Case Study

Estimating and Verifying United States Households' Potential to Conserve Water

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Abstract: Behavior and technological impacts on residential indoor water use and conservation efforts in the United States are identified. Preexisting detailed end-use data was collected before and after toilets, faucets, showerheads, and clothes washers were retrofitted in 96 owner-occupied, single-family households in Oakland, California; Seattle, Washington; and Tampa, Florida, between 2000 and 2003. Water volume, duration of use, and time of use were recorded and disaggregated by appliance for two weeks before and four weeks after appliances were retrofitted. For each appliance, observed differences in water use before and after retrofits are compared to water savings predicted by simple analytical, regression, and hybrid models. Comparisons identify prediction precision among models. Results show that observed and predicted distributions of water savings are skewed with a small number of households showing potential to save more water. Regression and hybrid model results also show the relative and significant influence on water saved of both technological (flow rates of appliances) and behavioral (length of use, frequency of use) factors. Additionally, regression results suggest the number of residents, performance, and the frequency of appliance use are key factors that distinguish households that save the most water from households that save less. Study results help improve engineering methods to estimate water savings from retrofits and allow water utilities to better target subcategories of households that have potential to save more water. **DOI: 10.1061/(ASCE)WR.1943-5452.0000182.** *© 2012 American Society of Civil Engineers.*

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Introduction

Urbanization and growing populations are placing increased demands on scarce, limited, municipal water supplies. Compared to expensive supply side options to expand municipal or regional water infrastructure, residential water conservation can cost effectively help demands match available supplies. Conservation can include technological changes, such as replacing old toilets, faucets, showerheads, dishwashers, and laundry machines with newer and more efficient appliances mandated by the Energy Policy Act of 1992. However, to include water conservation in water supply/demand planning, it is important to correctly know and forecast current and future water demands and the volume of water potentially saved by conservation actions.

Planners and water managers have forecasted water demand and estimated water savings for many conservation programs and measures (Berk et al. 1993; Buchberger and Wells 1996; Kenney et al. 2008; Michelsen et al. 1999; Renwick and Archibald 1998; Walski et al. 1985). For example, low flow showerheads and toilet dams were distributed among Hamilton Township residents in 1978; subsequently customers were surveyed to identify the number of devices actually installed, and coefficients obtained from this data were used in an algorithm to predict water savings (Walski et al. 1985). Data loggers have been installed on the supply line for single-family residences, recording the total instantaneous water demand of the household (Buchberger and Wells 1996). Models to estimate household-level water demands have been developed as a function of price, weather, house, and household characteristics, as well as other policy restrictions and interventions during the study periods (Kenney et al. 2008, Michelsen et al. 1999; Renwick and Archibald 1998). Water conservation program planners have also probabilistically described the volume of water saved from conservation actions by enumerating uncertainties associated with costumer demographic, behavioral, and technological parameters that influence water savings (Rosenberg 2007).

Tracking only the flow or usage rates of more efficient appliances doesn't provide a direct way to estimate savings because human behaviors also play an important role—the duration and frequency of appliance use. Additionally, when people know they are using a water-conserving appliance, they may use the appliance longer or more frequently. This increased use may swamp expected water savings (Campbell et al. 2004).

Still, the demand forecasting and conservation estimation methods discussed above can be improved in several ways. First, estimates of water saved by structural conservation actions need to be empirically verified. More carefully gathering and storing observations of water use and pairing observations to estimates can help with empirical verification (Walski et al. 1985). Second, household heterogeneity must be more explicitly considered (Whitcomb 1990; Rosenberg 2007). Studies typically include a wide variety of explanatory variables (such as income, household size, lot size, age of house) culled from secondary data sources to characterize household heterogeneity, but use only one aggregate and primary-sourced dependent variable—monthly billed water use (Kenney et al. 2008). Using disaggregated end-use data for each water appliance can add more specificity. Third, technological and behavioral factors influencing water savings can be better

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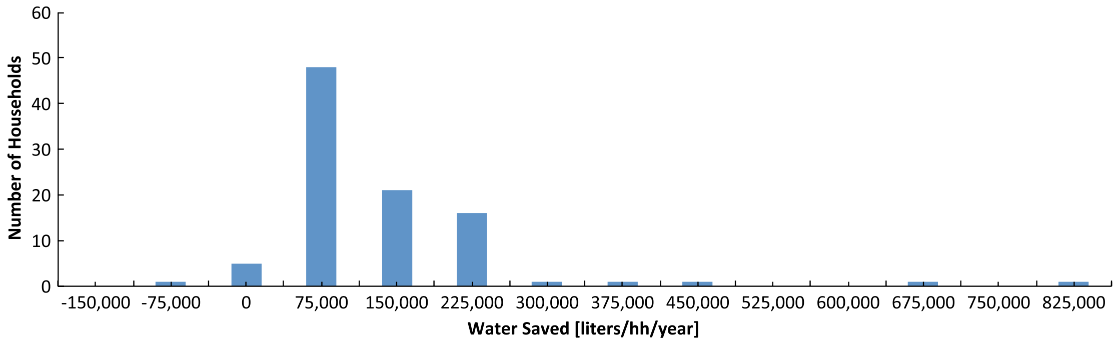

Fig. 1. Distribution among household of water saved by retrofitting toilets, showers, faucets, and clothes washers

described, disentangled, and considered as explanatory variables. For example, the duration and frequency each resident in a household uses an appliance may differ. At the same time, the flow, flush, or use rate of an existing appliance can depend on numerous factors including when the appliance was manufactured and whether it has been maintained. Similarly, the flow, flush, or use rate of a retrofitted appliance set by the manufacture may differ from the installed or actual rate. Thus, water use and savings depend on both technological and behavioral factors acting together.

Until recently, it has been difficult to separately measure and differentiate technological and behavioral factors. However, this separation is now possible using data logging and disaggregation methods deployed for a national study of nearly 1,200 households (Mayer et al. 1999) and a water appliance retrofit study for 96 households in Oakland, Seattle, and Tampa, between 2000 to 2003 (USEPA 2004). The latter retrofit study data include two weeks before and four weeks after each household was retrofitted with water efficient toilets, faucets, showers, dishwashers, and clothes washers. Prior work describes the disaggregation method (Mayer et al. 1999), organized the retrofit data, reported summary statistics such as average water saved by each appliance retrofit, and developed regression models to estimate demands using number of residents and house size as independent variables (USEPA 2004).

This case study presents analytical, hybrid, and regression models to estimate the water saved when retrofitting indoor water appliances and describe the prediction precision and efficacy among models. Models are built from and verified against the previously collected U.S. Environmental Protection Agency (USEPA) end-use retrofit study data (2005); model variables include preexisting and retrofitted flush and flow rates of water appliances, such as toilets, showerheads, faucets, and clothes washers. Also, the models use behavioral variables such as the duration and frequency of appliance use. In this way, the models identify separate and combined effects of technological and behavioral factors. We also show the distributions of water saved among households and regression models identify characteristics of households with the potential to save the most water from retrofits. Case study results highlight ways U.S. water utilities can target retrofits to households with potential to save the most water.

Data Set

This work uses end-use data previously collected from 96 single-family houses in Seattle, East Bay Municipal Utility District (EBMUD), and Tampa between 2000 and 2003 before and after each household was retrofitted with water efficient appliances (USEPA 2005). Water use was recorded by placing data loggers on each participating household's water meter and recording water flow through the meter at 10 s intervals. Flow signals were then postprocessed to determine the duration, water volume, and frequency of household leaks, outdoor and indoor water uses including toilets, showers, clothes washers, faucets (USEPA 2005). For details on the methods used to monitor and disaggregate end uses, see Mayer et al. (1999).

The houses selected for the study used more than 227 L (60 gal.) per capita per day and were representative of households in the three cities. Participating homes averaged 46 years in age. Old homes are less likely to have water-conserving appliances; however, participating homes initially showed a wide range of appliance flow and flush rates indicating varied old to newer, water-conserving appliances. Also, additional sociodemographic data was collected on each participating household, including adults per household, children per household, number of bedrooms, number of bathrooms, floor area, and price paid for water.

Water use data collected before the retrofit constituted the baseline water use for each household. Next, water appliances were retrofitted with more efficient ones, i.e., existing toilets were replaced with low flush volume toilets. One month after the retrofit, water use was again recorded for two weeks. Finally, six months after the retrofit, water use was logged for two more weeks to identify behavioral changes and the persistence of water savings from the retrofits.

In general, households reduced the water use after they were retrofitted with the new appliances (Fig. 1). The initial analysis found annual water savings averaged 79, 21, 6, and 5 m^3 per year, respectively, for toilet, clothes washer, showerhead, and faucet retrofits (USEPA 2004). Yet, six homes didn't save any water after retrofits, while other households saved more than 750 m^3 per year. Overall, 93% of the households saved water, showing that retrofits can be effective. Fig. 1 also suggests that utility companies can improve conservation program effectiveness with reduced effort if they can target programs to households on the right tail of the distribution with the most potential to conserve water.

Analysis Methods

Analytical and regression methods are used to estimate water saved and estimates are compared to the actual water saved by households participating in the USEPA study. The methods used in this research have as an objective to predict the savings observed. In the following, methods to calculate actual savings and develop analytical, hybrid, and regression models are presented. Hybrid models embed an analytical equation in the regression model.

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Actual Savings

First, actual water savings were calculated by subtracting the volume of water used by each appliance during the preretrofit period from the volume used during the postretrofit period. Household average daily use values are used and then extrapolated to a per year basis.

Analytical Models

Second, an analytical model was developed for each appliance retrofitted. Each analytical model calculates household water savings by simply multiplying the expected change in water volume per use associated with the appliance retrofit by the frequency of appliance use and by the number of people in the household. The expected change in water volume per use is calculated by subtracting the postretrofit flow rate (liters per use) from the preretrofit flow rate. Each analytical model is dimensionally consistent and all parameters can be determined or easily calculated from the monitored and disaggregated appliance end-use data. A separate analytical model was developed for each appliance. For example, the analytical model to estimate the water saved by retrofitting a showerhead was:

$$W_{\text{analytical}} = j[(g) - (h)]k * 365 \tag{1}$$

$W_{\text{analytical}}$ = water saved by the appliance (in this case, the showerhead) as estimated using the analytical model [liters/household/year]; j = persons per household (permanent residents in the homes at the time the study was done [persons/hh]); g = average flow rate of appliance preretrofit [liters/min]; h = average flow rate of appliance postretrofit [liters/min]; k = average shower time per person per day [min /person/day].

Average flow rates were calculated by dividing the total shower water use logged during the preretrofit and postretrofit periods by the total time the shower was used during each period. Average shower time is the total use time over the preretrofit and postretrofits periods divided by the number of residents in the house and the number of days of the preretrofit or postretrofit period. For toilets and clothes washers, the preretrofit and postretrofit use frequencies were different; hence, the parameter corresponding to k in Eq. (1) could not be factored out of the parenthesis; in those models, use terms were combined with flow rates as part of the difference term. Because some appliances weren't used every day during the study period, the use per day is calculated only taking into account days that the appliance was actually used. Analytical estimates are computed individually for each household using household-specific model parameters.

Hybrid Models

Hybrid (log-log) models were developed for each appliance [Eq. (2)]. These log-log regressions estimate savings using both technological and behavioral variables and are a hybrid between analytical and regression models (see the following). They take the log of the analytical model [Eq. (1)], then add coefficients to improve the fit between the observed and estimated water savings [Eq. (2)]. In this way, they (1) embed dimensionally consistent and measurable parameters included in the analytical model; (2) allow coefficient estimation to improve model fit associated with regression models; and (3) quantify the relative influence of technological and behavioral factors.

$$\ln(W_{\text{actual}}) = a_1 \ln(g - h) + a_2 \ln j + a_3 \ln k + y + z \tag{2}$$

$\ln(W_{\text{actual}})$ = natural log of actual water saved by the appliance (in this case, the showerhead) [liters/household/year]; α_n = regression coefficients; g, h, j, and k are as defined previously; y = intercept [liters/hh/year]; and z = random effects not explained by model variables [liters/hh/year].

The hybrid model excludes households whose water use increased after retrofits (negative savings). These households were dropped because it is not possible to take the log of a negative number. Also, use before and after retrofits was statistically different for toilets and clothes washers, so variables representing both preretrofits and postretrofits frequency of use were included in the hybrid models for these appliances. Despite these limitations, the hybrid model offers an intermediary comparison between fitted regression and not-fitted analytical models.

Regression Models

Third, we also used several regressions models to explain water savings as a function of different independent variables. Regression models use the same variables as the analytical models, but include coefficients to improve the fit between actual and estimated savings. Coefficients have units that depend on the regression equation, cannot be measured from the end-use data for an individual household (like for the analytical models), and can only be determined by regressing a large number of households. Independent variables include the number of persons per household, preretrofit and postretrofit volumes per use, and the frequency of use of each appliance. After regressing, examining the coefficient values can help disentangle technological (volume per use), behavioral (frequency of use), demographic (number of people), and economic (water price) factors, and their relative influences on water use and water saved by retrofits.

For example, Eq. (3) shows a semilog regression model.

$$W_{\text{actual}} = a_1 \ln j + a_2 \ln g + a_3 \ln h + a_4 \ln k + y + z \tag{3}$$

W_{actuual} = actual water saved by the appliance (in this case, the showerhead) [liters/household/year]; a_n = Regression coefficients; and, j, g, h, k, y, and z are as defined previously.

For the regression models developed for shower and other water appliances, the natural log of the independent variables was calculated, and then the regression coefficients were identified using linear least-squares regression.

Additional regressions also used independent variables related to socioeconomic characteristics of the households. These socioeconomic characteristics included the price paid per unit of water, number of full and three-quarter bathrooms (i.e., bathrooms without a bathtub/shower), location (city), and household size. Initial analyses showed that household location was not significant; these results are not presented, but are available upon request. Characteristics were taken from the written survey responses provided by households (USEPA 2005). These regressions allow us to identify and distinguish high savers from low savers households.

Results

Model results are presented by appliance. For each hybrid and regression model developed, regression coefficient values and the R^2 showing the fraction of variation in the dependent variable (water saved) that is explained by the model variables are reported. A Kolmogorov-Smirnov test (K-S test) was also used to compare resulting distributions of water saved among households by the analytical, hybrid, and regression models to the actual water saved. The K-S test indicates if the distributions of two datasets differ significantly, and makes no assumption about the distribution shapes or the sample size (Chakravarti et al. 1967). The K-S test gives a D value, D being the maximum difference between the two

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Table 1. Models Sample Size and Fit

Appliance	Hybrid model N	Hybrid model R^2	Regression model N	Regression model R^2
Toilet	85	0.64	96	0.88
Shower	58	0.36	94	0.27
Clothes washer	85	0.79	95	0.91
Faucet	83	0.73	96	0.7

cumulative density functions tested. The null hypothesis that the two distributions are the same when the associated probability P is less than 0.05 was rejected.

Toilet Models

Analytical, hybrid, and regression models were tried, with the regression model and model variables explaining more of the variations in actual water saved than the hybrid model (Table 1). In the hybrid and regression toilet models, both the technological and behavioral variables (i.e., flush volumes and frequencies of use) are significant, have the expected signs, and large influences as indicated by coefficient and elasticity values (Table 2, first six rows). On average, technological and behavioral factors have a greater effect on the water saved by retrofitting the toilet than does the demographic factor (number of residents). In Table 2, elasticity values indicate the percentage change in water use associated with a 1% change in the variable value, are unitless, and allow more ready comparisons of model variable effects among variables and across models. Elasticity and coefficient value results are the same for the hybrid model because the model uses a log-log equation form.

Fig. 2 is a normal probability plot and shows observed and modeled distributions of water savings among households when retrofitting toilets. It shows the distributions are not normally distributed, but that the analytical, hybrid, and regression models explain distributions of savings among households similar to observed savings. These observations are confirmed by K-S tests ($P \geq 0.05$ for all models; Table 3). The analytical and regression models have the smallest D values and their predicted distributions are statistically most similar to the observed distributions of savings. The regression and K-S test results show that the analytical and regression models can effectively estimate residential savings when retrofitting toilets.

Shower Models

Table 2 (rows 7 to 10) shows the results for the hybrid and regression models developed to estimate water saved by retrofitting showerheads. In these models, a single average shower length per person per day was used rather than separate preretrofit and postretrofit shower times, as these times were not significantly different ($t-\text{stat} = -0.59$; $P = 0.55$). Regression results show the appliance flow rates and number of permanent resident variables are significant.

Coefficient and elasticity values show what is expected—postretrofit showerhead flow rate variable reduces water use and increases savings. Technological variables are significant at the 95% level for both regression models, while the behavioral component is only significant at the 95% level in the hybrid model.

Table 2. Summary of Technological Regression Models for Water Saved When Retrofitting Toilets, Showers, Clothes Washers, and Faucets

Appliance	Variable	Hybrid Coefficient	Hybrid Elasticity	Hybrid t-stat	Regression Coefficient	Regression Elasticity	Regression t-stat
Toilet	a. Average preretrofit flush Volume [l/flush]	—	—	—	18,826.49	2.00	21.25[a]
	b. Average Postretrofit flush Volume [l/flush]	—	—	—	−8,180.29	−0.87	−4.96[a]
	c. Average change in water use [l/person/day][b]	1.78	1.78	11.41[a]	—	—	—
	d. Persons per household [# of permanent residents]	1.01	1.01	6.08[a]	7,263.36	0.77	8.18[a]
	e. Average flushes preretrofit [#/person/day]	—	—	—	17,431.67	1.85	16.67[a]
	f. Average flushes postretrofit [#/person/day]	—	—	—	−8,370.90	−0.89	−7.68[a]
Shower	g. Average preretrofit flow rate [l/ min]	—	—	—	7,119.39	4.17	4.47
	h. Average postretrofit flow rate [l/ min]	—	—	—	−5,381.74	−3.15	−2.05[a]
	i. Average change in flow rate [l/ min][c]	1.88	1.88	4.19[a]	—	—	—
	j. Persons per household [number of permanent residents]	0.82	0.82	3.13[a]	3,435.85	2.01	3.17[a]
	k. Average shower length [min utes/person/day]	0.48	0.48	2.56[a]	530.44	0.31	0.70
Clothes washer	l. Average Pre-Retrofit Load Volume [l/load]	—	—	—	25,646.17	2.41	23.92[a]
	m. Average postretrofit flush volume [l/load]	—	—	—	19,462.56	−1.83	−10.44[a]
	n. Average change in water use [l/person/day][d]	1.32	1.32	13.93[a]	—	—	—
	o. Persons per household	0.84	0.84	4.81[a]	10,600.49	1.00	7.84[a]
	p. Loads preretrofit [#/person/day]	—	—	—	29,912.17	2.81	23.85[a]
	q. Loads postretrofit [#/person/day]	—	—	—	−19,385.20	−1.82	−13.12[a]
Faucet	r. Average preretrofit flow rate [l/ min]	—	—	—	11,824.38	3.98	8.40[a]
	s. Average postretrofit flow rate [l/ min]	—	—	—	−9,084.77	−3.08	−7.40[a]
	t. Average change in flow rate [l/ min][e]	3.14	3.14	10.64[a]	—	—	—
	u. Persons per household [number of permanent residents]	0.76	0.76	4.56[a]	4,806.63	1.62	6.23[a]
	v. Average use [min utes/person/day]	0.99	0.99	7.43[a]	5,461.62	1.84	8.87[a]

Note: "—" indicates variables not used in the model.
[a]Significant at the 95% level.
[b]$c = (a \cdot e - b \cdot f)$.
[c]$I = (g - h)$.
[d]$n = (l \cdot p - m \cdot q)$.
[e]$t = (r - s)$.

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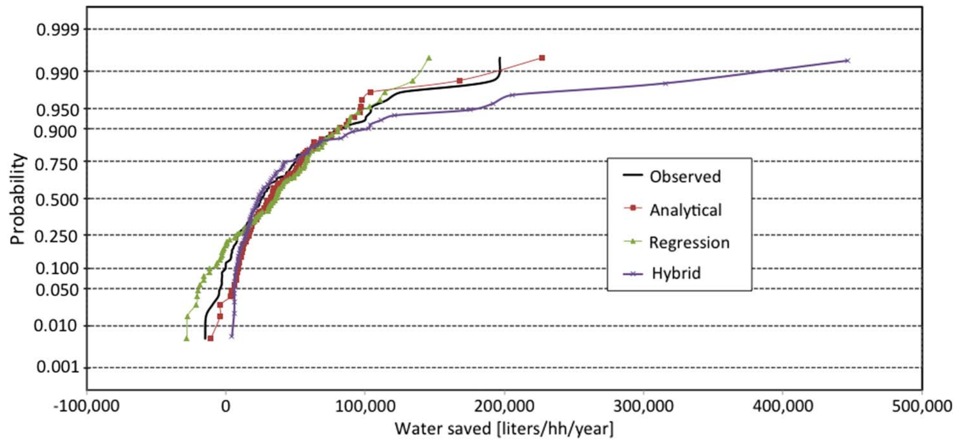

Fig. 2. Cumulative distribution among households of water saved by retrofitting toilets

Table 3. K-S test results—K-S stat (D) and (significance [P])

Appliance	Analytical	Hybrid	Regression
Toilet	0.167 (0.130)	0.186 (0.080)	0.167 (0.130)
Shower	0.128 (0.403)	0.472 (0.003)	0.160 (0.166)
Clothes washer	0.105 (0.644)	0.190 (0.070)	0.084 (0.875)
Faucet	0.250 (0.004)	0.188 (0.077)	0.156 (0.175)

According to the elasticity values shown in Table 2, technological factors have larger effects on savings than demographic or behavioral factors. For the regression model, the behavioral shower length variable is only significant at the 52% level.

Regression model variables explain 27% of the variation in water saved by retrofitting showerheads (Table 1) and suggest there are many other (unobserved) variables, which may also explain water savings. When the K-S test was applied to the regression model, a D value of 16% was obtained, but only significant at the 17% level. Results of the K-S test gave the analytical model a D value of 13% significant at the 40% level (Table 3). These results show that the distributions of savings estimated by the analytical and regression models are statistically similar to the observed distribution of savings (Fig. 3). In contrast, the hybrid model has a larger D value and significance less than 5%, which indicate this model is statistically different than the observed distribution of savings.

Clothes Washer Models

For the hybrid and regression models of water saved by retrofitting clothes washers, technological and behavioral variables are significant at the 95% level (Table 2). In both models all variables have the expected signs. The variables with the largest coefficient values are average preretrofit load volume and loads preretrofit [#/person/day]. Again, both technological and behavioral factors affect water savings.

K-S tests indicate the three modeled distributions of savings are statistically similar to the observed savings (Table 3; $P > 0.05$). The regression model distribution has the lowest D value and highest significance, and is the most similar to the observed distribution of savings.

Regression and K-S test results show that the analytical and regression models fit well, while the hybrid model overestimates savings. Estimating water savings by clothes washers can be done in precise way using analytical and regression models, and provides an efficient way to estimate water savings by households based on technological and behavioral characteristics.

Faucet Models

The analytical model of faucet savings was similar to the one used for the analytical shower model. The faucet model also used average use time because there was not a significant difference between preretrofit and postretrofit use time.

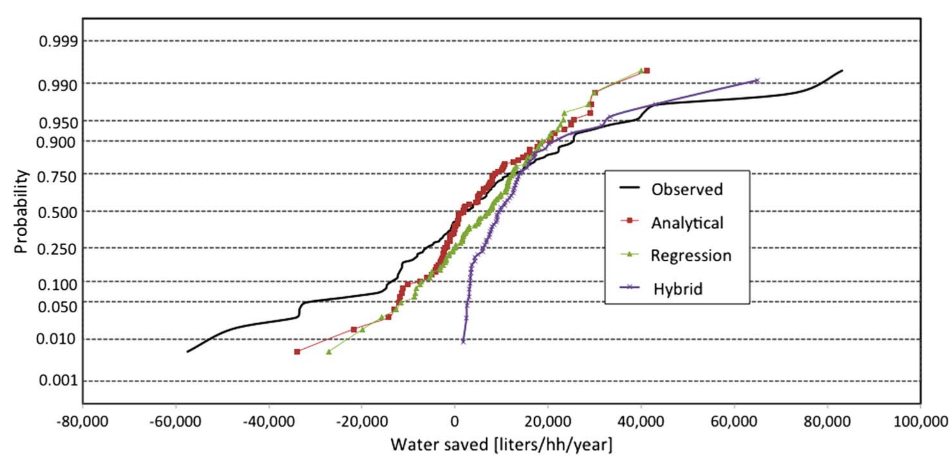

Fig. 3. Cumulative distribution among households of water saved by retrofitting showerheads

Table 4. Comparing Average Characteristics of Households that Save Most Water to Households that Save Less Water

Appliance	Largest savers ($n = 20$) Water price [USD$/ $m3$]	Residents [persons/hh]	Number of Full Baths +3/4 Baths	Volume per Use[c]	Frequency of Use[d]	Smaller savers ($n = 76$) Water price [USD$/ kgal]	Residents [persons/hh]	Number of Full Baths +3/4 Baths	Volume per Use[c]	Frequency of Use[d]
Toilet	1.93	3.4	2.0	22.3[a]	7.0[a]	1.88[b]	2.53[a]	1.9	13.2[a]	4.5[a]
Shower	1.62[a]	3.7[a]	2[a]	9.8[a]	6.9[a]	2.0	2.5	1.9	7.6[a]	4.8
Clothes Washer	1.73	3.2	1.8	166.8	1.9	1.9	2.6[a]	2.0	135.7	1.9[a]
Faucet	1.56	3.4	2.2	5.5[a]	34.4[a]	1.98[b]	2.5[a]	1.9	3.8[a]	8.6[a]

[a]Significant at the 95% level.
[b]Significant at the 90% level.
[c]Liters per flush, liters per minute, liters per wash, and liters per minute, respectively, for toilets, showers, laundry machines, and faucets.
[d]Flushes/person/day, minutes/person/day, washes/household/day, and minutes/person/day, respectively, for toilets, showers, laundry machines, and faucets.

The hybrid and regression models have as independent variables the average flow rates preretrofits and postretrofits, the number of residents, and the average length of use per person per day. Regression model variables can explain 70% of the variations in water savings (Table 1). Coefficients associated with each variable all have the expected sign and are significant. The average preretrofit and postretrofit flow rate have the largest coefficient values and most influence faucet water savings (Table 2). The hybrid model also has a similar R^2, although this model only estimates positive savings from the log-log formulation. These results suggest that technological and behavioral factors influence water savings, but that technological factors—the flow rates before and after faucet retrofits—are more important.

Three houses located on the right tail of the observed distribution of water saved by retrofits had a high faucet use time before the retrofit compared to the time after (a difference of more than 200 min/hh/day). This change suggests a significant behavioral change in those households. However, it is also possible that these households had uncommon uses prior to retrofits, or that malfunctioning faucets in these houses were logged as faucet use rather than leaks.

K-S test results show that the distributions of savings among households predicted by the hybrid and regression faucet models are similar (Table 3). However, the distribution predicted by the analytical model is likely different than the observed distribution. Water savings by faucet retrofits can be effectively estimated using hybrid and regression models.

Tail Analysis

One of the purposes of this study is to identify households with the potential to save more water. These houses are located in the right tails of the water savings distributions shown in Figs. 1–3. Surveys were used and and end-use data were collected about and at the houses to identify characteristics of households that will likely save the most water from retrofits.

Households were ranked by water volume saved by retrofitting each appliance, then the largest savers (top 20 households) for each appliance were separated from the rest. We chose this breakpoint to allow sufficient degrees of freedom to run regressions for each group. This segregation also means a certain household could be in the high savings group for one appliance, but not for other appliances. For each appliance, separate linear regressions were made for the groups of largest and smallest savers. For each group, water savings was regressed against the independent variables (water price, number of residents, number of full and three-quarter bathrooms, flow rate, and frequency of use).

For each appliance, households that saved the most water by retrofitting the appliance had more residents than households that saved less water (Table 4). On average, large savers had approximately one more person per household than small savers. Similarly, households that saved the most water from retrofits had, prior to retrofits, appliances that delivered larger volumes per use and were less water efficient. This difference was significant for the toilet, shower, and faucet models ($P < 0.05$). Another factor that differentiated high savers from low savers across most appliances was behavior. High savers tended to use appliances more frequently than low savers with this difference significant for the toilet and faucet models.

Interestingly, results also show that both high and lower savers used laundry machines with about the same frequency. Both groups also typically had the same number of bathrooms; as such, these two factors are not particularly helpful to differentiate users in the two groups.

Although not statistically significant, the largest savers generally faced lower water prices than smaller savers. This finding runs counter to microeconomic theory that suggests higher water prices should encourage larger reductions in water use. However, in this study, the participating cities paid for and installed all water efficient appliances for households. Thus, the counterintuitive result may occur because larger savers had a lower financial incentive prior to the study to invest in water conservation measures and possibly used more water then (price was also constant through the study period). Together, the tails analysis suggests that a large family size combined with a water efficient appliance and high frequency of use result in large water savings from retrofits.

Discussion

Analytical, regression, and hybrid models were developed to estimate water savings by retrofitting toilets, showerheads, clothes washers, and faucets. K-S test results show the three types of models all reasonably predict distributions of water saved except for the hybrid model for shower retrofits and the analytical model for faucet retrofits. Regression results indicate regression and hybrid models for toilet and clothes washer retrofits explain more of the variations in water saved than models for shower and faucet retrofits. This result is expected because toilets and clothes washers have a fixed water volume per use, whereas users can regulate shower and faucet flow rates during each use. Additionally, regression models for toilets and clothes washers explained more of the variations in water savings than the hybrid models. In these instances, behavior varied before and after retrofits and it was not possible to separate the behavior component in the hybrid models. For shower

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and faucet models where the behavioral variable was separated, hybrid models explained as much or more of the variation in water savings as regression models (Table 1). These comparisons emphasize the importance to include behavioral factors in models to estimate water savings by retrofits. They also suggest that a simple analytical approach to estimate savings may suffice when data are available to describe the technological and behavioral factors that influence savings.

More elaborate regression and hybrid models are warranted when it is important to show the separate and combined effects of technological and behavioral factors on water use and water savings (Table 2). Elasticity values shown in Table 2 provide a way to normalize and compare the relative effects of technological and behavioral factors on water savings. In all models, technological and behavioral factors are important and significant (Table 2). In several models such as for showers and faucets, the technology component contributes more to overall water savings than the behavioral component as represented by larger elasticity values in the regression results. This effect is magnified for appliances where behavior did not change preretrofits and postretrofits. In a few cases, households increased their water use after the retrofits, as a consequence of behavioral changes that offset technological improvements. For appliances such as toilets and clothes washers where household use behavior changed preretrofit and postretrofit, it was not possible to differentiate in the hybrid models effects of technology and behavioral factors. Instead, an average change in water use variable was introduced that aggregated behavioral and technological factors prior to regression. Otherwise, both the regression and hybrid models use the same natural log of the independent variables and the main difference is that the hybrid model regresses against the natural log of the dependent variable (water saved), whereas the regression model regresses against the actual value.

When comparing characteristics of households that saved the most water by retrofits to households that saved less water, in general, high saving households had more residents than households that saved less water. Also, prior to retrofitting, these households had less efficient appliances and used appliances more frequently than households that saved less water by retrofits. Utility companies can use these findings to identify and target households with high potential to save water. To target these households, utility companies should seek houses with larger number of residents and with least efficient appliances. Utility companies can determine high occupancy from household surveys or census records. Utility companies could also use property parcel or permitting records as an indicator of the age (and likely flow rates) of appliances inside a house. Study results also show that houses with a higher frequency of use save more water, but this household behavior may be difficult for a utility to identify and target in campaigns to motivate behavioral change. Utilities cannot install data loggers in the houses of all their customers. To identify households with potential to save the most water, water utilities can and sometimes do rely on large billed water use as a proxy for behavior; however, demographic and technologic factors such as household size and appliance flow rates can confound this practice. The finding and current practices identify the need for further research to identify household behavioral indicators that utility companies can readily measure and reliably act upon to target households with large potential to save water from retrofits.

It is important to point out that the models use as a variable the number of permanent residents and do not account for visitors during the study period. Unobserved visitors could alter the frequencies with which appliances are used. Also, the data collected by the loggers were aggregated by appliance type, which means technological and behavioral variable values for each appliance type were results of averaging across all appliances of the same type in a house. Further, the analysis excluded the leakage volume saved by retrofitting leaky appliances because intermittent leaks from faucet drips, unsealed toilet flappers, and other sources prior to retrofit were disaggregated separately apart from appliance water use. In the disaggregation, these leaks are easily identified by their very low flow rates (too low to be faucets), association with other events that might initiate a leak, or duration different than faucet use (Mayer et al. 1999). This exclusion means actual water savings from retrofits are larger than reported savings; it also identifies a further need for improved leak prediction and modeling capabilities. Finally, for hybrid models, some households were excluded from the analysis because it was not possible to calculate the log of water savings for households that increased use after retrofits and had negative savings. Thus, sample sizes were different among the analytical, hybrid, and regression models.

Conclussions and Recommendations

Analytical, hybrid, and regression models were developed to estimate water savings using detailed, disaggregated water end-use data collected before and after retrofitting toilets, showers, faucets, and clothes washers in 100 households in Oakland, Seattle, and Tampa. Water savings result from a combination of the technology installed in the households and the use of appliances. Our models use technological and behavioral variables and represent an improvement on prior models that rely on only demographic and household characteristics.

Results show analytical, hybrid, and regression models can all reasonably characterize distributions among households of water saved by retrofits. Use of analytical models to estimate water savings in a simple, dimensionally consistent way when data exist to describe the technological and behavioral factors that influence savings. Alternatively, use regression and hybrid models when there is a need to (1) estimate indoor residential water savings based on technological and behavioral components; and (2) separate out the effects of each component. For all the appliances, technological and behavioral variables such as flow rates, durations, and use frequency are significant with technological variables having a larger effect on water saved for appliances such as showers and faucets where the user regulates the appliance flow rate during each use event.

Houses that saved more water from retrofits tended to have more residents than those who saved little or no water. They also had less efficient appliances prior to retrofits, used appliances more frequently, and experienced lower water prices than lower savers. U.S. water utility companies can use these case study findings in conjunction with census data, customer surveys, and property parcel and permitting records to identify customers with high potential to conserve water indoors.

U.S. water utility companies can also use these case study results and findings to target customers with more residents, less efficient appliances, and high use frequency to replace old appliances for newer and more efficient ones to conserve water. With targeting, utility water conservation programs can save more water with less effort. The case study results also help improve engineering methods to estimate water savings from retrofits.

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