SIMULATION / OPTIMIZATION OF ALTERNATIVE WATER SUPPLY PLANNING USING PARCEL LEVEL DEMAND ESTIMATION AND MANAGEMENT STRATEGIES

By

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To my parents, Kathie and Larry Friedman

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Abstract of Dissertation Presented to the Graduate School
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Traditional water supplies are reaching their sustainable limits in many areas of the United States, and throughout the world. Several water stressed areas, particularly in the Western United States, are likely to face water scarcity problems in the near future. As a result, water stressed areas are considering alternative water supplies, including wastewater and stormwater reuse, system water loss control, and demand management to ensure that ample future water supply can be provided.

Demand management and water loss control initiatives have become more prevalent from the early 1990s to present with 23 states now having legislative mandates for some form of demand management as opposed to 9 states in 1990. Although these initiatives are a step in the right direction, current water conservation plans are often qualitative with unreliable aggregate savings estimates, even for the most reliable indoor residential sector. Recent initiatives focused on incorporating demand management in a broader context beyond reduced water supply needs are further requiring the need to better quantify demands with higher resolution.

To address these emerging needs, this dissertation presents a systematic data driven approach for evaluating parcel level water usage and demand management

options for urban systems. Water usage for all water using devices is estimated using a uniform statewide property appraiser's database combined with water utility customer billing data. Water using population is then determined with the addition of U.S. Census Block data, which is utilized to determine per capita usage rates. The potential effects of demand management are then determined directly as the difference between existing and proposed water usage after implementation. Water savings performance functions are then developed for each demand management option. These performance functions are then utilized to evaluate the optimal blend of demand management options to either maximize net benefits of water savings or to minimize the cost of reaching a target water savings from demand management. Both linear and nonlinear formulations and solutions to these problems are presented. Additionally, explicit analytical solutions are presented based on appropriate exponential best fits of water savings performance functions. Emphasis is placed on the residential water use sector, although generalizations to all urban water use sectors are described. Two primary case study utilities, Gainesville Regional Utilities and City of Sanford, are utilized to illustrate proposed methodologies.

CHAPTER 1
INTRODUCTION

Background

Traditional water supplies are reaching their sustainable limits in many areas of the United States, and throughout the world. Several water stressed areas, particularly in the Western United States, are likely to face water scarcity problems in the near future (Tanverakul and Lee 2012). These concerns have resulted in an increased effort towards reducing demands on existing supplies (Rashid et al. 2010). As a result, water stressed areas are considering alternative water supplies, including wastewater and stormwater reuse, system water loss control, and demand management to ensure that ample future water can be provided. These strategies have grown in popularity due to perception of achievable benefits from alternative supply and demand management programs (Rashid et al. 2010). In particular, demand management has been seen as "having the potential to defer, reduce, or even eliminate the need for expansion of water and wastewater facilities" (Rashid et al. 2010). The United Nations Development Program estimates vast water reduction is possible as per capita usage in the United States is over ten times the basic threshold of water needs for human consumption and sanitation set by the World Health Organization (United Nations Development Program 2006). Additionally, the per capita water usage of developed countries in Europe is roughly half that of the United States (United Nations Development Program 2006). Furthermore, Thornton et al. (2008) estimate that 75% of total distribution system losses can be feasibly recovered in the United States.

Demand management is an emerging alternative to traditional well established supply augmentation options such as well field development, reservoir and pipeline

construction, and desalination. Demand management can be defined as “A practical strategy which improves efficient and sustainable use of water resources by balancing the management of system losses and consumption with new or augmented supplies” (Aravidis 2007). In this context, sustainability refers to “determining values for economic, environmental, and social benefits, costs, and tradeoffs to base investment decisions on” (Shilling et al. 2011). Two related terms, “water efficiency” and “water conservation”, may also refer to such practices. The term “water efficiency” refers to “improved technologies and practices that deliver equal or better service with less water” while the term “water conservation” refers to “ curtailment of water use and doing less with less water” (North Carolina Department of Environment and Natural Resources 2009). These definitions have been adopted by the United States Environmental Protection Agency (USEPA 2012a). The term demand management has gained in popularity as it encompasses both water use efficiency and conservation.

Demand management and water loss control initiatives have increased in popularity from the early 1990s to present with 23 states now having legislative mandates for some form of demand management as opposed to 9 states in 1990 (Rashid et al. 2010). This movement was stimulated by the United States Environmental Protection Agency (USEPA) Energy Policy Act of 1992, which enacted uniform water efficiency standards for toilets, showerheads, faucets, and urinals installed after 1994 (USEPA 1992). These standards, which significantly lowered the required flow rating of indoor water using devices, were projected to reduce water usage from 121 to 55 gallons per capita per day (gpcd) by the year 2026 when the indoor fixture stock is projected to be fully replaced with “new generation” fixtures. (Vickers 1993).

Several case studies have demonstrated significant demand reduction from various strategies, including technological improvements, behavioral marketing campaigns, and adjustments of water pricing. Trends in declining residential (gpcd) have been observed from recent evaluations of single family residential water demands in the United States from 1995 through 2011 (DeOreo and Mayer 2012). They conclude that indoor water use has declined during this 16 year period and can be expected to continue to decline as new technologies enter the market. Their conclusions are based on results of four major studies of residential water use. Key findings are:

- Per capita indoor water use has declined from 60 gpcd in 1995 to about 40 gpcd in 2010 for homes built in that year.
- The long-term potential indoor of 40 gpcd is mainly dependent on the rate at which customers change from existing to new toilets and clothes washers.

Demand management strategies have primarily focused on reduction of indoor residential water use due to legislative initiatives such as the Energy Policy Act of 1992 as well as the relative importance and predictable nature of residential indoor water usage. The United States Geological Survey (USGS) estimated water use from public supplies across the United States in 1995 as 56% domestic (residential), 17% commercial, 12% industrial, and 15% public use and losses (Solley et al. 1998). Residential usage in Florida during 2005 was 95 gallons per capita per day or 60% of the total 158 gpcd used for public supply (Marella 2008). Single family residential (SFR) indoor usage represents half to two-thirds of total SFR usage, with the remaining portion being used for outdoor water usage (Mayer et al. 1999, Haley and Dukes 2010). Indoor usage is also consistent both spatially and temporally across the United States (Mayer et al. 1999).

Although these initiatives are steps in the right direction, current water conservation plans are often qualitative with unreliable aggregate savings estimates, even for the most reliable indoor residential sector. This is due to the fact that demand management initiatives have little to no requirements for quantitative analysis of projected savings (Tanverakul and Lee 2012). Additionally, these programs do not measure or track how much water was actually saved from implementation. These issues have resulted in conservation being viewed as a minor element of water resources planning, and not competitive with other supply options which have well-established quantitative analysis procedures (Vickers 2001). Thus, a major setback for the continued growth of demand management initiatives is the low reliability of anticipated water savings estimates.

Recent initiatives have been geared toward better understanding the nature of water demand and reliably quantifying and crediting historical and projected demand management in an effort to make conservation a more rigorous alternative supply option. One such initiative is California's 20x2020 plan, which strives to reduce California's water demands by 20% by the year 2020. This initiative, which began in 2009-2010, has prompted detailed discussions about how to determine conservation potential, and how to implement and track best management practices (California Water Resources Control Board 2009). Much interest has been in predicting "code based, basic, or passive" demand reductions from penetration of new technologies of indoor plumbing fixtures. Although penetration of new plumbing fixtures has resulted in declined residential indoor per capita water usage, it has been projected that additional utility incentivized measures will need to be implemented as "basic or passive" drivers

alone will not reach the 20% target reduction. A major component of this plan is to require every utility to maintain high quality water usage databases, including customer billing and water supply data to accurately quantify current demand patterns and to compile annual system water loss audits, which is anticipated to be complete by 2015 (Thornton 2005). Additionally, interim goals of 10% water savings from baseline average usage from 1995-2005 are set for 2015.

Demand management has gained further interest in the past several years due to growing concerns about energy efficiency, climate change, and an increased emphasis on green technologies and environmental awareness. Recent initiatives focused on incorporating demand management in a broader context beyond reduced water supply needs are further requiring the need to better quantify demands with higher resolution. A recent report for the Water Research Foundation includes demand management as a best practice in water treatment, storage, and transmission energy efficiency, which recognizes that reduced demands may result in reduced treatment and distribution needs thus saving energy inputs (Leiby and Burke 2011). This report emphasizes the need for metered customer water consumption data to effectively quantify water savings and develop demand management plans. Additionally, a hydro-economic model of California's water supply (California Value Integrated Network or CALVIN) was created to determine necessary changes to current water use management and operation in response to long term climatic and demographic changes (Tanaka et al. 2006). This model includes demand management strategies as one possible means toward responding to various climate predictions (Tanaka et al. 2006).

An increased emphasis on green technologies and environmental awareness has resulted in several recent programs promoting water efficiency and water conservation through product certification and setting demand usage milestones. Nationally, EPA Water Sense and Energy Star programs are aimed at certifying water or energy efficient devices, primarily within homes, which do not sacrifice performance (USEPA 2012b, USEPA 2012c). In Florida, the St. John's Water Management District's Water Star program and the South Florida Water Management District's Water Sip program allow residential homes and businesses to achieve various levels of recognition for efforts related to demand management (SJRWMD 2012, SFWMD 2012). Much work is needed in quantifying the impact these programs have made on water demands as these types of incentive programs remain qualitative in nature.

Applications of reliable water demand and water savings from demand reduction are recently expanding to include multi-objective optimization of distribution system operations and design, and for obtaining permitting credits from utility incentivized conservation. (Olford and Filion 2012, Florida Department of Environmental Protection 2012). The multi-objective optimization of distribution system operations minimizes system cost by reducing residential demand at a demand node subject to satisfying hydraulic and water quality requirements. The cost of demand reductions is modeled as a decrease in revenue from changes in billed water (Olford and Filion 2012). Although demand reductions are now being considered in water distribution optimization, demand estimates are primarily aggregate or simplistic assumptions based on small sample data sets.

Detailed accounting of historical demand patterns and accurate forecasts of future water usage has received increased interest as regulatory agencies are now considering incentivizing demand management by not reducing existing permitted amounts caused by utility incentivized conservation. Utilities would then be able to extend their permits and delay groundwater withdrawals as more customers could be added to the existing supply. This would require detailed water consumption and population growth estimates which are proposed to be integrated with long-term water supply planning efforts (Florida Department of Environmental Protection 2012). Attention is being given to quantifying decreased water demand from utility incentivized demand management vs. other factors such as climate, national plumbing code changes (i.e. basic or passive water savings), and the recent economic recession. Some utilities have already revised demand forecasts based on recent trends of reduced consumption. Decreased demands have resulted in Gainesville Regional Utilities projecting no additional needed permitted groundwater supply for its upcoming Consumptive Use Permit application. A significant portion of this has been projected to be the result of water conservation as shown in Figure 1-1 (Gainesville Regional Utilities 2012).

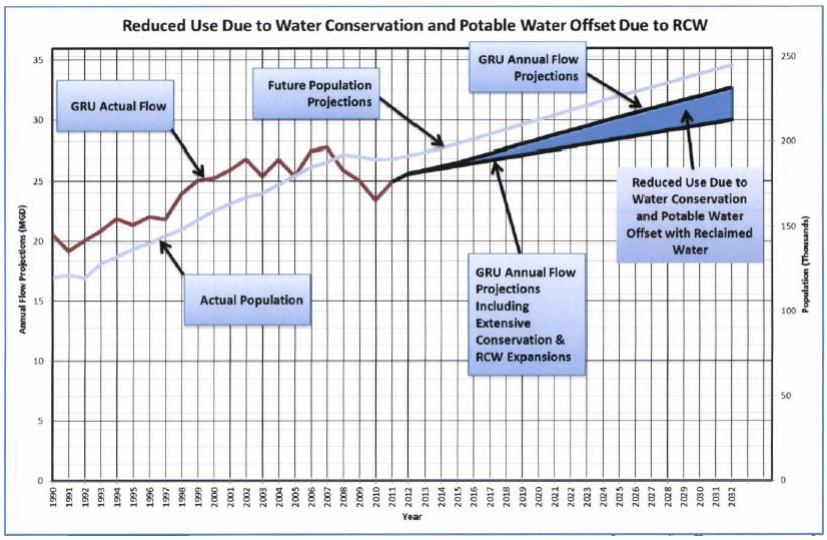

Figure 1-1. Projected water demand for Gainesville Regional Utilities including the impact of conservation (Gainesville Regional Utilities 2012)

Miami-Dade County Water and Sewer used an aggregate regression model which included past demand management efforts as a causal variable to reforecast their projected water demands (Fritche et al. 2012). This reforecast shows declining projected water usage which has resulted in anticipated deferral and/or elimination of several previously scheduled supply expansion projects for Miami-Dade. However, a process level understanding of the nature of these decreases would enhance the reliability of these projections, particularly in separating the effect of Miami-Dade's demand management program vs. other causal factors such as a period of economic recession.

Despite improvements in quantifying demand management, there remains no consensus as to a unified demand management modeling framework (Tanverakul and Lee 2012). Until recently, demand management programs have remained largely qualitative and a minor part of a utility's overall water supply planning efforts. However, rigorously quantifying demand management is becoming more prevalent to allow for

meaningful comparisons to competing alternative supplies and to expand to broader applications. Quantifying demand management is challenging since demand management options include specifying and/or replacing many small end uses which individually minimally impact overall water use but which collectively can constitute significant aggregate reductions in demand. Vickers (2001) presents a detailed description of demand management options. Some progress has been made in these efforts, particularly in addressing residential indoor demand reductions due to plumbing code changes for example, but much work remains, particularly for other demand sectors.

Goals and Objectives

To address these emerging needs related to better quantifying urban water demand estimation and associated demand management options, this dissertation presents a systematic data driven approach for evaluating water usage and demand management options for urban systems. This data driven approach evaluates water usage and associated demand management directly for each of the approximately nine million parcels of land in Florida. Water usage for all water using devices is estimated using a uniform statewide property appraiser's database combined with water utility billing data. Water using population is then determined with the addition of U.S. Census Block data, which is utilized to determine per capita usage rates. The potential effects of demand management are then determined directly as the difference between existing and proposed water usage after implementation. Water savings performance functions are then developed for each demand management option. These performance functions are then utilized to evaluate the optimal blend of demand management options to either maximize net benefits of water savings or to minimize the cost of reaching a target

water savings from demand management. Both linear and nonlinear formulations and solutions to these problems are presented. Additionally, explicit analytical solutions are presented based on appropriate exponential best fits of water savings performance functions. Emphasis is placed on the residential water use sector, although generalizations to all urban water use sectors are described. Two primary case study utilities, Gainesville Regional Utilities and City of Sanford are utilized to illustrate proposed methodologies.

Steady state deterministic parcel level water use and demand management optimization methodologies are addressed in Chapter 2. Applications utilizing the single family indoor sector are utilized to illustrate these methodologies. Single family outdoor water usage estimation and demand management strategies are the focus of Chapter 3. Unique insights are presented, as the result of analyzing irrigation patterns for all residential customers within a utility, which very few studies have previously considered. The deterministic methodologies presented in Chapters 2 and 3 are extended to account for uncertainty in key water use parameter estimates in Chapter 4. Both non-parametric and parametric representations of uncertain water usage and demand management potential are presented. The solution algorithm to the optimal demand management formulations presented in the previous chapters is formalized in Chapter 5. An explicit analytical solution is presented which determines the optimal blend of demand management practices to achieve a specified goal. A direct result of this solution is the dual variable which represents the marginal cost of water saved at a specified target water savings goal. The previous steady state formulations are extended into a dynamic process simulation to predict urban water usage at an annual

time step in Chapter 6. Parcel level data driven methodologies to estimate population and per capita water usage in the single and multi-family residential sectors are utilized within the simulation model. This approach allows for consistent benchmarking of water use efficiency across heterogeneous utilities as process model results are compared and validated against measured water use. The summary and conclusions and suggestions for further work are presented in Chapter 7.

The research presented in this dissertation is part of a team effort to develop a parcel level decision support system model for evaluating demand management options in Florida utilities. Methodologies developed as part of this research are utilized within a web based tool, called the Conserve Florida Water EZ Guide 2.0 (http://conservefloridawater.org), which is utilized by several utilities and water management agencies throughout Florida to develop optimal demand management plans for a variety of applications such as regional water supply planning and water use permitting. These methodologies are currently being expanded to include areas outside Florida to allow for larger regional and national analyses.

CHAPTER 2
WATER DEMAND MANAGEMENT OPTIMIZATION METHODOLOGY

Scope and Overview

Demand management can be a viable alternative to augmenting the supply system to meet future water needs. Demand management should be compared to traditional supply augmentation methods when deciding the extent to which it is a viable option. Methods of analysis are well established for choosing among supply augmentation options such as well field development, reservoir and pipeline construction, and desalination. Demand management is an emerging alternative, in which several case studies have been conducted illustrating significant demand reduction from various strategies, including technological improvements, behavioral marketing campaigns, and adjustments of water pricing. The major difference between traditional supply augmentation and demand management is that traditional supply options are capital intensive with long service lives, so capacity expansion is done in discrete, relatively large, increments. Demand management options include many small changes which reduce water use for individual customers by a few gallons per day but which collectively can bring about significant aggregate reductions in demand if they are applied to a significant portion of the utility's customers.

Recent advances in database availability, including an associated Geographic Information System (GIS), make it possible to do a bottom-up evaluation of water demand patterns across the utility and systematically determine the potential savings for all single family indoor retrofit options within a given utility. An optimal mix of demand-management strategies can then be selected by comparing each individual demand-management control with a few large supply augmentation options. Existing water

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demand management models rely on trial-and-error procedures to estimate the optimal mix of control options with little or no information for the actual identification of individual fixture savings potential.

This bottom up optimization method has been developed as part of activities of the Conserve Florida Water Clearinghouse (www.conservefloridawater.org) to develop software to identify the best mix of single family residential end-use options based on the desired objective. The objective function for the optimization can vary depending on the interests of the utility, including maximizing net benefits in comparison to other supply options, minimizing the cost of meeting a target water reduction, or maximizing water savings subject to a budget constraint.

The bottom-up approach is feasible in Florida thanks to the availability of attribute data for every one of Florida's 8.8 million property parcels. Due to Florida's government in the sunshine legislation, the state may be unique in reporting annually the attributes of all 8.8 million parcels in its 67 counties. Additional information regarding these parcels is available from the property appraisers' databases for each of Florida's 67 counties although this information varies from county to county. This parcel-level information is used, along with U.S. Census block data on persons per dwelling unit, and customer level water utility billing data, where available, to find the optimal mix of end-use options.

This methodology uses three core principles for evaluating end-use options: 1) determining existing end-use devices and water use for every customer in a utility; 2) directly determining water savings and associated costs with less water intensive end use devices; and 3) determining the optimal mix of end-use demand management

options and identifying the highest priority customers to target. These methodologies focus on determining the optimal mix of technological fixture end use improvements, assuming that behavior and price of water are constant.

Water Demand Management Methodology

The AwwaRF residential (Mayer et al. 1999 and Aquacraft, Inc. 2005) and Commercial/Institutional (Dziegielewski et al. 2000) end-use studies provide fundamental information regarding the nature of urban water use for individual end uses. End-use analysis provides an essential inventory of existing and projected water use devices and their attributes, e.g., 10,000 single-family residential customers with one bathroom that have 1.28-gallon-per-flush toilets. The decision variables in end-use optimization are the end-use devices, e.g., replace five thousand 3.5-gallon-per-flush toilets in one-bath houses with 1.28-gallon-per-flush toilets. Maddaus and Maddaus (2004) describe their proprietary Least Cost Planning Demand Management Decision Support System (DSS) that includes end use evaluations. This model has been widely applied in the United States and in Australia. White et al. (2004) describe the development of the Sydney Water End Use Model and its application in Australia. Maddaus and Maddaus (2006) provide a detailed description of water conservation planning in the AWWA Manual of Practices M52. Maddaus (2009) presents a detailed description of his end-use DSS to regional water supply planning in the East Bay Municipal Utility District. Green (2010) presents information regarding the expected costs, savings, and service lives for a variety of demand-management options based on information provided by William Maddaus.

Existing top-down procedures rely on aggregate water system data to estimate end uses. These highly aggregated average values are of little use in estimating the

variability of savings that exists across the utility because of differences in water use patterns of existing fixtures. Savings depend on the water use of existing and proposed fixtures. Using a single “average savings” for all fixture replacements provides only a very crude estimate of the actual savings rates and no information regarding the market share of this option.

The Conserve Florida Water Clearinghouse (www.conservefloridawater.org) has developed a bottom-up end-use optimization and decision support system model for evaluating water demand management options for utilities in Florida. The basic reporting unit is the individual parcel. The application of this methodology to the single-family residential sector using Gainesville Regional Utilities will be described as an example. A bottom-up methodology is preferable to reliance on a top-down approach since it provides a basis for evaluating customers individually or in smaller groups. The main limitation to bottom-up analyses has been lack of data at these disaggregated scales. Polebitski and Palmer (2010) evaluate water demand forecasting using the 100 census tracts that comprise Seattle, Washington. Chen (1994) argues that census block groups are preferable to census tracts due to the increased spatial disaggregation. The findings of this study suggest that spatial disaggregation is primarily limited by data availability. Hazen and Sawyer and PMCL (2004) used 1,500 U.S. Census Traffic Analysis Zones (TAZs) as the basic spatial unit in analyzing water use in the Tampa Bay area. They aggregate customer-level water use data to the TAZ levels for use in their regression models. The average number of people per spatial unit in Florida is shown in Table 2-1. Census tracts with about 4,000 people provide limited ability to do end-use evaluations using relatively homogeneous neighborhood clusters.

These exceptional databases provide the basis for accurate end-use evaluations at the parcel-level.

Table 2-1. Levels of aggregation by spatial unit for Florida based on 2009 conditions

Unit	Value	Persons/ Unit
Population	18,800,000	1
Parcels	8,800,000	2.14
Census Blocks	362,499	51.9
Traffic Analysis Zones	12,747	1,475
Census Tracts*	4,700	4,000
Utilities	2,633	7,140
Counties	67	280,597

*Value based on 4,000 persons per Census tract

The Conserve Florida Water Clearinghouse (www.conservefloridawater.org) has developed its water conservation software, called EZ Guide 2, using the 8.8 million parcels in Florida as the basic reporting unit. Utilities or the water management districts provide the Clearinghouse with the utility boundaries as GIS shapefiles, which are used to determine which parcels to analyze for a given utility. EZ Guide 2 uses this information to generate estimates of population, heated area, and irrigable area for each of 60 urban water land use types based on the land use codes of the Florida Department of Revenue. This parcel-level information is used to do a complete bottom-up evaluation of demand management options.

Parcel-Level End Use Evaluation

The basic structure of the database for parcel-level end-use evaluation can be represented as a single m by n matrix, A, with individual elements, aij. This single flat file format provides a convenient computing platform within contemporary spreadsheets

such as Excel 2007, which is the application EZ Guide 2 uses. The database includes all 8.8 million parcels in Florida. The parcels within an individual utility can be determined as the union of Florida parcel geometries and utility boundary geometries using GIS.

The only block level estimate included in the database is the estimated persons per residence that comes from U.S. Census Block data. From Table 2-1, a Census block contains about 20 to 25 parcels, so it should provide a fairly reliable estimate of persons per residence. An average of 2.5 persons per residence has been shown to be fairly stable spatially and temporally over the last few decades (Smith et al. 2002, Friedman 2009). Due to this stability, U.S. Census persons per residence data at the Census Block level of aggregation can be used without adjusting for the 10-year lag time between the Censuses. The FDOR data are updated annually. These data are generally of high quality since they are carefully audited to ensure accurate property value assessments.

The illustrative application presented in this paper is to m = 30, 903 SFR parcels with 46 attributes served by Gainesville Regional Utilities (GRU) in Gainesville, Florida shown in Table 2-2. Although only SFR will be analyzed in this paper, the same attributes can be obtained and analyzed for other sectors. GRU is located in Alachua County, Florida. The 46 attributes for the parcel-level database for GRU that are shown in Table 2-2 come from four sources: U.S. Census, Florida Department of Revenue (FDOR), Alachua County Property Appraiser (ACPA), and GRU. GRU represents a best-case utility where all parcel attribute data are known along with having billing data with separate indoor and outdoor meters for some of the accounts. Not all elements aij

in matrix A are directly known for all utilities. A minimum of 20 specific attribute columns per parcel (attributes 1-20 in Table 2-2) are required to perform a bottom-up parcel level analysis. Additional attributes, if available, can improve the accuracy of the method, such as the GRU billing data. Fields 1-11 in Table 2-2 can be obtained directly for any parcel in Florida from Census or FDOR data. Fields 12-20 are necessary, but the availability varies by county appraiser. These fields can be estimated if the data are not directly available. Billing data can greatly enhance the analysis methodology by allowing for improved calibration of water usage estimates, but are not necessary to perform this analysis. Significant effort is required to link billing data to the other data sources (Friedman 2010). County property appraiser and billing data are added and updated on a case-by-case basis as data become available.

Table 2-2. Description of 46 attributes for the parcel-level database for 30,903 single family residences served by Gainesville Regional Utilities and 50,920 single family residences in Alachua County

Field(s)	Data source	Attribute	Scale	Definition	Period of record	Type
1	Census	Census ID	Block	Can be linked with other GIS compatible databases	2000	Spatial
2	Census/GIS	GIS geometry	Block	GIS geometry can be linked with FDOR GIS geometry	2000	Spatial
3	Census	Average household size	Block	Average for the entire block. May include mixed uses.	2000	Spatial
4	FDOR*	Parcel ID	Parcel	ACPA database includes FDOR ID	1920-2008	Spatial
5	FDOR	Use code	Parcel	Indicates which parcels are in the single family sector	1920-2008	Spatial
6	FDOR/GIS**	Parcel geometry	Parcel	GIS geometry can be linked with other GIS data	1920-2008	Spatial
7	FDOR	Effective year built	Parcel	Year property built or year of major renovation	1920-2008	Spatial
8	FDOR	JustValue	Parcel	The current (2008) value of a property	1920-2008	Spatial
9	FDOR	Effective area	Parcel	The effective developed area of the property	1920-2008	Spatial
10	FDOR/GIS	Parcel area	Parcel	GIS calculated parcel area using DOR parcel geometry	1920-2008	Spatial
11	FDOR	Residential units	Parcel	Number of residential units per parcel	1920-2008	Spatial
12	ACPA***	ID	Parcel	Identification number that is linked to GRU database	1920-2008	Spatial
13	ACPA	Stories	Parcel	Number of stories per structure	1920-2008	Spatial
14	ACPA	Associated impervious area#	Parcel	Associated impervious area of a parcel	1920-2008	Spatial
15	ACPA	Gross area	Parcel	Gross area of the parcel	1920-2008	Spatial
16	ACPA	Bathrooms	Parcel	Number of bathrooms within a property	1920-2008	Spatial
17	ACPA	Heated area	Parcel	Heated area of a property	1920-2008	Spatial
18	ACPA	Inground irrigation system	Parcel	Yes or no	1920-2008	Spatial
19	ACPA/GIS	GIS geometry	Parcel	Linked with FDOR and GRU GIS databases	1920-2008	Spatial

Table 2-2. Continued

Field(s)	Data source	Attribute	Scale	Definition	Period of record	Type
20	ACPA	Inground pool	Parcel	Yes or no	1920-2008	Spatial
21	GRU****	Customer ID	Parcel	GRU database includes ACPA ID	1920-2008	Spatial
22	GRU	Dual meter tag	Parcel	Indicates a dual or single metered customer	1920-2008	Spatial
23-34	GRU	Irrigation meter water use	Parcel	One year of monthly data for irrigation meters	10/07-9/08	Temporal
35-46	GRU	Regular meter water use	Parcel	One year of monthly data for regular meters	10/07-9/08	Temporal

*Florida Department of Revenue

**Geographic Information System

***Alachua County Property Appraiser

****Gainesville Regional Utilities

Sum of areas of garage, driveway, patio, screened in areas, balconies, sheds/barns, etc.

The FDOR attributes in the parcel level database are updated annually. Due to the accuracy and quality of these data, this process is straightforward. U.S. Census block data are updated every 10 years and do not require much work unless the census block boundaries have been reconfigured.

It is simple to link the FDOR and county property appraisers' parcel-level databases. However, the content of the county property parcel-level databases varies and the county-level databases must be acquired for each county. A demographic analysis was done for Alachua and Hillsborough counties that include the two benchmark utilities: Gainesville Regional Utilities (Alachua County) and Hillsborough County Water Resources Services (Hillsborough County). The ACPA database has a wealth of parcel-level information for water demand management studies, including the 10 spatial attributes shown in Table 2-2. The results from the analysis of the Alachua and Hillsborough county databases are used to estimate attributes for other areas that do not include these attributes. For example, most Florida counties provide information about the number of bathrooms at each single-family dwelling; however, that information is absent in some counties. In counties where the information is available, a relationship between the heated area of the home and the number of bathrooms was found to produce a reliable estimate that could be substituted for the missing data in other counties.

Using SFR data for Alachua (N = 50,920) and Hillsborough counties (N = 316,258), the number of bathrooms can be estimated as a function of the heated area of the parcel. The regression equation is

$$B = 0.000732796*HA + 0.766547642 \qquad (R^2 = 0.545) \qquad (2\text{-}1)$$

Where:

B = number of bathrooms per account

HA = heated area (ft^2) per account.

The results are shown in Table 2-3 as a table lookup function with the square footage rounded to the nearest 50 ft^2.

Table 2-3. Default lookup table for estimating the number of bathrooms based on regression analysis of a sample of 367,178 single family residential parcels in Alachua and Hillsborough Counties

Heated area range		
minimum ft^2	maximum ft^2	Number bathrooms per house
0	650	1
651	1,350	1.5
1,351	2,000	2
2,001	2,700	2.5
2,701	3,400	3
3,401	4,050	3.5
4,051	4,750	4
4,751	5,450	4.5
5,451	infinity	5

The key indicator of size in the FDOR database is the effective area of the parcel, rather than heated area which is used to estimate number of bathrooms (Attribute 9 in Table 2-2). The effective area is not a physical area but is the heated area plus the associated impervious area multiplied by a weight that is less than 1. Fortunately, the county property appraisers report the heated area for each parcel. Thus, it is possible to estimate heated area as a function of effective area. The result for GRU is shown in Figure 2-1. The fit is excellent.

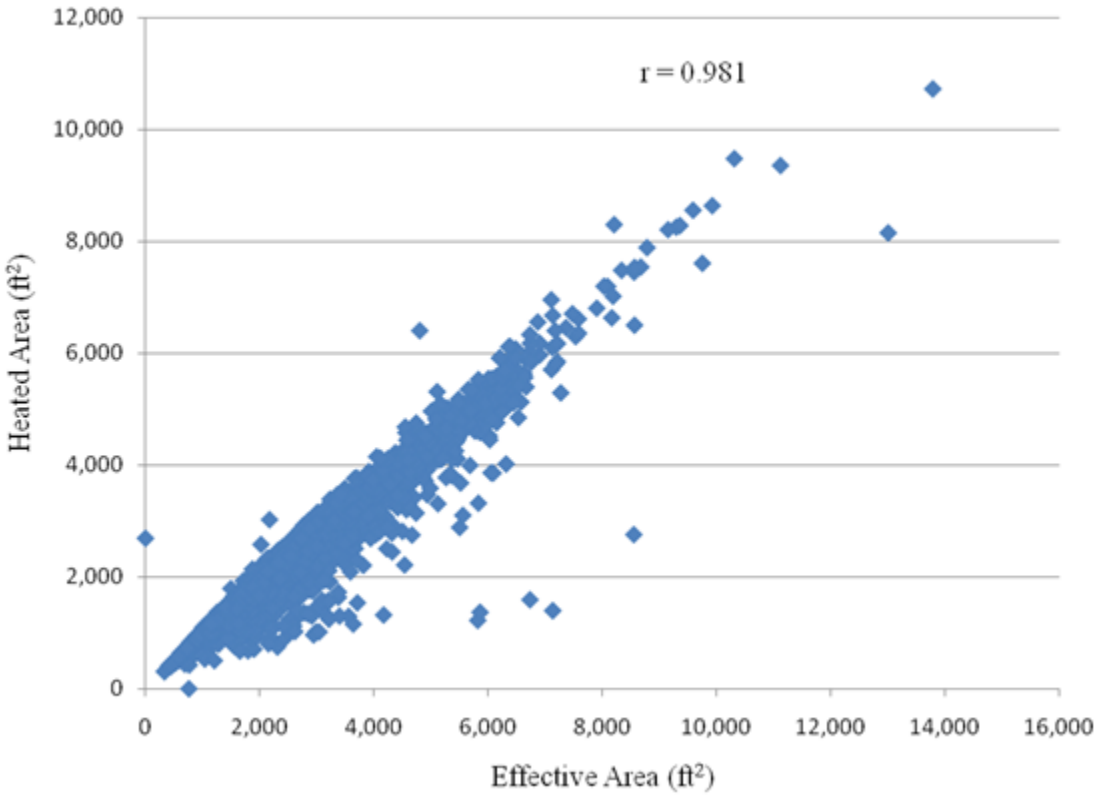


Figure 2-1. Relationship between effective and heated area for 30,903 single family residences in GRU

The HA/EA ratio for a single FDOR code, K_p, is calculated using Equation 2.

$$K_p = \sum_i (HA_{ip} / EA_{ip}) \qquad (2\text{-}2)$$

For, GRU, Kp = 0.87. Kp has been shown to be very consistent and stable throughout Florida for a given FDOR code (Morales 2010). Assuming Kp=0.87, Equations 2-1 and 2-2 can be used to estimate the heated area and number of bathrooms for any parcel within the single-family residential land use FDOR category in Florida.

Once the subset of matrix A is known for a given utility, a wide variety of analyses can be conducted. Due to the structure of the database, level of effort does not depend on the number of parcels selected in the analysis. Thus, the parcel level

methodology described can be conducted for small utilities, large utilities, or large planning regions with the same level of effort. As an example analysis, the Clearinghouse statewide database provides the effective year built (Attribute 7 in Table 2-2) for all customers. The annual number of new accounts and the cumulative total SFR accounts for GRU are shown in Figure 2-2.

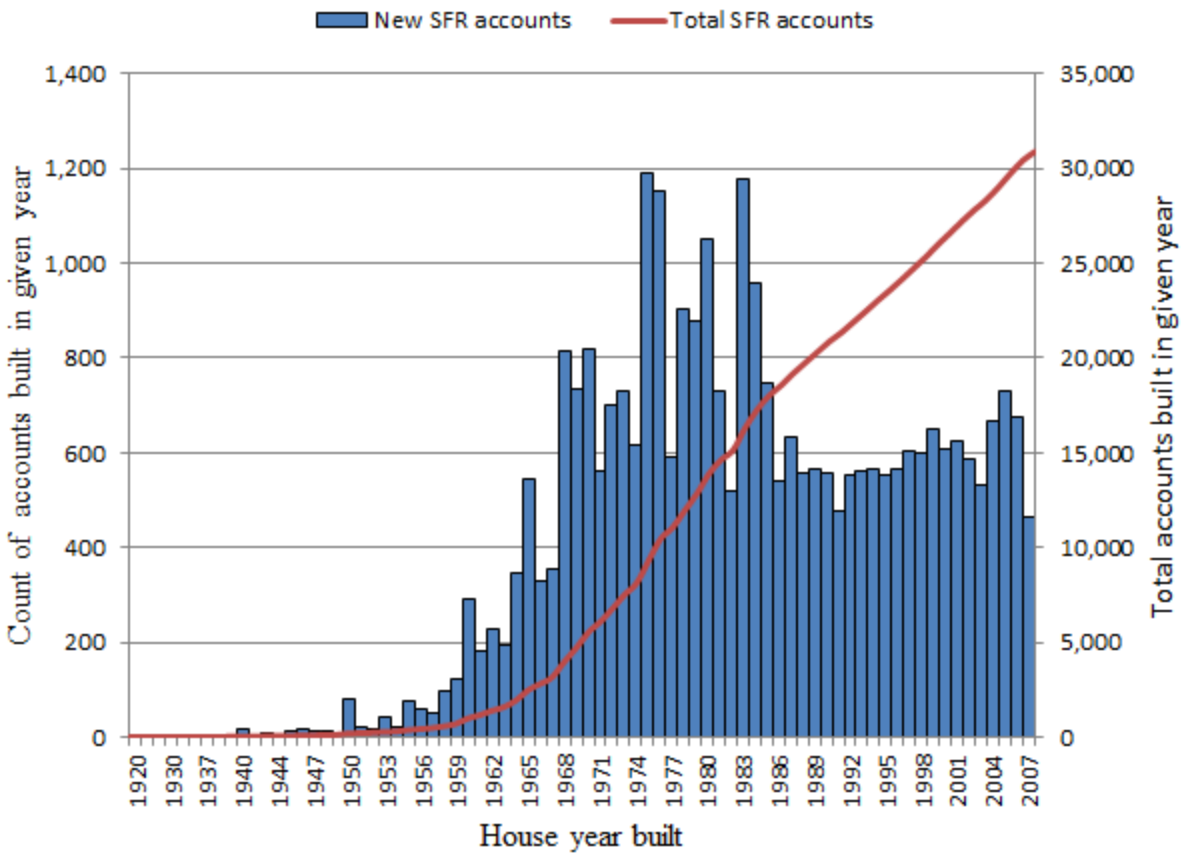


Figure 2-2. Annual new single family residential new and cumulative single family residential accounts of customers served by Gainesville Regional Utilities from 1920 to 2007

There were 30,903 SFR accounts as of 2007. The most rapid annual growth rates occurred from 1968 to 1985. The annual growth rate has remained steady since 1985 at about 600 new customers per year. This annual time series data at the individual customer level provides an excellent basis for evaluating historic growth

patterns and projecting future growth patterns. All calculations are done at the account level and the results are aggregated as needed. For example, the number of bathrooms per house for each five-year period is shown in Figure 2-3.

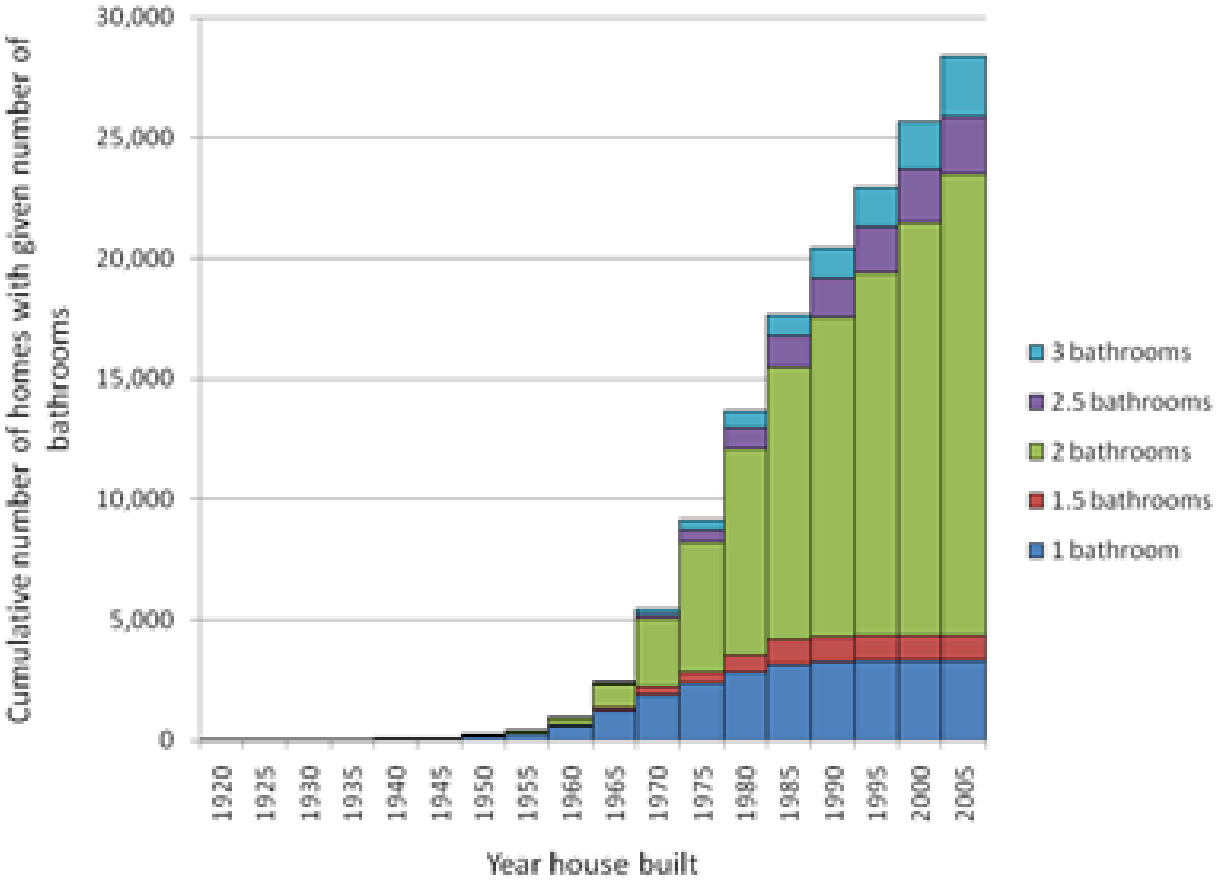


Figure 2-3. Trends in number of bathrooms per single family residence for 30,903 customers served by Gainesville Regional Utilities

This information was generated using a data table based on Attribute 7 (effective year built) and Attribute 16 (number of bathrooms) in the GRU combined database. Before 1970, the majority of new houses had only one bathroom. Since 1970, most houses have at least two bathrooms (Friedman 2010). The heated area of SFRs has also increased significantly from about 1,500 ft^2 in 1970 to 2,300 ft^2 in 2007. The number of people per house has remained constant since 1970. Thus, the number of

people per toilet has decreased from 1.8 in 1970 to 1.1 in 2007. This major decrease in people per toilet results in a proportionately lower utilization rate per toilet.

Key comparative statistics for these three periods for single-family residences served by GRU are shown in Table 2-4.

Table 2-4. Comparative summary statistics for 30,903 single family residences served by Gainesville Regional Utilities arranged by three historical periods

	Historical Analysis Period			
Statistic	Pre 1983	1983-1994	1995-present	Sum or weighted average
Count of SFR parcels	15,152	7,896	7,855	30,903
Percent of SFR parcels	49%	26%	25%	100%
Average daily gallons per account (10/07 - 09/08)	207	246	292	238
Coefficient of variation	0.17	0.24	0.26	0.22
Average effective year built	1972	1988	2001	1984
Average heated area, ft^2	1,657	1,811	2,171	1,827
Average just value, $	$ 154,544	$ 201,087	$ 275,104	$ 197,080
Average persons per house	2.50	2.49	2.63	2.53
Average number of bathrooms	1.90	2.18	2.42	2.10
Average parcel area, ft^2	18,097	16,717	15,144	16,994
Average irrigable area, ft^2	14,958	12,982	11,109	13,475
Percent of accounts with sprinkler systems	9%	27%	61%	27%

This table provides valuable insights into the nature of residential water demand in Gainesville. Nearly half of the residences were built before 1983 when little attention was paid to water demand management, although some percentage of these homes likely has newer fixtures due to fixture replacement, as is explained in more detail in the next section. About 25% of the residences were built after 1994 and have water-saving indoor fixtures due to improved plumbing codes (Heaney et al. 2010). The average daily gallons per account has increased significantly from 207 for the pre-1983 residences to 292 for the post-1994 residences. While the newer homes are larger, the average

persons per house has remained stable at about 2.5 persons per house. The number of bathrooms per house has increased from 1.90 to 2.42 from Period 1 to Period 3. Thus, the fixture utilization rate has decreased. The average irrigable area has decreased by about 25% from Period 1 to Period 3. The most dramatic change across these three periods is the major increase in the use of in-ground irrigation systems. The use of in-ground irrigation systems appears to be the major reason why the average daily gallons per account is 292 for Period 3 and 207 for Period 1 residences.

Subgroupings of Single-Family Residential Accounts

Based on trend analysis in the previous section, SFR accounts can be subgrouped separately depending on whether indoor or outdoor usage is being analyzed. The SFR indoor usage subgrouping methodology will be presented in this paper. SFR accounts are arranged into subgroups based on fixture efficiency (based on three discrete plumbing code periods) and number of bathrooms per residence (based on six discrete values) which reflect distinct indoor usage characteristics shown in the previous section. Three fixture efficiency periods reflect significant differences in SFR fixture water usage rates, frequency of use, and market penetration. Historical water use is summarized for the following three periods: pre-1983, 1983-1994, and 1995 to present. The pre-1983 period represents an uncontrolled situation when few conservation practices had been implemented. The period from 1983 to 1994 reflects the beginning of conservation programs and plumbing codes that reduced the allowable water use per event. The period from 1995 to present reflects the impact of much more proactive demand management practices. Rashid et al. (2010) summarize the wide variety of demand-management initiatives that have been taken at the state and federal levels. Most of these activities have occurred during the past 20 years.

SFR accounts are divided based on six discrete number-of-bathrooms-per-account categories. Five values are recommended for the discrete baths per account values of 1, 1.5, 2, 2.5, and 3. The final value is for residences with more than 3 bathrooms. These residences are assumed to have an average of 3.5 bathrooms.

SFR accounts can be categorized into one of 18 subgroups, based on which of the three fixture efficiency periods and which of the six number-of-bathrooms-per-house categories it falls in. For example, accounts with fixtures reflective of those installed pre 1983 having 2 bathrooms would be grouped together. The total number of bathrooms for accounts in each of these 18 subgroups was determined for GRU based on property appraiser's data and is shown in Table 2-5. This information is generated from the master data matrix using a pivot table that sums over the three fixture efficiency periods and the six bathroom values.

Table 2-5. Distribution of bathrooms in 30,903 GRU single family residential accounts as of the year 2008

Period	Total SFRs	Bathrooms 1	1.5	2	2.5	3	3.5*
Pre 1983	15,152	2,913	828	9,408	965	762	276
1983-1994	7,896	374	221	5,278	916	756	351
1995-2008	7,855	20	14	5,023	606	1,300	892
Total	30,903	3,307	1,063	19,709	2,487	2,818	1,519
% of Total	100.00%	10.70%	3.44%	63.78%	8.05%	9.12%	4.92%

*Residences with more than 3 bathrooms are assumed to have an average of 3.5 bathrooms.

Generation of End-Use Estimates

The number of bathrooms is the basic driver that determines the number of toilets and other fixtures per residence. The number of toilets per bathroom is found using Equation 2-3.

$$\text{Toilets} = \text{roundup (baths, 0)} \qquad (2\text{-}3)$$

The Excel roundup function rounds up to the next integer.

The above information above can be combined to estimate the number of indoor fixtures. This procedure created 12 toilet subgroups, 3 clothes washer subgroups, 9 showerhead subgroups, and 12 faucet subgroups, creating a total of 36 subgroups based on fixture efficiency and number of bathrooms per house for indoor end-use analysis. This is a refinement of the initial 18 subgroups, where each home is now assigned to one subgroup for each of the four fixtures. Partitioning the total SFR customer base into these categories allows for much more accurate determination of SFR indoor water usage and how it varies. Dziegielewski and Opitz (2002) also suggest disaggregating customers into non-conserving, standard, and ultra-conserving classes. In addition, this methodology allows for selecting target groups to retrofit for a conservation plan.

To estimate the mix of each fixture for a particular year, one has to account for replacement of older fixtures. Knowing the effective year built and an assumed fixture service live for each of the SFR accounts, it is straightforward to calculate the mix of fixtures for any assumed scenario year. Initially, SFR accounts are classified into fixture subgroups by assuming fixture efficiencies based on the effective year built of the home. Accounts are reclassified if a more efficient device is assumed to exist based on service life assumptions. Previous retrofit programs can be incorporated if specific accounts retrofitted can be identified. As an example, the estimated mix of toilets in 2008 in GRU, based on a service life of 40 years, is contained in Table 2-6. Estimates of service lives for a variety of end uses are available in National Association of Home Builders (2007), Maddaus (2009) and Green (2010).

Table 2-6. Number of toilets in the SFR category of GRU's 30,903 customers in 2008 based on a toilet service life of 40 years.

Year Built Group	Total	Toilets/single family residence 1	2	3	4	Average Toilets/ SFR
Pre 1983	23,088	1,306	16,358	4,488	936	2.22
1983-1994	18,128	553	11,130	5,037	1,408	2.40
1995-2008	25,626	1,448	14,056	6,390	3,732	2.48
Total	66,842	3,307	41,544	15,915	6,076	2.37
% of Total	100.00%	4.95%	62.15%	23.81%	9.09%	

Water Use Performance Functions for Toilets

Water use intensity depends on the number of persons per single-family residence. The persons per house is estimated using U.S. Census block level data that provide average values at an approximate scale of 50 to 100 residences. U.S. Census reports persons per residential dwelling unit. Sometimes this estimate is an average of single- and multi-family population densities for mixed use within a census block. Fortunately, census blocks can be divided into three categories: SFR only, Multi-family Residential (MFR) only, and SFR/MFR blends. For the SFR, the persons-per-residence estimate is calculated using Equation 2-4:

Persons/SFR = Census block average for the nearest block that is SFR only. (2-4)

In most cases the nearest block is the block in which the parcel is located. The resulting estimates of persons per residence are shown in Table 2-4. The persons per SFR has remained relatively constant during the three periods; thus utilizing Census reported persons per SFR is accurate, even though the data are available at 10-year intervals. However, the toilet utilization rate has decreased significantly because of the increasing number of toilets per SFR in recent years.

The next step is to estimate the daily usage per existing toilet. These results are shown in Table 2-7.

Table 2-7. Daily gallons per day per toilet

	Toilets/house				Toilet Attributes		
Period	1	2	3	4	Gallons/ flush	Daily flushes/ person	Daily gallons/ person
Pre 1983	63.7	31.8	21.2	15.9	5	5.1	25.5
1983-1994	44.5	22.2	14.8	11.1	3.5	5.1	17.85
1995-2008	21.5	10.7	7.17	5.37	1.6	5.1	8.16

Additional input information is the attributes of toilets associated with each period. The gallons per flush and daily flushes per day are based on the results of the national SFR end-use evaluations and summaries of usage estimates in earlier periods (Mayer et al. 1999, Vickers 2001, Aquacraft, Inc. 2005). As shown in Table 2-7, the average daily gallons per person has decreased from 25.5 before 1983 to 8.16 after 1994 due to the reduction in gallons per flush from 5.0 to 1.6. The daily water use per toilet is based on the number of persons per toilet. These results show the combined effects of technological improvement in reducing the gallons per flush and the reduced number of people per toilet that results in a lower utilization rate.

Assume that it is desired to evaluate whether it is cost-effective to convert some or all of the above toilets to 1.28-gallons-per-flush (gpf) toilets. The daily flushes per toilet are assumed to remain at 5.1. The savings from switching the existing toilets to the 1.28-gpf model are shown in Table 2-8 for each of the 12 categories. The savings vary widely from as high as 48.0 gallons per toilet per day to a low of 1.10 gallons per toilet per day. This way of calculating savings is a significant improvement over using a single savings rate for all toilets that provides no information regarding the pre- and post-conditions.

The information from Tables 2-6 and 2-8 can be combined to generate a performance function for replacing existing toilets with 1.28-gpf toilets. The results are shown in Figure 2-4.

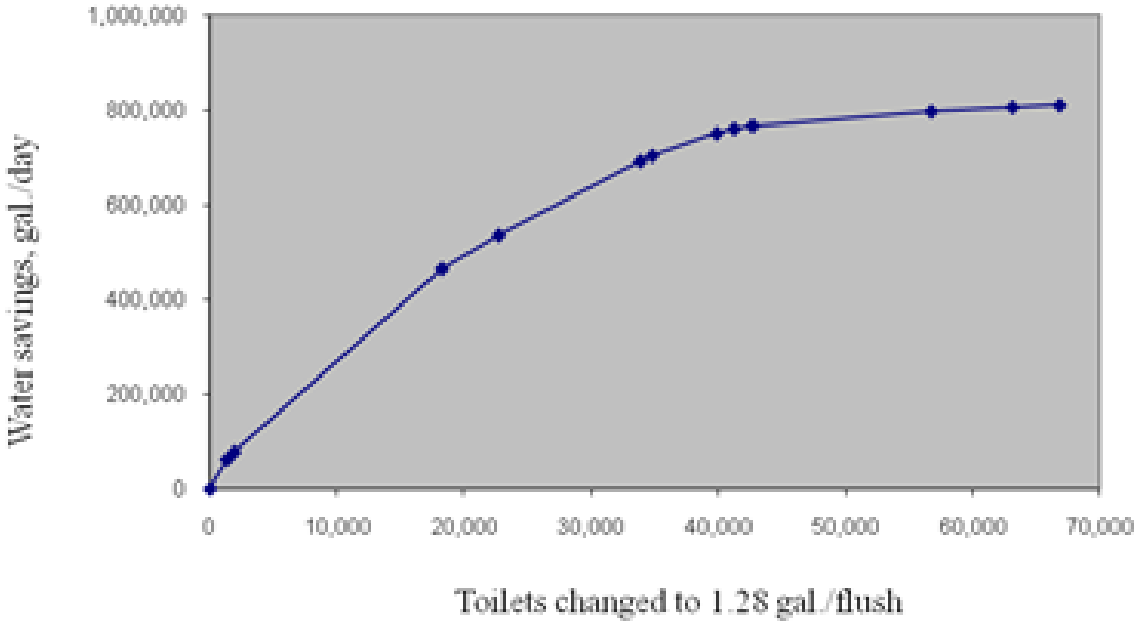


Figure 2-4. Total savings performance function for changing to 1.28 gpf toilets

The performance function is generated by ranking the retrofit options from highest to lowest savings rates. By definition, this function exhibits diminishing marginal productivity since the savings rate decreases as the number of toilets retrofitted increases. The slopes of each chord in the resulting piecewise linear function shown in Figure 2-4 are the water savings rates from Table 2-8.

Table 2-8. Daily water savings if all customers use 1.28 gallon per flush toilets

	Toilets/ single family residence			
Period	1	2	3	4
Pre 1983	47.4	23.7	15.8	11.8
1983-1994	28.2	14.1	9.41	7.05
1995-2008	4.30	2.15	1.43	1.07

Optimal Toilet Replacement Policy

Given the performance function for toilet retrofits (Figure 2-4), the unit cost of a toilet retrofit per day of service life (c) and the associated unit utility savings (p), it is possible to find the optimal number of toilets to change to 1.28-gpf models in this illustration. This problem can be formulated as a linear program to maximize net benefits as follows:

Maximize Z = p*y –c*x

Subject to:

$$y = \sum_j a_j x_j \tag{2-5}$$

$$x_j \leq (x_j)_{\max}$$

$$x_j \geq 0$$

Where: Z = total benefits – total costs, $/day

p = value of water saved, $/gallons

y = quantity of water saved, gallons/day

c = unit cost of a 1.28 gpf toilet, $/day

a_j = savings rate for the jth chord in the piecewise linear function, gallons/toilet/day

x_j = number of toilets in the jth category with an upper bound of $(x_j)_{max}$

A linear program has been set up within EZ Guide 2 to automatically find the optimal blend of demand-management options. The value of water saved and unit cost parameters are determined case by case for individual utilities. The value of water saved can include several benefits seen by the utility, including avoided production cost, avoided expansion or alternative sources, etc. Groves et al. (2008) describe categories

of savings that can be included depending on the accounting stance of the utility. The unit cost is based on the present value of the initial replacement cost, factoring in installation costs, rebate programs, etc. and the estimated operating costs over the service life of the end-use device. This formulation extends the linear program detailed above to simultaneously find the optimal blend across all demand-management options. Lund (1987) used linear programming to find the mix of conservation options that could reduce or eliminate the need for expanding the supply system. Lee et al. (2005) use production function theory to find the optimal blend of land-use adjustments and stormwater BMPs to satisfy low-impact-development stormwater goals. Rosenberg (2007a) uses probability theory to derive a normalized performance function for evaluating conservation options. Griffin (2006) presents a general overview of production economics and how water systems can be optimized. Baumol (1977) describes how production economics problems can be solved using linear programming. It is also possible to solve this optimization problem by fitting an equation to the production function and finding the value of x such that

$$dy/dx = c/p \qquad (2\text{-}6)$$

Where dy/dx = slope of the production function and c and p are defined above.

In this case the maximum net benefits are $1,438 per day that will save 762,000 gallons of water per day by converting 41,216 older toilets from residences with fewer toilets per residence.

EZ Guide 2 also allows other formulations of the decision problem, including maximizing the amount of water saved for a given budget or minimizing the cost of meeting a performance goal, e.g., gross gpcd $\leq$ 100. (See Heaney et al. (2010) for a

description of Florida definitions of gpcd). Economic optimization is not the only consideration in selecting the preferred alternative. Maddaus and Maddaus (2006) show how to set up a scoring matrix that incorporates non-economic factors.

Is 1.28 gpf The Best Toilet Retrofit Option?

In the illustrative example presented above, only a 1.28-gpf toilet was considered as the retrofit option. However, depending on the water savings rates and the relative savings and control costs, other toilet gpf options may be better. The linear program in EZ Guide 2 finds this best blend of 1.6-, 1.28-, 1.1-, and 0.8-gpf toilets. The 0.8- and 1.1-gpf toilets are more expensive but save more water whereas the 1.6 gpf toilet is less expensive but saves less water. The linear program was run for the unit cost of the four toilet options being $100 (1.6 gpf), $150 (1.28 gpf), $200 (1.1 gpf), and $300 (0.8 gpf). The results are shown in Table 2-9. If a single gpf value is used, the net benefits are largest if 1.6-gpf toilets are used. The 1.28-gpf option has lower net benefits. The net benefits are maximized by using a blend of 0.8- and 1.6-gpf toilets. These preliminary linear programming solutions and associated sensitivity analysis provide valuable insights into the best blends within and among end-use options.

Table 2-9. Net benefits and water saved by retrofitting toilets to a single flush rate or the optimal blend of flush rates

Option	Net benefits $/day	Daily 1,000 gal. saved
1.6 gpf only	$1,484	683
1.28 gpf only	$1,438	762
1.1 gpf only	$1,295	795
0.8 gpf only	$1,459	1,052
All options*	$1,564	997

*Optimum is blend of 1.6 and 0.8 gpf

Location of Priority Retrofits

The databases described in Table 2-2 include GIS spatial information that allows the results to be presented in terms of the location of the more promising parcels to retrofit. Illustrative results for toilets and irrigation systems in single family residences in Gainesville are shown in Figure 2-5. The spatial clustering indicates the priority areas. In this case the priority toilet retrofit areas are in the older sections of the city with smaller houses, fewer bathrooms, and older fixtures. The priority irrigation areas are the newer homes that have in-ground sprinkling systems.

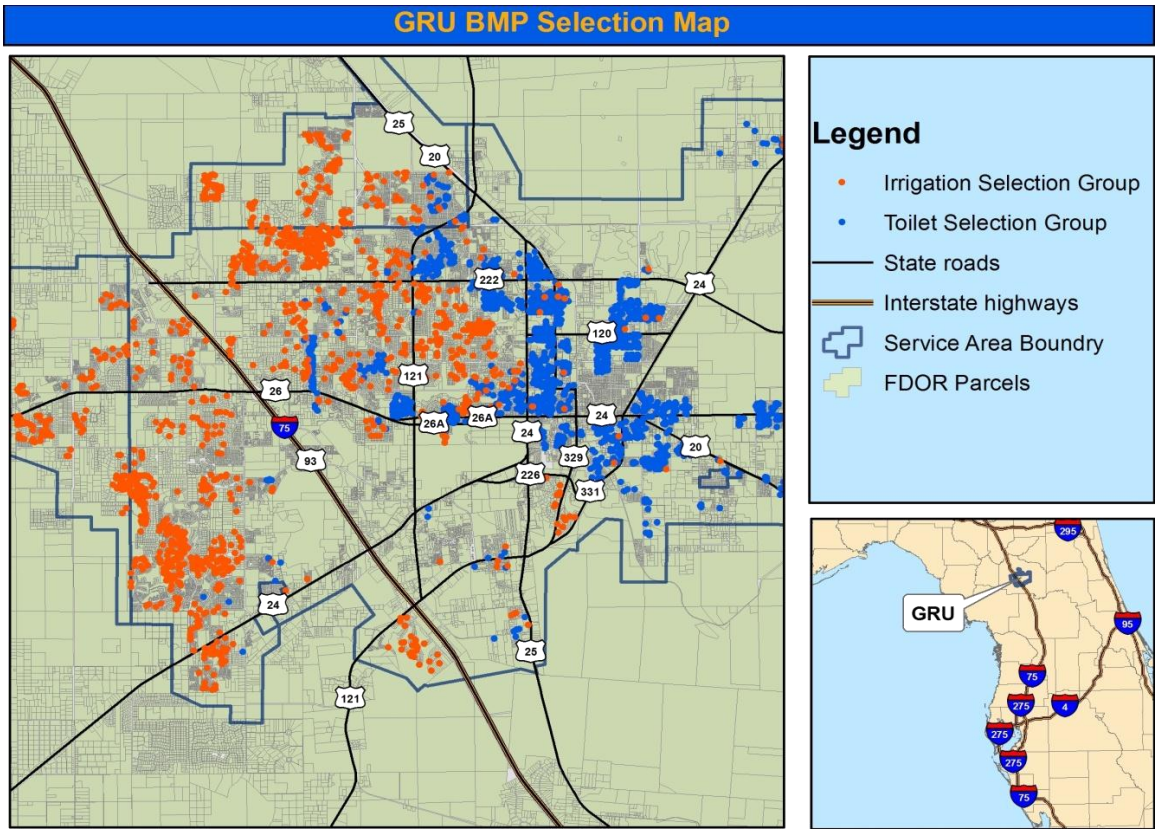


Figure 2-5. Illustrative map showing the priority parcels for toilet and irrigation single family residential retrofits, Gainesville, Florida

Synopsis

Acceptance of water demand management as a viable alternative to traditional supply augment options has been limited due to concern that the estimated savings might not materialize. The recent availability of accurate measurements of indoor end use patterns and accurate parcel-level information about customer attributes and historical water use patterns is making it possible to develop reliable estimates of the savings from demand management. Government in the sunshine legislation in Florida has made it possible to obtain accurate information on parcel attributes for every one of the state's 8.8 million parcels. Also, parcel-level water use data are available for selected utilities that have linked the parcel attribute and customer billing databases. The Conserve Florida Water Clearinghouse has used this unusual, if not unique, information to develop bottom-up water demand management decision support system for utilities within the state. This paper shows how this information can be used to develop performance functions for each end use and combine this information with savings and cost data to develop a linear program that can find the optimal demand management program that describe the optimal blend of the intensity of the option, .e.g., 1.28- vs. 0.8-gpf toilets, as well as across options, e.g., toilets vs. clothes washers. This entire procedure is programmed into EZ Guide 2, which provides Florida water utilities with a unique analysis tool driven by a uniform statewide database. Interested utilities can obtain these data sets already loaded into the EZ Guide 2 software. Output from this evaluation provides new insights into the opportunities and challenges of demand management. The approaches outlined in this paper provide a solid basis toward planning and allocating resources toward targeted conservation technology changes. Follow-up steps include implementing and evaluating actual water savings.

These results can then be used to improve the next iteration of the model run. Utilities outside of Florida should find this information and approach of value because EZ Guide 2 includes default equations or lookup tables to estimate important parameters if detailed data are unavailable.

CHAPTER 3
PREDICTING AND MANAGING RESIDENTIAL POTABLE IRRIGATION USING PARCEL LEVEL DATABASES

Scope and Overview

Single family residential (SFR) outdoor water usage can account for the majority of total and peak SFR usage in public supply especially during drier months in warmer climates (Mayer et al. 1999, Palenchar 2009, Haley and Dukes 2010, Chesnutt et al. 2004, Dziegielewski et al. 1993, Marella 2004,; Mays 2002, Vickers 2001, Whitcomb 2006). Based on direct measurements of single family residential water use patterns for a sample of 1,188 homes across 12 North American cities as shown in Table 3-1, SFR irrigation water use ranges from only about 10% of indoor water use in Waterloo, Ontario to 270% of indoor water use in Las Virgenes Water Utility in Southern California (Mayer et al. 1999). In contrast, indoor water usage is homogeneous across North America, with a coefficient of variation (COV) of only 0.12. The predominance of outdoor usage is likely to increase due to the growing popularity of in-ground sprinkling systems (Palenchar 2009) whereas indoor usage is declining due to recent technological improvements of indoor devices (DeOreo and Mayer 2012). Due to significant seasonal and spatial variability resulting from a wide range of factors influencing irrigation practices including climate, price signals, individual irrigation practices, irrigation restrictions, irrigation technology, etc., outdoor water usage can be much more challenging to predict compared to indoor usage. This paper describes a parcel level database approach toward estimating outdoor water usage at the household level, which can greatly reduce error associated with depicting the nature of outdoor water usage and associated demand management potential.

Reprinted with permission from Journal of American Water Works Association. Friedman, K. , Heaney,J., Morales, M. ,and J. Palenchar. 2013. Predicting and Managing Residential Potable Irrigation Using Parcel Level Databases. Journal of American Water Works Association. 105, 7,pp. E372-E388.

Table 3-1. Directly logged annual indoor, outdoor, and total water use for 12 U.S. cities (Adapted from Mayer et al. 1999)

Study site	Sample size	Persons/ house	Mean gpcd	Indoor gpcd	Outdoor gpcd
Waterloo	95	3.1	77.5	70.6	6.9
Seattle	99	2.8	78.3	57.1	21.2
Tampa	99	2.4	100.6	65.8	34.8
Lompoc	100	2.8	104.8	65.8	39.0
Eugene	98	2.5	134.7	83.5	51.2
Boulder	100	2.4	147.9	64.7	83.2
San Diego	100	2.7	159.1	58.3	100.8
Denver	99	2.7	175.5	69.3	106.2
Phoenix	100	2.9	230.6	77.6	153.0
Scottsdale	99	2.3	233.9	81.4	152.5
Walnut Valley WD	99	3.3	163.1	67.8	95.3
Las Virgenes MWD	100	3.1	258.0	69.6	188.4
Total	1,188				
Average	99.0	2.8	155.3	69.3	86.0
Standard deviation	1.4	.3	61.0	8.2	57.7
Coef. of variation	0.01	0.11	0.39	0.12	0.67

Recent advances in database technology and reporting in Florida make it possible to link parcel attribute metadata for every parcel in the state of Florida with monthly water use billing data for each parcel in specific test utilities. Each of the 67 counties in Florida submits property appraisal information to the state on an annual basis. This information is presented in a consistent format for each county for each of 64 land use sectors. A major advantage of a consistent statewide land use database is that sectors such as single family residential are defined consistently. Many utilities don’t have land use data for customers and rely on meter sizes to estimate the type of user, e.g., assume 5/8 and 3/4 inch meters are single family residential. This may be incorrect.

Average annual irrigation water use by the ith customer, QO(i), is the product of irrigated area multiplied by the average application rate, or:

$$QO(i) = k*AR(i)*AI(i) \quad (3\text{-}1)$$

Where: QO(i) = irrigation water use by the ith customer, gallons per account per day (gpad), k = 1.708 conversion factor, AR(i) = average irrigation application rate, in./yr, AI(i) = irrigable area, 1,000 square feet

The irrigable area is directly known for every SFR parcel using property appraisal data on parcel area and impervious area. The proportion of the irrigable area that is irrigated ranges between 0 and 1 with a default value of 1.0.

Customer billing data for Gainesville Regional Utilities (GRU) are used to estimate total outdoor water usage per home for 30,903 homes. For the 1,402 homes with separate potable indoor and outdoor meters, potable irrigation water usage is known directly. Otherwise, outdoor water usage is determined via hydrograph separation as shown by Equation 3-2. Indoor water usage estimates were estimated using an end use modeling framework, shown in Friedman et al. (2011). Given outdoor water usage and irrigable area, application rates can be determined using Equation 3-1.

$$QO(i) = QT(i) – QI(i) \quad (3\text{-}2)$$

Where: QT(i) = measured daily total water use by the ith customer (gpad), and QI(i) = estimated or measured daily indoor water use by the ith customer (gpad)

Additionally, some SFR customers have private irrigation wells. The identity of these customers is unknown and this use is not metered. Other SFR customers in GRU rely on reuse water for irrigation. About 700 of these customers have reuse meters.

These non- potable irrigators will not be addressed in this paper, as the focus of this paper is potable irrigation.

The next section describes long-term annual trends in irrigation water use for various subsets of GRU potable irrigators, including analysis of the effect of in-ground sprinkler systems, which is known in the database. Subsequent sections evaluate annual irrigation water use as a function of irrigated area, application rate, and their covariance at the parcel level. This agent-based approach indicates which SFR customers are significant irrigators and would have a significant potential for demand management activities. Finally, the summary and conclusions are presented.

Parcel Level Outdoor Water Use Trends

Consider the 1,402 SFR customers in GRU who have dual meters, and thus separately measured indoor and outdoor water usage. The billing data for water year 2008 depict the nature of monthly indoor and outdoor water use patterns as shown in the left part of Figure 3-1. The total water use of the 1,402 dual metered customers is shown in the left figure. The monthly indoor water use is relatively stable at about 180 gallons per account per day (gpad). On the other hand, outdoor water use varies widely from month to month ranging from a low of about 200 gpad in January to about 750 gpad in May with an annual average of about 600 gpad. It was assumed that outdoor water usage is primarily attributable to irrigation, although uses such as filling pools, car washing, power cleaning, etc. may constitute a small percentage of outdoor usage. Thus, over 75% of the average annual water use and 80% of the May peak use is for irrigation for these dual metered customers. For GRU, seasonal residents do not have a significant impact on seasonal water use patterns for indoor water users, as indoor usage showed little variability. Seasonal outdoor water users with in-ground irrigation

systems can continue to use water while they are not home to maintain their landscapes. Thus, it seems safe to assume that the vast majority of SFR outdoor water use is for irrigation.

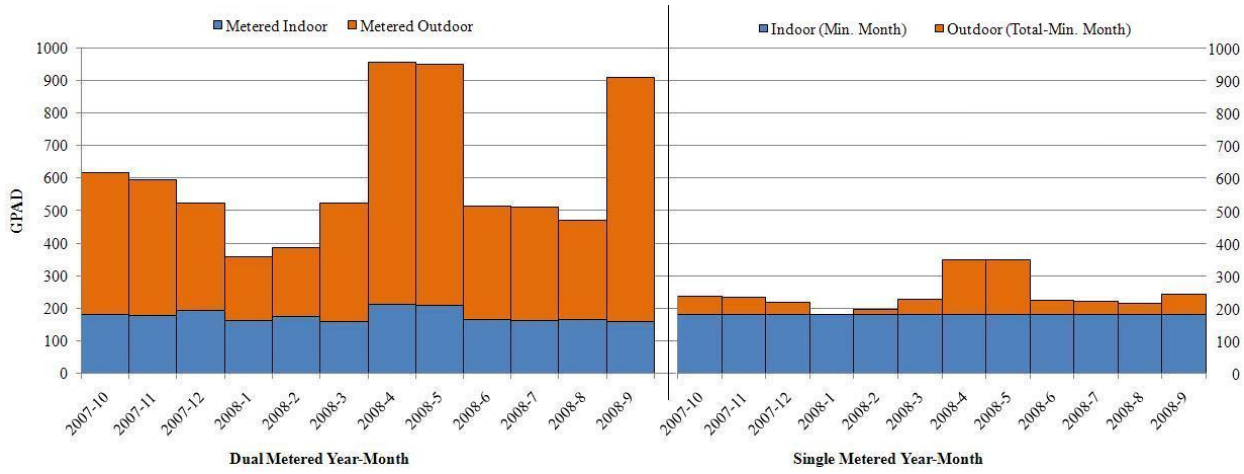


Figure 3-1. Average indoor and outdoor water use for 1,402 dual metered (left figure) and 29,501 single metered (right figure) SFR accounts in GRU for water year 2008.

The indoor and outdoor water use patterns for the 29,501 single meter SFR residences in GRU show a dramatically different blend of indoor and outdoor water use with outdoor water use constituting an average of only about 20% of total water use as shown in the right portion of Figure 3-1. These large differences in outdoor water usage are due to dual metered customers being atypical of the utility as a whole. However, estimated average indoor water usage for single metered residences using the minimum month method is the same as for the dual metered customers, showing the consistent nature of indoor water usage. Indoor water usage estimates can be improved using an end use modeling framework, such as that shown in Friedman et al. (2011). Water year 2008 (10/07 to 9/08) was selected to estimate indoor water usage to be consistent with the time period of the available billing data. Comparative statistics for dual metered customers in relation to GRU as a whole are shown in Table 3-2. The

overall average SFR gpad of 261 consisting of 62% indoor use (163gpad/261gpad) and 38% outdoor usage. However, not all SFR customers are irrigators as will be demonstrated later in the paper. Dual metered customers use slightly less indoor water usage compared to GRU as a whole due to these homes being relatively new with more efficient indoor fixtures. These phenomena are directly captured for each parcel using the indoor water end use model, which allows for a more accurate analysis of outdoor water usage.

Table 3-2. Comparative statistics of dual metered and in-ground sprinkler customers with total single family residential population in Gainesville Regional Utilities for water year 2008

Item	No in-ground Sprinkler	In-ground Sprinkler	Dual-meter accounts	Total or Overall
Count	22,599	8,304	1,402	30,903
% total accounts	73%	27%	5%	100%
Average effective year built	1980	1993	1993	1983
Average just value ($)	$151,061	$302,837	$345,824	$198,072
Average persons per house	2.50	2.62	2.59	2.53
Average gpad	211#	394#	611#	261#
Peak month gpad	433#	852#	1,371#	546#
Total peaking factor	2.05	2.44	2.24	2.09
Average indoor gpad	167*	151*	152#	163*
Count of potable irrigators	9,998	6,305	1,294	16,303
% potable irrigators	44%	76%	92%	53%
Average application rate of potable irrigators (in./yr.)	11.04	19.32	22.24	14.24
Std. deviation application rate of potable irrigators (in./yr.)	11.68	17.11	17.10	14.60

Table 3-2. Continued

Item	No in-ground Sprinkler	In-ground Sprinkler	Dual-meter accounts	Total or Overall
Average irrigable area of potable irrigators (ft^2)	11,229	14,023	16,527	12,309
Std. deviation irrigable area of potable irrigators (ft^2)	9,645	13,349	12,947	11,306

*Flow estimated based on indoor end use model (Friedman et al. 2011), # Flow directly metered

A prominent driver of future residential irrigation trends is the recent prevalence of sprinkler systems in newly constructed homes. For GRU, in-ground sprinklers have gone from being installed in less than 10% of new homes prior to 1983 to the present pattern of having them installed in nearly 90% of the new homes as shown in Figure 3-2. This trend can be expected to have a major impact on water demand if these homes are using potable water from the utility. Comparative statistics for in-ground sprinkler customers are shown in Table 3-2. Approximately 76% of customers with in-ground irrigation systems irrigate significantly from the potable supply compared to only 44% irrigating significantly from potable without an in-ground system. Additionally, in-ground irrigators have an average irrigation application rate that is 43% higher than those without an in-ground system, as shown in Table 3-2. These in-ground sprinkler customers also tend to be larger, more affluent, homes.

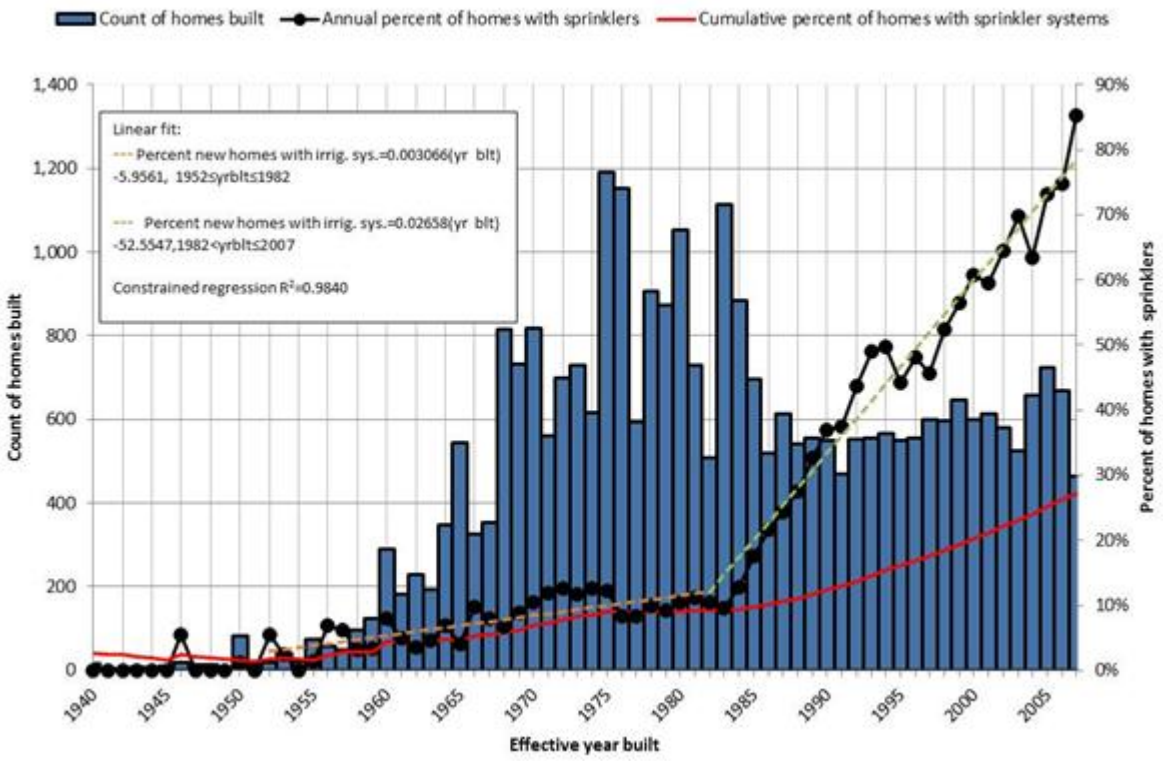


Figure 3-2. Long-term trends in the popularity of in-ground sprinkler systems in Gainesville, Florida.

An irrigator is defined as a customer whose application rate is ≥ 1 inch per year. A lower bound irrigation application rate of one inch per year is used since many customers have a positive, but very small, application rate. Similarly, the few customers with application rates over 100 inches per year are treated as outliers and excluded from the analysis in this paper.

Analogously, minimum and maximum bounds were placed on the irrigable area (IA) of 1,000 and 100,000 square feet, respectively. These filters removed 7% of total customer population and 18% of total irrigable area. A total of 16,303 of 30,903 (53%) of GRU customers are irrigators utilizing these criteria. A detailed analysis of the subset of irrigators in GRU is presented later in this paper.

The GRU data in Figure 3-2 regarding the market penetration of in-ground sprinkling systems can be used to estimate the prevalence of in-ground systems in other utilities. The relative mix of old and new homes within a community dictates current and future irrigation trends. For GRU, about 27% of all SFR's now have in-ground irrigation systems as shown in Figure 3-2. This percentage will continue to rise, as about 90% of new homes are currently being constructed with an in- ground sprinkler system.

Given this excellent database, it is straightforward to estimate the percent of homes for each year with irrigation systems. The pre-1952 era represents negligible in-ground sprinkler installation. Two distinct linear trends were fit for the 1952 to 1982 and 1983 to 2007 periods respectively, shown in Figure 3-2. These trends were fit using constrained regression to ensure continuity at the breakpoint year of 1982, as shown as Equation 3-3. The resulting fits are shown as Equation 3-4. The latter equation can be extrapolated through 2011, with an expected saturation percentage of 90% of homes built after 2011 with in-ground sprinkler systems.

$$\begin{aligned} &\min SSE = \sum_{yrblt=1952}^{1982}\left[persys_{yrblt} - \left(a_1 + b_1 \cdot yrblt\right)\right]^2 + \sum_{yrblt=1983}^{2007}\left[persys_{yrblt} - \left(a_2 + b_2 \cdot yrblt\right)\right]^2 \\ &s.t. \\ &a_1 + b_1 \cdot 1982 - \left(a_2 + b_2 \cdot 1982\right) = 0 \end{aligned} \tag{3-3}$$

Where: SSE= sum of squared errors, $persys_{yrblt}$ = actual percent of homes built with sprinkler systems in given year, yrblt= year house built, a_1= intercept of linear fit from 1952-1982, b_1= slope of linear fit from 1952-1982, a_2= intercept of linear fit from 1982-2007, b_2= slope of linear fit from 1982-2007

The resulting fits are:

$$\text{persys}_{\text{yrblt}} = \begin{cases} 0, & yrblt < 1952 \\ (0.003066 \cdot yrblt) - 5.9561, & 1952 \le yrblt \le 1982 \\ (0.02658 \cdot yrblt) - 52.5547, & 1982 \le yrblt \le 2011 \\ 0.90, & yrblt > 2011 \end{cases} \tag{3-4}$$

Customer billing and associated property attribute data for the utility as a whole are essential to determine which customers have significant outdoor water use due to the wide variability of irrigation practices among customers. However, this information is only available for a small percentage of utilities. Dual metered and in-ground sprinkler system customer data provide insight regarding the relative importance of indoor and outdoor usage, although water usage patterns for these customers are atypical of the population as a whole. This assessment of outdoor water use patterns is based on a detailed analysis of monthly water use billing and customer attribute data for the GRU SFR customers. These benchmark results can be used to supplement available information regarding outdoor water use without using billing data. However, utilities are strongly encouraged to link property appraiser data to customer billing data as it provides significant value added for evaluating outdoor water usage trends as well as usage trends in other sectors of urban water systems.

Description of Parcel Level End Use Database

The generation of a parcel level end use database is a critical first step in evaluation of urban water demand for a given area. The development of the Florida parcel level end use database involves two major steps:

- Generation of a standardized statewide parcel level database utilizing data sources available for all 8.8 million parcels in Florida
- Generation of benchmark utility databases which allow for enhanced analysis but which are available on a case by case basis
- The procedures utilized to generate these databases are described below.

Generation of Statewide Parcel Level Database Using Common Data Sources

Two primary sources utilized for urban water demand analysis which contain data available for all 8.8 million parcels in Florida are:

- Florida Department of Revenue (FDOR) statewide tax assessors database
- U.S. Census Block data

The FDOR statewide tax assessors database contains standardized property attributes for all parcels in Florida which is the fundamental building block of parcel level water use analysis. It is assumed that these databases are generally of high quality since they are carefully audited to ensure accurate property value assessments. Additionally, this dataset provides a standardized method for classifying parcels into water use sectors based on well-defined land use codes rather than using approximations based on attributes such as meter size. This data is available on an annual basis from 2009 to present as geo-referenced GIS shapefiles linked to tabular attribute files. FDOR provides separate links to the GIS parcel shapefile and tabular attribute files. The GIS parcel shapefile contains only the Parcel ID, which can be linked to the attribute table to generate the complete dataset. Direct links to this data are shown below. Significant effort was involved in geo-referencing paper maps into digital files for use within GIS. For details please refer to the following metadata description:

ftp://sdrftp03.dor.state.fl.us/Map%20Data/00%20Mapping%20Data%20Information/MapGuidelines.pdf. The link to the GIS shapefile is: ftp://sdrftp03.dor.state.fl.us/Map%20Data/. The link to the tabular attribute file is: ftp://sdrftp03.dor.state.fl.us/Tax%20Roll%20Data%20Files/

The only block level estimate included in the database is the estimated persons per residence and occupancy that comes from U.S. Census Block data. A residential

Census block contains about 20 to 25 parcels, so it is assumed that it should provide a fairly reliable estimate of persons per single and multi-family residences. Census block data is available for the entire country at the following website: http://www.census.gov/geo/maps-data/data/tiger.html. Census block data is available as GIS shapefiles which have been updated annually from 2007 to the present, and which include updated data from the recent 2010 Census in the 2012 version of these files. Similarly to FDOR, a rigorous initial geo-referencing process was undertaken to generate the initial digitized files. A detailed description of this process is available at:

http://www.census.gov/geo/www/tiger/tgrshp2012/TGRSHP2012_TechDoc.pdf

Significant effort is required to join the FDOR spatial GIS files with tabular files and then spatially link the FDOR parcel database with the U.S Census Block database. Fortunately, the Florida Geographic Data Library (FGDL) of the University of Florida's GeoPlan Center refines and distributes both of these sources. Additionally, FGDL provides the linking Census Block ID for each parcel as a result of a spatial join in GIS between parcel centroids and Census Block boundaries. FGDL conducts extensive QA/QC and provides complete metadata for all source data and data processing. The resulting data can be downloaded directly at the following website:

http://www.fgdl.org/metadataexplorer/explorer.jsp. FGDL provides FDOR parcel data linked to U.S. Census data for 2009 to 2012. This database is compiled and updated annually by our urban water systems group for use with our EZ Guide software (www.conservefloridawater.org). The basic structure of the compiled database required for parcel level end use evaluation can be represented as a single m by n matrix, **A**, with individual elements, a_{ij}.

Each row of this matrix represents an individual parcel, with each column being geo-referenced land use attributes and/or water use records of the associated parcel. A list of statewide attributes from FDOR and U.S. Census applicable to single family outdoor water usage analysis are shown in the upper portion of Table 3-3. This database structure can be used for end use evaluations for any urban water sector. For example, Morales et al. (2011) show how such data can be used to analyze end uses for the commercial, industrial, and institutional sectors. For a complete list of fields applicable to residential parcel level urban water analysis, refer to Friedman et al. (2011).

Table 3-3. Attributes available for outdoor water usage analysis for 8.8 million parcels in Florida

Attributes available statewide		
Attribute	Florida data source	Definition
Land use classification	FDOR	Indicates single family homes
Effective year built	FDOR	Year property built or year of major renovation
Just value	FDOR	Just value of property for indicated year
Total lot area	FDOR/ GIS	Total parcel area, calculated using GIS analysis tools
Heated area	FDOR/ ACPA	Heated (climate controlled) or living area
Census block ID	FDOR/ U.S. Census	Links property appraisal data with 2000 & 2010 U.S. Census data
Persons per house	U.S. Census	Average persons per house in a census block
Occupancy rate	U.S. Census	Average occupancy rate in a census block

Table 3-3. Continued

Additional attributes available from Gainesville Regional Utilities benchmark database		
Attribute	Florida data source	Definition
Associated impervious area (multiple fields)	ACPA	Area of miscellaneous features not contiguous with primary property
Number of bathrooms	ACPA	Number of bathrooms per home
Gross area	ACPA	Total heated and unheated area of for primary structure
Number of stories	ACPA	Number of stories per home
Dual meter tag	ACPA	Indicates homes with dual meters
Sprinkler system tag	ACPA	Indicates homes with in ground sprinkler system
Monthly water usage from 10/2007-09/2008	GRU	Total water usage for all customers, separate indoor/outdoor usage for dual metered customers

Generation of Benchmark Utility Databases

An address based geocoding algorithm was utilized to join customer billing data to the FDOR and Alachua County Property Appraiser (ACPA) parcel data. Ideally, a utility will keep track of parcel ID when a new meter is installed to create a direct link between customer billing and parcel data without the need to perform after the fact geocoding based on addresses. Typically, a utility will maintain a tabular file of meter installations and associated addresses for meter reader route scheduling. Additionally, a link between physical meter location and customer consumption data is needed to ensure proper billing. Geocoding meter locations based on address matching to a reference address service can be executed within GIS. The process works similarly to address location algorithms within web services such as Google Maps. Potential errors in this process arise either when addresses do not match or when the geocoded meter location is positioned on a street rather than within parcel boundaries, which is

necessary to then link to parcel data. In general, single family homes are less prone to error than other sectors due to the fact that there is generally one meter per parcel. For GRU, geocoding accuracy data was unavailable as GRU directly provided data post geocoding. However, extensive QA/QC of the final GRU database was performed to ensure source data as well linkages were accurate.

Additional attributes contained in this benchmark database for 30,903 residential homes in Gainesville Regional Utilities are shown in the lower portion of Table 3-3. Note the additional added value of critical fields such as associated impervious areas, number of bathrooms, number of stories, monthly billing, etc. These fields are added as an extension of the m$\times$n matrix for GRU parcels.

These benchmark results can supplement available information regarding outdoor water use without using billing data, if only statewide input data is available. Given the increasing availability of property appraisal databases and advances in database and GIS technology, this data driven approach can be utilized elsewhere as the required model inputs shown in Table 3-3 are becoming more prevalent. Additionally, such databases can be utilized for related applications such as development of water budget based rate structures (Mayer et al. 2008).

Data Driven Irrigable Area Approach

Directly measured areas from the county and state property appraisal databases are used to estimate irrigable area. The basic method is to estimate irrigable area as the difference between total and impervious area, both of which are determined from the property appraisal databases. Total and heated areas are available statewide. The proportion of the irrigable area that is irrigated ranges between 0 and 1 with a default value of 1.0. Irrigated area is difficult and expensive to determine for every customer in

a utility. Irrigated areas at the parcel level can be directly determined by digitizing over high resolution aerial imagery, if not hidden by tree cover (Milesi et al. 2005). However, this method is time consuming and relies on discerning impervious areas from pervious areas, which can be challenging. Newer methods utilize a combination of parcel geometry, multi-spectrum aerial imagery and high frequency elevation data from light detection and ranging (LIDAR) techniques (Zhou and Troy 2008). These methods require highly detailed imagery and LIDAR in order to classify parcel sub-areas accurately. As the national LIDAR database is developed, this may prove to be an efficient and even more accurate method to determine actual irrigated area and differentiate between turf, shrub, and tree cover. Due to these current limitations, irrigable area is an appropriate unit of size for parcel level outdoor water usage analysis, which can be determined using the following methodology. Accordingly, irrigated area is assumed to equal irrigable area. This assumption appears reasonable since overspray to non-irrigated areas is a common feature of irrigation systems and can be expected to offset the fact that irrigated area may be less than irrigable area.

The irrigable area of a SFR parcel is the calculated residual of total parcel area minus the footprint of the heated and unheated portions of the primary structure, the associated impervious area, and the non-applicable area, or

$$IA = TA – FS – AIA - NA \quad (3\text{-}5)$$

Where: IA = irrigable parcel (pervious) area (ft^2), TA = total parcel area (ft^2), FS = footprint of the heated and unheated portions of the primary structure on the parcel (ft^2), AIA = associated impervious areas on the parcel in ft^2 (drive/walkways, etc…) (ft^2), and NA = non-applicable or other area (ft^2), (lakes, wetlands, etc...)

Each of the unknown terms is discussed below.

Total Parcel Area

Direct reporting of total parcel area within county property appraisal databases is inconsistent. Fortunately, FDOR provides annual Geographic Information system (GIS parcel) geometries electronically as shapefiles (.shp) for nearly every parcel in the state of Florida. Total parcel area for every parcel can be calculated simply using ESRI ArcGIS® software tools. Long-term trends in total parcel area for GRU from 1940 to 2007 are shown in Figure 3-3. The total area is the sum of the irrigable and the impervious areas for the houses built in the indicated year.

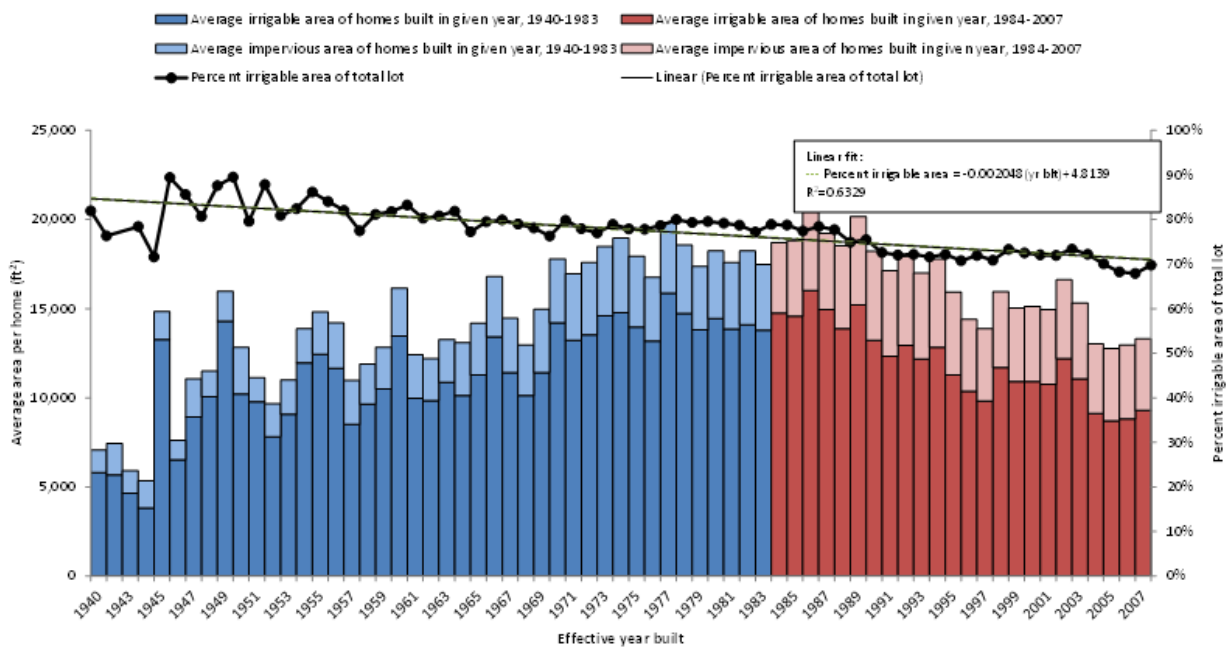


Figure 3-3. Trends in average irrigable and total area for GRU homes built in the indicated year.

Footprint of Structure

Footprint of structure refers to the heated and unheated impervious areas of the primary structure on a parcel. Data for footprint of the structure (FS) were estimated as a function of heated area and the number of stories. The resulting relationship is shown

in Equation 3-6. This function accounts for unheated 1st floor area with the 1.1346 coefficient.

$$FS = 1.1346 * N^{-0.686} * HA \qquad \text{for } N \geq 1 \qquad (3\text{-}6)$$

Where: FS= footprint of structure, ft^2, HA = total heated area of structure, ft^2, N= number of stories

Associated Impervious Area

Associated impervious area refers to all miscellaneous features of a single family parcel which are not part of the primary structure. A summary of the major components of associated impervious area for 16,303 GRU irrigators is shown in Table 3-4. These individual areas are measured directly by the ACPA. For GRU, driveways and walkways account for 54% of total AIA, with decks, patios, pools, and screened enclosures and porches comprising most of the remaining AIA. The average AIA/HA ratio is 0.76 for GRU.

Table 3-4. Major components of parcel area for 16,303 GRU irrigators

Parcel area component	Mean (ft^2)	% occurrence of component on lot
Total lot area	16,327	100.0%
Heated area	2,017	100.0%
Footprint of structure	2,492	100.0%
Associated impervious areas		
Decks	294	13.9%
Drive/Walkways	827	96.6%
Patios	476	47.0%
Pools	494	21.7%
Screened Enclosures	2,075	15.9%
Screened Porches	246	10.9%
Other*	313	1.1%
Weighted average associated impervious area	1,532	100.0%

Table 3-4. Continued

Parcel area component	Mean (ft^2)	% occurrence of component on lot
Total impervious	4,024	100.00%
AIA/HA	0.76	
FS/HA	1.24	
AIA/FS	0.61	

*Denotes average area and percent occurrence of all other AIA components.

Non-Applicable Area

In order to eliminate parcel sub-areas that are not applicable to analysis for irrigation, a distinction must be made between the applicable and non-applicable parcel areas. The issue arises occasionally for larger parcels where a portion of the parcel is a lake, wetland, or forest easement. Typically, these areas are not reported in the property appraiser's database. It is possible to directly measure these areas by overlaying the parcel geometry on top of current aerial imagery and/or land use maps. However, this can be a time consuming task for large datasets such as the 16,303 GRU irrigators. Since non-applicable areas are only significant for very large lots, it can be reasonably assumed that non-applicable area is negligible for all parcels within the 100,000 ft^2 irrigable area filter, which is utilized to remove outliers.

Trends in Average Irrigable Area

Given the above information on total parcel area and impervious areas, irrigable area was determined for all 16,303 GRU irrigators using Equation 3-5. Temporal trends in average irrigable area for the 16,303 GRU irrigators in the year that they were built are shown in Figure 3-3. Two clear trends are evident, with average irrigable area increasing until roughly 1983, and then decreasing steadily from 1984 to present. This reflects the trend toward smaller lots and higher density construction in recent years. Irrigable area as a percent of total parcel area has trended slightly downward with time

since 1940 as shown in Figure 3-3. A 3 year centered moving average from 1980-2007 shown in Figure 3-4 further illustrates these trends. Associated impervious areas have slightly declined in recent years while heated area has remained fairly stable over this time period. Equation 3-7 can be used to predict parcel level irrigable area, given total lot area and effective year built which are commonly available in property appraisal databases. However, this ratio may vary by utility.

$$\text{Percent irrigable area} = \left(-0.002048 \cdot yrblt\right) + 4.8139 \text{ for } 1940 <= \text{yrblt} <= 2007, R^2 = 0.633 \quad (3\text{-}7)$$

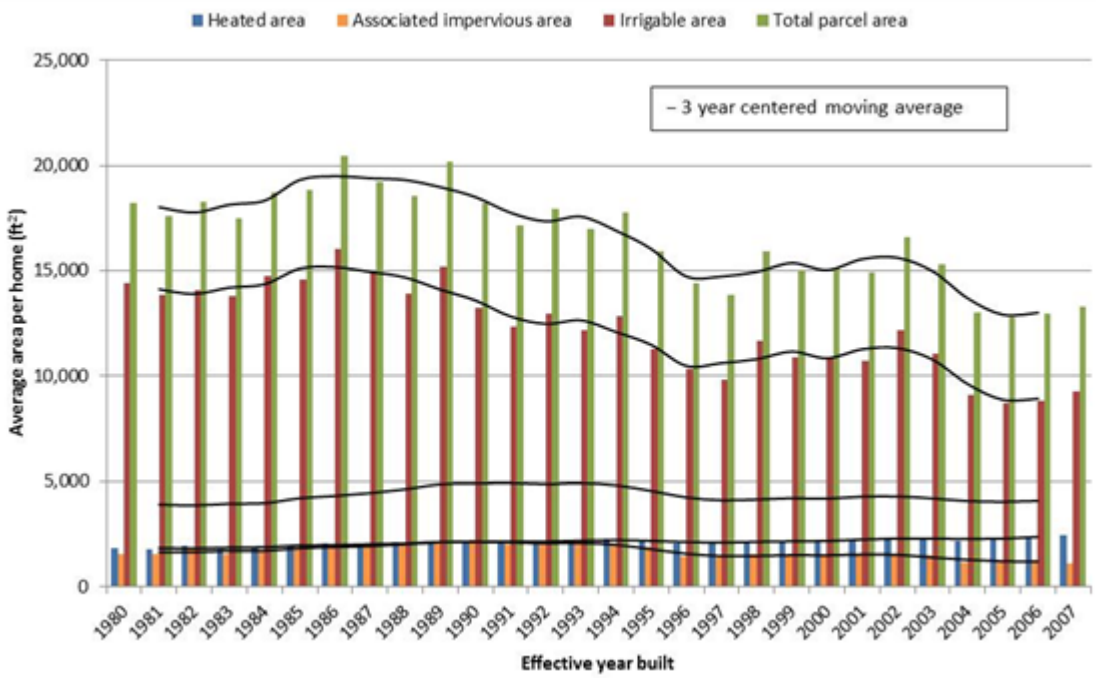


Figure 3-4. Three year centered moving average for various components of parcel area.

Irrigable Area Distribution for GRU

Subsequent analysis of irrigation application rates for all of the 30,903 SFR customers indicates that only 16,303 or 52.8% of them are significant irrigators. Based on the parcel level irrigable area methodology described previously, the relative frequency histogram of irrigable area for the 16,303 GRU SFR irrigators is shown in Figure 3-5. The mean irrigable area for GRU irrigators is 12,310 ft^2 with a standard deviation of 11,300 ft^2. Recall that an irrigator is defined to be a customer who applies at

least one inch per year of water to their irrigable area. This probability density function (pdf) can be approximated by a log-normal distribution.

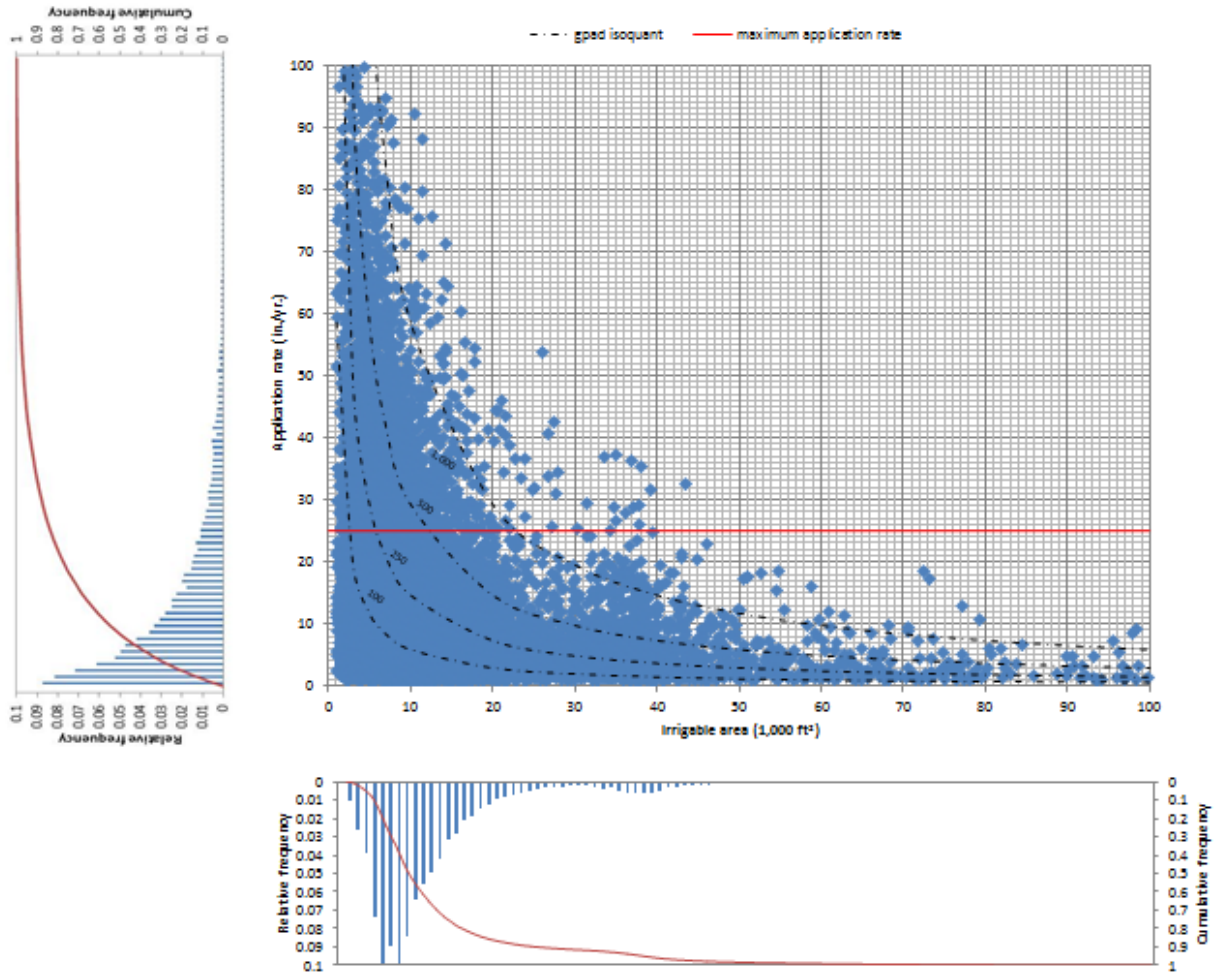


Figure 3-5. Annual application rates and irrigable areas for 16,303 irrigators served by GRU and their associated probability density functions. 1<=IA<=100 and 1<=AR<= 100.

Estimation of Annual Irrigation Application Rate

The annual application rate for each irrigating parcel can be calculated using Equation 3-2, knowing the total water use and the estimated indoor water use as well as the irrigable area for a given home. The relative frequency histogram of irrigation application rate for the 16,303 GRU SFR irrigators is shown in Figure 3-5. This histogram can be approximated by an exponential probability density function. An SFR

is considered to be an irrigator if their application rate is at least one inch per year. The mean application rate for GRU irrigators is 14.24 in./yr. with a standard deviation of 14.60 in./yr. These results are consistent with similar studies (Dukes 2012 approximate n=8,600, Mayer et al. 2009 n=2,294).

Trends in household application rates were analyzed to develop a predictive model for determining mean application rate when billing data is unavailable. As a first step in predicting application rate, the relation between mean theoretical irrigation requirements and mean actual observed outdoor irrigation was analyzed.

Romero and Dukes (2011a) compared estimated irrigation rates of 11 utilities in central Florida with calculated average monthly irrigation requirements from 2001-2007. Romero and Dukes (2011a) estimate actual irrigation as assumed per capita indoor usage subtracted from total billed monthly usage for the top 50% of users by volume over the period of record. Romero and Dukes (2011a) calculated required irrigation rates for warm-season turfgrass using a soil water balance simulation. For a detailed explanation of their irrigation requirement assumptions, refer to Romero and Dukes (2011a).

These results, along with that of GRU analyzed in this paper, are displayed in Table 3-5. Irrigation demands for Gainesville were obtained from Romero and Dukes (2011b), which shows net turfgrass irrigation requirements for several areas throughout the state of Florida.

Based on Table 3-5, the ratio of estimated irrigation to calculated irrigation needs for the 12 utilities varies within the range of 0.46 to 1.02 with a weighted average of 0.78. A similar value of 0.72 was determined for GRU irrigators. Romero and Dukes

(2011a) found the correlation between estimated application rate and irrigation requirements to be statistically significant with at least 95% confidence for 7 of the 11 utilities. These results suggest that mean application rate for single family residential irrigation can be reasonably predicted based on monthly irrigation demands, which can be predicted using process level modeling.

Table 3-5. Actual vs. calculated irrigation requirements for 12 Utilities in Florida

Location	Number of households	Mean actual irrigation (in./yr.)	Calculated irrigation requirements (in./yr.)	Actual irrigation to irrigation requirement ratio
Apollo Beach*	1,020	23.62	25.51	0.93
Brandon*	3,514	18.90	25.98	0.73
Dover*	103	15.12	25.98	0.58
Gibsonton*	369	12.28	26.93	0.46
Lutz*	1,599	25.51	27.87	0.92
Riverview*	3,315	20.31	26.93	0.75
Ruskin*	1,443	19.37	28.35	0.68
Seffner*	1,364	15.12	25.98	0.58
Sun City*	122	26.93	26.46	1.02
Tampa*	12,209	21.26	27.40	0.78
Valrico*	3,704	25.04	26.93	0.93
Total or Weighted Average	28,762	21.17	27.04	0.78
Gainesville Regional Utilities#	16,303	14.24	19.90	0.72

*adapted from Romero and Dukes (2011a)
#mean irrigation derived from GRU data presented in this paper, required irrigation adapted from Romero and Dukes (2011b)

Water Savings Potential of Outdoor BMPs

The total potential daily water savings, y, is simply the difference between individual outdoor water usage before BMP implementation, $QO(i)_1$, and individual outdoor water usage after BMP implementation $QO(i)_2$ or:

$$y = (Q0(i)_1 - Q0(i)_2 \qquad \text{for } i \in n \qquad (3\text{-}8)$$

A BMP can reduce outdoor irrigation demand by decreasing the application rate on a fixed irrigable area. Therefore, potential savings are the net difference in application rate before, $AR(i)_1$, and after implementation $AR(i)_2$ as shown by Equation 3-9.

$$y = k*[(AR(i)_1-AR(i)_2)*IA(i)] \quad (3\text{-}9)$$

For non-potable source rebates (i.e. reuse), $AR(i)_2$ is zero since these customers no longer irrigate from the potable system. Therefore, maximum conservation potential is equal to current potable outdoor usage for all irrigators.

For irrigation control strategies such as audits and soil moisture sensors, $AR(i)_2$ reflects a target maximum application rate (MAR) for potable irrigation. Based on Equation 8, only irrigators who currently irrigate above this threshold are considered since savings are positive only for this subgroup.

A strong negative correlation of -0.27 exists between application rate and irrigated area, indicating that homes with smaller irrigable areas tend to irrigate at higher rates. Isoquants of gpad as a function of IA and AR are also shown in Figure 3-5. Recall from Figure 3-1 and Table 3-1 that average indoor water use in GRU is 163 gpad and average outdoor water use for all SFRs is 98 gpad (261gpad-163gpad). However, only 16,303 out of 30,903 SFR customers are irrigators. Thus, these customers use an average of 186 gpad for outdoor water use. The popular rule of thumb for water use in Florida that indoor and outdoor water use are equal needs to be modified to account for the proportion of customers who are irrigators. The pdf and cdf's of total outdoor water use, shown in Figure 3-6, indicate that outdoor water use of about 48 % of the SFR customers exceeds the average indoor water use of 163 gpad.

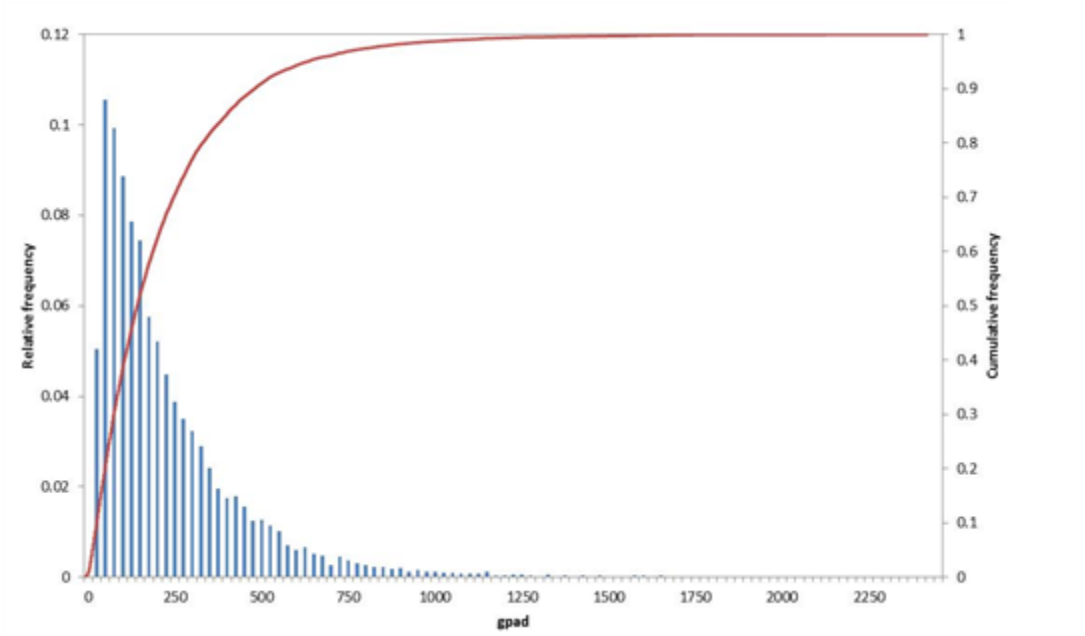


Figure 3-6. Pdf and cdf of total outdoor water use for 16,303 irrigators served by GRU.

The highlighted horizontal line shown on Figure 3-5 designates a selected target maximum application rate (MAR) for an outdoor BMP. In this example, the BMP would reduce all application rates above 25 inches per year down to 25 inches per year. Homes with application rates under this threshold would not be targeted as water usage would increase to 25 inches per year with BMP implementation. The number of eligible irrigators as a function of the minimum application rate for GRU is shown in Figure 3-7. Using the two database filters, 1 ≤ IA ≤ 100, and 1 <=AR<=100, reduces the 30,903 SFR customers to 16,303 irrigators. If the benchmark application rate is increased to 5 inches/ year, then the number of irrigators of interest drops to 11,385. If a cutoff of 40 inches/year per year is used, the number of affected irrigators drops to 1,070, only about 7% of the original total. The number of over irrigators declines exponentially with increasing MAR according to Equation 3-10. Therefore, selection of an appropriate MAR for an outdoor BMP to achieve greatly affects the resulting number of “over irrigators” to target and resulting water savings potential.

$$Number\ of\ affected\ irrigators = 17{,}191e^{-0.06965(MAR)} \quad R^2 = 0.9743 \qquad (3\text{-}10)$$

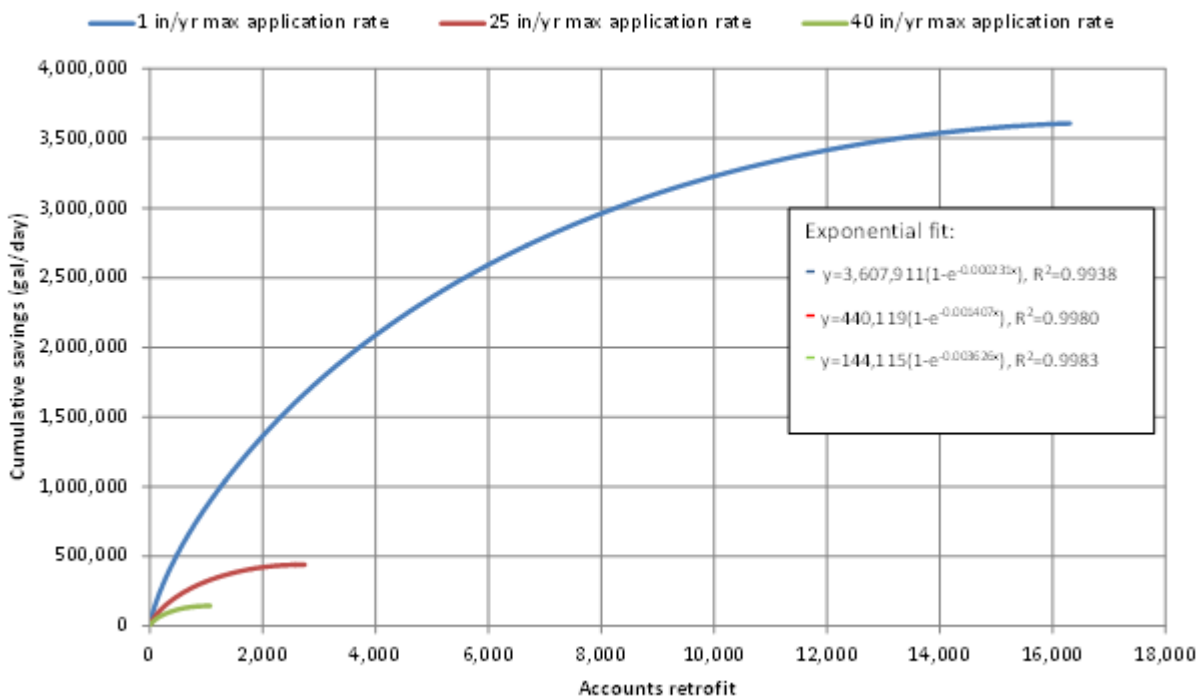


Figure 3-7. Comparison of savings potential for varying maximum application rates for GRU irrigators

For reuse programs, the MAR is clearly equal to zero, eliminating all irrigation. However, for control strategies such as soil moisture sensors and irrigation audits, selection of an appropriate MAR is less obvious. An aggressive approach would be to set MAR equal to the average annual theoretical irrigation requirements for a given region. The MAR can be set above this value depending on desired risk aversion. The former approach was taken in a study of 2,294 homes in California indicates that about 53% of the properties over-irrigate, defined to be irrigation with an application ratio of actual to theoretical irrigation above 1.0. (Mayer and DeOreo 2010). Soil moisture sensors were installed in all of these California homes, regardless of whether they irrigated above or below theoretical requirements prior to installation. The net effect of increasing water use for 47% of the California properties that were under-irrigating and

reducing water use on the 53% of the homes that were over-irrigating was a net reduction in water use of only 6.1%. These results stress the importance of identifying the subset of the irrigators who are over-irrigating and evaluate the efficiency of outdoor BMPs only for this group.

A comparison of the California soil moisture sensor study with the 16,303 GRU irrigators presented in this study is shown in Table 3-6. The results of the GRU study indicate the presence of far fewer irrigators above theoretical needs (23.4%) as compared to the 54.4% from the California study. The mean irrigable area for GRU is 12,310 ft^2 as compared to 28,384 ft^2 in the California study. Inspection of Figure 3-5 indicates that only 9% of the GRU irrigators exceed the average California irrigated area. These results suggest that more small irrigators exist than previously thought. One possible explanation is that small irrigators, which account for the majority of irrigators based on the GRU parcel level irrigation analysis, may not have been well represented in the California study. Dukes (2012) also suggested that the results of the California study may not be representative of the utility population as a whole. The results of this study offer improved estimates as outdoor water usage was directly evaluated for all SFR homes in GRU as opposed to a cross sectional sample.

Table 3-6. Comparative results from 2,294 California homes (Mayer and DeOreo 2010) with the 16,303 GRU irrigators from this study

Statistic	Gainesville Regional Utilities	California sites in Mayer and DeOreo 2010
Number of irrigators	16,303	2,294
Mean irrigable area (ft^2)	12,310	28,384
Mean application rate w/o intervention (in/yr)	14.24	54.40
Theoretical application rate (in/yr)	19.90	36.10
Average application ratio	0.72	1.51

Table 3-6. Continued

Statistic	Gainesville Regional Utilities	California sites in Mayer and DeOreo 2010
Percent of total irrigators above theoretical needs	23.4%	53.0%
Mean application rate of irrigators below theoretical needs (in/yr)	7.72	19.9
Mean application ratio of irrigators below theoretical needs (in/yr)	0.39	0.55
Mean application rate of irrigators above theoretical needs (in/yr)	35.56	85
Mean application ratio of irrigators above theoretical needs (in/yr)	1.79	2.37

Outdoor Water Savings Production Function

Based on the water savings per home from Equation 3-9, a cumulative water savings performance function of a given outdoor BMP with a specified MAR can be approximated by an exponential function of the form:

$$y = y_{\max}\left(1 - e^{-kx}\right) \qquad 0 \le x \le x_{\max} \tag{3-11}$$

Where: y= cumulative water savings (gal/day), y_{max} = maximum cumulative water savings (gal/day), k = rate constant, x = number of homes targeted for BMP, x_{max} = number of eligible homes to target for BMP

A simple optimization problem is solved to find the value of k that minimizes the mean squared error between the measured data and the equation estimate. Best fit production functions for GRU over irrigators from an outdoor BMP with a MAR of 1, 25, and 40 in./yr. respectively are shown in Figure 3-7. The fit is very good, with R^2 values above 0.99. The best fit parameters of these functions are shown in Table 3-7. As

shown previously, the maximum savings potential and number of eligible irrigators drops significantly with increased MAR.

Table 3-7. Parameter estimates for savings potential for varying maximum application rates for GRU irrigators

MAR (in./yr.)	y_{max} (gal./day)	x_{max} (number of irrigators)	k	R^2
1	3,607,911	16,303	-0.000231	0.9938
25	440,119	2,746	-0.001407	0.9980
40	144,115	1,070	-0.003626	0.9983

The water savings production functions shown in Figure 3-7 assume only over irrigators are targeted, as only these irrigators would reduce water usage with BMP implementation. Figure 3-8 quantifies the impact of not exclusively targeting over irrigators. The red portion of the curve shows the positive savings achieved from first targeting over irrigators with a MAR of 25 in./ yr. This curve is identical to that of Figure 3-7. However, the cumulative savings function then declines as existing under irrigators begin to be targeted. At x=7,187, there is zero net savings from the outdoor BMP, as the positive savings from targeting over irrigators is cancelled out by the increased water usage from under irrigators. If all 16,303 irrigators were targeted for a MAR of 25 in./yr., a net increase of nearly 5 mgd would occur. This exercise stresses the importance of exclusively targeting over irrigators for outdoor BMP controls.

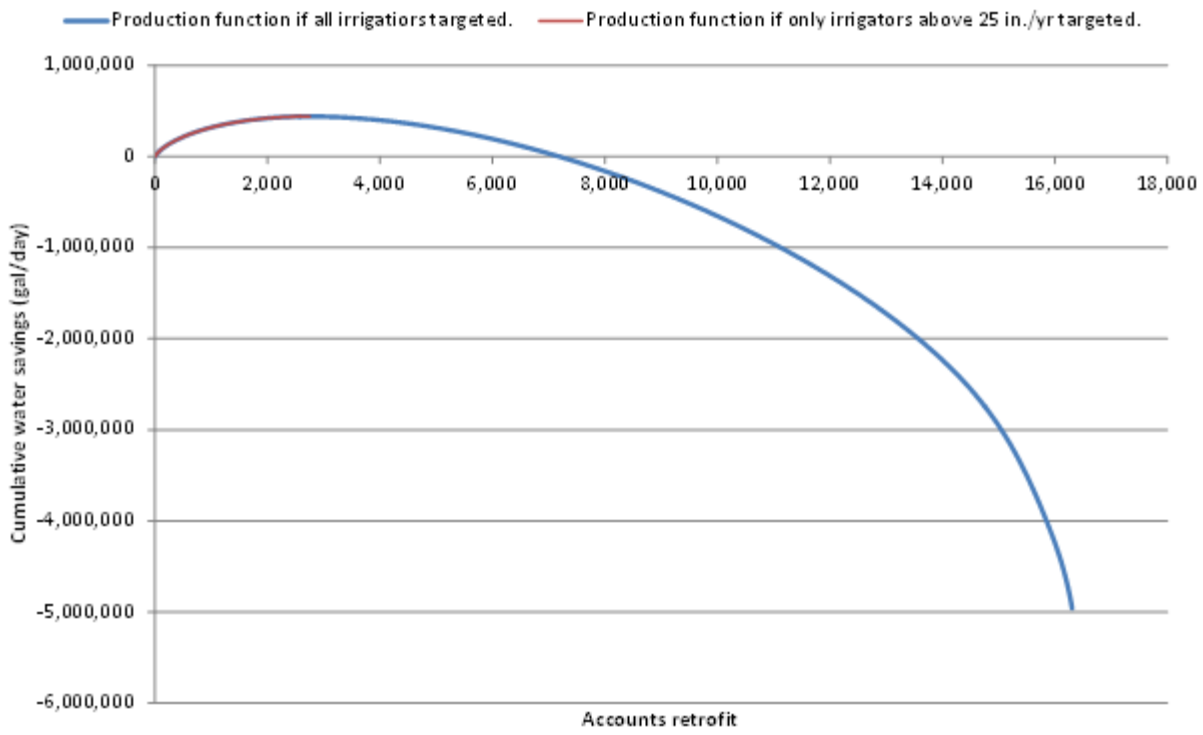


Figure 3-8. Water savings production function if over irrigators are not exclusively targeted for a target MAR for 25 in./yr.

Synopsis

Household level modeling of residential outdoor water usage is challenging due to significant seasonal and spatial variability resulting from a wide range of factors influencing irrigation practices including climate, price signals, individual irrigation practices, irrigation restrictions, irrigation technology, etc.

This paper presents a systematic parcel level data driven procedure to quantify and predict trends and patterns of single family residential potable irrigation and associated savings potential of single family residential irrigation demand management strategies. First, current irrigation practices, irrigable area, and irrigation application rate are derived for each single family residence based on parcel level tax assessor's data linked to customer level monthly water billing data. The results from a case study of 30,903 single family residential (SFR) parcels in Gainesville Regional Utilities were

utilized to demonstrate these procedures, in which 16,303 SFRs were determined to irrigate from the potable system. The results of this study show a dramatic rise in the prevalence of in-ground sprinkler systems over the last few decades, which has led to increased irrigation application rates. However, housing trends show a decline in irrigable area over the same time period, which may help offset the predominance of in-ground sprinkler systems. Predictive equations are presented for utilities where directly linked property and billing data is unavailable, although this data linkage greatly enhances the robustness of analyzing outdoor water usage patterns.

Next, customers are clustered into relatively homogeneous groups based on existing irrigation practices, irrigable area, and average application rate. Water savings are calculated directly as the difference between current and proposed use after implementation of a management option for each group. This information is used to develop performance functions that estimate total water savings as a function of number of implementations for each group. This procedure allows demand management options to be compared directly with other supply augmentation options when determining the optimal blend (Friedman et al. 2011). The performance functions can be approximated as exponential equations, which can easily be solved for finding an optimal solution given unit costs and value of water saved. Only the small subset of customers who over irrigate should be considered for outdoor BMPs which are aimed at reducing irrigation to a desired threshold. The performance of outdoor BMPs is greatly affected by selection of a desired threshold or maximum application rate to achieve. These methodologies are being incorporated into The Conserve Florida Water Clearinghouse internet based

software called EZ Guide to assist Florida water utilities in evaluating water use efficiency. http://conservefloridawater.org/

CHAPTER 4
ESTIMATION OF SINGLE FAMILY RESIDENTIAL IRRIGATION DEMAND MANAGEMENT EFFECTIVENESS

Scope and Overview

Demand management initiatives have increased in popularity from the early 1990s to present, with 23 states now having legislative mandates for some form of demand management as opposed to 9 states in 1990 (Rashid et al. 2010). This movement was stimulated by the United States Environmental Protection Agency (USEPA) Energy Policy Act of 1992, which enacted uniform water efficiency standards for toilets, showerheads, faucets, and urinals installed after 1994 (USEPA 1992). However, demand management efforts remain largely qualitative in nature, and often utilize simple average savings to measure effectiveness which does not capture the variability among customer's water usage patterns (White et al. 2004, Maddaus 2006, Rosenberg 2007a, Green 2010).

Demand management strategies have primarily focused on reduction of indoor residential water use due to legislative initiatives such as the Energy Policy Act of 1992 as well as the relative importance and predictable nature of residential indoor water usage. The focus of demand management is shifting away from indoor fixture retrofits due to observed declines in residential per capita usage as a result of the rate at which low flow toilet and clothes washer technologies have been adopted (DeOreo and Mayer 2012). Single family outdoor usage, on the other hand, is increasing rapidly due to the recent prevalence of in-ground potable irrigation systems (Palenchar 2009, Friedman et al. 2013). Single family residential (SFR) outdoor water usage can account for the majority of total and peak SFR usage especially during drier months in warmer climates (Mayer et al. 1999, Palenchar 2009, Haley and Dukes 2010). Irrigation accounts for

nearly one third of all residential water use in the U.S. and this percentage increases in warmer climates (Mayer et al. 1999; Vickers 2001). Additionally, irrigation tends to be the single most significant driver of peak seasonal demand in public water supply (Chesnutt et al. 2004; Dziegielewski et al. 1993; Marella 2004; Mayer et al. 1999; Mays 2002; Vickers 2001; Whitcomb 2006).

The need to better understand urban water demand, particularly residential irrigation, and associated effects of demand management has gained further interest in the past several years in an effort to improve water quality modeling, water supply planning, and water distribution system sizing. Reducing irrigation can have a major impact on both peak and average design flow conditions. Additionally, recent initiatives focused on incorporating demand management in a broader context beyond reduced water supply needs, such as reduced energy utilization, are further requiring the need to better quantify demands with higher resolution. A recent report by the Water Research Foundation includes demand management as a best practice in water treatment, storage, and transmission energy efficiency, which recognizes that reduced demands may result in reduced treatment and distribution needs thus saving energy inputs (Leiby and Burke 2011).

This paper presents alternative bottom up approaches toward evaluating and managing single family residential potable irrigation demand management. This is possible due to the availability of a Florida statewide parcel level urban water demand database, containing property appraisal data for 8.8 million parcels in Florida. Additional benchmark utilities, such as Gainesville Regional Utilities (GRU), allow for direct

evaluation of customer water use data linked with detailed property attributes which includes irrigable area.

The next section describes the general expression for determining potable irrigation and associated water savings from demand management for a given residence. A nonparametric data driven approach can be utilized given a sufficient sample of irrigators, such as is the case for GRU. Parametric models are derived from benchmark parcel level datasets for evaluation of other utilities where direct measurements are unavailable. Probability distributions are defined for key uncertain irrigable area and application rate parameters based on a sample of 16,303 single family residential (SFR) customers in GRU which irrigate from the potable system. Finally, performance functions describing demand management potential for potable irrigation can be derived directly from estimated distributions. This framework can be generalized to apply to any urban water sector.

Probabilistic Water Savings of Single Family Irrigation Demand Management

The volume of water saved for a given demand management implementation for a given customer per unit time can be expressed as the difference between existing water usage rate and water conserving water usage rate multiplied by the size of the implementation (Rosenberg 2007a). Using this framework, the generalized water savings specific to demand management strategies aimed to reduce single family irrigation application rates can be expressed as Equation 4-1.

$$Q_{saved} = c \cdot \left(X_1 Y_1 - X_2 Y_2 \right) \tag{4-1}$$

Where Q_{saved} = volume of water saved from a single demand management implementation to reduce irrigation application rate for a given customer per unit time;

X_1 = current irrigable area (size) of a given customer's residence which irrigates from the potable system; X_2 = reduced irrigable area (size) of a given customer's residence which irrigates from the potable system after implementation of demand management strategy; Y_1 = current irrigation application rate of a given customer which irrigates from the potable system;Y_2 = water conserving application rate after implementation of demand management strategy; c= unit conversion factor.

An important feature of this framework is that the sample space to be considered only consists of known single family residences which irrigate from the potable system. This is necessary as including the set of customers who do not irrigate from the potable system (i.e. X_1 or Y_1=0) would skew the distribution of actual application rates. The prevalence of potable irrigators varies by utility and is of critical importance to determine accurately. In contrast, indoor retrofit programs focusing on domestic household uses potentially apply to all residential customers.

Typically, water conserving usage rates can be modeled with certainty as the utility has direct control over this variable. For indoor fixture replacements, this can relate to a high efficiency toilet (e.g., 1.28 gal/flush). For outdoor controls, the water conserving application rate can be specified with an irrigation control device such as a soil moisture sensor or can simply be zero in the case of switching customers to an alternative irrigation source. It is also possible to construct a program which reduces irrigable area while holding application rate constant (e.g. turf buyback program). Typically, an individual BMP will either affect application rate or irrigable area but not both simultaneously. For the simplified case in which a BMP only affects application rate

while holding irrigable area constant, the water savings function can be reduced to Equation 4-2.

$$Q_{saved} = c \cdot X \cdot Y \tag{4-2}$$

Where X= unaffected existing irrigable area; Y= savings from existing to water conserving irrigation application rate = (Y_1-y_2); y_2= fixed target water savings application rate. The illustrative examples presented in this paper analyze this scenario. BMPs targeting irrigable area exclusively can be handled in an analogous manor.

In an ideal case, direct measurements of irrigable area and current outdoor water use are available for every customer within a utility. Given this data, as well as the anticipated irrigable area and application rate post demand management, water savings can be defined directly using nonparametric approaches. As part of developing a goal based water demand management model called EZ Guide, parcel level data have been collected for every parcel in the state of Florida (www.conservefloridawater.org). Thus, it is possible to estimate the irrigable area accurately for any Florida utility. The more challenging problem is to estimate the annual application rates that require the use of customer billing data that is not generally available in a form that is linked to the parcels. Thus, benchmark utilities such as GRU have been analyzed wherein direct measurements of water use are available. The GRU database consists of directly measured irrigable areas for 16,303 single family residences which irrigate from the potable system. This database will be analyzed in greater detail in the following section.

If such a database is not directly available for a given utility, alternative parametric approaches can be utilized to estimate water savings. One approach would be to perform a Monte Carlo simulation of water savings, given appropriate input

distributions and associated parameter estimates for irrigable area per residence and existing application rate per residence as follows:

- Generate random samples for each input distribution and determine water saved according to Equation 2.
- Repeat step 1 for a large number of random samples.
- Determine the probability of discrete water savings ranges as the fraction of samples in the given range divided by bin size.
- Develop the normalized cumulative water savings production function with the x axis being normalized cumulative percent accounts targeted and the y axis being the normalized cumulative water savings.

An alternative approach is to utilize a jointly distributed random variable which defines the probability of a given customer having a specified water savings as follows:

- Define a discrete density function f(X,Y) to be the probability of a customer having a given water savings from a demand management implementation (i.e. the joint probability of a customer having both irrigable area X=x and reduction in application rate Y=y)
- Use this discrete joint density function to determine the expected value of total water savings for each discrete range of possible irrigable area and application rate savings as shown by Equation 4-3:

$$\bar{q}_{xy} = c \cdot x \cdot y \cdot p(x, y) \qquad (4\text{-}3)$$

- Where $\bar{q}_{xy}$ = expected water savings for all customers with specified discrete values of irrigable area(x) and irrigation application rate savings (y) , p(x,y)= joint probability of a customer having both irrigable area X=x and reduction in application rate Y=y.
- Sort each discrete range by descending water savings rate and develop the normalized cumulative water savings performance function with the x axis being the normalized cumulative percent accounts targeted and the y axis being the normalized cumulative water savings.

Nonparametric methods as well as Monte Carlo simulation and joint probability distribution approaches to determine cumulative distributions of water savings from SFR

irrigation demand management strategies will be presented in the following sections utilizing the GRU benchmark dataset.

Data Driven Nonparametric Approach for Analyzing Single Family Potable Irrigation

The University of Florida urban water systems group has developed a high quality database for analyzing customer demand in urban water systems at the parcel level in Florida. This database contains property appraisal land use information for all 8.8 million parcels in Florida from the Florida Department of Revenue (FDOR) tax assessors database which is linked to U.S Census Block demographic data. The GRU dataset represents a benchmark utility allowing for enhanced analysis beyond that of data available statewide with the additions of one year of monthly billing data from October 2007 to September 2008 linked to the Alachua County Property Appraiser (ACPA) database, which provides direct measurements of irrigable area. (For details regarding the contents and processing of these databases refer to Friedman et al. 2011, Friedman et al. 2013, Morales et al. 2011, Morales et al. 2013a). Given the increasing availability of property appraisal databases and advances in database and GIS technology, this data driven approach can be utilized elsewhere as the required model inputs are becoming more prevalent.

Given such a benchmark database, irrigable area can be directly determined for all 30,903 SFR homes in GRU using FDOR and ACPA data on parcel area and impervious area. Customer billing data for GRU are used to estimate total outdoor water usage per home for 30,903 homes. For 1,402 homes with separate potable indoor and outdoor meters, potable irrigation water usage is known directly. Otherwise, outdoor water usage is determined by subtracting estimated indoor usage from total metered

usage (See Friedman et al. 2011, and Friedman et al. 2013 for details). Given annual outdoor water usage (q_i) and irrigable area ($x_{1,i}$), the annual application rate ($y_{1,i}$) is

$$y_{1,i} = c \cdot \left(\frac{q_i}{x_{1,i}} \right) \tag{4-4}$$

Where q_i= current average annual outdoor water usage for household i; $y_{1,i}$= current annual application rate for household i; $x_{1,i}$= current irrigable area for household i

As alluded to previously, not all customers served by a utility irrigate from the potable system. Utilizing known application rates for all customers, a potable irrigator is defined as a customer whose application rate is ≥ 1 inch per year. All other customers are non-potable irrigators and/or customers who do not irrigate, thus defining the sample space of all potable irrigators in the system. A lower bound irrigation application rate of 1 inch per year is used since many customers have positive, but very small, application rates. Similarly, the few customers with application rates over 100 inches per year are treated as outliers.

Analogously, minimum and maximum bounds were placed on the irrigable area (IA) of 1,000 ft^2 and 10,000 ft^2, respectively. These filters removed 7% of total customer population and 18% of total irrigable area. A total of 16,303 of 30,903 (53%) of GRU customers are potable irrigators utilizing these criteria. A detailed analysis of the subset of these potable irrigators in GRU is presented in this paper.

In addition to potable irrigators, some SFR customers in GRU have private irrigation wells. The identity of these customers is unknown and this use is not metered. Other SFR customers in GRU rely on reuse water for irrigation. About 700 of these customers have reuse meters. These non- potable irrigators will not be addressed in this paper.

Joint Nonparametric Probability Density Function of GRU Outdoor Water Usage Savings

For the nonparametric data driven approach, water savings for each individual household from a specified outdoor BMP with target irrigation application rate and irrigable area is calculated directly from Equation 4-5.

$$q_{saved,i} = c \cdot \left(x_{1,i} y_{1,i} - x_{2,i} y_{2,i} \right) \tag{4-5}$$

Where $q_{saved,i}$= outdoor water usage savings for household i; c = unit conversion coefficient; $y_{1,i}$= current application rate for household i; $x_{1,i}$= current irrigable area for household i; y_2 = water conserving application rate after implementation of demand management strategy; x_2 = reduced irrigable area (size) of a given customer's residence which irrigates from the potable system after implementation of demand management strategy

If a BMP only affects application rate, while holding irrigable area constant, the calculation of water savings is reduced to Equation 4-6.

$$q_{saved,i} = c \cdot x_{1,i} \left(y_{1,i} - y_{2,i} \right) \tag{4-6}$$

Given calculated water savings for a sufficient sample of potable irrigators, the cumulative non-parametric water savings distribution can be determined by Equation 4-7 (Kvam and Vidakovic 2007).

$$\hat{F}(q_{saved}) = \frac{\# q_{saved,i} \le q_{saved}}{n}, q_{saved} \ge 0 \tag{4-7}$$

Where $\hat{F}(q_{saved})$= sample cumulative distribution function of outdoor water savings; $\# q_{saved,i} \le q_{saved}$= number of data points less than or equal to given value of q_{saved}; n= number of data points.

The pdf and nonparametric cdf of total outdoor water use savings for all 16,303 GRU irrigators is shown in Figure 4-1 in the case where y_2=1 (i.e., switch customers to non-potable irrigation) and irrigable area remains constant. The mean outdoor usage savings for GRU irrigators is 221 gallons per account per day (gpad) with a standard deviation of 222 gpad using this criterion. By definition, the sample nonparametric cdf, $\hat{F}(q_{saved})$, is a step function which becomes a more accurate indicator of the true underlying continuous distribution $F(q_{saved})$with increasing sample size as the approximation becomes smoother. The nonparametric cdf shown Figure 1 is very smooth as it contains a near 100% sample size for GRU irrigators. This cdf can be approximated by a lognormal distribution based on the Kolmogorov-Smirnoff (K-S) criterion (Kvam and Vidakovic 2007).

It is unnecessary to obtain a near 100% sample of irrigators to provide a representative water savings distribution. Hypothesis testing of a random 1% sample of irrigators (n=163) with mean savings of 228 gpad and a standard deviation of 194 gpad in comparison with the large sample statistics (n=16,303) yielded a p value of 0.618 (test statistic t=0.50, df=166), which would fail to reject the null hypothesis that the sample comes from the population at 99% confidence. Similarly, a Rank Sum Test used to test if the sample cdf's are statistically equivalent (not shifted) resulted in a p value of 0.208 (test statistic=1,390,740), which fails to reject the null hypothesis that the distributions are statistically equivalent (not shifted) at 99% confidence.

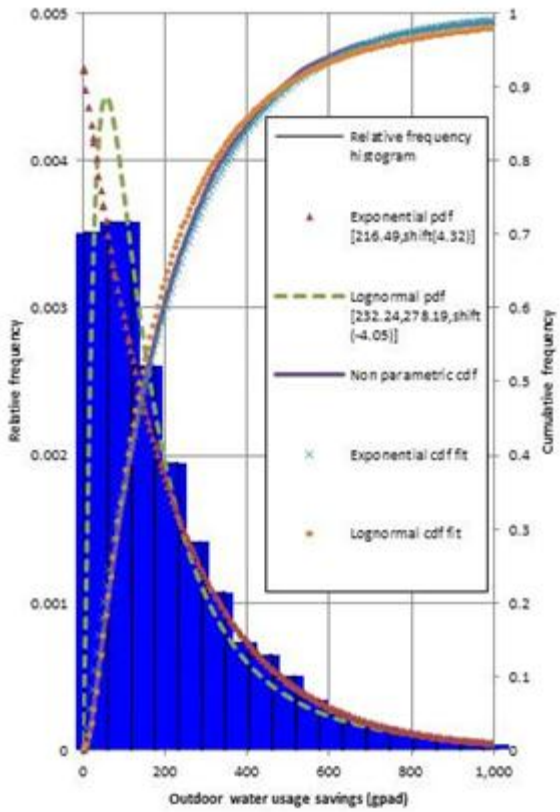


Figure 4-1. Total outdoor water usage savings (gpad) relative and cumulative frequency distributions for 16,303 GRU SFR irrigators reducing application to 1 in./yr (mean= 221 gpad., std. dev.= 222 gpad). Fits were done using @Risk (Palisade Corp. 2012)

Parametric Methods for Evaluating Outdoor Water Usage Savings

The above section provided a nonparametric framework to evaluate water savings from outdoor water usage BMPs based on direct evaluation of rate and size input distributions. An alternative approach is to utilize continuous probability distributions and associated parameter estimates to approximate key input distributions which can then be utilized to estimate the output water savings cdf and associated production function.

The validity of parametric approaches relies on three elements:

- goodness of fit of irrigable area marginal distribution $f_x(x)$ to appropriate continuous distribution.

- goodness of fit of application rate savings marginal distribution $f_y(y)$ to appropriate continuous distribution.
- accurately accounting for correlation between inputs.

Best fit marginal distributions for GRU irrigators are shown in the next section followed by determination of an appropriate correlation coefficient. Exponential and lognormal distributions were considered as candidate fitted distributions by visual inspection as well as the relatively straightforward analytical interpretation of these distributions. Both Monte Carlo simulation and bivariate probability density function techniques are then utilized to estimate output water savings given different input assumptions.

Irrigable Area Distribution for GRU

Recall that an irrigator is defined to be a customer who applies at least 2.54 cm per year of water to their irrigable area. Based on the parcel level irrigable area methodology described previously, the relative frequency histogram of irrigable area for the 16,303 GRU SFR potable irrigators is shown in Figure 4-2. Their mean irrigable area is 12,310 ft^2 with a standard deviation of 11,300 ft^2. This probability density function (pdf) can be approximated by a log-normal distribution, based on the K-S criterion.

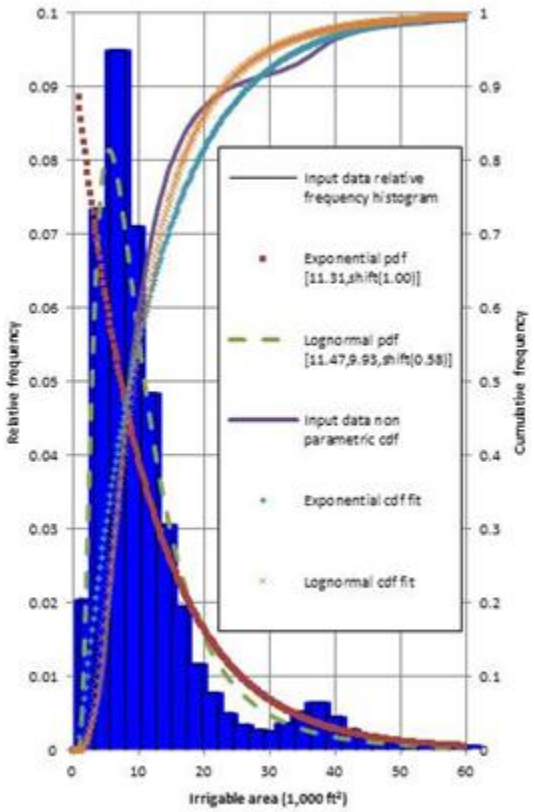


Figure 4-2. Relative and cumulative frequency irrigable area distribution for 16,303 GRU SFR irrigators (mean=12,310 ft^2, std. dev. = 11,300 ft^2) with irrigable areas of less than 100,000 square feet and greater than 1,000 square feet

Annual Irrigation Application Rate Distribution for GRU

The annual application rate for each irrigating parcel in GRU was directly calculated knowing the total water use and the estimated indoor water use as well as the irrigable area for a given home. The relative frequency histogram of irrigation application rate for the 16,303 GRU SFR potable irrigators is shown in Figure 4-3. This probability density function can be approximated by an exponential distribution with a mean of 14.24 in./yr., based on the K-S criterion. The lognormal approximation of the distribution has a mean application rate of 14.24 in./yr. with a standard deviation of 14.60 in./yr. These results are consistent with similar studies (Dukes 2012 approximate n=8,600, Mayer et al. 2009, Mayer et al. 2010 n=2,294).

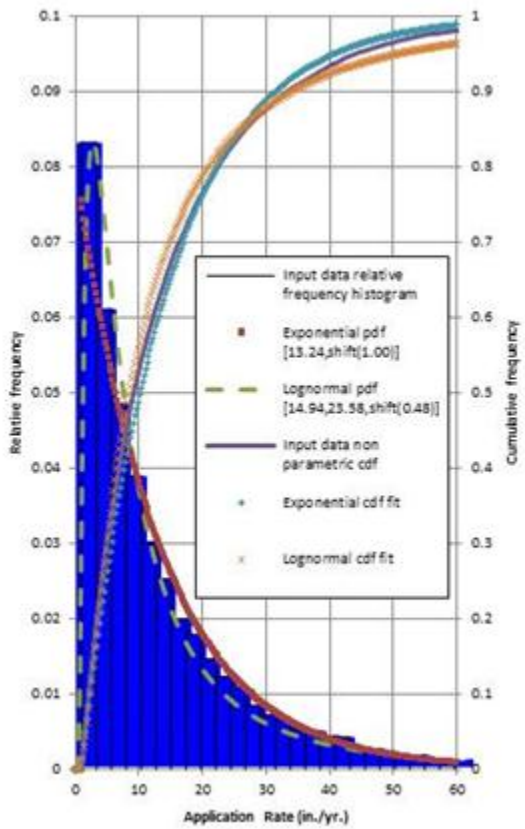


Figure 4-3. Application rate relative and cumulative frequency distributions for 16,303 GRU SFR customers who apply at least one inch per year of irrigation water (mean= 14.24 in./yr., std. dev.= 14.60 in./yr.).

Correlation

Correlation must be accounted for when utilizing parametric approaches since not all customers are affected equally by a given BMP. The joint frequency probability mass function of GRU irrigators, shown in Figure 4-4, shows a nonlinear negative correlation between irrigable area and application rate indicating that homes with smaller irrigable areas tend to irrigate at higher rates.

The Spearman's rank order correlation was utilized rather than the Persons correlation coefficient to account for the nonlinear correlation, which can be calculated using the following equation (Kvam and Vidakovic 2007).

$$\rho = 1 - \frac{6\sum d_i^2}{n^2(n-1)} \tag{4-8}$$

Where $d_i = x_i - y_i$; n = sample size; ρ= Spearman's rank order correlation coefficient.

The resulting Spearman's rank order correlation coefficient between irrigable area and application rate for GRU irrigators is ρ=-0.38.

Given input distributions and parameter estimates for irrigable area (X_1) and current application rate (Y_1) as well as the correlation coefficient, ρ, water savings (Q_{saved}) from an outdoor BMP with a set target water conserving application rate y_2 can be determined using Equation 4-2, by a simple linear translation of parameter estimates. Given a known mean existing application rate and constant water savings target application rate, the expectation of this linear combination is known, as shown in Equation 4-9. Analogous equations can be utilized if analyzing BMPs which solely target irrigable area.

$$E(Y) = E(Y_1 - y_2) = E(Y_1) - y_2 \tag{4-9}$$

Where E(Y), $E(Y_1-y_2)$= expected value of application rate savings; $E(Y_1)$= expected value of existing application rate distribution; y_2= constant water savings target application rate.

The variance of this linear combination is:

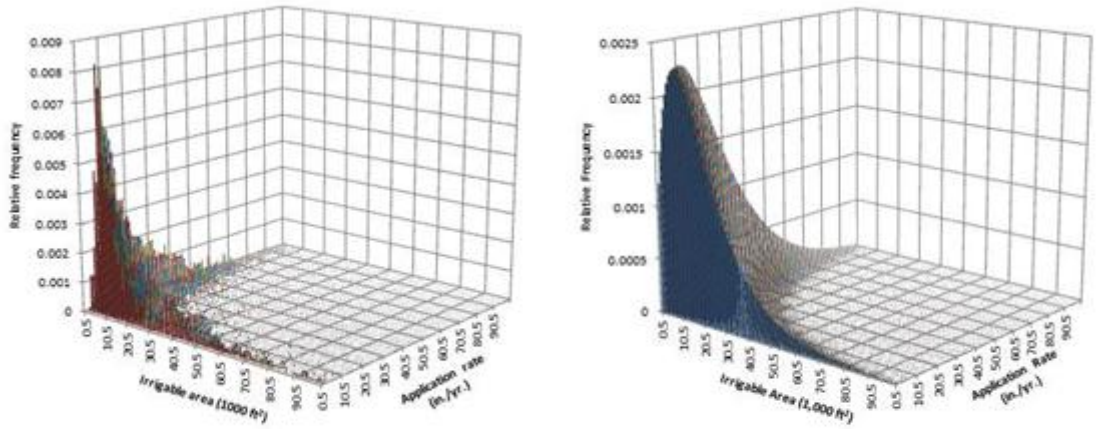
$$Var(Y_1 - y_2) = Var(Y_1) \tag{4-10}$$

The following section shows six parametric approaches, based on assuming each of the two input distributions is either exponential or lognormal. Four Monte Carlo simulations were performed, for each combination of possible input distributions. Two analytical approximations are later shown for the case where both marginal are

exponential or lognormal respectively. These alternative methods are then compared to the non-parametric approach to evaluate accuracy and water saving performance functions.

Monte Carlo Simulation

Monte Carlo simulation with @Risk (Palisade Corp. 2012) was used to estimate the probability density function (pdf) and cumulative density function (cdf) of outdoor water use savings as the product of the pdf's of irrigable area and application rate as previously defined. The Monte Carlo simulation also included the negative correlation (ρ=-0.38). The Monte Carlo simulations performed here calculated the outdoor water use savings using Equation 2 assuming an outdoor BMP with a target application of y_2=1 in./yr. based on taking a 1,000 samples. For each iteration, a sample value of application rate is selected from a pre-defined distribution. Then, a sample value of irrigable area is selected from a pre-defined distribution that accounts for the correlation. The resulting outdoor water use savings pdf and cdf utilizing respective lognormal irrigable area and exponential application rate savings distributions are shown in Figure 4-4. Exponential and lognormal fits to output water savings are also shown in Figure 4-4, with lognormal being the best fit, based on the K-S criterion. Resultant water savings cdf's from the other three Monte Carlo Simulation scenarios (X~Exponential, Y~Lognormal; X~ Lognormal, Y~Lognormal; X~ Exponential, Y~ Exponential) are shown in Figure 4-5.



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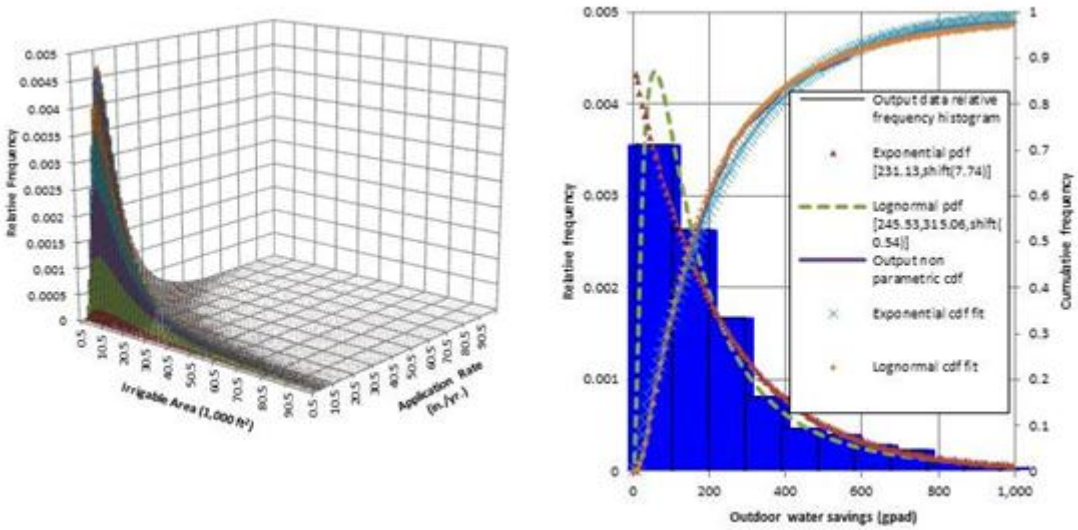

C D

Figure 4-4. Comparison of water savings output distribution for GRU irrigators reducing application rate to y_2=1 in./yr; A) Non parametric; B)Bivariate exponential; C) Bivariate Lognormal; D) Monte Carlo Simulation with X~Lognormal, Y~Exponential

Bivariate Exponential

A continuous joint density function f(X,Y) can be defined as the probability of a customer having a given water savings from a demand management implementation to reduce irrigation application rate (i.e. the joint probability of a customer having both irrigable area X=x and reduction in application rate Y=y). The validity of using of a

bivariate joint distribution was tested to see if an analytic formulation for the joint frequency distribution in Figure 4-4 could be obtained. Based on the validity of utilizing exponential marginal distributions shown previously as well as the general shape of the joint pdf, the bivariate exponential distribution was tested as a representative distribution. Balakrishnan and Lai (2009) present a literature review of the wide range of formulations and applications for bivariate exponential distributions. A primary use has been in the modeling of correlated failure times of components in electrical and mechanical systems (Balakrishnan and Lai 2009). Many forms of bivariate exponential distributions exist which operate for different ranges of the correlation coefficient, although only the Gumbel Type I ($-0.40365 \leq \rho \leq 0$) and Gumbel Type II ($-0.25 \leq \rho \leq 0.25$) allow for negative correlation. Singh et al. (2007) present these distributions with applications to hydrologic design. The Gumbel Type I distribution was applied to a storage (mean soil depth)-translation model to predict rainfall- runoff relationships for several experimental basins (Moore and Clark 1981). This distribution was selected as observed correlation between storage and translation was -0.38. Coefficient of determination (R^2) values ranged from 0.57 to 0.88 for the various test basins when compared against measured runoff. Likewise, the Gumbel Type I was utilized in this application due to its allowable correlation coefficient range.

The Gumbel Type I bivariate exponential distribution, applied to the demand management of potable irrigation, is shown as Equation 4-11 (Gumbel 1960).

$$f(x,y) = (\sigma_x \sigma_y)^{-1} \left\{ (1+\delta x/\sigma_x)(1+\delta y/\sigma_y) - \delta \right\} \cdot \exp\left(-x/\sigma_x - y/\sigma_y - \delta xy/\sigma_x \sigma_y\right) \qquad (4\text{-}11)$$

Where: f(x,y)= joint density function of outdoor water savings per customer; σ_x = standard deviation of irrigable area; σ_y = standard deviation of application rate savings; δ = parameter related to correlation coefficient.

The correlation coefficient, ρ, decreases from zero when δ tends to zero to -0.40365 when δ =1. The approximate relationship can be utilized to determine an appropriate value of δ given known correlation coefficient ρ. An alternate analytical approximation is also presented in Gumbel 1960, Moore and Clark 1981, and Singh et al. 2007. In our case, ρ= -0.38, so δ = 0.85.

The utilized parameters to determine the bivariate exponential distribution representing the probability of an SFR having a given total outdoor water usage for GRU are shown in Table 4-1. The standard deviations, derived previously, are shown in Figures 4-2 and 4-3. A value of 0.85 was utilized for δ given an observed correlation coefficient of -0.38. The resultant distribution is shown in Figure 4-4. The coefficient of determination for the overall model was R^2=0.5236.

Table 4-1. Input parameters for bivariate exponential distribution of GRU Irrigators

Variable	Standard deviation
X, Irrigable area (1,000 ft^2)	11.31
Y, application rate (in./yr.)	14.61
Correlation coefficient, ρ	-0.38
Parameter δ	0.85

Bivariate Lognormal

The bivariate lognormal distribution, applied to the demand management of potable irrigation, is shown as Equation 4-12 (Tung et al. 2006). This assumes both input marginal distributions are lognormal.

$$f(x,y) = \frac{1}{2\pi xy\sigma_{\ln x}\sigma_{\ln y}\sqrt{1-\rho^2}} \cdot \exp\left(-\frac{1}{2(1-\rho^2)} \cdot \left[\left(\frac{\ln(x)-\mu_{\ln x}}{\sigma_{\ln x}}\right)^2 - 2\rho\left(\frac{\ln(x)-\mu_{\ln x}}{\sigma_{\ln x}}\right)\left(\frac{\ln(y)-\mu_{\ln y}}{\sigma_{\ln y}}\right) + \left(\frac{\ln(y)-\mu_{\ln y}}{\sigma_{\ln y}}\right)^2\right]\right) \quad (4\text{-}12)$$

Where: σ_{lnx} = standard deviation of the log transform of x; σ_{lny} = standard deviation of the log transform of y; μ_{lnx} = mean of the log transform of x; μ_{lny} = mean of the log transform of y; ρ= correlation coefficient of ln(x) and ln(y). The utilized parameters to determine the bivariate lognormal distribution representing the probability of an SFR having a given total outdoor water usage for GRU are shown in Table 4-2. These parameter estimates are based on empirical data from GRU irrigators shown previously. The resultant distribution is shown in Figure 4-4. The coefficient of determination for the overall model was R^2=0.8605.

Table 4-2. Input parameters for bivariate lognormal distribution of GRU irrigators

Variable	Mean	Standard deviation
ln(x), Irrigable area (1,000 ft^2)	2.24	0.69
ln(y), application rate (in./yr.)	2.18	1.02
Correlation coefficient of ln(x) and ln(y) , ρ	-0.38	

Comparison of Methods Used To Determine Outdoor Water Savings Distribution

From the results shown in the previous sections, it is straightforward to generate a probability distribution of water savings from an outdoor BMP for the generalized case using either a nonparametric approach, Monte Carlo simulation given assumed input distributions, or bivariate exponential or bivariate lognormal distributions. For the illustrative example in which a BMP reduces application rate to a target of y_2=1 in./yr. while holding irrigable area constant, all seven methods yield similar water savings cumulative density functions as shown in Figure 4-5. The non-parametric approach requires a sufficient sample of potable irrigators to utilize, but is the most straightforward approach. The required inputs for the six parametric approaches are parameter estimates of current application rate and irrigable area probability distributions along with desired target conservation application rate and irrigable area as well as the

correlation coefficient. Estimates of input pdf functional form and parameter estimates derived from the GRU database can be utilized in the general case if direct data is unavailable.

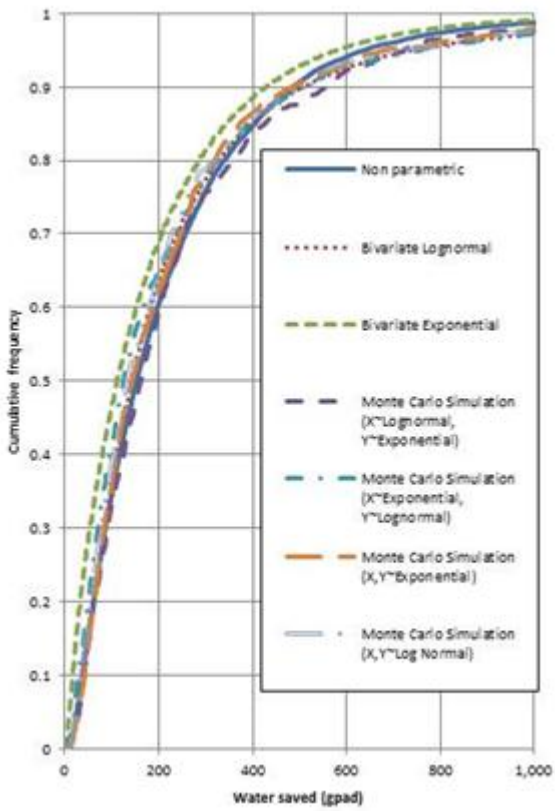

Figure 4-5. Comparison of water savings cdf's for GRU irrigators reducing application rate to y_2=1 in./yr.

Determination of Water Savings Production Function

The final step in analyzing the physical effectiveness of a single family residential outdoor BMP is to develop a production function of cumulative water savings as a function of number of accounts targeted. This procedure allows single family outdoor demand management options to be compared directly with other supply augmentation options when determining the optimal blend (Friedman et al. 2011).

The cumulative water savings production function can be obtained based on a previously defined probability distribution of water savings from a specified single family residential outdoor BMP as follows:

Nonparametric Approach

- Sort customers by descending water savings.
- Develop the production function with the x axis being the normalized cumulative percent accounts targeted and the y axis being the normalized cumulative water savings.

Monte Carlo Simulation

- Sort the output water savings pdf in descending order and invert the x and y axes.
- Develop the production function with the x axis being the normalized cumulative percent accounts targeted and the y axis being the normalized cumulative water savings.

Bivariate Distribution

- Convert the continuous joint density function into a discrete function and determine the expected value of total water savings for each discrete ranges using Equation 4-3.
- Sort each discrete range by descending water savings rate and develop the water savings performance function with the x axis being the normalized cumulative percent accounts targeted and the y axis being the normalized cumulative water savings.

A comparison of cumulative water savings production functions for various water savings probability distribution methods is presented in Figure 4-6. The normalized cumulative water savings performance function of a given outdoor BMP with a specified target irrigable area and application rate can be approximated by an exponential function of the form:

$$Q_{norm} = \left(1 - e^{-kn}\right) \tag{4-13}$$

Where: Q_{norm}=normalized cumulative water savings; k = rate constant; n = percent of total eligible irrigators targeted for BMP

A simple optimization problem is solved to find the value of k that minimizes the mean squared error between the sorted data and the equation estimate. Best fit production function rate constants (k) for varying assumed probability distributions for GRU irrigators reducing application rate to y_2=1 in./yr. are shown in Figure 4-6. The fit is very good, with R^2 values above 0.99. All estimated production functions resulted in higher k values as compared to the function derived from direct data with the bivariate exponentials having the most deviation.

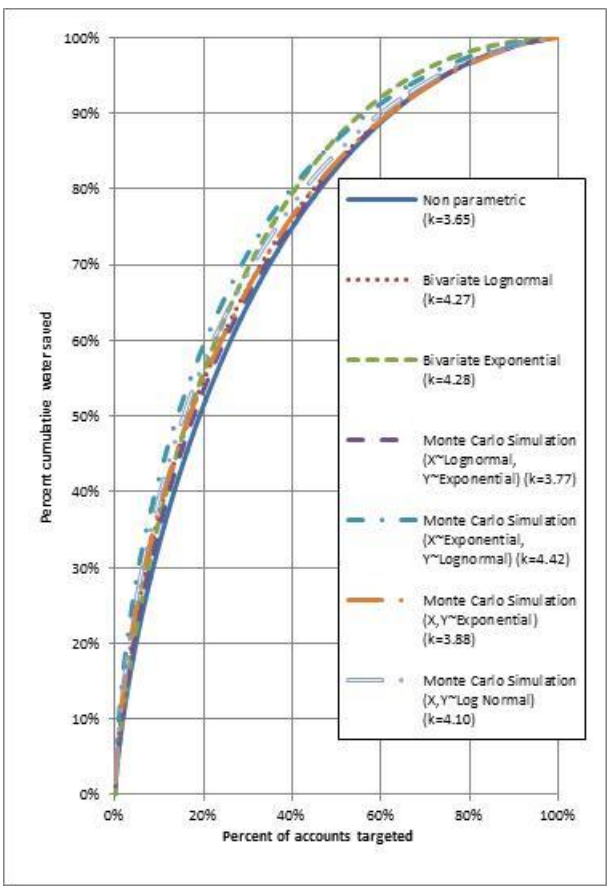

Figure 4-6. Comparison of normalized cumulative water savings production functions for GRU irrigators reducing application rate to y_2=1 in./yr.

Synopsis

This paper presents a systematic procedure to quantify savings potential of single family residential irrigation demand management strategies. A nonparametric data driven approach can be utilized given a sufficient sample of irrigators which evaluates current irrigation practices, irrigable area, and irrigation application rate for each single family residence based on parcel level tax assessor's data linked to customer level monthly water billing data. Water savings are calculated directly as the difference between current and proposed use after implementation of a management option for each group. This information is used to develop performance functions that estimate total water savings as a function of number of implementations for each group. This procedure allows demand management options to be compared directly with other supply augmentation options when determining the optimal blend. Six parametric models were derived from benchmark parcel level datasets, for a generalized utility where direct measurements are unavailable. Using either exponential or lognormal marginal distributions along with the Spearman's rank order correlation coefficient provided reasonable predictions as compared with the non-parametric approach. Future work includes investigating further the nature of irrigation variability among individuals as well as utilities to develop stronger predictive models which include factors such as price signals and irrigation restrictions.

CHAPTER 5
ANALYTICAL OPTIMIZATION OF DEMAND MANAGEMENT STRATEGIES ACROSS ALL URBAN WATER USE SECTORS

Scope and Overview

Demand management initiatives have increased in popularity from the early 1990s to present, with 23 states now having legislative mandates for some form of demand management as opposed to 9 states in 1990 (Rashid et al. 2010). This movement was stimulated by the United States Environmental Protection Agency (USEPA) Energy Policy Act of 1992, which enacted uniform water efficiency standards for toilets, showerheads, faucets, and urinals installed after 1994 (USEPA 1992). However, demand management efforts remain largely qualitative in nature, and often utilize simple average savings to measure effectiveness which does not capture the variability among customers' water usage patterns (White et al. 2004, Maddaus 2006, Rosenberg 2007a, Green 2010).

The focus of demand management is shifting away from indoor fixture retrofits due to observed declines in residential per capita usage as a result of the rate at which low flow toilet and clothes washer technologies have been adopted (DeOreo and Mayer 2012). Single family outdoor usage, on the other hand, is increasing rapidly due to the recent prevalence of in-ground potable irrigation systems (Friedman et al. 2013). Single family residential (SFR) outdoor water usage can account for the majority of total and peak SFR usage especially during drier months in warmer climates (Mayer et al. 1999, Palenchar 2009, Haley and Dukes 2010). Irrigation accounts for nearly one third of all residential water use in the U.S. and this percentage increases in warmer climates (Mayer et al. 1999; Vickers 2001). Additionally, irrigation tends to be the single most

significant driver of peak seasonal demand in public water supply (Chesnutt et al. 2004; Dziegielewski et al. 1993; Marella 2004; Mayer et al. 1999; Dziegielewski and Opitz 2002; Vickers 2001; Whitcomb 2006).

This paper focuses on generation of a decision support system for determining the optimal blend of utility incentivized water conservation best management practices to maximize net benefits as seen by the water utility. A unified methodology applicable to all urban water sectors is presented, with residential irrigation demand management strategies being the primary emphasis. The focus here is on optimal technological improvements which can be modeled utilizing process based models rather than conservation policy which relies on statistical or agent based simulation and/or regression techniques. Generation of such a process based model requires evaluation of existing end uses of demand for every water user served by the utility. This is required as water savings is modeled for each SFR as the difference of existing and proposed end use after demand management implementation. However, few models have utilized such a framework to evaluate demand management. The next section presents a literature review of current techniques to evaluate demand management.

Literature Review

The need to better understand urban water demand, particularly residential irrigation, and associated effects of demand management has gained further interest in the past several years in an effort to improve water quality modeling, water supply planning, and water distribution system sizing in addition to promoting more water use. Reducing irrigation can have a major impact on both peak and average design flow conditions. Additionally, recent initiatives focused on incorporating demand

management in a broader context beyond reduced water supply needs, such as reduced energy utilization, are further requiring the need to better quantify demands with higher resolution. A recent report for the Water Research Foundation includes demand management as a best practice in water treatment, storage, and transmission energy efficiency, which recognizes that reduced demands may result in reduced treatment and distribution needs thus saving energy inputs (Leiby and Burke 2011).

As a result, the field of urban water demand modeling has gained significant attention in the last few decades with much of the focus being placed on long-term forecasts for water supply planning applications (House- Peters and Chang 2011). Much of this literature utilizes statistical techniques, such as time series regression of aggregate panel data, to predict system wide water usage based on a wide variety of causal factors including weather, water price, household income, household size, house square footage, the presence of homeowner associations, etc. (Refer to House-Peters and Chang 2011, Donkor 2012, and Tanverakul and Lee 2012 for detailed reviews of this literature). A small subset of these demand forecasting models includes factors related to water conservation including conservation rate structures, homes built after 1992, type of water fixtures, watering restrictions, presence of pools, variation in size and type of outdoor landscape, etc. (Polebitski and Palmer 2010, House- Peters and Chang 2011). As an alternative statistical demand forecasting technique, Ghiassi et al. (2008) uses a dynamic artificial neural network model to forecast urban water demand at a variety of time steps ranging from hourly to monthly. These methods may offer improved predictive accuracy as compared to regression techniques, particularly for short term forecasts (Ghiassi et al. 2008 House- Peters and Chang 2011). However

such models may be less useful for demand management decision support systems as they do not provide process level causal explanations for customer water usage.

The spatial scale of the majority of these models is aggregated to the system wide scale with a smaller subset focusing on variations by census tract or block (House-Peters and Chang 2011). Polebitski and Palmer (2010) evaluate water demand forecasting using the 100 census tracts that comprise Seattle, Washington. Chen (1994) argues that census block groups are preferable to census tracts due to the increased spatial disaggregation. The findings of this study suggest that spatial disaggregation is primarily limited by data availability. However, recent advances in spatial data and computational technology make it possible to evaluate demand at the customer level using combined statistical and process based modeling approaches, which is necessary for analysis of demand management options.

A separate class of “hybrid” demand forecasting models utilizes a combination of process and statistical modeling techniques. The process level component ranges from simple hydrograph separation to micro simulation of each end use event. For example, Gato et al. (2007) use regression techniques to estimate base residential water usage, which can then be subtracted from total billed usage to obtain seasonal usage via hydrograph separation. Seasonal usage is further explained using regression techniques with climatic explanatory variables to account for seasonality. On the other extreme, Aksela and Aksela (2011) describe how customers can be clustered based on high frequency (15 second) automatic meter readings to account for differing but unknown consumption habits. Process level micro simulation is then done to account for intra-cluster variability. Suero et al. (2012) compares using pure statistical regression,

pure analytical or technological, and hybrid techniques for modeling the effect of residential indoor fixture retrofits. This paper concluded that the technological component explains the majority of differences in observed usage, although demographic differences, captured in the regression model, explained some of the variability.

A separate group of hybrid models use an agent based modeling framework to simulate demand and the effect water demand management at the household agent scale. Chu et al. (2009) group individuals into one of three categories: random choice, habitual, and economically rational agents, to predict indoor fixture replacement based on utility maximization. Schwarz et al. (2008) includes agents that are influenced by the percentage of other agents who retrofit in their physical proximity or within their social network. Coefficients for terms in these cluster's objective functions are derived based on empirical survey data. Other water demand agent based models utilize other causal factors rather than fixture replacement to explain water usage signals. For example, Athanasiadis et al. (2005) used an econometric regression model to simulate behavioral changes in agent water usage based on price signals and influence of neighbors. Rosenberg et al. (2007b) presents a micro simulation model to predict numerous interconnected customer decisions relating to alternative supply and demand management options based on a two-stage optimization with resource objective function which accounts for variable future water supply availability.

Conventional process level demand management analysis has focused on the effect of retrofitting indoor water using fixtures in single family residences to lower flow devices due, in part, to the predictable and homogeneous nature of indoor water usage

around the country (Buchberger and Wells 1996, Mayer et al. 1999, Tanverakul and Lee 2012). Buchberger and Wells (1996) utilized Poisson rectangular pulses to describe indoor water usage events based on arrival time, intensity (flow) and duration based on a small sample of four homes. Mayer et al. (1999) classified ten second water use data into end uses for 100 homes each in 12 North American cities. Rosenberg (2007a) used probability theory to derive a normalized performance function for evaluating conservation options based on analytical propagation and Monte Carlo simulation of uncertain parameters. Input parameter distributions are based on direct measurements of water use per fixture based on studies such as that of Mayer et al. (1999). Blokker et al. (2010) generates probabilistic residential indoor demand estimates through simulation of end use parameter probability distributions based on the Poisson pulse framework proposed by Buchberger and Wells (1996), but does not explicitly use this model to quantify the effects of demand management or to develop optimal demand management strategies from the utility's perspective. Friedman et al. (2011) shows how demand management of residential indoor water usage can be optimized to maximize net benefits utilizing linear programming.

The existing literature provides a well-established theoretical framework for evaluating residential indoor demand management using a combination of process based and statistical approaches. However, little has been done to evaluate residential irrigation in such a manner. Furthermore, little has been done to apply such a framework to large-scale system wide analysis which can be used to form the basis of a decision support system for optimal utility conservation planning as extensive end use parcel level databases are required. This is since the majority of existing hybrid and

pure process models are based on small sample data sets which have limited use for such applications. Household level modeling of residential outdoor water usage is more challenging than indoor water usage due to significant seasonal and spatial variability resulting from a wide range of factors influencing irrigation practices including climate, price signals, individual irrigation practices, irrigation restrictions, irrigation technology, etc. and therefore also requires high quality customer billing data linked to GIS-based property appraisal data.

This paper presents a systematic procedure to evaluate the optimal blend of single family residential irrigation demand management strategies to achieve a specified goal based on performance functions derived from parcel level tax assessor's data linked to customer level monthly water billing data. Two alternative formulations are presented to maximize the net benefits, or to minimize total cost subject to satisfying a target water savings. Explicit analytical solutions are presented for both formulations based on appropriate exponential best fits of performance functions. A direct result of this solution is the dual variable which represents the marginal cost of water saved at a specified target water savings goal. A case study of 16,303 single family irrigators in Gainesville Regional Utilities where high quality tax assessor and monthly billing data are available is utilized as an illustrative example of these techniques. This methodology is then generalized to apply to any urban water sector, as exponential functions can be fit to all resulting cumulative water savings functions thus providing a unified framework for evaluating BMPs across numerous water use sectors.

Data Driven Non-Parametric Approach for Analyzing Single Family Potable Irrigation

The University of Florida urban water systems group has developed a high quality database for analyzing customer demand in urban water systems at the parcel level in Florida. This database contains property appraisal land use information for all 8.8 million parcels in Florida from the Florida Department of Revenue (FDOR) tax assessors database which is linked to U.S Census Block demographic data via GIS software. The GRU dataset represents a benchmark utility allowing for enhanced analysis beyond that of data available statewide with the additions of one year of monthly billing data from October 2007 to September 2008 linked to the Alachua County Property Appraiser (ACPA) database, which provides direct measurements of irrigable area. For details regarding the contents and processing of these databases refer to Friedman et al. 2011, Friedman et al. 2013, Morales et al. 2011, and Morales et al. 2013a. Given the increasing availability of property appraisal databases and advances in database and GIS technology, this data driven approach can be utilized elsewhere as the required model inputs are becoming more prevalent.

Given such a benchmark database, irrigable area can be directly determined for all 30,903 SFR homes in GRU using FDOR and ACPA data on parcel area and impervious area. Customer billing data for GRU are used to estimate total outdoor water usage per home for 30,903 homes. For 1,402 homes with separate potable indoor and outdoor meters, potable irrigation water usage is known directly. Otherwise, outdoor water usage is determined via hydrograph separation of total water usage subtracted from process level modeling of indoor usage (See Friedman et al. 2011, and Friedman

et al. 2013 for details). Given annual outdoor water usage (q_j) and irrigable area ($IA_{1,j}$), the average annual application rate ($AR_{1,j}$) is

$$AR_{1,j} = c \cdot \left(\frac{q_j}{IA_{1,j}} \right) \tag{5-1}$$

Where q_j= average annual outdoor water usage for household j; $AR_{1,j}$= annual application rate for household j; $IA_{1,j}$= irrigable area for household j.

Not all customers served by a utility irrigate from the potable system. Utilizing known application rates for all customers, a potable irrigator is defined as a customer whose application rate is ≥ 1 inch per year. All other customers are non-potable irrigators and/or customers who do not irrigate, thus defining the sample space of all potable irrigators in the system. A lower bound irrigation application rate of one inch per year is used since many customers have a positive, but very small, application rate. Similarly, the few customers with application rates over 100 inches per year are treated as outliers.

Analogously, minimum and maximum bounds were placed on the irrigable area (IA) of 1,000 and 100,000 square feet, respectively. These filters removed 7% of total customer population and 18% of total irrigable area. A total of 16,303 of 30,903 (53%) of GRU customers are potable irrigators utilizing these criteria. A detailed analysis of the subset of these potable irrigators in GRU is presented in this paper. The non-parametric joint pdf for the 16,303 potable GRU irrigators is shown as Figure 5-1.

In addition to potable irrigators, some SFR customers in GRU have private irrigation wells. The identity of these customers is unknown and this use is not metered. Other SFR customers in GRU rely on reuse water for irrigation. About 700 of these

customers have reuse meters. These non- potable irrigators will not be addressed in this paper.

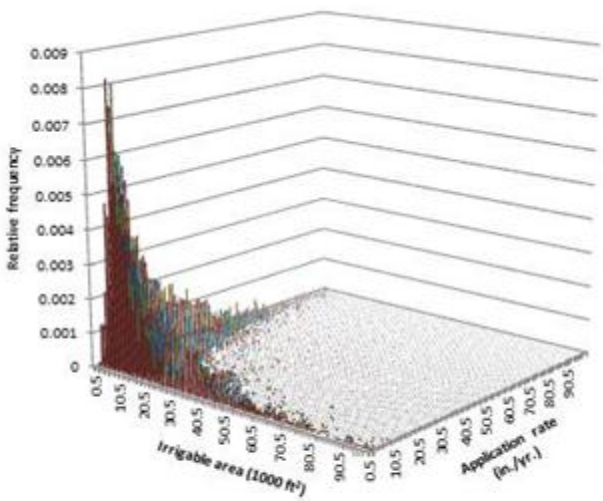

Figure 5-1. Non parametric joint relative frequency distribution of irrigation water usage for 16,303 residences in Gainesville Regional Utilities

Water savings performance function: For the non-parametric, data driven, approach, water savings for each individual household from a specified outdoor BMP with target irrigation application rate and irrigable area is calculated directly from Equation 5-2.

$$q_{saved,j} = c \cdot \left(IA_{1,j} AR_{1,j} - IA_{2,j} AR_{2,j} \right) \tag{5-2}$$

Where $q_{saved,j}$= outdoor water usage savings for household j; c = unit conversion coefficient; $AR_{1,j}$= current application rate for household j; $IA_{1,j}$= current irrigable area for household j; $AR_{2,j}$ = water conserving application rate after implementation of demand management strategy for household j; $IA_{2,j}$ = reduced irrigable area (size) of a given customer's residence which irrigates from the potable system after implementation of demand management strategy for household j.

In the case where a BMP only affects application rate, while holding irrigable area constant, the calculation of water savings is reduced to Equation 5-3. This simplification is valid for many outdoor BMP controls, including switching customers to non-potable irrigation, soil moisture sensors, and irrigation audits.

$$q_{saved,j} = c \cdot IA_{1,j}\left(AR_{1,j} - AR_{2,j}\right) \tag{5-3}$$

Given calculated water savings for a sufficient sample of potable irrigators, the reverse or complimentary cumulative non-parametric water savings frequency distribution can be determined by Equation 5-4 (Kvam and Vidakovic 2007).

$$x = \tilde{F}(q_{saved}) = \# q_{saved,j} \geq q_{saved}, q_{saved} \geq 0 \tag{5-4}$$

Where x= $\tilde{F}(q_{saved})$ = sample reverse or complimentary cumulative frequency distribution of outdoor water savings; $\# q_{saved,j} \geq q_{saved}$ = number of data points greater than or equal to given value of q_{saved}.

This function can be interpreted as the number of irrigators with outdoor usage water savings from a given BMP greater than or equal to a specified value of water savings, since the bin size of one represents individual household outdoor water savings.

Given the reverse cumulative frequency distribution, the water savings performance function can be determined by Equation 5-5.

$$y = \int_0^x \tilde{F}^{-1}(x)dx \tag{5-5}$$

Where y = cumulative water savings, $\tilde{F}^{-1}(x)$= inverse sample reverse cumulative frequency distribution

The cumulative water savings performance function of a given outdoor BMP with a specified target irrigable area and application rate can be approximated by an exponential function of the form:

$$y = y_{\max}\left(1 - e^{-kx}\right), x \le x_{\max} \tag{5-6}$$

Where: y= cumulative water savings; k = rate constant; x = number of irrigators targeted, y_{max}= maximum achievable water savings, x_{max} = maximum eligible irrigators to target

Alternatively, the cumulative water savings performance function can be expressed in normalized form as Equation 5-7.

$$y = 1 - e^{-kx} \tag{5-7}$$

Where: y= percent of maximum achievable water savings; k = rate constant; x = percent of total eligible irrigators targeted for BMP

A simple optimization problem is solved to find the value of k that minimizes the mean squared error between the measured data and the equation estimate. The normalized cumulative water savings performance function and best fix exponential approximation for an illustrative soil moisture sensor BMP applied to GRU irrigators who irrigate in excess of $AR_{2,j}$ = 25 in./yr. are shown in Figure 5-2, with a best fit k=3.77. The fit is very good, with R^2 above 0.99. For this application, the absolute values of y_{max} and x_{max} are 440 kgal/day for 2,746 eligible irrigators currently above 25 in./yr. In this example, about 50% of the savings can be attained by retrofitting 20% of the irrigators. The popular Pareto principle, also known as the 80:20 rule of thumb (Wiki, Pareto Principle), is equivalent to a k value of 8.04. Thus, the normalized form of the savings function provides a single parametric measure of system performance.

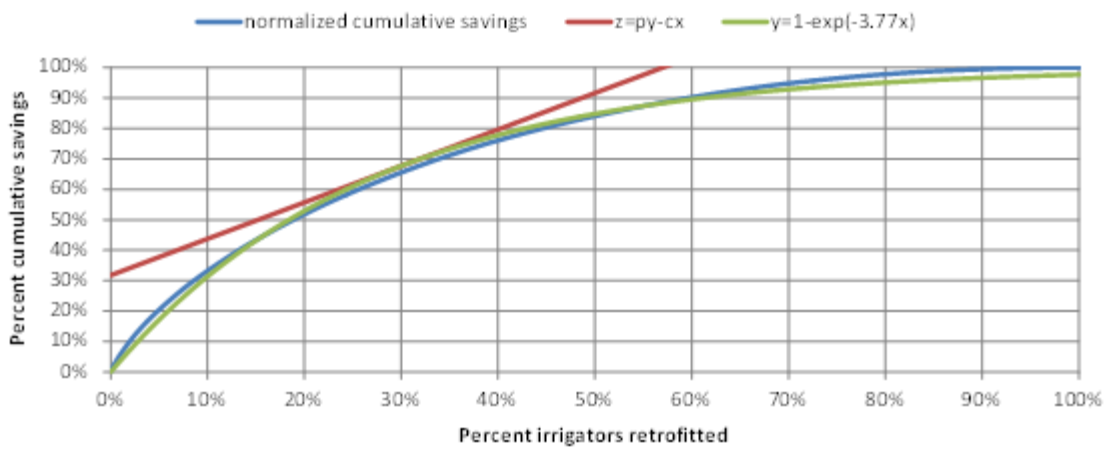

Figure 5-2. Normalized cumulative savings from soil moisture sensor retrofits and associated benefit-cost objective function for 2,746 eligible irrigators currently above 25 in./yr.

Optimization of Outdoor Water Use BMPs

Given the water savings performance function for a given outdoor BMP as well as the unit cost of a retrofit per day of service life (c) and the associated unit utility savings (p), it is possible to find the optimal number of BMP implementations. This problem can be formulated as a nonlinear program as follows:

Maximize Z= py-cx

Subject to:

$$y = y_{\max} \cdot (1 - e^{-kx}) \tag{5-8}$$

$0 \leq x \leq x_{\max}$

Where: Z=total benefits-total costs, p=value of water saved, y= quantity of water saved with an upper bound of y_{max}, c=unit cost of a retrofit, x=number of irrigators to retrofit, with an upper bound of x_{max}, k = rate constant

This optimization problem can be solved explicitly by finding x such that dy/dx = c/p as follows:

$$\frac{dy}{dx} = k \cdot y_{\max} \cdot e^{-kx} = \frac{c}{p}$$

$$x^* = -\frac{1}{k} \cdot \ln\left(\frac{c}{p \cdot k \cdot y_{\max}}\right) \qquad \text{for } 0<x<x_{max} \qquad (5\text{-}9)$$

It is necessary to add the condition of x* ≥ 0 since c/p could be greater than $(dy/dx)_{max}$. In this case, the optimal solution is to do nothing (i.e. x*=0). Analogously, if c/p is less than $(dy/dx)_{min}$ the optimal solution would be to retrofit all eligible irrigators, (i.e. $x^*=x_{max}$)

The graphical solution to this problem is shown in Figure 5-2 for a soil moisture sensor BMP applied to GRU irrigators who irrigate in excess of $AR_{2,i}$ = 25 in./yr.. The budget line is plotted on Figure 5-2 and then moved parallel until it is tangent to the performance function. The budget line has a slope of c/p. The optimal solution occurs where c/p = dy/dx if 0<x<xmax.

Soil moisture sensors were assumed to have a 5 year service life (SWFWMD 2011) and SJRWMD (2011) as well as a unit cost of $700/account. This translates to c=$0.38/account/day of service or $1,053/percent applicable irrigators retrofitted/day. Assuming a value of water saved of $2/kgal or $879/percent maximum water savings, the optimal solution can be found graphically, as shown in Figure 5-2, or analytically, from Equation 5-9.

$$x^* = -\frac{1}{3.77} \cdot \ln\left(\frac{1{,}053}{879 \cdot 3.77 \cdot 1}\right) = 0.30 \qquad (5\text{-}10)$$

The resulting percent total water saved and net benefits can be solved for by substituting into Equation 5-8:

$$y^* = (1 - e^{-3.77 \cdot (0.3)}) = 0.68 \qquad (5\text{-}11)$$

Z^{*}=\$880*0.68 –\$1,053*0.30 = \$282/day (5-12)

The optimal solution is to install soil moisture sensors on 30% of eligible irrigators (824 of 2,746 irrigators), saving 68% of the physically attainable savings (299 of 440 kgal/day) with the maximum net benefits being Z = \$282 per day.

The above methodology can be utilized to evaluate any individual best management practice which reduces outdoor water use application rate and/or irrigable area. The next two sections describe the solution techniques when multiple BMPs are considered simultaneously. This approach was utilized to evaluate the optimal strategy for irrigation audits and switching customers to reuse water for irrigation in addition to the illustrated soil moisture sensor BMP for GRU irrigators.

Analytical solution for n independent BMP options

The previous section considers the optimization of a single BMP. The solution can be generalized to optimize n independent BMPs simultaneously by solving following the nonlinear program to maximize net benefits:

$$\text{Maximize } Z = py - \sum_{i=1}^{n} (c_i \cdot x_i)$$

Subject to:

$$y = \sum_{i=1}^{n} y_{\max,i} \cdot (1 - e^{-k_i x_i}) \qquad (5\text{-}13)$$

$$0 \leq x_i \leq x_{\max,i}$$

Where: Z= total net benefits, y= total quantity of water saved, $y_{max,i}$ = maximum possible water savings for BMP i , c_i=unit cost of BMP i, p= value of water saved, x_i=number of irrigators to retrofit with BMP i with an upper bound of $x_{max,i}$, k_i= rate constant of performance function for BMP i.

Substitution of the performance function into the objective function, and ignoring maximum resource availability and non-negativity constraints results in:

$$\max z = f(x) = p\sum_{i=1}^{n} y_{\max,i} \cdot (1 - e^{-k_i x_i}) - \sum_{i=1}^{n} \left(c_i \cdot x_i\right) \tag{5-14}$$

The optimal solution of this convex function is obtained by setting partial derivatives equal to zero and solving the resulting system of equations.

$$\frac{\partial f(x)}{\partial x_i} = p y_{\max,i} k_i e^{-k_i x_i} - c_i = 0 \tag{5-15}$$

Since each partial derivative only depends on a respective single variable, the solution is a simple generalization of the single BMP case, or:

$$x_i^* = -\frac{1}{k_i} \cdot \ln\left(\frac{c_i}{p \cdot k_i \cdot y_{\max,i}}\right), 0 < x_i^* < x_{\max,i} \tag{5-16}$$

The above solution applies for the case where $0 < x_i^* < x_{\max,i}$. If these conditions do not hold, then the possibilities of $x_i^*=0$ or $x_i^*=x_{\max,i}$ should be investigated. It is necessary to add the condition of $x_i^* \geq 0$ since c_i/p could be greater than $\left(\partial f(x)/\partial x_i\right)_{\max}$. In this case, the optimal solution is to do nothing (i.e. $x_i^*=0$). Analogously, if c_i/p is less than $\left(\partial f(x)/\partial x_i\right)_{\min}$ the solution would be to retrofit all eligible irrigators, (i.e. $x_i^*=x_{\max,i}$)

Cost Minimization Formulation of Outdoor BMP Water Savings

An alternative formulation is to minimize the cost of BMP implementations subject to reaching a target water savings goal as shown by Equation 5-17:

$$\text{Minimize } Z = \sum_{i=1}^{n} \left(c_i \cdot x_i\right)$$

Subject to:

$$\sum_{i=1}^{n} y_{\max,i} \cdot (1 - e^{-k_i x_i}) \geq y_{\min} \tag{5-17}$$

$x_i \leq x_{maxi}$
$x_i \geq 0$

Where: Z= total costs, y_{min}= water savings target from demand management BMPs, y= total quantity of water saved, $y_{max,i}$ = maximum possible water savings for BMP i , c_i=unit cost of BMP i, p= value of water saved, x_i=number of irrigators to retrofit with BMP i with an upper bound of $x_{max,i}$, k_i= rate constant of performance function for BMP i.

Given independent exponential water savings functions and a linear cost function, the optimization problem shown as Equation 17 can be solved analytically for the necessary and sufficient Karush-Kuhn- Tucker (KKT) conditions (Hillier and Lieberman 2010). The derivation of this solution is as follows:

To begin, all constraints must be written in standard form to achieve the formulation shown in Equation 5-18.

Minimize $f(x) = \sum_{i=1}^{n} (c_i \cdot x_i)$

Subject to:

$$h(x) = y_{\min} - \sum_{i=1}^{n} y_{\max,i} \cdot (1 - e^{-k_i x_i}) \leq 0$$

$g_i(x) = x_i - x_{max,i} \leq 0$

$g_{i+n}(x) = -x_i \leq 0$ (5-18)

The KKT conditions state that for a local minimum x*, unique Lagrange multipliers $\lambda^*, \mu_i^*, \mu_{i+n}^*$, exist which satisfy the following conditions:

$$\nabla f(x^*) + \lambda^* \nabla h(x^*) + \sum_{i=1}^{n} \mu_i^* \nabla g_i(x^*) + \sum_{i=1}^{n} \mu_{i+n}^* \nabla g_{i+n}(x^*) = 0 \qquad (5-19)$$

$$\lambda^* h(x^*) = 0 \qquad (5-20)$$

$$\mu_i^* g_i(x^*) = 0 \qquad (5-21)$$

$$\mu_{i+n}^* g_{i+n}(x^*) = 0 \qquad (5-22)$$

$$\lambda^*, \mu_i^*, \mu_{i+n}^* \geq 0 \qquad (5-23)$$

Therefore, the KKT conditions for this problem are:

$$c_i - \lambda^* k_i y_{\max,i} e^{-k_i x_i^*} + \mu_i^* - \mu_{i+n}^* = 0 \qquad (5-24)$$

$$\lambda^* \left[y_{\min} - \sum_{i=1}^{n} y_{\max,i} \cdot (1 - e^{-k_i x_i^*}) \right] = 0 \qquad (5-25)$$

$$\mu_i^* \left[x_i^* - x_{\max,i} \right] = 0 \qquad (5-26)$$

$$\mu_{i+n}^* \left[- x_i^* \right] = 0 \qquad (5-27)$$

$$\lambda^*, \mu_i^*, \mu_{i+n}^* \geq 0 \qquad (5-28)$$

Equations 5-24 through 5-28 are necessary conditions for a local minimum. Since the objective function is linear and all constraints are convex functions, the solution to the above equations is the global optimum.

Depending on parameters c_i, k_i, $y_{max,i}$, y_{min} the optimal value of implementations x_i^* will either be zero, $x_{max,i}$ or a value between zero and $x_{max,i}$.

Two trivial cases exist where $\lambda^* = 0, \mu_i^* \geq 0, \mu_{i+n}^* = 0 \; or \; \lambda^* = 0, \mu_i^* = 0, \mu_{i+n}^* \geq 0$. These conditions equate to all $x_i^* = x_{max,i}$ or $x_i^* = 0$ from Equations 5-26 and 5-27 respectively.

Consider the non-trivial case where $\lambda^* > 0, \mu_i^* = 0, \mu_{i+n}^* = 0$. This equates to $0 < x_i^* < x_{\max,i}$.

The optimal solution can be found by first solving the gradient term (Equation 5-24) for x_i^* in terms of λ^*.

$$x_i^* = -\frac{1}{k_i}\ln\left[\frac{c_i}{\lambda^* k_i y_{\max,i}}\right] \tag{5-29}$$

Equation 5-29 can then be substituted into Equation 25 and solved for λ. Recognizing that $\lambda^* > 0$,

$$y_{\min} - \sum_{i=1}^{n} y_{\max,i} \cdot (1 - e^{-k_i x_i^*}) = 0$$

or

$$y_{\min} - \sum_{i=1}^{n} y_{\max,i} \cdot (1 - e^{-k_i - \frac{1}{k_i}\ln\left[\frac{c_i}{\lambda^* k_i y_{\max,i}}\right]}) = 0$$

or

$$\lambda^* = \frac{\sum_{i=1}^{n} \frac{c_i}{k_i}}{\left(\sum_{i=1}^{n} y_{\max,i}\right) - y_{\min}} \tag{5 – 30}$$

Thus the value of λ^* can be directly determined from Equation 30, given parameters c_i, k_i, $y_{max,i}$, $y_{min.}$ The optimal mix of implementations per BMP can be determined by substituting back into Equation 28. The value of λ^* represents the dual variable solution (shadow price) and can be interpreted as the marginal value of saving an additional gallon of water from outdoor BMPs.

Now consider the more generalized case where at least one value of $x_i^*=x_{max,i}$ $\left(\mu_i^* > 0\right)$or $x_i^*=0\left(\mu_{i+n}^* > 0\right)$. The gradient term of the KT conditions (Equation 5-24) becomes:

$$c_i - \lambda^* k_i y_{\max,i} e^{-k_i x_i^*},\ \forall i \middle| \mu_i^* = 0, \mu_{i+n}^* = 0 \tag{5 – 31}$$

$$c_i - \lambda^* k_i y_{\max,i} e^{-k_i x_i^*} + \mu_i^* = 0,\ \forall i \middle| \mu_i^* > 0, \mu_{i+n}^* = 0 \tag{5 – 32}$$

$$c_i - \lambda^* k_i y_{\max,i} e^{-k_i x_i^*} - \mu_{i+n}^* = 0,\ \forall i \middle| \mu_i^* = 0, \mu_{i+n}^* > 0 \tag{5 – 33}$$

From Equations 5-26 and 5-27, it is easy to show that

$x_i^* = x_{\max,i}, \ \forall i \middle| \mu_i^* > 0, \mu_{i+n}^* = 0$

$x_i^* = 0, \ \forall i \middle| \mu_i^* = 0, \mu_{i+n}^* > 0$

Similarly to the previous case, the optimal solution for all other BMPs can be found as

$$x_i^* = -\frac{1}{k_i} \ln\left[\frac{c_i}{\lambda^* k_i y_{\max,i}}\right], \forall i \middle| \mu_i^* = 0, \mu_{i+n}^* = 0 \tag{5-34}$$

$$\lambda^* = \frac{\sum_{i=1}^{m} \frac{c_i}{k_i}}{\left(\sum_{i=1}^{m} y_{\max,i}\right) - y_{\min}}, \forall i \middle| \mu_i^* = 0, \mu_{i+n}^* = 0 \tag{5-35}$$

Where m= number of BMPs (i) for which $0 < x_i^* < x_{\max,i}$

Optimal Blend of Outdoor BMPs for GRU

As an illustrative example, this section describes the procedure used to find the least costly blend of outdoor BMPs for GRU. Reuse, soil moisture sensors, and irrigation audits were evaluated as illustrative outdoor BMP options. This analysis assumes that these three outdoor BMPs are mutually exclusive. It is possible to model the case where BMP savings is not mutually exclusive, but it greatly complicates the analysis.

Supply Curve of Outdoor BMP Water Savings

The relevant coefficients for the nonlinear program to find the least costly blend of outdoor BMPs subject to reaching a target water savings for GRU irrigators are in presented in Table 5-1. Costs and service lives are derived from literature estimates (Friedman et al. 2011). Identifying the target market for reuse is utility specific since it depends on the existing reuse network and reclaimed treatment plant locations. For GRU, it was assumed that 10% (1,630 of 16,303) of irrigators were readily eligible for a reuse water connection based on existing GRU reuse infrastructure (Gainesville

Regional Utilities 2008). The water conserving application rate ($AR_{2,j}$) was assumed to be 1 in./yr. for reuse as these customers would no longer irrigate from the potable system. For soil moisture sensors and irrigation audits, the water conserving application rate was assumed to be 25 in./yr. based on typical irrigation needs in GRU (Friedman et al. 2013). A typical average savings rate for irrigation audits can be assumed to be 25% of net application rate (SWFWMD 2011) between current application and minimum application rates. Water savings potential from irrigation audits therefore equal 25% of SMS potential. The performance function for irrigation audits is also simply the SMS production function multiplied by 0.25. However, irrigation audit evaluation procedures vary widely and are site specific, thus introducing a high degree of uncertainty in predicted savings.

Table 5-1. Parameters for the outdoor BMP optimization

BMP	c_i ($/account)	Service life (years)	k_i (normalized)	$y_{max,i}$ (kgal/day)	$x_{max,i}$
Reuse (x_1)	5,000	25	3.65	360	1,630
Soil moisture sensors (x_2)	700	5	3.77	440	2,746
Irrigation audits (x_3)	150	5	3.77	110	2,746
Total	n/a	n/a	n/a	910	7,122

The supply curve for water savings from SFR outdoor BMPs can be obtained by solving the cost minimization program with varying values of y_{min} as shown in Table 5-2 and Figure 5-3 for the GRU application. An exponential approximation to the total cost curve is also shown in Figure 5-3, with an R^2 of 0.87. Note that the marginal cost of water saved is equivalent to the shadow price (dual variable) which is equal to the optimal Lagrange multiplier λ^*. The case where y_{min}=0.01 mgd represents a special case where x_1^*= 0. Thus, the generalized cost minimization solution shown by Equations 5-34

and 5-35 must be utilized. For all other tested values of y_{min}, Equations 5-29 and 5-30 can be utilized as all $0<x_i^*<x_{max,i}$.

These solutions were verified by solving the cost minimization formulation, shown in Equation 5-17, directly using the GRG nonlinear solver within Microsoft Excel. Once Solver has reached the optimum solution, the marginal cost is reported directly from the sensitivity report as the "Lagrange multiplier".

Table 5-2. Least costly combination of the three outdoor BMPs to meet a specified target savings for GRU.

Target conservation savings, y_{min} (mgd)	Total cost ($/d)	Percent irrigators to retrofit reuse (x_1)	soil moisture sensors (x_2)	irrigation audits (x_3)	Marginal cost ($/kgal)[a]
0.01	6.41	0.00%	0.48%	0.51%	0.65
0.05	33.20	0.43%	2.23%	2.25%	0.69
0.1	68.80	2.07%	3.82%	3.84%	0.73
0.2	147	5.68%	7.31%	7.34%	0.84
0.3	237	9.84%	11.34%	11.36%	0.97
0.4	343	14.75%	16.09%	16.11%	1.16
0.5	473	20.73%	21.88%	21.90%	1.45
0.6	639	28.39%	29.29%	29.32%	1.92
0.7	870	39.06%	39.62%	39.65%	2.83
0.8	1,254	56.77%	56.77%	56.80%	5.40
0.85	1,614	73.38%	72.85%	72.88%	9.90

[a]Marginal cost is the shadow price (dual variable) with respect to the target conservation savings

The optimal solution to the cost minimization problem gives the supply curve in standard demand-supply equilibrium analysis. If a single savings rate, p, is used to represent the value of reduced demand, then one can find the solution that maximizes net benefits by inspection of Figure 5-3. For example, if the value of the water saved is $2.00/kgal., then the optimal solution is to save 0.62 mgd using the mix of BMPs shown in Table 5-2 since the demand curve is a horizontal line that intersects the supply curve at 0.62 mgd. This framework allows for direct comparison to alternative water supply

augmentation by comparing the cost of BMP implementations with the value of deferred alternative water supply.

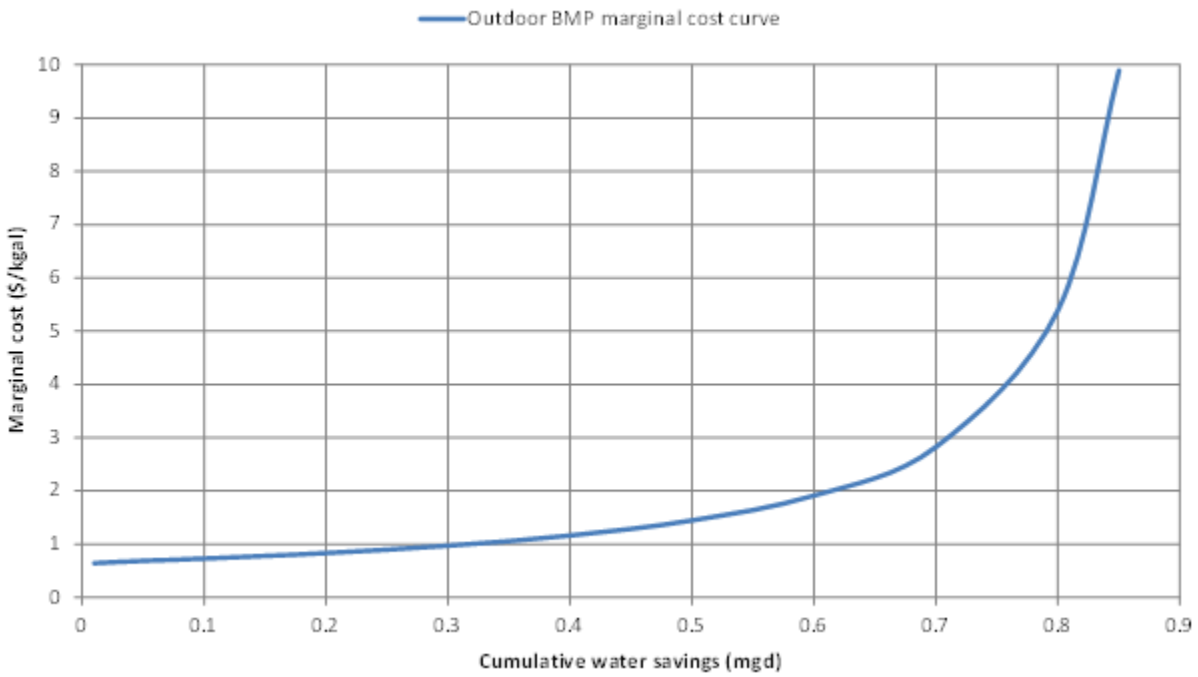

Figure 5-3. Marginal cost curve as a function of outdoor water saved for GRU

Optimal Blend of BMPs Across All Water Use Sectors For GRU

The methodology for evaluating the optimal blend of single family residential outdoor BMPs to achieve either maximum net benefits or to minimize cost subject to satisfying a minimum target water savings can be generalized to include BMPs for all sectors of urban water use. Each generic BMP is evaluated based on analysis of parcel level data to determine the appropriate water savings performance function. Friedman et al. (2011) describe the methodology for single family indoor BMPs. Morales et al. (2013b) describe the methodology for commercial, institutional, and industrial BMPs. In all cases, exponential functions can be fit to the resulting cumulative water savings function thus providing a unified framework for evaluating BMPs across numerous water use sectors. Since water savings are assumed to be mutually exclusive for all BMPs,

total water saved is simply the summation of each individual water savings performance function. Therefore, the solutions described in this paper can easily extend to numerous BMP options across all demand sectors.

As an illustrative example, consider the optimal blend of four indoor fixture retrofit programs (toilets, clothes washers, showerheads, and faucets) in addition to the three outdoor BMPs described in this paper to minimize cost subject to satisfying a target water savings for GRU single family residences. Water savings performance functions were obtained for each indoor BMP independently based on calculated differences between modeled existing and proposed low flow fixture intensities for each residence (Friedman et al. 2011). Given these four functions, Equations 5-29 and 5-30 as well as Equations 5-34 and 5-35 can be utilized to develop marginal cost curves of demand management water savings for indoor retrofit BMPs only, and for both indoor and outdoor BMPs combined, shown in Figure 5-4 with the addition of the three outdoor BMP water savings performance functions. The combined marginal cost curve can be obtained as the sum of the individual indoor and outdoor curves.

Similarly to the case where outdoor BMPs were considered mutually exclusive, if a single savings rate, p, is used, then the solution that maximizes net benefits for the combined set of indoor and outdoor BMPs can be found by inspection of Figure 5-4. For example, if the value of the water saved is $2.00/kgal., then the optimal solution is to save 0.62 mgd from outdoor BMPs (as shown before) plus an additional 1.0 mgd from indoor BMPs totaling 1.62 mgd from all combined BMPs. Thus, 38% of optimal savings is the result of outdoor BMPs while 62% of optimal savings comes from indoor BMPs. Indoor BMPs account for more of the total optimal savings due to the target market

potentially being all SFR homes whereas outdoor BMPs are limited to select over-irrigators. Additionally, indoor BMPs are significantly more promising if added benefits such as reduced end use energy consumption and reduced wastewater charges are included (Morales et al. 2013b).

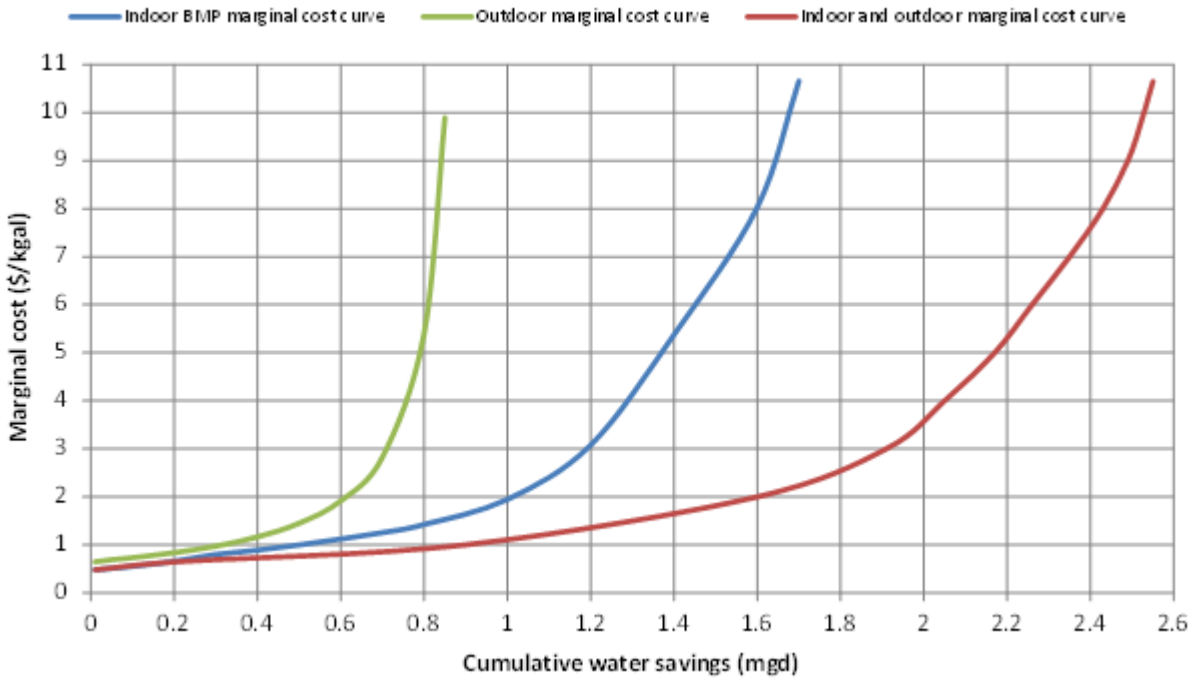

Figure 5-4. Marginal cost curve as a function of indoor and outdoor water saved for the single family residential sector served by GRU

This methodology can be further extended to compare demand management options across all water use sectors in addition to single family indoor and outdoor BMPs, as shown in Figure 5-5. In this illustrative example, commercial, industrial, and institutional BMPs are more promising than single family BMPs due to the increase rate of utilization of plumbing fixtures. Multi-family is less promising due to decreased utilization and occupancy rates as well as minimal irrigation compared to single family BMPs. Additionally, water loss controls, such as replacing inaccurate meters, pressure management, and active leakage detection, can be evaluated along with customer demand management options. This is due to both water loss control and customer

demand management both contributing to reducing the quantity of water needed to be pumped and treated for water supply. Therefore, a single marginal savings, p, can be utilized across all options, allowing for direct comparison to alternative water supply augmentation by comparing the cost of BMP implementations with the value of deferred alternative water supply. For example, if the value of the water saved is $2.00/kgal., then the optimal solution is to save 7.73 mgd from all BMPs comprising of 7% multi-family, 21% single family, 41% commercial, institutional, and industrial, and 31% water loss management.

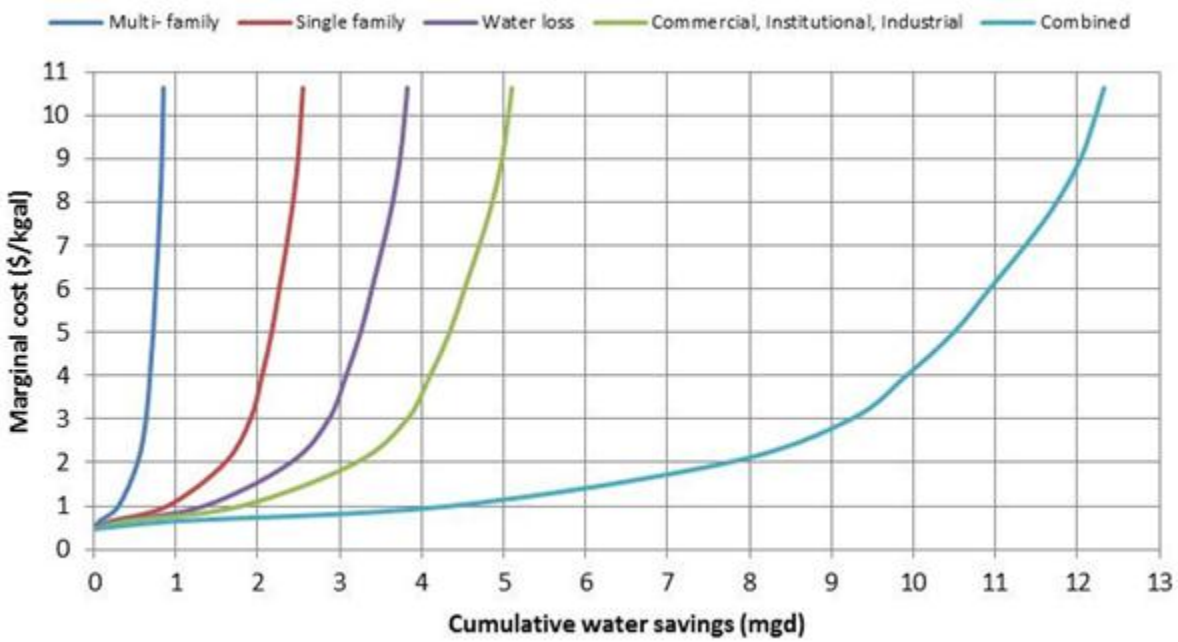

Figure 5-5. Illustrative marginal cost curve as a function of water saved across all water use sectors served by GRU

Spatial Analysis of Priority Retrofits for the SFR Sector

A unique feature of the methodology presented in this paper allows for direct targeting of individual households once the optimal solution has been determined since the identity of each customer is maintained throughout the analysis. The location of all homes selected for retrofit can be visualized using GIS, which allows for spatial

clustering of priority areas. Results can be grouped to any desired level of aggregation, such as census block, land use code, etc. based on common attributes in the University of Florida urban water demand database. Illustrative results for toilets and irrigation systems in single family residences in Gainesville are shown in Figure 5-6. The spatial clustering indicates the priority areas. In this case, the priority toilet retrofit areas are in the older sections of the city with smaller houses, fewer bathrooms, and older fixtures. The priority irrigation areas are the newer homes that have a high prevalence of in-ground sprinkling systems.

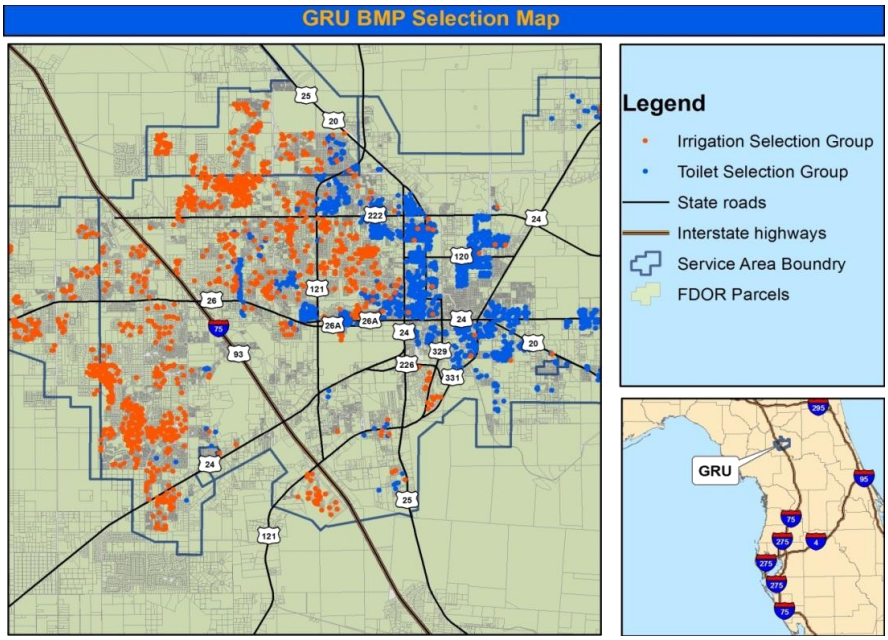

Figure 5-6. Illustrative map showing the priority parcels for toilet and irrigation single family residential retrofits, Gainesville, Florida

Synopsis

This paper presents a systematic procedure to evaluate the optimal blend of single family residential irrigation demand management strategies to achieve a specified goal based on performance functions derived from parcel level tax assessor's data linked to customer level monthly water billing data. Two alternative formulations are

presented to maximize the net benefits, or to minimize total cost subject to a satisfying a target water savings. Explicit analytical solutions are presented for both formulations based on appropriate exponential best fits of performance functions. A direct result of this solution is the dual variable which represents the marginal cost of water saved at a specified target water savings goal. A case study of 16,303 single family irrigators in Gainesville Regional Utilities where high quality tax assessor and monthly billing data are available is utilized as an illustrative example of these techniques. This framework can be generalized to apply to any urban water sector and to show the aggregate optimal solution across sectors.

The performance functions can be approximated as exponential, which can easily be solved for optimality given unit costs and value of water saved. The optimal value of the dual variable can be found directly using the Karush-Kuhn-Tucker conditions. This represents the marginal value of saving an additional gallon of water from outdoor BMPs. This framework allows for direct comparison to alternative water supply augmentation by comparing the cost of BMP implementations with the value of saved alternative water supply. Spatial clustering of targeted homes can be easily performed in GIS to identify priority demand management areas.

CHAPTER 6
PROCESS EVALUATION OF RESIDENTIAL WATER USE AND POPULATON SERVED

Scope and Overview

A key measure of efficiency in the urban water demand field is gallons per capita per day (gpcd) of water use. From a process point of view, it is important to define which component(s) of water use and population are being used in the numerator and denominator of the gpcd calculation. Many areas are developing standardized terminology and definitions to allow for consistent water use benchmarking across utilities among other applications. For example, extensive efforts have been taken in California to define both water usage and population terms for consistent benchmarking in response to the per capita target of 20% reduction in gpcd by 2020 (California Dept. of Water Resources 2010).

One popular metric is gross gpcd which can be defined as total treated water delivered to the water distribution system divided by total population served. This gpcd measure can be misleading since it includes non-residential uses which range from less than 5 % to more than 50% of the total usage depending upon the blend of customers. This measure also includes water losses based on comparing the water delivered from the treatment plant(s) with the sum of the water delivered to all customers as measured by their meters. Water loss ranges from 5 to 25% of the water produced. Additionally, accounting for the functional water using population of the non-residential sectors is challenging and not well defined. Alternative methods for evaluating non -residential uses based on heated area rather than population are presented in Morales et al. (2011).

This paper addresses the calculation of total residential water use defined as the product of population and per capita water usage solely associated with people physically present and using water in the single and multi-family residential sector at a given time. This approach allows for consistent benchmarking as per capita usage multiplied by population yields actual water delivered to the residential sector. Residential water using population and indoor and outdoor per capita water usage process models are presented to estimate total residential water usage, incorporating variability among fixture end uses and irrigable area for every household in a utility. Residential water using population is based on the designated water utility boundaries as opposed to political boundaries. High quality property appraisal and U.S. Census block data is used to estimate the actual population served including accounting for occupancy.

Predicted total water usage is then determined as the product of modeled population and modeled per capita water usage for residential users physically present and using water at a given time. Predicted total residential water usage is then compared to actual measured total residential water delivered to validate both the population and per capita process model, if water delivered data is available. This data driven, bottom up, approach allows for more precise evaluations of population and water use trends as it directly accounts for variability among heterogeneous users based on well-defined land use codes and Census Block delineations. However, few models have utilized such a framework to evaluate population and water usage within a utility. A case study of 13,555 single and multi-family residential parcels in Sanford, FL where high quality tax assessor and monthly billing data are available is utilized as an

illustrative example of these techniques. Future work includes incorporating the residential model presented here with analogous non-residential water usage and water loss models to evaluate total potable water supplied, which can be validated against measured monthly production records for the utility.

The next section presents a literature review of current techniques to evaluate population and water usage within a utility. All sections after the literature review describe the data driven methodology to determine residential population served and per capita water usage at the parcel level beginning with a description of databases utilized. The following section shows the overall parcel level modeling framework in which residential water usage is the product of rigorously modeled population and per capita water usage. Then detailed descriptions of residential population and residential indoor and outdoor per capita water usage process models are provided. The paper concludes by validating model assumptions as compared to measured residential water usage. These approaches are applied to the Sanford, FL benchmark utility to illustrate methodologies. These parcel level methodologies are used for a variety of applications within the Conserve Florida Water EZ Guide 2.0 tool available at http://conservefloridawater.org

Literature Review

The field of urban water demand modeling has received significant attention in the last few decades with much of the focus on long-term forecasts for water supply planning applications (House- Peters and Chang 2011). Much of this literature utilizes statistical techniques, such as time series regression of aggregate panel data, to predict water usage per home or connection based on a wide variety of causal factors including weather, water price, household income, household size, house square footage, the

presence of homeowner associations, etc. (Refer to House-Peters and Chang 2011, Donkor et al. 2013, and Tanverakul and Lee 2012 for detailed reviews of this literature). A small subset of these demand forecasting models includes factors related to water conservation including conservation rate structures, homes built after 1992, type of water fixtures, watering restrictions, presence of pools, and variation in size and type of outdoor landscape (Polebitski and Palmer 2010, House- Peters and Chang 2011).

The majority of these models aggregate to the system wide scale with a smaller subset focusing on spatial variations by census tract or block (House- Peters and Chang 2011). Polebitski and Palmer (2010) evaluate water demand forecasting using the 100 census tracts that comprise Seattle, Washington. Chen (1994) argues that census block groups are preferable to census tracts due to the increased spatial disaggregation. The findings of Chen (1994) suggest that spatial disaggregation is primarily limited by data availability. Additionally, these models primarily focus solely on a small subset of single family homes, thus not capturing the variability among single family and multi-family homes as well as differing water usage from other sectors. However, recent advances in spatial data availability and computational technology make it possible to evaluate demand at the customer level.

A necessary first step to evaluate water usage is to evaluate trends in population served by the utility. This is especially important for single family and multi-family water usage as household size and number of households are the primary measures used to determine system wide water usage. Additionally, accurate population estimates are needed to determine per capita usage, which is often utilized as a performance indicator. Traditional top down methods for estimating population served by a utility are

based on U.S. Census estimates from political boundaries, such as the primary city or county to approximate utility population served (McJunkin 1964, Viessman et al. 2009). Several demographic techniques, including curve fitting of historical data, comparison with similar cities, employment forecasts, etc. are then utilized to forecast population for water demand estimation (Smith et al. 2008).

In Florida, the mandated default population is prepared by the Bureau of Economic and Business Research (BEBR) at the U. of Florida. The purpose of the BEBR analysis is to estimate permanent residents of Florida; they do not estimate seasonal or other types of temporary residents that may be customers of the utility (Smith et al. 2002, Smith and Cody 2004). BEBR uses a combination of data on building permits, electric customers, and homestead exemptions to estimate the number of households. Persons per household are estimated from U.S. Census data along with site specific surveys. BEBR prepares permanent population estimates for subcounty areas defined as incorporated cities and unincorporated areas of each county. The county and state population estimates are sums of the relevant subcounty areas. These estimates are then apportioned to estimate population served within utility boundaries associated with one or multiple subcounty areas. However, for water utilities, the most direct measure of population served by the utility is the bill paying customers that physically use water at a given time.

Existing water use and population estimation methods may not be accurate or applicable to most utilities due to different political and utility boundaries as well as inconsistent land use definitions. Additionally, aggregate statistical approaches are of limited use for providing a process level explanation of water demand time series, which

is becoming increasingly important for a variety of applications including meaningful predictions of parcel level per capita water usage. Given these limitations, a new process based methodology to estimate single and multi-family residential population and water use patterns, based on parcel-level land use and water billing databases, is presented in this paper.

Florida Demographic Databases

The Florida Department of Revenue (FDOR) database provides attributes for every parcel in the State along with their land use classification, which can be grouped into defined single and multi-family sectors (Florida Department of Revenue 2009). The FDOR database, in conjunction with Florida County Property Appraisers (FCPA) and U.S. Census, allow for a parcel-level evaluation of water usage and population as well as direct evaluation of demand management best management practices (BMPs) which can be applied to any utility in Florida given an accurate utility service area GIS shapefile in order to delineate parcels served. Customer billing data provided by our benchmark utilities such as the Sanford, FL case study presented in this paper allow for refinement of parameter estimates for utilities without billing data readily available as parameter estimates relating to a specific sector's water usage can be calibrated against known billed usage for that sector. The Sanford, FL benchmark utility dataset contains monthly water usage for 13,555 residential parcels as well as 1,547 non-residential parcels from 10/2005- 5/2011 along with impervious area per parcel from the local Seminole County Property Appraiser's database in addition to land use attributes in the statewide database such as land use classification and heated building area. This paper will focus on analysis solely of the residential sector. This database consists of approximately 95% of all parcels containing residential customers served by the City of

Sanford. The remaining 5% were filtered out since customer billing and parcel attribute data could not be linked for this subset (For details regarding the contents and processing of these databases refer to Friedman et al. 2011& 2013 and Morales et al. 2011& 2013).

Water Use and Population Estimation Methodology

Monthly water use, Q, at a given time t, in any sector can be estimated using Equation 6-1, as the product of a water use coefficient, α_{it}; a measure of the size of the activity, x_{it}, e.g., people per dwelling unit; the occupancy rate for this activity, r_{it}; and the number of activity units in subset i of a given sector, n_{it}, summed over all subsets, m, within the sector.

$$Q_t = \sum_{i=1}^{m} (\alpha_{it} \cdot x_{it} \cdot r_{it} \cdot n_{it}) \tag{6-1}$$

For the single and multi-family residential sectors, where the measure of size is based on number of persons, the population of physically present water using customers in the residential sector, p, at a given time t in any sector can be estimated using Equation 6-2, as the product of persons per occupied dwelling unit as the measure of size (x_{it}), the occupancy rate (r_{it}), and the number of total (vacant + occupied) dwelling units on water using residential parcels (n_{it}) in each subgroup i within the residential sector . Each of these terms will be defined in more detail.

$$p_t = \sum_{i=1}^{m} (x_{it} \cdot r_{it} \cdot n_{it}) \tag{6-2}$$

Population is defined to represent solely the people physically residing and using water on single and multi-family parcels at a given time, to allow for validation against measured residential consumption when combined with modeled per capita usage.

Other population sources, such as group quarters and temporary users such as tourists are evaluated separately within the commercial, industrial, and institutional (CII) sectors and are not considered here. In contrast, the CII sectors utilize a variety of size measures such as number of employees and heated area per unit (Morales et al. 2013).

The water use coefficient, α_{it}, can be defined to be the per capita water usage associated with the physically based water using population. Therefore, the product of the water use coefficient and the physically based water using population yields total residential water usage, Q_t. The next section of this paper focuses on methodologies for estimating residential water using population served.

Residential Water Using Population

Defining the Utility Service Area

A critical first step in determining water using residential population served is to accurately determine parcels served within a given utility service area. This can be done utilizing spatial join tools within ArcGIS, given GIS layers of both parcels and utility service area boundaries. A GIS layer containing all Florida parcels is available from FDOR. Utility service area GIS layers are publically available for portions of Florida, although accuracy should be checked by the utility. The Sanford, FL city and Sanford, FL water utility service area boundaries are compared in Figure 6-1. These two boundaries are significantly different, with approximately 40% of the utility service area being outside city boundaries. This highlights the need for bottom up parcel driven population and water use analysis methodologies within water utilities as opposed to top down disaggregation procedures which rely on political boundary approximations that are difficult, if not impossible, to downscale accurately because of the irregular nature of many utility and city boundaries.

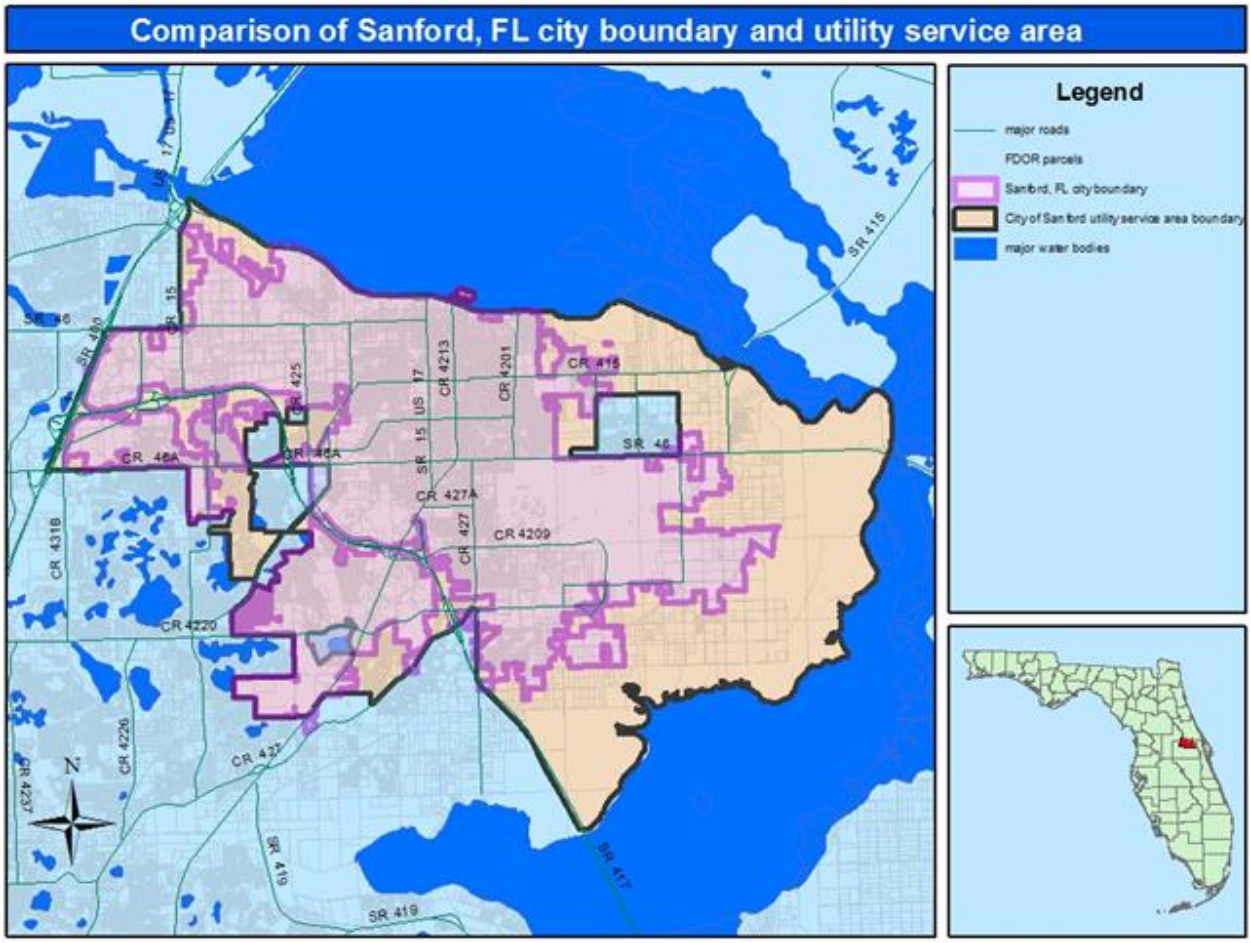

Figure 6-1. Comparison of Sanford, FL city boundary and utility service area

Number of Parcels, Accounts, and Residential Dwelling Units

The fundamental size unit for single and multi-family sectors is the number of dwelling units, defined as the total number of occupied and vacant residences per parcel. FDOR directly reports number of dwelling units per parcel for all sectors. Additionally, The FDOR database provides a land use description for every parcel in Florida which is then grouped into standardized sector definitions (Florida Department of Revenue 2009). Number of dwelling units represents a standardized size unit which allows for accurate population estimates when combined with U.S. Census persons per dwelling unit data.

An alternative measure of size is number of accounts. However, account breakdowns by sector vary depending on how sectors are defined by the utility. In addition, determining population for multi-family accounts is challenging since persons per account varies widely depending on how each account is metered. Few multi-family developments meter water use at the individual unit level. For these reasons, number of dwelling units is preferred to accounts.

Summary statistics of size attributes for the Sanford, FL case study are shown in Table 6-1. The majority of developed residential parcels are within the single family residential sector. However, 20% of the total heated area is comprised of multi-family housing structures with 10 units or more with an average of 145 residential units per parcel

Table 6-1. Size attributes for 13,555 Sanford single and multi-family parcels in FDOR 1-8, and 28.

FDOR land use code	Water use sector group	FDOR land use code description	Total parcels	Percent of total parcels	Total heated area (1,000 ft^2)	Percent of total heated area	Heated area/parcel (ft^2)	Total residential units	Resid. units/parcel	Heated area/residential unit (ft^2)
1	SFR	Single family residential	13,118	96.78%	19,753	76.99%	1,506	13,265	1.01	1,489
2	SFR	Mobile homes	12	0.09%	23	0.09%	1,924	12	1.00	1,924
3	MFR	Multi-family-10 units or more	37	0.27%	5,156	20.10%	139,352	5,347	144.51	964
4	SFR	Condominiums	78	0.58%	103	0.40%	1,324	78	1.00	1,324
7	MFR	Miscellaneous residential	5	0.04%	9	0.04%	1,796	n/a	n/a	n/a
8	MFR	Multi-family-less than 10 units	298	2.20%	602	2.35%	2,020	708	2.38	850
28	MFR	Mobile home parks	7	0.05%	9	0.03%	1,256	564	80.57	16
		Total or weighted average	13,555	100.00%	25,655	100.00%	1,893	19,974	1.47	1,284

Utilizing the standardized definition of terms provided in the FDOR database, Equation 6-2 can be more explicitly written as shown by Equation 6-3 to evaluate population for water using residential parcels of a utility. In this approach, every parcel is a subgroup within a residential sector. Total residential population is the summation over the nine single and multi-family residential land use codes, as defined by FDOR.

$$p_t = \sum_{i=1}^{m} (x_{it} \cdot r_{it} \cdot n_{it} \cdot \gamma_{it}),\ \gamma_{it} = \begin{cases} 1, & parcel\ consists\ of\ at\ least\ 1\ active\ account \\ 0, & parcel\ does\ not\ have\ any\ active\ accounts \end{cases} \tag{6-3}$$

Where: p_t = water using population for a residential sector at time t, x_{it} = persons per occupied residential unit for parcel i at time t, r_{it} = percent of occupied water using residential units for parcel i at time t, n_{it} = number of total residential units for parcel i at time t, γ_{it} = binary activity of parcel i at time t, m= total number of parcels in sector

The binary parcel activity term, γ_{it} combined with the percent occupied residential units for active parcels, r_{it}, and the number of residential units per parcel, n_{it}, determine the number of total residential units that have people physically present using water at time t for parcel i. Therefore, multiplying by persons per occupied home, x_{it}, the population associated with people physically present and using water in the single and multi-family residential sector at a given time can be determined.

The activity term, γ_{it} , representing which parcels consist of residential units which are active customers of a utility in a given month can be determined directly if customer level water use data is available. Otherwise, the utility may be able to provide a listing of their active customers without providing actual water use data. The percent occupied water using residential units for active parcels, r_{it}, as well as average persons per residential unit, x_{it}, can de estimated from U.S. Census Block data, as described in the next section.

People per Residence and Occupancy Rate

The data driven methodology for estimating parcel level average persons per residence (ppr) and occupancy rates is discussed in this section. The U.S. Census conducts a country-wide survey every 10 years at the individual parcel level to document many attributes of the nation's population, including housing data. Data from the 2000 and the recent 2010 Censuses are available at the census block level of spatial aggregation. (http://www.census.gov/geo/maps-data/data/tiger.html). Both 2000 and 2010 Census files were combined with current utility boundaries in GIS to determine the 881 census blocks that were in the Sanford Utility as of 2010. Each SFR and MFR developed parcel was then assigned to the census block that included the centroid of its parcel boundary which includes average 2000 and 2010 residential ppr and percent occupancy. The U.S. Census does not distinguish single family from multi-family ppr and percent occupancy, which is a critical missing element to determine separate SFR and MFR population accurately.

A proposed algorithm to prorate combined ppr and percent occupancy into its components is as follows. First, each Census block is classified as SFR only, MFR only, or hybrid based on parcel land uses within a given block. Proration of ppr and percent occupancy into SFR and MFR components is then determined for hybrid blocks based on the relative mix of SFR to MFR residential units and assumed ratios of SFR to MFR ppr and percent occupancy based on SFR only and MFR only block averages as shown in Equations 6-4 and 6-5. Average persons per residence and percent occupancy for years other than 2000 and 2010 are determined from linear interpolation of the 2000 and 2010 benchmark years. Once baseline parcel level water use and population

estimates are determined, reliable projections based on future build out of land uses for a utility can be made as undeveloped parcels are developed (GIS Associates 2009).

$$X_b = \lambda_b X_{b,SFR} + (1-\lambda_b) X_{b,MFR}, \quad \frac{X_{b,SFR}}{X_{b,MFR}} = k \tag{6-4}$$

Where: X_b = reported average persons per residential unit for hybrid census block b, $X_{b,SFR}$ = average persons per residential unit for single family residences in census block b, $X_{b,MFR}$ = Average persons per residential unit for multi-family residences in census block b, λ_b = The percentage of single family residential units in census block b ($0 \le \lambda_b \le 1$), k= fixed SFR to MFR persons per house ratio

$$r_b = \lambda_b r_{b,SFR} + (1-\lambda_b) r_{b,MFR}, \quad \frac{r_{b,SFR}}{r_{b,MFR}} = m \tag{6-5}$$

Where: r_b = Reported average occupancy rate for hybrid census block b, $r_{b,SFR}$ = Average occupancy rate for single family residences in census block b, $r_{b,MFR}$ = Average occupancy rate for multi-family residences in census block b, λ_b = The percentage of single family residential units in census block b ($0 \le \lambda_b \le 1$), m = fixed SFR to MFR occupancy ratio

The 881 Census blocks in the Sanford Water Utility were divided into the three categories shown in Table 6-2. A total of 726 out of the 881 Census blocks had only SFR or MFR parcels with an SFR average of 15.2 residences per census block. The remaining 155 Census blocks were hybrids with a blend of SFR and MFR housing. The reported average persons per unit and occupancy rates from the 2000 and 2010 Census for hybrid Census blocks were disaggregated into their SFR and MFR components using Equations 6-4 and 6-5. The relative blend of SFR to MFR residences is known for each block in Sanford from the FDOR parcel database. Average SFR/MFR

ppr and percent occupancy ratios based on SFR and MFR only blocks, shown in Table 6-2, were then utilized to determine SFR and MFR ppr and occupancy components for each of the 155 hybrid Census blocks.

Table 6-2. Average persons per residential unit and percent occupancy at the Census block level of aggregation for Sanford, FL

Item	Category	Census blocks in Sanford	Number of Parcels	Number of residential units	Average persons per occupied residential unit (2000 Census)	Average persons per occupied residential unit (2010 Census)	Average percent occupancy (2000 Census)	Average percent occupancy (2010 Census)
Census Blocks With Either SFR or MFR	Single Family Residential	695	10,465	10,567	2.79	2.85	0.93	0.90
	Multi-Family Residential	31	75	3,720	2.41	2.49	0.89	0.83
	Total Residential	726	10,540	14,287	2.69	2.76	0.92	0.88
	SFR/MFR Ratio				1.16	1.14	1.04	1.08
Census Blocks With Both SFR or MFR Present	Single Family Residential*		2,665	2,710	**2.75**	**2.82**	**0.93**	**0.90**
	Multi-Family Residential*		350	2,977	**2.38**	**2.46**	**0.90**	**0.84**
	Total Residential	155	3,015	5,687	2.50	2.59	0.92	0.87
All Census Blocks	Single Family Residential		13,130	13,277				
	Multi-Family Residential		425	6,697				
	Total Residential	881	13,555	19,974	2.64	2.71	0.92	0.88

* SFR and MFR average persons per occupied unit and occupancy rate estimated from proration procedure in hybrid block

Process Level Model of Residential Water Usage

The discussion up to this point has focused on a methodology to determine population based on property appraisal data combined with Census block persons per residential unit and occupancy data. The next sections focus on modeling per capita indoor and outdoor residential water usage using a process level approach. Total water usage is then determined as the product of modeled population and total per capita usage. The paper then concludes with model calibration and evaluation as compared to measured usage.

Indoor residential per capita model

The first step in modeling indoor per capita water usage is to determine how many of each end use device exists in each residential unit as defined by FDOR land use codes. Four primary end use devices are tracked: toilets, showerheads, clothes washers, and faucets. Dishwashers are excluded since they are a relatively minor water use. These four end use devices represent approximately 95% of single family indoor usage, assuming customer leakage can be prorated to each end use (DeOreo 2011).

The quantity of each end use device within a single family or multi-family residential unit can be determined based on number of bathrooms per home using the lookup table shown in Table 6-3. A half bath is assumed to have a toilet and faucet, but not a showerhead. All homes are assumed to have one kitchen faucet. 97% of single family and 63% of multi-family residential units are assumed to have one clothes washer within the unit based on the 2007 American Housing Survey for Tampa, FL (U.S. Census 2009).

Table 6-3. Fixture lookup table based on number of bathrooms in residential units

Bathrooms/ res. unit	Toilets/ res. unit	clothes washers/ res. unit*	Showerheads/ res. unit	Faucets/ res. unit
1	1	1	1	2
1.5	2	1	1	3
2	2	1	2	3
2.5	3	1	2	4
3	3	1	3	4
3.5	4	1	3	5
4	4	1	4	5
4.5	5	1	4	6
5 or more	5	1	5	6

*for percent of residences estimated to have clothes washers

Determination of rated flow for a given fixture within a given home is governed by the required/available technology when the home was built, and what is required/available when a homeowner decides to replace existing fixtures. For any given point in time, a fixture can be categorized as either the required or lowest available rated flow in one of the five available demand management periods shown in Table 6-4. Average flow rates and frequencies of usage are based on an extensive literature review. (Brown and Caldwell 1984, Mayer et al. 1999, Aquacraft 2005, DeOreo and Mayer 2012). These studies found frequency and duration to be constant both spatially and temporally. Therefore, only changes in rated flow per device need to be determined.

Table 6-4. Lowest available and required rated flow average values

	toilet		showerhead*		clothes washer		faucet	
Demand management period	Lowest available gal/flush	required gal/flush#	Lowest available gal/min	required gal/min#	Lowest available gal/load	required gal/load#	Lowest available gal/min	required gal/min#
Pre 1983	5	5	6.5	6.5	56	56	5	5
1983-1994	3.5	3.5	3	3	51	51	2.8	2.8
1995-2004	1.6	1.6	2.5	2.5	41	41	2.2	2.2
2005-2009	1.28	1.6	2	2.5	27	41	1.5	2.2
2010- present	1.1	1.6	1.5	2.5	14	41	0.5	2.2
frequency (uses/person/d)	5.1		0.7		0.37		8.1	

*Showerheads also have a duration of 8 minutes/shower. # Number required by plumbing code standards of given period

As an initial condition, all fixtures are assigned to the demand management period corresponding to the effective year built of the home, which is available for every developed parcel in Florida. All fixtures are initially assigned to the required flow for that period, as this corresponds to the required plumbing codes upon construction. Homes are not assigned any fixtures if the year being simulated precedes the effective year built.

For any time period after the initial year of construction, each household decides whether to replace their existing fixtures with either the lowest available or required rated flow fixtures available during the current year's demand management period. Two driving forces are assumed to determine a household's fixture replacement decision: fixture service life and economic optimization. Of course, other factors affect the replacement decision. The use of a "rational economic person" model provides a consistent way to assign a value that represents propensity to replace. The results from this model can be compared with historical water use to calibrate the forecast against observed behavior.

The fixture service life consideration assumes that all households replace an existing fixture at the end of the useful (service) life with the plumbing code required rated flow fixture during the current year's demand management period.

The economic optimization considers each household making an annual independent decision whether to replace an existing fixture with the lowest rated flow available based on the cost effectiveness of the water saved over the device life vs. the initial cost of fixture purchase and installation. A household decides to replace if the net present value of this investment is greater than some threshold, NB_{min}, which factors in

a household's indifference or transaction cost towards making the investment. Both the economic optimization and service life criteria can be used as calibration parameters.

Although all households are assumed to follow these rules, several different clusters of households arise based on physical attributes of each home including year built, persons per home, and fixture inventory. Therefore, this type of modeling framework can be classified as a process level agent based model, in which physical attributes as well as behavioral variation among households affect the overall water usage within a utility. For example, an older community with smaller homes will yield different results than a newer community with larger homes. The relative blend of physical attributes among homes drives the overall household behavior of the community.

Morales et al. (2013) present a detailed review of service lives and costs for popular indoor end use devices in all urban water use sectors. The service lives and costs (includes capital and installation cost) for fixtures modeled in the residential indoor simulation presented in this paper are shown in Table 6-5. All costs are in 2011 dollars.

Table 6-5. Lowest available rated flow unit costs (2011$) and annual service lives for modeled fixtures.

	toilet		showerhead		clothes washer		faucet	
Demand management period	Service life, years	$/lowest flow fixture*	Service life, years	$/lowest flow fixture*	Service life, years	$/lowest flow fixture*	Service life, years	$/lowest flow fixture*
Pre 1983	40	n/a	8	n/a	11	n/a	15	n/a
1983-1994	40	325	8	43	11	550	15	67
1995-2004	40	325	8	43	11	550	15	67
2005-2009	40	355	8	44	11	650	15	77
2010-present	40	475	8	46	11	850	15	92

*2011 dollars

Based on the data presented, the Lagrangian household based residential fixture tracking simulation model can be formulated. This model considers both service life fixture attrition and economic optimization for each household's fixture replacement decision. All equations and terms are described in the following text.

This model tracks two state variables: installed rated flow (F_t), and remaining existing service life (RSL_t) throughout the period of simulation with a step size of $\Delta t = 1$ year. A time step of one year is adequate to simulate long-term trends in fixture rated flow and indoor water usage since seasonal differences are minimal for indoor uses. For each home, the simulation starts the year the house is built as shown as Equation 6-6. Based on the year built (yrblt) of the house, the initial installed rated flow for a given fixture is assigned to the plumbing code required rated flow fixture during the current year's demand management period as shown in Equation 6-7. Initial remaining service life of a new fixture is set equal to full service life as shown in Equation 6-8.

$$t_o = yrblt_i \tag{6-6}$$

$$F_{o,fi} = F_{req,t_o,f} \tag{6-7}$$

$$RSL_{o,fi} = SL_f \tag{6-8}$$

Where: Fo,fi = initial fixture rated flow (gal/use) at year t=0 (start year) for fixture f on parcel i, RSLo,fi = initial remaining service life (years) at year t=0 (start year) for fixture f on parcel i, SLf= service life of a given fixture type (years) for fixture f, yrblti= year house built for parcel i,Freq,to,f= required rated flow technology based on plumbing codes installed in year t=0 (gal/use) for fixture f

For each year after the house was built, the household determines the net benefits of exchanging their existing fixtures for the lowest rated flow technology available in the current demand management period using Equations 6-9 through 6-13. The net benefits weigh the total cost of the new device vs. the total benefits of water savings to the customer over the service life. An important feature of this calculation is how weighted average savings are calculated in Equation 6-9. The unit water savings of the new fixture is the average of water saved between existing fixture and lowest rated flow technology available during the remaining service life of the existing device and additional water saved from the difference between potential required rated flow technology and lowest rated flow technology available from the end of remaining service life of the existing fixture to the end of service life of a new fixture. This reflects a decreased savings from a mandated reduction of rated flow at the end of the existing fixture's service life.

$$q_{s,t+1,fi} = \left[\left(F_{t,fi} - F_{low,t+1,f}\right)\frac{RSL_{t,fi}}{SL_f} + \left(F_{t,fi} - F_{req,t+1,f}\right)\frac{SL_f - RSL_{t,fi}}{SL_f} \right] * \frac{util_f * x_{it} * dur_{fi}}{nfix_{fi}} \tag{6-9}$$

$$Q_{s,t+1,fi} = \frac{q_{s,t+1,fi} * SL_f * 365 * nfix_{fi}}{1000} \tag{6-10}$$

$$B_{t+1,fi} = b_t * Q_{s,t+1,fi} \tag{6-11}$$

$$C_{t+1,fi} = c_{xlow,t+1,f} * nfix_{fi} \tag{6-12}$$

$$NB_{t+1,fi} = B_{t+1,fi} - C_{t+1,fi} \tag{6-13}$$

Where: $NB_{t+1,fi}$ = net benefits of retrofitting all of a given fixture type f on parcel i to lowest rated flow technology available in year t+1 ($), $B_{t+1,fi}$ = total benefits of retrofitting all of a given fixture type f on parcel i to lowest rated flow technology available in year t+1 ($),

$C_{t+1,fi}$ = total costs of retrofitting all of a given fixture type f on parcel i to lowest rated flow technology available in year t+1 ($), $c_{xlow,t+1,f}$ = unit cost of retrofitting one of a given fixture type f on parcel i to lowest rated flow technology available in year t+1($/toilet) in year t dollars. $nfix,_{fi}$ = number of a given fixture f on parcel i, b_t = value of water saved to the homeowner ($/kgal) based on water rates in year t,$Q_{s,t+1,fi}$ = total water saved from retrofitting all of a given fixture type f on parcel i to lowest rated flow technology available in year t+1 (kgal) over the new device service life. $q_{s,t+1,fi}$= average of daily water saved between existing fixture and lowest rated flow technology available in year t+1 during the remaining service life of the existing device and additional water saved from the difference between potential required rated flow technology and lowest rated flow technology available from end of remaining service life of existing fixture to end of service life of new device. (gal/toilet), $F_{low,t+1,f}$ = lowest rated flow technology available in year t+1 for fixture type f (gal/use), $F_{req,t+1,f}$ = required rated flow technology based on plumbing codes installed in year t+1 for fixture type f (gal/use), $util_f$= utilization rate (use/person/day) for fixture type f, dur_f= duration of use (min) (applies only to showerheads), $F_{t,fi}$ =installed rated flow (gal/flush) at year t for fixture type f on parcel i, $RSL_{t,fi}$ remaining service life (years) at year t for fixture type f on parcel i

Once net benefits are calculated, the fixture rated flows and remaining service lives are updated based on economic considerations and/or device attrition due to useful service life, as shown by Equations 6-14 and 6-15. Installed rated flow can be updated to one of three states each year: lowest available rated flow, required plumbing code rated flow, or existing rated flow (i.e. no change). For a given year, a fixture switches to lowest rated flow available if the net benefits (NB) are positive and exceed

the threshold, NB_{min}. The middle condition states that if the net benefits of the lowest rated flow are below this threshold, but the remaining service life is one year, the required plumbing code rated flow will be installed the next year since the existing fixture is replaced due to attrition. If neither of these two conditions is true, then the fixture is not replaced and rated flow does not change. The value of NB_{min} reflects the propensity to retrofit fixtures and can be calibrated to reflect actual household decisions. Remaining service life either resets to the full service life if a retrofit occurred or decreases by one if no replacement occurs.

$$F_{t+1,fi} = \begin{cases} \mathrm{F}_{\mathrm{low,t+1,f}} & \text{if } \mathrm{NB}_{\mathrm{t+1,fi}} > NB_{\min} \\ \mathrm{F}_{\mathrm{req,t+1,f}} & \text{if } \mathrm{RSL}_{\mathrm{t,fi}} = 1 \text{ and } \mathrm{NB}_{\mathrm{t+1,fi}} \le NB_{\min} \\ F_{t,fi} & otherwise \end{cases} \tag{6-14}$$

$$RSL_{t+1,fi} = \begin{cases} SL_f & if\ NB_{t+1,fi} > 0\ or\ RSL_{t,fi} = 1 \\ RSL_{t,fi} - 1 & otherwise \end{cases} \tag{6-15}$$

Where: NB_{min} = decision threshold, $F_{t+1,fi}$ = installed rated flow (gal/flush)at year t+1 for fixture type f on parcel i, $RSL_{t+1,fi}$ remaining service life (years) at year t+1 for fixture type f on parcel i

As an example, consider a house built in 1985 with two people using one toilet with five flushes per person per day and a toilet service life of 40 years. In 2010, assume the current installed rated flow is 3.5 gal/flush, the remaining service is 15 years [40-(2010-1985)] and the required rated flow to be installed at the end of remaining service (2025) is 1.6 gal/flush. Now assume that in 2010, a new 0.8 gal/flush toilet comes to market. If the value of water saved to the household is $2/kgal and the initial cost of a 0.8 gpf toilet is $475, then the net benefits of this investment from the

perspective of the individual customer can be computed by Equations 6-9 through 6-13. The incremental operating cost of the toilet is assumed to be zero.

$$q_{2010} = \left[(3.5gpf - 0.8gpf)\frac{15}{40} + (1.6gpf - 0.8gpf)\frac{40-15}{40} \right] * \frac{5\,flush/\,person/d * 2\,people}{1\,toilet} = 15.13gal/toilet/d$$

$$Q_{s,t+1} = \frac{15.13gal/toilet/d * 40\,years * 365day/yr * 1toilet}{1000} = 220.90\,kgal$$

$$B_{t+1} = \$2/kgal * 220.90kgal = \$441.80, C_{t+1} = \$475/toilet * 1\,toilet = \$475$$

$$NB_{t+1} = \$441.80.78 - \$475 = -\$33.20$$

The negative net benefits and a remaining service life > 1 indicate that no change is made, i.e., the homeowner would keep the 3.5 gal/flush toilet. The remaining service life for 2011 would become 14 years as no retrofit was made. Equivalently, the above calculation can be generalized to determining break even (or prespecified NB_{min}) number of years of remaining service life. If the remaining service life is >= this threshold, then the customer would replace the fixture. This analysis can also be used by the utility to estimate the potential impact of financial incentives, e.g., a $50 incentive would result in a positive NB for the above example.

Determination of simulated aggregate per capita indoor water usage trends

Simulated aggregate per capita indoor water usage trends for a given fixture are calculated as the weighted average flow rate across all parcels within a given sector at time t multiplied by the average utilization rate, shown as Equation 6-16. DeOreo (2011) shows that leakage is a significant component of water usage which can be prorated to fixtures based on the relative household usage of each fixture. An initial value of 10% of total indoor usage is assumed to be leakage within the simulation model.

$$q_{in,t} = \sum_{f=1}^{4} \overline{F}_{f,t} * util_{f,t} + leak_{f,t} \qquad (6\text{-}16)$$

Where: $q_{in,t}$ = sectoral weighted average per capita indoor use at year t (gpcd), $\overline{F}_{f,t}$ = average usage intensity (gal/use) for fixture f in year t, $util_{f,t}$ = utilization rate for fixture f in year t, $leak_{f,t}$= prorated household leakage attributable to fixture in year t.

Outdoor Residential Per Capita Model

The purpose of this section is to describe the methodology utilized for process level modeling of residential outdoor water usage. Due to significant seasonal and spatial variability resulting from a wide range of factors influencing irrigation including climate, price signals, individual practices, restrictions, and technology, outdoor water usage can be much more challenging to predict compared to indoor usage. Friedman et al. (2013) present a detailed analysis of parcel level irrigation trends and patterns. This paper shows that significant variability exists among household irrigation patterns as a function of application rate and irrigable area. Furthermore, the percent of residential homes irrigating from the potable system varies widely among utilities with only a portion of these irrigators irrigating at or above theoretical requirements. Despite this variability, Romero and Dukes (2011a) found the correlation between average actual application rate and average net irrigation requirements to be statistically significant with at least 95% confidence for 7 of the 11 utilities studied. The ratio of estimated to calculated irrigation needs for the 12 utilities varies within the range of 0.46 to 1.02 with a weighted average of 0.78. A similar value of 0.72 was determined for Gainesville Regional Utilities irrigators (Friedman et al. 2013). These results suggest that mean application rate for residential irrigation can be reasonably predicted based on irrigation requirements, which can be predicted using process level modeling. A critical element

of this methodology is that irrigation usage is evaluated for all residential customers served by a utility as opposed to a cross sectional sample focusing on large irrigators.

Based on these results, a process level model of average irrigation usage as a function of net irrigation requirements was utilized as an appropriate modeling framework. The model formulation is shown as Equation 6-17.

$$q_{out,t} = \frac{\left(\overline{AR}_{req,t} \cdot \frac{\sum_{i=1}^{m} \left(IA_{i,t} \cdot \gamma_{i,t} \right)}{\sum_{i=1}^{m} \left(\gamma_{i,t} \right)} \cdot \sum_{i=1}^{m} \left(\gamma_{i,t} \right) \cdot \frac{\overline{AR}_{act,t}}{\overline{AR}_{req,t}} \cdot Pirrig_t \right)}{p_t} \qquad (6-17)$$

Where: $q_{out,t}$= average sectoral per capita outdoor water usage at time t, $\overline{AR}_{req,t}$ = average net irrigation requirement at time t, $\frac{\overline{AR}_{act,t}}{\overline{AR}_{req,t}}$ = average actual net irrigation to irrigation requirement ratio, $Pirrig_t$= percent of active water using parcels which irrigate from potable supply at time t IA_{it}= irrigable area for parcel i at time t, γ_{it} = binary activity of parcel i at time t, m= total number of parcels in sector

The irrigable area is directly known for every residential parcel using property appraisal data on parcel area and impervious area (for details refer to Friedman et al. 2013). Reported average net irrigation requirements over a 30 year period from 1980-2009 for ten Florida locations and one Alabama location based on a daily soil water balance simulation presented in Romero and Dukes (2011b) were utilized to estimate average irrigation requirements.

Model Calibration and Validation

Both indoor and outdoor per capita usage process models were applied to the 13,118 SFR parcels in DOR 1 (single family residential) and the 335 MFR parcels in DOR 3 and 8 (multi-family ≥10 and multifamily < 10 units) in Sanford, FL. The simulation

period was from 10/2005-5/2011 to match available billing records which allow for calibration and validation. Population was modeled with a monthly time step to account for variability in number of active accounts each month. Indoor usage was modeled at an annual time step and outdoor usage was modeled as an annual average to depict long term trends which are appropriate for evaluating utility gpcd trends.

The indoor model assumed a value of water, b, of $2/kgal and a retrofit decision threshold, NB_{min}, of $100. The outdoor model assumed a constant average actual net irrigation to irrigation requirement ratio of 0.75 (Friedman et al. 2013). Orlando, FL net irrigation requirements were utilized representing the closest city to Sanford, FL with available data with an average net irrigation requirement of 1.98 in./mo.(Romero and Dukes 2011b). Initial estimates of percent irrigators was set to 25% to reflect extensive reuse irrigation in Sanford, FL The percent irrigators was the primary parameter used for calibration as direct data on which customers irrigate from the potable system is difficult to obtain.

Model calibration and validation compared predicted annual trends in total indoor and outdoor usage with annual trends in measured total residential usage for the period of record. A commonly utilized approach to perform model calibration and validation is to split the data into a training dataset and a validation dataset. The training dataset is utilized to perform model calibration while the validation dataset is utilized to evaluate the model's predictive performance (Shmueli et al. 2010). Both model calibration and validation error were evaluated with the mean absolute error (MAE) criterion, defined by Equations 6-18 and 6-19. The term mean absolute error of prediction (MAEP) is utilized to distinguish predictive model error utilizing the validation dataset from error associated

with calibration utilizing the training dataset. The model was calibrated using a training dataset which included data from 10/2005 up through 5/2010, with the exception of 5/2008 for the MFR sector as reported water usage for this month was an unusually low outlier. The final 12 months of available data (6/2010-5/2011) were utilized as the validation dataset. Model calibration and validation were performed separately for both the SFR and MFR sector by solving a simple optimization problem to minimize MAE between measured and predicted total water usage for the training period by estimating parameters for percent potable irrigators. All other parameters were unchanged. Aggregate modeled vs. estimated per capita and total water usage trends for the SFR and MFR residential sectors in Sanford are shown in Figures 6-2 through 6-5. Best parameter estimates for percent potable irrigators and model error for the SFR and MFR residential sector in Sanford, FL are summarized in Table 6-6. Parameter estimation resulted in a small percent potable irrigators for SFR, reflecting an extensive reuse irrigation network in Sanford. Both SFR and MFR process population and per capita models provide reasonable prediction of measured total residential water usage. The results show that SFR water usage has declined in Sanford over the period of study caused by a decline of indoor gpcd with only a slight decline in population. The results for SFR suggest, perhaps, that a slightly larger number of irrigators existed before 2007 as modeled usage was slightly less than the observed annual trend for this period. MFR water usage and population have declined at similar rates, thus indicating a relatively stable gpcd over the period of study. Future work includes further investigating other possible sources of error, including the relationship between actual and required irrigation needs as well as the effect of price on irrigation demand. Additionally,

investigating seasonal occupancy trends, particularly in the MFR sector, could explain the remaining error for this sector.

$$MAE = \frac{1}{\omega}\sum_{t=1}^{\omega}\left[Q_t - p_t\left(q_{in,t} + q_{out,t}\right)\right] \qquad (6-18)$$

Where: MAE= mean absolute error, ω= number of months in period of training data, $q_{out,t}$= average sectoral per capita outdoor water usage at time t, $q_{in,t}$ = sectoral weighted average per capita indoor use at year t (gpcd), Q_t = total sectoral water usage during time period t, p_t= sectoral population at time t

$$MAEP = \frac{1}{v}\sum_{t=1}^{v}\left[Q_t - p_t\left(q_{in,t} + q_{out,t}\right)\right] \qquad (6-19)$$

Where: MAEP= mean absolute error of prediction, v= number of months validation period

Table 6-6. Summary of best parameter estimate for percent potable irrigators and model error for the SFR and MFR residential sector in Sanford, FL

Item	SFR	MFR
MAE (mgd)	0.0566	0.0083
MAEP (mgd)	0.0217	0.0325
Estimated percent potable irrigators	13%	45%

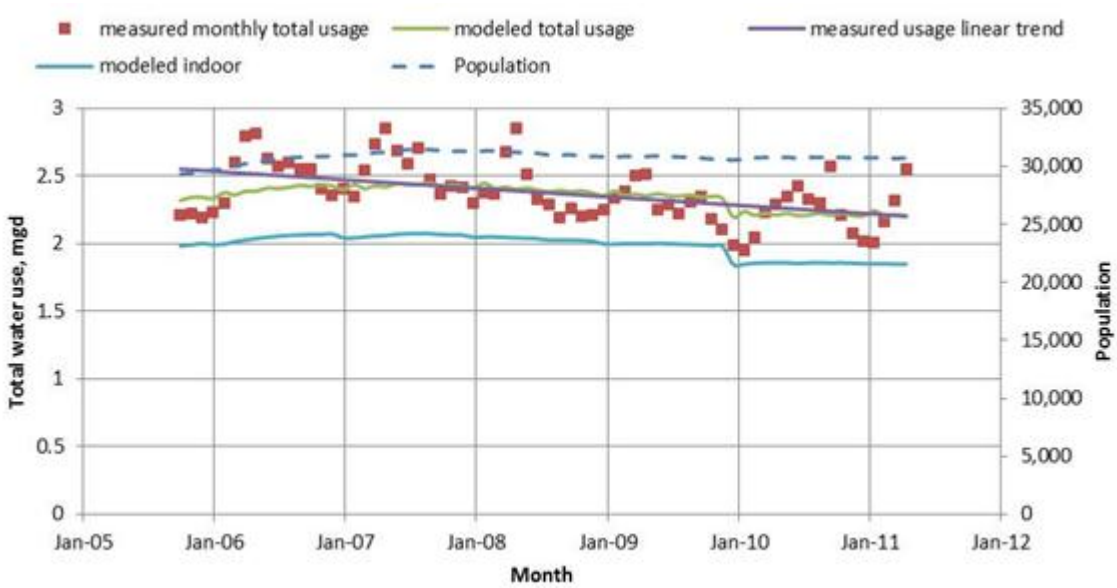

Figure 6-2. Measured total water usage, population, and modeled total water usage for 13,118 single family residential parcels in Sanford, FL

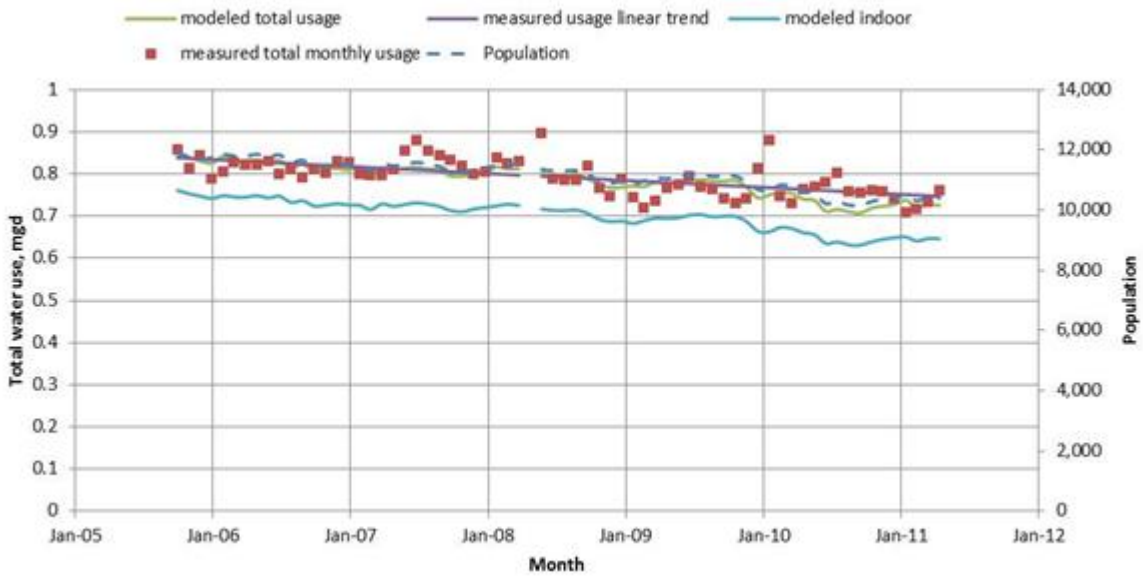

Figure 6-3. Measured total water usage, population, and modeled total water usage for 335 multi- family residential parcels in Sanford, FL

Figure 6-4. Measured vs. modeled per capita water usage for 13,118 single family residential parcels in Sanford, FL

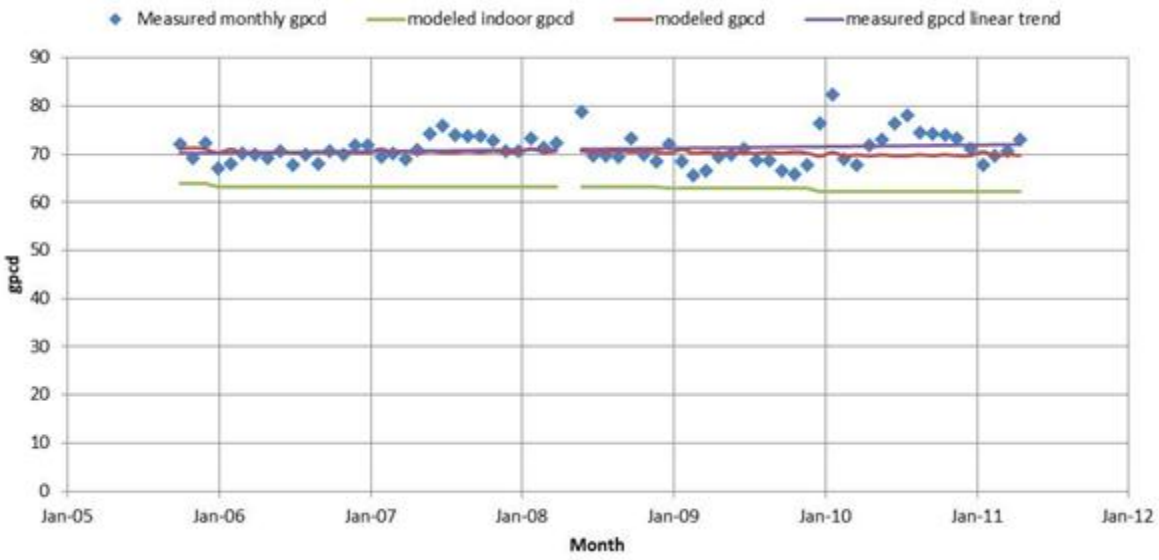

Figure 6-5. Measured per capita vs. modeled per capita water usage for 335 multi-family residential parcels in Sanford, FL

Synopsis

A key measure of efficiency in the urban water demand field is gallons per capita per day (gpcd) of water use. Existing water usage and population forecasting methods may not be accurate or applicable to most utilities due to inconsistent definitions or unavailable data. Given these limitations, a new process based methodology to estimate single and multi-family residential population and water use patterns based on parcel-level land use databases is presented in this paper. The Florida Department of Revenue (FDOR) database provides attributes for every parcel in the State along with their land use classification, which can be grouped into defined sectors, including single and multi-family (Florida Department of Revenue 2009). The FDOR database, in conjunction with Florida County Property Appraisers (FCPA) and the U.S. Census, allow for a parcel-level evaluation of water usage and population applicable to any utility in Florida.

The methodology presented in this paper provides a consistent water usage and population analysis methodology with standardized definitions and input parameters. Of particular importance is the ability to treat SFR and MFR as independent sectors, which properly accounts for the many differences between them. A unique methodology to prorate combined persons per residence and percent occupancy into SFR and MFR components is presented which accounts for the differing housing characteristics of these two sectors. Given the increasing availability of property appraisal databases and advances in database and GIS technology, data driven approaches can be utilized elsewhere as the required inputs are becoming more prevalent.

Residential population and indoor and outdoor per capita water usage process models are presented to estimate total residential water usage, incorporating variability among fixture end uses and irrigable area for every household in a utility. Predicted total residential water usage is determined as the product of modeled population and modeled per capita water usage for residential users physically present and using water at a given time. This approach allows for consistent benchmarking as per capita usage multiplied by population yields actual water delivered to the residential sector.

Parameter estimation for the Sanford, FL case study resulted in a small percent potable irrigators for SFR, reflecting an extensive reuse irrigation network in Sanford. Both SFR and MFR process models provide reasonable prediction of measured total water usage. Future work includes further investigating other possible sources of error, including the relationship between actual and required irrigation needs as well as the effect of price on irrigation demand. Additionally, investigating seasonal occupancy

trends, particularly in the MFR sector could explain much of the remaining error for this sector.

CHAPTER 7
SUMMARY AND FUTURE WORK

Summary

Traditional water supplies are reaching their sustainable limits in many areas of the United States, and throughout the world. Several water stressed areas, particularly in the Western United States, are likely to face water scarcity problems in the near future. As a result, water stressed areas are considering alternative water supplies, including wastewater and stormwater reuse, system water loss control, and demand management to ensure that ample future water can be provided.

Demand management and water loss control initiatives have increased in popularity from the early 1990s to present with 23 states now having legislative mandates for some form of demand management as opposed to 9 states in 1990. Although these initiatives are a step in the right direction, current water conservation plans are often qualitative with unreliable aggregate savings estimates, even for the most reliable indoor residential sector. Recent initiatives focused on incorporating demand management in a broader context beyond reduced water supply needs are further requiring the need to better quantify demands with higher resolution.

To address these emerging needs related to better quantifying urban water demand estimation and associated demand management options, this dissertation presented a systematic data driven approach for evaluating parcel level water usage and demand management options for urban systems. Water usage for all water using devices is estimated using a uniform statewide property appraiser's database combined with water utility billing data. Water using population is then determined with the addition of U.S. Census Block data, which is utilized to determine per capita usage rates. The

potential effects of demand management are then determined directly as the difference between existing and proposed water usage after implementation. Water savings performance functions are then developed for each demand management option which are utilized to evaluate the optimal blend of demand management options to achieve a specified goal utilizing both linear and nonlinear formulations. Explicit analytical solutions are presented based on appropriate exponential best fits of performance functions. Emphasis is placed on the residential water use sector, although generalizations to all urban water use sectors are described. Two primary case study utilities, Gainesville Regional Utilities and City of Sanford are utilized to illustrate proposed methodologies.

Steady state deterministic parcel level water use and demand management optimization methodologies are presented in Chapter 2. Applications utilizing the single family indoor sector are utilized to illustrate these methodologies. This chapter shows how detailed parcel level databases can be used to develop performance functions for each end use and combine this information with savings and cost data to develop a linear program that can find the optimal demand management program that describe the optimal blend of the intensity of the option, .e.g., 1.28- vs. 0.8-gpf toilets, as well as across options, e.g., toilets vs. clothes washers. This entire procedure is programmed into EZ Guide 2, which provides Florida water utilities with a unique analysis tool driven by a uniform statewide database. Interested utilities can obtain these data sets already loaded into the EZ Guide 2 software.

http://www.conservefloridawater.org/ezguidedescription.asp

Output from this evaluation provides new insights into the opportunities and challenges of demand management. The approaches outlined in this chapter provide a solid basis toward planning and allocating resources toward targeted conservation technology changes.

Methodologies for evaluating single family outdoor water usage and demand management strategies are described in Chapter 3. Unique insights are presented, as the result of analyzing irrigation patterns for all residential customers within a utility, which very few studies have previously considered. This chapter presents a systematic parcel level data driven procedure to quantify and predict trends and patterns of single family residential potable irrigation and associated savings potential of single family residential irrigation demand management strategies. First, current irrigation practices, irrigable area, and irrigation application rate are derived for each single family residence based on parcel level tax assessor's data linked to customer level monthly water billing data. The results from a case study of 30,903 single family residential (SFR) parcels in Gainesville Regional Utilities were utilized to demonstrate these procedures, in which 16,303 SFRs were determined to irrigate from the potable system. The results of this study show a dramatic rise in the prevalence of in-ground sprinkler systems over the last few decades, which has led to increased irrigation application rates. However, housing trends show a decline in irrigable area over the same time period, which may help offset the predominance of in-ground sprinkler systems. Predictive equations are presented for utilities where directly linked property and billing data is unavailable, although this data linkage greatly enhances the robustness of analyzing outdoor water usage patterns.

Next, customers are clustered into relatively homogeneous groups based on existing irrigation practices, irrigable area, and average application rate. Water savings are calculated directly as the difference between current and proposed use after implementation of a management option for each group. This information is used to develop performance functions that estimate total water savings as a function of number of implementations for each group, in a similar manor to indoor water savings as described in Chapter 2. This procedure allows demand management options to be compared directly with other supply augmentation options when determining the optimal blend. The performance functions can be approximated as exponential equations, which can easily be solved for finding an optimal solution given unit costs and value of water saved. Only the small subset of customers who over irrigate should be considered for outdoor BMPs which are aimed at reducing irrigation to a desired threshold. The performance of outdoor BMPs is greatly affected by selection of a desired threshold or maximum application rate to achieve. Similarly to indoor water savings as described in Chapter 2, these methodologies are being incorporated into EZ Guide to assist Florida water utilities in evaluating water use efficiency.

The deterministic methodologies presented in Chapters 2 and 3 are extended in Chapter 4 to account for uncertainty in key parameter estimates. Both non-parametric and parametric representations of uncertain water usage and demand management potential are presented here. Single family residential irrigation demand management strategies are utilized as illustrative examples. A nonparametric data driven approach can be utilized given a sufficient sample of irrigators which evaluates current irrigation practices, irrigable area, and irrigation application rate for each single family residence

based on parcel level tax assessor's data linked to customer level monthly water billing data. Water savings are calculated directly as the difference between current and proposed use after implementation of a management option for each group, similar to that of the deterministic formulations. This information is used to develop performance functions that estimate total water savings as a function of number of implementations for each group. This procedure allows demand management options to be compared directly with other supply augmentation options when determining the optimal blend. Six parametric models were derived from benchmark parcel level datasets, for a generalized utility where direct measurements are unavailable. Both analytical models and empirical simulation are utilized to derive resultant performance functions, depending on desired model formulation. Using either exponential or lognormal marginal distributions along with the Spearman's rank order correlation coefficient provided reasonable predictions as compared with the non-parametric approach.

The solution algorithm to the optimal demand management formulations presented in the previous chapters is formalized in Chapter 5. An explicit analytical solution is presented which determines the optimal blend of demand management practices to achieve a specified goal. This chapter presents a systematic procedure to evaluate the optimal blend of demand management strategies to achieve a specified goal based on performance functions derived from parcel level tax assessor's data linked to customer level monthly water billing data. Two alternative formulations are presented to maximize the net benefits, or to minimize total cost subject to a satisfying a target water savings. Explicit analytical solutions are presented for both formulations based on appropriate exponential best fits of performance functions. A direct result of

this solution is the dual variable which represents the marginal cost of water saved at a specified target water savings goal. A case study of 16,303 single family irrigators in Gainesville Regional Utilities where high quality tax assessor and monthly billing data are available is utilized as an illustrative example of these techniques applied to single family irrigation BMPs. This framework is then generalized to apply to any urban water sector and to show the aggregate optimal solution across sectors.

The performance functions can be approximated as exponential, which can easily be solved for optimality given unit costs and value of water saved. The optimal value of the dual variable can be found directly using the Karush-Kuhn-Tucker conditions. This represents the marginal value of saving an additional gallon of water from outdoor BMPs. This framework allows for direct comparison to alternative water supply augmentation by comparing the cost of BMP implementations with the value of saved alternative water supply. Spatial clustering of targeted homes can be easily performed in GIS to identify priority demand management areas.

The previous steady state formulations are extended into a dynamic process simulation to predict urban water usage at an annual time step in Chapter 6. Parcel level data driven methodologies to estimate population and per capita water usage in the single and multi-family residential sectors are utilized within the simulation model. Predicted total residential water usage is determined as the product of modeled population and modeled per capita water usage for residential users physically present and using water at a given time. This approach allows for consistent benchmarking of water use efficiency across heterogeneous utilities as process model results are compared and validated against measured water use.

The methodology presented in this chapter provides a consistent water usage and population analysis methodology with standardized definitions and input parameters. Of particular importance is the ability to treat SFR and MFR as independent sectors, which properly accounts for the many differences between them. A unique methodology to prorate combined persons per residence and percent occupancy into SFR and MFR components is presented which accounts for the differing housing characteristics of these two sectors. Given the increasing availability of property appraisal databases and advances in database and GIS technology, data driven approaches can be utilized elsewhere as the required inputs are becoming more prevalent.

Residential population and indoor and outdoor per capita water usage process models were applied to the Sanford, FL case study with13,555 residential parcels to illustrate proposed methodologies. Both SFR and MFR process models provide reasonable prediction of measured total water usage. Parameter estimation for the Sanford, FL case study resulted in a small percent potable irrigators for SFR, reflecting an extensive reuse irrigation network in Sanford.

Future Work

The methodologies presented in this dissertation provide a standardized approach to evaluating urban water demand and associated demand management based on a uniform statewide property appraisal database linked to U.S. Census block data as well as customer billing data for select benchmark utilities. These methodologies are being incorporated into EZ Guide to assist Florida water utilities in evaluating water use efficiency. Future work includes expanding these datasets and methodologies to include areas outside of Florida. Work is currently being done to

include data from Austin, TX in the urban water demand database. This work will allow for large regional and national analyses of urban water demand and demand management to better cope with increasing water scarcity issues across the United States.

Additionally, future work includes further investigating possible sources of error within the proposed methodologies, including the relationship between actual and required irrigation needs as well as the effect of price and irrigation restrictions on irrigation demand. Additionally, investigating seasonal occupancy trends, particularly in the MFR sector could explain much of the remaining error for this sector.

Furthermore, future work should incorporate financial planning and projections of water demand and demand management in order to include uncertain future utility operating budgets as well as growth patterns and demands. This is of particular importance as the demand management optimization formulations presented in this dissertation do not factor in lost revenue as a result of decreased demands. There is a need to generate financial incentives for utilities to promote water efficiency in order for successful implementation of demand management programs. These issues represent significant challenges to demand management which remain to be addressed in the body of research literature.

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BIOGRAPHICAL SKETCH

Kenneth Friedman was born in Highland Park, IL in 1984. He is an only child and moved to Coral Springs, FL at age 6. While attending high school in Coral Springs, he developed his passion for problem solving and environmental studies.

Ken decided to major in environmental engineering at the University of Florida since it combined his two main academic passions. He started his undergraduate work in 2003 and received his undergraduate environmental engineering degree in 2007.

Starting in August 2007, Ken began his work as a graduate student studying water conservation under Dr. Heaney. He began working with customer billing databases and summarizing water usage by sectors. Later, Ken studied the areas of system water loss and residential end use analysis. These areas of study led to GIS analysis and Excel modeling, both of which were very rewarding and exciting analysis tools. Ken received his M.E. from the University of Florida in the fall of 2009 and continued on to finish his Ph.D. in the fall of 2013. Ken now works professionally in the water resources and water conservation planning fields.