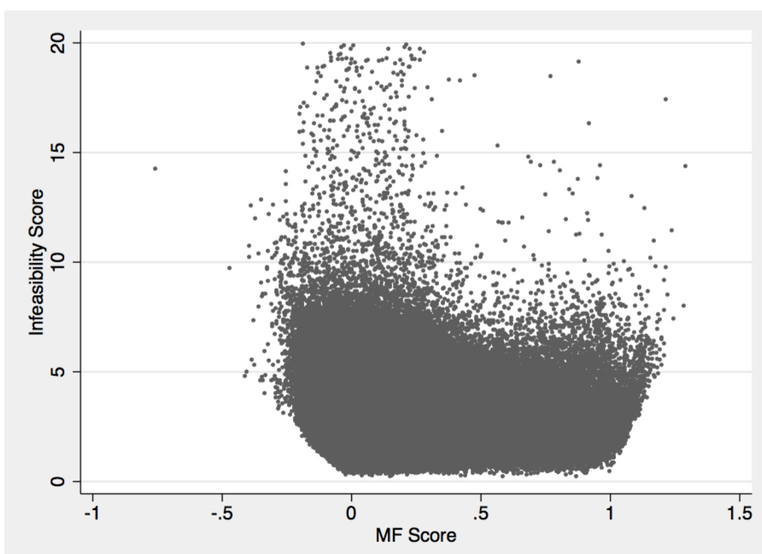

Figure 3-5. Infeasibility score compared with the MF score. 214 out of 3.3 million points are excluded by limiting the y-axis to 20, as in this figure. There are many

more pixels with low-MF scores than with high-MF scores, but there is not a strong systematic relationship between the infeasibility score and the MF score.

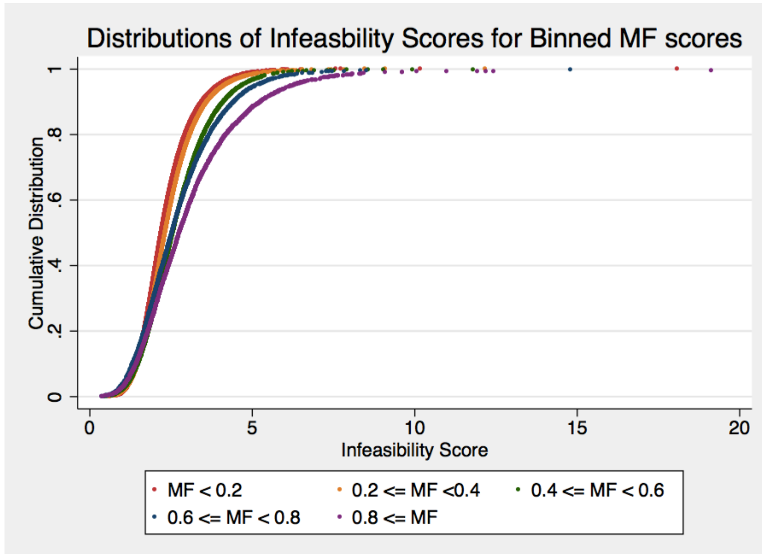

Figure 3-6. The cumulative distribution of different groups of MF scores. An infeasibility score between about 2 and 7 will preferentially select pixels with a lower MF score than pixels with higher MF scores, and so could have an influence on MF distributions in the full dataset.

3.4.4 Validation Method

The full validation dataset is shown in Figure 3-7. It is obvious that there is a clear positive relationship between *hand* and *mtmf*, but that the relationship is noisy. The high concentration of points with low *mtmf* and *hand* values compared to higher values make it difficult to determine if there is any evidence of non-linearity between *hand* and *mtmf*. The light grey points have a negative *mtmf* score, and make up 25% of the dataset. Because of the high rate of negative values in this dataset, it is not possible to directly interpret the MF score as a target abundance score or fractional vegetation area. It is mathematically possible to get MF scores outside of the [0,1] window, but determining how to interpret those scores has not been widely considered in the literature. When MTMF has been used for target detection rather than abundance estimation, it is assumed that there is no target in pixels with a negative MF score.

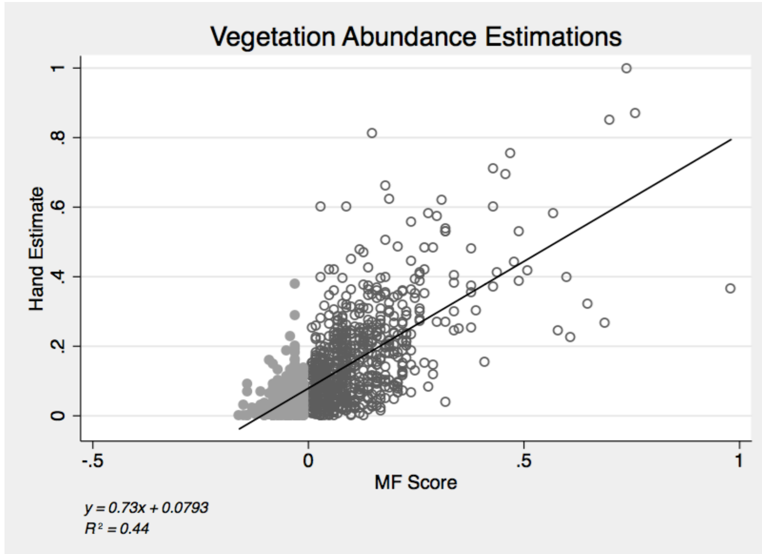

Figure 3-7. *Hand* versus *mtmf* results. An ordinary least squares regression of *hand* on *mtmf* gives y =0.73x + 0.0793, with an R^2 of 0.44.

Many methods have been used to interpret negative MF scores when the MF score has been compared to target abundance estimates. Negative MF scores have been interpreted as zero target abundance (Mundt, Streutker, and Glenn 2007; Robichaud et al. 2007; Sankey et al. 2010) dropped (Sankey and Glenn 2011), included as-is in the regression analysis but used only to inform target detection rather than abundance estimation (Im et al. 2012; Mitchell and Glenn 2009) or not recorded as observed (Ha et al. 2006; Parker Williams and Hunt 2002). For this dataset, the large number of negative values and clear positive relationship between the MF score and hand estimate even for negative MF scores suggests that the data should be neither dropped nor uniformly interpreted as zero. Figure 3-7 shows the results of an ordinary least squares regression between *hand* and *mtmf*, including all points from all years in the dataset.

Table 3-1 shows raw statistics on the datasets. It is clear that the *mtmf* validation dataset is representative of the full MTMF dataset based on the mean, median and standard deviation. It is also notable that the standard deviation for the *hand* dataset is very close to the standard deviation for both MTMF datasets. The mean, median, and standard deviation are very similar between the validation *mtmf* dataset and the full *mtmf* dataset, demonstrating that the pixels selected for inclusion in the 995-pixel validation dataset are representative of the full dataset. This suggests that in spite of the observed difference in the means of the *hand* and *mtmf* datasets, the MTMF algorithm does capture some important properties of the true distribution of sub-pixel vegetation area.

Table 3-1. Summary statistics for all three datasets: *hand* and *mtmf* for the validation dataset, and the MF scores for the full dataset including all 9 annual images.

	hand	***mtmf-validation***	***mtmf-full dataset***
Min	0	-0.16	-0.76
Max	1	0.98	1.29
Mean	0.13	0.07	0.07
Median	0.09	0.05	0.05
Std Dev	0.13	0.12	0.12
Observations	995	995	3,282,560

It is possible for specific spectral signatures to generate large positive MF scores, which become false positive detections in an MTMF target detection approach. Similarly, it is plausible that a specific spectral signature could generate large negative MF scores, which would cause errors of target under-detection when using MTMF for abundance estimation. Impervious surfaces such as asphalt, concrete, roofing, and other man made, non-porous surfaces are very common in urban environments. Based on the MF algorithm, they should be interpreted as background and have no relationship to errors in MF scores for vegetation. If impervious surfaces did have a negative influence on MF scores for vegetation, I would expect a negative relationship between the area of impervious surfaces in a pixel and the difference between *mtmf* and *hand*. Figure 3-8 shows no such relationship. Similarly, there is no relationship between the area of soil in a pixel and the difference between the MF score and hand estimate for vegetation. This shows that these two common surfaces have been correctly interpreted as background by the MTMF algorithm and are not causing systematic bias in the MF scores.

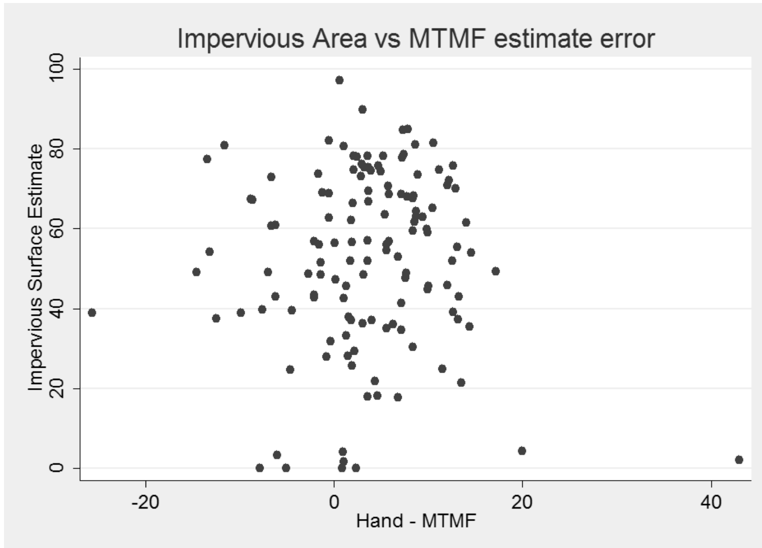

Figure 3-8. There is no evidence of a relationship between the area of impervious surfaces within a pixel and the difference between the *hand* and mtmf scores in the same pixel.

The validation results show that there is a meaningful relationship between the ground truth and MTMF scores, but the relationship is not direct enough to justify using the strict 1:1 correspondence between target abundance and MF score that is predicted by theory. Some form of calibration is necessary to ensure that the MF results are unbiased and the calibration does not distort the higher order moments of the distributions.

3.4.5 Calibration

The *mtmf-hand* validation dataset shows two problems that need to be managed before the full MTMF dataset can be used to predict the true vegetation abundance. First, there is a bias between *mtmf* and *hand*. Without correction, this will cause a systematic under-estimation of the true vegetation area. Second, the relationship between *hand* and *mtmf* is very noisy. This reduces the reliability of comparisons in fractional vegetation area across space or through time.

The bias problem is addressed by applying a uniform shift to all pixels in the *mtmf* dataset, as shown in Equation 1, where m_{it} is an individual pixel from the *mtmf* dataset in year t and h_{it} is the corresponding pixel from the *hand* dataset. The Kolmogorov-Smirnov (K-S) (Marsaglia, Tsang, and Wang 2003; Smirnov 1938) test is a nonparametric method for comparing the cumulative distribution functions of two samples; *hand* and *mtmf* in this case. The shifting factor, s_t, is selected to minimize the K-S distance between the two distributions in each time period t.

$$m'_{it} = m_{it} + s_t \text{ and } h'_{it} = h_{it} \tag{1}$$

Figure 3-9a shows that the optimal shift varies considerably by year and so selecting a unique shifting factor for each annual image is necessary. Other transformations on m_{it} were also tested, but any method that changed the variance of the *mtmf* dataset in addition to changing the mean performed worse.

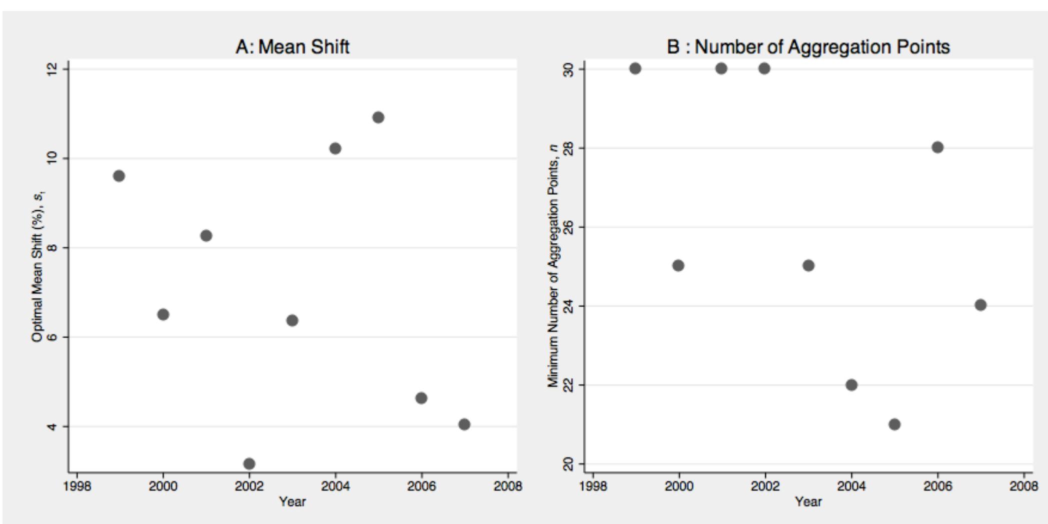

Figure 3-9. Optimal mean shift (a) and minimum necessary number of aggregation points by year. (b) There is no significant time trend in either variable, but the clear spread demonstrates the necessity of addressing the negative bias in MTMF on a year-by-year basis

Even after adjusting for the bias between *hand* and *mtmf,* the raw *mtmf* and *hand* distributions require some level of averaging in order to minimize the effect of noise. In much remote sensing work, a spatial filter is applied by averaging many neighboring pixels to create a single, composite "pixel" that is larger than the original image resolution. In this case, the validation pixels were randomly selected across the entire image. As a result, none of the validation pixels are actual neighbors and it is not possible to create a true spatial filter from the validation dataset. In my calibration algorithm, I also use randomly selected pixels from that dataset instead of a neighboring pixels filter approach.

I present a method rooted in Information Theory to calibrate the large MTMF set using the smaller, validated *hand-mtmf* set that reduces noise through averaging. For each calibrated data point $(\widetilde{m}_{jt}, \tilde{h}_{jt})$, n pixels are randomly selected with replacement from the *mtmf-hand* validation dataset. The selected pixels are averaged and the shifting factor selected in Equation 1 is added, as shown in Equation 2.

$$\widetilde{m}_{jt} = \frac{1}{n}\sum_{i=1}^{n} m_{it} + s_t \; and \; \tilde{h}_{jt} = \frac{1}{n}\sum_{i=1}^{n} h_{it} \qquad 2$$

The mutual information(Cover 1991; Shannon 1964) between two datasets is defined in Equation 3. I use this metric to show that random averaging of the *mtmf* dataset increases the mutual information between the *mtmf* and *hand* datasets by one bit. Conceptually, this means that I am now capable of making a "true/false" decision about the relationship between my datasets. In this case, my decision is if the amount averaging I applied to the *mtmf* dataset has sufficiently smoothed the noise such that the *mtmf* distribution matches that of the *hand* distribution. Practically, I increase the number of pixels, *n,* included in the random averaging of the *mtmf* set by discrete values and calculate the change in mutual information for each n relative to the baseline of

$n = 1$. I then choose the minimum n at which the mutual information has been increased by one bit. Figure 3-9b shows that the minimum amount of averaging required also varies by year, again showing the necessity of calibrating each annual image individually.

$$I(hand, mtmf) = \sum_{hand} \sum_{mtmf} p(hand, mtmf) \log_2 \left(\frac{p(hand, mtmf)}{p(hand)p(mtmf)} \right) \quad 3$$

After finding the amount of aggregation that satisfies the above constraints, I now calibrate the full MTMF dataset, approximately 3.3 million points versus the 995 points used for the initial calibration. If the validated *hand-mtmf* sets chosen for calibration are unrepresentative of the overall dataset for each year, then the methods proposed will fail to generate full, calibrated MTMF sets. To calibrate the full MTMF set, I apply the level of aggregation and mean shift found for each year and shown in Figure 3-9.

Figure 3-10 and Figure 3-11 show that I am able to calibrate drastically different distributions of green space values (due to the negative bias of MTMF) using the validation, aggregation, and mean shift technique outlined above. This technique is statistically robust, producing correctly calibrated *mtmf* datasets for thousands of random samplings for each year out of the full MTMF dataset.

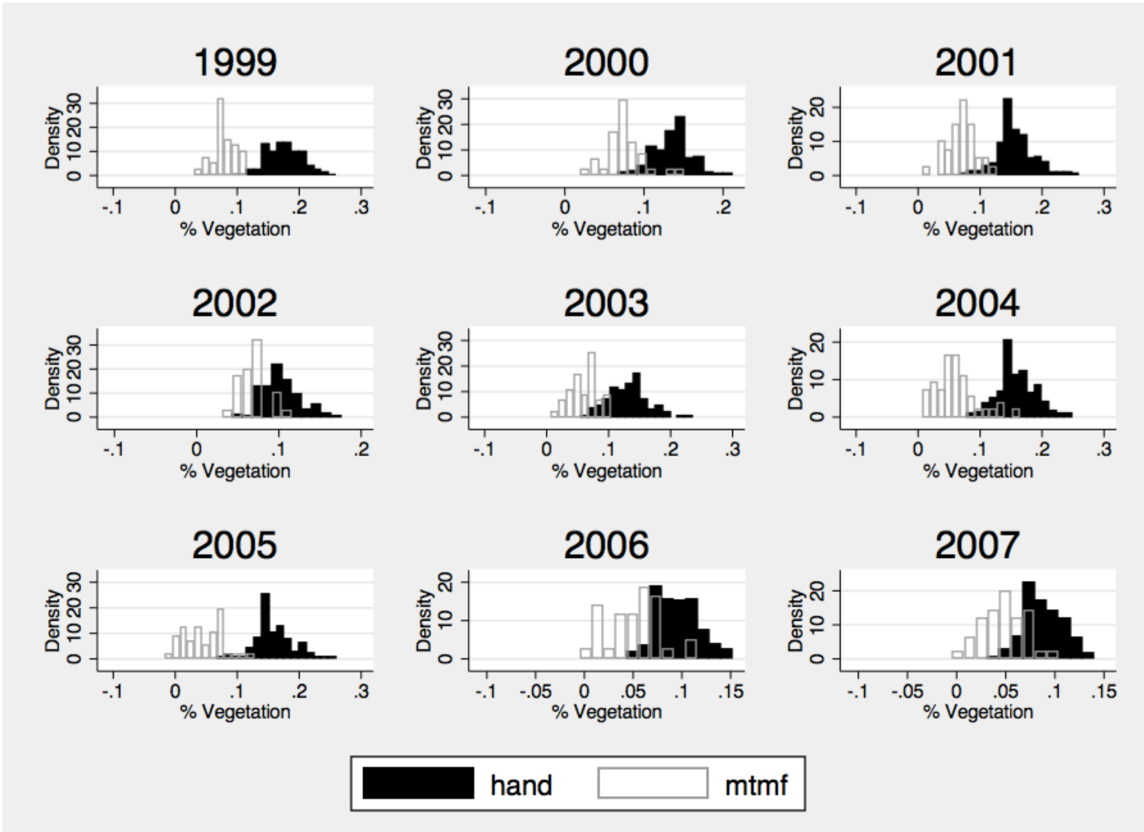

Figure 3-10. Normalized probability distributions for hand-mtmf datasets in 1999 to 2007 before calibration.

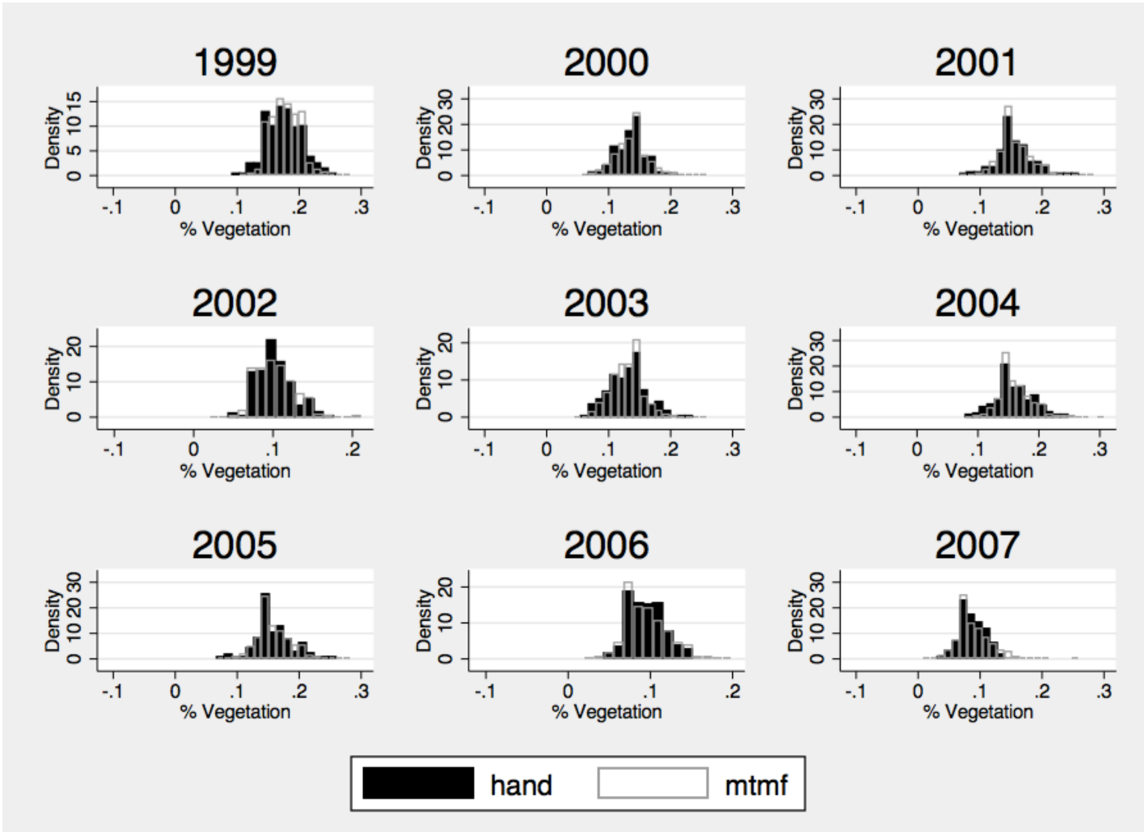

Figure 3-11. Normalized probability distributions for calibrated hand-mtmf datasets in 1999 to 2007. It is important to note that I have not transformed the higher moments of each distribution, yet still manage to capture outlier points such as those in year 2001.

3.5 Results

Figure 3-12 shows the distribution of tract level vegetation percentage change through time, including only tracts with established populations in 1999. The trend of declining vegetation intensity is small, about 0.8% per year. This is consistent with the LVVWD's stated policy goals of reducing irrigated turf in public and residential land areas in order to conserve water. The spatial and temporal trends in changes in vegetation area are consistent with what is expected from known infrastructure changes in Las Vegas. This supports the validity of this method for calculating and calibrating MF results to measure changes in vegetation area in an urban environment over a long time period.

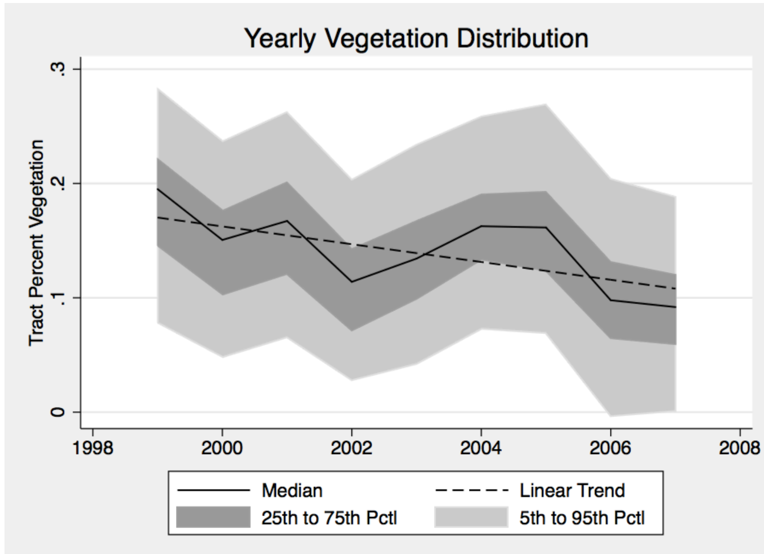

Figure 3-12. Change in percentage of vegetation area in Las Vegas for tracts with established populations in 1999. The trend in percentage of vegetation in each tract is small, 0.8% per year, but statistically significant.

3.6 Conclusions

The main objective of this study is to demonstrate a method to correctly extract changes in vegetation area from Landsat image datasets. In contrast to previous studies, I find that it is possible to obtain meaningful estimates of the fractional area of vegetation when a large ground truth dataset is available for calibration. By comparing the MTMF dataset to a ground truth dataset generated from aerial photography, I find that it is possible estimate changes in vegetation area in Las Vegas, Nevada between 1999 and 2007 utilizing a unique calibration technique. I achieve this calibration by determining the mean shift that minimized the Kolmogorov-Smirnov distance between the hand measured dataset and the automated MTMF dataset. Additionally, I reduce the effect of noise by randomly averaging MTMF pixels and utilizing concepts from Information Theory to ensure that this averaging provides a distribution of calibrated

MTMF data for each year that matches the distribution of hand measured data and preserves the higher order moments of the dataset. This latter point is key, as it preserves the heterogeneity in my MTMF datasets, accounting for the role of outliers and providing a clear downward trend in fractional vegetation area. This study is the first to show the feasibility of using an MTMF dataset in combination with a large ground truth dataset to quantify the sub-pixel changes in vegetation area and provides a viable path forward to using MTMF to quantify other trends of interest in Landsat imagery.

4 DRIVERS OF WATER CONSUMPTION CHANGE IN THE LAS VEGAS VALLEY WATER DISTRICT

4.1 Introduction

Historically, water scarcity has primarily been managed by developing new supplies (Howarth 1999). However, the supply of unallocated water is now low in most areas, and demand side management is an increasingly important tool for water managers (Inman and Jeffrey 2006). Researchers focused on the determinants of residential water demand have only recently been able to access the fine scale data necessary to understand the role that infrastructure and the built environment play in determining residential water consumption (e.g. House-Peters, Pratt, and Chang 2010; Gober et al. 2012). There has been little attention to the role that changes in infrastructure can play in shaping long-term water demand as a city grows. This chapter fills a significant gap in the literature by examining the role that population growth and the attendant changes in the built environment play in determining changes in household consumption in Las Vegas. This allows the first quantitative estimate of the role that changing household infrastructure characteristics, changing vegetation area, and population growth and new construction played in defining household consumption in the context of a rapidly growing city.

The LVVWD and the SNWA have developed a number of innovative demand side management techniques, and household water consumption in the city has fallen significantly since their implementation. However, the demand side management policy changes also occurred during a period of rapid infrastructure change driven by population growth and large changes in the distribution of the population across the city and so careful econometric work is necessary to untangle the different drivers of change in residential water consumption. Understanding the various contributions of population growth, infrastructure change, and conservation policy to changes in household water consumption will provide other cities with an estimate of the scope of conservation possible from demand side management techniques, and support a better understanding of how demand may change with population growth.

Figure 4-1 shows total residential water consumption each June between 1996 and 2007 for the LVVWD service area. Total June single family residential water consumption for the service area as a whole increased by about 30%, or 4,000 acre-feet between 1996 and 2007, while the share of consumption in the core declined from 80% of total consumption to about 45% of total consumption. Total population in the LVVWD service area grew rapidly during the study period, but nearly all new residents moved into the periphery, rather than the established core. Population in the core was close to constant through the study period and so the absolute decline in consumption in the city core shown in this figure demonstrates the significance of changes in average household consumption there, while the absolute increase in consumption in the periphery is caused by population growth there.

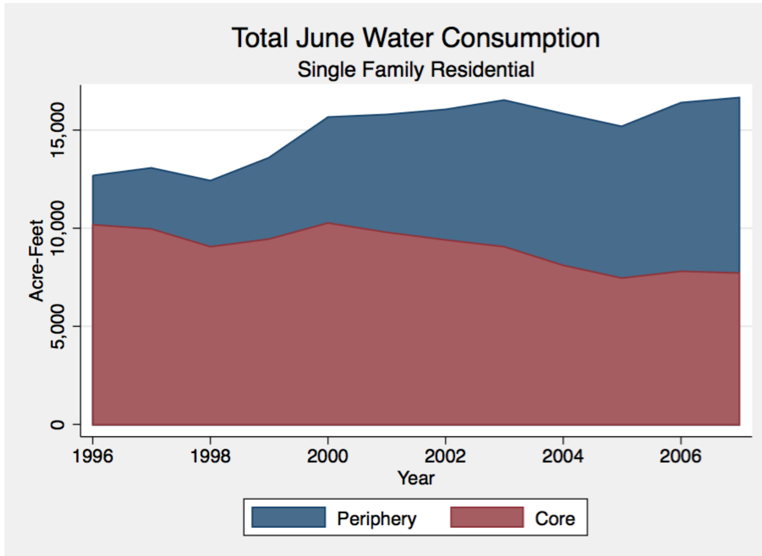

Figure 4-1. Total single-family residential water consumption in the LVVWD service area each June.

Household-level water consumption in Las Vegas declined by 55% between 1996 and 2007, and the city used less water than they are permitted in 19 of the last 21 years. On its surface, this appears to be sufficient evidence that the conservation policies that were implemented succeeded in solving Las Vegas's water scarcity problem. However, Las Vegas also grew rapidly, leading to a decline in the average age of water infrastructure and rapid uptake of newer, water conserving technology. Large declines in household level water consumption have been observed in most cities in the United States since the 1980s (Rockaway et al. 2011), and very few studies have attempted to estimate the different factors influencing this decline in urban household water consumption. There are no peer-reviewed analyses that quantitatively separate the effect of changes in infrastructure and land use from SNWA's water conservation policy.

Figure 4-2 shows the population-weighted average consumption in both the city core and periphery. Average consumption was lower in the city periphery than the core, and average consumption also declined more in the periphery than the core. This means that the increasing share of population in the periphery, shown by the orange dashed line, also played an important role in the citywide decline in average household consumption. Structures in the periphery are, on average, younger than structures in the city core, and so the declining age of infrastructure in the periphery will be an important factor to consider as a driver of citywide changes in household consumption.

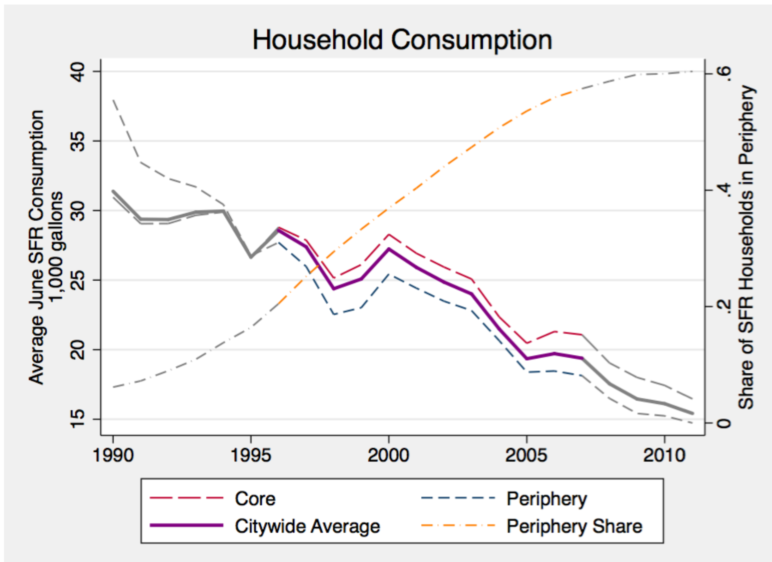

Figure 4-2. Widespread patterns of declining household water consumption are clearly observable in both the core and periphery. The colored area of this graph shows the study period, while the grey lines show the longer-term context.

Las Vegas is an archetype of what can happen to a water system under rapid development. The goal of the dissertation is to separate out the effects on household water consumption of endogenous factors like policy changes from exogenous factors like population growth, infrastructure change, and technology change. My research question is *how much of the observed decline in per capita consumption can be explained by Las Vegas land use, land cover, and physical infrastructure change that resulted from extensive new construction and installation of newer water conserving technology, and how much can be attributed to water conservation policy choices?*

In this chapter, I show the proportion of the observed decline in household water consumption that resulted from changes in infrastructure and newer technology; the proportion that results from population growth and new construction; and as a residual, the proportion that results from Las Vegas specific water policy changes, including conservation incentives, behavior change campaigns, and policy that influences the water consuming infrastructure. This analysis uses water consumption records, conservation policy implementation records, and contract documents from SNWA; satellite images and weather records from the USGS; and physical infrastructure data from the Clark County Assessor's Office to create a dataset tracking changes in these variables for each Las Vegas census tract on an annual basis from 1996 to 2007.

I find that the largest drivers of changes in household water consumption are the effect of population growth and new construction. Within the city core, changes in the area of vegetation had a measureable impact on household water consumption, while changes in lot size influenced household consumption in the periphery. However, these factors only explain about 30% of Las Vegas's total decline in household consumption.

4.2 Background

4.2.1 Las Vegas Population Growth

The most obvious story in Las Vegas' water development in the 1990s and 2000s was its very rapid population growth. Clark County had a population of approximately 1.1 million in 1996 (United States Census Bureau 2012a) and 1.9 million in 2007 (United States Census Bureau 2012b), making the area one of the fastest growing metropolitan regions in the United States. This rapid population growth meant that the residential land area in the Las Vegas MSA area grew from 175 km^2 to 320 km^2 between 1996 and 2007, while the number of single-family residential structures in the study area more than doubled, increasing from 217,000 to 442,000 between 1996 and 2007.

This rapid population growth drove substantial changes in average structure age, with attendant changes in appliances like dishwashers, washing machines, plumbing fixtures, and irrigation systems that govern patterns of indoor and outdoor consumption and change slowly once the house has been constructed. Las Vegas saw very little urban infilling or density increases in the existing urban structure. Nearly all new construction occurred along an expanding urban periphery that forms an increasingly large ring around Las Vegas's oldest urban core. This tight geographic concentration of new construction allows analysis of the influence of infrastructure characteristics of different ages, by considering the established urban core separately from the newly constructed city periphery. For this study, the city core is defined as tracts where there were fewer than 200 new residential structures built between 1996 and 2007, shown graphically in Figure 4-3. Other approaches of classifying the core and periphery show similar patterns.

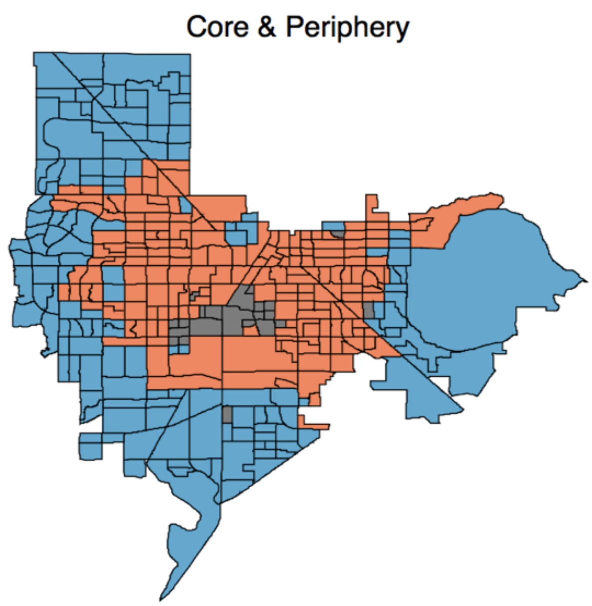

Figure 4-3. Orange tracts denote the city core, blue tracts denote the city periphery, and tracts in grey have no single-family homes, and so are not included in this study. The population of tracts in the city core was largely established by 1996, while tracts in the periphery saw a great deal of new construction between 1996 and 2007.

Table 4-1 summarizes the major conservation policy changes, which were discussed in detail in Chapter 1. The key years in which major citywide changes first went into effect were in 2002, when LVVWD first got functional permission to levy fines for water waste, 2004 when they stepped up the enforcement rate, fine size, and types of citable water waste violations, and potentially in 2005, when fines were increased again. Some policies had the potential to have immediate conservation effects through their influence on behavior. These include the LVVWD service area influence short-term behavioral choices, are the irrigation clock rebate program, water waste citations and fines, the car wash coupon program, the pool cover program, ad campaigns encouraging conservation, and pricing changes. These policies will be included through annual dummy variables, because spatially explicit data on policy uptake is not available. Other policies operate on the water efficiency of new capital stock, and therefore have a slower, but potentially large cumulative effect on water use. These infrastructure-based policies include the building code changes restricting the area of turf permitted in new construction, the types of water features permitted, and the Water Smart Homes program. Finally, in this chapter, the effects of the WSL program will be observed through its effect on the area of vegetation.

Table 4-1: Timeline of major conservation policy changes

1996	WSL begins as a pilot program
1999	Irrigation clock rebate program begins
2000	Restrictions on turf in new construction
2002	Water Waste Citations by LVVWD legally possible
2004	WSL program scales up Car wash coupon program begins More restrictions on turf in new construction Water price increase Water waste citations by LVVWD practically possible Restrictions on water features
2005	Water Smart Homes program begins Pool Cover program begins Water waste fines increased
2007	Conservation TV ads

4.3 Data Sources and Calculation Methods

In this section, I describe the sources of data and methods used for calculating each variable. There are four major sources of data used in this study. First, averaged monthly household water consumption at the census tract level was obtained through a public records request to the LVVWD. Second, the Clark County Assessor's Office provided tax assessors records on the characteristics of individual parcels. This includes records of variables like the number of rooms, bedrooms, and bathrooms, as well as some outdoor characteristics like lot size and the existence of a swimming pool. Figure 4-5 shows a map of the metropolitan Las Vegas parcels. Third, the Parameter-elevation Relationships on Independent Slopes Model (PRISM) climate group data have been used to find the monthly average for daily minimum temperature and total precipitation. Finally, the mean area of vegetation per lot was created from carefully processed remotely sensed data, as discussed in Chapter 3 (Brelsford and Shepherd 2014).

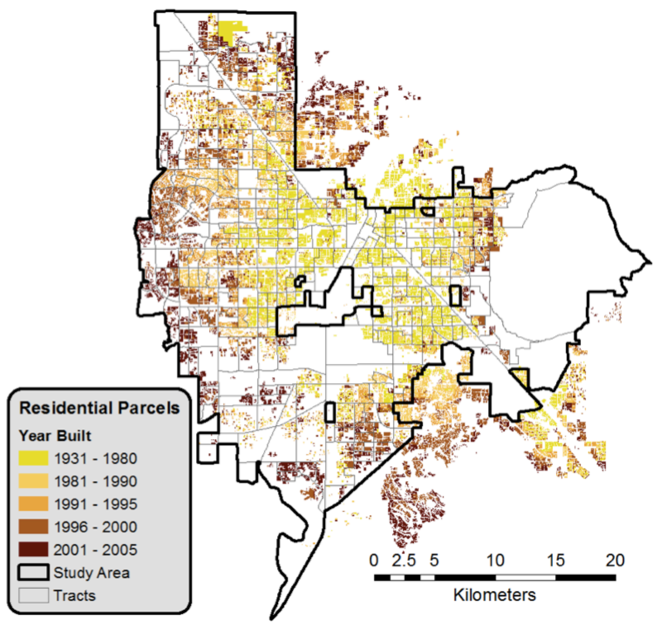

Figure 4-4. All single family residential parcels, colored by construction year for the Las Vegas metro area. The outward moving pattern of development is clearly visible.

4.3.1 LVVWD Records: Household Water Consumption

Total water consumption by census tract and total number of active accounts by census tract was accessed through a public records request to the LVVWD. Total consumption is divided by the number of active accounts to find the monthly average household consumption for each tract. This dataset only includes meters billed by the LVVWD, which covers the city of Las Vegas and all of unincorporated Clark County.

4.3.2 Assessor's Office Records: Infrastructure Characteristics

The Clark County Assessor's Office has assessed each parcel in Las Vegas to calculate property taxes. Information on the lot size and structure size, physical properties like construction type, number of rooms and bathrooms, water source, and some characteristics of the outdoor area are included for each parcel. Based on construction year, this list of parcels is telescoped backwards to create a panel dataset by tract of the average characteristics of all parcels that had been constructed in each tract before a given year. However, the data reflect structures and structural characteristics as they were in August 2012. Therefore, characteristics of a structure prior to the occurrence of renovations that changed structural characteristics are also not included in this dataset. During the study period, 2.5% of all parcels were renovated, on average 21 years after they were first built.

To handle renovations, the tract averages for characteristics of a parcel that are likely to be influenced by renovations (living area, bedrooms, plumbing fixtures, and pool percentage) only include the records for renovated properties after their renovation date, when the parcels characteristics are reliable. However, for characteristics that were not likely to have changed with a renovation (lot area or the number of existing structures) parcels were included in tract averages beginning at their construction year.

Changes in tract averages of living area, the number of plumbing fixtures, the number of bedrooms, and the percentage of parcels with a pool within any tract are, by definition, driven by new construction, as no changes in the characteristics of an individual structure are recorded in the Assessor's data. Aside from the small number of renovations in parcels in established tracts, this means that there is essentially no change in the average indoor characteristics of established tracts through time.

Like wine, parcel vintage is defined as the year in which a structure was first constructed. This analysis only includes 11 years, which is short relative to the expected lifespan of a house, and so I expect that the stability of vintage effects in terms of infrastructure composition is a reasonable simplification. In the academic literature, there has been very little attention to the role of structure vintage or age on household water consumption and no studies have been identified that consider how the effect of structure age or vintage may change through time.

As discussed in Section 4.4.1 vintage may have an important effect on water consumption patterns. I hypothesize that this mechanism occurs through the quality of the household plumbing installed when the structure was built, a factor that is essentially fixed for the life of the structure, as well as the technology that was installed through long-lived but ultimately malleable appliances and fixtures like home appliances toilets, sink fixtures, washing machines, and dishwashers. Because technology and construction techniques do not change linearly through time, there is no particular reason to expect a linear relationship between parcel vintage and household consumption.

To allow for a flexible, nonlinear relationship, I create seven different 'bins' of parcel vintages, each representing the proportion of structures in that tract constructed during the years of that vintage bin. The first bin, used as the baseline level, includes the percentage of structures within each tract constructed before 1960. The second bin includes parcels constructed between 1960 and 1984. The third bin includes structures from 1984 to 1992. The fourth includes structures constructed between 1992 and 1996, the fifth includes structures constructed between 1996 and 2001, the sixth shows structures between 2001 and 2004, and the seventh bin includes structures constructed between 2004 and 2007.

When possible, the bin cutoffs were chosen to coincide with years in which policy changes likely to affect infrastructure and land cover for residential parcels built after that date went into effect. These include the Energy Policy Act of 1992 (Sharp 1992) at the federal level or the WSL program at the regional level. The 1992 bin cutoff was chosen to allow for variation in response to the Energy Policy Act, which changed efficiency standards in many kinds of household plumbing fixtures, including toilets, bathroom faucets, showerheads, clothes washers, and dishwashers. The study period begins in 1996, the same year the first WSL pilot program was implemented. The WSL program began to grow in importance in 2001, and in 2004, the LVVWD and SNWA implemented a broad suite of policy changes intended to reduce household water consumption. The study period also includes the effects of the new Water Smart Homes program, begun in 2005. Finally, the study period ends in 2007. There is not a strong policy-driven justification for the choices of the 1960 and 1984 vintage bin cutoffs. However, these years are effective in splitting up the parcels constructed between 1900 and 1992, and the regression results are not strongly dependent on these choices.

4.3.3 PRISM Records: Temperature and Precipitation

The monthly average for daily minimum temperature and total monthly precipitation are measured based on the work of the Parameter-elevation Relationships on Independent Slopes Model climate group at Oregon State University (Daly et al. 2008). Data are provided on 800-m grid cells, which are spatially interpolated using PRISM. To find an appropriate estimate of temperature at the census tract level, a spatially weighted average is constructed including each PRISM grid cell that completely or partially contains the tract. This is stated formally in Equation 4:

$$t_i = \frac{\sum_{j=1}^{J} \alpha_j t_j}{A_i} \qquad 4$$

where α_j is the area of gridcell j that is contained in tract i, t_j is the interpolated temperature in gridcell j, and A_i is the total area of tract i, and J is the set of all PRISM grid cells that overlap census tract i. In the Las Vegas area during the study period, the data are interpolated from about 20 measured weather stations. Total monthly precipitation at the census tract level is calculated from the PRISM grids in the same manner. This calculation is run for each census tract and each month in the study period.

4.3.4 LANDSAT Images: Vegetation and Dirt area

Vegetation percentage is calculated as described in Chapter 3 and Brelsford and Shepherd (2014)by applying MTMF to 12 Landsat images taken in June of each year between 1996 and 2007. The MTMF procedure generates an estimate of the percentage of each pixel from each Landsat image that is vegetated. In Chapter 3, I note that the MTMF procedure generates a biased estimate of the total vegetation area, and estimate the bias for each individual year, shown in Figure 3-9a. It is not possible to calculate the bias directly in 1996, 1997, and 1998 because calibration images were not collected in those years. Thus, for this chapter, I apply the appropriate correction for the best estimate of the bias calculated from 1999 to 2007 across all 12 years in the dataset. The MTMF method has not been used to identify target spectra for series of images through time, so there are no examples in the literature that address whether observed biases change through time. All pixels whose centroids are within an existing single-family residential lot are included in the estimate for the mean percentage of vegetation in each tract in each year. The total single-family residential area and the total number of structures in each tract are then used to generate an estimate of the mean area of vegetation per lot in each tract in each year.

The rest of the lot is made up of either non-vegetated outdoor areas, hereafter referred to as 'dirt,' and the footprint of the structure. Dirt includes non-vegetated porous surfaces like soil and gravel, swimming pool areas, and also impervious outdoor surfaces like driveways, walkways, and patios. The footprint of the structure is drawn from the Assessor's data on the first floor living area and includes both the main living area and any garage area. These are shown formally in Equation 5 and Equation 6:

$$va_i = vp_i * \frac{\sum_{j=1}^{N_i} la_j}{N_i} \qquad (5)$$

and

$$da_i = (1 - vp_i) * \frac{\sum_{j=1}^{N_i} la_j}{N_i} - \frac{\sum_{j=1}^{N_i} ff_j}{N_i} \qquad (6)$$

where va_i is the mean vegetation area per parcel in tract i, vp_i is the percentage of vegetation across the total zoned residential land area within tract i, N_i is the number of residential structures in tract i, and la_j is the lot area for structure j, $j \in N_i$. The mean dirt area per structure in tract i, da_i, is calculated based on Equation **6**, where ff_j is the first floor area of structure j in tract i.

4.4 Spatial and Temporal Trends in Drivers of Water Use

In this section, I describe the major spatial and temporal trends in each variable in the analysis. Based on the literature outlined in Chapter 2, the major factors expected to influence residential water consumption are price effects, demographic changes, infrastructure changes, weather variation, and institutional changes. There is a broad literature focused on the effect of price differences on residential water consumption (e.g. Worthington and Hoffman 2008a), and a substantial body of work is also focused on the relationship between residential water consumption and weather or climate (e.g.

Gober et al. 2012). There has been little attention to the role that infrastructure change plays in determining household water consumption. While I include appropriate controls for weather and price changes, the primary focus of this study is to understand the role of infrastructure change in the context of a changing policy environment.

Residential water consumption can be separated into two categories: indoor use and outdoor use. In both settings, the amount of water consumed depends on both on what the infrastructure water is used in or for (for example, the size of a swimming pool), and the behavioral choices of the residents (for example, the length of time one spends in the shower). Indoor water use patterns are not expected to be as strongly climate-dependent as outdoor use patterns.

4.4.1 Indoor Drivers

If it were possible to perfectly measure all factors that I expect to be important for indoor water consumption, I would measure the existence, vintage, and age of each installed major appliance and faucet, as well as the length of pipes within each parcel and general age and condition of the household plumbing system. Finally, I would measure the number, age, and behavior patterns of all residents of the household. The actual available data for indoor infrastructure include a variety of measures of indoor infrastructure characteristics and the year in which a parcel was built. I rely on a strong expected relationship between a structure's vintage and appliance and plumbing system vintage, and use structure vintage to estimate the effects of different ages and technology embedded in a structure's water infrastructure system. To estimate the potential for leaks, which are related to the age and condition of a plumbing system as well as pipe length and fixtures, I include direct measurements of indoor area and the number of plumbing fixtures.

Figure 4-4 shows the year in which each residential parcel in Las Vegas was constructed. Spatial patterns in development are clearly visible, showing that nearly all of the new construction has occurred on what was the outer edge of the city at the time. This spatial pattern is mirrored in the tract level aggregations of parcel vintage into the different vintage bins, and shown in Figure 4-5. Although there is a distribution of parcels of each vintage in each tract, in general, the range of vintages in a tract is narrow relative to the citywide range of vintages: Construction in the city has been spatially concentrated throughout the cities entire history. The central concentration of Las Vegas's oldest houses, just north of the Las Vegas strip, is clear in Figure 4-5A. Houses built between 1960 and 1984 are shown in Figure 4-5B, and the concentric pattern of development expanding outward from the oldest part of the city is visible in this and all additional vintage bins.

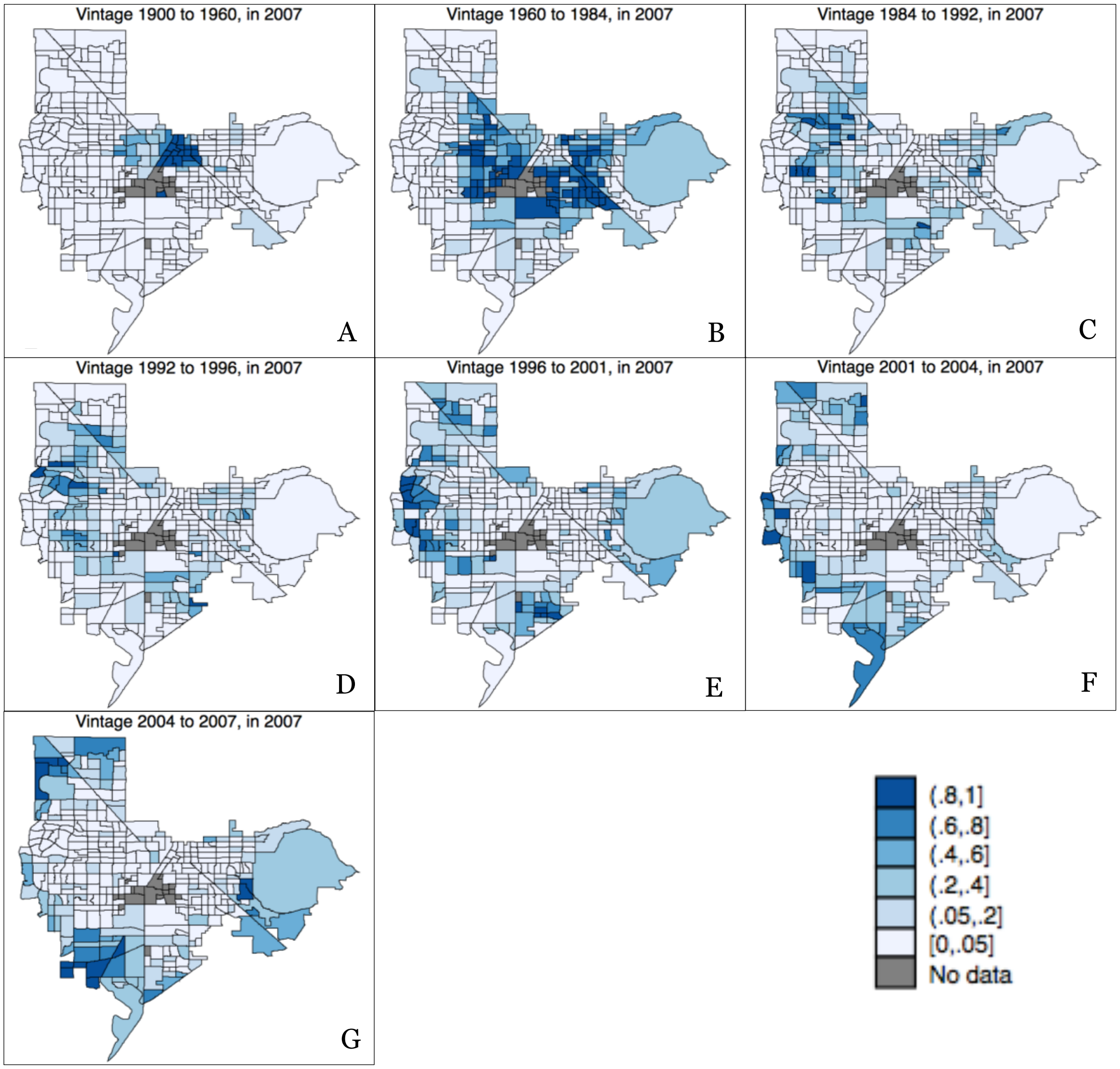

Figure 4-5: Maps showing the spatial distribution of the all seven vintage bins. Again, the outward moving pattern of development is clear.

This pattern of development expanding outward is also visible in a time series showing changes in the relative importance of the different vintage bins in the city core and periphery, shown in Figure 4-6. In the city core there was very little change in the relative share of different age groups of structures because there was very little new construction in the core during the study period. In the periphery, new groups of structures appear in the same year that vintage bin began to exist, and the rapid growth in importance of the younger structures is obvious. By 2007, parcels built in or before 1996 comprised only 22% of all structures in the periphery.

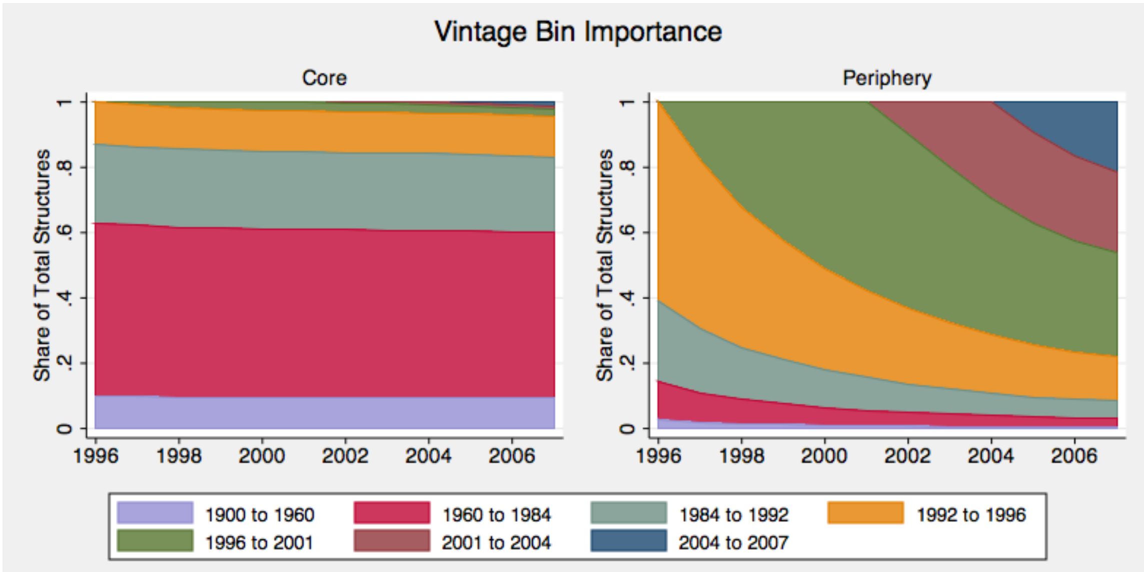

Figure 4-6. The share of different vintage bins in the core and periphery shown through time demonstrates the increasing importance of new construction in the periphery relative to the core.

Figure 4-8 shows the spatial distribution of changes in average indoor area between 1996 and 2007 by tract. There are large changes in average living area in tracts in the city periphery, while in the city core average living area is essentially constant between 1996 and 2007. This occurs because there is little new construction in the city core to cause changes in living area. The same spatial pattern of small changes in the city core and larger changes in the periphery holds for all the other indoor infrastructure characteristics measured in addition to living area. Figure 4-9 shows the evolution of the citywide average in the different major indoor characteristics through time. The average numbers of rooms, bedrooms, and bathrooms increased very slightly over time, while the average living area increased by about 10%.

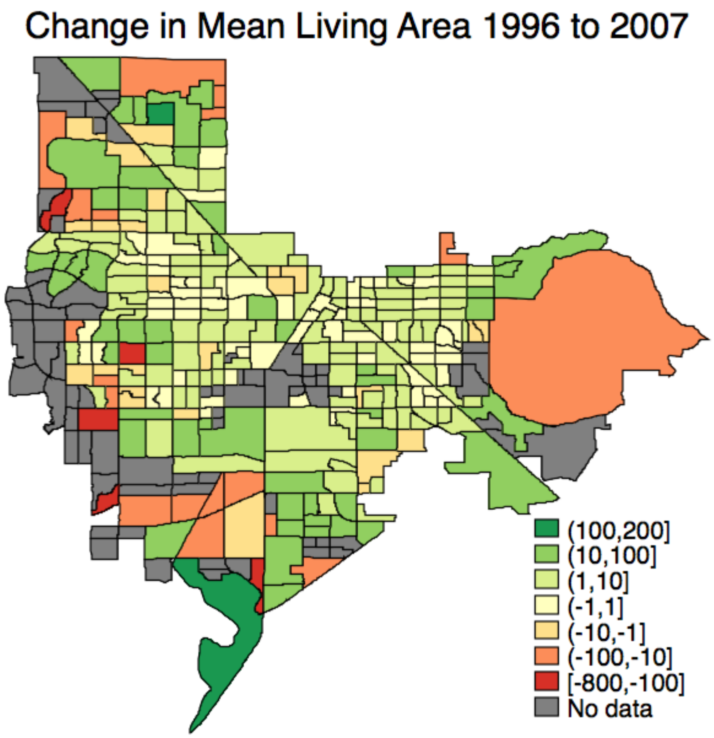

Figure 4-7. The spatial patterns in changes in mean indoor living area per parcel show that the largest changes in average living area occur where the most new houses were constructed, in the city periphery.

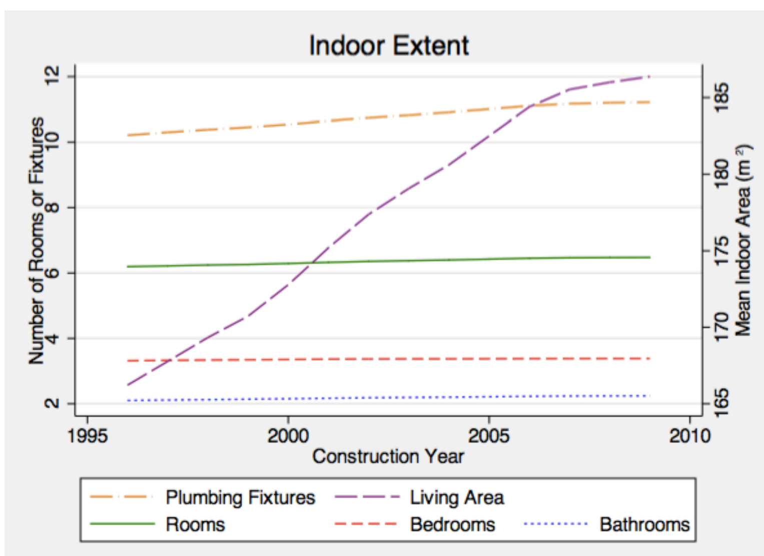

Figure 4-8. A time series of changes in the citywide average indoor infrastructure characteristics demonstrates the long-term trend of increasing indoor size.

Figure 4-9A shows the average number of plumbing fixtures in the core and periphery in each year, as well as the average number of plumbing fixtures in houses of each annual vintage. In the city core, the average number of plumbing fixtures per parcel rises by almost 0.2 fixtures per parcel, while in the periphery it rises by about 0.8 fixtures per parcel between 1996 and 2007. Thus the citywide increase in average number of plumbing fixtures is driven by both an increase in plumbing fixtures in the periphery relative to the core, and by an increase in the share of population in the city periphery. Figure 4-9B shows a very similar story with the number of bedrooms per parcel. Tract level averages for indoor infrastructure characteristics are generally stable through time, but newer houses do have different characteristics than older houses. New houses are likely to have larger living areas and more plumbing fixtures.

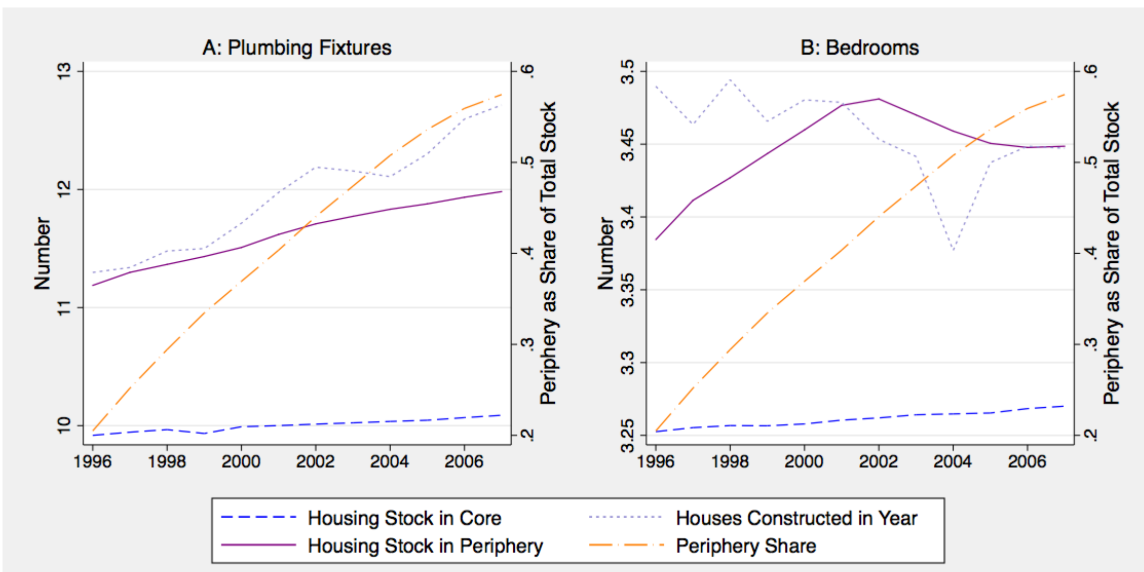

Figure 4-9. The number of plumbing fixtures and bedrooms in the housing stock rises much more slowly in the core than in the periphery. The share of population in the periphery also rises significantly during the study period, and both of these factors drive the citywide increase in bedrooms and fixtures per parcel.

4.4.2 Outdoor Drivers

The primary uses of water outdoors in a residential setting are for irrigating vegetation, pool and landscape maintenance, and non-productive uses including leaks, runoff, and evaporation. Outdoor water consumption in a residential setting is influenced by long-run infrastructure choices like the extent and type of vegetation used, as well as short-run choices like how intensely the existing vegetation is watered. Long-run landscaping choices constrain short-run choices about watering intensity, but do not completely govern outdoor water consumption. If it were possible to perfectly measure the outdoor characteristics of each lot that are expected to be the most important drivers of outdoor residential water consumption, I would include measurements of pool area, the area of turf grass, the area of non-turf vegetation, the health of the installed grass, and the water requirements of the entire landscape. The water needs of a landscape are significantly affected by the weather. The Matched Filter Vegetation Index (MFVI) developed in Chapter 1, combined with interaction terms between vegetation area and temperature or precipitation, imperfectly captures many of these factors. A household on a large lot may consume more water than a similar household on a smaller lot with equal vegetation areas because the higher density of vegetation on the smaller lot may lower the local radiative heat island (Middel et al. 2014). Daily minimum temperature and precipitation are key descriptors of the weather, and interaction terms between vegetation area and outdoor area are related to the water requirements of the landscape for a particular parcel. I would also like to include measurements of pool area or pool presence to capture the effect of evaporation from swimming pools, which is expected to be an important driver of outdoor water consumption.

Variables that primarily influence outdoor consumption are the percentage of parcels with a swimming pool, mean daily minimum temperature, monthly precipitation, and, finally, the area of vegetation per structure and the area of non-vegetated outdoor space per structure.

Figure 4-10 shows swimming pool prevalence in the city core and periphery. As is the case with all of the structural characteristics of a parcel, pool percentage in a tract only changes when new structures are constructed. This means that the city core, with very little new construction, saw only a very small change in pool ownership rates, while the entire citywide decline in pool ownership rates is driven by the decline in pool ownership in the city's newly constructed periphery. The only conservation policy that creates any incentives to avoid pool construction is the Water Smart Homes program, started in 2005, where pools and water features are counted against each parcels turf allowance.

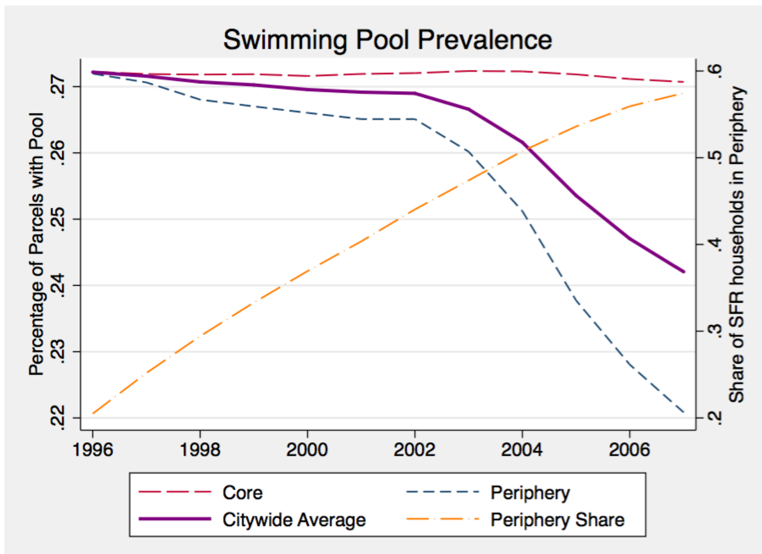

Figure 4-10. A time series if the prevalence of swimming pools in the core, periphery, and the citywide average.

Figure 4-11 shows a time series of vegetation area changes per parcel in the core, periphery, and the citywide average. Average vegetation area in the periphery has always been lower than in the core, but the decline in vegetation area in the core was greater than in the periphery. The decline in the citywide average vegetation area occurred both because of broad declines in vegetation area and also the increasing share of the population in the periphery.

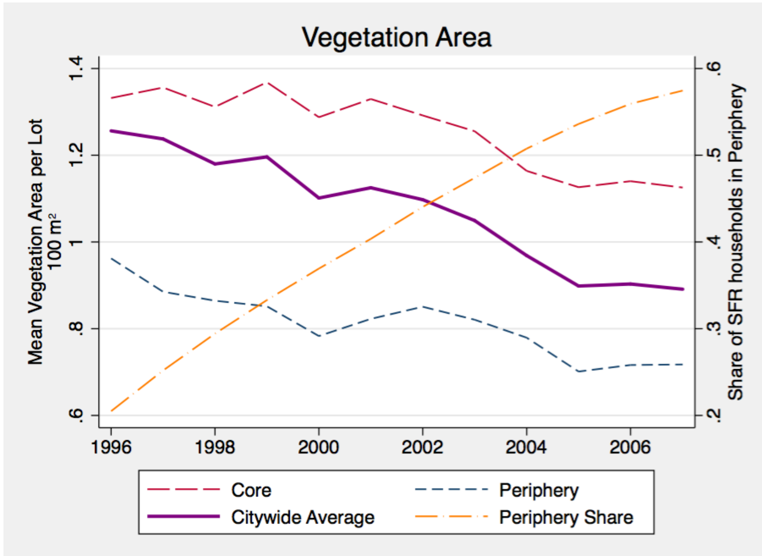

Figure 4-11. This time series of vegetation levels in the core and periphery shows that while the average area of vegetation declined in the core and periphery, the lower average area in the periphery and increasing share of the periphery in the total population also contributed to the decline in citywide average vegetation area.

Figure 4-12 shows temporal changes in the composition of an average lot. In both the core and periphery, the share of the average lot dedicated to the house's footprint was stable through the entire study period. Total residential living area increased during this time period because multi-story houses became more common. For lots in the city core, the decline in the share of a lot that is vegetated is clear, and the share of the lot with vegetation was higher in the core than in the periphery.

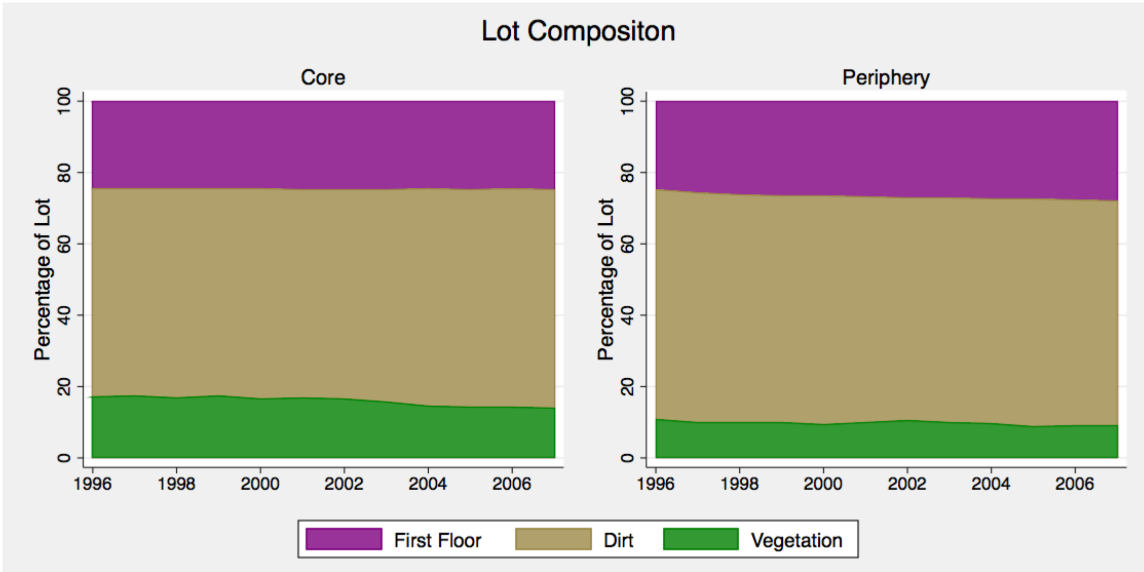

Figure 4-12. A time series showing changes in the composition of the typical lot in the core and periphery. The city core has a higher percentage of vegetation coverage and also has greater changes in vegetation coverage than the periphery.

Figure 4-13 shows temporal changes in the mean lot area in the core and periphery. It is clear that the average size of newly constructed lots is much smaller than the average size of older lots, and that most of the new construction is occurring in the periphery. This is why the average lot size in the core remains nearly constant, while the average lot size in the periphery declines by about 150 m^2. *As a consequence, the decline in total vegetation area per lot in the core is driven primarily by changes in lot composition, while the decline in total vegetation area per lot in the periphery is driven by changes in the average lot area in the periphery.*

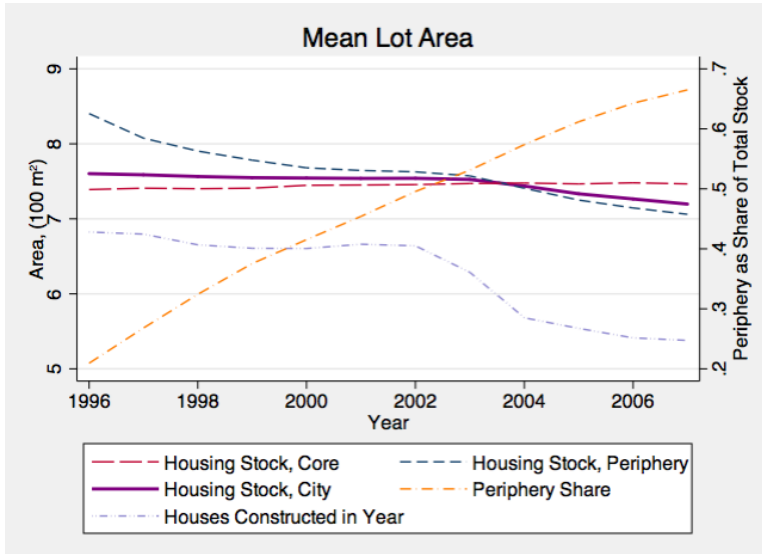

Figure 4-13. The mean lot area in the core is nearly constant over the entire study period, while there are significant declines in the mean lot area for the periphery. The declines in the average lot area in the periphery are driven by the much greater declines in average lot area in newly constructed houses

The role of new construction in changing vegetation area is observable through trends in newly constructed structures, and is also easily visible in maps of the change in outdoor area and the change in vegetation area between 1996 and 2007, as shown in Figure 4-14. In the core of the city, the mean outdoor area per structure does not change dramatically between 1996 and 2007, while the mean vegetation area does show a consistent decline across the core area. There is more variability in the change in outdoor area in the periphery than in the core, but the average outdoor area did decline between 1996 and 2007. Similarly, the average vegetation area in the periphery increased in some areas and declined in others, but the overall trend showed a decline in vegetation area in the periphery.

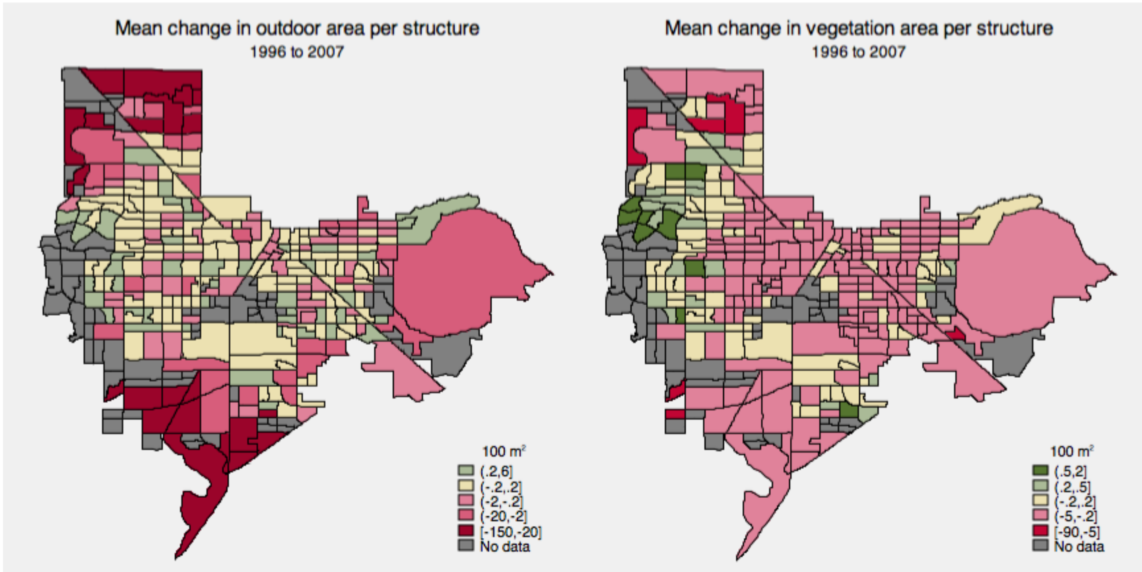

Figure 4-14. The map of changes in outdoor area shows that the outdoor area remained relatively constant in the city core, and declined in most parts of the city periphery, excluding the Summerlin master planned community on the west side of the city. The map of changes in vegetation area shows that despite little change in outdoor area, there was widespread decline in the vegetation area in the city core.

As shown in Figure 4-15, there is no significant time trend in the temperature record in this study period. There is a very strong seasonality to monthly temperature, but this analysis only considers June temperature and precipitation, highlighted by colored dots in the figures. Similarly, there is no time trend in the precipitation record, and precipitation is zero in 6 of the 12 years in the study period. It is notable that 1998 and 1999 were cooler than average and had higher precipitation than average. These two years also had much lower consumption than average.

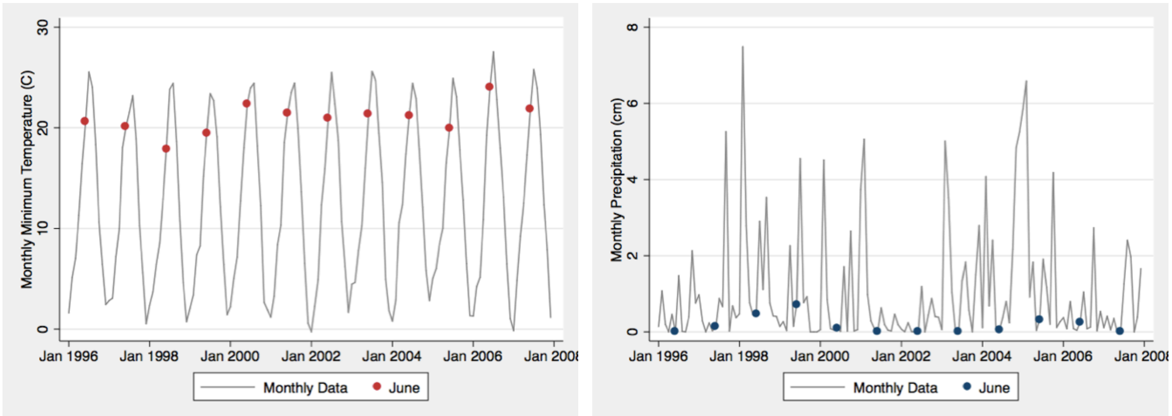

Figure 4-15. Time series for temperature and precipitation.

Figure 4-16 show the spatial variation for temperature and precipitation in June 1999. This is a typical temperature distribution, and also a typical distribution of precipitation when it occurs. The west side of Las Vegas abuts Red Rock Canyon, and the higher elevation there drives a pattern of lower temperature and higher precipitation.

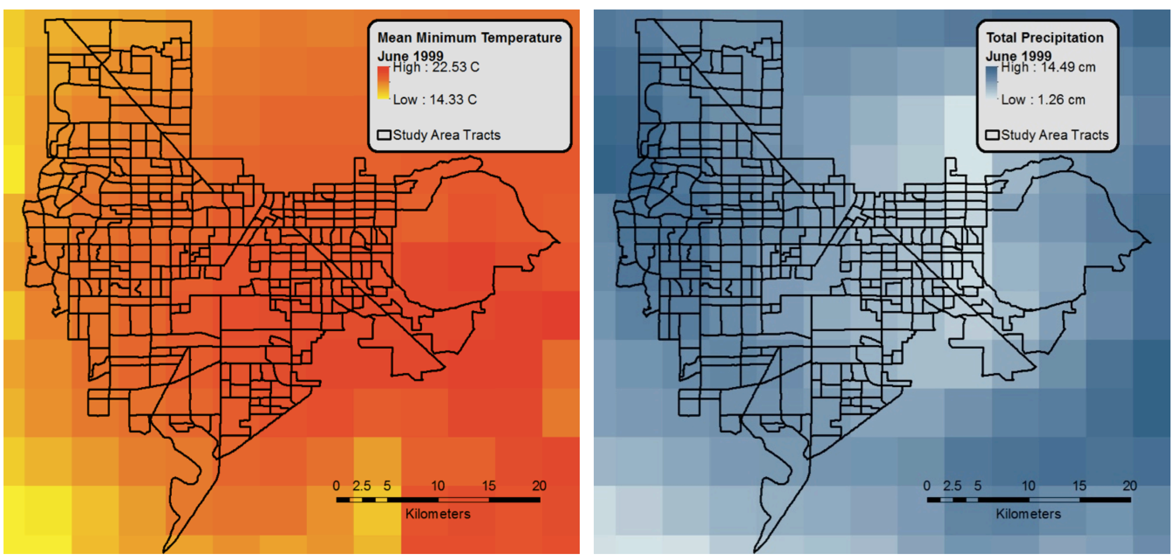

Figure 4-16. Spatial variation in temperature and precipitation for a typical June month.

4.5 Regression Specification

The main objective of this regression is to determine the role that indoor characteristics, outdoor characteristics, measures of parcel vintage characteristics, and weather play on household consumption. In order to do this, I need to choose the regression's functional form; which set of temporal dummies and spatial fixed effects should be included; and the exact variables to include for the outdoor specification, indoor specification, and how to characterize interactions with weather related variables.

I use a semi-log regression of the form $\ln C_{it} = \beta_0 + \beta_1 x_1 + \beta_2 x_2$. Exponentiating both sides gives $C_{it} = e^{\beta_0} e^{\beta_1 x_{1it}} e^{\beta_2 x_{2it}}$. Taking the partial derivative of C_{it} with respect to x_j gives $\% \Delta C_{it} = \beta_j \Delta x_j$ for small changes in x_j. A temporal dummy variable for each year is used to account for annual changes in water price, citywide policy, and all other citywide temporal variation that is not otherwise explained by the control variables.

To estimate the role that outdoor size and composition plays in household consumption, I use two constructed variables, vegetation area, and dirt area. Implicitly, a one-unit increase in either of these control variables assumes a one-unit increase in the lot size, assuming that I control for the structural footprint. From a biological perspective, I expect that both temperature and precipitation will primarily influence household consumption through their effects on the water needs of vegetation. Thus, I include an interaction term between vegetation and temperature, and also vegetation and precipitation. Similarly, as an additional control, I include interaction terms between dirt area and both temperature and precipitation. Similarly to the physical effect of vegetation area, I expect that pools consume water through both normal use and maintenance, and also through evaporation. Thus, I include an interaction term between the proportion of pool ownership and minimum temperature.

I choose three terms to characterize the indoor area: living area, number of plumbing fixtures, and number of bedrooms. Because rooms, bathrooms, and bedrooms are so highly collinear, only one of the three can be chosen. I chose plumbing fixtures over bathrooms due to its more direct link to water consumption. The number of bedrooms is more likely to be correlated with the number of residents than living area. Most importantly, though, the broad patterns of the results are robust to variation in the specification choices of indoor variables.

The full regression specification is as shown in Equation 7, where the variables are as defined in Table 4-2. The dependent variable, $\ln C_{it}$, is the natural log of mean household consumption by tract, measured in thousands of gallons. In all cases, a variable with an accent has been renormalized as $v\acute{a}r_{it} = var_{it} - \overline{var_{i96}}$. All variables except those with a naturally meaningful zero value have been renormalized to the 1996 mean value in order to make interpretation in terms of changes from the 1996 levels more direct. This renormalization process permits me to interpret interactions in such a way that the base coefficient is the marginal effect in 1996. The variables that have not been renormalized have a dummy or proportional interpretation: vintage and pools.

$$\begin{aligned}\ln C_{it} = y_t + n_i + \beta_l l\acute{i}ving_{it} + \beta_b b\acute{e}d_{it} + \beta_{pb} pl\acute{u}mb_{it} + \boldsymbol{\beta'_{vn} vintage_{it}} \\ + \beta_{pl} pool_{it} + \beta_{pt}(pool_{it} t\acute{e}mp_{it}) + \beta_{pr} pr\acute{e}cip_{it} + \beta_d d\acute{i}rt_{it} \\ + \beta_{dt}\left(d\acute{i}rt_{it} t\acute{e}mp_{it}\right) + \beta_{dp}\left(d\acute{i}rt_{it}\, pr\acute{e}cip_{it}\right) + \beta_v v\acute{e}g_{it} \\ + \beta_{vt}(v\acute{e}g_{it} t\acute{e}mp_{it}) + \beta_{vp}\,(v\acute{e}g_{it}\, pr\acute{e}cip_{it}) + \beta_t t\acute{e}mp_{it} \\ + \epsilon_{it}\end{aligned} \qquad 7$$

Table 4-2: Variable definitions.

Variable	Definition and units
C	Mean household consumption by tract (1,000 gallons)
y	Dummy variable for year

n	Tract fixed effect
$living$	Mean living area (m^2)
bed	Mean number of bedrooms
$plumb$	Mean number of plumbing fixtures
$\boldsymbol{vintage}$	Percentage of structures in tract constructed in a given range of years
$pool$	Percentage of structures in tract with a swimming pool
$precip$	Total June rainfall in tract (cm)
$dirt$	Mean outdoor area per structure that is not vegetated (100 m^2)
veg	Mean vegetated area per structure (100 m^2)
$temp$	Mean June daily minimum temperature (C)

Annual dummy variables are included as y_t; $\acute{living}_{it}$ is the mean living area across all structures within tract i in time t, measured in m^2. The variables named $\acute{bed}_{it}$ and $\acute{plumb}_{it}$ represent the renormalized mean number of bedrooms or plumbing fixtures per parcel. The variable $\boldsymbol{vintage_{it}}$ is a vector representing the six vintage bins shown in Figure 4-5B–G. The binned group from 1900 to 1960 is used as a baseline. Each vintage bin in tract i and year t represents the share of structures in tract i in a particular vintage. The variable $pool_{it}$ shows the percentage of structures with a swimming pool, while the variables $\acute{dirt}_{it}$ and $\acute{veg}_{it}$ show the renormalized area of dirt and vegetation measured in 100 m^2, defined as in Equation **5** and Equation **6** in Section 4.3.4. Finally, $\acute{precip}_{it}$ shows the total June rainfall measured in cm, while $\acute{temp}_{it}$ shows the renormalized mean daily minimum temperature in Celsius degrees, calculated from the PRISM data as shown in **4** in Section 4.3.3 Recall that there was no precipitation at all in Las Vegas in June 1996, so a zero $\acute{precip}_{it}$ value also represents true zero precipitation.

The base unit of analysis in all cases is the census tract, because that is the spatial extent at which water consumption data are available. Tracts are defined using 2010 census tract geometry, and contain the same land area the entire study period. Consequently, the population of an individual tract changes each year as residents move in or out and new homes are constructed. The total number of active accounts in a tract/year combination varies from one to nearly 3,000. Because this analysis seeks to explain household level water consumption, each household should be given equal weight, and so in all calculations unless otherwise noted, each tract/year observation has been given a weight based on the total number of active accounts in each tract.

I expect the coefficients on the indoor variables $\beta_l, \beta_b,$ and β_{pb} to be generally positive; all else held equal, increasing the living area, number of bedrooms, or number of plumbing fixtures should cause an increase in household water consumption. Additionally, I expect that newer houses are likely to consume less water than older houses both because aging plumbing and appliances are more likely to leak, newer houses are built with more water efficient technology, and some of the local conservation policies specifically influence the water needs of newly constructed homes. Consequently, I expect the $\boldsymbol{\beta'}_{\boldsymbol{vn}}$ vector to become more negative for newer structures.

Interpretation of the expectations on coefficients for outdoor variables is somewhat more complex because of the interaction between the structural variables and weather variables. I expect that pool ownership will increase household consumption, so the coefficients β_{pl} and β_{pt} should be such that $\frac{\%\Delta C}{\Delta pool} = \beta_{pl} + \beta_{pt}t\acute{e}mp > 0$. Additionally, because increased temperatures are likely to increase the rate of evaporation from a pool, I expect the coefficient on the pool and temperature interaction term β_{pt} to be positive.

I expect that vegetation area is one of the strongest drivers of residential water consumption, so $\frac{\%\Delta C}{\Delta veg} = \beta_v + \beta_{vt}t\acute{e}mp + \beta_{vp}precip > 0$. I also expect that increasing temperature should increase vegetation's water demand, and so β_{vt} should be positive, while increasing precipitation should decrease vegetation's water demand to the extent that users reduce their irrigation system use in response to rainfall, so β_{vp} should be negative.

I expect that increases in dirt area should not have a strong effect on household consumption. However, increasing lot area without a corresponding increase in vegetation area may increase the evapo-transpiration needs of vegetation on the lot because of locally higher temperatures and lower humidity. Thus, for two lots with equal areas of vegetation, the one with a larger dirt area may have higher consumption, so the derivative of consumption with respect to dirt is expected to be positive. Additionally, larger lots increase the potential for leaks in irrigation systems, and permit larger pool areas. Then $\frac{\%\Delta C}{\Delta dirt} = \beta_d + \beta_{dt}\acute{temp} + \beta_{dp}precip$ would be zero or weakly positive. This means that the coefficients β_{dt} and β_{dp} should have the same sign as the corresponding coefficients β_{vt} and β_{vp}. Further, I expect that increasing temperature will increase the water needs of swimming pools and vegetation, and thus, indirectly, would also increase the effect of non-vegetated lot area, so $\frac{\%\Delta C}{\Delta temp} = \beta_t + \beta_{pt}pool + \beta_{dt}\acute{dirt} + \beta_{vt}\acute{veg} > 0$ should hold, and the coefficients $\beta_{pt}, \beta_{dt},$ and β_{vt} should also be positive. Finally, I expect that consumption will fall as precipitation rises, $\frac{\%\Delta C}{\Delta precip} = \beta_{pr} + \beta_{dp}\,\acute{dirt} + \beta_{vp}\acute{veg} < 0$.

4.6 Regression Estimation and Results

In this analysis, I run three sequential models to show that the broad conclusions across different specifications are consistent, independent of the exact details of the regression specification. The full results are shown in Table 4-3. Model 1 below regresses just annual dummy variables on the natural log of average household consumption. Model 2 includes both the annual dummy variables as well as all of the control variables shown in Table 4-2. Finally, model 3 adds spatial fixed effects to the model 2 specification, including annual dummies, all right hand side variables, and spatial fixed effects.

Spatial fixed effects are used to soak up unobserved spatial heterogeneity in the drivers of tract level water use that are time invariant. The Hausman test (Cameron and Trivedi 2005) is used to check the consistency of the random effects estimator, to determine if fixed effects are needed in order to obtain consistent coefficient estimates. I use Hoechle's (2007) Stata implementation of Driscoll and Kraay (1998) standard errors to ensure that the Hausman test is robust to general forms of spatial and temporal dependence. The null hypothesis, that the random effects estimator is consistent, is rejected at the 0.1% level. Thus, using spatial fixed effects instead of random effects is necessary to ensure that the estimation results are consistent. To test if the idiosyncratic residuals are spatially independent, I follow Hoechle's implementation of Pesaran's test for cross-sectional dependence (2007). The results show that I should reject the null hypothesis of spatial independence, and assume spatial dependence when choosing the type of standard errors to use in the full regressions[3].

Table 4-3 shows fully robust standard errors based on Hoechle's (2007) Stata implementation of Driscoll and Kraay (1998) standard errors. They are robust to general forms of both spatial and temporal dependence. Table 7-1 in Appendix compares these fully robust standard errors to the Huber White sandwich standard errors (Huber 1967; White 1980) and ordinary standard errors. All three sets of standard errors are calculated for model 3, using temporal dummies and spatial fixed effects. With some exceptions, the standard errors become larger when increasingly robust methods of estimating the standard errors are used. This leads to a corresponding decrease in the reported statistical significances of the model for some explanatory variables, but does not meaningfully change the qualitative results.

[3] Like my implementation of the Hausman test, Pesaran's test is run on a model with no frequency weights, and tract and year combinations with less than 10 accounts excluded. Further, I force exclusion of strongly unbalanced panels by keeping only the tracts where the number of active accounts is greater than 10 in at least 8 of the 11 study years.

In a model with spatial fixed effects, only variations around the within-tract means of each regressor are used to estimate the model. This means that for all variables derived from the Assessors data, the **only** variation in each variable is due to new construction within a tract. In the city core, this method removes almost all of the variation in all variables except vegetation percentage and the weather. Parcels constructed in 1996 or earlier make up 100% of all structures in the city core in 1996 by definition, and they make up 95.4% of all structures in the core at the end of 2007. Because the periphery was specifically chosen to include most of the new construction that occurred in Las Vegas between 1996 and 2007, parcels constructed between 1996 and 2007 make up just over half of all structures in the periphery in 2007, and so there is much more scope for variation in these variables in the periphery, the estimation for the citywide effects of these variables must be driven primarily by changes that occur in the city periphery. Thus, most of the variation model 3 is responding to will be in the periphery, and may not fully represent the consumption behavior of households in the older urban core.

Table 4-3: Results

	Model 1: Year	**Model 2: Year, Controls, RE**	**Model 3: Year, Controls, FE**
1997 Dummy	-0.0437***	-0.0290	-0.0248*
	(9.63e-15)	(0.0218)	(0.0122)
1998 Dummy	-0.158***	-0.108	-0.0852*
	(1.15e-14)	(0.0763)	(0.0431)
1999 Dummy	-0.148***	-0.0694	-0.0584
	(1.05e-14)	(0.107)	(0.0609)
2000 Dummy	-0.0552***	-0.0172	-0.0164
	(1.03e-14)	(0.0152)	(0.0102)
2001 Dummy	-0.103***	-0.0755***	-0.0818***
	(1.02e-14)	(0.0101)	(0.00486)
2002 Dummy	-0.143***	-0.108***	-0.112***
	(1.05e-14)	(0.0111)	(0.00509)

2003 Dummy	-0.178***	-0.129***	-0.131***
	(1.02e-14)	(0.00978)	(0.00457)
2004 Dummy	-0.299***	-0.228***	-0.220***
	(1.12e-14)	(0.0117)	(0.00658)
2005 Dummy	-0.406***	-0.267***	-0.251***
	(1.11e-14)	(0.0499)	(0.0285)
2006 Dummy	-0.395***	-0.242***	-0.240***
	(1.07e-14)	(0.0313)	(0.0231)
2007 Dummy	-0.417***	-0.256***	-0.262***
	(1.02e-14)	(0.00901)	(0.00468)
Living Area (m^2)		0.00114**	0.00251**
		(0.000465)	(0.00113)
Plumbing Fixtures		0.0514***	0.00938
		(0.00391)	(0.0129)
Bedrooms		0.145***	0.0225
		(0.0213)	(0.0259)
Vintage 1960 to 1984		-0.102***	0.0812
		(0.0115)	(0.155)
Vintage 1984 to 1992		-0.0661***	0.0722
		(0.0112)	(0.150)
Vintage 1992 to 1996		-0.292***	-0.216
		(0.0372)	(0.120)
Vintage 1996 to 2001		-0.353***	-0.147
		(0.0566)	(0.118)
Vintage 2001 to 2004		-0.467***	-0.249*
		(0.0118)	(0.115)
Vintage 2004 to 2007		-0.914***	-0.566***
		(0.0269)	(0.148)
Pool Percentage		0.549***	0.525*
		(0.0278)	(0.262)
Pct. Pool* Min Temp (% * C)		0.0149	0.0000850
		(0.0120)	(0.00306)
Total Precipitation (cm)		-0.0821	-0.0990
		(0.145)	(0.0828)
Dirt*Min Temp (100 m^2 * C)		0.00351*	0.000612
		(0.00181)	(0.000444)
Veg*Min Temp (100 m2 * C)		-0.0125*	0.00380
		(0.00568)	(0.00234)
Dirt*Precip. (100 m^2 * cm)		0.00300	-0.00206
		(0.00856)	(0.00299)
Veg*Precip. (100 m^2 * cm)		-0.0213	-0.00941
		(0.0290)	(0.0118)

Dirt (100 m²)		0.00697	-0.0294***
		(0.00431)	(0.00468)
Area Veg (100 m²)		0.111***	0.225***
		(0.00886)	(0.0257)
Min June Temp (C)		-0.00581	0.00429
		(0.00564)	(0.00397)
Constant	3.291***	3.395***	3.012***
	(1.02e-14)	(0.0257)	(0.269)
Observations	3502	3492	3492
R-squared	0.606	0.944	0.998

Driscoll and Kraay standard errors in parentheses
*p<0.10, ** p<0.05, *** p<0.01

Figure 4-17 shows the change in citywide average household consumption explained by the temporal dummy variables. In all three models, there is a strong pattern of the temporal dummies driving declining consumption in later years, with a structural break in 2004, when the temporal dummy variables were consistently low. In model 1, with only temporal dummy variables, average household consumption in June is 30% lower in 2007 than it was in 1996. In model 2, the newly included control variables have explained a significant portion of Las Vegas's observed decline in household consumption, so each temporal dummy variable has a smaller effect on household consumption in model 2 than in model 1. In models 2 and 3, average household consumption is about 4,400 gallons per month lower in 2007 than it would have been if the temporal dummies were zero. The coefficients on the temporal dummy variables are also generally consistent between model 2 and model 3. Standard errors decline somewhat between model 2 and model 3, but fundamentally, the three models show that regardless of the exact model specification, the patterns in the temporal dummy variables are consistent, have some ability to be explained by the control variables, and there is evidence of a structural break in 2004.

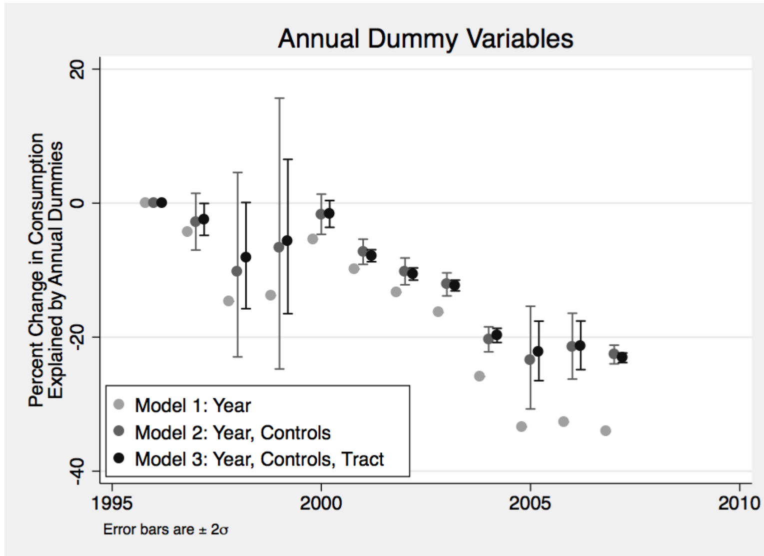

Figure 4-17. The estimated coefficient on each annual dummy variable for each of the three models, when 1996 is used as the base category. Two standard error confidence intervals are shown for each model. In this and all subsequent figures, percentage effects are based on the $e^{\beta} - 1$ transformation.

Las Vegas's average household consumption in 1998 and 1999 was significantly lower than in any of the surrounding years. This is partly absorbed into the lower temporal dummies for 1998 and 1999 shown in Figure 4-17. The model 1 temporal dummies drive consumption lower by about 3,700 gallons, while the model 2 and 3 temporal dummies drive consumption lower by only about 2,000 gallons. This shows that for 1998 and 1999, about half of the decline is explainable by some combination of the control variables, more than is explainable by the control variables in the post-2004 period. Figure 4-17 also shows that after 2004, a decline of about 4,000 gallons per household per month across the entire city cannot be explained by infrastructure, vegetation, weather, or policy change whose implementation varies spatially, while a decline of about 2,000 gallons per household per month can be explained by those factors. The remaining unexplained part of this decline may be due to the citywide policy changes that began in 2004 as described in Table 4-1, like the water price increase and new capability to enforce water waste citations.

Figure 4-18 shows the magnitude of the coefficients on the vintage dummy variables through time. The overall sign and magnitude are consistent in both model 2 and model 3, although the confidence intervals are very large for model 3. The general pattern of declining consumption for newer structures holds for both model 2 and model 3, which is consistent with my hypothesis. The largest decline in the effect of vintage on household consumption occurs at the 2004 break, which is the same time that a wide range of policy changes were made, some of which influenced the water efficiency of new construction. The second largest decline in the effect of vintage on household consumption occurs at the 1992 break, which includes parcels constructed after the Energy Policy Act was passed. This is evidence that both local and federal policy changes had meaningful effects on household water efficiency.

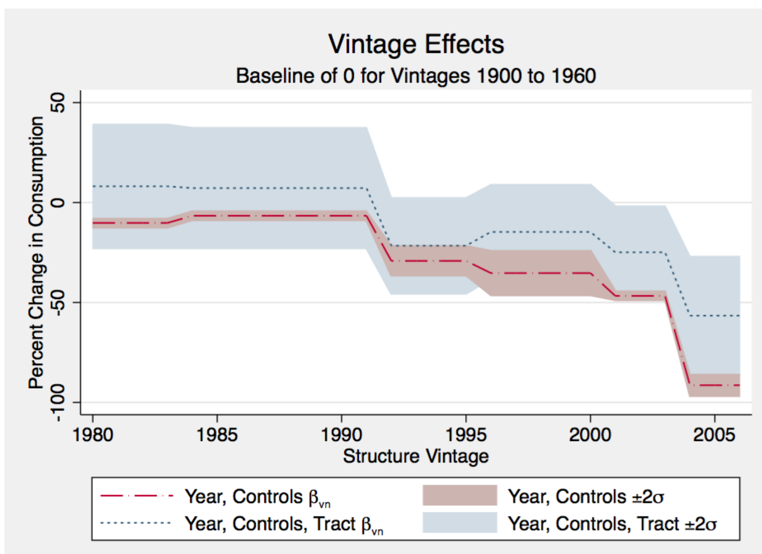

Figure 4-18. The estimated coefficient on each vintage bin for model 2 and model 3, when the 1900 to 1960 bin is used as the base category. Two standard error confidence intervals are shown for each model. In this and all subsequent figures, percentage effects are based on the $e^{\beta} - 1$ transformation.

Figure 4-19 shows a histogram of the proportional shift of the tract fixed effects. The proportional shift ranges from -1 to 1.7, the tracts entire consumption for the month. Figure 4-20 maps the spatial fixed effects. Based on visual analysis, the distribution of coefficients does not appear completely random: there are clusters of tracts with high consumption and clusters with relatively low consumption. The west side of the city is more likely to have higher consumption, while the east side is more likely to have lower consumption. The west side areas with high consumption include the Summerlin and Canyon Gate master-planned communities. Additionally, the west side of the city is at higher elevation, and further from Lake Mead and the Las Vegas wash, so it may be windier and have lower average humidity.

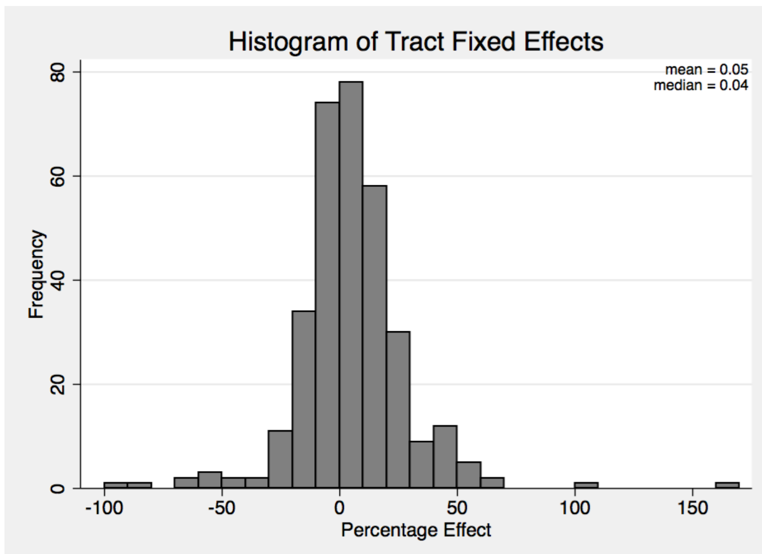

Figure 4-19. Histogram showing the distribution of tract fixed effects.

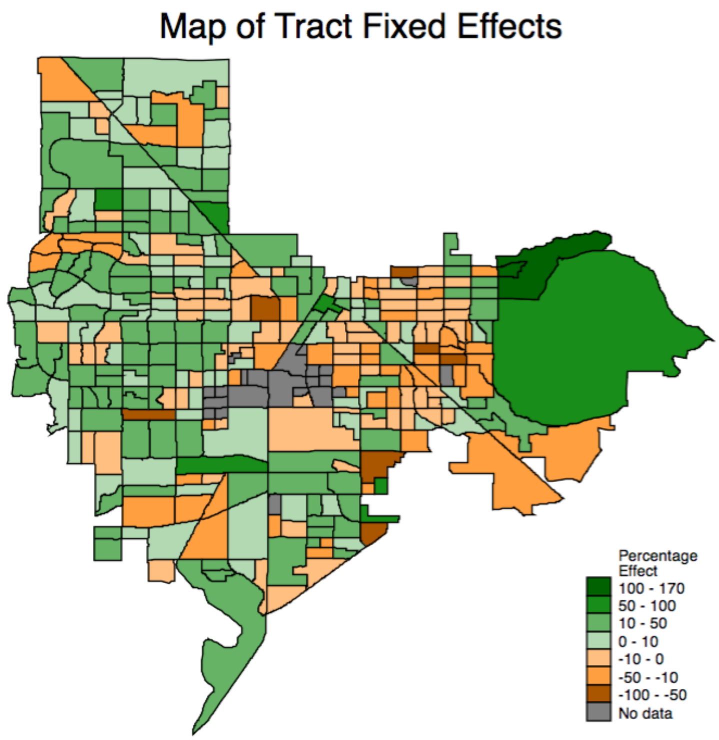

Figure 4-20. This map of spatial fixed effects shows clustering in tract level average consumption. Percentage effects are based on the $e^{\beta} - 1$ transformation.

The results on the coefficients for the other right hand variables are also generally consistent with expectations in both model 2 and model 3. The three direct 'indoor' variable coefficients, living area, plumbing fixtures, and bedrooms, are all positive. Each is significant in model 2, when spatial fixed effects are not included. Only living area is significant when spatial fixed effects are included. This shift in significance makes some intuitive sense: there is very little variation in the indoor control variables over time within each tract, and so once the spatial variation across tracts has been removed through the spatial fixed effects the amount of variation to explain will decline, and thus also the statistical significance. The magnitude of the living area coefficient is similar in both model 2 and model 3, but the magnitude of the plumbing and bedrooms coefficients are both much smaller in model 3 than in model 2. This may be because in model 3 there is simply less variation in each variable to be of significance.

In both model 2 and model 3, the coefficients on the 'outdoor' control variables are nearly all consistent with expectations, and the coefficients on pools, dirt, and vegetation are significant. The coefficients on dirt and vegetation and their interactions with temperature and precipitation show similar patterns, and are summarized in Table 4-4. The coefficient on vegetation alone in model 2 suggests that an increase in of 100 m^2 of vegetation, with all else held constant, will increase the mean household consumption by about 12%, which is 3,300 gallons in June 1997, and 2,300 gallons in June 2007. Considering the effect of the vegetation and temperature interaction term, increasing vegetation by 100 m^2 from the 1996 mean and increasing temperature by 1 degree C will decrease the average household consumption by an additional 2.5%, equating to 700 gallons in June 1996 and 500 gallons in 2007. This is the opposite sign of what is expected, but the magnitude is small compared to the total effect of vegetation change.

Table 4-4: Summary of physical effects of outdoor interaction terms from Model 2.

Term and Interactions	**Change in Mean Household Consumption**	
	Percent	**Gallons (June 2007)**
Δ 100 m^2 Vegetation* **	11.7%	2,270
Δ 100 m^2 Vegetation & Δ 1 cm Precip.	9.6%	1,870
Δ 100 m^2 Vegetation & Δ 1°C Temperature*	10.5%	2,040
Δ 100 m^2 Dirt	0.7%	140
Δ 100 m^2 Dirt & Δ 1 cm Precip.	1%	190
Δ 100 m^2 Dirt & Δ 1°C Temperature*	1.1%	210
Pool Presence* **	73%	14,150
Pool Presence + Δ 1°C Temperature	74.5%	14,440

*$p<0.10$, ** $p<0.05$, *** $p<0.01$

Increasing the area of dirt by 100 m^2 by increasing the lot area increases household consumption by 0.7%, which is about 200 gallons in June 2007. Increasing dirt area by 100 m^2 from the 1996 mean and temperature by 1 C drives an additional increase in consumption of about 90 gallons per household per month in June 2007. While the absolute magnitude of these changes in consumption are small relative to the magnitude of changes in consumption driven by vegetation change, only about 20% of the outdoor area in a typical lot is vegetated, so changes in dirt area can have a similar physical effect when lot area is changed and the new area is proportionally distributed between dirt and vegetation.

The effect of swimming pools is large: the average household in a tract where every structure has a pool would consume 75% more water than the average household in a tract where no structures have pools. For the mean tract-level consumption, this is an additional 20,900 gallons in June 1996 and 14,200 gallons in June 2007. An increase in temperature of 1 degrees C, is expected to increase average consumption in a tract where every structure has a pool by 1.5%: 450 gallons in June 1996 and 300 gallons in June 2007.

Figure 4-21 shows the expected June 2007 household consumption, for a household living in a structure of a particular vintage. Each year's estimate is based on a prediction from the model 2 regression using the average infrastructure characteristics of houses built in that year to fill in the right hand side variables. Vegetation area is the only right hand side variable related to the individual household that is available at the tract level only, not the household level, so I estimate 2007 vegetation area for houses of a particular vintage based on the average 2007 vegetation area for tracts with large shares of houses of that vintage[4].

[4] I find the average vegetation area for all census tracts in which the parcels built during the relevant vintage bin comprises more than 70% of the structures in that tract. I estimate that structures built between 1996 and 2001 have an average vegetation area in 2007 of 81 m^2, structures built between 2001 and 2004 have an average vegetation area of 50 m^2, and structures built between 2004 and 2007 have an average vegetation area of only 7m^2. Because this method estimates vegetation area using the fixed vintage bins, I apply the same estimate for all years within the relevant bin.

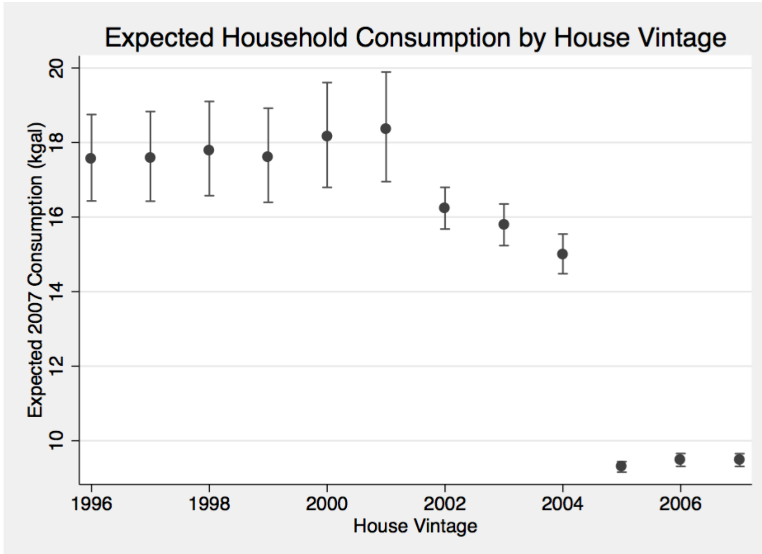

Figure 4-21. Household consumption by home vintage.

This figure shows that the expected consumption for a household in a typical home built in 2007 is only 53% of the expected consumption for a home built in 1996. This dramatic decline in expected consumption for newer homes is consistent with the major policy changes enacted in the Las Vegas area that influence the water efficiency of newly constructed homes. The first policies restricting turf in new construction were implemented in 2000, when the expected consumption for new household begins to decline, and in 2004, a suite of policies influencing the water efficiency of new homes was implemented.

4.6.1 Robustness Checks

There are large differences in demographics, infrastructure characteristics, and neighborhood structure between the city core and the city periphery. These differences may influence the relationship between some of the right hand side variables and household consumption. I test this hypothesis by running the model 2 regression specification on the city core and the city periphery individually. These results are shown in Table 7-3 in **Error! Reference source not found.**. The coefficient on dirt is the only one with a different sign in the core and periphery models and both are statistically significant. It is positive and significant at $p<0.01$ in the city core, and negative and significant at $p<0.01$ in the city periphery. In the citywide model, the coefficient is positive but not significant. The coefficient on Vintage between 2004 and 2007 is the only one that has a different sign in the core and periphery models and is statistically significant. This probably occurs because there was very little construction in the city core in that time period. Considering the model as a whole, an F-test soundly rejects the null hypothesis that all coefficients are equal between the two individual models. Structural differences between the effect of vegetation, dirt area, and lot size on household consumption in the core compared to the periphery will be an interesting avenue for further research.

The effect of an increase in dirt area on household water consumption is expected to be close to zero. To test the importance of the dirt variable on the full model, I run a variation on model 2 with the dirt coefficient excluded. Table 7-2 in Appendix shows the results of this model. Recall that this model, by excluding a measurement of dirt area, then implicitly removes the ability for lot size to vary independently of vegetation area. The coefficients are generally consistent between model 2 and the no dirt model. The coefficients with the biggest differences between the two models are those that co-vary significantly with lot size. In general, these variables (indoor area, plumbing fixtures, and vintage) have a larger magnitude and are more likely to be statistically significant, which is more likely evidence of omitted variable bias rather than a truly better model for describing household consumption.

The effect of precipitation is also small, and statistically insignificant. In analyses of water consumption in Phoenix, Arizona, precipitation is excluded from regressions because it does not appear to have any measurable effect on household water consumption. I run a model with precipitation excluded, and find that its exclusion does not meaningfully change any regression coefficients. The result of this model is compared to model 2 in Table 7-2 in **Error! Reference source not found.**.

4.7 Counterfactual Scenarios

The direct regression results discussed in Section 4.3 are an important way of showing the magnitude of change in consumption as the different right hand side variables change. This provides some hypotheses about which of the measured right hand side variables had the largest effects on household water consumption, but to quantify the relative importance of the effects of changes in different right hand side variables in a physical sense, I also need an understanding of the magnitude of changes that actually occurred within the right hand side variable.

I can estimate how water consumption would have been different if changes in some right hand side variables had not occurred by creating a counterfactual dataset with the data for that variable held at it's 1996 levels: $x_{it} = x_{i1996}$. I use the regression results from the previous section to predict expected consumption based on counterfactual data. For each scenario I find the difference between the true consumption and what I expect consumption would have been if x had stayed at the 1996 baseline. This difference in consumption can be can be attributed to the changes in x that actually occurred.

In these scenarios, I address three primary questions:

1) How did changing household infrastructure characteristics like house size, number of bedrooms or plumbing fixtures, and pool prevalence influence household water consumption?

2) How did changing vegetation area per household influence household consumption?

3) How did population growth and new construction influence household water consumption?

Question 1 is addressed by running counterfactual scenarios where the relevant household infrastructure characteristics in each tract are held constant at their 1996 levels, and all other variables follow the data as actually measured. Question 2 can only be addressed by simultaneously considering the percentage change in vegetation area and also changes in average lot area per tract, especially for tracts in the periphery with significant population growth. Question 3 is examined by considering the role that changes in average house vintage in the core and periphery played in influencing household consumption, as well as considering what would have occurred if the new population had moved into locations and structures with characteristics that matched the residences of the established population.

To test these effects, I use the results of the regression model two, shown in Table 4-3, and find the average household consumption based on the estimated regression coefficients if levels of the control variables had developed in some other manner. I use model 2, without spatial fixed effects, despite the results of the Hausman test suggesting that model 3, with spatial fixed effects, is preferred. Model 2 is used because Las Vegas's development was very spatially concentrated, and so there is very little within tract variation in any variable derived from the Assessor's data, especially in the city core. Thus, subtracting spatial fixed effects from the model removes nearly all of the important variation in the distribution of these variables across time and space, making it very challenging to determine the role that they play in influencing household consumption.

Each scenario estimates the difference between the average household consumption that was actually measured in Las Vegas, and the estimated average household consumption that would have occurred if the city's infrastructure had developed differently. These differences are measured over the city as a whole, the city core, and the periphery. If the changes that occurred in the infrastructure between 1996 and 2007 caused an increase in household consumption, it is shows as a positive result in Figure 4-22, Figure 4-23, and Figure 4-25. Conversely, if the infrastructure changes in question caused a decrease in household consumption, it shows as a negative result in those figures. Because most of the observed changes became more significant over time, I report the differences between the measured consumption and counterfactual consumption in 2007.

4.7.1 Question One: Household Infrastructure

I would like to assess the importance of infrastructure change through new construction on core, periphery, and the citywide average of residential water consumption. Newer houses have, on average, larger living areas (Figure 4-8), more plumbing fixtures (Figure 4-9A), and more bedrooms (Figure 4-9B), which implies that the changes that occurred in these variables compared to a 1996 baseline caused an increase in average household consumption. Pools are associated with higher water consumption and pool prevalence declined in both the core and periphery (Figure 4-10). Consequently, the changes that occurred in pool ownership rates, relative to the 1996 baseline must have caused a decrease in residential water consumption. I check the two groups of characteristics both together and separately.

I consider three scenarios. Scenario 1A holds the indoor living area, number of plumbing fixtures, and number of bedrooms constant at 1996 levels. Scenario 1B holds pool prevalence constant at 1996 levels. Finally, Scenario 1C combines 1A and 1B, holding all major household infrastructure characteristics in the regression constant at 1996 levels[5].

Figure 4-22 shows the annual difference between the actual level of consumption and the three counterfactual scenarios addressing question 1. The magnitude of influence for both the indoor characteristics and pools are significantly smaller in the core than in the periphery because there was much less construction in the core to cause changes in infrastructure characteristics. In Scenario 1A, increases in indoor living area, number of plumbing fixtures, and bedrooms lead to an increase in consumption of 330 gallons in the core and 980 gallons in the periphery. In Scenario 1B, declines in swimming pool prevalence lead to a decrease in per capita consumption of about 50 gallons per household per month in the city core and about 390 gallons per month in the periphery. In Scenario 1C, the extra influence of larger changes in average indoor characteristics is counterbalanced by larger changes in pool prevalence, and so the combined influence of all household infrastructure characteristics in the core and periphery is similar: a change of 390 gallons per household per month in the periphery compared to 280 in the core by 2007. For household infrastructure, the same factors are driving changes in per capita consumption, but the effect of both pools and indoor characteristics is much larger in the city periphery than in the core. Because they influence changes in opposite directions, the total effect is relatively small and of similar magnitude in both the core and periphery.

[5] Tracts with zero population in 1996, which are all in the city periphery by design, are assigned the mean value of that variable for tracts in the city periphery. This value should represent the "typical" household in the city periphery at 1996.

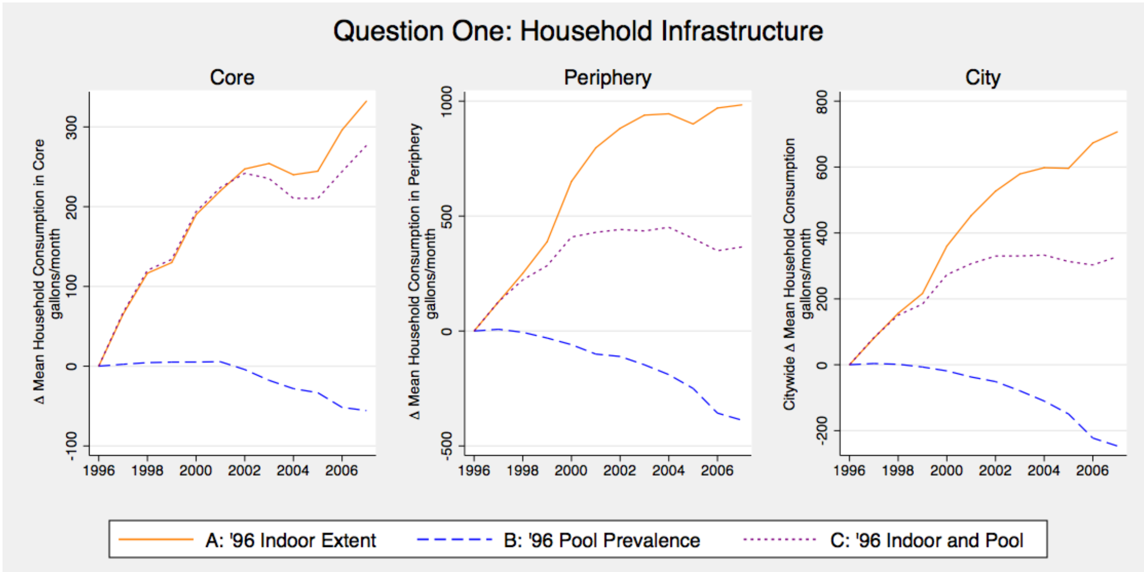

Figure 4-22. This figure shows the difference between the actual consumption and expected consumption under the three counterfactual scenarios addressing question one, where positive values indicate that the infrastructure changes that occurred between 1996 and 2007 caused higher consumption. In both the core and periphery, changes in indoor characteristics lead to higher consumption, while changes in pool ownership rates lead to lower consumption. In 2007, average June household consumption in the city core was 21,000 gallons.

4.7.2 Question Two: Vegetation Change

I would like to estimate the importance of changes in average vegetation area per household on household water consumption. To do this, I need to simultaneously consider the role that total outdoor area has on household consumption. I consider three scenarios. In Scenario 2A, the average percentage of vegetation per lot is held constant at the 1996 levels, while the mean lot area varies as it actually occurred. In Scenario 2B, the average percentage of vegetation per lot varies as it actually occurred, while the mean lot area is held constant at 1996 levels. Finally, in Scenario 2C, both vegetation percentage and lot area are held constant at 1996 levels[6]. The area of dirt is defined to be the difference between the outdoor area and the area of vegetation assumed in each scenario.

[6] Tracts with zero population in 1996 have no 1996 value for vegetation area or lot area, and so like in Question One, these tracts are assigned the mean value of that variable for tracts in the city periphery.

The mean lot size in the core stayed nearly constant, while the mean lot size in the periphery declined by almost 20% during the study period, as shown in Figure 4-13. The share of vegetation per lot declined in both the core and periphery, but it declined more in the core than in the periphery (Figure 4-12). The regression coefficients on dirt and vegetation area are both positive, but the total levels of each variable must move in opposite directions by definition, so it is not immediately obvious what direction the total influence on household water consumption is expected to be.

As shown in Figure 4-23, in the city core, measured average household consumption is about 400 gallons per month lower than what is predicted if vegetation levels had stayed at the measured 1996 values as in Scenario 2A and 2C. This shows that the decline in vegetation percentage that did actually occur between 1996 and 2007 caused a decrease in average household consumption in the core of about 400 gallons per month relative to the baseline scenario of no change in the vegetation percentage. The 2007 difference between maintaining lot area at the 1996 levels and the measured level is about 100 gallons per month. It is small because there was little new construction in the core, so there were only very small changes in lot area between 1996 and 2007. This means that in the city core, changes in the area of vegetation per lot did drive a physically meaningful decline, about 2.3% of total consumption, while changes in lot area caused a change of only about 0.4%.

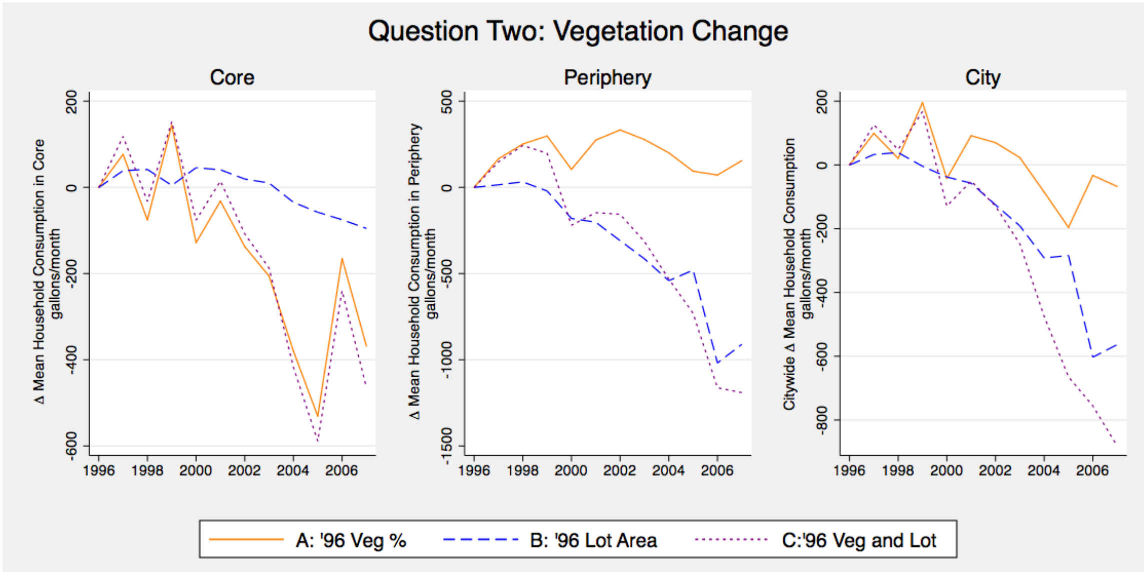

Figure 4-23. This figure shows the difference between the actual consumption and expected consumption under the three counterfactual scenarios addressing the role of vegetation change in household consumption, where positive values indicate that the infrastructure changes that occurred between 1996 and 2007 caused higher consumption. In the city core, changes in the area of vegetation and lot area lead to declines in household consumption, while in the periphery, vegetation area changes drove a small increase in consumption and lot area changes drove lower consumption.

As shown in the periphery panel of Figure 4-23, in the city periphery measured average household consumption is about 50 gallons per month higher than what is predicted if vegetation levels had stayed at the measured 1996 values as in Scenario 2A. This shows that the changes in vegetation intensity that actually occurred in the periphery caused an increase in household consumption compared to the 1996 baseline. In Scenario 2B and 2C, lot sizes are held at the 1996 baseline level, and both scenarios show that changes in lot area caused a decline in household consumption of about 1000 gallons per month. Thus, in the city periphery, lot area was a primary driver of the observed decline in household consumption, while vegetation change did not matter as much. Finally, over the city as a whole, lot area played a larger role in Las Vegas' decline in household water consumption than changes in vegetation intensity did because of the periphery's growing population.

4.7.3 Question Three: Population Growth and New Construction

The number of active accounts in Las Vegas nearly doubled between 1996 and 2007. This new population drove an enormous increase in the number of residential structures in the same period, and a consequent decrease in the average age of structures in the city. Figure 4-18 shows that newer homes consume significantly less water than older homes. They are likely to make use of the latest appliance technology and plumbing fixtures, have had less time for the pipes to develop leaks, and also are more likely to be influenced by the conservation policies that target new construction. I would also like to test the physical importance of these changes in the effect of different vintages within the Las Vegas housing stock. In Scenario 3A, I test the importance of new construction on Las Vegas consumption through its effect on housing vintage by assuming all parcels constructed after 1996 are built with 1992 to 1996 vintage characteristics.

New construction was primarily located on previously vacant land in the city periphery, and so the new population moved into the city periphery rather than the city core. Citywide average household consumption is a weighted average of the core and periphery, so as the population in the periphery grows, the periphery's importance in the citywide average also grows. Households in the periphery consume less water on average than households in the city core and so the additional share of population in the periphery in later years caused a decline in citywide average consumption. I quantify this effect using scenario 3B, where I hold the relative weight of each tract at its 1996 level through the entire study period. This is equivalent to imagining what would have occurred if all new population was spatially distributed among the existing 1996 population rather than being disproportionally located in the city periphery. Finally, in Scenario 3C, I estimate current consumption compared to what would have occurred if both the vintage effects and population distribution remained as they were in 1996.

The prevalence of different vintages in Scenarios 3A and 3C is shown in Figure 4-24, in comparison to the measured values shown in Figure 4-7. The difference between the core measured and counterfactual scenarios is very small compared to that difference in the periphery. Figure 4-25 shows the difference in average household consumption between the measured and counterfactual scenarios for Scenarios 3A, 3B, and 3C.

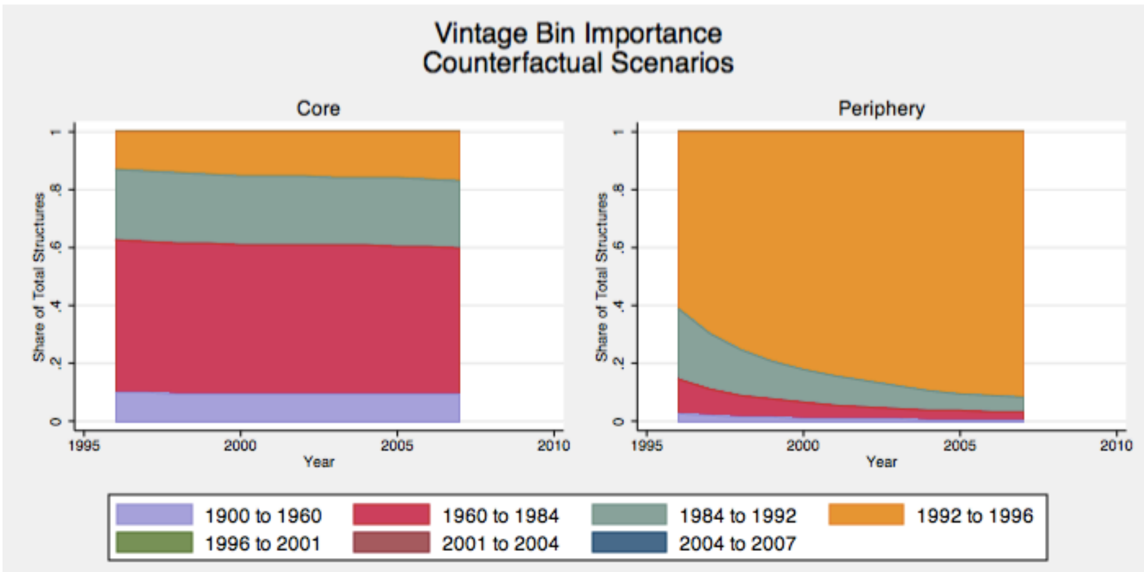

Figure 4-24. A time series of vintage bin importance used for the counterfactual Scenarios 3A and 3C. For comparison, Figure 4-7 shows the true values.

In Scenario 3A, I consider what consumption would have been if new construction had not gotten so much more water efficient- instead keeping the water efficiency typical of homes constructed between 1992 and 1996. In the city core, I find that increases in the water efficiency of new construction caused a decrease in average household consumption of 270 gallons per month. The magnitude of this effect is notable, because it is driven by very little new construction. In the city periphery, increases in the water efficiency of new construction caused a very large effect on household consumption: about 3,250 gallons of water per month, which is 18% of the average households consumption.

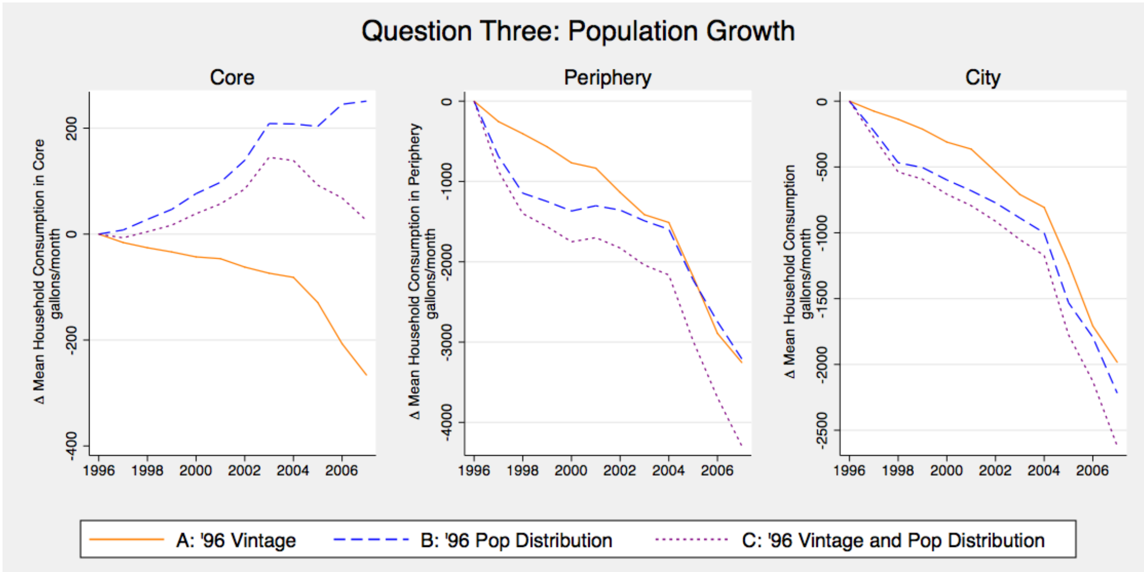

Figure 4-25. This figure shows the difference between the actual consumption and expected consumption under the three counterfactual scenarios addressing the role new construction played in influencing household consumption, where positive values indicate that the infrastructure changes that occurred between 1996 and 2007 caused higher consumption.

In Scenario 3B, the change in the relative weights of each tract that occurred between 1996 and 2007 caused a small increase in household consumption in the city core. There was little new construction in the city core, but the new houses that were constructed there must have been located in tracts with higher than average consumption in order to cause an increase in the core's average consumption.

The opposite was the case in the city periphery: newer houses were located in tracts with lower than average consumption, and so the changed spatial distribution led to a reduction in average household consumption of about 3,210 gallons per month. Finally, Scenario 3C combines the population distribution and vintage changes in Scenarios 3A and 3B. In this scenario, the combinations of increased water efficiency in new construction and changes in the location of population across the city caused household consumption to increase by a very small amount in the city core, and decrease by 4,290 gallons per month in the periphery, 23% of the average households consumption. The combined effect of population in new locations and increased water efficiency in new construction is by far the largest effect of the three questions posed.

To test the combined explanatory power for all three questions I run a final scenario, number 4, which combines the counterfactual changes made for Scenarios 1C, 2C, and 3C. In Scenario 4, household infrastructure, pool prevalence, lot size, vegetation percentage, and housing vintage remain at the 1996 level for each tract. Additionally, the relative weight of each tract is held at the 1996 levels, simulating the case where the new population moved into the city with the same spatial distribution as existed in 1996.

The results of Scenario 4 are shown in Figure 4-26. This scenario clearly shows that nearly the entire citywide decline in household consumption that is explainable through the effects considered in Questions 1, 2 and 3 operates on the city periphery. There are still significant unexplained factors that influence household consumption: the temporal dummy variables shown in Figure 4-17 area associated with a reduction in household consumption of about 20%. The effect of the explainable factors on total consumption in the city core is very small—about 150 gallons per household per month, compared to about 3,990 gallons per month in the periphery. The citywide reduction in household consumption due to these factors is 2,700 gallons per household per month. This is a significant water savings across the entire city. Between 1996 and 2007, in the city core, consumption declined by 7,720 gallons per month, while Scenario 4 only explains a decline of 150 gallons per month, or about 2% of the total decline observed. In the city periphery, consumption declined by 9570 gallons per month, while Scenario 4 can explain a decline of 3,990 gallons per month, about 40% of the total observed decline in consumption. Finally, the citywide average household consumption declined by 9,190 gallons per month, and Scenario 4 can explain a decline of 2,700 gallons per month, or about 30% of the total.

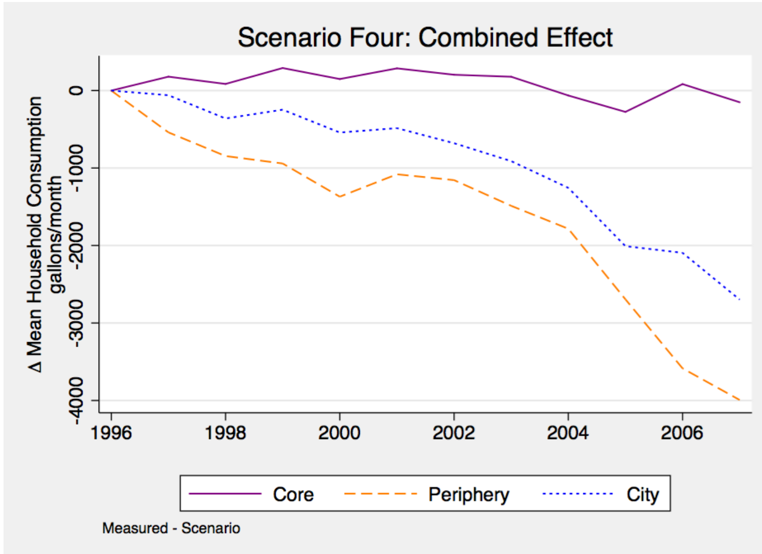

Figure 4-26. Differences between actual and hypothetical consumption for Scenario 4, summarizing the combined effect of all three questions considered.

Table 4-5 shows a summary of the 2007 difference between the measured average household consumption and the average household consumption under each scenario. The factors explored in these scenarios can explain an important share of the observed decline in household consumption in the city periphery, and by extension, an important share of the decline in the citywide average household consumption. Even when all of the scenarios are combined, they explain very little of the observed decline in household consumption in the city core, partially because the effects of household infrastructure cancel out the effects of vegetation area change. These questions can explain a large share, but not the entire observed decline in household consumption in the city periphery.

Table 4-5: Summary of Counterfactual Scenario results, showing the 2007 difference between the measured household consumption and household consumption under each scenario. Due to the semi-log functional form and interaction terms, the different scenarios do not sum to the total effect.

	Core (Gallons per household per month)	Periphery	Citywide
1C: Indoor + Pools	280	370	330

2C: Veg + Lot	-460	-1190	-880
3C: Vintage + Population	30	-4290	-2620
4: Combined Effects	-150	-3990	-2700

4.8 Conclusions

These scenarios can explain about 30% of the observed decline in household consumption across the entire city. That leaves a significant portion of the change in household consumption that is not explained by observable changes in the capital stock. In this model, these changes are wrapped into the temporal dummies, which include the effect of any non-spatially distinguishable factors like citywide policy changes, price changes, and demographic or behavioral changes. Changes in the size of the unexplained part line up with key policy changes, especially the suite of new policies that were implemented in 2004. Thus, the key story here is that the suite of policy changes that Las Vegas implemented in order to conserve water probably did play a significant role in reducing per capita consumption in the city.

Figure 4-21 shows that expected consumption for a household living in the typical home constructed in 2007 is about half what would be expected for a household living in a home constructed in 1996. These savings from new construction are partly due to naturally occurring changes in the water efficiency of appliances, smaller lot sizes, and other economically driven choices, and area also likely to be partially driven by conservation policies that influence the water efficiency of new construction. The results of the counterfactual scenarios clearly demonstrate that lower consumption from newly constructed homes is the single biggest measureable factor driving changes in average household water consumption in Las Vegas.

As a result, I can conclude that the biggest explainable driver of the observed changes in Las Vegas's average household consumption were the changes in housing vintage and population location that were driven by population growth in conjunction with much more water efficient new construction. These factors only had a meaningful influence on consumption in the city periphery, but the share of population in the periphery grew to nearly 70% of the total population, so the citywide effect was also large. *In the city core, the largest explainable driver of changes in household consumption is the observed decline in vegetation area. This suggests that policies to reduce turf do have significant potential to influence household consumption even in established cities and neighborhoods, although in Las Vegas, the magnitude of the effect is small compared to the effects from population growth.*

5 ESTIMATING THE EFFECTIVENESS OF THE WATER SMART LANDSCAPING PROGRAM

5.1 Introduction & Problem Background

There has been a great deal of research focused on determining the price elasticity of water (Espey, Espey, and Shaw 1997; Arbues, Garcia-Valinas, and Martinez-Espineira 2003; Dalhuisen et al. 2003; Worthington and Hoffman 2008a), but it is rare for water districts and cities to change water prices in response to concerns about water scarcity (Olmstead and Stavins 2009), whether that scarcity is in response to drought or just long term imbalances between available supply and expected water demand. The literature finds a wide range in the efficacy of water conservation strategies. Mandatory programs typically have larger effects than voluntary programs (Kenney, Klein, and Clark 2004; Grafton et al. 2011), but not all programs designed to conserve water actually have the intended effect (Castledine et al. 2014). Infrastructure upgrades have significant potential for water conservation, but those gains can be lost due to behavioral offsetting (Campbell, Johnson, and Larson 2004). Thus, quantitative analyses of the effects of water conservation programs are important to ensure that the water district's demand management goals are met.

In this chapter, I estimate the specific contribution of the WSL program to citywide reductions in household water consumption, using a pair of regressions aimed at estimating the effect of the WSL program on vegetation area, and the combined effect of both vegetation area and WSL directly on household water consumption. I find that the short-run savings from the WSL program are about 82 gallons of water saved each June for each meter of landscape converted under the WSL program, and that long run savings are about 32 gallons per square meter. In the only other published assessment of the WSL program, Sovocool, Morgan and Bennett (2006) estimate that the savings from WSL conversions are about 95 gallons per square meter each June, and they do not find that the water savings effects of the WSL program attenuate as the landscape ages. Based on my best estimates of the long-run WSL water savings and the cost of WSL rebates, I estimate that for every $4,850 the SNWA spent on subsidizing residential landscape conversions before 2007, enough long run water savings were generated to support one additional household living in a newly constructed home.

5.2 Spatial and Temporal Trends in WSL and Vegetation Area

Our analysis relies on a subset of the data described in detail in Chapter 4. I use only 2001 to 2007, and only tracts within the city core. Extensive new construction in the city periphery drove infrastructure changes that may be correlated with WSL uptake. For example, many of the Las Vegas policy changes in the late 1990s and early 2000s influenced the area of vegetation installed with new construction, and the results of Chapter 4 show that houses of newer vintage consume less water. These new construction based effects may be large enough to overshadow the effects of the WSL program, and so I use only the stable city core for my primary analysis. The counter-factual analysis performed in Chapter 4 demonstrated that landscape change was a significant contributor to water consumption change in the city core, while other observable factors that were operating in the periphery weren't relevant in the core. Additionally, an F-test performed on the Chapter 4 model suggests that the relationship between vegetation and household consumption in the core is structurally different than it is in the periphery. Unless otherwise noted, all figures and data presented here are drawn from only the city core in order to avoid the confounding effect of the changes in water efficiency associated with new construction. I also limit the length of time used in this analysis. I include only years 2001 to 2007 in order to capture the effects of the WSL program when it was a large, citywide program, and exclude analysis of the WSL program between 1996 and 2000, when it was a very small pilot program and rebates were much lower. During WSL's pilot phase, the program may have qualitatively different effects than it did as a citywide program, because of selection effects on participation and different screening and monitoring processes. The history of the WSL program is discussed in detail in Section 1.2.1 on page 10.

Our analysis uses records of household water consumption, weather, lot size, WSL conversion, and the Matched Filtering Vegetation Index (MFVI) generated in Brelsford and Shepherd (2014). The LVVWD collected data on household water consumption, which is averaged to the census tract level in order to protect resident privacy. Average household consumption declined by 22% in the city core, and 26% in the city periphery between 2001 and 2007. Section 4.4 provides more detailed descriptions of the spatial and temporal trends in household water consumption. Weather data, including temperature and precipitation as described in Section 4.4.2 is interpolated from 6 weather stations in the Las Vegas area using the PRISM climate model (Di Luzio et al. 2008). There is no clear time trend in precipitation patterns, while there is a very weak trend of increasing minimum temperature in the city core. Lot size data are derived from the Clark County Assessor's Office records. In both the city core and periphery, average household lot size declined, but the decline was very small in the city core, because there was very little new construction. Patterns in lot size and composition are described in detail in Section 4.4.2.

5.2.1 WSL

SNWA's conservation department provided data on the land area converted under the WSL program. WSL is measured as the area of turf converted per account in between the current and previous June, and aggregated to the census tract. In each year, the annual conversions in the core and periphery follow similar patterns, and are primarily driven by changes in recruitment effort for the WSL program. The WSL program began as a small pilot program in 1996. About 71,000 square meters of turf were converted during this pilot phase. There was almost no participation in the WSL program in 2000, but it was restarted and rebranded as a formal citywide program in 2001. Program participation increased dramatically when the rebate per square foot increased from $0.40 to $1 in February 2003. The second big wave of participation occurred in 2007, 2008, and 2009, after the rebate increased from $1 to $2 per square foot in December 2006.

About 1.4 km^2 (340 acres) of turf in the city core, and 0.8 km^2 (200 acres) of turf in the city periphery were converted under the WSL program between 1996 and 2007. This is about 1.8% of all outdoor single-family residential land in the city core, and about 0.8% in the periphery. The 25th to 75th percentile shaded area in Figure 5-1 compared to the solid line for the mean WSL conversion shows that the conversions across tracts in the city core are highly right-skewed. It would be natural to think of this figure as representing the average WSL conversion area for households that participated in the WSL program, but the only data available is average WSL conversions across all households in the tract, even though only some households in the tract participated in the program. Thus the figure shows the distribution of average conversions for all households in the tract, across all tracts in the city core.

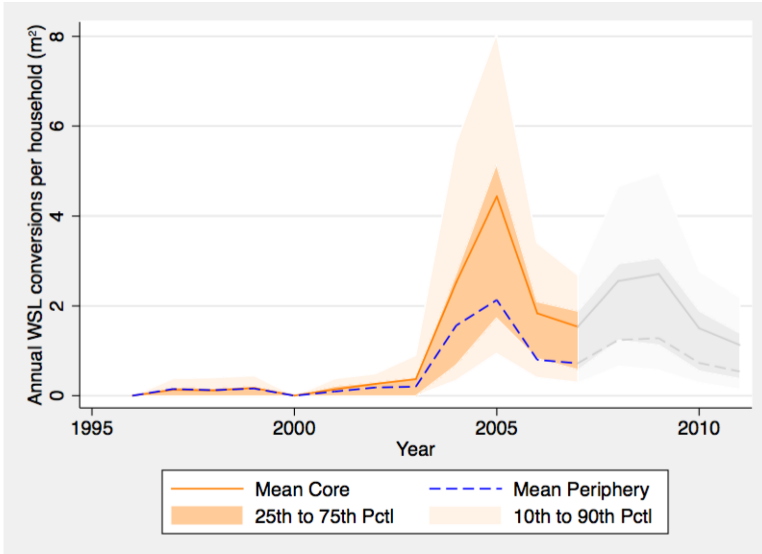

Figure 5-1. Annual average WSL conversions per household in the city core and periphery. Years plotted in grey are shown for reference but are not included in this analysis.

Figure 5-2 shows the spatial distribution of cumulative WSL conversions by tract over the entire history of the WSL program. The median total area converted is about 4 m^2 per household, while the mean is about 8 m^2 per household. In the city core only, the median converted area per household is 8 m^2, and the mean is 11 m^2. In the city core, the mean lot size is about 750 m^2. The mean lot size for the city as a whole is 723 m^2. By any metric, conversion levels in the city core are higher than in the periphery, both in total area and in percentage of the lot area converted. There are clear spatial clusters of high or low investment in WSL conversions. The northeast part of the service area has less investment in WSL conversions, as do the few tracts in the east part of the city along the Las Vegas wash. The core neighborhoods to the west of the city center had much higher than average investments in WSL conversions. Finally, there was almost no WSL conversion in the most newly developed area of the periphery on the western edge. This is not surprising, as most of the houses built there were constructed under city development policy that placed strict limits on the amount of turf permitted in new construction, and are also new enough that there has not been much time for landscape changes to accrue.

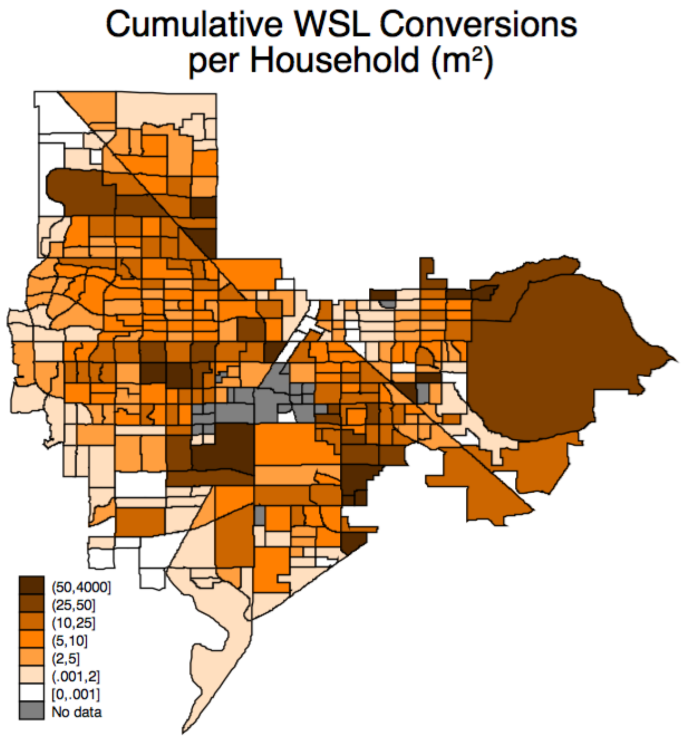

Figure 5-2. This figure shows the spatial distribution of all WSL conversions that occurred between 1996 and 2007. Tracts in the city core are shown in Figure 4-3.

It is plausible that the water savings effects of WSL landscape conversions attenuate as the landscape ages. This could occur because of program non-compliance, vegetation requiring more water as it matures, irrigation system breakdown, residents gradually reverting to their pre-conversion irrigation behavior, new residents in the home, or other behavioral offsetting effects. To test the durability of water savings from WSL conversions separately from savings in the first year of the converted landscape, I create two separate measures of WSL participation. The first, WSL, measures WSL conversions in the current year. The second, lagWSL, measures all prior WSL conversions excluding those in the most recent year, measured from June to June. This is a one year lagged measure of cumulative WSL conversions. Thus, the sum of the two measures of WSL is equal to cumulative WSL conversions. I use a single lagged measure of cumulative WSL conversions because our short time series and the pattern of WSL adoption does not allow for more disaggregated specifications.

Figure 5-3 shows the distribution of cumulative WSL conversions through time. The significant increase in uptake beginning in 2003 is quite clear. The grey area is shown for context- WSL conversion uptake continued at a rapid pace, and by 2011, total conversions per household were about twice what they were in 2007.

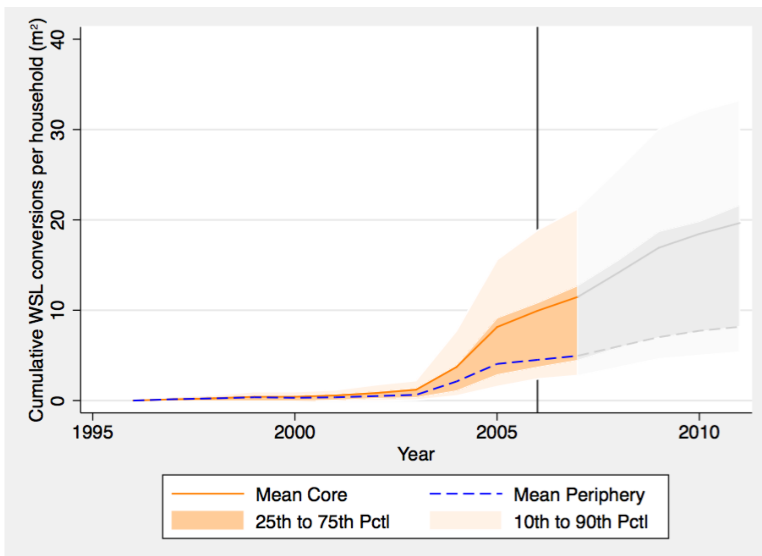

Figure 5-3. This figure shows the distribution of cumulative WSL conversions per household. The vertical line at 2006 shows when the lagged measure of cumulative WSL, used to test the durability of WSL savings, stops being included in the dataset.

5.2.2 Vegetation

The Matched Filter Vegetation Index (MFVI) is developed from satellite imagery as described in Chapter 3, and is interpreted as the average area of vegetation per parcel, in square meters. This index captures all green vegetation, not just turf. Variations in vegetation intensity are partially wrapped into the MFVI: that is, a golf course fully covered in turf is likely to have a higher MFVI than an equivalent area of less intense greenery like desert plants. Consequently, systematic conversions from turf to less green vegetation types are likely to cause decreases in the estimated MFVI, even if the total irrigated area remains the same[7]. Despite these caveats, I believe that MFVI is closely related to the true subpixel vegetation area.

Within the city core, there is a small but meaningful decline in the average MFVI per household. Figure 5-4 shows that there have been declines in MFVI in all measures of the MFVI distribution across tracts in the city core. MFVI is interpreted as the mean vegetation area per household. In Figure 5-4, I compare the quartiles of MFVI across all tracts after frequency weighting each tract by its population in each year. In the periphery, the spread in MFVI increased during the study period, but the mean and median measures still declined. MFVI is significantly smaller in the periphery than in the core over the entire study period, even though the declines in MVFI in the core are larger than in the periphery.

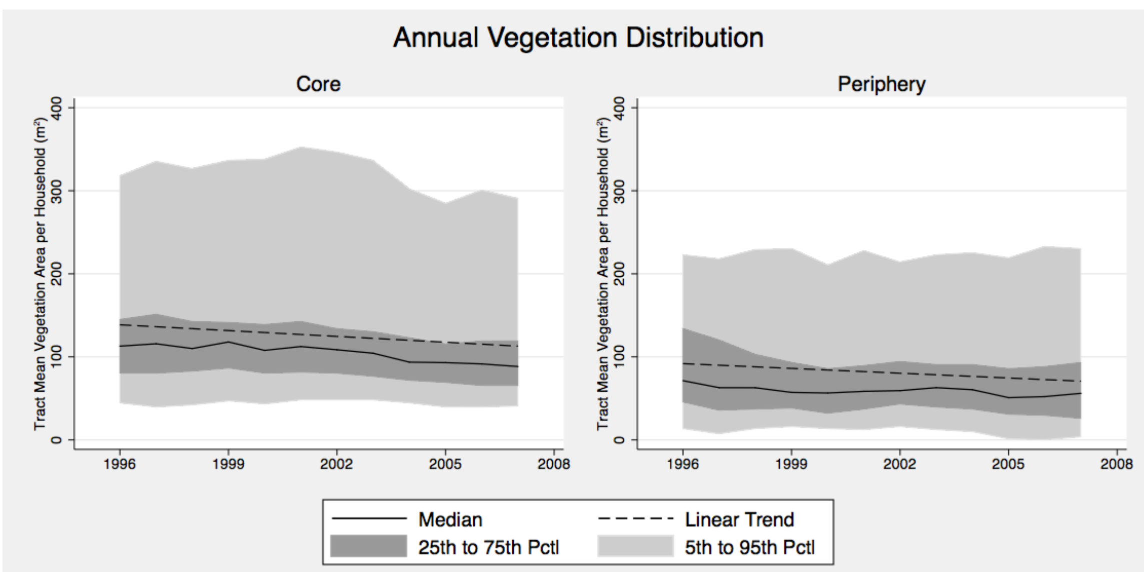

Figure 5-4. A time-series of the population weighted distribution of the vegetation area per household in the core and periphery shows that there was a small but significant decline in average vegetation area per household in the city core. In periphery, the decline was smaller, and the distribution of vegetation area across tracts became wider.

[7]Unfortunately, separating the effect of sub-pixel changes in vegetation intensity from changes in vegetation area is not easily testable from the available data.

Figure 5-5 shows the spatial distribution of change in MFVI during the main years of analysis for this chapter. Most tracts, especially in the city core, show a significant decline in the area of vegetation, while newly developed areas on the west side of the city had significant increases in green area per household.

The WSL program influences *both* the total area of vegetation and the greenness, or intensity of the remaining vegetation. WSL influences the total area of vegetation because significant areas of vegetation are removed and converted to rocks, mulch, and other non-vegetated surfaces. WSL also influences the greenness, or intensity of the remaining area of vegetation because a post-WSL conversion landscape must have changed from intensely green turf, to some set of low water use plants. This means that the change in MFVI will be slightly greater than the true change in vegetation area due to the lowered "greenness" of the remaining vegetation. Unfortunately, it is not possible to separate the effect of WSL's direct influence on true vegetation area and WSL's effect on the green intensity that is also wrapped into MFVI.

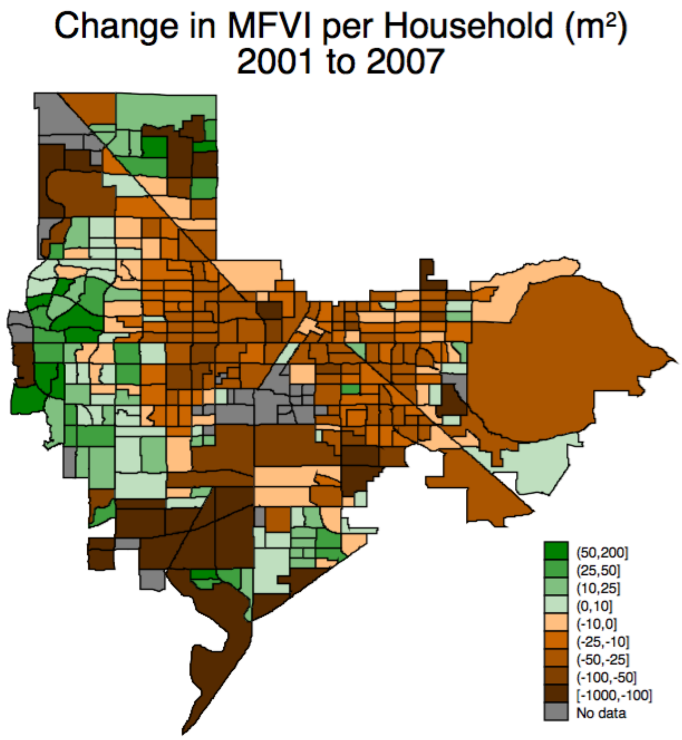

Figure 5-5. In most of the study area, average vegetation area per household declined between 2001 and 2007. The biggest area with consistent increases in vegetation area was the western edge of the city. Tracts in the city core are shown in Figure 4-3.

5.3 Methods

Figure 5-6 shows a path diagram of the potential relationships between the current year's WSL conversions, previous years' WSL conversions, MFVI, and current household water consumption. WSL conversions in both this year and in previous years should influence MFVI through the direct effects of the landscape conversions, and through their influence on vegetation intensity. These effects are represented in relationships 1 and 3, respectively. The net effect of prior years' WSL conversions on MFVI may be smaller than the effect of current year's WSL conversions. The MFVI for a given landscape may increase as the installed plants grow and mature. This effect may be exacerbated by paid landscapers whose main incentive is to maintain a lush, oasis style landscape and consequently overwater because they see no individual benefit from water conservation. Finally, although there is little evidence that this occurs, program non-compliance could influence the long-term effect of WSL conversions on the MFVI. If some homeowners choose to revert to a more mesic landscape, the estimated effect of older WSL conversions on MFVI would be smaller than newer conversions.

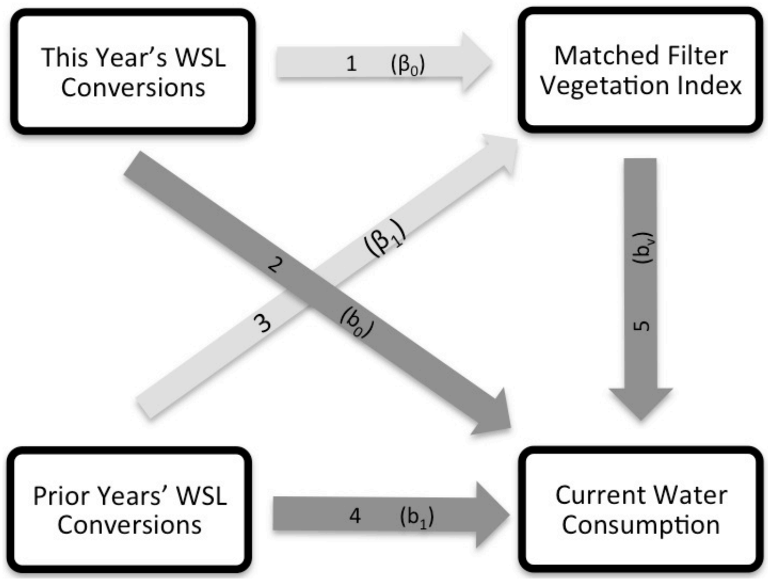

Figure 5-6. This schematic diagram shows the relationships between WSL conversions, MFVI, and water consumption. The light grey arrows are estimated through the vegetation regression, while the dark grey arrows are estimated through the water regression.

In addition to estimating the effect that current and previous WSL conversions have on MFVI, I also believe that WSL can influence water consumption directly, independent of it's effect on measured vegetation area. The distinct role of WSL as an explanatory variable in the model, separate from it's effect on the vegetation index, is to account for aspects that aren't captured by the "greenness" measure alone. Because WSL requires converting some of a mesic landscape to non-vegetated surfaces, and some of the landscape to less water intensive plants, a landscape conversion will necessarily change the composition of the remaining vegetation area, and is also very likely to change the water intensity of the remaining vegetation, thus reducing the water needed to maintain a given MFVI level. This effect is estimated through relationship 2 for current WSL conversions, and 4 for previous WSL conversions. Again, it seems reasonable to estimate the effect of historical WSL conversions separately from the effect of current year WSL conversions, because there may be some degradation in the effect of conversions directly on water consumption. During many WSL landscape conversions, automatic irrigation systems are upgraded or recalibrated. As these new irrigation systems age, the irrigation system may become less efficient, thus increasing the water consumption required to maintain the landscape. Finally, relationship 5 estimates the effect of the current estimate of MFVI, which can be explained in part by both current and historical WSL conversions, on household water consumption.

I estimate the path diagram in Figure 5-6 using two separate regressions. First, I estimate a "Vegetation" regression, with MFVI as the dependent variable, and current and historical WSL conversions in the set of right hand side variables. Second, I estimate a "Water" regression, with both measures of WSL conversions, and also MFVI in the set of right hand side variables. Relationships 1 and 3 are estimated in the Vegetation regression, while relationships 2, 4, and 5 are estimated through the Water regression.

I include parallel sets of right hand side variables for the Vegetation regression and the Water regression. Each tract has its own idiosyncratic level of vegetation or water consumption, and that level may be influenced by unmeasured factors that are also correlated with some of the right hand side variables, especially the variables of interest- current and historical WSL uptake[8]. In addition to tract fixed effects, I include temporal dummies to control for unobserved factors that vary through time and influence both vegetation area or water consumption and the right hand side variables. This could include broad citywide trends like the 2004 drought and drought policy response, and

[8] Additionally, a Hausman test on fixed effects and random effects models rejects the null hypothesis that the random effects estimator is consistent- further supporting the use of tract fixed effects.

also other time varying factors like social preferences around vegetation type and extent, or changing water consumption patterns.

I include lot size as an explanatory variable because lot area bounds the potential area of vegetation and also potential WSL conversion. The correlation between MFVI and lot area is 0.62. In part, this is because there is a direct physical relationship between the potential area of vegetation per household and the outdoor area per household, and in part, the high correlation occurs because I construct MFVI by finding the percentage of the residential area that has vegetation from satellite data, and then multiplying the vegetation percentage by lot size to estimate vegetation area per household.

Finally, the results of Chapter 4 show that temperature and precipitation have meaningful influences on household water consumption. Temperature and precipitation may influence the MFVI through heat stress on vegetation, which would lower the greenness of an area, or precipitation, which may increase both the greenness and total area of vegetation. Temperature and precipitation may also both influence water consumption through their effect on irrigation behavior, with higher temperatures encouraging residents to water more, or more rainfall encouraging residents to water less.

To demonstrate that my results are broadly robust to variations in the econometric specification, and level of econometric control, I estimate the Vegetation and Water regressions using three related models. The first model's vegetation regression is shown in Equation 8 and water regression is shown in Equation 9. These two equations each use tract level fixed effects to control for a tract's base level of vegetation or water consumption, and are referred to as Fixed Effects (FE) models. The FE model relies on the assumption that the undifferenced errors are strictly exogenous;

that is, once I have controlled for the unobserved spatial effect ζ_i, there is no correlation between ϵ_{it} and any of the right had side variables at any time.

$$veg_{it} = \alpha + \gamma_t + \zeta_i + \beta_0 WSL_{it} + +\beta_1 lagWSL_{it} + \beta_2 lot_{it} + \beta_3 lot_{it}^2 + \beta_4 temp_{it} + \beta_5 temp_{it}^2 + \beta_6 precip_{it} + \epsilon_{it} \quad \mathbf{8}$$

$$water_{it} = a + y_t + z_i + b_v\, veg_{it} + b_0 WSL_{it} + b_1 lagWSL_{it} + b_2 lot_{it} + b_3 lot_{it}^2 + b_4 temp_{it} + b_5 temp_{it}^2 + b_6 precip_{it} + \epsilon_{it} \quad \mathbf{9}$$

The second model's vegetation regression is shown in Equation 10 and water regression is shown in Equation 11. These equations take the first difference (FD) of the corresponding FE model. The FD model relies on an assumption of sequential exogeneity, which is formally weaker but practically similar to the strict exogeneity assumption of the FE model. The FE and FD model should yield similar results.

$$\Delta veg_{it} = \alpha + \gamma_t + \beta_0 \Delta WSL_{it} + \beta_1 \Delta lagWSL_{it} + \beta_2 \Delta lot_{it} + \beta_3 \Delta lot_{it}^2 + \beta_4 \Delta temp_{it} + \beta_5 \Delta temp_{it}^2 + \beta_6 \Delta precip_{it} + \epsilon_{it} \quad \mathbf{10}$$

$$\Delta water_{it} = a + y_t + b_v\, \Delta veg_{it} + b_0 \Delta WSL_{it} + b_1 \Delta lagWSL_{it} + b_2 \Delta lot_{it} + b_3 \Delta lot_{it}^2 + b_4 \Delta temp_{it} + b_5 \Delta temp_{it}^2 + b_6 \Delta precip_{it} + \epsilon_{it} \quad \mathbf{11}$$

Finally, the third model extends the FD model by adding tract fixed effects, as shown in Equation 12 and Equation 13. Functionally, this gives each tract its own time trend in vegetation area or water consumption in addition to the differencing in the FD model that subtracts out time invariant factors. As in Chapter 4, the base unit of analysis is the census tract, and each observation is weighted by the number of active accounts. This ensures that each household is given equal weight in the analysis.

$$\Delta veg_{it} = \alpha + \gamma_t + \zeta_i + \beta_0 \Delta WSL_{it} + \beta_1 \Delta lagWSL_{it} + \beta_2 \Delta lot_{it} + \beta_3 \Delta lot_{it}^2 + \beta_4 \Delta temp_{it} + \beta_5 \Delta temp_{it}^2 + \beta_6 \Delta precip_{it} + \epsilon_{it} \quad \textbf{12}$$

$$\Delta water_{it} = a + y_t + z_i + b_v\, \Delta veg_{it} + b_0 \Delta WSL_{it} + b_1 \Delta lagWSL_{it} + b_2 \Delta lot_{it} + b_3 \Delta lot_{it}^2 + b_4 \Delta temp_{it} + b_5 \Delta temp_{it}^2 + b_6 \Delta precip_{it} + \epsilon_{it} \quad \textbf{13}$$

In the year that WSL is removed, β_0, the coefficient on MFVI, should be between 0 and 1 square meter for each square meter of WSL conversion. WSL turf conversions should not *increase* the area of vegetation, and it is not possible to cause the removal of greater area of vegetation than the total converted area. Given that MFVI conflates vegetation area and vegetation intensity to a certain extent, it is possible that a large conversion from very intensely green vegetation to no vegetation or very low intensity vegetation could result in MFVI changes that appear greater than the total vegetation area removed. This is not expected to be a widespread concern since the WSL program has always required newly converted landscapes to be designed such that there will be at least 50% live vegetation cover at maturity. Therefore, I expect the net area of vegetation removed to be close to half of the total WSL conversion area, estimated through β_0. Cacti and other xeric landscapes take time to mature, and so I expect that the area of vegetation in a post-WSL conversion landscape will increase after the initial installation.

5.4 Results

To test if the idiosyncratic residuals are spatially independent, I follow Hoechle's implementation of Pesaran's test for cross-sectional dependence (2007). The results show that I should reject the null hypothesis of spatial independence, and assume spatial dependence when choosing the type of standard errors to use in the full regressions. Thus, I present Driscoll and Kraay (1998) standard errors for the Vegetation and Water regressions because these standard errors are robust to general forms of both spatial and temporal dependence. As discussed in Chapter 4, I use a regression weighted by accounts to ensure that each household is given equal weight, rather than equally weighting the census tracts. The results of the three Vegetation regressions are shown in Table 5-1, and the results of the three Water regressions are shown in Table 5-2.

5.4.1 Vegetation Regression Estimation

Table 5-1: Vegetation Regression Results

	FE	FD	FD + trend
(Δ)[9] Annual WSL	-0.381***	-0.282***	-0.313**
	(0.0387)	(0.0480)	(0.103)
(Δ) Last Year's Cumulative WSL	-0.000292	0.0294	-0.0228
	(0.0198)	(0.0164)	(0.121)
(Δ) Lot Size (m2)	0.100***	0.0573**	0.0469
	(0.0192)	(0.0169)	(0.0308)
(Δ) Lot Area²	0.0000352**	0.0000482***	0.0000527***
	(0.00000992)	(0.0000114)	(0.0000130)
(Δ) Min June Temp (C)	-10.62	-21.41**	-22.64**
	(12.92)	(7.743)	(6.996)
(Δ) Min Temp²	0.193	0.474*	0.512*
	(0.308)	(0.227)	(0.218)
(Δ) Total June Precip. (cm)	4.030	-8.326	-9.590
	(13.09)	(8.409)	(13.10)
2002 Dummy	-5.176***	-7.498***	-7.580**
	(0.344)	(1.936)	(2.509)
2003 Dummy	-8.148***	-6.242	-6.672
	(0.132)	(3.676)	(4.581)
2004 Dummy	-16.92***	-11.05**	-11.14**
	(0.517)	(2.989)	(3.843)
2005 Dummy	-24.68***	-6.460*	-5.743
	(3.876)	(2.787)	(4.334)
2006 Dummy	-15.08***	-0.361	-2.479
	(1.752)	(12.52)	(14.63)
2007 Dummy	-19.08***	-5.192	-4.554

[9] (Δ) denotes temporal differencing that is only used for the FD and FD + trend models.

	(0.462)	(5.116)	(6.165)
Constant	187.9	2.763	0.664
	(139.6)	(2.850)	(2.971)
Observations	1260	1260	1260
R-squared	0.996	0.383	0.442

Driscoll and Kraay standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

The results of the vegetation regression are generally consistent with expectations. In the FE model, the estimated effect of WSL conversions on household water consumption is -0.38: for every 1 square meter of landscape converted under the WSL program this year; there is a net reduction in estimated vegetation area of about 0.38 square meters. The FD model estimates that the net reduction is 0.28 square meters, and the FD model with tract level time trends estimates a net reduction of 0.31 square meters. These are all consistent with the expectation that WSL conversions reduce the net area of vegetation, and that residents have at least 50% vegetation coverage in the newly converted landscaped.

The effect of last year's cumulative WSL is not significantly different from zero in any of the three models. This is somewhat surprising, as I would expect at least some long-term net reduction in both vegetation area and intensity from WSL conversions. However, the estimate is quite robust to minor changes in the specification aimed at the long-term effects of WSL conversions. If I switch from including all previous WSL conversions to only WSL conversions after the end of the pilot phase, including only WSL conversions from the previous three years either separately or individually, the results are still not different from zero. This strongly suggests that regardless of the exact specification, landscapes with established WSL conversions are indistinguishable from other landscapes from the perspective of the MFVI. This is plausible - SNWA was invested in ensuring that WSL-converted landscapes did not appear to be just plain dirt, and their example gardens have very high vegetation coverage rates. Thus, the long run effects of WSL on water use cannot be traced through MFVI; it must influence water consumption through other mechanisms.

5.4.2 Water Regression Estimation

The main results of the three specifications for estimating the water equations, shown in Table 5-2, are generally consistent in the variables I am interested in estimating, except in the role that vegetation changes play in influencing household water consumption. The effect of annual WSL conversions directly on water consumption, not through WSL's effect on vegetation area, is quite consistent across all three specifications. In the FE model, the effect is about 60 gallons per meter of WSL removed, while in the FD + trend model, it is about 50 gallons. These are well within the range of each model's respective standard errors. In the FD + trend model, as with the parallel vegetation regression, I have removed a great deal of the variance through econometric techniques, and are specifying the estimation results based only on the within-tract, demeaned and detrended variance in water consumption and WSL conversions. In this sense, it is notable that the results are consistent even with this high level of econometric control.

The direct effect of last year's cumulative WSL conversions on current water consumption is also consistent across specifications, and is generally consistent with expectations. The FE model estimates that each meter of WSL conversions that is over one year old reduces household water consumption by 33 gallons per month, while the equivalent FD model estimates savings of 43 gallons per month, and the FD model with time trends estimates savings of about 19 gallons per month. The standard errors on the FD + trend model are quite large, so these estimates do fall within each other's standard errors. This suggests that the long term direct effect of WSL conversions is on the order of half of its short-run effect, something that seems plausible given potential growth in vegetation intensity and potential degradation of water conserving behaviors inspired by the landscape conversion effort.

The estimated effect of changes in MFVI on household water consumption is less robust to different specification choices. The fixed effects model estimates that for each meter of vegetation removed, 59 gallons of water are saved each June. The two first differences models estimate that for each meter of vegetation removed, only about 15 gallons of water are saved. These differences are significant, and may suggest that the assumption of strict exogeneity between the right hand side variables and errors in all different time steps has been violated. This could be further examined by using an instrumental variables regression.

Table 5-2: Water Regression Results

	FE	**FD**	**FD + trend**
(Δ) Veg Area (m2)	58.99***	15.13	13.38
	(11.23)	(13.85)	(14.27)
(Δ) Annual WSL	-59.82**	-56.95**	-49.87
	(18.70)	(15.99)	(32.87)
(Δ) Last year's Cumulative WSL	-32.69***	-43.03*	-18.51
	(8.236)	(21.72)	(40.29)
(Δ) Lot Size (m2)	-11.82**	-7.429*	-3.749
	(3.490)	(3.525)	(3.842)
(Δ) Lot Area ^ 2	0.00728***	0.00337	0.000335
	(0.00144)	(0.00201)	(0.00225)
(Δ) Min June Temp (C)	-2915.8	-5788.6**	-5791.3**
	(3748.9)	(2160.8)	(2230.6)
(Δ) Min Temp ^ 2	65.86	130.2**	130.8*
	(88.54)	(51.91)	(54.52)
(Δ) Total June Precip. (cm)	3125.2**	2669.8***	2796.8***
	(879.2)	(457.3)	(377.4)
2002 Dummy	-830.9***	100.5	55.86
	(93.92)	(132.6)	(176.4)

2003 Dummy	-1429.5***	492.4**	429.3*
	(108.0)	(180.8)	(219.8)
2004 Dummy	-3599.2***	-1391.7***	-1488.9***
	(256.6)	(144.7)	(259.8)
2005 Dummy	-6186.5***	-1746.8***	-1873.5***
	(578.1)	(159.9)	(260.6)
2006 Dummy	-5174.5***	2495.3**	2282.8**
	(1228.6)	(839.0)	(813.8)
2007 Dummy	-4200.1***	2230.5***	2240.1***
	(272.0)	(528.4)	(595.2)
Constant	54452.0	-1224.2***	-1308.5***
	(39019.9)	(159.5)	(262.7)
Observations	1260	1260	1260
R-squared	0.993	0.457	0.527

Driscoll-Kraay standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

5.4.3 Total WSL Effects

In order to calculate the combined effect of WSL on household water consumption through both mechanisms shown in Figure 5-6, I substitute Equation 8 into Equation 9 to estimate the effect for the FE model. To estimate the combined effect for the equivalent FD model, I substitute Equation 10 into Equation 11. Finally, to estimate the effect of the FD model with tract level trends, I substitute Equation 12 into Equation 13. Then, the derivative of Equation 9, 11, or 13 with respect to WSL is $\frac{dWater}{dWSL} = b_v * \beta_0 + b_0$. These results are summarized in Table 5-3.

The total short run effect of WSL on household water consumption is 82.3 gallons of water saved per square meter of turf removed in June based on the Fixed Effects model, of which about 27% can be attributed to WSL's effect on measured vegetation area changes, and the rest to behavior change, changes in the water intensity of existing vegetation, or other factors. Based on the first differences model, the total effect is 61.2 gallons of water saved per square meter of turf removed in June, of which about 7% is due to WSL's effect on vegetation area, and the remaining 93% is due to other factors. Finally, when the model is based on first differences and also includes time trends for each tract, I estimate that 54.1 gallons of water are saved in June per square meter of turf removed, of which about 8% is due to WSL's effect on vegetation area, and the remaining 92% is due to other factors. For all three specifications, the effect of WSL conversions in their first year is statistically significant at the 5% level.

The significance of the effect of WSL conversions independent of their effect as measured through the vegetation index means that even after controlling for differences in landscapes, non-adopters still consume more water than adopters. There are several potential reasons that this may occur. MFVI is an imperfect measure of the area and greenness of existing vegetation, so after WSL conversions, the remaining vegetation may systematically require less water for general maintenance, even though it has the same MFVI estimate as a non-converted landscape. Additionally, differences between people who choose to participate and people who did not, an increased attention to water savings on the part of people who chose to participate because of increased awareness of water scarcity, or upgrades in the irrigation system that was installed with the new landscape could also influence the water consumption patterns of households who participated in the WSL program. Any combination of these factors could influence the lower water consumption of participating households even after controlling for landscape changes.

The total long run effects of WSL can be estimated through the combined effect of last year's cumulative WSL on vegetation, vegetation's effect on water consumption, and the effect of last years' cumulative WSL directly on water consumption. Then, the derivative of Equation 9, 11, or 13 with respect to cumulative WSL is $\frac{dWater}{dlagWSL} = b_v * \beta_0 + b_0$. The fixed effects models estimate that the long-run savings from WSL conversions are 32.70 gallons per square meter, with a standard error of 11.61. The first differences model estimates the savings as 42.59 gallons per square meter with a standard error of 22.25, and the first differences model that includes a time trend estimates total savings as 18.82 gallons per square meter, while the standard error is 26.08. For the first differences model with time trends, the long run effect of WSL conversions is not statistically distinguishable from zero. Based on this analysis, I can conclude that nearly all of the long run savings from WSL conversions occur through the programs effect on the water intensity of existing vegetation or other behavioral factors because the long run WSL conversions have basically no effect on measures of current vegetation area, but still have a meaningful influence on current water consumption.

Standard errors on the total effect of WSL conversions are calculated by assuming the two regressions are unrelated and using the delta method (Oehlert 1992) to estimate the standard errors based on the non-linear combination of the coefficients b_v, β_0, β_1, b_0, and b_1 from the two regressions.

This attenuation of the effects of WSL conversions is counter to what Sovocool, Morgan, and Bennett find. They do not show any meaningful reduction of the effect at the household level over a five-year period. In their 2006 paper, Sovocool, Morgan and Bennett consider the long-term effects of WSL conversions by looking at the difference in outdoor water consumption for a given household before and after WSL conversions. In Figure 2, they demonstrate that average consumption for a household after it participates in the WSL program is essentially stable for five years after the landscape conversion occurs. However, if average consumption for households that did not participate in the WSL program has declined over that same time period, this means that the effect of the WSL program would degrade with time. For the effect of the WSL program to remain constant as the landscape ages, the WSL treated households would need to see average annual declines in consumption equal to the average annual consumption declines in the non-treatment group. Sovocool, Morgan and Bennett do not report the results of this type of difference in differences analysis in their study. The failure of WSL-treated households to adopt the behaviors or technology that are driving declining household consumption in the non treated group could be a result of offsetting behavior as described by Campbell, Johnson and Larsen (2004). The neighborhood level consumption data I have access to does show a strong trend in declining household consumption independent of the effects of the WSL program as shown in Chapter 4, which suggests that this difference in estimation methods is the most likely source of the divergence between my estimations of the long-term water savings from the WSL program. Using a difference in differences model on household level data could resolve these disparate findings.

Table 5-3. Total effects of WSL

	FE	FD	FD+ trend
$\frac{dWater}{dWSL}$	-82.32**	-61.21**	-54.06**
	(35.32)	(26.15)	(21.54)
$\frac{dWater}{dlagWSL}$	-32.70***	-42.59*	-18.82
	(11.61)	(22.25)	(26.08)

Standard errors based on the delta method in parentheses
* p<0.10, ** p<0.05, *** p<0.01

5.4.4 Robustness Checks

I test the robustness of my results to several variations in sample selection and variable definition. First, I test the robustness of the results to the number of years included in the sample. Second, I examine robustness to definitions of the city core, used to define the sample. Finally, I check if the estimates are sensitive to the method used to calculate vegetation area.

The full dataset includes all years between 1996 and 2007. The WSL program was a small pilot program between 1996 and 2000, so I include only 2001 through 2007 in the full regression. To test whether the effects of the WSL program varied through time, I run the same fixed effects regression specification outlined in equations 8 and 9 on two non-overlapping subsets of the full dataset: first, the pilot period with years from 1996 to 2000, and second the later years from 2001 to 2007. The early panel estimates the total effect of WSL conversions to be 170 gallons, while the late panel estimates that the effect is only 82 gallons. There were few landscape conversions in the early years and the standard errors are large. As a result, these estimates are not statistically distinguishable but are suggestive of a temporal instability in program effectiveness.

To test if excluding the WSL pilot program years from my main analysis influences the total results, I run a sensitivity analysis by changing the number of years included in the sample testing samples including years 1997 to 2007, 1999 to 2007, 2001 to 2007, and 2003 to 2007. The total effects of WSL for each variation are shown in Table 5-4. Table 7-4, and Table 7-5 in Appendix A.3 show the estimated total WSL effect for each sample definition. For all but the shortest panel, which begins to rely on a very short time series for each tract, the estimated total effect of WSL is quite consistent. Thus, even though this analysis suggests that WSL conversions in early years had a larger effect on household water consumption than WSL conversions in later years, I believe that the average effectiveness of the WSL program between 1996 and 2007 is well represented by the regressions shown in Table 5-1 and Table 5-2. While not conclusive, this suggests that the WSL program was less effective in later years than earlier years.

Table 5-4. The total gallons of water saved in June per square meter of WSL landscape conversions, by sample start year.

Sample Years:	$\frac{dWater}{dWSL}$	$\frac{dWater}{dlagWSL}$
1997-2007	-84.41**	-31.08**
	(40.35)	(13.59)
1999-2007	-85.93**	-33.05**
	(39.06)	(13.37)
2001-2007, Main Model	-82.32**	-32.70***
	(35.32)	(11.61)
2003-2007	-57.86**	-25.82***
	(26.36)	(9.84)

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

The base definition of the city core used in this analysis contains all tracts where less than 200 new structures were built between 1996 and 2007, as shown in panel D in Figure 5-7. There is no natural boundary between the city core and periphery, so I test the robustness of my results to different specifications of the city core. I test this regression on the set of tracts where there were fewer than 10, 50, 100, 400, and 800 new houses constructed in the tract between 1996 and 2007. Figure 5-7 shows the city core under each of these definitions. The full results from the fixed effects model run on each of these specifications is shown in Table 7-6 and Table 7-7 in Appendix 7A.4. Table 5-5 summarizes the estimated total WSL effect for different core definitions. Again, the results are relatively stable over different definitions of the city core, except for the very tightest definitions of the core. For very small sets of tracts included in the city core, the total effect of WSL is smaller than my best estimate, while for very large definitions of the core, the estimated effect is larger than my baseline. This suggests that the either the effect of the program is different in the core than it is in the periphery, or the confounding effects of new construction and policy changes occurring in the city periphery make estimating the effect of the WSL program less accurate, by attributing other time varying water conserving measures to the WSL program.

Table 5-5. Total estimated WSL savings for several definitions of the city core. There are 326 tracts in the full study area.

Change in Accounts between 1996 and 2007	$\frac{dWater}{dWSL}$	$\frac{dWater}{dlagWSL}$
10 (113 tracts)	-38.43**	-10.17**
	(18.61)	(4.81)
50 (142 tracts)	-46.00**	-11.82**
	(21.40)	(5.41)
100 (165 tracts)	-90.06**	-25.34**
	(37.73)	(9.85)
200 (181 tracts) (Main Model)	-82.32**	-32.70***
	(35.32)	(11.60)
400 (198 tracts)	-83.51***	-33.54***
	(31.72)	(10.60)
800 (226 tracts)	-99.00***	-41.32***
	(34.08)	(12.08)

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

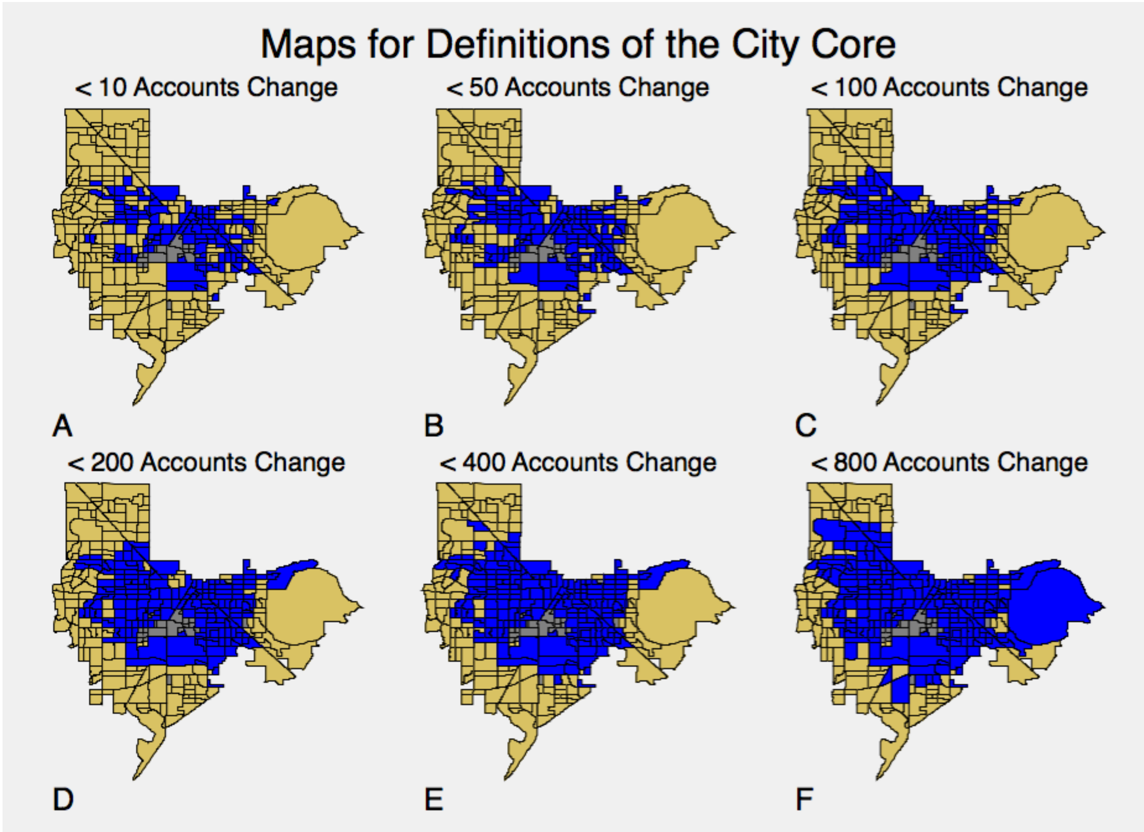

Figure 5-7. These maps show the area included under different possible definitions of the core.

The Normalized Difference Vegetation Index (NDVI) is an index that is commonly used do describe vegetation area, and differences in vegetation across space or time (Elmore et al. 2000; Guhathakurta and Gober 2007). It is defined as the difference between the spectral reflectance of the near-infrared measurement and the visible (red) spectra, and then normalized by the sum of the two spectral reflectance measurements. Although NDVI is one of the most commonly used metrics for vegetation in the water literature due to its ease of calculation, it is not a true measure of subpixel vegetation area, and so caution should be used when interpreting any vegetation area based effects from the index. The vegetation index I develop in Chapter 3, MFVI, is closer to a measure of sub-pixel vegetation area, and comparing the results of my estimation based on the two indices is a natural way to test if using MFVI provides any gains compared to using NDVI.

When the regression is run interpreting NDVI as the percentage of each pixel with vegetation, and using an NDVI based vegetation area measure instead of the vegetation area measure I develop in Chapter 3, the total effect of WSL on water consumption is identical between the two measures. However, the estimated effect of WSL on NDVI is statistically significant and positive, implying that WSL conversions increase vegetation area, and so the total effect of WSL on vegetation appears to come entirely from WSL's direct effect on consumption, rather than WSL's effect on vegetation area, and vegetation's effect on water consumption. The same pattern holds when focusing on the effect cumulative WSL conversions. This is evidence both of the robustness of the broad consumption to WSL relationship, as well as demonstrating the importance of using a more accurate measure of vegetation area than NDVI can provide when focused on the effect of landscape changes on water use. Key coefficients for the NDVI and MFVI regressions are shown in Table 5-6, while the full results are shown in Table 7-8 and Table 7-9 in Appendix 7A.5.

Table 5-6. Comparison of the effects of NDVI and MFVI on results.

	NDVI	**MFVI**
(1) WSL → Veg	0.181*	-0.381**
	(0.101)	(0.167)
(2) WSL → Water	-86.64**	-59.82*
	(39.84)	(30.74)
(5) Veg → Water	23.84**	58.99***
	(10.10)	(9.967)
Total effect WSL on water	-82.32**	-82.30**
(1*5+2)	(35.32)	(35.32)
(3) lagWSL → Veg	-0.118**	-0.000292
	(0.0476)	(0.0347)
(4) lagWSL → Water	-29.89**	-32.69***
	(12.15)	(12.49)
(5)Veg → Water	23.84**	58.99***
	(10.10)	(9.967)
Total effect lagWSL on water	-32.70***	-32.71***

(3*5+4)	(11.61)	(11.60)

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

5.5 Conclusions and Policy implications

In the city core, the total land area converted under WSL by 2007 was 1.37 square kilometers. Based on the FE model, I estimate the total long-term water savings from a square meter of WSL conversion to be 32.7 gallons each June. Thus, these landscaping conversions lead to a long run water savings of 137.4 acre-feet[10] each June in the city core. These June water savings could support the June consumption for an additional 2125 households consuming water at the rate of the average household in the city core[11].

If I assume that the water savings from WSL conversions estimated on the core only are consistent across the whole city, then the total long run June water savings from *all* residential WSL conversions before June 2007 are 217.6 acre-feet[12]. In tracts where at least 75% of the 2007 housing stock was built after 2004, the average household consumption is 9,500 gallons in June 2007[13]. Thus, the total long run June water savings from WSL conversions can support the June consumption of 7,450 households living in newly constructed homes. In 2013 dollars, the total expenditures on the WSL program

[10] There are 325,851 gallons per acre-foot.

[11] This is a minimum estimate of the potential for growth supported by savings in the subset of all WSL conversions that I have directly estimated.

[12] This relies on the assumption that WSL conversions have the same effect on household water consumption in the city periphery as they do in the core. I restricted my formal analysis to the core to avoid the confounding effects of widespread new construction and changes landscaping policy in the municipal code. Based on my check on the robustness of my results to different definitions of the city core, there is very weak evidence that WSL conversion have stronger effect on household consumption in the periphery than they do in the core. Thus, I believe that using my estimate of the effectiveness of WSL conversions based on the city core only to consider water savings in the city periphery is justified and likely conservative.

[13] It is reasonable to assume that most population growth will move into newly constructed homes, where average consumption is much lower than in the current housing stock. Based on the results of model 2 in Chapter 4, average consumption for a household that lives in a home with the infrastructure and vintage characteristics typical for structures built in 2007 is about 9,480 gallons in June 2007. This regression based estimate matches up closely with the raw averages that I use.

between 1996 and 2007 were $36.1 million. As a result, for every $4,850 the water district spent subsidizing WSL conversions, they saved enough water in June to support the June consumption of one additional household living in a newly constructed home in perpetuity[14]. This shows that even with significant attenuation in the long-term water savings from WSL conversions compared to the water savings in the first year of landscaping conversions, the WSL program is an effective way to generate water savings that can support substantial population growth.

It is difficult to contextualize the value of the water savings generated by the WSL program, but the cost of WSL generated water savings could be compared to costs associated with accessing other sources of water. These could be either conserved water generated by different conservation programs, or new water supplies that were purchased from other water rights owners. If a transparent market for water existed in the Las Vegas area, the logical comparison point would be an estimate of the price of the water rights required to service a family in perpetuity. However, there are no functioning and transparent water markets within the Las Vegas area or between Nevada and other Colorado River Basin states, and water prices vary widely between the few functioning water markets that do exist, so a cost estimate based on a water market in an unrelated state is not relevant. Since 1989, SNWA has been seeking to build a pipeline that would bring between 125,000 and 210,000 acre-feet of water per year from White Pine County to Las Vegas (Manning 2008). A 2005 estimate of the cost to build the pipeline was around 12.8 billion dollars. However, the pipeline has faced significant political, economic, and environmental challenges, and construction of the 300 mile long

[14] It is challenging to justify any interpolation to yearly water savings from my regression, which only considers June behavior. I expect that the water savings from WSL, both in absolute levels and as a share of household consumption, are substantially lower in the winter months than they are in the summer months. Thus, WSL driven water savings probably cannot support the winter consumption of as many households as they can in the summer months. The June water savings estimate is probably close to the other summer months.

pipeline still has not started 25 years after the idea was first publically formulated. In the Las Vegas context, purchasing rights to additional water supplies is not straightforward. Alternatively, the cost of water saved through the WSL program could be compared to the cost of water saved through SNWA's other conservation policies like the car wash coupon program, irrigation clock rebates, and other similar measures. Unfortunately, there are no rigorous estimates of the water saved from other conservation programs. Future research could contextualize the cost of the water saved from the WSL program in comparison with the cost of water savings from other conservation programs or the price of buying rights and developing new water supplies.

6 CONCLUSIONS

As water scarcity becomes a salient concern for more and more cities, water mangers are increasingly turning to demand side management as a tool to ensure that water demand is in line with the available water supply. Residential water demand is significantly influenced by household infrastructure, and so stronger theories around interactions between the built environment and water demand will support more effective water conservation policy. I quantify the role that infrastructure change in conjunction with new construction, population growth, and aggressive conservation policy has played in changing Las Vegas' residential water demand.

Most water used in single-family residential homes is used outdoors, and the area and composition of vegetation is a significant driver of a household's outdoor water needs. In order to quantify changes in vegetation area and then address the effect that vegetation area has on household water consumption, I develop a new technique for reducing the bias in sub-pixel area estimates of a target land cover that were generated using Mixture Tuned Match Filtering. This technique is used to estimate the average vegetation area in single-family homes within Las Vegas census tracts over an eleven-year period. I find that there is a small but significant decline in average vegetation area in the established city core between 1996 and 2007.

Next, I perform an analysis focused on estimating the role that household infrastructure plays in determining residential water demand. Existing literature on the determinants of residential water demand has not rigorously addressed the role that fixed infrastructure like lot size, vegetation area, and structural characteristics play in determining residential water demand, although early evidence suggests that these factors have a significant role in governing long run demand for water. I use the vegetation area index developed previously in conjunction with a dataset of household level infrastructure characteristics and census tract averages of household water consumption. I find that in 2007, the average June consumption for a household living in a typical home constructed in 2007 is about half of the average consumption for a household living in a typical home constructed in 1996.

In addition to estimating the role that each individual factor plays in determining residential water demand, I also estimate the practical importance that these different factors played in reducing household water demand in the LVVWD service area. I find that changes in household infrastructure characteristics like the number of bedrooms, and plumbing fixtures, the size of the living area, and the number of pools caused a very small increase in household water consumption. Declines in vegetation area caused a small but significant decline in residential water consumption in the city core, while changes in lot size caused a larger decrease in average household water consumption in the periphery. The largest measurable driver of changes in residential water consumption in Las Vegas is the increased water efficiency associated with new construction in combination with rapid population growth.

Finally, I estimate the water savings generated by the Water Smart Landscaping program. I estimate that in the first year after a landscape conversion, for each square meter of turf converted to desert landscaping, 82 gallons of water are saved each June. This estimate is closely in line with Sovocool, Morgan and Bennett's (2006) estimate of 95 gallons of water saved each June per meter of turf removed. As the landscape ages, I find that the long term water savings attenuate to 33 gallons of water saved per meter of turf converted. Even with this high level of attenuation, for every $4,850 that SNWA has spent incentivizing turf conversions, enough water is saved each June to support the water consumption of an additional household living in a newly constructed home in perpetuity.

In future research, teasing out the specific causes of the increased water efficiency associated with new construction would further frame the potential role that demand side management water policy can play in reducing household water consumption. It is clear from this research that incentivizing water efficiency in new construction is an effective way to ensure that water efficiency is built into the infrastructure of a city as it grows, and has the potential to have a significant impact on average household consumption in a rapidly growing city like Las Vegas. However, I have not specifically estimated the effect that policies like the Water Smart Homes program or restrictions on turf in new construction played in the increased water efficiency of new construction in comparison to the effect of exogenous factors like changes in lot size, technology changes that allow more water efficient appliances, and fewer leaks associated with younger plumbing systems. Quantifying the effects of policy changes compared to exogenous changes on the water consumed by newly constructed homes would further demonstrate the potential scope of effective conservation policy.

Additionally, I consider total household water consumption but in Las Vegas most water used outdoors is ultimately lost to evaporation, while most water used indoors stays in the infrastructure system and can be used again. Estimating policy effects on outdoor water use separately from indoor water use would be an additional method for specifying the effect these conservation programs have on Las Vegas' water supply. Finally, this analysis is performed on census tract level averages of household water consumption, but the natural unit of measurement for water consumption is the household. Understanding the role that this level of spatial aggregation plays in determining household water consumption could be another important avenue for understanding the role that infrastructure and conservation policy play in determining household water consumption.

The most significant result that water policy makers should take from this dissertation is that the most effective way to ensure long term, sustainable reductions in water consumption in a growing city without resorting to politically risky water price increases is to support and incentivize the construction of water efficient infrastructure. In this way, water efficiency can be built into the infrastructure of the city as it grows, rather than requiring expensive retrofits to existing infrastructure. I also show that there is scope for conservation programs incentivizing infrastructure change to generate water savings that can support substantial population growth at relatively low cost.

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APPENDIX A

ADDITIONAL MODEL SPECIFICATIONS

A.1 CITYWIDE DRIVERS STANDARD ERROR ESTIMATION

Table 7-1: Model 3, comparison of different standard error estimation.

	Model 3: Regular Std Errors	Model 3: Robust Std Errors	Model 3: Driscoll- Kraay Std Errors
1997 Dummy	-0.0248**	-0.0248**	-0.0248+
	(0.00656)	(0.00610)	(0.0122)
1998 Dummy	-0.0852**	-0.0852**	-0.0852+
	(0.0130)	(0.0139)	(0.0431)
1999 Dummy	-0.0584**	-0.0584**	-0.0584
	(0.0147)	(0.0179)	(0.0609)
2000 Dummy	-0.0164*	-0.0164*	-0.0164
	(0.00796)	(0.00702)	(0.0102)
2001 Dummy	-0.0818**	-0.0818**	-0.0818**
	(0.00651)	(0.00490)	(0.00486)
2002 Dummy	-0.112**	-0.112**	-0.112**
	(0.00606)	(0.00458)	(0.00509)
2003 Dummy	-0.131**	-0.131**	-0.131**
	(0.00633)	(0.00500)	(0.00457)
2004 Dummy	-0.220**	-0.220**	-0.220**
	(0.00630)	(0.00601)	(0.00658)
2005 Dummy	-0.251**	-0.251**	-0.251**
	(0.00862)	(0.0104)	(0.0285)
2006 Dummy	-0.240**	-0.240**	-0.240**
	(0.0121)	(0.0123)	(0.0231)
2007 Dummy	-0.262**	-0.262**	-0.262**
	(0.00721)	(0.00690)	(0.00468)
Living Area (m^2)	0.00251**	0.00251**	0.00251*
	(0.000578)	(0.000905)	(0.00113)
Plumbing Fixtures	0.00938	0.00938	0.00938
	(0.0145)	(0.0245)	(0.0129)
Bedrooms	0.0225	0.0225	0.0225
	(0.0329)	(0.0505)	(0.0259)
Vintage 1960 to 1984	0.0812	0.0812	0.0812
	(0.213)	(0.282)	(0.155)
Vintage 1984 to 1992	0.0722	0.0722	0.0722
	(0.187)	(0.258)	(0.150)
Vintage 1992 to 1996	-0.216	-0.216	-0.216
	(0.179)	(0.253)	(0.120)
Vintage 1996 to 2001	-0.147	-0.147	-0.147

	(0.174)	(0.247)	(0.118)
Vintage 2001 to 2004	-0.249	-0.249	-0.249+
	(0.171)	(0.244)	(0.115)
Vintage 2004 to 2007	-0.566**	-0.566*	-0.566**
	(0.171)	(0.245)	(0.148)
Pool Percentage	0.525**	0.525**	0.525+
	(0.130)	(0.200)	(0.262)
Pct Pool* Min Temp (% * C)	0.0000850	0.0000850	0.0000850
	(0.00540)	(0.00575)	(0.00306)
Total Precipitation (cm)	-0.0990**	-0.0990**	-0.0990
	(0.0185)	(0.0234)	(0.0828)
Dirt*Min Temp (100 m² * C)	0.000612	0.000612	0.000612
	(0.000403)	(0.000427)	(0.000444)
Veg*Min Temp (100 m2 * C)	0.00380**	0.00380**	0.00380
	(0.00127)	(0.00136)	(0.00234)
Dirt*Precip (100 m² * cm)	-0.00206	-0.00206	-0.00206
	(0.00286)	(0.00298)	(0.00299)
Veg*Precip (100 m² * cm)	-0.00941	-0.00941	-0.00941
	(0.00842)	(0.0108)	(0.0118)
Dirt (100 m²)	-0.0294**	-0.0294**	-0.0294**
	(0.00292)	(0.00393)	(0.00468)
Area Veg (100 m²)	0.225**	0.225**	0.225**
	(0.00753)	(0.0113)	(0.0257)
Min June Temp (C)	0.00429	0.00429	0.00429
	(0.00312)	(0.00339)	(0.00397)
Constant	3.118**	3.118**	3.118**
	(0.0978)	(0.130)	(0.109)
Observations	**3492**	**3492**	**3492**
R-squared	**0.978**	**0.978**	**0.997**

Standard errors in parentheses
+p<0.10, * p<0.05, ** p<0.01

A.2 CITYWIDE DRIVERS, SPECIFICATION ROBUSTNESS CHECKS

Table 7-2: Full Specification Model 2 compared to a model without dirt area included.

	Model 2, RE	Model 2, No Precip	Model 2, No Dirt
Living Area (m²)	0.00114*	0.00168**	0.00113*

	(0.000465)	(0.000256)	(0.000492)
Plumbing Fixtures	0.0514**	0.0366**	0.0517**
	(0.00391)	(0.00300)	(0.00434)
Bedrooms	0.145**	0.161**	0.146**
	(0.0213)	(0.0238)	(0.0234)
Vintage 1960 to 1984	-0.102**	-0.0848**	-0.104**
	(0.0115)	(0.00540)	(0.0137)
Vintage 1984 to 1992	-0.0661**	-0.0355*	-0.0698**
	(0.0112)	(0.0156)	(0.0104)
Vintage 1992 to 1996	-0.292**	-0.257**	-0.297**
	(0.0372)	(0.0220)	(0.0443)
Vintage 1996 to 2001	-0.353**	-0.321**	-0.355**
	(0.0566)	(0.0406)	(0.0596)
Vintage 2001 to 2004	-0.467**	-0.428**	-0.469**
	(0.0118)	(0.0182)	(0.0134)
Vintage 2004 to 2007	-0.914**	-0.865**	-0.915**
	(0.0269)	(0.0161)	(0.0273)
Pool Percentage	0.549**	0.513**	0.547**
	(0.0278)	(0.0281)	(0.0270)
Pct Pool* Tmin Jun (% * C)	0.0149	0.0272*	0.0177
	(0.0120)	(0.0105)	(0.0121)
Total June Precip (cm)	-0.0821	-0.0799	
	(0.145)	(0.137)	
Dirt*Tmin Jun (100 m² * C)	0.00351+		0.00344+
	(0.00181)		(0.00171)
Veg*Tmin Jun (100 m² * C)	-0.0125+	-0.00620+	-0.0122*
	(0.00568)	(0.00285)	(0.00499)
Dirt*Precip Jun (100 m² * cm)	0.00300		
	(0.00856)		
Veg*Precip Jun (100 m² * cm)	-0.0213	-0.0142	
	(0.0290)	(0.0117)	
Area Dirt (100 m²)	0.00697		0.00742
	(0.00431)		(0.00509)
Area Veg (100 m²)	0.111**	0.123**	0.108**
	(0.00886)	(0.00394)	(0.0116)
Min June Temp (C)	-0.00581	-0.00380	-0.00623
	(0.00564)	(0.00577)	(0.00506)
1997 Dummy	-0.0290	-0.0269	-0.0392**
	(0.0218)	(0.0204)	(0.00473)
1998 Dummy	-0.108	-0.0954	-0.143**
	(0.0763)	(0.0716)	(0.0162)
1999 Dummy	-0.0694	-0.0655	-0.126**

	(0.107)	(0.102)	(0.0113)
2000 Dummy	-0.0172	-0.0237	-0.0264**
	(0.0152)	(0.0148)	(0.00691)
2001 Dummy	-0.0755**	-0.0794**	-0.0763**
	(0.0101)	(0.00850)	(0.00927)
2002 Dummy	-0.108**	-0.110**	-0.108**
	(0.0111)	(0.00980)	(0.0105)
2003 Dummy	-0.129**	-0.133**	-0.130**
	(0.00978)	(0.00828)	(0.00894)
2004 Dummy	-0.228**	-0.229**	-0.232**
	(0.0117)	(0.0109)	(0.00833)
2005 Dummy	-0.267**	-0.265**	-0.292**
	(0.0499)	(0.0490)	(0.0114)
2006 Dummy	-0.242**	-0.253**	-0.263**
	(0.0313)	(0.0312)	(0.0102)
2007 Dummy	-0.256**	-0.261**	-0.258**
	(0.00901)	(0.00719)	(0.00796)
Constant	3.271**	3.257**	3.274**
	(0.0139)	(0.0114)	(0.0171)
Observations	3492	3492	3492
R-squared	0.896	0.891	0.895

Standard errors in parentheses
+p<0.10, * p<0.05, ** p<0.01

Table 7-3: Model 2, run on the city as a whole, as well as the core and periphery individually.

	Full City	Core Only	Periphery Only
Living Area (m^2)	0.00114*	0.000885*	0.00242**
	(0.000465)	(0.000347)	(0.000635)
Plumbing Fixtures	0.0514**	0.0348**	0.0329*
	(0.00391)	(0.00384)	(0.0123)
Bedrooms	0.145**	0.127**	0.144**
	(0.0213)	(0.00890)	(0.0288)
Vintage 1960 to 1984	-0.102**	-0.108**	-0.133+
	(0.0115)	(0.00544)	(0.0704)
Vintage 1984 to 1992	-0.0661**	-0.0495**	-0.0253
	(0.0112)	(0.00912)	(0.0372)
Vintage 1992 to 1996	-0.292**	-0.255**	-0.450**
	(0.0372)	(0.0400)	(0.0533)

Vintage 1996 to 2001	-0.353**	-0.518**	-0.487**
	(0.0566)	(0.0711)	(0.0651)
Vintage 2001 to 2004	-0.467**	-0.654*	-0.608**
	(0.0118)	(0.218)	(0.0411)
Vintage 2004 to 2007	-0.914**	0.126	-1.052**
	(0.0269)	(0.0931)	(0.0649)
Pool Percentage	0.549**	0.709**	0.536**
	(0.0278)	(0.0204)	(0.0687)
Pct Pool* Min Temp (% * C)	0.0149	0.0118	-0.00409
	(0.0120)	(0.0111)	(0.0188)
Total Precipitation (cm)	-0.0821	0.0255	-0.136
	(0.145)	(0.163)	(0.0802)
Dirt*Min Temp (100 m² * C)	0.00351+	-0.0000345	0.000183
	(0.00181)	(0.000666)	(0.000875)
Veg*Min Temp (100 m2 * C)	-0.0125+	-0.00341	0.00943
	(0.00568)	(0.00319)	(0.00540)
Dirt*Precip (100 m² * cm)	0.00300	-0.00000430	-0.000701
	(0.00856)	(0.00784)	(0.00750)
Veg*Precip (100 m² * cm)	-0.0213	-0.0244	0.0101
	(0.0290)	(0.0194)	(0.0412)
Dirt (100 m²)	0.00697	0.0412**	-0.0210**
	(0.00431)	(0.00316)	(0.00432)
Area Veg (100 m²)	0.111**	0.0368**	0.180**
	(0.00886)	(0.00772)	(0.0130)
Min June Temp (C)	-0.00581	-0.00434	0.00993
	(0.00564)	(0.00954)	(0.00645)
1997 Dummy	-0.0290	-0.0341	-0.00843
	(0.0218)	(0.0239)	(0.0104)
1998 Dummy	-0.108	-0.143	-0.0519
	(0.0763)	(0.0819)	(0.0406)
1999 Dummy	-0.0694	-0.128	-0.00841
	(0.107)	(0.120)	(0.0487)
2000 Dummy	-0.0172	-0.0198	0.00258
	(0.0152)	(0.0134)	(0.0105)
2001 Dummy	-0.0755**	-0.0678**	-0.0541**
	(0.0101)	(0.00413)	(0.0113)
2002 Dummy	-0.108**	-0.105**	-0.0829**
	(0.0111)	(0.00151)	(0.0114)
2003 Dummy	-0.129**	-0.138**	-0.0923**
	(0.00978)	(0.00448)	(0.00968)

2004 Dummy	-0.228**	-0.267**	-0.168**
	(0.0117)	(0.00593)	(0.00867)
2005 Dummy	-0.267**	-0.357**	-0.172**
	(0.0499)	(0.0546)	(0.0224)
2006 Dummy	-0.242**	-0.322**	-0.163**
	(0.0313)	(0.0316)	(0.0158)
2007 Dummy	-0.256**	-0.332**	-0.184**
	(0.00901)	(0.00932)	(0.00982)
Constant	3.271**	3.233**	3.385**
	(0.0139)	(0.00525)	(0.0555)
Observations	3492	2156	1336
R-squared	0.896	0.884	0.975

Driscoll and Kraay standard errors in parentheses
+p<0.10, * p<0.05, ** p<0.01

A.3 WSL ESTIMATION ROBUSTNESS TO YEARS IN SAMPLE

Table 7-4: Fixed Effects Vegetation Regression, Robustness to years included in sample

	1997	**1999**	**2001, Main Model**	**2003**
Annual WSL	-0.381**	-0.375**	-0.381**	-0.375**
	(0.181)	(0.171)	(0.167)	(0.172)
Last year's Cumulative WSL	0.0259	0.0221	-0.000292	-0.00630
	(0.0386)	(0.0371)	(0.0347)	(0.0472)
Lot Size (m2)	0.0764***	0.0638**	0.100***	0.110***
	(0.0234)	(0.0282)	(0.0269)	(0.0351)
Lot Area ^ 2	0.0000404***	0.0000487***	0.0000352***	0.0000325***
	(0.00000692)	(0.00000856)	(0.00000751)	(0.00000986)
Min Temp (C)	27.70***	14.98*	-10.62*	-22.60***
	(6.698)	(8.821)	(6.053)	(5.430)
Min Temp ^ 2	-0.736***	-0.418*	0.193	0.506***
	(0.160)	(0.214)	(0.150)	(0.135)
Precip (cm)	-9.934***	5.912	4.030	-6.915*
	(3.384)	(5.091)	(4.118)	(4.072)
1997.Year	18.75***			
	(2.275)			
1998.Year	16.30***			
	(3.684)			

1999.Year	24.65***	14.80***		
	(3.396)	(4.491)		
2000.Year	19.33***	16.89***		
	(1.105)	(1.147)		
2001.Year	18.26***	18.66***	19.08***	
	(1.232)	(1.228)	(1.224)	
2002.Year	12.85***	13.57***	13.90***	
	(1.417)	(1.348)	(1.209)	
2003.Year	10.34***	10.74***	10.93***	11.71***
	(1.201)	(1.104)	(0.973)	(0.967)
2004.Year	2.074	1.894	2.155*	3.543***
	(1.468)	(1.377)	(1.162)	(0.955)
2005.Year	-1.773	-5.680**	-5.602**	-0.0258
	(2.450)	(2.770)	(2.365)	(2.097)
2006.Year	17.67***	9.247***	3.993	1.301
	(2.398)	(3.099)	(2.559)	(2.495)
2007b.Year	0	0	0	0
	(.)	(.)	(.)	(.)
Constant	-205.1***	-77.26	168.8***	273.6***
	(72.37)	(91.90)	(63.88)	(58.53)
Observations	1978	1619	1260	900
R-squared	0.992	0.993	0.996	0.997

OLS Robust standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 7-5: Fixed Effects Water Regression, robustness to years included in Sample

	1997	**1999**	**2001, Main Model**	**2003**
Veg Area (m2)	50.39***	40.15***	58.99***	48.51***
	(6.281)	(7.170)	(9.967)	(15.92)
Annual WSL	-65.19*	-70.89*	-59.82*	-39.65*
	(35.38)	(36.42)	(30.74)	(22.94)
Last year's Cumulative WSL	-32.38**	-33.93**	-32.69***	-25.52**
	(14.02)	(14.16)	(12.49)	(10.85)
Lot Size (m2)	-2.649	-4.511	-11.82**	-5.320
	(4.952)	(6.825)	(5.608)	(6.494)
Lot Area ^ 2	0.00340**	0.00568**	0.00728***	0.00504***
	(0.00160)	(0.00224)	(0.00171)	(0.00190)
Min Temp (C)	-1343.4	-3279.1***	-2915.8**	-4035.5***
	(926.9)	(1118.3)	(1139.0)	(1096.8)

Min Temp ^ 2	22.64	68.76***	65.86**	96.05***
	(21.57)	(26.34)	(27.32)	(26.81)
Precip	-1817.0***	1776.2**	3125.2***	3330.1***
	(599.3)	(818.8)	(871.4)	(834.8)
1997.Year	4802.6***			
	(333.0)			
1998.Year	1799.1***			
	(593.8)			
1999.Year	3315.1***	1006.7		
	(578.2)	(696.3)		
2000.Year	6374.4***	6056.8***		
	(243.7)	(255.8)		
2001.Year	4281.4***	4473.6***	4200.1***	
	(207.0)	(217.4)	(251.3)	
2002.Year	3283.9***	3440.9***	3369.2***	
	(213.1)	(224.5)	(243.7)	
2003.Year	2757.2***	2866.1***	2770.7***	3111.5***
	(175.0)	(180.9)	(189.2)	(238.6)
2004.Year	685.8***	569.1***	600.9***	795.1***
	(200.0)	(199.9)	(182.5)	(180.1)
2005.Year	-894.6**	-2048.6***	-1986.3***	-1772.9***
	(391.6)	(422.4)	(405.7)	(395.5)
2006.Year	1240.0***	-98.40	-974.3**	-1612.3***
	(342.3)	(428.9)	(442.4)	(429.5)
7200.Tract	30158.6***	29657.9***	32156.0***	30928.5***
	(1365.0)	(1663.3)	(1610.2)	(2221.1)
Constant	32960.8***	54745.3***	50251.9***	57953.1***
	(10636.8)	(12364.3)	(12277.2)	(11783.4)
Observations	1978	1619	1260	900
R-squared	0.987	0.989	0.990	0.991

OLS Robust standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

A.4 WSL ESTIMATION ROBUSTNESS TO TRACTS IN SAMPLE

Table 7-6: Vegetation Regression, testing robustness to different specifications of the core.

	Core 10	Core 50	Core 100	Core 200, Main Model	Core 400
Annual WSL	-0.125*	-0.175*	-0.299**	-0.381**	-0.398**

	(0.0759)	(0.100)	(0.141)	(0.167)	(0.155)
Last year's Cum WSL	0.00324	0.00537	-0.0270	-0.000292	-0.00885
	(0.0147)	(0.0204)	(0.0289)	(0.0347)	(0.0326)
Lot Area	0.174***	0.193***	0.139***	0.100***	0.127***
	(0.0449)	(0.0398)	(0.0288)	(0.0269)	(0.0231)
Lot Area²	-0.0000199	-0.0000286	0.0000254***	0.0000352***	0.0000313***
	(0.0000222)	(0.0000218)	(0.00000934)	(0.00000751)	(0.00000713)
Min Temp	-12.17*	-6.168	-8.248	-10.62*	-6.862
	(6.669)	(6.435)	(6.544)	(6.053)	(6.095)
Min Temp²	0.260	0.0989	0.138	0.193	0.123
	(0.165)	(0.160)	(0.161)	(0.150)	(0.153)
Precip	4.428	5.310	4.541	4.030	4.711
	(4.484)	(4.198)	(4.344)	(4.118)	(4.268)
2001b.Year	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)
2002.Year	-6.970***	-6.331***	-5.902***	-5.176***	-3.894***
	(1.139)	(1.098)	(1.047)	(1.022)	(1.065)
2003.Year	-10.33***	-9.331***	-8.860***	-8.148***	-7.096***
	(1.059)	(1.003)	(0.966)	(0.944)	(0.991)
2004.Year	-20.64***	-18.60***	-18.04***	-16.92***	-15.13***
	(1.133)	(1.119)	(1.110)	(1.093)	(1.108)
2005.Year	-25.72***	-25.74***	-26.09***	-24.68***	-21.86***
	(2.018)	(2.062)	(2.117)	(2.070)	(2.070)
2006.Year	-22.76***	-17.48***	-15.86***	-15.08***	-14.82***
	(3.517)	(3.391)	(3.359)	(3.150)	(3.238)
2007.Year	-24.06***	-21.36***	-20.31***	-19.08***	-17.16***
	(1.359)	(1.299)	(1.263)	(1.224)	(1.273)
Constant	168.6**	103.2	141.3**	187.9***	121.8*
	(73.03)	(68.88)	(69.38)	(64.16)	(62.37)
Observations	784	987	1148	1260	1379
R-squared	0.991	0.994	0.995	0.996	0.995

OLS Robust standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 7-7: Water regression, testing robustness of results to different definitions of the city core.

	Core 10	Core 50	Core 100	Core 200, Main Model	Core 400

Veg Area	52.59***	50.06***	67.42***	58.99***	63.44***
	(7.816)	(7.243)	(8.837)	(9.967)	(8.640)
Annual WSL	-31.86*	-37.24*	-69.88**	-59.82*	-58.28**
	(16.81)	(18.99)	(32.49)	(30.74)	(26.95)
Last years' Cum WSL	-10.34**	-12.08**	-23.52**	-32.69***	-32.98***
	(5.031)	(5.714)	(9.564)	(12.49)	(11.24)
Lot Area	-2.074	-1.146	-20.66***	-11.82**	-8.728*
	(5.698)	(5.769)	(5.271)	(5.608)	(5.163)
Lot Area^2	-0.00319	-0.00372	0.0102***	0.00728***	0.00652***
	(0.00321)	(0.00337)	(0.00225)	(0.00171)	(0.00172)
Min Temp	-2754.2**	-2423.6**	-2103.0*	-2915.8**	-2234.7**
	(1374.0)	(1228.5)	(1166.7)	(1139.0)	(1011.8)
Min Temp^2	62.15*	53.76*	45.00	65.86**	49.67**
	(32.65)	(29.49)	(28.00)	(27.32)	(24.40)
Precip	2712.4***	2775.5***	3423.5***	3125.2***	3206.8***
	(983.8)	(911.6)	(899.7)	(871.4)	(831.6)
2001b.Year	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)
2002.Year	-681.6***	-785.4***	-785.9***	-830.9***	-852.1***
	(128.1)	(121.7)	(144.0)	(142.8)	(134.4)
2003.Year	-1338.2***	-1372.6***	-1323.3***	-1429.5***	-1397.5***
	(124.6)	(113.3)	(137.9)	(142.0)	(128.5)
2004.Year	-3622.1***	-3698.8***	-3513.5***	-3599.2***	-3445.5***
	(196.4)	(185.0)	(216.3)	(219.3)	(194.7)
2005.Year	-6283.3***	-6277.6***	-6191.9***	-6186.5***	-6022.6***
	(411.6)	(387.8)	(399.0)	(410.6)	(374.5)
2006.Year	-5390.8***	-5165.9***	-4770.2***	-5174.5***	-4856.1***
	(574.5)	(546.7)	(553.5)	(545.9)	(501.5)
2007.Year	-4557.9***	-4486.9***	-4048.1***	-4200.1***	-4028.1***
	(224.9)	(205.5)	(237.7)	(251.3)	(216.5)
Constant	51755.2***	48457.0***	50192.8***	54452.0***	44879.8***
	(14564.2)	(12880.4)	(12533.0)	(12315.4)	(10773.6)
Obs	784	987	1148	1260	1379
R-squared	0.986	0.990	0.990	0.990	0.990

OLS Robust standard errors in parentheses
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

A.5 WSL ESTIMATION ROBUSTNESS TO VEGETATION AREA ESTIMATION METHOD

Table 7-8: Vegetation Regression, testing robustness of results to vegetation area estimation method.

	NDVI-based Vegetation	MTMF-based Vegetation, Main Model
Annual WSL	0.181*	-0.381**
	(0.101)	(0.167)
Last year's Cum WSL	-0.118**	-0.000292
	(0.0476)	(0.0347)
Lot Area	0.221***	0.100***
	(0.0281)	(0.0269)
Lot Area²	0.00000637	0.0000352***
	(0.0000100)	(0.00000751)
Min Temp	5.667	-10.62*
	(6.144)	(6.053)
Min Temp²	-0.152	0.193
	(0.150)	(0.150)
Precip.	2.558	4.030
	(4.540)	(4.118)
2001.Year	21.39***	19.08***
	(1.103)	(1.224)
2002.Year	17.23***	13.90***
	(1.147)	(1.209)
2003.Year	11.12***	10.93***
	(0.911)	(0.973)
2004.Year	9.215***	2.155*
	(1.068)	(1.162)
2005.Year	14.34***	-5.602**
	(2.287)	(2.365)
2006.Year	3.317	3.993
	(2.294)	(2.559)
2007b.Year	0	0
	(.)	(.)
Constant	26.56	168.8***
	(68.81)	(63.88)
Observations	1260	1260
R-squared	0.998	0.996

OLS Robust standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 7-9: Water Regression testing robustness to different vegetation area specifications

	NDVI-based Vegetation	MTMF-based Vegetation, Main Model
Vegetation Area	23.84**	58.99***
	(10.10)	(9.967)
Annual WSL	-86.64**	-59.82*
	(39.84)	(30.74)
Last year's Cum WSL	-29.89**	-32.69***
	(12.15)	(12.49)
Lot Area	-11.17*	-11.82**
	(5.897)	(5.608)
Lot Area^2	0.00920***	0.00728***
	(0.00162)	(0.00171)
Min Temp	-3677.6***	-2915.8**
	(1237.8)	(1139.0)
Min Temp^2	80.88***	65.86**
	(29.67)	(27.32)
Precip.	3301.9***	3125.2***
	(912.5)	(871.4)
2001.Year	4815.5***	4200.1***
	(228.0)	(251.3)
2002.Year	3778.4***	3369.2***
	(235.4)	(243.7)
2003.Year	3150.2***	2770.7***
	(180.9)	(189.2)
2004.Year	508.3***	600.9***
	(194.1)	(182.5)
2005.Year	-2658.8***	-1986.3***
	(429.1)	(405.7)
2006.Year	-817.8*	-974.3**
	(469.4)	(442.4)
2007b.Year	0	0
	(.)	(.)
Constant	59578.2***	50251.9***
	(13702.7)	(12277.2)
Observations	1260	1260
R-squared	0.989	0.990

OLS Robust standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01