HOUSEHOLD WATER USE AND CONSERVATION MODELS USING MONTE CARLO TECHNIQUES FOR THE EAST BAY MUNICIPAL UTILITY DISTRICT

By

RYAN J. CAHILL
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Approved:

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Jay R. Lund, Chair

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Fabián Bombardelli

____

Samuel Sandoval-Solis

Committee in Charge

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Abstract

The increased availability of water end use measurement studies allows for more mechanistic and detailed approaches to estimating household water demand and conservation potential. Here, probability distributions for parameters affecting water use are estimated from end use studies and randomly sampled in Monte Carlo iterations to simulate water use in a single-family residential neighborhood. This model represents the existing conditions and is calibrated to metered data. A two-stage mixed integer programming optimization model is then developed to estimate the least-cost combination of long- and short-term conservation actions for each household. This least-cost conservation model provides an estimate of the upper bound of reasonable conservation potential for varying pricing and rebate conditions. The models were adapted from previous work in Jordan and are applied to a neighborhood in San Ramon, CA in the EBMUD service area. The existing conditions model produces seasonal use results very close to the metered data, and the least-cost conservation model suggests water demand is relatively inelastic with respect to price, “cash for grass” programs will not be effective, and clothes washer rebates are the most cost-effective rebate programs.

Introduction

Models predicting residential water use and conservation potential based on empirically estimated parameters, device turnover rates, and regressive relationships are quite frequent. Many water utilities develop regressive relations for total single-family residential water use based on historical trends for planning purposes (Sacramento Department of Utilities 2011, SJ ESD 2011). Such models may assume increasing levels of conservation in the future, but often give little indication of how the reduced water use will be achieved. Estimating realistic conservation potential requires an understanding of where water is currently being used in homes and savings potential for each end use under various drought, pricing, and demographic conditions. Measurement-based studies now provide reliable data on water consumption for each end use (e.g. toilets, showers, irrigation, etc.) (Mayer & DeOreo 1999).

Using such water end use data, some models have attempted to estimate conservation potential by assuming natural replacement rates of appliances with more efficient ones and determining the expected amount of water saved (Gleick 2003, CALFED 2006). These models often assume average savings values for retrofitting devices and apply them uniformly to the proportion of the population expected to adopt the devices. Estimates of the cost-effectiveness of such retrofits are often also included. Such a modeling approach has use for long-term predictions and may be the only possible approach for a statewide estimate, but it does not allow for much heterogeneity of the population, which can cause varying effectiveness of retrofits and rebates.

Still other household use models attempt to calculate the water used for each end use of individual homes using regressive relationships (DeOreo et al. 2011). These models build heavily on end use measurement data paired with survey responses, and find statistically significant parameters affecting each end use of water. Regressive equations are then developed to predict each end use as a function of these significant parameters. The strength of the regressive relationships is often low, with coefficients of determination (R^2) typically around 0.4 (DeOreo et al. 2011). Such models do an acceptable job of estimating current average water use for groups of homes, and they can estimate the effectiveness and potential for water conservation measures under different scenarios. However, any concept of water price or more complex rationing conditions is absent from these models, although many studies have shown that price is an important factor affecting water use (Dalhuisen et al. 2001, Rosenberg 2010).

While the aforementioned empirical models are useful for different purposes, a more mechanistic modeling approach to household water use and conservation potential can now be undertaken with the large amounts of data available from end use measurement studies. In contrast to more empirical modeling approaches, this paper presents household use model based on physical parameters affecting water use that vary by household. These physical parameters are used to estimate water consumption for each end use, and no empirical relationships without physical meaning are present. Using a Monte Carlo approach to include variability in household physical characteristics and behavior, the model estimates the distributions of household water use and conservation potential. The perspective of individual homeowners, rather than utilities, is considered in the model. Conservation decisions that make financial sense for households can be added to make up the total conservation potential for a neighborhood or service area. This is a novel way to estimate household water demands and potential for conservation, differing substantially from more statistical approaches. This model is applied to a neighborhood in the East Bay Municipal Utility District (EBMUD) service area.

The model developed here can be thought of as two interrelated models: an "existing conditions" use model and a "least-cost conservation" model. The existing conditions model estimates water use rates based on uncertain physical parameters for each Monte Carlo iteration (household). The results can be calibrated to metered data, and the model can also be used directly to examine simple conservation alternatives (i.e. what would water use be if all toilets were retrofitted with high efficiency toilets?). It is a simulation model where households do not make any decisions. The "least-cost conservation" model is a companion optimization model. It builds on the existing conditions use model, and finds the combination of conservation actions each household should use to minimize costs. The output from this model suggests an upper bound of conservation savings—EBMUD should not expect more conservation than the levels produced by this model, as it is an optimistic scenario. Alternatives such as differing rebate strategies or pricing schemes can be considered in the least-cost conservation model.

This model is an extension of a model developed to estimate household water use in Amman, Jordan (Rosenberg et al. 2007) and builds on Garcia (2006) and Lund (1995). Much of the framework of the model is identical to Rosenberg's model, but the parameters affecting water use and available conservation actions have been modified. Rosenberg's model was able to accurately reflect actual water use patterns in Jordan, but such an approach has not been attempted in the U.S. Household water use patterns in Jordan are much different than the Bay Area for many reasons, including: (Rosenberg et al. 2007)

- Residents often lack continuous access to piped water in Amman.
- Outdoor water use is much less in Amman than the East Bay.
- Water price is higher in Amman than the East Bay (~twice as expensive)
- Incomes are generally lower in Amman than the East Bay.
- Cultural differences lead to different water use behavior

Despite the differences between Jordan and the EBMUD service area, the model can be tailored and recast for the EBMUD metered homes.

A summary of the data sources used to develop the model is presented, followed by a review of the neighborhood being modeled. After that, the existing conditions use model and least-cost conservation model are detailed and results are discussed.

Summary of Data Sources

An increasingly popular technique to estimate indoor end uses of water is to install data loggers that record meter readings at short time intervals (~10 seconds), and then apply signal processing software to disaggregate water use events by end use from the meter readings. The signal processing software developed by Aquacraft (TraceWizard) has been used in end use studies throughout the U.S. and other countries (Mayer & DeOreo 1999, Roberts 2005, DeOreo et al. 2011). The data from these end use studies is the foundation for this modeling effort, and Aquacraft has provided the base data from several of its studies. A summary of the studies and their applicability to the model developed here is discussed next, followed by a summary of the market penetration studies used to develop the model.

End Use Studies

Much of the data used in the development of the model comes from end use studies. As the first major measurement study attempting to classify residential water use into end uses, the Residential End Uses of Water Study (REUWS) analyzed 10-second meter readings at over 1,000 houses across the U.S (Mayer & DeOreo 1999). It has the largest sample size of any of the end use studies, but its results have been superseded by newer end use studies more likely to reflect more recent water use patterns. The EBMUD Retrofit dataset contains end use measurements on pre- and post-retrofit homes to assess the effectiveness of retrofits (Mayer et al. 2003). The Yarra Valley Homes Study was one of the first applications of the end use measurement techniques outside the U.S., providing data on the relative frequency of full flushes and half flushes, since dual-flush toilets are popular in Australia (Roberts 2005). The California single-family residential (SFR) dataset includes sites across California, and its relatively large sample size means the data are more reliable for parameters that do not vary much from study to study (e.g. number of toilet flushes per day) (DeOreo et al. 2011). Many of the parameter distributions in the model are based on the "standard new homes" dataset, which only included houses built after 2001 (DeOreo 2011). The "high efficiency homes" dataset, while small, contains only homes built after 2001 that have been equipped with the best available conserving devices (DeOreo 2011). This dataset provides information on flow rates of new fixtures, such as high efficiency toilets. A summary of the datasets is in Table 1.

Table 1: Summary of End Use Study Datasets

Dataset	Location	Sample Size	Source
REUWS	United States	1188	Mayer & DeOreo (1999)
EBMUD Retrofit	EBMUD	33	Mayer et al. (2003)
Yarra Valley Homes	Melbourne, AUS	100	Roberts (2005)
California SFR	California	735	DeOreo et al. (2011)
Standard New Homes	United States	302	DeOreo (2011)
High Efficiency Homes	CA, OR	22	DeOreo (2011)

Market Penetration Studies

Other information used to develop the model comes from market penetration studies of conservation devices. These studies either include site visits to homes or surveys to estimate the adoption and use of conservation devices (e.g. high efficiency toilets). A market penetration study from 2002 included 287 site visits to residential homes in the EBMUD service area (EBMUD 2002). A similar study in Santa Clara is also helpful to verify reasonable ranges of the data (Santa Clara 2004). In addition to these site-visit studies, nearly all of the end use studies previously mentioned also included surveys (DeOreo 2011, DeOreo et al. 2011). While site visits are more reliable, the surveys reflect more recent conditions, so they were more appropriate in estimating some parameters.

EBMUD Metered Data

EBMUD provided metered data for 151 households in a neighborhood in San Ramon, CA to calibrate the model. The physical addresses of the homes were provided so that information about the lots could be retrieved, but the metered data records were placed in random order to maintain anonymity. Since a small, localized sample of homes was used, the results are not representative of the EBMUD service area as a whole. Understanding the location and types of houses metered is essential to appropriately use the metered data. A discussion of the data quality follows this, and initial findings from the metered data are reported.

Site Locations

The EBMUD service area is split by the Oakland Hills. West of the hills, there is more precipitation, cooler temperatures, and fewer sunny days. Residential parcels east of the hills are generally larger and have warmer temperatures. This leads to more outdoor water use east of the hills, causing the overall household water use rates to be higher, as Figure 1 shows (EBMUD 2011).

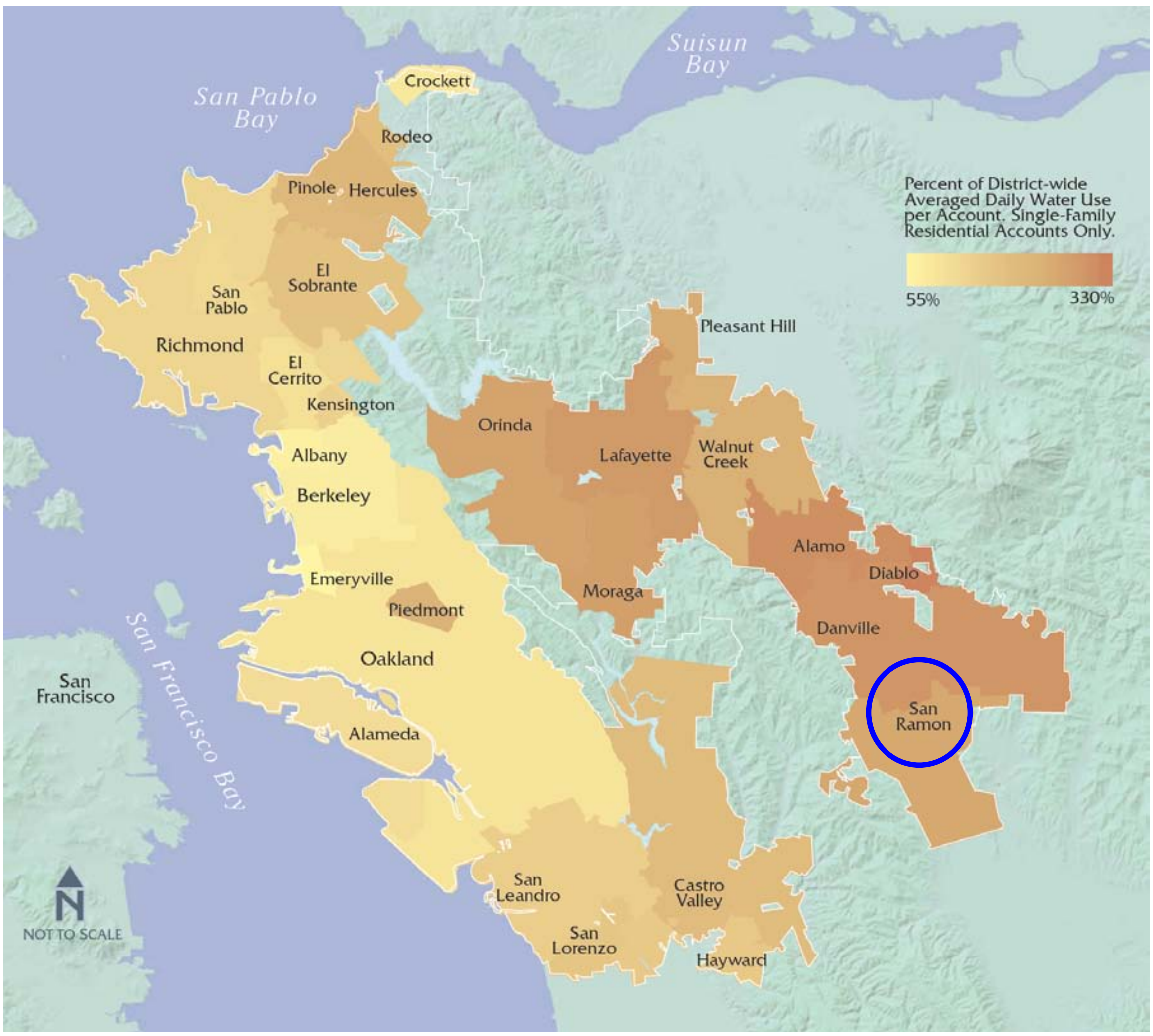

Figure 1: Geographic distribution of household water use rates (the circled area is the location of the metered data) (EBMUD 2011)

The metered single-family residential homes are in San Ramon, east of the hills, so the metered data should have more outdoor water use than the average EBMUD household. Furthermore, the houses are in an affluent neighborhood near a golf course, where the median selling price of homes was approximately $900,000 as of 2011 (Zillow 2011). Since many of the homes were built around 2000, the standard new homes dataset is particularly applicable to the neighborhood (Zillow 2011). The locations of the metered homes are shown in Figure 2.

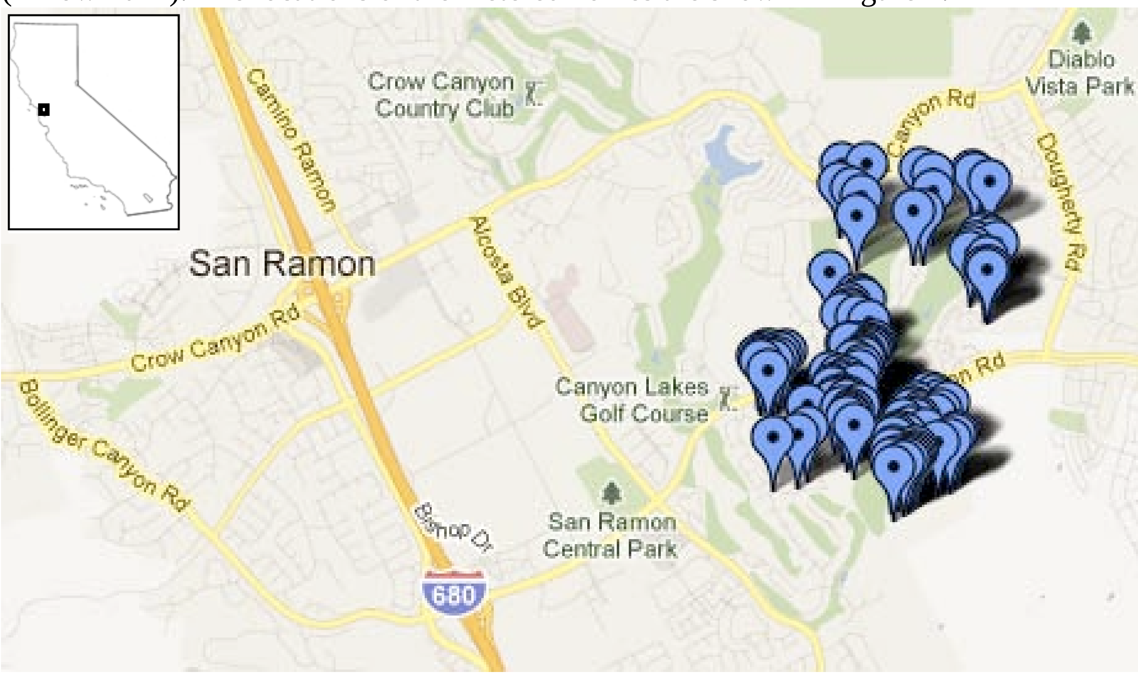

Figure 2: Metered Data Sites

Data Quality

While the most homes in the EBMUD service area are billed bimonthly, approximately hourly meter readings were taken from the homes that the metered data was provided for using automatic metering systems (AMS). This hourly data can be used to discern diurnal and weekly trends that billing records do not capture. The metered data provides readings from September 2006 to May 2011. During this period, a drought and a financial recession reduced water usage across EBMUD (EBMUD 2011). Not all measurements are reliable, and 17 of the meters were screened out due to spurious data, such as erratic readings, abrupt changes, and metered durations less than 6 months. Other small errors existed in the data, but these were screened and corrected. A summary of the data and screening procedures is given in Appendix A.

Findings from the Metered Data

Since the data provided was nearly hourly, it provides a wealth of insight into the water use patterns in the neighborhood. The annual use patterns, diurnal use patterns, and leakage rates can all be derived from the hourly metered data.

Seasonal Use Rates

The seasonal pattern of use has the expected pattern of higher water use in the summer and lower use rates in the winter. However, these metered sites appear to have more difference between summer and winter use rates than the average EBMUD home. This is expected, as these homes are east of the hills and have larger lot sizes, leading to more outdoor use. The seasonal use pattern can be used as a proxy for the split between indoor uses and outdoor uses, as most of the difference between summer and winter use rates is from outdoor uses (Mayer & DeOreo 1999). Figure 3 shows the seasonal pattern of use at the metered sites and the EBMUD service area as a whole.

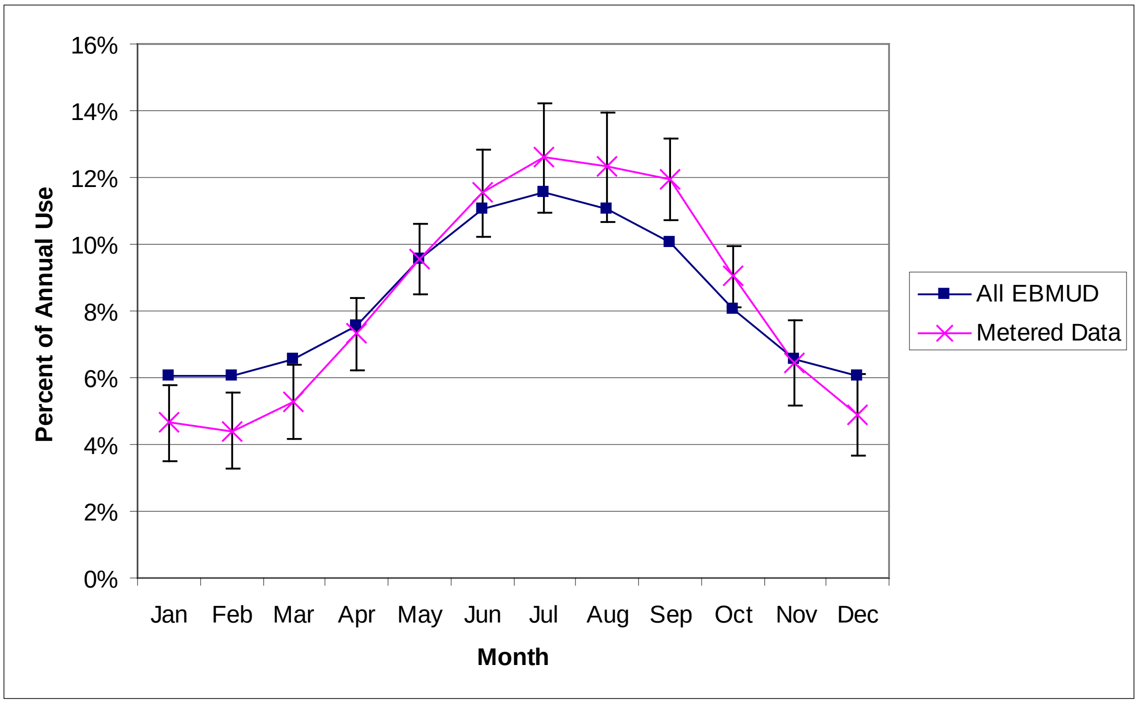

Figure 3: Seasonal Patterns of Water Use, 2006-2011 (error bars are 25th and 75th percentiles) (EBMUD 2011)

Diurnal Use Rates

Examining the diurnal use of the metered sites can reveal what times of day water use rates are highest. Early morning use rates can provide indirect estimates of outdoor use, but the data was not consistent enough to make this inference valid. Figure 4 shows a comparison of the diurnal use patterns of the metered homes to diurnal patterns across California (DeOreo et al., 2011).

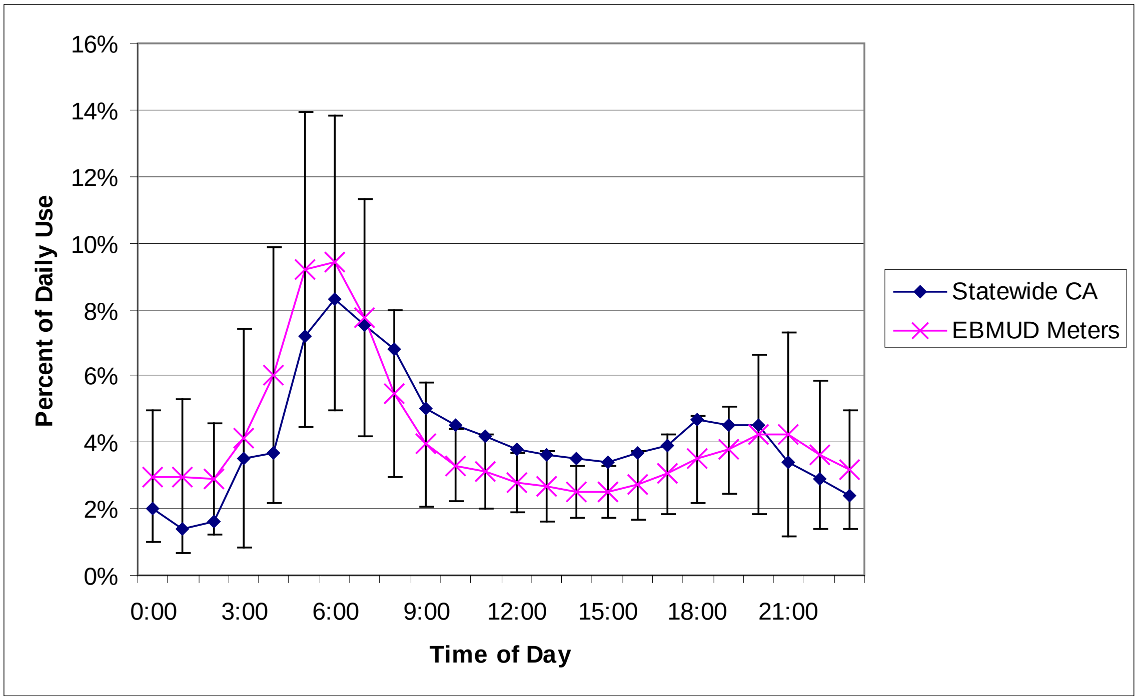

Figure 4: Diurnal Water Use Patterns, 2006-2011 (error bars are 25th and 75th percentiles) (DeOreo et al., 2011)

The large variability of water use in the morning and evening precludes sweeping generalizations from the data, but a dual-peak pattern is evident. Interestingly, the average water use in the early morning (midnight-4:00 a.m.) is slightly higher than the average use rates in the afternoon (noon-4:00 p.m.) at the metered homes, signaling the outdoor use in the metered houses is above average. The early morning water use for the metered sites also exceeds the statewide average, implying that these metered homes are using more water outdoors than the statewide average.

Leakage Rates

Inferring leakage rates from the metered data is not as straightforward as calculating the seasonal and diurnal use patterns. While leakage is intuitively easy to understand as a constant source of water use (e.g. leaking toilet flapper, dripping faucet), there are many ways to estimate leakage rates from hourly metered data. Possible confounding factors in the calculations include:

1. **Meter error:** There are measurement errors in any field measurements—water meters are no exception.
2. **Slow leaks:** Some leaks may be too gradual for AMS meters to detect on an hourly basis due to limited precision.
3. **Vacancy:** If a house changes ownership, water use may drop to zero occur during the transition period.
4. **Temporally-varying water use habits:** Some homeowners may manually turn off the water when going on vacation, which would conceal any normal leakage actually present in the system. Other homes may not ever have a time of day that no water is being used inside or outside the house (e.g. forgetting to change the automatic sprinkler timer, irregular sleeping patterns leading to frequent night-time toilet use).

The method employed in this paper to estimate leakage rates for individual homes attempts to circumvent some of these confounding factors. A cyclic analysis is performed on the hourly data, developing statistics for water use at each hour of the day, and the minimum hourly 10th percentile water use was taken as the leakage rate. This usually occurs in the early morning when other water uses are low, and since the minimum hourly point is taken, it constitutes a "base" water use that all the other hours of the day build off of. The 10th percentile was chosen to compensate for the confounding factors, as the absolute minimum hourly use rate was 0 for every house. The results from this method of calculating leakage are plotted along with a statewide average from an end use study in Figure 5.

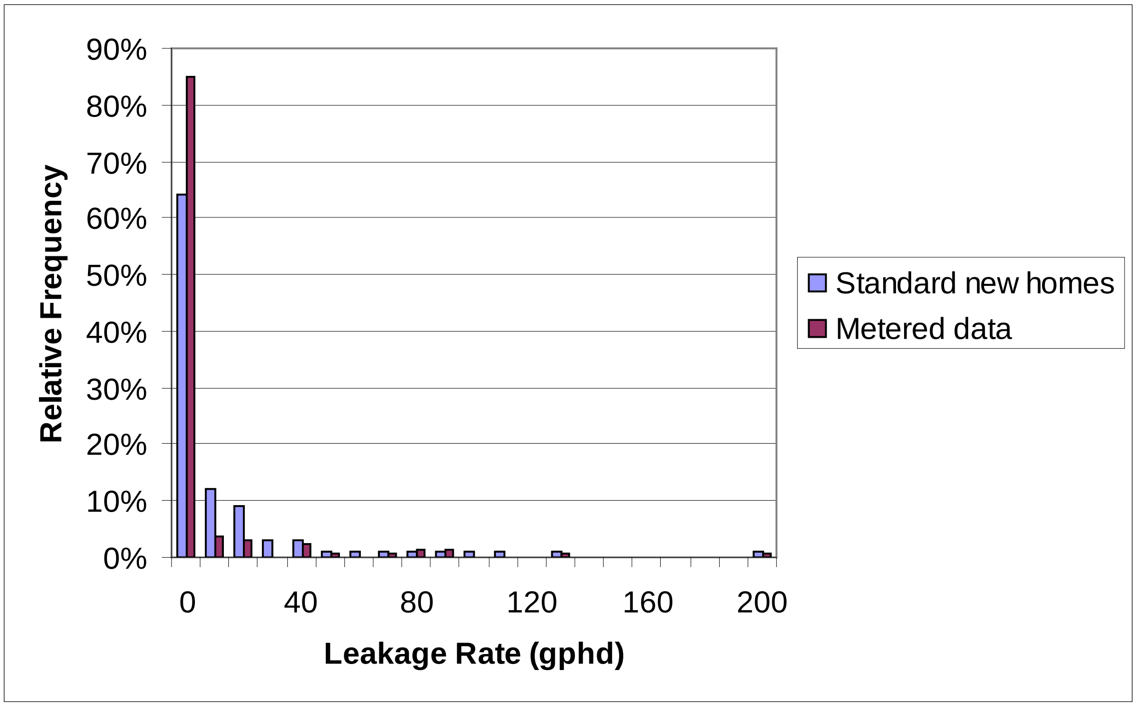

Figure 5: Leakage rates from metered data compared to estimates of "standard new home" leakage rates (DeOreo 2011)

The leakage rates calculated from the metered data show a larger proportion of houses with no leakage (85%) than typical standard new homes. Overall, the leakage rates are lower in the metered data—only two of the metered homes had leakage rates above 100 gallons per household per day (gphd). It is possible that the actual leakage rates of the home are higher than the values calculated, but the calculated leakage rates are in the same general range as the literature suggests.

"Existing Conditions" Use Model

The "existing conditions" model estimates household water use by end use. In this model, conservation devices such as high efficiency toilets (HETs) are present in their assumed market penetration rates, and the households make no behavioral changes. Since it models existing conditions, calibration uses metered data. The model is partially a stepping-stone to the "least-cost conservation" model. Also, as a simulation model, it allows evaluation of specific alternatives for their effect on total water use (e.g. What would the water use be if all households installed warm-season turf?, Where is most water being used indoors?, etc.). The model also produces conservation device sizing curves, which show the expected water savings for varying market penetration rates. Microsoft Excel was used to develop the existing conditions model. The steps to develop the model are:

1. Develop parameter probability distributions
2. Sample distributions to create a "house"
3. Calculate water use from parameter sample
4. Repeat steps 2-3 until convergence (Monte Carlo iterations)
5. Calibrate and test results to metered data

Parameter Probability Distributions

Many parameters affect household water use (e.g. type of toilets, number of people, lot size, etc.). Instead of assuming average numbers for each parameter, probability distributions are used, which capture the variance as well as the mean values. In the model, 69 parameters are used to define the water use of each house. A sample parameter distribution for the length of showers is shown in Figure 6. Appendix B identifies the parameters and summarizes the distributions.

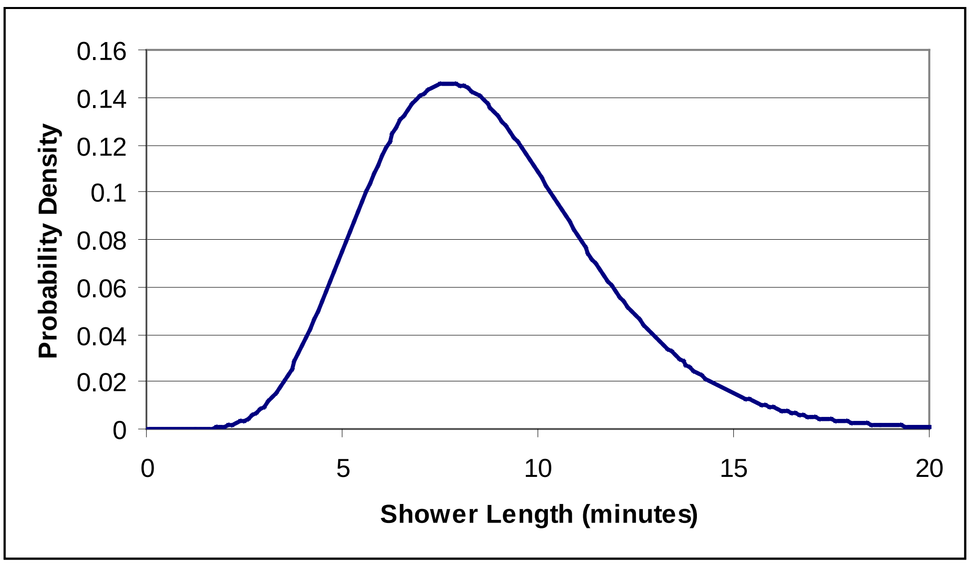

Figure 6: Distribution of shower lengths (DeOreo et al. 2011)

The distributions of these parameters were taken from end use studies or other literature, when available; otherwise, engineering estimates were used. Since Aquacraft shared the base data from their end use studies, distributions could be fit to the data. The distribution with the smallest Kolmogorov-Smirnov goodness of fit value was used when fitting distributions (Smirnov 1948).

If no distribution fit the data well, then histograms with small spacing were used as the distributions. Such was the case with leaks, as most homes have little leakage, but a few homes have very large leakage, and no simple distribution can accommodate this extreme double-peaked nature (DeOreo et al. 2011). Generally, data from the standard new homes dataset was used, but developing distributions for some parameters was a bit more complex.
The distributions of flow rates of indoor devices could not be drawn directly from the data, as most of the studies included a mix of houses with varying device classifications (i.e. some homes in the study had efficient clotheswashers while others did not). Since the homes are heterogeneous, it is impossible to determine the distributions of the flow rate of a "standard" device (e.g. showerheads) from one dataset alone. Fortunately, one end use dataset included exclusively high-efficiency homes, which contained the best available water conserving devices, such as HETs and efficient laundry machines. This dataset could be used directly to determine the distributions of the flow rate of HETs, efficient laundry machines, etc. Calculating the distribution of a "standard" device could then be back-calculated. The frequency of the high-efficiency appliances for an end use study is estimated from surveys, and the known distributions of the high-efficiency fixtures can be factored and subtracted off of the base distribution to arrive at a distribution representing the flow rate of a "standard" device. Such an approach was used for toilets, showerheads, and laundry machines (DeOreo et al. 2011).

Random Sample Process

Once the parameter distributions have been defined, the physical and behavioral skeleton of each house must be constructed before water use can be calculated. To create a "house" (single Monte-Carlo sample), each parameter distribution must be randomly sampled. For example, using the shower length distribution mentioned previously, the corresponding cumulative probability density (CDF) plot for the shower length parameter is shown in Figure 7.

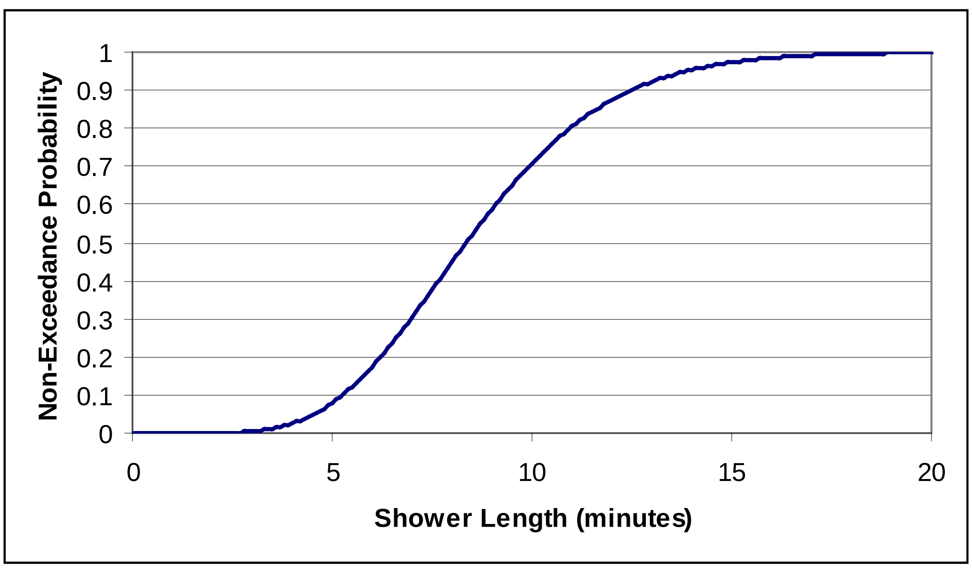

Figure 7: Cumulative distribution function (CDF) for shower length. Non-exceedance probability is the proportion of houses with parameters below the given value (DeOreo et al., 2011)

To randomly sample each parameter, a random number between 0 and 1 is drawn and taken as the non-exceedance probability. The corresponding parameter value is then used for the house. For example, if the random number drawn is 0.95, the household is assumed to take 15 minute showers. Each parameter is sampled independently, without accounting for covariances between parameters. While such covariances do exist in the end use data, they were not included to simplify the model. Random numbers are drawn for each parameter, and the process is repeated for each household to create the "initial conditions".

Calculation of Water Use from Parameters

After the parameters have been randomly sampled for a household, relations between the parameters are used to estimate the water demand by end use. For example, water used for laundry purposes is taken as (Q in units of gphd):

$$Q = \left(\frac{\text{gal}}{\text{cycle}}\right)\left(\frac{\text{cycles}}{\text{week} \cdot \text{person}}\right)\left(\frac{\text{persons}}{\text{house}}\right)\left[\frac{1\,\text{week}}{7\,\text{days}}\right]$$

Equations have been developed for each end use, and they can be found in Appendix C. The water use for each end use is calculated for each house in the Monte Carlo loop. The model used two seasons (winter and summer) to further disaggregate the water use, as precipitation and evapotranspiration values are quite different in the summer and winter (CIMIS 2011, WRCC 2011). Calibrating the seasonal split of water use can also provide an indirect estimate of how well the model is predicting the indoor/outdoor split of water use.

Calibration to Metered Data

The results produced by the existing conditions model are compared to metered data to ensure that reasonable ranges of results are being produced. The model is fairly stable at 500 Monte Carlo iterations (i.e. 500 households). Only one parameter was calibrated to match the metered data—the percent of landscaped area that is lawn. This parameter was calibrated to a value of 65%, which seems reasonable (EBMUD 2002). Model results are compared to metered data to evaluate the goodness of fit.

Goodness of Fit

The Kolmogorov-Smirnov (K-S) 2-variable test can be used to test if the modeled and metered results are drawn from different distributions (Smirnov 1948). It tests:

H_0: Modeled and observed results are drawn from the same underlying distribution

H_a: Modeled and observed results are not drawn from the same underlying distribution

The Kolmogorov test statistic is calculated, and a p-value for the test is obtained. If this p-value is lower than some significance level (e.g. a=0.05), then the null hypothesis is rejected, signifying the modeled and observed results do not fit well. This goodness of fit method does not require the same number of modeled and observed data points, which makes it particularly well suited for Monte Carlo models. There are many other measures often used for goodness of fit testing, including Nash-Sutcliffe efficiencies and indices of agreement (Legates & McCabe 1999). However, such methods require that the underlying predictor variable values (parameters) are known for the observed data points. Since the household metered data were not provided with any information about the data points other than the geographic location, these measures cannot be used to quantify goodness-of-fit. In this application, there is no one-to-one relationship between a metered data point and a modeled data point.

Total Use

The metered data and the modeled results match well on average water use and distribution of use. The p-value for the K-S test is 0.36, so the Kolmogorov-Smirnov method suggests modeled and metered data may come from the same distribution. Figure 8 shows a plot of the CDF of the metered data and modeled use.

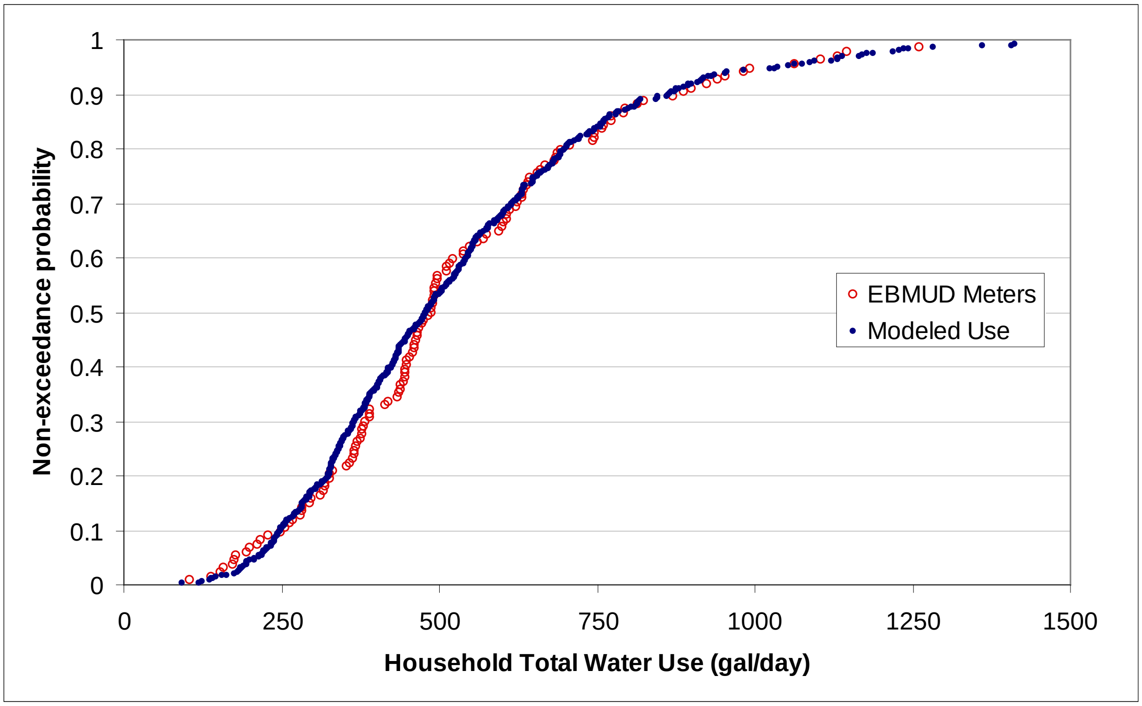

Figure 8: CDF of calibration of modeled use to metered data

Seasonal Use

If the model output is close to the metered summer and winter uses, it is likely that the model accurately predicts the split between indoor and outdoor uses. The K-S p-value for the summer months is 0.77, while the winter months only have a p-value of 0.14. This means that the modeled summer results more closely with the metered data than the results in the winter. Figure 9 shows that the model is indeed close to the metered seasonal split of water use. April through September comprise the summer months, while winter is taken as October-March.

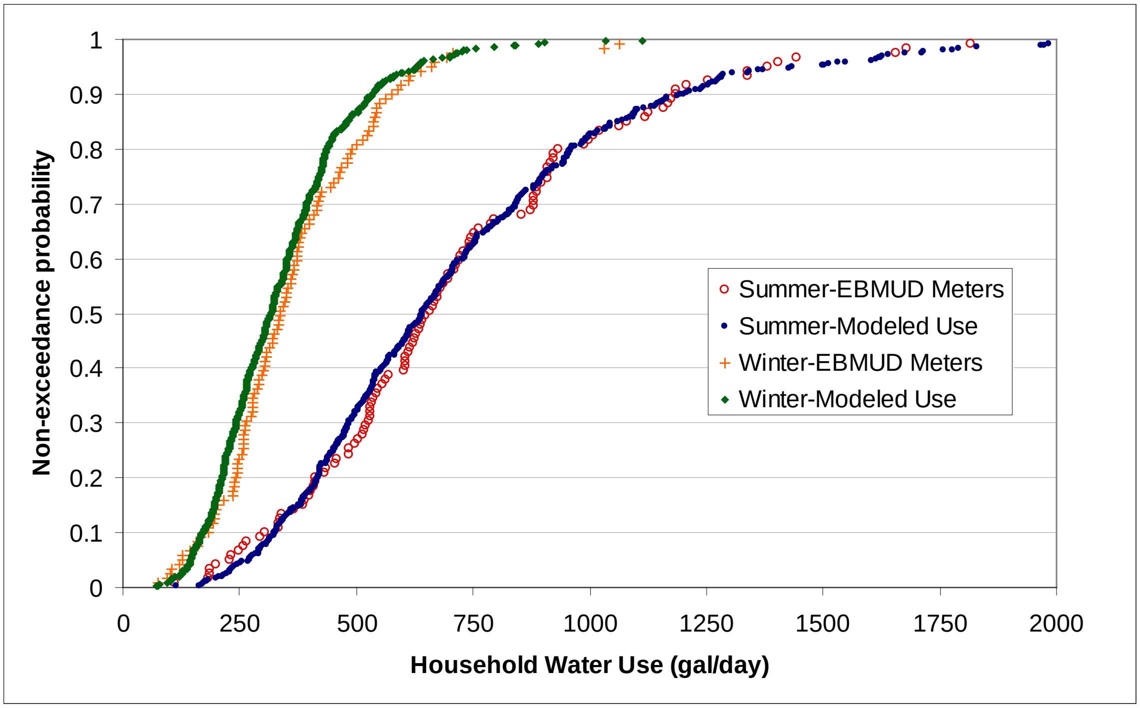

Figure 9: Calibration of modeled seasonal use to metered seasonal use

Comparison to End Use Studies

Even though many of the parameter distributions were taken directly from literature, it is important to check that each modeled end use is within a reasonable range. Comparing to end use studies can test the model and help catch oversights or miscalculations.

Summary of End Uses

Before moving on to individual end use distributions, a summary of the modeled results for each end use is compared to the findings from other end use studies in Figure 10. The modeled results line up closely with the standard new homes dataset, with the exception of outdoor use, as discussed earlier.

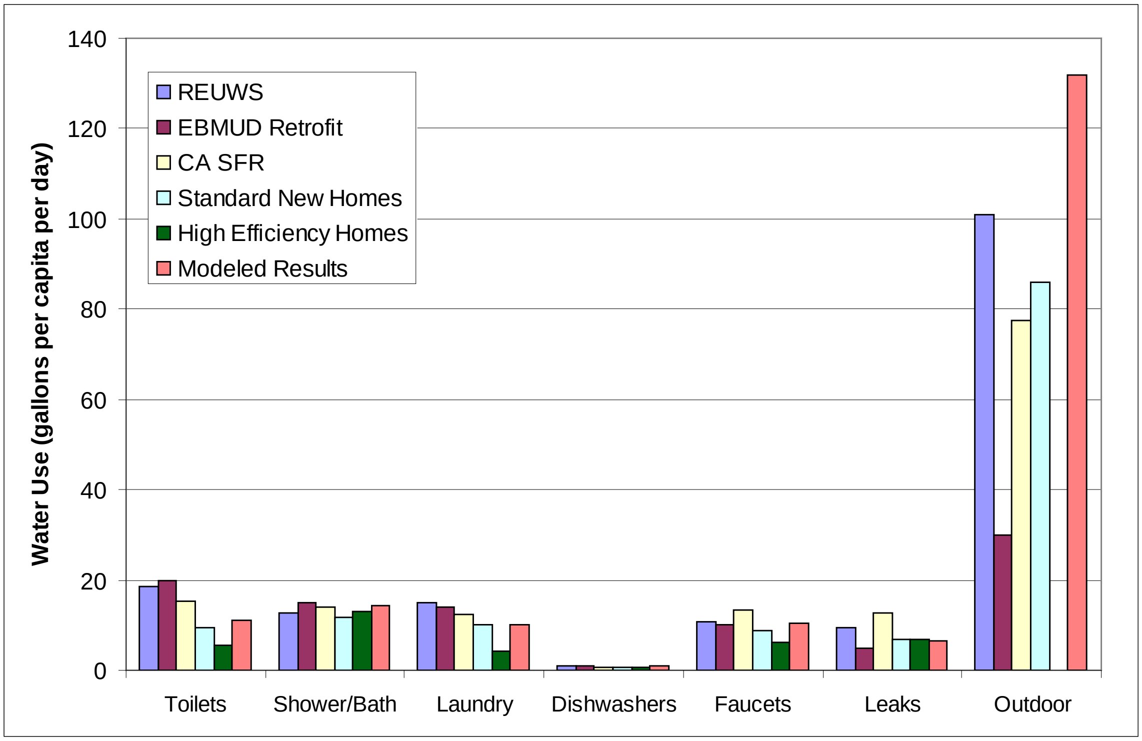

Figure 10: Average modeled end uses of water compared to end use studies

Total Indoor Water Use

Figure 11 shows a histogram of the modeled total indoor use compared to other end use studies. The modeled results line up most closely with the standard new home dataset, as expected.

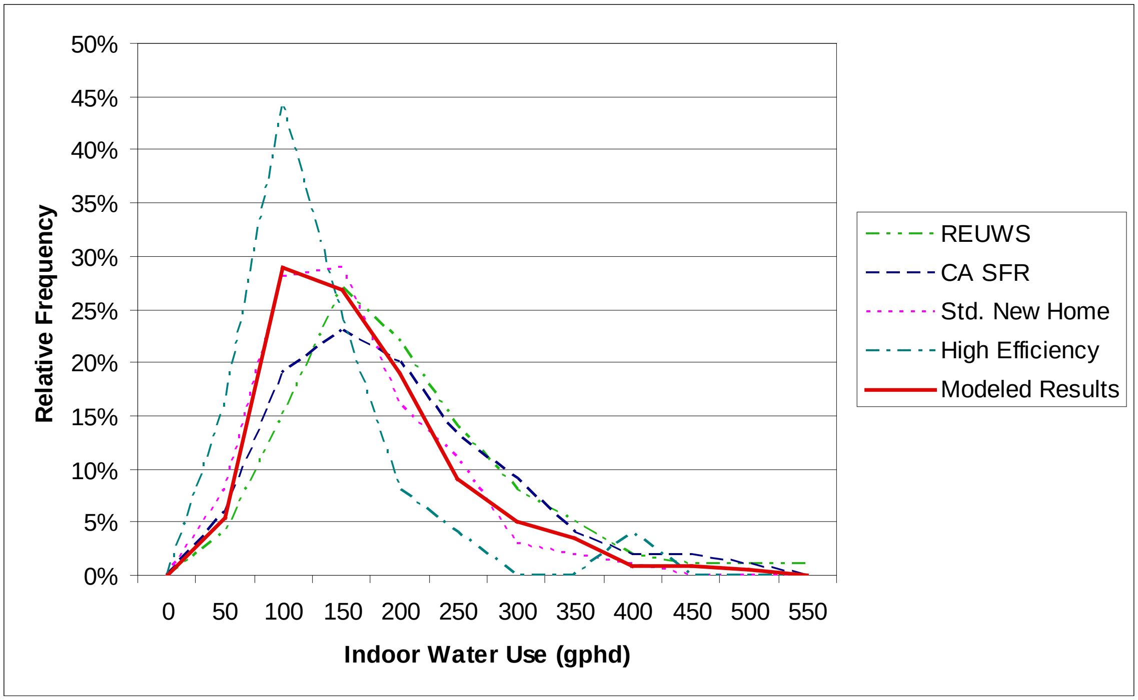

Figure 11: Modeled indoor use compared to end use studies

Toilet

Figure 12 compares the modeled toilet use to other end use studies. The modeled results are in a reasonable range of values.

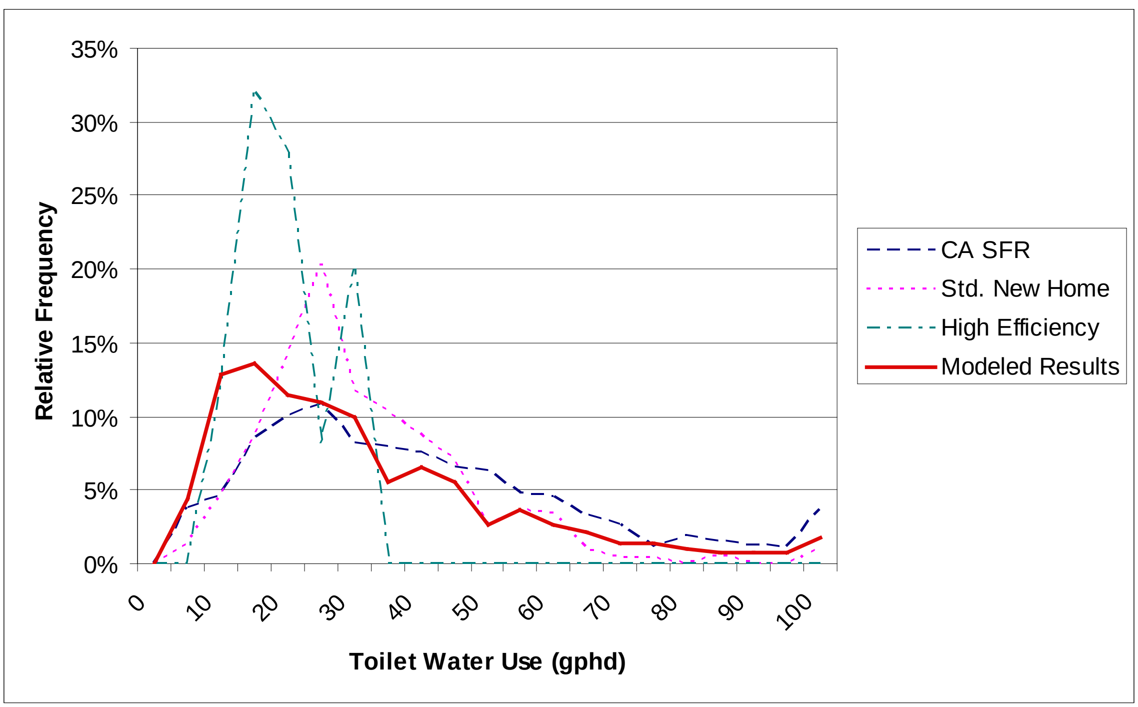

Figure 12: Modeled toilet use compared to end use studies

Shower

Figure 13 compares the modeled shower use to end use studies. The shower end use does not align as closely to other end use studies, perhaps partly from the lack of a "throttle factor" in the model. Often, residents don't use the full flow capacity of the showerhead, but instead use a reduced shower flow for comfort or temperature control (Mayer & DeOreo 1999). Gleick (2003) estimates this throttle factor as 66%, but there are no reliable, measurement based estimates of the range and frequency of this throttle factor, as the study would be invasive of privacy. This is a likely reason that many houses have high shower usage in the modeled results.

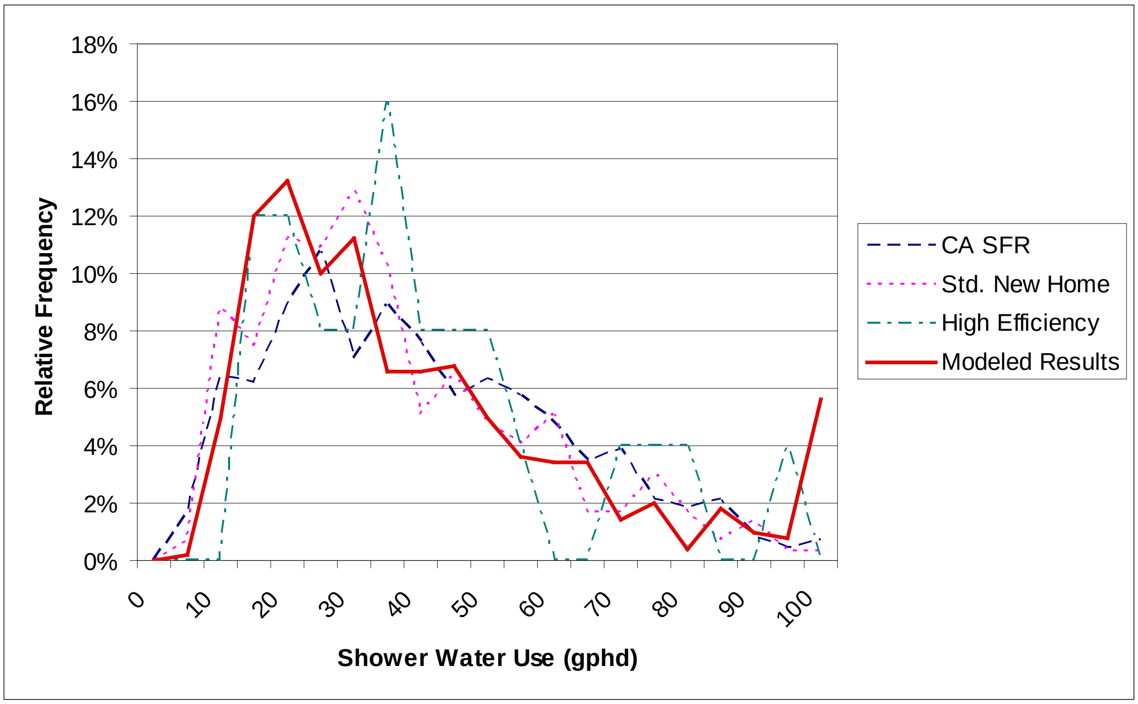

Figure 13: Modeled shower use compared to end use studies

Laundry

Figure 14 shows the modeled laundry uses compared to end use studies. The modeled laundry use appears reasonable in the range of end use studies.

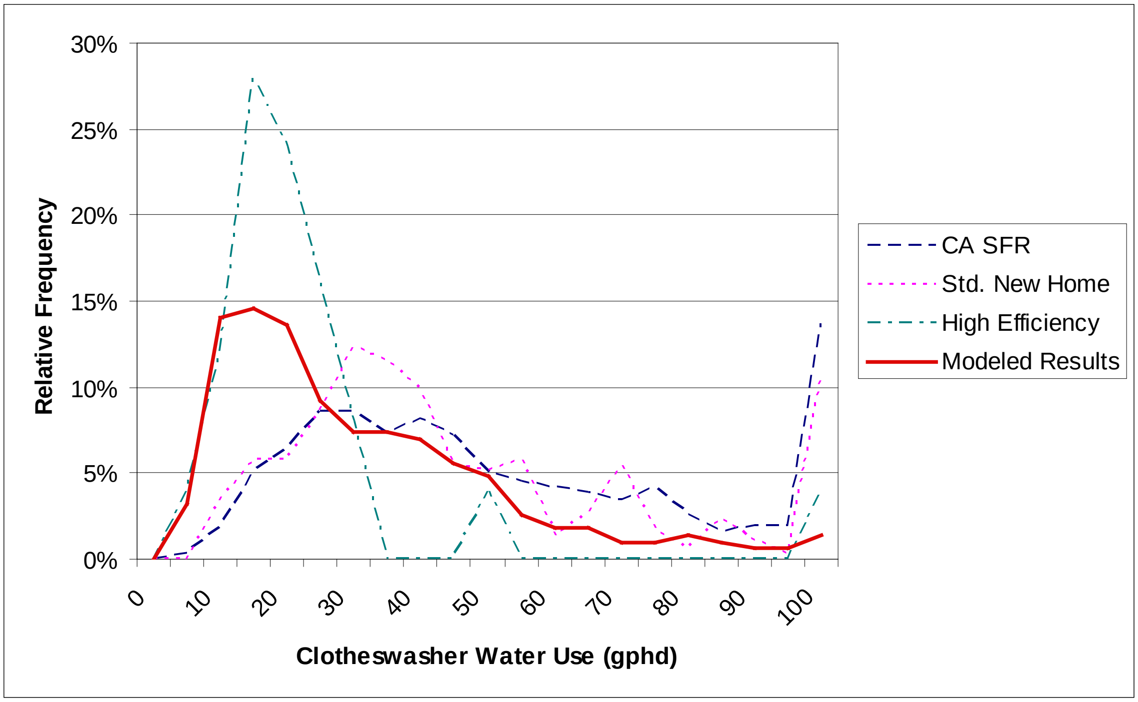

Figure 14: Modeled laundry use compared to end use studies

Faucets

Figure 15 shows a comparison of modeled faucet use to end use studies. The faucet use category is a kind of "catch-all" for many miscellaneous flow trace events, but the modeled results appear reasonable in the range of end use studies.

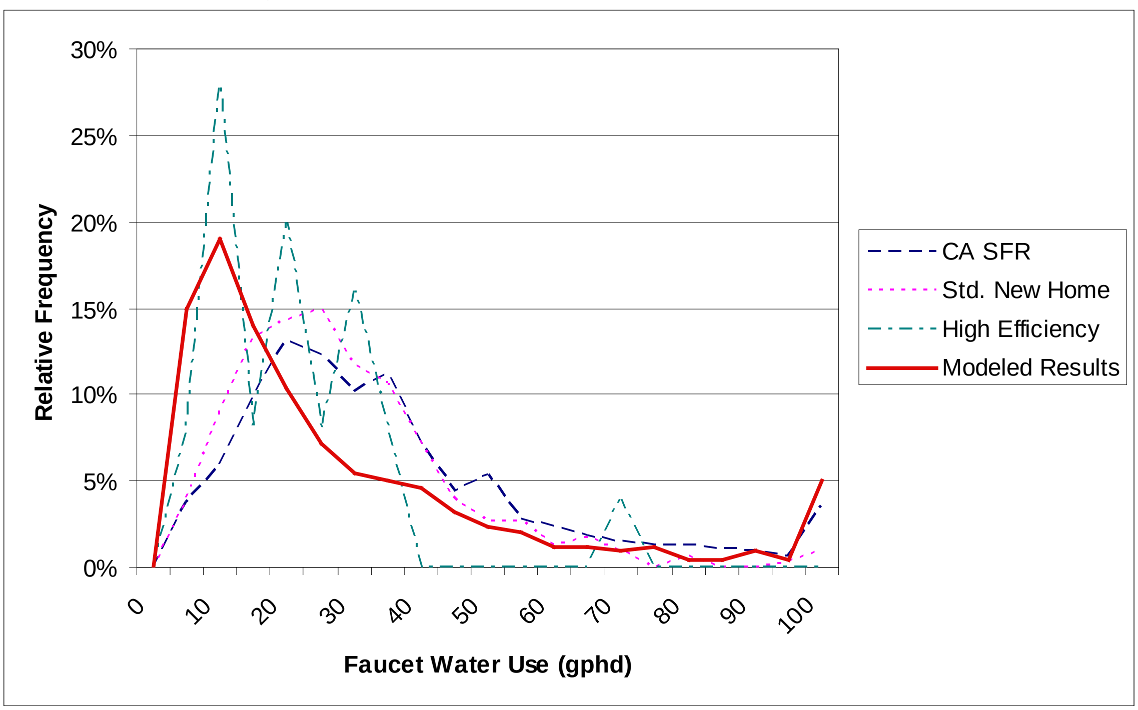

Figure 15: Modeled faucet use compared to end use studies

Assumption of Linearity with Household Size

The model assumes that indoor water uses linearly increases with household size. End use studies have repeatedly shown that this is not entirely the case, as Figure 16 shows.

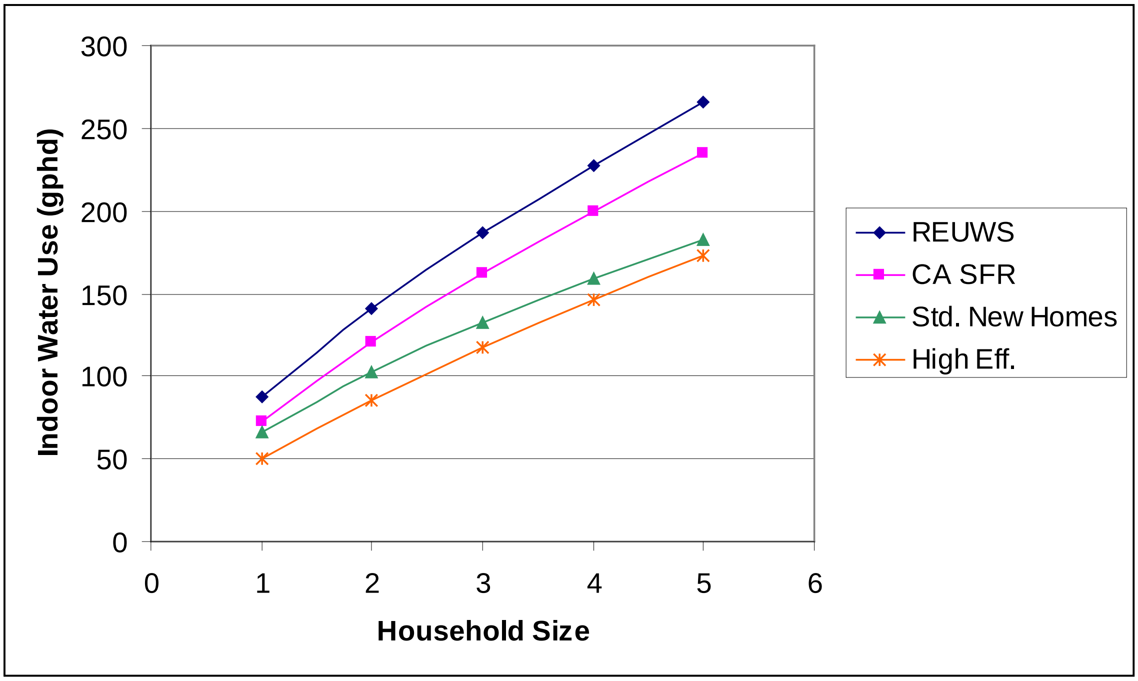

Figure 16: Nonlinear relationship between indoor water use and household size from multiple end use studies (DeOreo et al. 2011)

While the nonlinearity is not drastic, with each increase in household size, the indoor water increases by smaller amounts (i.e. a household of 4 uses slightly less water than double the use of a household of 2). While nonlinearity of total indoor use is informative, the relationship between household size and each end use shows which end uses are nonlinear with household size. Figure 17 shows these relationships using the data from the California SFR study.

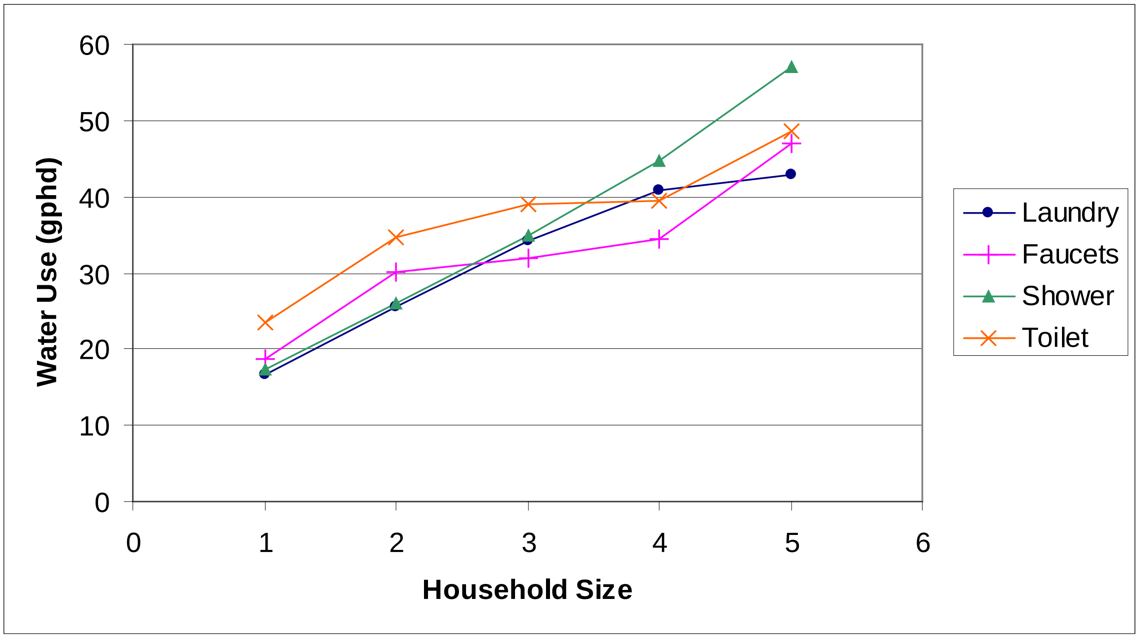

Figure 17: End use dependence on household size (DeOreo et al. 2011)

This graph does not show what is intuitively expected for some of the end uses. It seems reasonable to assume that the amount of water used to flush toilets would be linear with respect to residents, but per-capita toilet use decreases with increasing residents. Residents in larger households may spend less time at home, reducing per-capita toilet usage. Shower usage is linear with household size, while laundry use shows the expected pattern of tapering off with increasing household size, both of which seem reasonable. The faucet end use also tapers off with increasing residents. The sample size to generate this plot was just over 400, so a larger sample size might smooth the curves.

The assumption of linearity was used to simplify the model, as the curves in Figure 16 are fairly close to linear. Incorporating an indoor end use that does not depend linearly on household size, such as a "kitchen faucet" category, could introduce some non-linearities that might better reflect reality (Rosenberg et al. 2007).

Limitations of the Model

The existing conditions model computes quickly, taking about 10 seconds to sample parameters and calculate water use for 500 homes. However, it has limitations, including its inability to:

- **Predict individual home water usage**: Even if the physical characteristics of a real-world house are perfectly known, the model results should not be used for a point estimate, as there is wide variation in the water use of an individual house due to behavioral patterns. A point estimate could be made from a sample of predictions, however.
- **Predict actions homeowners will take to reduce water use**: This is the role of the least-cost conservation model.
- **Incorporate the effect of changing costs or rebates**: This is the role of the least-cost conservation model.

“Least-cost Conservation” Model

The “least-cost conservation” model builds on the existing conditions use model to include household behavior. In the least-cost model, each household has several available long-term and short-term conservation actions. Each conservation action has a house-specific effectiveness in reducing water use and an associated cost. For each household, a combination of these long-term and short-term conservation decisions exists that will minimize cost, and the least-cost conservation model finds this mix of actions. Each household is aware of the probabilities of future shortages and the price increases that will occur during each shortage event. As a stochastic optimization model with recourse decisions, the model may not actually predict what real homeowners will do, as it assumes cost-minimizing, rational behavior of all homeowners. However, the model results do provide a likely upper-bound of the conservation potential for the neighborhood. Viewed in this light, the model is a helpful complement to the existing conditions model. Since costs are embedded into the model, alternatives can be run through the least-cost conservation model reflecting different rebate policies or water pricing schemes, where the existing conditions model omits price in its calculations. Two runs of the least-cost conservation model are developed—one with financial costs only and one with financial and estimated hassle costs. Hassle costs reflect inconvenience costs to households beyond financial costs of conservation actions.

The steps to develop the model are as follows:

1. Define conservation actions and effectivenesses
2. Define event probabilities and water bill increases
3. Define costs of actions
4. Define and solve the optimization equations using linear programming

Conservation Actions

A list of the short-term and long-term conservation actions and the end use they apply to appears in Table 1. Note that short-term actions can be activated during each event, while long-term actions apply to all events, if activated. None of the decisions households can make will increase their water use, although in reality some homeowners might be willing to pay more for increased use (e.g. operating a slip ‘n slide, purchasing a decorative fountain, etc.).

Table 2: Conservation actions available to households in the model

End Use Affected	Long-term Actions	Short-term Actions
Shower	Retrofit showerheads	Reduce shower length Reduce shower-taking frequency
Toilet	Retrofit all standard toilets with HETs Retrofit all standard toilets with ULFTs Retrofit all ULFTs with HETs	Flush only when necessary
Faucet	Retrofit bathroom faucets	Turn off faucets while washing
Laundry	Install conserving laundry machine	Reduce laundry-washing frequency
Leaks		Find and fix leaks
Lawn	Install xeriscape Install warm-season turf Install artificial turf Install smart irrigation controller	Stress irrigate
Garden/Landscape	Install xeriscape Install drip irrigation system Install smart irrigation controller	Stress irrigate
Car Wash		Wash car with buckets Wash car at gas station
Pool		Stop filling swimming pool

Effectivenesses of Actions

Each conservation action saves a given amount of water (effectiveness), depending on the initial state of the household. For example, the relationship estimating the amount of water saved by installing a water-conserving laundry machine is shown below: (homes that already have an efficient laundry machine have an effectiveness of 0)

$$Q_s = \left(\left(\frac{\text{gal}}{\text{cycle}} \text{Std.} \right) - \left(\frac{\text{gal}}{\text{cycle}} \text{Efficient} \right) \right) \left(\frac{\text{cycles}}{\text{week} \cdot \text{person}} \right) \left(\frac{\text{persons}}{\text{house}} \right) \left[\frac{1\,\text{week}}{7\,\text{days}} \right]$$

Since each house in the Monte Carlo iterations has a different value for each of the randomly sampled parameters in the above equation, the amount of water saved by replacing a laundry machine will vary by household. Equations to determine the effectiveness of each conservation action are listed in Appendix D.

Mutually Exclusive Actions

Some conservation actions are mutually exclusive, and the model includes these interdependencies. For example, a household cannot choose to wash their cars with buckets and choose to wash their cars at the car wash. The mutual exclusivities include:

1. Converting all standard toilets to ULFT, converting all standard toilets to HET, and converting all ULFT toilets to HET
2. Installing xeriscape, installing warm-season turf, and installing artificial turf
3. Washing cars with buckets, washing cars at a car wash

Mutually Requiring Actions

None of the short-term actions depend on the enactment of long-term actions, but if such a relation existed, it could be easily blended into the model. This could be the case if rainwater harvesting was included—the rainwater collecting tank would have to be installed before a household could decide whether or not to use it during each event (Rosenberg et al. 2007). However, some actions in the model require the enactment of other actions due to the discretization of the end uses. For example, since the "lawn" and "garden" are separate end uses to the model, a decision like installing a smart irrigation controller is assumed to apply to both lawn and garden, not just one or the other. The mutually requiring actions affecting both lawn and garden include:

1. Installing xeriscape
2. Installing a smart irrigation controller
3. Stress irrigation

Interactions Among Conservation Actions

One complication with having multiple conservation actions applying to the same end use is the interaction between conservation actions. A fundamental assumption in the formulation of a linear programming model is that the effectivenesses of actions are independent of the implementation levels of other actions (Dantzig 1963). This assumption is not completely accurate in the model—the amount of water saved is not a simple superposition of the effectiveness of each independent action. For example, a household could choose to reduce shower lengths and reduce shower frequencies. However, the total effectiveness of these actions together is not the sum of the effectiveness of each of these actions when implemented independently. Rather, the total water saved will be less than the sum of the effectiveness of each independent action, as taking shorter showers will reduce the effectiveness of reducing the frequency of showers and vice versa. To deal with this complication, the maximum possible savings is calculated for each end use based on the existing parameters, and the amount of water saved from each end use in the model is defined as a decision variable and capped to this amount. This approach works since only a few actions apply to each end use—if more actions are to be considered, a non-linear program would be needed to deal with this complication.

Costs

In any optimization model, the costs (penalties) of actions are the main driver of the results. Two distinct cost structures are considered: financial costs only, and financial plus hassle costs. Three components comprise the total cost to a household: the water bill, the cost of long-term actions, and the cost of short-term actions. Costs are summarized in Appendix E.

Water Bill

EBMUD bills its residential accounts bimonthly, and an increasing block rate is used to calculate the water bill. The water bill used in this model was based on the 2010 rate schedule, and includes both water and wastewater charges, more accurately reflecting the true cost to the homeowner (EBMUD 2010). The water and wastewater charges used in the model are in Table 3.

Table 3: Bimonthly water bill rates for elevation zone 2, 2010-2011 (EBMUD 2010)

		Volume Use Charges ($/CCF)		
	Fixed Charges	Block 1 (0 - 172 gphd)	Block 2 (172 - 393 gphd)	Block 3 (Above 393 gphd)
Water	$25.24	$2.69	$3.24	$3.88
Wastewater	$14.29	$0.63	$0.63	$0.63

The pricing scheme changes during shortages. Table 4 shows a summary of the additional water charges that vary with shortage levels. Various surcharges can be incurred by households during droughts, including (EBMUD 2011):

- **Water shortage surcharge**: When there is a water shortage, all water charges based on volume usage are increased by 10%. This is assumed to occur in 30% of all years.
- **Freeport surcharge**: In severe drought years, the water supply from the Sacramento River located at Freeport must be activated. The facility has substantial operating costs, which are passed on to the consumer as a 14% surcharge.
- **Rationing penalty surcharge**: EBMUD asks its residential customers to reduce their water by a percentage (20%-30% in this model) during shortages. A surcharge of $2.00/CCF applies to water use above the rationed amount.

Long-Term Actions

All long-term conservation actions include installing some sort of new water-saving feature (as opposed to behavioral change). Since the devices do not have an infinite lifespan, design lives were used to amortize the costs into annualized amounts, assuming a discount rate of 6%. Since each device in the house is modeled, the number of devices needing replacement is considered in the cost. For example, a house may have 3 toilets, one of which is HET, one of which is ULFT, and one of which is "standard". The model recognizes that 2 toilets must be replaced if all toilets are to become HET, and adjusts the cost accordingly.

The costs in the model reflect both the capital cost of the device and the installation cost. When only financial costs are considered, installation costs are the cost of professional installation. When hassle costs are considered, the installation cost is a bit more complex. Not all homeowners are assumed to be equally capable of installing devices, so cutoff proportions were used to reflect this in the model. Each house has a random "handiness factor" between 0 and 1, and if the household's handiness factor exceeds the cutoff proportion for a given action, the household is not able to install the device personally and must use professional installation. Households with handiness factors below the cutoff have the option of installing the device themselves or having it professionally installed (whichever is cheaper). Some tasks can be done by nearly anyone (e.g. changing out showerheads), while other, more difficult tasks have more restrictive handiness cutoffs (e.g. installing xeriscape). This arrangement better represents reality, as not all households are equally likely to self-install devices.

Short-Term Actions

The financial costs of nearly all short-term actions are zero, as they are behavioral changes rather than retrofits. There is no concept of a "handiness" factor for the short-term actions, as it is assumed that everyone can carry out these actions. This leads to some unrealistic behavior in the model run with financial costs only—nearly all short-term actions are implemented in every event because they save water and cost nothing to the household. To better reflect reality, hassle costs of actions must be included.

Hassle Costs

Often, households do not reduce consumption due to the hassle costs of conservation (Dolnica & Hurlimann 2010). As such, any model of conservation should include hassle costs, as financial costs alone do not explain homeowner behavior. Unfortunately, little has been written on calculating hassle costs of conservation activities. Contingent valuation studies are the preferred method of estimating hassle costs, but such studies do not exist for the water conservation activities considered in the model. In the absence of contingent valuation studies, economic literature relating to opportunity costs is the most appropriate. When hassle costs are included, the conservation actions are assumed to take a given amount of time, which can then be translated into a dollar amount based on the value of time to a particular household (Narasimhan 1984). To introduce uncertainty, the annual household income was converted to an hourly amount and used as the value of time for a household. Such an approach reflects a higher opportunity cost of time for higher income-earners, a common assumption in economics literature (Narasimhan 1984, Anderson and Song 2004). While these assumed hassle costs are certainly not scientific, they produce more realistic behavior than assuming no hassle costs.

Event Descriptions

Six different water shortage events are considered in the model—three events in the winter and the same three corresponding events in the summer to incorporate seasonal use patterns into the results. These events were based on the water shortage contingency plan in the EBMUD UWMP. The only difference between the water shortage events is the price paid for water by the homeowners. In other words, a household may use as much water as desired during a shortage event, but the price paid for water use will be higher. The optimization model assumes that households have knowledge of these drought probabilities and price increases, and consider them when determining the optimal mix of conservation actions. Table 4 gives a summary of the events and their corresponding water price increases.

Table 4: Description of events in the model

Event	Description	Probability	Volumetric use price increase (%)	Freeport surcharge? (14% increase)	Ration amount (% reduction in original use)	Penalty for exceeding rationed amount ($/CCF*)
	Summer					
1	Regular delivery	0.35	0%	no	0%	$0
2	Shortage	0.1	10%	no	20%	$2
3	Severe Shortage	0.05	10%	yes	30%	$2
	Winter					
4	Regular delivery	0.35	0%	no	0%	$0
5	Shortage	0.1	10%	no	20%	$2
6	Severe Shortage	0.05	10%	yes	30%	$2

* CCF=hundred cubic feet

Model Formulation

A two-stage mixed-integer linear program was used to formulate the optimization problem. The first stage consists of long-term actions and costs, and the second stage includes actions and costs for each short-term shortage event. For a complete description of all inputs to the optimization model, see Appendix F.

Decision Variables

To keep the model linear, a few non-intuitive decision variables are necessary. The decision variables are listed below.

$\underline{\mathbf{S}}_{s,e}$ = short term actions
$\underline{\mathbf{L}}_{l}$ = long term actions
$\underline{\mathbf{B}}_{e}$ = water bill ($/billing period)
$\underline{\mathbf{U}}_{e}$ = water use (gallons/day)
$\underline{\mathbf{E}}_{u,e}$ = end use saved (gallons/day)
$\underline{\mathbf{W}}_{e}$ = water saved (gallons/day)

Each subscript indicates a set that the decision variable is defined over. For example, B_e means that there is a separate decision variable for the water bill for each event e. Decision variables for the water bill, water use, etc. are not really "decisions" that the household has direct control over, but they are defined as decision variables to incorporate complexities, such as the piecewise-linear nature of water bills and interactions between conservation actions.

Objective Function

The objective function is:

$$\text{Minimize } Z = c_l(\underline{\mathbf{L}}) + j\sum_e \left[p_e\left(i\sum_s \left(c_s \underline{\mathbf{S}}_{s,e} \right) + \underline{\mathbf{B}}_e \right) \right]$$

Where:

c_l = annualized long-term action costs ($/year)
c_s = short-term action costs ($/day)
p_e = probability of event e
i = number of events per billing period (60 days/billing period)
j = number billing periods per year (6 billing periods/year)

Constraints

A summary of the constraints to the model is given below:

1. **Non-negativity**: No conservation action can have a negative value, which would increase the water use of a household.
2. **Discrete choices**: No conservation action can be partially implemented (e.g. a homeowner cannot replace half of his lawn with warm-season turf). Such a formulation would require a non-linear program to deal with the interactions among conservation actions.

3. **Maximum effectiveness**: The total amount of water saved cannot exceed the initial water use rate.
4. **Mutually exclusive actions**: Some actions are mutually exclusive (e.g. a homeowner cannot install warm-season turf and artificial turf).
5. **Mutually requiring actions**: Some actions are co-dependent on other actions (e.g. a smart irrigation controller must apply to both the lawn and garden end uses).
6. **Interactions between actions**: A maximum effectiveness was used to cap the amount of water saved for each end use, accounting for interactions between conservation actions (e.g. reducing shower length and reducing shower frequency).
7. **Increasing block water bills**: The price of a unit of water increases with the amount of water used.
8. **Rationing penalties**: If a household exceeds their rationed water use during a drought event, then a surcharge applies to the water bill. Including this constraint would not be possible if a decreasing block pricing scheme is used—in such a case a non-linear program would be required.

Solution Method

GAMS (Generic Algebraic Modeling System), an optimization software package, was used to perform the optimization (Rosenthal 2011). A total of 198 equations and 152 decision variables were used. The problem was formulated as a mixed-integer linear program, and the BDMLP solver package was used solve the model (Bussieck & Drud 2011). If more interrelated conservation actions are incorporated or the water bill is nonlinear instead of piecewise linear, then a nonlinear formulation will be necessary, as Rosenberg (2007) has shown. The current model formulation used simplifications to enable use of a linear program to decrease compute times.

Results

Results from base condition runs are presented, followed by the results of changing water price, indoor device rebates, and outdoor landscaping rebates.

Base condition runs

The results from "base conditions" runs are a benchmark for all alternative runs. These runs do not have rebates for any conservation actions, and water prices are at 2010 levels. Two separate base condition runs were computed—one with financial costs only and one including hassle costs. The average household use after adopting least-cost conservation actions is 480 gphd with financial costs only (510 gphd with hassle costs), while the average household use under the existing conditions model was 540 gphd. This is a reduction of 12% with financial costs only (6% with hassle costs), meaning it would be unexpected to achieve conservation beyond this amount under current water price rate structures and no rebates, as more conservation would not be cost-effective for the neighborhood and each home individually. Figure 18 shows water use after least-cost conservation compared to existing conditions use. Many high water users reduce consumption by large amounts, while the lower portion of the curve stays more stable, as low water users have less to save.

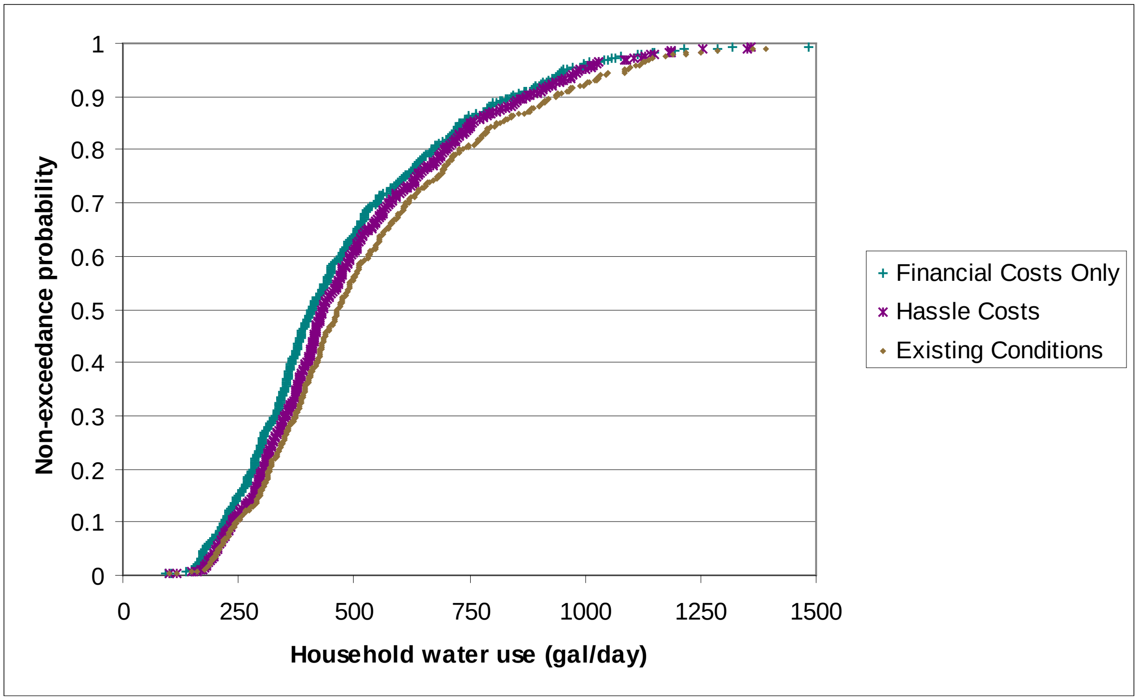

Figure 18: CDF of water use under existing conditions and least-cost conservation

The modeled adoption rates and ranges of effectiveness when indoor and outdoor long-term actions are implemented are shown in Figure 19 and Figure 21, respectively, for financial costs only. The corresponding graphs when hassle costs are considered are shown in Figure 20 and Figure 22. Note the differences in scales between the indoor and outdoor conservation action savings.

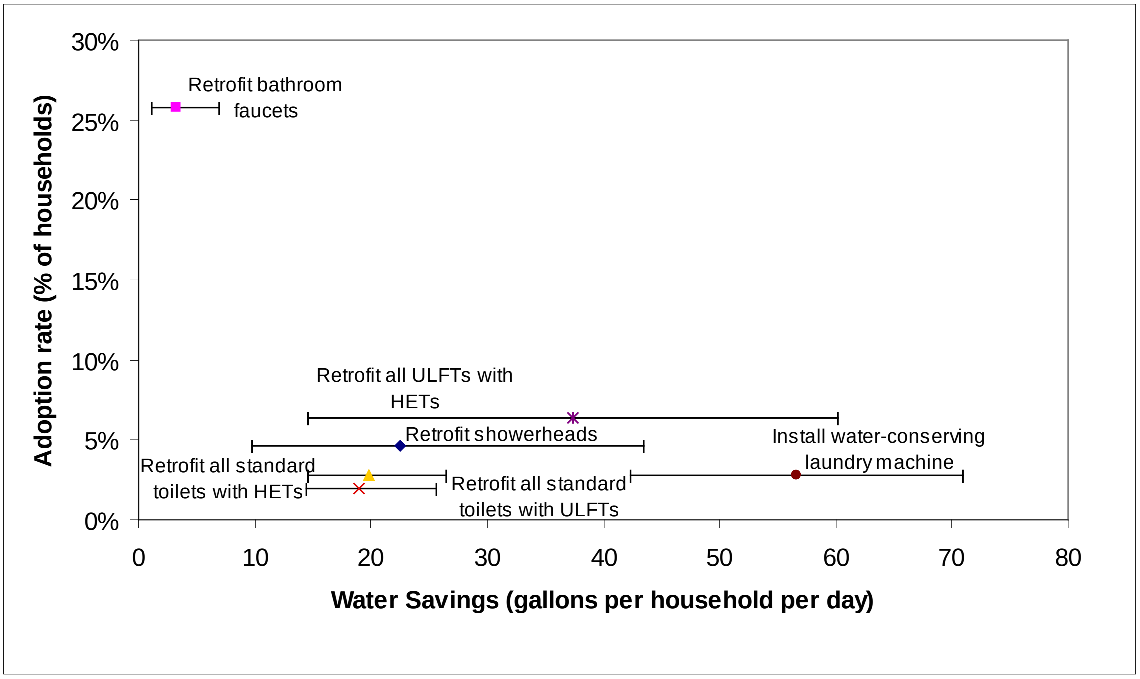

Figure 19: Modeled market penetration and water savings for long-term indoor conservation actions, base conditions run with financial costs only and artificial turf disallowed (error bars are 10th and 90th percentiles)

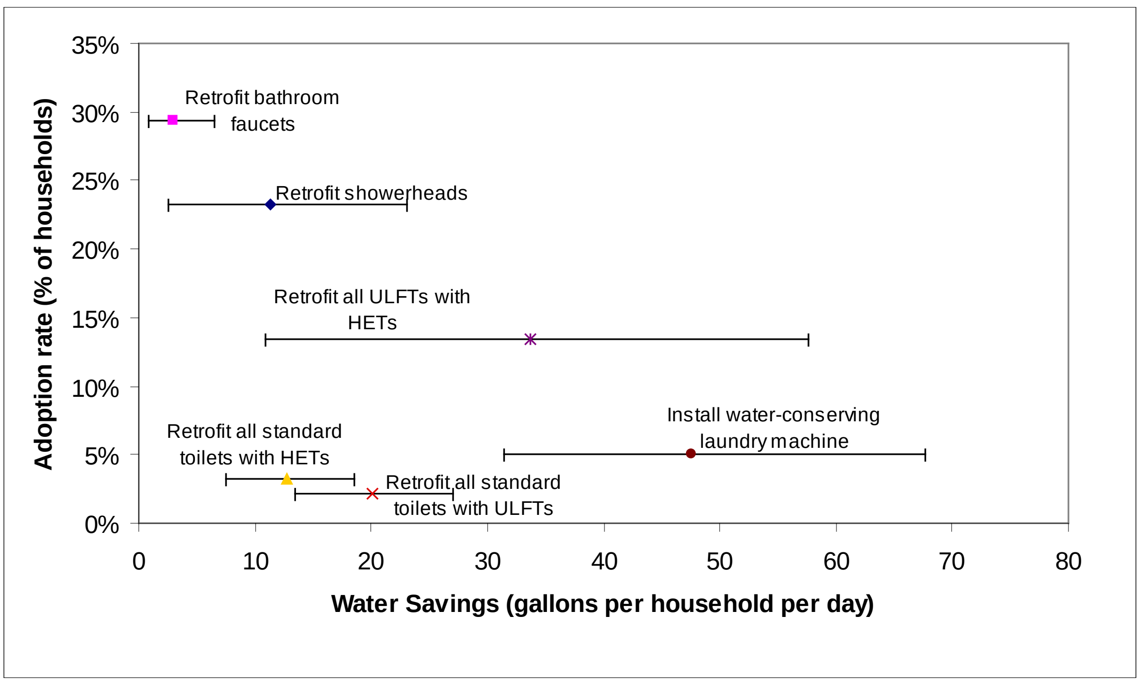

Figure 20: Modeled market penetration and water savings for long-term indoor conservation actions, base conditions run with hassle costs and artificial turf disallowed (error bars are 10th and 90th percentiles)

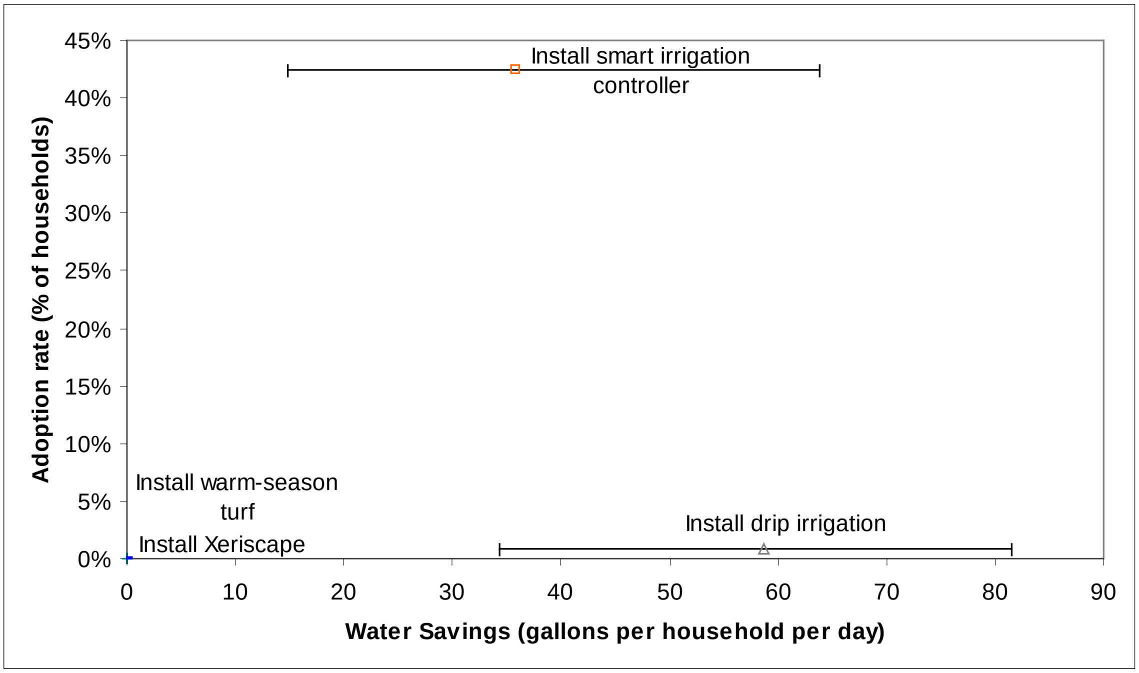

Figure 21: Modeled market penetration and water savings for long-term outdoor conservation actions, base conditions with financial costs only and artificial turf disallowed (error bars are 10th and 90th percentiles)

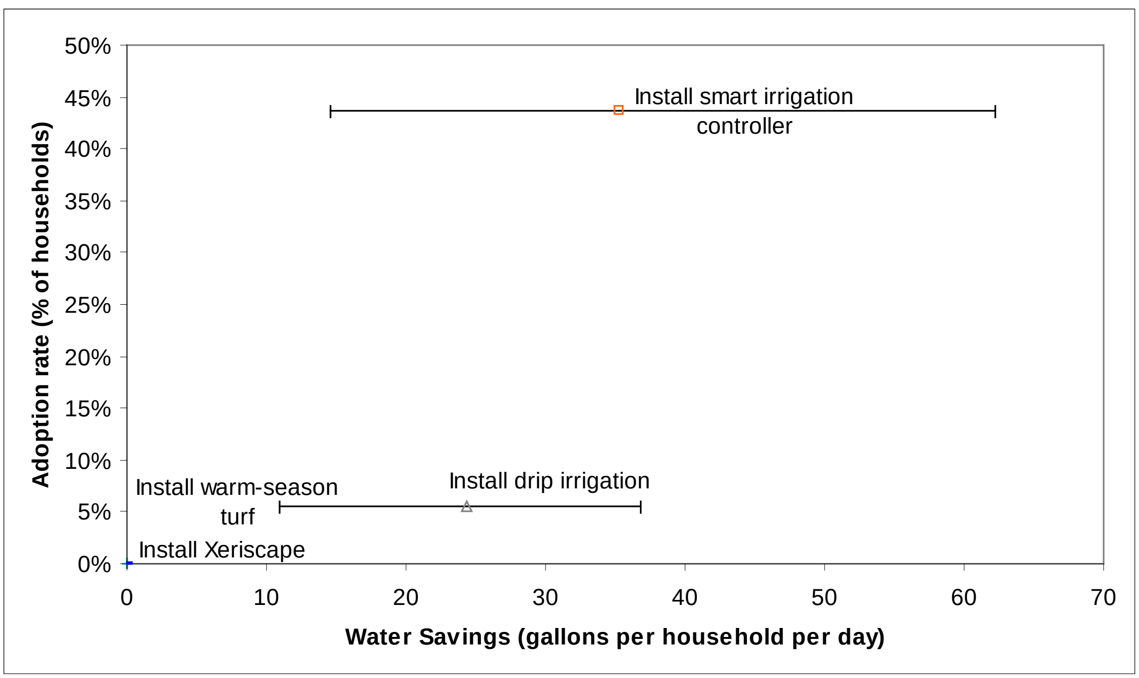

Figure 22: Modeled market penetration and water savings for long-term outdoor conservation actions, base conditions with hassle costs and artificial turf disallowed (error bars are 10th and 90th percentiles)

The relatively low implementation rates of the outdoor conservation activities signal that these conservation actions are not cost-effective for most households, but the households that implement them save large amounts of water. With current water price structures, no household finds it worthwhile to install xeriscape or warm-season turf. The indoor actions are implemented more often, but their savings are much less than outdoor conservation. Including hassle costs does not greatly affect the adoption rates of the long-term actions, but the frequency of implementation is actually higher when hassle costs are included. When hassle costs are not included, households must use professional installation, which is often more expensive to houses than doing the installation themselves.

The effectiveness and adoption frequency of short-term actions is not very interesting in the financial costs only scenario, because nearly all short-term actions are behavioral modifications that have no financial cost to adopt. In runs where hassle costs were considered, adoption of short-term conservation actions is not universal, and the relative frequency of adoption and effectiveness are shown in Figure 23.

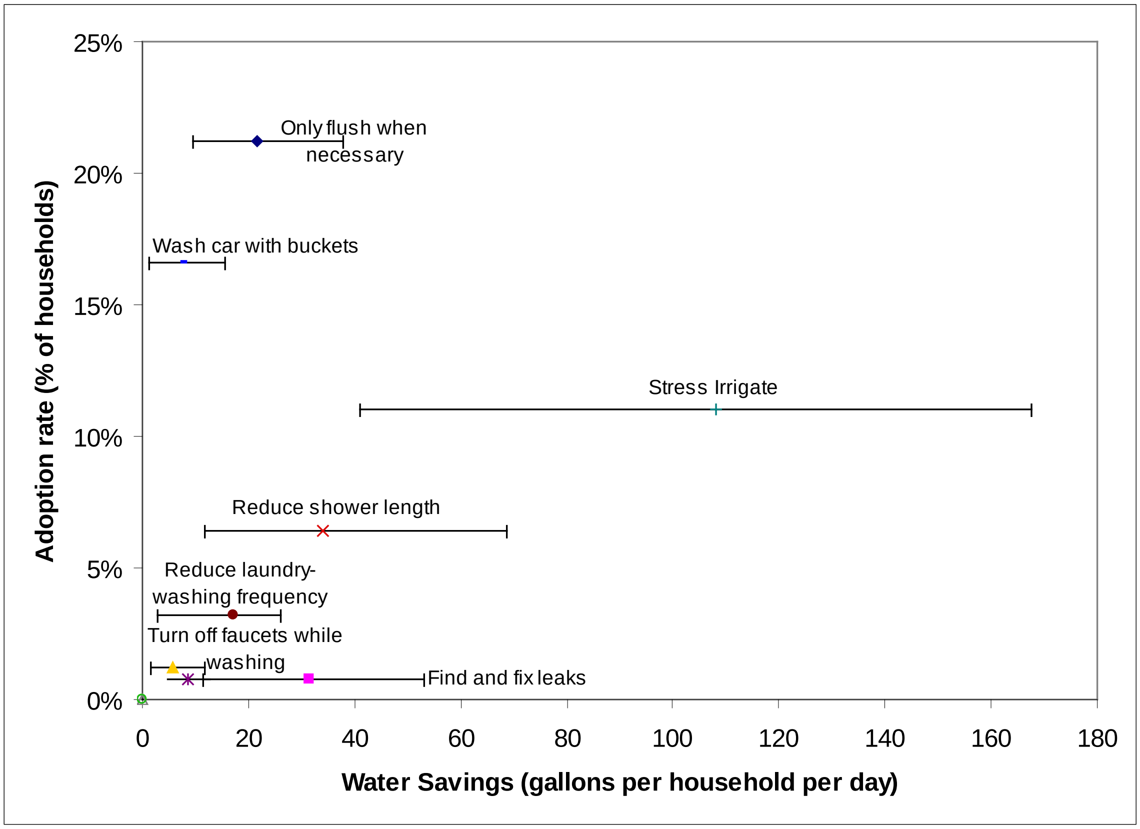

Figure 23: Modeled average market penetration and water savings for short-term outdoor conservation actions, base conditions with hassle costs (error bars are 10th and 90th percentiles)

Stress irrigation is the most effective short-term conservation action, and the other actions are implemented only by houses that will save substantial amounts of water from enacting them.

Another interesting result for short-term actions are the shortage events in which the short-term actions are expected to be adopted. The adoption rates of short-term actions by the shortage event and season are shown in Figure 24.

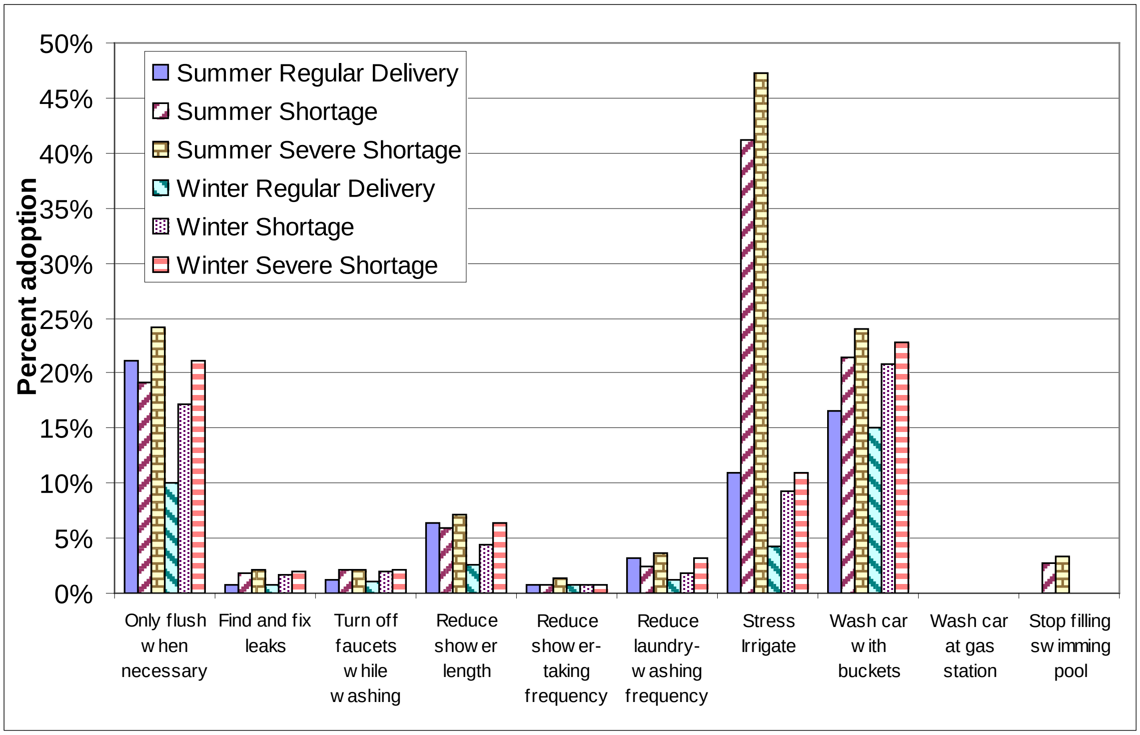

Figure 24: Modeled short-term action adoption rates by shortage event type and season, base conditions with hassle costs

The short-term actions are adopted with highest frequency during severe shortages in the summer, which is when adopting these actions will save the most water and money. However, it is still worthwhile for some homes to adopt short-term actions even when there is no shortage occurring. Stress irrigation shows the greatest seasonal variation, as the water saved by stress irrigation in the winter is much lower than in the summer.

Artificial Turf

The "install artificial turf" option had a large effect on the results, as adopting the action greatly reduces outdoor use. However, artificial turf is not popular in residential settings and its environmental effects remain unclear. There are no restrictions on artificial turf in the EBMUD service area, but it may increase contamination of stormwater and reduce attenuation (Connecticut DEP 2010). Since artificial turf is rare for households and EBMUD has yet to endorse it as a water-conserving action, most of the model runs do not include artificial turf as a potential action.

Water Price Modifications

The effects of price increases on water use have been studied frequently, usually with an emphasis on price elasticity (the percent decrease in water use that occurs with a 1% increase in water price). Reported values in literature for price elasticities of residential water use have wide ranges but are often between -0.2 and -0.4 (Dalhuisen et al. 2001). However, these elasticities have been developed for many different types of homes in different geographical areas. Since the modeled homes in the EBMUD service area are a small subset of physically similar homes that differ from an "average" home, price elasticities from literature might not apply to these homes.

Varying rate structures in the studies also detract from the effectiveness of price elasticity estimates, as differing rate structures can strongly affect price elasticities (Rosenberg 2010). For example, increasing block rate schedules often cause higher price elasticities than uniform rates (Dalhuisen et al. 2001). Furthermore, price elasticities from studies are usually a point estimate at a single price level (Dale et al. 2009, Nataraj 1996). In reality, price elasticity varies with water price (Rosenberg 2010). A more robust approach to linking price and water use is to develop a demand curve, where a proxy for the price elasticity at any price level is the magnitude of the slope of the line tangent to the curve. Even using this approach instead of a point estimate is a simplification, as it shows the relation between price and average water use in the neighborhood. In theory, each individual house would have a different demand curve based on physical and behavioral characteristics of the home.

While the capability exists in the least-cost conservation model to build these curves for each home, such an approach is unwieldy. Instead, Figure 25 shows the relationship between increasing water price and average household water use, and Figure 26 shows the point estimates of price elasticity at each price level considered. Model runs with variable water prices (up to double the current rates) were used to develop the curves. Only the price per unit consumption at the first block of the rate structure is shown, but the price of water at each block is factored up as well.

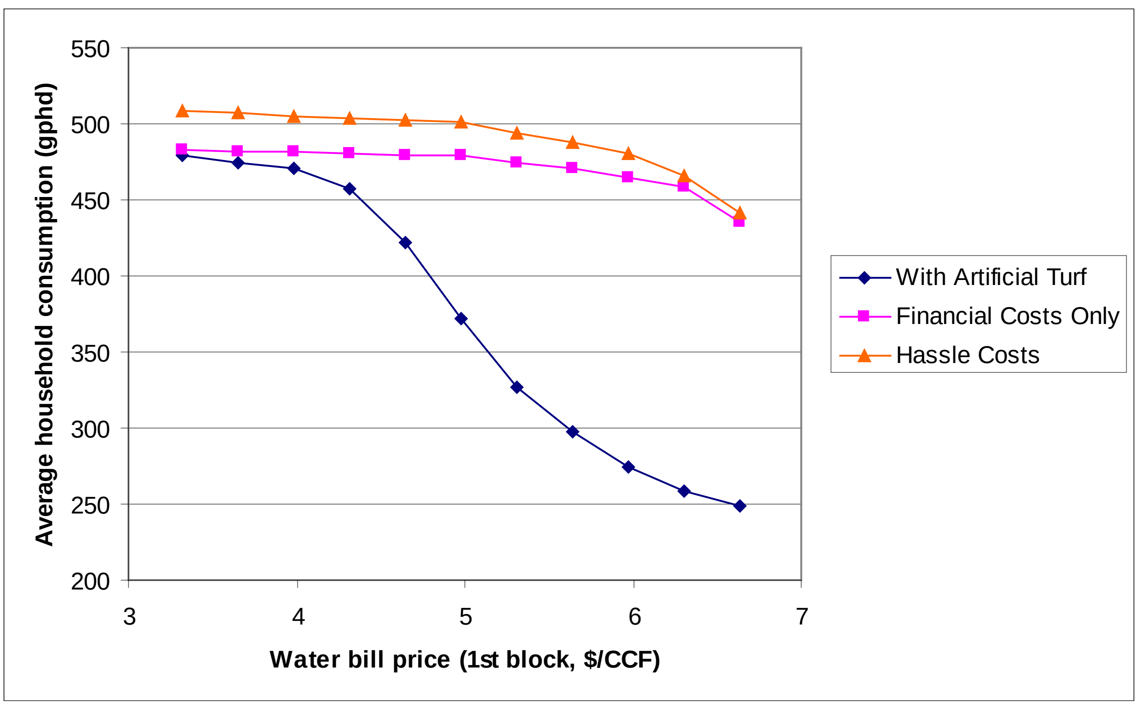

Figure 25: Modeled average household use with water price changes (the slope of the line tangent to the curve is a proxy for the price elasticity)

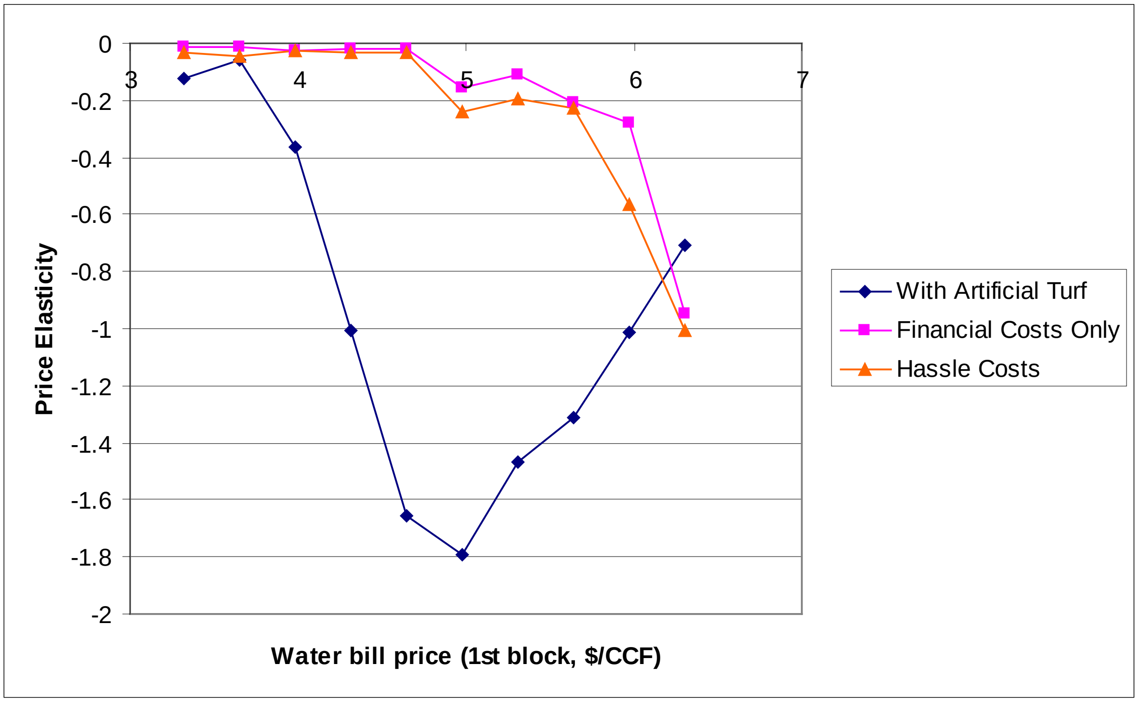

Figure 26: Modeled price elasticity as a function of water price

The model suggests homeowners will progressively increase the efficiency of their indoor fixtures as price increases, which reduces water use in small increments. As the price gets larger (about twice the current rates), households find it worthwhile to replace outdoor landscapes or improve irrigation efficiencies, which substantially reduce water use. However, the price elasticities computed are generally smaller than the values usually found in the literature (-0.2 to -0.4) (Dalhuisen et al. 2001). The costs to implement conservation actions are a bit too high in the model, which will deter homeowners from implementing conservation.

The expected revenue increase or decrease with increasing price is also of interest to the water utility. Water use does not decrease at the same rate as the price increases (because elasticities < 1), so utility revenue is expected to increase with increasing water price, as Figure 27 shows.

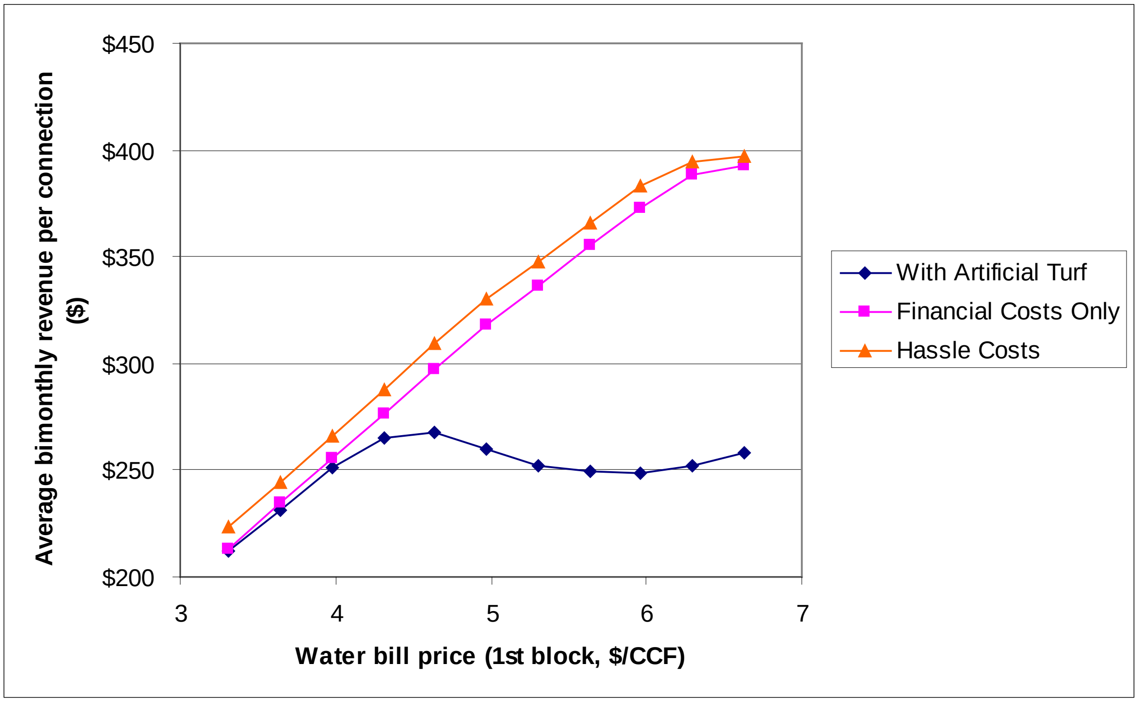

Figure 27: Modeled bimonthly utility revenue per connection

Indoor Device Rebates

The effectiveness of indoor rebates also can be estimated by the least-cost conservation model. The current rebate scheme at EBMUD does not offer rebates for replacing toilets that are rated 1.6 gpf or higher, and most homes in the neighborhood in San Ramon contain ULFTs (rated 1.6 gpf). This would make many of them ineligible for rebates, but the model explores the possibility of EBMUD offering rebates only for HETs (rated 1.28 gpf), regardless of the toilet being retrofitted. The only actual rebates received by the metered homes were for replacing washing machines—42% of the metered homes have received rebates for clotheswashers (EBMUD personal communication). The modeled percent of the population adopting a conservation strategy as a function of the rebate amount is shown in Figure 28.

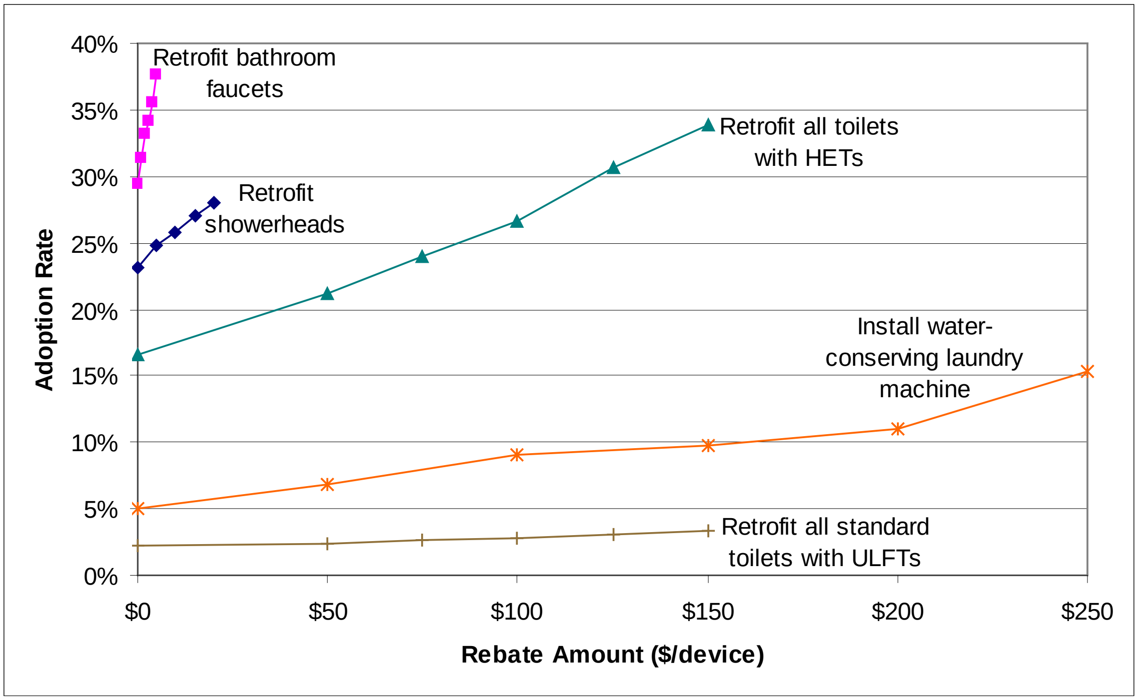

Figure 28: Modeled percent of households adopting conservation actions as a function of rebate amount

The expected disbursement of funds for varying nominal rebate levels can help utilities budget for conservation programs. Figure 29 shows this relation. For example, if EBMUD planned to offer rebates of $250 for clothes washers, about $40 per household in the neighborhood is expected to be disbursed by the rebates. For the neighborhood of 150 homes, $6,000 would need to be budgeted for clothes washer rebates. The plot also shows the effect of free riders, as all curves are upwardly concave. Higher rebates entice more households to retrofit, but the households that would have been enticed by lower rebates become partial free riders. For example, homes that are enticed at rebate levels of $100 will still retrofit their clothes washers and benefit from higher rebate levels, making the rebate disbursement inefficient for the utility.

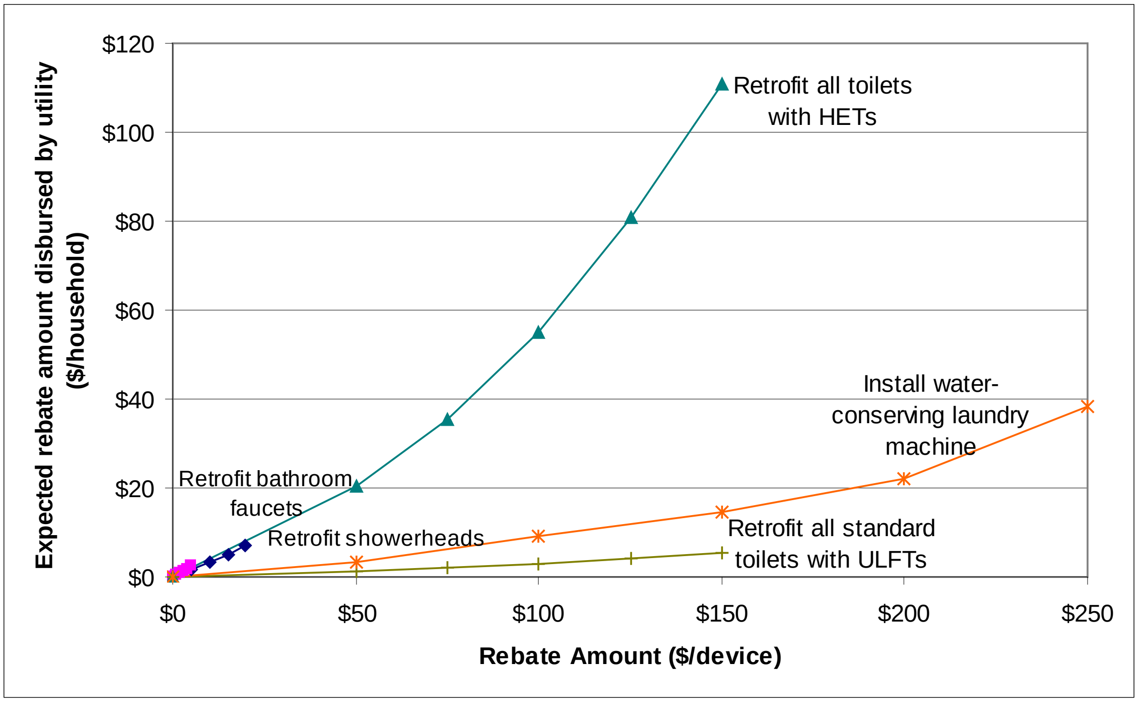

Figure 29: Expected cost of rebate programs to utility

Instead of budgeting for conservation programs or estimating adoption rates, a utility may wish to estimate which rebate strategy is most cost-effective. The ratio of water saved to total rebates disbursed is used as an indicator of cost-effectiveness here. The rebate strategy that yields the highest ratio provides the greatest “bang for buck”. Figure 30 shows this relation for varying rebate levels. Providing rebates for efficient clothes washers is the most cost-effective, saving the most water per dollar invested. As nominal rebate levels increase, the cost-effectiveness decreases due to free riders.

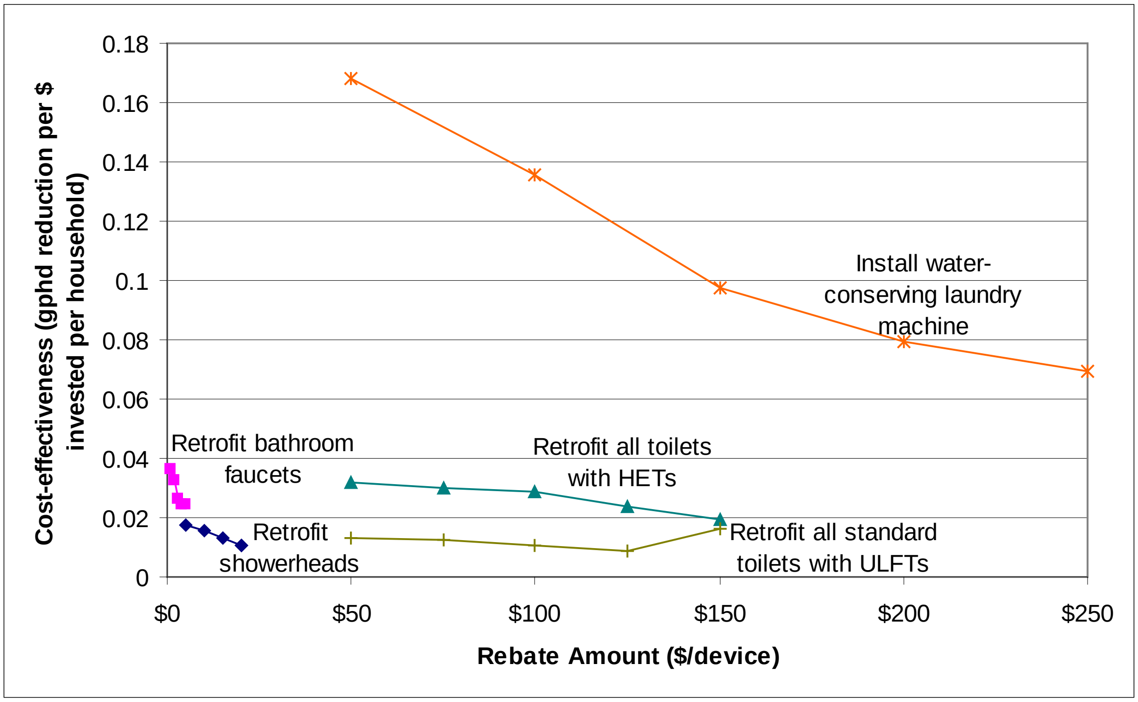

Figure 30: Cost-effectiveness of rebate programs, gphd reduction per dollar invested per household.

"Cash for Grass" Rebates

Since most water use occurs outdoors, some utilities have attempted to reduce outdoor use by implementing "cash for grass" programs, where rebates are offered to replace traditional turf with xeriscapes or less water intensive plants. North Marin Water District had one of the first "cash for grass" programs in 1989, offering rebates of $0.50 per square foot to convert to xeriscape, with a cap of $310 per house (Addink 2005). Beginning in 1996, Albuquerque gives $0.40 per square foot to convert to xeriscape; the program continues today (Addink 2005). Las Vegas offered a rebate of $1.00 per square foot to convert to xeriscape as of 2005 due to drought conditions (Sovocool 2005).

Such programs reduce outdoor water use, but there can be problems with free riders who intended to replace their landscaping regardless of the presence of a rebate—the North Marin Water District program estimated almost half of rebates went to free-riders (Addink 2005). Furthermore, many residents might be reluctant to replace their lawns. One survey found that only 27% of respondents disagreed with the statement "Having a lawn is very important to me" (CUWCC 2007). While promoting warm season turf instead of xeriscape may alleviate some misgivings of homeowners, such landscapes save less water than xeriscapes (Hanak & Davis 2006).

How effective might a "cash for grass" rebate scheme be for the modeled neighborhood? The model does not incorporate household's aesthetic preferences outdoors, as the only goal is to minimize cost. The modeled results show that no households will replace their landscapes until the rebate reaches a level of $1.00/sq. ft., and only 1% of the community will adopt the new landscape. While the amount of water saved is large for those homes adopting the new landscapes included in the model, the high "threshold" rebate rate of $1.00/sq. ft (equal to rebates in Las Vegas) is not encouraging evidence for "cash for grass" schemes. Since the rebates must be relatively high before it is cost-effective for homeowners to replace their landscape, free-ridership could be a major problem.

Sizing Curves

Sizing curves show the expected water savings at varying levels of conservation action market penetration levels (Rosenberg 2007). A major assumption in the construction of these sizing curves is that households which have the most to save will be the first to adopt the conservation strategy. For example, a penetration rate of 20% in the "Install water-conserving laundry machine" category means that the top 20% of laundry users will replace their laundry machines. Such a curve is optimistic—it is assumed there are no "free riders" who replace efficient devices with other efficient devices. However, some rebate policies by EBMUD do not dispense rebates unless the product is claimed as inefficient, which limits free-ridership (EBMUD 2011). The market penetration rates in the charts are developed for the conservation actions, not the conservation devices themselves. For example, a market penetration of 10% in the "Retrofit showerheads" category does not mean that if 10% of households have efficient showerheads, then an average saving of 3 gphd could be expected. Instead, it means that if 10% of households take the action to retrofit their showerheads, then a saving of 3 gphd (with respect to existing use) throughout the service area can be expected. This formulation of the sizing curve already assumes that some households have efficient showerheads and does not count them toward the savings numbers. The flat portions at higher market penetration rates reflect this, because replacing an already efficient device will not save any water. The estimated average savings are an average for all houses, not just the houses implementing the action. This formulation is more useful to the utility, as the total number of houses in a given service area can be multiplied by the average savings rate to determine the total expected savings. The sizing curves for indoor long-term conservation actions are given in Figure 31, and the sizing curves for outdoor long-term conservation actions are given in Figure 32 (note the different scales). Sizing curves for short-term actions have little meaning, as most short-term actions are behavior modification rather than technological improvements.

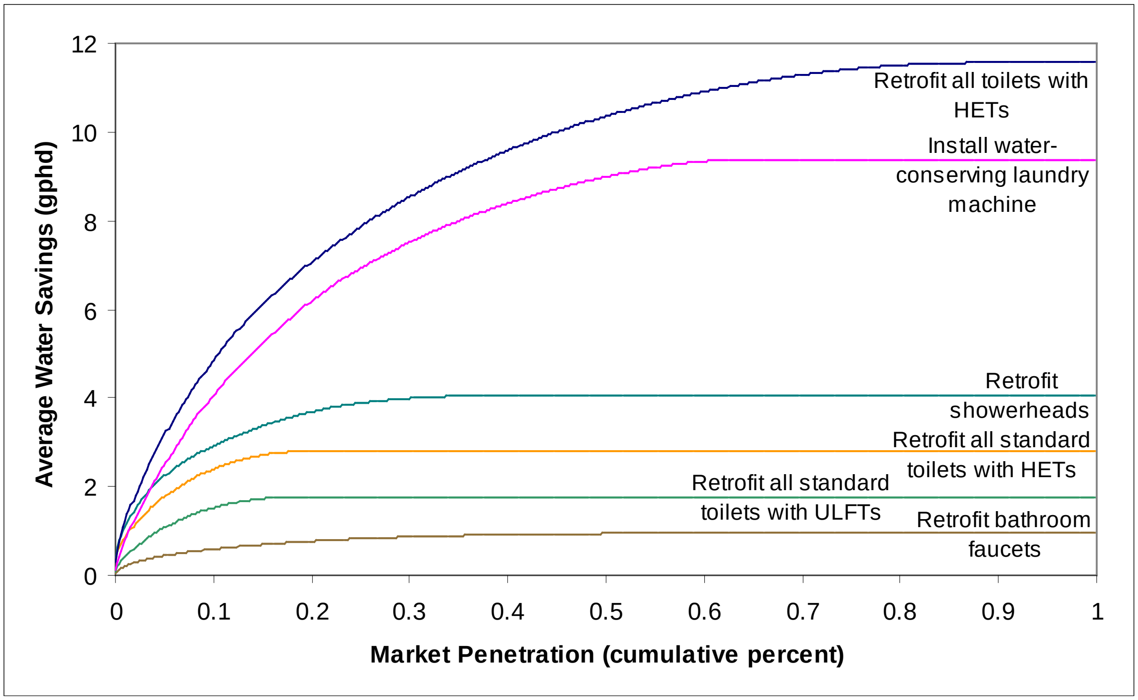

Figure 31: Modeled sizing curves for indoor water conservation programs

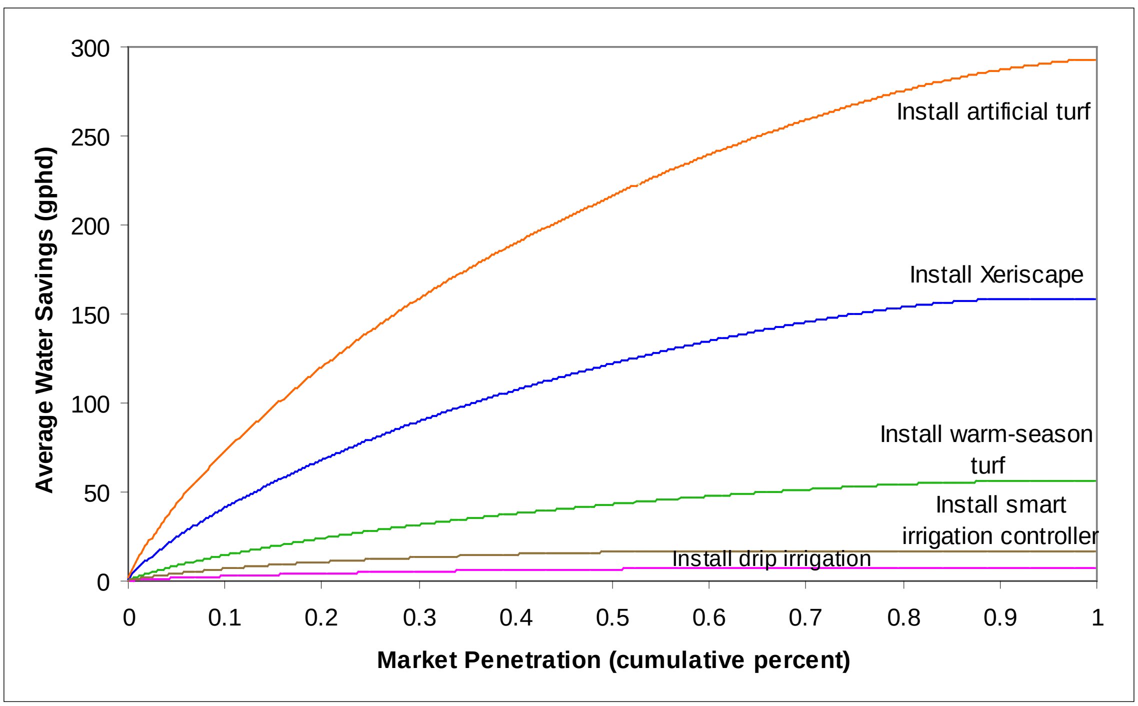

Figure 32: Modeled sizing curves for outdoor water conservation programs

The sizing curves give a quick indicator of where most water can be conserved by households. Among indoor uses, retrofitting toilets with HETs and installing more efficient laundry machines are the top two ways to save water (assuming behavioral habits do not change). Artificial turf saves the most water outdoors, but the environmental impacts of artificial turf have yet to be fully explored, making it a less likely option to implement.

Limitations of the model

While the least-cost conservation model has many capabilities, its limitations are important and include:

- **Linearity**: A non-linear program could incorporate more complexities to the water bill or interactions between actions.
- **Free riders**: The model does not account for "free riders"—people who intend to replace their devices anyway and reap the benefit of a rebate without being enticed by it (Sovocool 2005). These free riders decrease the effectiveness of rebates.
- **Assumption of rationality**: The model assumes that all households behave rationally to minimize the cost to themselves, which is not entirely true in the real world. Many decisions on conservation are not affected strongly by the actual savings gained or the reduction in cost to the household (Komor & Wiggins 1988). Conservation beyond the optimal amount due to some non-financial motivation (e.g. civic duty to conserve) is not considered, but could be included in the model using negative hassle costs representing the non-monetary benefit to the homeowner.
- **Homeowner perspective**: The optimization model is built from a homeowner's perspective, so it cannot calculate the best suite of rebates from the utility's perspective directly. However, a similar model from a utility's perspective might be formulated and used (Wilchfort & Lund 1997), and might be calibrated based on household model results.
- **Single family residential**: Since the model was developed for single-family residential homes, its applicability to multi-family residential complexes needs testing and refinement before use.
- **No temporal scale**: The model does not predict how long it will take to reach a given level of water savings—it just shows the maximum expected conservation levels. The model could be extended to include delayed responses (Lund 1988), but this would add much complexity.
- **Maintenance costs**: The model does not include maintenance costs in the analysis, which mainly affects the outdoor conservation action costs. For instance, the reduced amount of landscaping work required after conversion to xeriscape is significant, but was not included in this model (Sovocool 2005).
- **Compute times**: The optimization takes about 1.5 hours to solve 500 households.

Further Work

Existing Conditions Model

The first, most natural extension is to apply the existing conditions model to a larger area. The model has done well in this small neighborhood in San Ramon, but it should be tested with a larger area to assess its formulation and calibration. If data from a set of single-family homes with separate irrigation meters could be obtained, the calibration of outdoor and indoor uses could be more precise than simply calibrating the seasonal use. The existing conditions model also could be extended to multi-family residential areas, based on the assumption that there is outdoor use for the apartment complex as a whole and separable indoor use for each apartment.

Least-cost Conservation Model

Other conservation actions could be considered, such as rainwater tanks and recycled water systems. Additional uncertainty could be added into the cost of actions instead of assuming fixed capital costs for each action. The aesthetic values of different landscaping types were ignored in this model, and perhaps a parameter could be added to reflect the value of a well-kept lawn to a homeowner based on surveys. The model could also assume separate behavioral patterns for different members of households, with distributions for adults, teenagers, children, etc. It would also be interesting to see the effects of incorporating a water-budget based rate structure. Under such schemes, each home is allotted an amount of water each billing period based on outdoor area and number of residents, and any water use above this rate incurs a higher cost. Such pricing schemes are possible with the widespread use of geographical information systems, and over 20 water utilities across the U.S. use this rate structure (Mayer 2009).

Conclusions

Each model developed here has distinct capabilities and limitations. The existing conditions model estimates household water use by end use using Monte Carlo techniques with no additional household conservation, assuming current market penetration rates of conservation devices. The least-cost conservation model builds on the existing conditions model, finding the optimal combination of long and short term conservation actions households should take to minimize costs. The least-cost conservation model depends on the existing conditions model to calculate the house-specific effectiveness of each conservation action, but the existing conditions model does not require a companion least-cost conservation model. To make the distinction between the models a bit more clear, a list of possible results desired by utilities is presented along with the model that can provide the output. The list in Table 5 is not comprehensive, but it provides a practical feel for the capabilities of each model.

Table 5: Example capabilities of existing conditions and least-cost conservation models

Result desired by utility	Existing Conditions	Least-Cost Conservation
Water use by end use in 1990	x	
Expected water use after price increase of 10%		x
Savings after penetration of HETs increases to 40%	x	
Cost-effectiveness of "cash for grass" proposal		x
Budget for showerhead replacement rebate program		x
Water consumption of proposed new subdivision	x	
Outdoor water consumption with climate change		x

The approach taken here produces reasonable “existing conditions” water use estimates and provides valuable insights in household conservation potential for the metered homes in a San Ramon neighborhood. The largest area of concern when developing the existing conditions model for the neighborhood was outdoor water use, as outdoor uses usually comprise over half of all water use and are highly variable (DWR 2009). However, the model results seemed to accurately predict outdoor use, as shown by the good fit of the seasonal results to the metered data. Since the modeled results were comparable to measurements from other end use studies and were calibrated without much difficulty to the metered data, the existing conditions use model appears to be robust.

Although the least-cost conservation model has many limitations, it can still provide useful insights. It appears that current price levels do not make it worthwhile for homeowners to reduce outdoor use—the biggest end use. As water price increases, outdoor conservation actions become attractive to more homeowners. Indoor conservation is more widespread, but the savings are lower than outdoor conservation. The most cost-effective conservation action is retrofitting bathroom faucets, but retrofitting toilets with HETs holds the highest potential of water savings. The rebates for high-efficiency laundry machines give EBMUD the most “bang for their buck”. Cash-for-grass schemes may hold potential for significant water reduction, but high program costs and problems with free-riders may limit their effectiveness. Price increases paired with higher rebates will likely keep utility revenue levels stable while decreasing water use.

This type of modeling approach, after further testing, has the potential to be applied to any neighborhood or city after adjusting the parameter distributions. The existing conditions model can be easily adapted to other communities or service areas using reasonable market penetration assumptions and adjusting for geographical factors. Furthermore, the model developer has considerable freedom to easily explore alternatives and their effect on water use.

An advantage to applying this modeling approach is the reduced dependence on end use measurement studies. While periodic end use measurement studies are critical to ensure that reasonable distributions for the parameters are used, adapting the existing conditions model would be much less expensive than doing repeated measurement studies when models of end uses are desired. Periodic end use measurement studies combined with this model would be much more cost-effective than installing AMS meters at households in a service area.

Acknowledgments

This work could not have occurred without the large amount of support received from all quarters. Bill DeOreo of Aquacraft was tremendously willing to share data from Aquacraft's end use studies for this model, and I thank him humbly for the generosity. Hopefully the results are of some interest to Aquacraft's future modeling efforts. Special thanks also belong to David Rosenberg for sharing his previously developed model for adaptation to the EBMUD neighborhood, saving me weeks of work. Clifford Chan, Richard Harris, and David Wallenstein over at EBMUD were willing to experiment with a new approach to modeling household demand, and I thank them for their input into the model development and support of the effort. Lisa Maddaus also provided helpful information about studies on residential use throughout California. My research group deserves some credit for sitting (or sleeping) through many of my presentations about the work and offering helpful suggestions. Lastly, without an advisor like Jay Lund steering the work and offering big-picture perspectives, the modeling effort could have gotten derailed easily.

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Appendix A-Metered Data Summary

House #	EBMUD ID #	# of readings	Duration (months)	Used in Analysis?	Data screening notes (see key)
1	40165542, 1380790	1338	47	YES	
2	40165543, 1380791	24051	57	YES	
3	40165544, 1380800	33156	57	YES	
4	40165536, 1380799	33429	57	YES	
5	1513609	8704	9	YES	2
6	40165538, 40000298	8207	36	YES	
7	40165537, 40000300	8017	36	YES	
8	40000299, 1513615	10761	45	YES	
9	1513615	9252	9	YES	
10	1451919	9623	12	NO	1
11	40165532	7216	10	YES	
12	40000292, 1513647	7782	45	YES	2
13	1513647	6527	9	YES	2
14	40165531, 40000297	8283	36	YES	
15	1513619	9219	9	YES	2
16	40165535, 40000293	8224	36	NO	1
17	40165530, 40000294	6786	36	YES	
18	40000295, 1513620	10432	45	YES	
19	40165539, 40000286	7092	36	YES	
20	1451908	2445	10	YES	3,4,5
21	2024541, 1916712	10887	15	YES	2
22	2024540, 1451917	13802	46	NO	1
23	2024544, 1451914	16614	46	NO	1
24	1451910	3564	29	NO	4,5
25	2024556, 1451907	14413	52	NO	4,5
26	1451916	2616	30	NO	4,5
27	2024543, 1451906	13801	46	NO	4,5
28	2024539, 1451911	20443	46	NO	4,5
29	2195096, 1392590	41838	57	NO	4,5
30	40165528, 1392593	35698	57	YES	
31	2024545, 1451920	22437	45	NO	4,5
32	1451918	2309	7	NO	4,7
33	2195093, 1380782	39321	57	YES	4
34	2195103, 1392580	41653	57	YES	4
35	2195102, 1380786	39644	57	YES	4
36	2195108, 1380785	41869	57	YES	4
37	40165578, 1380773	40404	57	YES	
38	40165577, 1392575	39322	57	YES	4
39	40165526, 1392577	38067	57	YES	
40	40165525, 1380796	38671	57	YES	

House #	EBMUD ID #	# of readings	Duration (months)	Used in Analysis?	Data screening notes (see key)
41	2195112, 1392567	41941	57	YES	4
42	2195110, 1392568	38352	57	YES	4
43	2195105, 1392560	36013	57	YES	4
44	2195099, 1392562	41424	57	YES	4
45	2195095, 1392563	40246	57	YES	4
46	2195109, 1392570	41008	57	YES	4
47	2195104, 1392571	41864	57	YES	4
48	40165529, 1380778	44197	59	YES	
49	2195100, 1392574	42425	57	YES	4
50	1848935, 1380757	41663	57	YES	4
51	40165576, 1380758	15351	57	YES	
52	2024549, 1451915	4638	41	NO	4,5
53	1513635	6196	5	YES	2
54	2195111, 40000283	17541	36	YES	
55	1513646	8481	9	YES	2
56	2195097, 40000282	13475	36	YES	
57	1848940, 1848940	23176	16	YES	
58	1848945, 1380752	40668	57	YES	4
59	1848926, 1380759	31601	45	YES	3,4
60	40165580, 1392541	21194	54	YES	4
61	40165581, 1380756	21556	57	YES	4
62	40165582, 1380751	25466	57	YES	4
63	40165584, 1380775	32164	57	YES	4
64	40165583, 1380750	36607	57	YES	3,4
65	2024547, 1451913	14075	46	NO	4,5
66	2024546, 1451912	13697	46	NO	4,5
67	1848930, 1380780	27160	57	YES	2,3,4
68	40165575, 1392558	37742	57	YES	
69	1848944, 1392556	41121	57	YES	4
70	1848939, 1392555	41401	57	YES	4
71	1848929, 1392551	26527	57	YES	2
72	1848934, 1392543	37430	57	YES	4
73	1848943, 1392550	41721	57	YES	4
74	1848938, 1392554	39771	57	YES	4
75	1848933, 1392552	39167	57	YES	4
76	1848928, 1392553	38091	57	YES	4
77	1848942, 1392544	25364	47	YES	3,4
78	1848937, 1392548	41310	57	YES	4
79	1848932, 1392549	31791	57	YES	4
80	1848927, 1392540	40671	57	YES	4

House #	EBMUD ID #	# of readings	Duration (months)	Used in Analysis?	Data screening notes (see key)
81	1848941, 1392546	31730	57	YES	4
82	1848936, 1392545	35557	57	YES	4
83	1848931, 1392547	40945	57	YES	4
84	2195106, 40000284	24756	36	YES	
85	1513634	8979	9	YES	2
86	40000532, 4000532	23921	36	YES	
87	1513644	6086	9	NO	2,7
88	40000533, 4000533	14033	36	YES	
89	2024548, 1451909	14387	46	NO	4,5
90	1513643	8610	9	YES	2
91	40000285, 4000285	21591	36	YES	
92	1513645	9176	15	YES	
93	40165534, 40000531	24518	36	NO	1
94	1513639	6258	9	YES	
95	2195101, 40000288	17161	36	YES	
96	1513640	8585	9	YES	2
97	2195107, 40000281	20112	36	YES	
98	1513641	9333	9	YES	2
99	40000290, 4000290	20742	36	YES	
100	1380783	6966	8	YES	2
101	40165533, 40000289	19510	36	YES	2, 6
102	40165571, 1392569	37391	57	YES	
103	1380792	19302	57	YES	
104	40000296, 1380772	17166	57	YES	
105	1392594	21166	38	YES	3
106	1392587	31893	57	YES	4
107	1380777	35995	51	YES	4
108	1392597	28373	57	YES	4
109	1392599	38462	57	YES	4
110	1392588	36639	57	YES	4
111	1392596	35853	50	YES	4
112	1392584	37949	57	YES	4
113	1392598	40271	57	YES	4
114	1392592	28651	57	YES	
115	1392581	26530	36	YES	8
116	1392583	36596	50	YES	
117	1392582	38032	57	YES	
118	1380784	38188	52	YES	
119	1392595	34411	50	YES	
120	1392589	35235	50	YES	

House #	EBMUD ID #	# of readings	Duration (months)	Used in Analysis?	Data screening notes (see key)
121	1380787	37376	56	YES	4
122	40165579, 2195094	11533	16	YES	4
123	1380788	34295	50	YES	
124	40165570, 2195098	11653	16	YES	4
125	1380789	35707	50	YES	
126	1392576	37230	57	YES	
127	1380795	36310	57	YES	
128	1392579	39077	57	YES	
129	1392578	32972	50	YES	
130	1380797	33807	57	YES	4
131	1380781	33230	50	YES	
132	1380798	33179	50	YES	
133	1392542	29611	51	YES	
134	1380776	27670	50	YES	4
135	1392565	30260	51	YES	
136	1392566	33018	50	YES	4
137	1392561	26291	50	YES	
138	1392564	36839	51	YES	
139	1380779	35023	50	YES	6
140	1380770	39621	57	YES	
141	1380771	36562	50	YES	3
142	1392572	38567	57	YES	
143	1380794	40611	57	YES	4
144	1380769	19170	50	YES	
145	1392573	38667	57	YES	
146	1380754	21961	50	YES	
147	1380753	34862	50	YES	
148	1392559	36937	57	YES	4
149	1380755	31517	57	YES	4
150	1392557	31721	50	YES	
151	1392591	38519	57	YES	

Key to data screening notes:

1 Poor Data
2 Discontinuities
3 Blank/unreasonable values at beginning or end of period
4 Meter tops out at a number and begins reading from 0 again
5 Scaling factor is off by a factor of 10
6 Outlier(s) deleted
7 Less than 6 months of real data
8 Meter stops reading after some time

Appendix B-Parameter Distributions

Parameter	Units	Low value	High value	Average	St. Dev	Distribution[1]	Reference
Geographic							
A. Precip-Summer	in/season	-	-	1.8	1.3	FG	WRCC, 2011
B. Precip-Winter	in/season	-	-	12.1	4.5	FG	WRCC, 2011
C. ET-Summer	in/season	-	-	37.2	1.4	NM	CIMIS data, 2011
D. ET-Winter	in/season	-	-	12.4	0.8	NM	CIMIS data, 2011
Demographic							
E. Square footage of house	sq. ft.	-	10,000	2,907	1,071	FG	Zillow, 2011
F. Lot size	sq. ft.	-	18,000	8,604	3,444	FG	Zillow, 2011
G. Outdoor area	sq. ft.	-	18,000	5,222	2,806	FG	Zillow, 2011
H. Household size	persons/house	-	-	-	-	HSD	Census 2010 SF1 H013
I. Household Income	$	-	-	-	-	HSC	Census 2000 SF4 PCT088
Technologic-Indoor							
J. Number of showers	number	-	-	-	-	HSD	EBMUD, 2002
K. High-flow showers	probability of one shower	-	-	0.24	-	FV	DeOreo, 2011; func. of (J.)
L. Low-flow showers	probability of one shower	-	-	0.76	-	FV	DeOreo, 2011; func. of (J.)
M. Shower flow rate - standard device	gal/min	-	-	-	-	HSC	DeOreo et al., 2011
N. Shower flow rate - low flow	gal/min	-	-	-	-	HSC	DeOreo et al., 2011
O. Number of toilets	number	-	-	-	-	HSD	EBMUD, 2002
P. Standard toilets	probability of one toilet	-	-	0.07	-	FV	DeOreo, 2011; func. of (O.)
Q. ULFT toilets	probability of one toilet	-	-	0.88	-	FV	DeOreo, 2011; func. of (O.)
R. HET toilets	probability of one toilet	-	-	0.05	-	FV	Engineering Estimate; func. of (O.)
S. Toilet flush volume - standard	gal/flush	-	-	-	-	HSC	DeOreo, 2011
T. Toilet flush volume - ULFT	gal/flush	-	-	-	-	HSC	DeOreo, 2011
U. Toilet flush volume - HET	gal/flush	-	-	-	-	HSC	DeOreo, 2011
V. Number of faucets	number	-	-	-	-	HSD	EBMUD, 2002
W. Standard bathroom faucets	probability of one faucet	-	-	0.15	-	FV	EBMUD, 2002; func. of (V.)
X. Aerated bathroom faucets	probability of one faucet	-	-	0.85	-	FV	EBMUD, 2002; func. of (V.)
Y. Faucet flow rate - standard	% above aerated gpm	-	-	0.3	-	FV	EBMUD, 2003
Z. Faucet flow rate - aerated	gal/min	-	-	-	-	HSC	DeOreo, 2011
AA. Laundry efficiency type	1=not efficient, 2 =efficient	-	-	0.31	-	FV	DeOreo, 2011
AB. Laundry use - inefficient	gal/cycle	-	-	-	-	HSC	DeOreo, 2011
AC. Laundry use - efficient	gal/cycle	5.0	-	21.8	4.5	NM	EBMUD, 2003
AD. Dishwasher use	gal/day	-	-	2.4	2.1	FG	DeOreo et al., 2011
AE. Bath use	gal/day	-	-	3.5	-	FV	DeOreo, 2011
Technologic-Outdoor							
AF. Landscaped area	% of yard area	-	-	0.62	-	FV	EBMUD, 2002
AG. Lawn area	% of landscaped area	-	-	0.65	-	FV	Calibrated
AH. Xeriscape present?	1=no, 2=yes	-	-	0.1	-	FV	Engineering Estimate
AI. Cool-season turf Kc	%	-	-	0.8	-	FV	CIMIS, 2000
AJ. Garden Kc	%	-	-	0.5	-	FV	CIMIS, 2000
AK. Xeriscape Kc	%	-	-	0.3	-	FV	PPIC, 2006
AL. Warm-season turf Kc	%	-	-	0.6	-	FV	CIMIS, 2000
AM. Irrigation fixture type	1=hose, 2=sprinkler, 3=drip	-	-	-	-	HSD	EBMUD, 2002
AN. Hose irr. max. efficiency	%	-	-	0.91	0.05	NM	PPIC, 2006
AO. Sprinker irr. max. efficiency	%	0.7	0.8	-	-	UN	Fresno State, 1988
AP. Drip irr. max. efficiency	%	0.75	0.9	-	-	UN	Fresno State, 1988
AQ. Pool present?	0 = no, 1 = yes	-	-	0.1	-	FV	EBMUD, 2002
AR. Pool area	sq. ft.	50.0	-	342.3	133.1	NM	Google Earth
AS. Number cars	# cars	-	-	-	-	HSD	Census 2000 SF3 H044
AT. Bucket size	gal	3.0	7.0	-	-	UN	Rosenberg, 2007
AU. Hose flow rate	gal/min	5.0	10.0	-	-	UN	Engineering Estimate
AV. Leaks	gal/day	-	-	-	-	HSC	DeOreo, 2011
Behavioral-Indoor							
AW. Shower length - current	min	1.0	-	8.7	2.9	FG	DeOreo et al., 2011
AX. Shower length - shortened	min reduction	1.0	6.0	-	-	UN	Rosenberg, 2007
AY. Shower frequency - summer	#/week/person increase	-	-	0.6	0.3	NM	Engineering Estimate
AZ. Shower frequency - winter	#/week/person	1.0	-	5.3	2.9	FG	DeOreo, 2011
BA. Shower frequency - reduced	#/week/person reduction	0.5	-	0.8	-	ED	Rosenberg, 2007
BB. Toilet flushes	#/person/day	2.0	-	4.7	2.3	FG	DeOreo, 2011
BC. Flushes requiring full flush	fraction of flushes	0.4	0.6	-	-	UN	Yarra Valley, 2004
BD. Faucet use - normal	min/day/person	2.0	20.0	-	-	HSC	EBMUD, 2003
BE. Faucet use - shortened	min/person/day reduction	0.1	-	0.5	-	ED	Rosenberg, 2007
BF. Laundry frequency - normal	cycles/person/week	0.5	-	2.2	0.8	NM	DeOreo et al., 2011
BG. Laundry frequency - reduced	fraction of normal	0.1	0.5	-	-	UN	Rosenberg, 2007
BH. % of leaks fixed	%	0	0.5	-	-	UN	Engineering Estimate
BI. Handiness factor	0-1 (0 is most handy)	0	1.0	-	-	UN	Engineering Estimate
Behavioral-Outdoor							
BJ. Irrigation method	1=manual, 2 = auto, 3 = sma	-	-	-	-	HSD	DeOreo et al., 2011
BK. Manual irr. eff. reduction	%	-	-	0	-	FV	PPIC, 2006
BL. Automatic irr. eff. reduction	%	-	-	0.5	0.1	NM	PPIC, 2006
BM. Smart irr. eff. reduction	%	-	-	0.1	0.1	NM	Mayer, 2009
BN. Stress irrigation reduction	%	0.1	0.2	-	-	UN	Engineering Estimate
BO. Car wash time	minutes/wash	5.0	10.0	-	-	UN	Engineering Estimate
BP. Car washes	washes/week	-	-	-	-	HSD	Smith & Shilley 2009
BQ. Car wash method	1=auto, 2=bucket, 3=hose	-	-	-	-	HSD	ICA, 2005

1. ED = exponential decay, FG = fitted gamma, HSD = histogram with discrete categories, HSC = histogram with interpolation between categories, NM = normal, UN = uniform, FV = fixed value (constant)

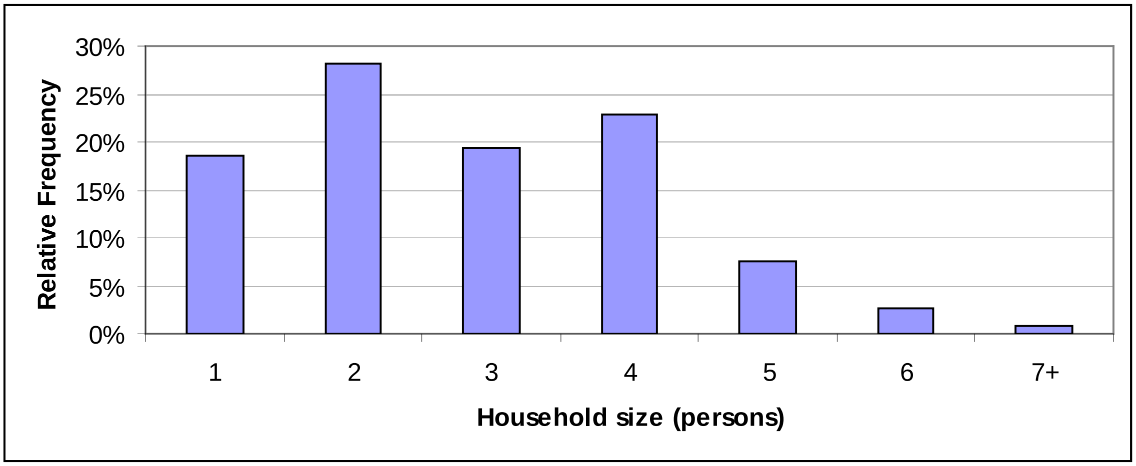

Figure 33: Histogram of parameter H

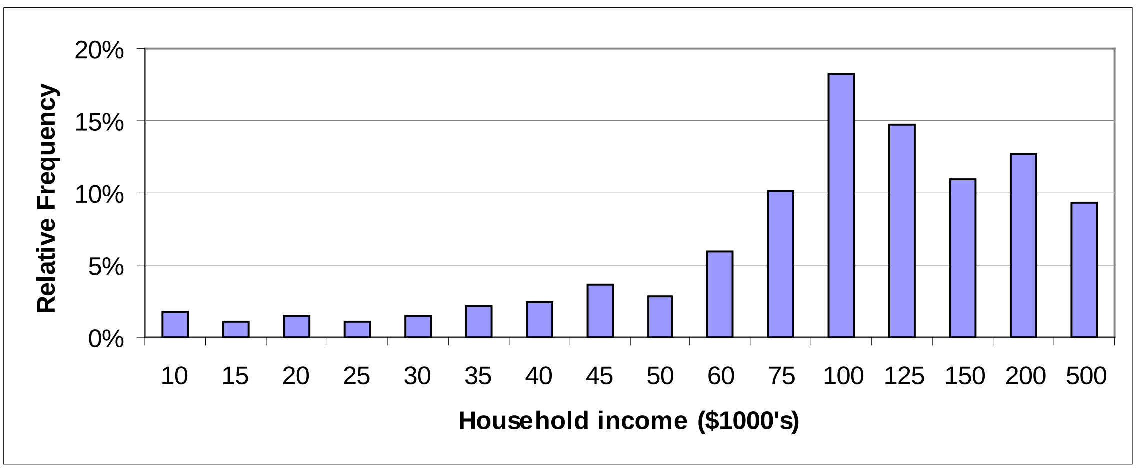

Figure 34: Histogram of parameter I

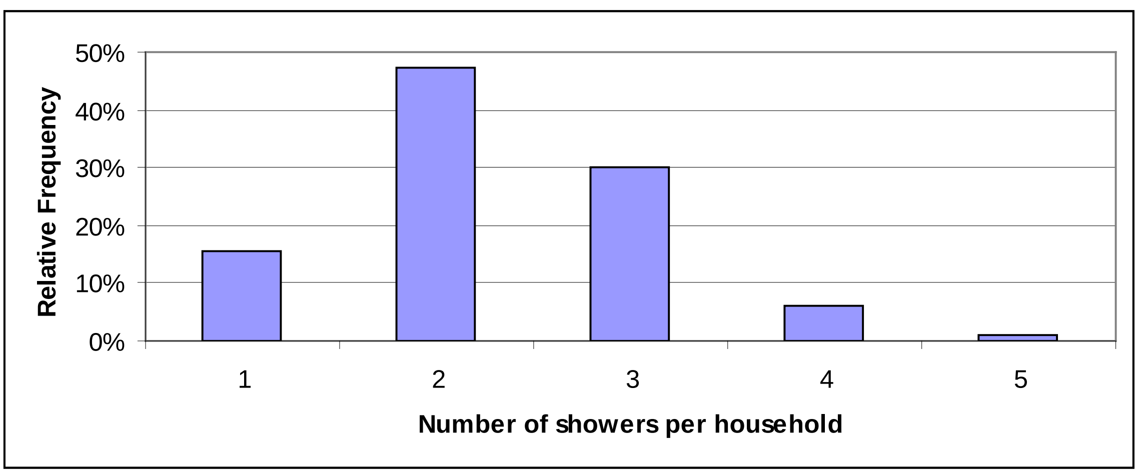

Figure 35: Histogram of parameter J

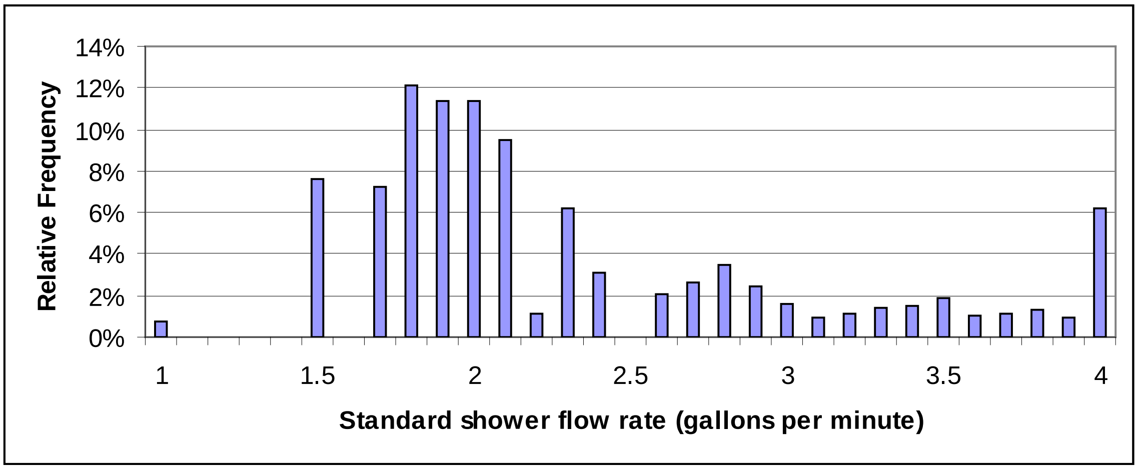

Figure 36: Histogram of parameter M

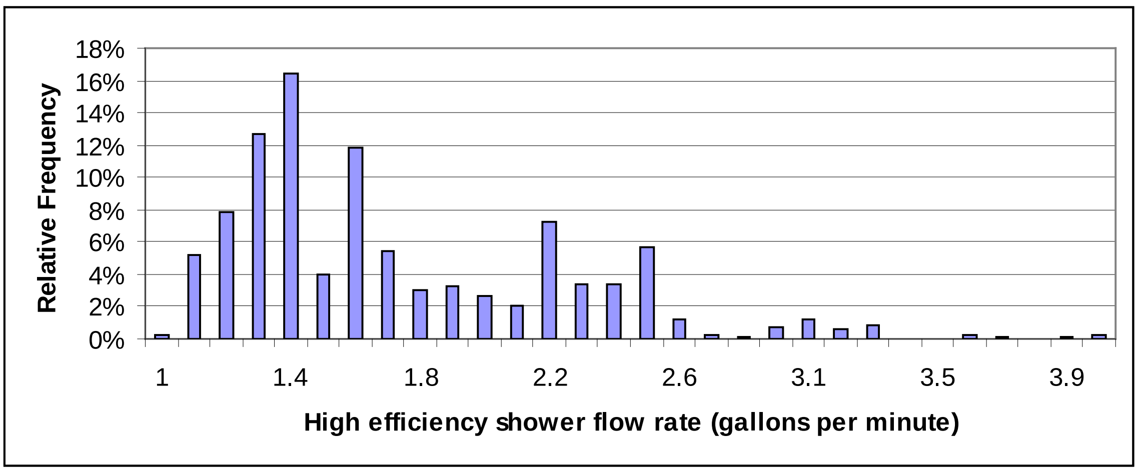

Figure 37: Histogram of parameter N

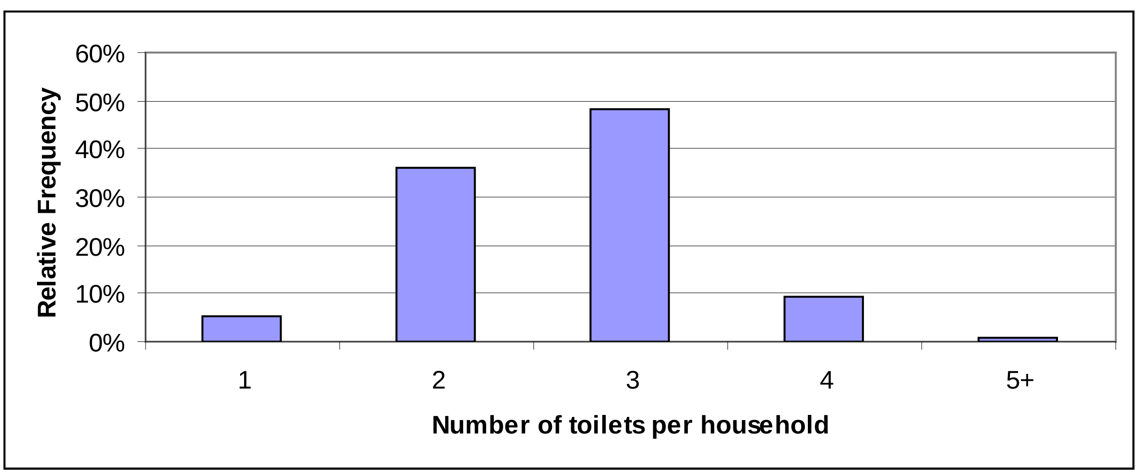

Figure 38: Histogram of parameter O

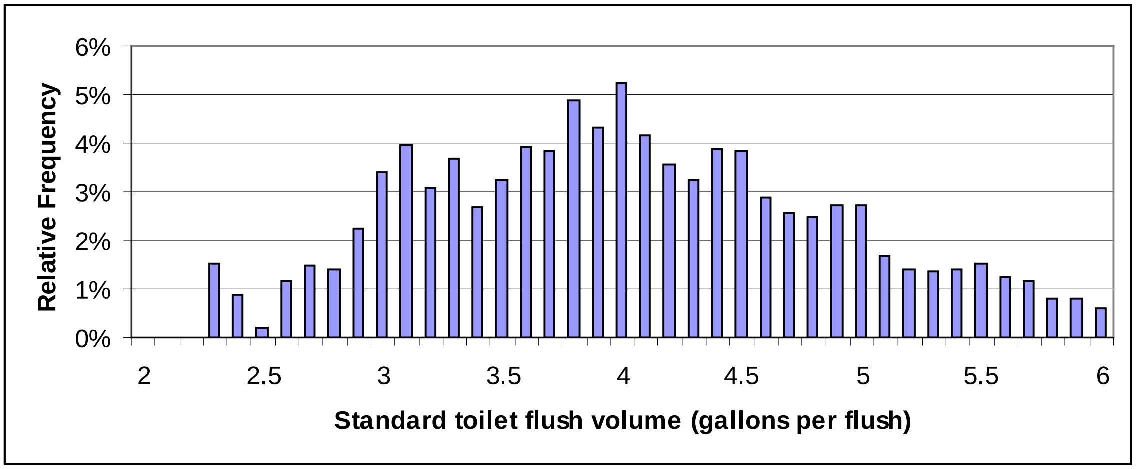

Figure 39: Histogram of parameter S

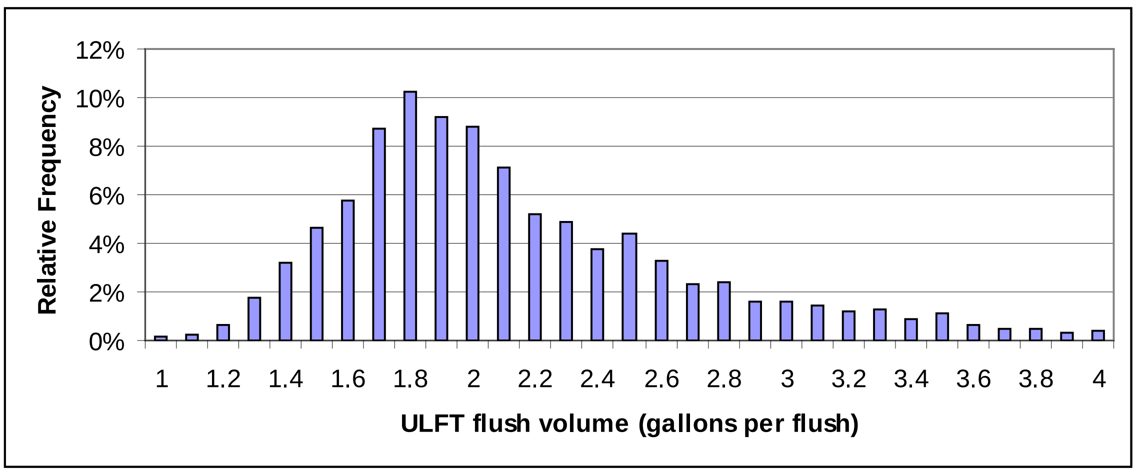

Figure 40: Histogram of parameter T

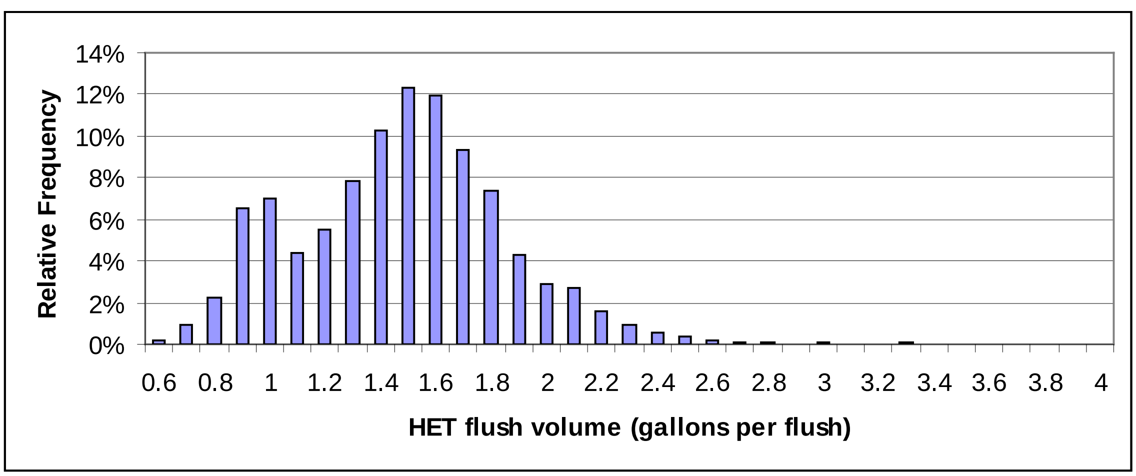

Figure 41: Histogram of parameter U

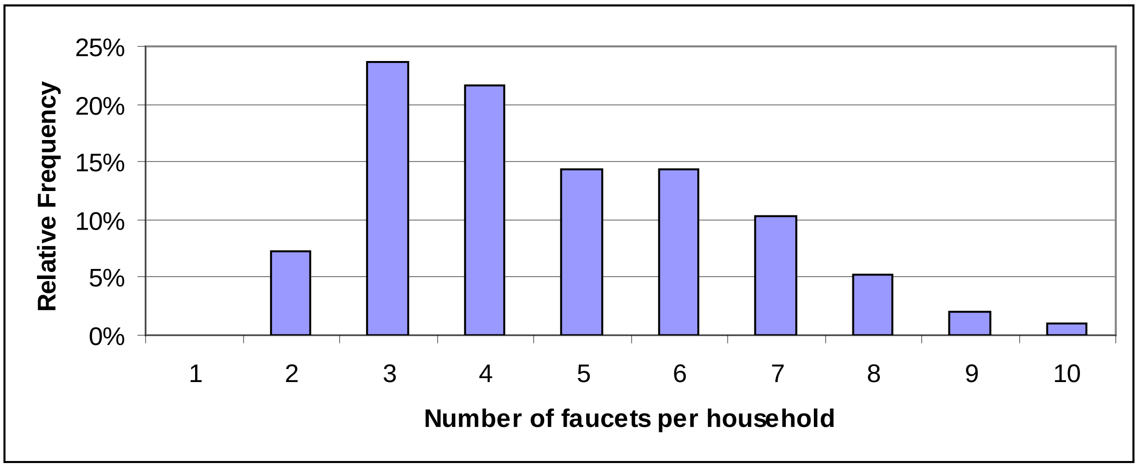

Figure 42: Histogram of parameter V

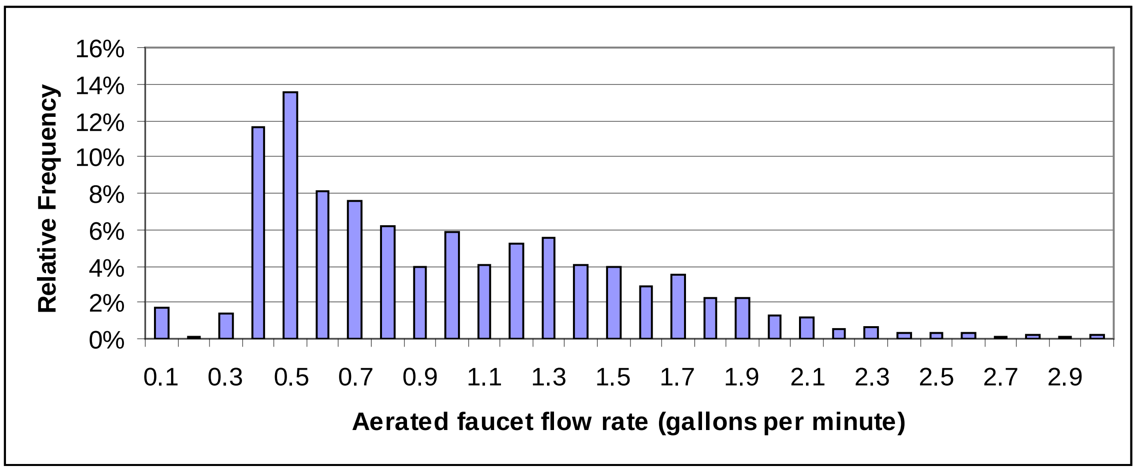

Figure 43: Histogram of parameter Y

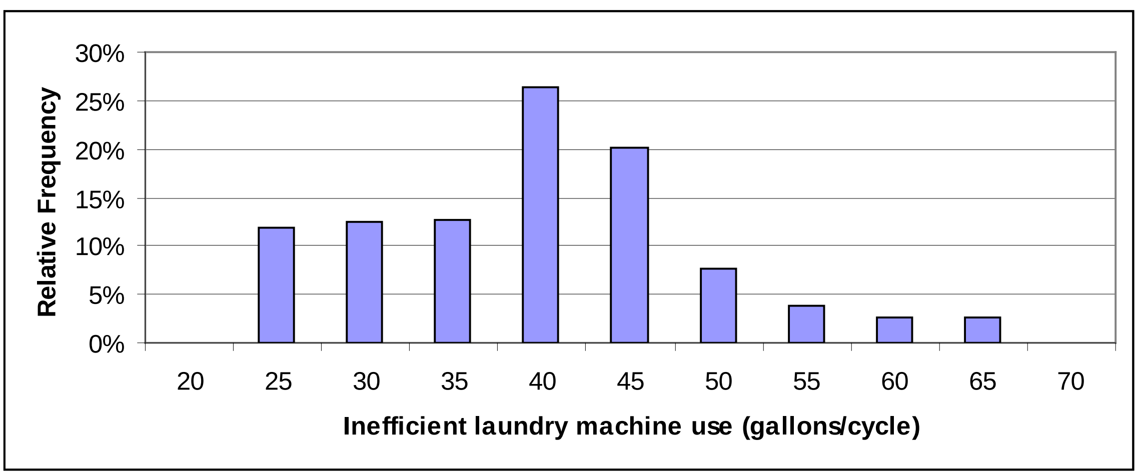

Figure 44: Histogram of parameter AB

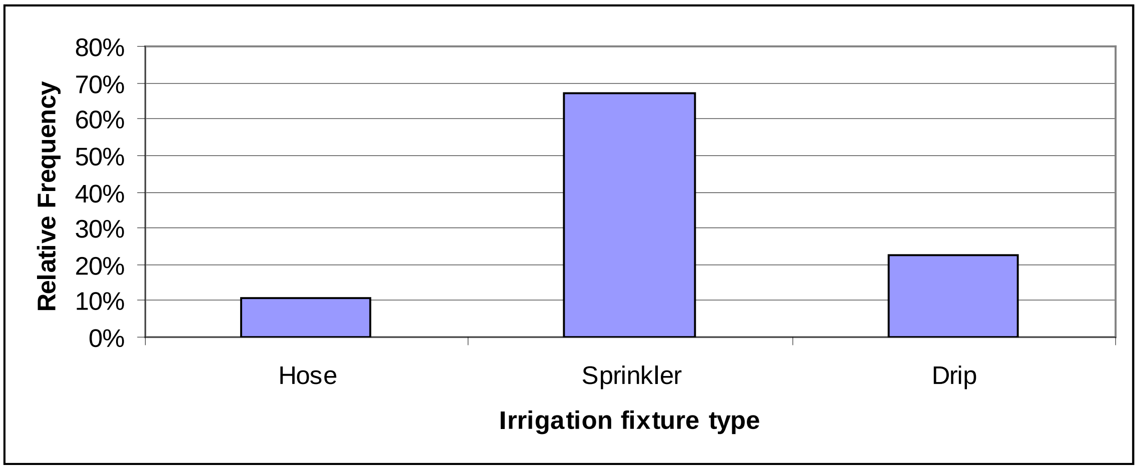

Figure 45: Histogram of parameter AM

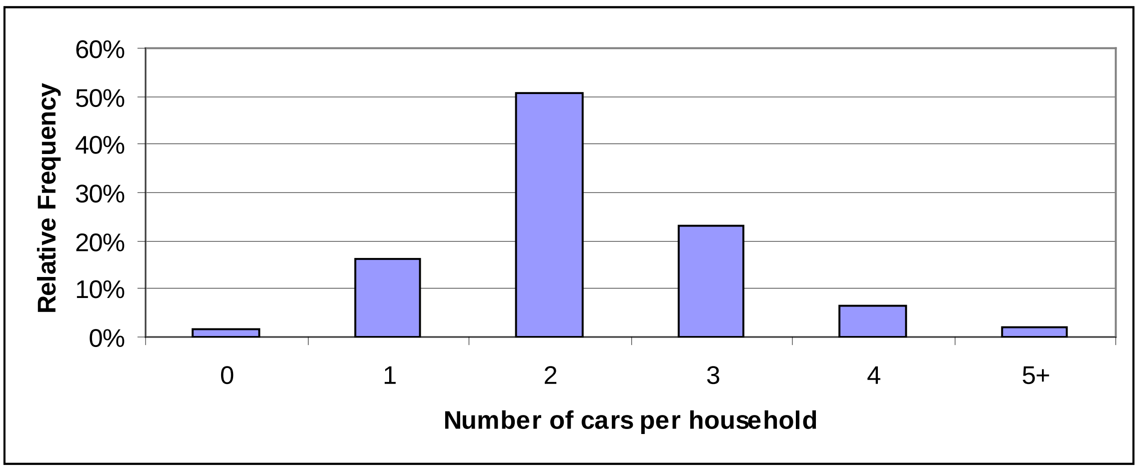

Figure 46: Histogram of parameter AS

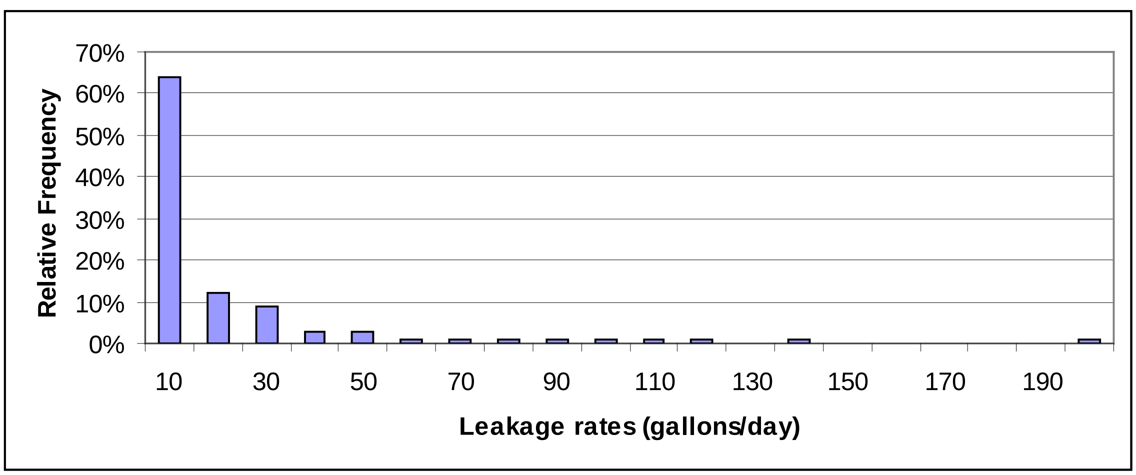

Figure 47: Histogram of parameter AV

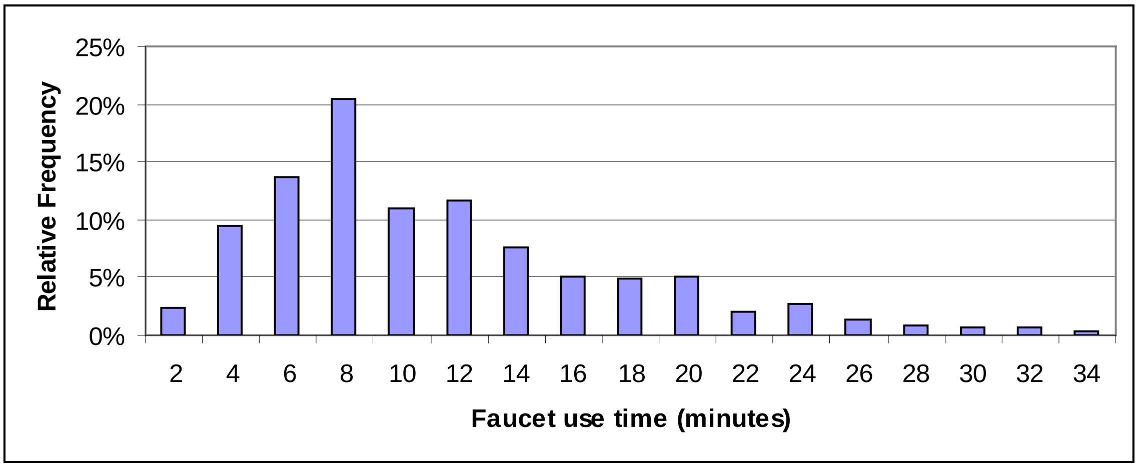

Figure 48: Histogram of parameter BD

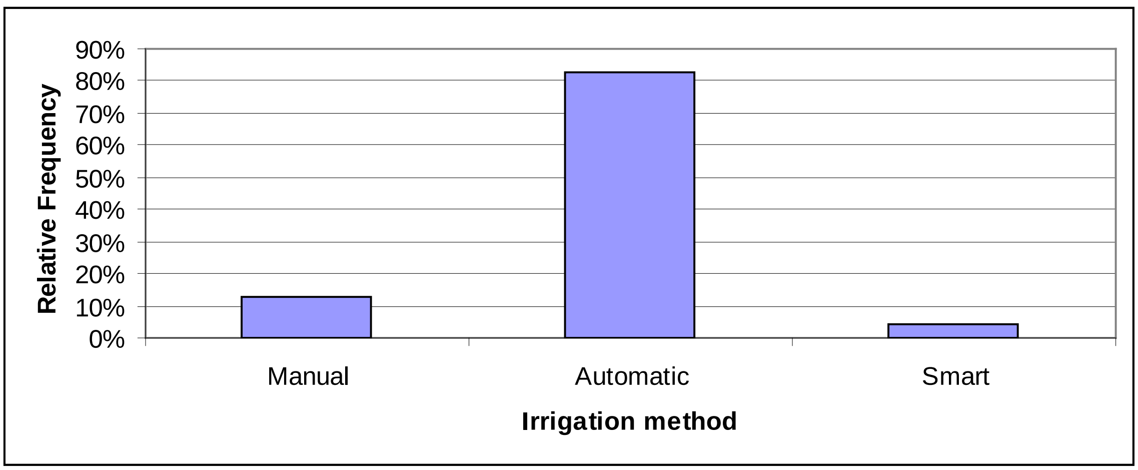

Figure 49: Histogram of parameter BJ

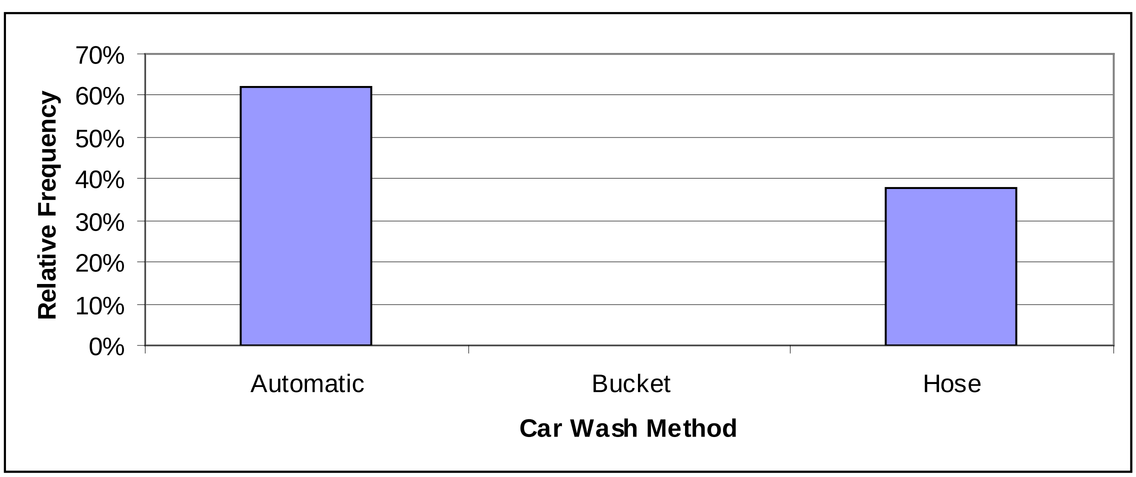

Figure 50: Histogram of parameter BQ

Appendix C-Water Use Equations

The following equations are the relations between the parameters and the end use demands. Items enclosed in parentheses are randomly sampled parameters—constants are enclosed in brackets. The units of Q in all calculations are gallons per household per day.

Toilet

$$Q=\left[\text{weighted avg.}\,\frac{\text{gal}}{\text{flush}}\right]\left(\frac{\text{flushes}}{\text{day}\cdot\text{person}}\right)\left(\frac{\text{persons}}{\text{house}}\right)$$

Where:

$$\left[\text{weighted avg.}\,\frac{\text{gal}}{\text{flush}}\right]=\left(\frac{(\#\,\text{Std.})\left(\frac{\text{gal}}{\text{flush}}\,\text{Std.}\right)+(\#\,\text{ULFT})\left(\frac{\text{gal}}{\text{flush}}\,\text{ULFT}\right)+(\#\,\text{HET})\left(\frac{\text{gal}}{\text{flush}}\,\text{HET}\right)}{(\#\,\text{Toilets in house})}\right)$$

Shower/Bath

$$Q=\left[\text{weighted avg.}\,\frac{\text{gal}}{\text{min}}\right]\left(\frac{\text{minutes}}{\text{shower}}\right)\left(\frac{\text{showers}}{\text{week}\cdot\text{person}}\right)\left(\frac{\text{persons}}{\text{house}}\right)\left[\frac{1\,\text{week}}{7\,\text{days}}\right]+\left(\text{Bath Use}\,\frac{\text{gal}}{\text{day}}\right)\text{Where:}$$

$$\left[\text{weighted avg.}\,\frac{\text{gal}}{\text{min}}\right]=\left(\frac{(\#\,\text{Std.})\left(\frac{\text{gal}}{\text{min}}\,\text{Std.}\right)+(\#\,\text{LowFlow})\left(\frac{\text{gal}}{\text{min}}\,\text{LowFlow}\right)}{(\#\,\text{Showers in house})}\right)$$

Faucet

$$Q=\left[\text{weighted avg.}\,\frac{\text{gal}}{\text{min}}\right]\left(\frac{\text{minutes}}{\text{day}\cdot\text{person}}\right)\left(\frac{\text{persons}}{\text{house}}\right)$$

Where:

$$\left[\text{weighted avg.}\,\frac{\text{gal}}{\text{min}}\right]=\left(\frac{(\#\,\text{Std.})\left(\frac{\text{gal}}{\text{min}}\,\text{Std.}\right)+(\#\,\text{Aerated})\left(\frac{\text{gal}}{\text{min}}\,\text{Aerated}\right)}{(\#\,\text{Faucets in house})}\right)$$

Laundry

$$Q=\left(\frac{\text{gal}}{\text{cycle}}\right)\left(\frac{\text{cycles}}{\text{week}\cdot\text{person}}\right)\left(\frac{\text{persons}}{\text{house}}\right)\left[\frac{1\,\text{week}}{7\,\text{days}}\right]$$

Leaks

$$Q=\left(\frac{\text{gal}}{\text{day}}\right)$$

Car Wash

$$\text{If hose car wash: }Q=\left(\frac{\text{hose gal}}{\text{minutes}}\right)\left(\frac{\text{minutes}}{\text{car}\cdot\text{wash}}\right)\left(\frac{\text{washes}}{\text{week}}\right)\left(\frac{\text{cars}}{\text{house}}\right)\left[\frac{1\,\text{week}}{7\,\text{days}}\right]$$

If bucket car wash: $Q = \left(\frac{\text{gal}}{\text{bucket}}\right)\left(\frac{\text{buckets}}{\text{car} \cdot \text{wash}}\right)\left(\frac{\text{washes}}{\text{week}}\right)\left(\frac{\text{cars}}{\text{house}}\right)\left[\frac{1\,\text{week}}{7\,\text{days}}\right]$

If automatic car wash: $Q = 0$

Pool

$$Q = \left(\text{pool area (ft}^2)\right)\left(\frac{\text{ET(inches)}}{\text{season}}\right)\left[\frac{1\,\text{ft}}{12\,\text{inches}}\right]\left[\frac{7.48\,\text{gal}}{1\,\text{ft}^3}\right]\left[\frac{1\,\text{season}}{182\,\text{days}}\right]$$

Lawn

$$Q = \left(\frac{\left[\text{lawn area (ft}^2)\right]\left(\frac{\text{ET(inches)}}{\text{season}}\right)\left(K_{c,\,\text{Lawn}}\right)\left[\frac{1\,\text{ft}}{12\,\text{inches}}\right]\left[\frac{7.48\,\text{gal}}{1\,\text{ft}^3}\right]\left[\frac{1\,\text{season}}{182\,\text{days}}\right]}{\left[\text{irrigation efficiency(\%)}\right]}\right)$$

Where:

$$\left[\text{lawn area (ft}^2)\right] = \left(\text{lot size - house size(ft}^2)\right)\left(\text{\% landscaped}\right)\left(\text{\% lawn}\right)$$

$$\left[\text{irrigation efficiency (\%)}\right] = \left(\text{Max. irrigation efficiency(\%)}\right)\left(\text{Watering Method Reduction(\%)}\right)$$

Garden

$$Q = \left(\frac{\left[\text{garden area (ft}^2)\right]\left(\frac{\text{ET(inches)}}{\text{season}}\right)\left(K_{c,\,\text{Garden}}\right)\left[\frac{1\,\text{ft}}{12\,\text{inches}}\right]\left[\frac{7.48\,\text{gal}}{1\,\text{ft}^3}\right]\left[\frac{1\,\text{season}}{182\,\text{days}}\right]}{\left[\text{irrigation efficiency(\%)}\right]}\right)$$

Where:

$$\left[\text{garden area (ft}^2)\right] = \left(\text{lot size - house size(ft}^2)\right)\left(\text{\% landscaped}\right)\left(1 - \text{\% lawn}\right)$$

$$\left[\text{irrigation efficiency (\%)}\right] = \left(\text{Max. irrigation efficiency(\%)}\right)\left(\text{Watering Method Reduction(\%)}\right)$$

Appendix D-Water Use Reduction from Conservation Measures

The following equations determine the water saved (effectiveness) of each conservation action. In all equations, Q_s = water saved, and the units are gallons per household per day. Items enclosed in parentheses are randomly sampled parameters, and items in brackets are constants. Some of the items have already been defined in Appendix C.

Long-Term conservation actions

Retrofit Showerheads

$$Q_s = \left(\left[\text{weighted avg.}\frac{\text{gal}}{\text{min}}\right] - \left(\frac{\text{gal}}{\text{min}}\text{LowFlow}\right)\right)\left(\frac{\text{minutes}}{\text{shower}}\right)\left(\frac{\text{showers}}{\text{week}\cdot\text{person}}\right)\left(\frac{\text{persons}}{\text{house}}\right)\left[\frac{1\,\text{week}}{7\,\text{days}}\right]$$

Retrofit Bathroom Faucets

$$Q_s = \left(\left[\text{weighted avg.}\frac{\text{gal}}{\text{min}}\right] - \left(\frac{\text{gal}}{\text{min}}\text{Aerated}\right)\right)\left(\frac{\text{minutes}}{\text{day}\cdot\text{person}}\right)\left(\frac{\text{persons}}{\text{house}}\right)$$

Replace all standard toilets with HETs

$$Q_s = \left(\left[\text{weighted avg.}\frac{\text{gal}}{\text{flush}}\right] - \left[\text{new weighted avg.}\frac{\text{gal}}{\text{flush}}\right]\right)\left(\frac{\text{flushes}}{\text{day}\cdot\text{person}}\right)\left(\frac{\text{persons}}{\text{house}}\right)$$

Where:

$$\left[\text{new weighted avg.}\frac{\text{gal}}{\text{flush}}\right] = \left(\frac{(\#\,\text{ULFT})\left(\frac{\text{gal}}{\text{flush}}\text{ULFT}\right) + (\#\,\text{HET}+\#\,\text{Std.})\left(\frac{\text{gal}}{\text{flush}}\text{HET}\right)}{(\#\,\text{Toilets in house})}\right)$$

For the other toilet replacement actions, the equation for water saved remains the same, but the new weighted average of the flush rates changes:

Replace all standard toilets with ULFTs

$$\left[\text{new weighted avg.}\frac{\text{gal}}{\text{flush}}\right] = \left(\frac{(\#\,\text{ULFT}+\#\,\text{Std.})\left(\frac{\text{gal}}{\text{flush}}\text{ULFT}\right) + (\#\,\text{HET})\left(\frac{\text{gal}}{\text{flush}}\text{HET}\right)}{(\#\,\text{Toilets in house})}\right)$$

Replace all ULFT toilets with HETs

$$\left[\text{new weighted avg.}\frac{\text{gal}}{\text{flush}}\right] = \left(\frac{\text{gal}}{\text{flush}}\text{HET}\right)$$

This conservation action actually includes replacing all ULFTs and standard toilets with HETs.

Retrofit Laundry Machine

$$Q_s = \left(\left(\frac{\text{gal}}{\text{cycle}}\text{Std.}\right) - \left(\frac{\text{gal}}{\text{cycle}}\text{Efficient}\right)\right)\left(\frac{\text{cycles}}{\text{week} \cdot \text{person}}\right)\left(\frac{\text{persons}}{\text{house}}\right)\left[\frac{1\,\text{week}}{7\,\text{days}}\right]$$

Install Xeriscape

$$Q_s = \left(\left(K_{\text{c, Lawn}}\right) - \left(K_{\text{c, Xeriscape}}\right)\right)\left(\text{lawn use}\,\frac{\text{gal}}{\text{day}}\right) + \left(\left(K_{\text{c, Garden}}\right) - \left(K_{\text{c, Xerixcape}}\right)\right)\left(\text{garden use}\,\frac{\text{gal}}{\text{day}}\right)$$

The lawn use and garden use have already been calculated using the expression in Appendix C.

Install Warm-Season Turf

$$Q_s = \left(\left(K_{\text{c, Lawn}}\right) - \left(K_{\text{c, Warm-Season Turf}}\right)\right)\left(\text{lawn use}\,\frac{\text{gal}}{\text{day}}\right)$$

Install Drip Irrigation

$$Q_s = \left(\frac{\left([\text{new irr. eff.}] - [\text{old irr. eff.}]\right)}{[\text{new irr. eff.}]}\right)\left(\text{garden use}\,\frac{\text{gal}}{\text{day}}\right)$$

$$[\text{new irr. eff.}] = \left(\text{Max. irrigation efficiency}_{\text{drip}}\,(\%)\right)\left(\text{Watering Method Reduction}(\%)\right)$$

Install Smart Irrigation Controller

$$Q_s = \left(\frac{\left([\text{new irr. eff.}] - [\text{old irr. eff.}]\right)}{[\text{new irr. eff.}]}\right)\left(\text{total outdoor use}\,\frac{\text{gal}}{\text{day}}\right)$$

$$[\text{new irr. eff.}] = \left(\text{Max. irrigation efficiency}(\%)\right)\left(\text{Watering Method Reduction}_{\text{Smart}}\,(\%)\right)$$

Install Artificial Turf

$$Q_s = \left(\text{lawn use}\,\frac{\text{gal}}{\text{day}}\right)$$

Short-Term Conservation Actions

Only Flush when Necessary

$$Q_s = \left[\text{weighted avg.}\frac{\text{gal}}{\text{flush}}\right](1 - (\text{\% requiring full flush}))\left(\frac{\text{flushes}}{\text{day}\cdot\text{person}}\right)\left(\frac{\text{persons}}{\text{house}}\right)$$

Reduce Shower Length

$$Q_s = \left[\text{Weighted Avg.}\frac{\text{gal}}{\text{min}}\right]\left(\text{reduction}\frac{\text{min.}}{\text{shower}}\right)\left(\frac{\text{showers}}{\text{week}\cdot\text{person}}\right)\left(\frac{\text{persons}}{\text{house}}\right)\left[\frac{1\,\text{week}}{7\,\text{days}}\right]$$

Reduce Shower Frequency

$$Q_s = \left[\text{Weighted Avg.}\frac{\text{gal}}{\text{min}}\right]\left(\frac{\text{minutes}}{\text{shower}}\right)\left(\text{reduction}\frac{\text{showers}}{\text{week}\cdot\text{person}}\right)\left(\frac{\text{persons}}{\text{house}}\right)\left[\frac{1\,\text{week}}{7\,\text{days}}\right]$$

Turn Off Faucets while Washing

$$Q_s = \left[\text{weighted avg.}\frac{\text{gal}}{\text{min}}\right]\left(\text{reduction}\frac{\text{minutes}}{\text{day}\cdot\text{person}}\right)\left(\frac{\text{persons}}{\text{house}}\right)$$

Reduce Laundry Washing Frequency

$$Q_s = (\text{\% reduction in washing frequency})\left(\text{laundry use}\frac{\text{gal}}{\text{day}}\right)$$

Find and Fix Leaks

$$Q_s = (\text{\% of leaks detected and fixed})\left(\text{leakage rate}\frac{\text{gal}}{\text{day}}\right)$$

Stress Irrigate

$$Q_s = (\text{\% reduction in water use})\left(\text{outdoor use rate}\frac{\text{gal}}{\text{day}}\right)$$

Wash Car with Buckets

$$Q_s = \left(\text{car wash use}\frac{\text{gal}}{\text{day}}\right) - \left(\frac{\text{gal}}{\text{bucket}}\right)\left(\frac{\text{buckets}}{\text{car}\cdot\text{wash}}\right)\left(\frac{\text{washes}}{\text{week}}\right)\left(\frac{\text{cars}}{\text{house}}\right)\left[\frac{1\,\text{week}}{7\,\text{days}}\right]$$

Wash Car at Car Wash

$$Q_s = \left(\text{car wash use}\frac{\text{gal}}{\text{day}}\right)$$

Stop Filling Swimming Pool

$$Q_s = \left(\text{pool use}\frac{\text{gal}}{\text{day}}\right)$$

Appendix E-Conservation Action Costs

The following table gives the assumed costs for conservation actions. These are the only costs used in the model runs with financial costs only.

Action	Capital Cost ($)	Source	Professional Installation Cost ($)	Source	Lifespan (years)	Source
Long-term						
A. Retrofit one showerhead	20	HomeDepot, 2011	80	Rotorooter, 2011	10	Gleick, 2003
B. Install one faucet aerator	5	HomeDepot, 2011	10	Rotorooter, 2011	10	Engineering Estimate
C. Retrofit one toilet as HET	170	HomeDepot, 2011	250	Rotorooter, 2011	25	CUWCC, 2009
D. Retrofit one toilet as ULFT	160	HomeDepot, 2011	250	Rotorooter, 2011	25	CUWCC, 2009
E. Retrofit a laundry machine as front-loading	500	Maddaus, 2009	170	Rotorooter, 2011	10	CUWCC, 2009
F. Install low-water consuming landscape ($/sq.ft)	2.5	PPIC, 2006	0.5	Sovocool, 2005	15	PPIC, 2006
G. Install warm-season turf ($/sq.ft)	2	PPIC, 2006	0.5	Sovocool, 2005	15	PPIC, 2006
H. Install drip irrigiation system	100	Galt Homes, 2011	0.5	Sovocool, 2005	15	PPIC, 2006
I. Install artificial turf ($/sq. ft)	3.5	HomeDepot, 2011	0.5	Sovocool, 2005	10	Morrison, 2005
J. Install smart irrigation controller	140	HomeDepot, 2011	160	Maddaus, 2009	15	PPIC, 2006
Short-term						
L. Only flush when necessary	-	-	-	-	-	-
M. Find and fix leaks	-	-	-	-	-	-
N. Turn off faucets while washing	-	-	-	-	-	-
O. Reduce shower length	-	-	-	-	-	-
P. Reduce shower-taking frequency	-	-	-	-	-	-
Q. Reduce laundry-washing frequency	-	-	-	-	-	-
R. Stress Irrigate	-	-	-	-	-	-
S. Wash car with buckets	-	-	-	-	-	-
T. Wash car at gas station	10	Engineering Estimate	-	-	-	-
U. Stop filling swimming pool	-	-	-	-	-	-

The following table shows the estimated hassle times taken to either install a long-term conservation device or perform a short-term conservation action. The amount of time is multiplied by the value of time to a particular household to derive the hassle costs of the actions. The financial costs in the previous table are applied in addition to these hassle costs. The handiness cutoffs are also included-if a house has a handiness factor higher than this cutoff, it must use professional installation.

Action	Hassle Time (hours/day)	Source	Handiness Cutoff (% that can perform action)
Long-term			
A. Retrofit one showerhead	1	Rotorooter, 2011	0.9
B. Install one faucet aerator	1	Rotorooter, 2011	0.95
C. Retrofit one toilet as HET	4	Rotorooter, 2011	0.5
D. Retrofit one toilet as ULFT	4	Rotorooter, 2011	0.5
E. Retrofit a laundry machine as front-loading	4	Rotorooter, 2011	0.3
F. Install low-water consuming landscape (hrs/sq.ft)	0.01	Engineering Estimate	0.1
G. Install warm-season turf (hrs/sq.ft)	0.01	Engineering Estimate	0.1
H. Install drip irrigiation system (hrs/sq.ft)	0.01	Engineering Estimate	0.2
I. Install artificial turf (hrs/sq.ft)	0.01	Engineering Estimate	0.1
J. Install smart irrigation controller	8	Engineering Estimate	0.2
Short-term			
L. Only flush when necessary	0.02	Engineering Estimate	-
M. Find and fix leaks	0.05	Engineering Estimate	-
N. Turn off faucets while washing	0.01	Engineering Estimate	-
O. Reduce shower length	0.05	Engineering Estimate	-
P. Reduce shower-taking frequency	0.05	Engineering Estimate	-
Q. Reduce laundry-washing frequency	0.05	Engineering Estimate	-
R. Stress Irrigate	0.05	Engineering Estimate	-
S. Wash car with buckets	0.05	Engineering Estimate	-
T. Wash car at gas station	0.01	Engineering Estimate	-
U. Stop filling swimming pool	0.05	Engineering Estimate	-

Appendix F - Optimization Equations

GAMS was used to solve the optimization problem. "Sets" are lists (e.g. the set "l" is the long term actions = {"Replace Showerheads", "Install Artificial Turf", …}). Parameters are numeric values that are defined over sets or as scalars. Parameters with subscripts are defined over the set corresponding to the subscript. For example, the parameter f_s means that there is a separate effectiveness defined for each short-term action. Decision variables are defined in the same way as parameters, with subscripts indicating the decision variable is defined over the subscripted set. Decision variables are bold and underlined to indicate their vector nature and to differentiate them from parameters.

Sets:
e = events
s = short term actions (a copy of the set is called s2)
l = long term actions (a copy of the set is called l2)
u = end uses
$t_{l,u}$ = long-term conservation actions belonging to end use u
$t_{s,u}$ = short-term conservation actions belonging to end use u

Parameters:
a_l = maximum limit of implementation of long-term actions
a_s = maximum limit of implementation of short-term actions
b_e = initial water use
c_l = long-term action costs
c_s = short-term action costs
$d_{u,e}$ = Maximum effectivess for conservation actions relating to each end use
f_l = effectiveness of long-term actions (reduction in water use)
f_s = effectiveness of short-term actions (reduction in water use)
g = unit conversion constant (gallons to CCF)
h_e = rationed water amount during drought events
i = number of events per billing period
j = number billing periods per year
k = fixed water charge each billing period
$m_{l,l2}$ = symmetric matrix of mutually exlusive long-term actions
$m_{s,s2}$ = symmetric matrix of mutually exlusive short-term actions
n_e = surcharge on volumetric use during drought events
o_e = surcharge for using the Freeport water supply
p_e = probability of event e
q_e = penalty for exceeding the rationed amount of water
$r_{l,l2}$ = symmetric matrix of mutually required long-term actions
$r_{s,s2}$ = symmetric matrix of mutually required short-term actions
v = upper limit of water bill block 1
w = upper limit of water bill block 2
x = Charge on water use in water bill block 1
y = Charge on water use in water bill block 2
z = Charge on water use in water bill block 3

Decision Variables:
$\underline{\mathbf{S}}_{s,e}$ = short term action
$\underline{\mathbf{L}}_{l}$ = long term action
$\underline{\mathbf{B}}_{e}$ = water bill
$\underline{\mathbf{U}}_{e}$ = water use
$\underline{\mathbf{E}}_{u,e}$ = end use saved
$\underline{\mathbf{W}}_{e}$ = water saved

Objective Function:

Minimize $Z = c_l(\underline{\mathbf{L}}) + j\sum_{e}\left[p_e\left(i\sum_{s}\left(c_s\underline{\mathbf{S}}_{s,e}\right) + \underline{\mathbf{B}}_e\right)\right]$

Subject to:

Max. implementation limits

$\underline{\mathbf{L}}_l \le a_l \ \forall \mathrm{l}$

$\underline{\mathbf{S}}_{s,e} \le a_s \ \forall \mathrm{s,e}$

Integer

$\underline{\mathbf{L}}_l = \text{integer} \ \forall \mathrm{l}$

$\underline{\mathbf{S}}_{s,e} = \text{integer} \ \forall \mathrm{s} \forall \mathrm{e}$

Max. effectivenesses

$\underline{\mathbf{W}}_e \le b_e \ \forall \mathrm{e}$

$\underline{\mathbf{E}}_{u,e} \le d_{u,e} \ \forall \mathrm{u} \forall \mathrm{e}$

Water Saved

$\underline{\mathbf{W}}_e \le \sum_{u}\underline{\mathbf{E}}_{u,e} \ \forall \mathrm{e}$

Water Used

$\underline{\mathbf{U}}_e \ge b_e - \underline{\mathbf{W}}_e \ \forall \mathrm{e}$

Mutually exclusive actions

$\sum_{l2}\underline{\mathbf{L}}_{l2} m_{l,l2} \le 1 \ \forall \mathrm{l}$

$\sum_{s2}\underline{\mathbf{S}}_{s2,e} m_{s,s2} \le 1 \ \forall \mathrm{s} \forall \mathrm{e}$

Mutually requiring actions

$\sum_{l2}\underline{\mathbf{L}}_{l2} r_{l,l2} = 0 \ \forall \mathrm{l}$

$\sum_{s2}\underline{\mathbf{S}}_{s2,e} r_{s,s2} = 0 \ \forall \mathrm{s} \forall \mathrm{e}$

Short-term interactions

$\underline{\mathbf{E}}_{u,e} \le \sum_{t_{s,u}}\left(f_{t_{l,u},e}\underline{\mathbf{L}}_{t_{l,u}}\right) + \sum_{t_{s,u}}\left(f_{t_{s,u},e}\underline{\mathbf{S}}_{t_{s,u},e}\right) \ \forall \mathrm{u} \forall \mathrm{e}$

Water bill

$\underline{\mathbf{B}}_e \ge k + gi(1 + n_e o_e)(x\underline{\mathbf{U}}_e) \ \forall \mathrm{e}$

$\underline{\mathbf{B}}_e \ge k + gi(1 + n_e o_e)(xv + y(\underline{\mathbf{U}}_e - v)) \ \forall \mathrm{e}$

$\underline{\mathbf{B}}_e \geq k + gi(1 + n_e o_e)(xv + y(w - v) + z(\underline{\mathbf{U}}_e - w))$ $\forall$e

Penalties above rationed amounts

$\underline{\mathbf{B}}_e \geq k + gi(1 + n_e o_e)(xh_e + (q_e + x)(\underline{\mathbf{U}}_e - h_e))$ $\forall$e

$\underline{\mathbf{B}}_e \geq k + gi(1 + n_e o_e)(xv + y(h_e - v) + (q_e + y)(\underline{\mathbf{U}}_e - h_e))$ $\forall$e

$\underline{\mathbf{B}}_e \geq k + gi(1 + n_e o_e)(xv + y(w - v) + z(h_e - w) + (q_e + z)(\underline{\mathbf{U}}_e - h_e))$ $\forall$e