How Much Water Does Turf Removal Save? Applying Bayesian Structural Time-Series to California Residential Water Demand

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1. ABSTRACT

California water utilities have invested historic amounts of money in turf rebates to incentivize customers to remove their turf grass and replace it with more water efficient landscaping. This study utilizes a data set of 545 unique single-family residential turf rebates across 3 California water utilities, totaling 635,713 square feet of converted turf grass to estimate the water savings from turf removal. Monthly water savings are estimated at the household level as the difference between actual usage and a synthetic control and then aggregated using a mixed-effects regression model to investigate the determinants of water savings. Analysis of turf removal at the monthly level is found to be critical for understanding the seasonal behavior inherent in outdoor water use. Mean predicted savings for single-family residential accounts are estimated at 24.6 gallons per square foot per year for the households used in this study.

2. INTRODUCTION

With outdoor landscaping representing approximately half of urban water usage, the water community has identified outdoor water usage in general (Mayer, Lander, and Glenn 2015), and ornamental lawns specifically (CUWCC 2015) as a key opportunity in the larger effort to increase water conservation. Between July 2014 and April 2016, the Metropolitan Water District (MWD), the regional wholesaler of Colorado and Bay Delta water for Southern California, paid out $270.7 million directly for turf rebates under its regional program and another $15.1 million to supplement member agency spending on turf replacement. Metropolitan indirectly serves 6.1 million residential households across Southern California (MWD 2016). In addition, millions in local retailer turf rebate supplements have been paid out (for example in Los Angeles, Long Beach, San Diego and Moulton Niguel).

A small number of studies have investigated the impact of turf removal conservation rebate programs on water usage. In 2005, the Southern Nevada Water Authority (SNWA) conducted a turf removal and Xeriscape planting study that found these rebates led to 55 gallons in water savings per year per sq. ft. of turf removed (Sovocool, Authority, and Morgan 2005). These results may not be reflective of the impact of such policies in the climate in Los Angeles and the absence of a requirement for Xeriscape landscaping. Indeed, P. Atwater, Schmitt, and Atwater (2015) found a more modest residential reduction of approximately 18 gallons per year per sq. ft. in the Moulton Niguel Water District in south Orange County, California. Similarly, the Metropolitan water district conducted a study in 2014 with robust hydrological variation that found an average relative water reduction of 18.2% from participating residential households and 24% from participating commercial accounts (MWD 2014).

This study builds on previous research and develops a novel methodology for assessing the impact of water conservation actions. Previous work in P. Atwater, Schmitt, and Atwater (2015) utilized a multilevel quantile regression model to control for the determinants of water use and isolate the average reduction in usage due to turf removal. However, the authors were unsatisfied with the methodology used to control for behavioral elements such as environmental attitudes, and structural shifts in usage like California's 2015 mandatory water conservation requirements. The approach used here instead borrows from the marketing context to match residential households based on their past water usage behavior instead of using static descriptive attributes like household size and irrigable area. A synthetic control is then created and a difference-in-differences approach is applied to estimate monthly water savings at the level of individual households. This enables analysis of the full distribution of water use changes, including seasonal fluctuations in the amount of water saved that highlight peak summer demand reduction. Finally the individual estimates are aggregated using a meta-analytic mixed-effects model to control for moderator variables of interest.

3. METHODOLOGY

3.1 Data

The data used in this study was provided by 3 water utilities: Moulton Niguel Water District (MNWD), Irvine Ranch Water District (IRWD), and Eastern Municipal Water District (EMWD). Each utility provided two data sources. The first is a panel data set of monthly billed water usage and customer characteristics identified by account and service

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point (water meter) identifiers for single family households. The second is a data set detailing participation in water efficiency rebate programs, of which turf removals are the primary interest for this study.

These two data sets are merged, and any turf rebate instances tied to accounts that appear more than once are dropped to prevent overcounting. These accounts are then further restricted to those that have at least two years of data (24 observations) in the pre-rebate period and one year of data (12 observations) in the post-rebate period. The pre- and post-rebate periods are determined relative to the month that the post-rebate inspection was performed. Finally, the water districts make use of default values in cases where the actual value is unknown. Some districts substitute default values for irrigable area when actual values are not known. Customers with default values were dropped in cases where this was obvious due to bunching of many customers at the same value of irrigable area.

The working dataset contains 545 observations of either traditional or synthetic turf rebates after filtering. The variables are defined as follows:

- `Customer ID`: unique identifier for each household.
- `Month` and `Year`: the month and year of the water bill.
- `HH Size`: number of permanent residents at the property.
- `Irr Area Sf` and `Rebate Quantity`: the square feet of irrigable area and square feet of turf removed during rebate, respectively.
- `Rebate Area Ratio`: the proportion of turf area removed, calculated as $\frac{\texttt{Rebate Quantity}}{\texttt{Irr Area Sf}}$.
- `Evapotranspiration`: The reference evapotranspiration, $ET0$, in inches.

3.2 Time Series Matching and Rebate Impact Estimation

The estimation of rebate water savings is implemented using the `R` programming language. It is done in three steps. Given $N = 545$ treatment accounts which participated in a turf removal rebate and are examined in this study:

1. Each treatment account $tr_i, i \in 1 \dots N$ which has participated in a turf rebate is matched with a set of control accounts $C_i = \{c_i^j\}, j \in 1 \dots 6$ from the same zip code which did not participate in a turf rebate. These control accounts are chosen by how similar their historical usage patterns are to the usage patterns of the treatment account tr_i, based on a weighted combination of their Pearson correlation and their warping distance.

2. After the c_i have been chosen, we fit a Bayesian structural time series model and use it to estimate the monthly impact of turf removal on water savings. The structural time series (STS) model uses the water usage patterns of the control accounts to create a synthetic control corresponding to the expected water usage of tr_i if there had been no turf removal. The predicted usage in the post-rebate period is then subtracted from observed usage to obtain a monthly water savings estimate for tr_i.

3. After a water savings estimate has been calculated for each treatment account, the last step is to obtain an overall summary estimate. This is done with a meta-analytic approach that uses the estimates and variances from each treatment account as the inputs into a random effects model.

The first two steps are implemented into a workflow by the `MarketMatching` package. [1].

3.3 Choosing Control Accounts

The first step in obtaining an estimate of the turf removal impact for account tr_i is to find accounts that did not remove their turf that show similar behavior to tr_i. Candidate accounts were identified by choosing controls from within the same zip code as tr_i. Within each zip code there may still be thousands of possible controls. These remaining possibilities are ranked by how similar their historical water usage patterns are to the historical usage of tr_i.

Account matching is often based on variables like property size, property value, or education levels. However, the importance of environmental attitudes, for example arising from public awareness actions and social change has been shown to influence water consumption (Hollis 2016). The difficulty of incorporating these and other difficult-to-quantify factors driving household water usage, and the fairly stable water consumption patterns observed by most households, make matching based on water consumption patterns attractive. The premise of using historically predictive relationships between accounts to perform counterfactual analysis in this fashion has been advocated by cf. Abadie, Diamond, and Hainmueller (2010) and Brodersen et al. (2015).

Let tr and c be a treatment and control time series with m observations each for which a similarity ranking is desired. This similarity ranking is done as a weighted composite of two other similarity measures. The first is the Pearson correlation:

$$\rho(tr, c) = \frac{\sum_{t=1}^{p}(tr_t - \bar{tr})(c_t - \bar{c})}{\sqrt{\sum_{t=1}^{p}(tr_t - \bar{tr})^2}\sqrt{\sum_{t=1}^{p}(c_t - \bar{c})^2}} \tag{1}$$

The second ranks them according to their dynamic time warping (DTW) distance from tr_i. To compute the warping distance between two time series, we must identify the warping curve $\phi(t) = (\phi_{tr}(t), \phi_c(t))$ that has the minimum warping distance,

$$D(tr, c) = \sum_{t=1}^{p} d(\phi_{tr}(t), \phi_c(t)) p_\phi(t), \tag{2}$$

where $d(\phi_{tr}(t), \phi_c(t))$ is the local of the points at time t after they have been remapped by the warping functions $\phi_{tr}(t)$ and $\phi_c(t)$, and $m_\phi(t)$ is per-step weight that control the slope of the warping curve. The calculation of the DTW distance is done using the `dtw` package. For details about the package and about dynamic time warping see Giorgino and others (2009).

Let the vector $\boldsymbol{r}$ denote the similarity scores for K candidate control accounts $c_k, k = 1, \dots, K$ with respect to tr_i,

[1]The code was modified and is available at https://github.com/christophertull/MarketMatching/tree/usability-improvements

where the kth element of $\boldsymbol{r}$ is given by:

$$r_k = (1-\alpha)\rho(tr_i, c_k) + \alpha D(tr_i, c_k),$$

with $\alpha \in [0,1]$. Then, the control households corresponding to the first m values of the sorted $\boldsymbol{r}$ are used as controls for tr_i in the structural time series model for that series discussed in the next section.

3.4 Estimating Water Savings

A widely used approach for estimating the causal impact of interventions, like rebate offerings, is differences-in-differences. Taking this approach in the turf removal context, the estimated causal impact of turf removal on water savings is the difference between water usage when turf was removed, and the amount of water that would have been used if no turf had been removed (Bamezai 1995).

To accurately estimate the reduction in water usage due to turf removal, a model for the counterfactual case needs to account for other variables determining water usage. Water use is determined by a multitude of factors, such as weather, user size, social perspectives on water usage, and turf removal. Covariates like weather and user size are measured by agencies and are straightforward to account for with a model.

This leaves the matter of accounting for dynamic behavioral patterns. Recognizing the need to address this aspect of water use, Hollis (2016) took variables measuring media factors, like advertising volume, to explain water use patterns. The inclusion of media presence explicitly in a usage model is desirable, but two issues that arise with this approach are properly quantifying media presence and accounting for the different levels of exposure experienced by water users.

Another way to account for dynamic behavior is to explicitly model the counterfactual of a time series observed both before and after the rebate and use the resulting model to construct a synthetic control (cf. Abadie, Diamond, and Hainmueller (2010)). The approach of Brodersen et al. (2015) is to construct a synthetic control by combining three sources of information using a state-space time-series model, where one component of state is a linear regression on the contemporaneous predictors. The first source of information is the behavior of the response prior to the turf removal. A second is to use other time series that were predictive of the target series before the turf removal. In particular, a relationship between a time series which removed turf and others that did not can be used to estimate a synthetic control after the rebate. These series allow us to account for unmodeled causes of variance such as a general decline in water usage due to media campaigns or mandatory reductions due to drought restrictions. Thirdly, in a Bayesian framework prior knowledge about the model parameters, from prior studies, for example, can be used to construct the counterfactual.

We will use static regression coefficients in our Bayesian structural time series model, which assumes that the linear usage relationship between the controls and the counterfactual expected usage for customers who did remove turf from their lawn remains fixed even after the turf is removed. Furthermore, we will allow for a local linear trend. For a time series $\boldsymbol{y}$, this model has the form:

$$y_t = \underbrace{\mu_t}_{\text{level}} + \underbrace{Z_t}_{\text{regression}} + \varepsilon_t, \tag{3}$$

$$Z_t = \beta' \boldsymbol{x}, \tag{4}$$

$$\underbrace{\mu_{t+1} = \mu_t + \delta_t + \eta_{\mu,t}}_{\text{random walk and trend}}, \tag{5}$$

$$\underbrace{\delta_{t+1} = \delta_t + \eta_{\delta,t}}_{\text{random walk for trend}}, \tag{6}$$

where $\varepsilon_t \sim \mathcal{N}(0, \sigma_t^2)$, $\eta_{\mu,t} \sim \mathcal{N}(0, \sigma_{\mu,t}^2)$ and $\eta_{\delta,t} \sim \mathcal{N}(0, \sigma_{\delta,t}^2)$. The regression component, Z_t captures the static linear relationship between the control series and the treatment series, while the level component μ_t captures local linear trends, enabling the model to react to unobserved sources of variability the control and treatment series are exposed to.

By placing a spike-and-slab prior on the set of regression coefficients, and by allowing the model to average over the set of controls, it is possible to choose from many candidate controls (George and Mcculloch 1997). To combine information about the target time series and the controls, the posterior distribution of the counterfactual time series is computed given the value of the target series in the pre-intervention period, along with the values of the controls in the post-intervention period. Given a predicted and observed water use $\hat{y}_t$ and y_t, the difference $\hat{y}_t - y_t$ yields a semiparametric Bayesian posterior distribution for the water savings attributable to the turf removal, which can be used to obtain credible intervals. We take these estimates and adjust them to gallons saved per square foot to obtain:

- μ `gpsf`: monthly gallons saved per square foot of turf removed, calculated as

$$\frac{748.052 \times (y_{it} - \hat{y_{it}})}{\text{rebate\_instance\_quantity}}$$

  where y_t and $\hat{y_t}$ are the actual and estimated usage in hundred cubic feet (CCF) of household tr_i at month t.

The structural time series model was fit using the `CausalImpact` package provided by Google for estimating the effectiveness of marketing campaigns (Brodersen et al. 2015). A number of differences exist between the Google marketing context described in Brodersen et al. (2015), for which this approach was originally proposed, and the turf removal rebate context. Firstly, Google is able to assess the impact of the marketing campaign in terms of participation using this method, where participation is measured in number of clicks, because they have data on number of clicks prior to the campaign. It is in their interest to distinguish how many clicks after the start of the campaign were driven by the campaign, as opposed to organic. In contrast, prior to the rebate programs, the water districts did not track turf removal. The number of rebate claims before the start of the rebate programs is zero, and the number of rebates claimed afterwards is best summarized using simple statistics.

Another difference is that in the marketing context, the impact to estimate is the number of clicks generated as a consequence a marketing campaign, where a marketing campaign is either active or is not. The scale of the marketing campaign is not addressed. We could stop at estimating an average effect of turf removal, but this neglects the important relationship between how much water use is reduced

Parameter	Values
WARPING LIMIT	0, 1
DTW EMPHASIS	0, 0.25, 0.5, 0.75, 1
NUMBER OF MATCHES	6, 12

Table 1: Parameter Values tested in sensitivity analysis.

and the amount of the turf removed. To account for this, the estimated savings are divided by the square feet of turf removed, as calculated by utility staff in a post-rebate inspection. This allows for a normalized measure of rebate impact in terms of gallons per square foot of turf removed. Additionally, variables to quantify the magnitude of the turf removal are included in the meta-model in the final step.

An added complexity in this study is that in place of a single treatment cohort, or perhaps a few, hundreds of customers participated in the rebate program. The approach proposed in Brodersen et al. (2015) stops at providing impact estimates on a single time series at a time. To obtain a broad overview of the impact of turf removal, it is desirable to aggregate estimates from all of the customers. In the section that follows, this issue and the inclusion of the amount of turf removed in our framework will be addressed using a meta-analytic approach.

3.4.1 Example

Figure 1 below shows two examples of the process described above. Specifically, the output of the matching process is shown through charts of water usage over time for the treatment household and its six closest matches. The output of the STS model is given by showing the actual and predicted consumption for the two examples. The example households were chosen for their wildly different behavior patterns in the post-rebate period. One household appears to cease outdoor watering completely after their turf removal, causing their usage to stabilize at winter levels and achieving an estimated 66% reduction in overall water use. The other example household shows a decrease in usage relative to its own past behavior, but shows no significant reduction compared to its similarly-behaving peers. This effect may be due to increased awareness of the California drought and the mandatory restrictions put in place in April 2015. Thus the water savings would be attributed to behavioral change among households in the region but not directly to the removal of turf.

3.5 Parameter selection for the matching and STS steps

A number of parameters must be chosen when applying the matching procedure and STS model. We assessed these in terms of their impact on the mean water savings estimates obtained from the STS models.

A sensitivity analysis was performed to determine the effect of parameter choices at the matching stage on final estimates of water savings. Specifically, a random sample of 150 accounts that made it through the filtering were rerun under all combinations of the different parameter configurations visible in Table 3. While these are not the only parameters in the model, they are three of the ones most likely to impact the water savings estimates because they directly impact the choice of control accounts.

In the STS model, the value for $\sigma^2_{\mu,t}$ in the local linear trend must also be selected. This is the local level standard deviation which controls the prior standard deviation of the local linear trend submodel. The local level term modifies how adaptable the model is to short term changes, and its standard deviation is important because it effects the breadth of the posterior intervals. Brodersen et al. (2015) recommend that the value of 0.01 can be used when the relationship between the controls and the treatment is strong enough to obtain an informative model. The authors indicate that this is more likely when many control candidates are available. The water usage data set contains a large pool of control candidates, and matching results are typically strong. The choice of 0.01 results

After calculating savings estimates under each parameter set, the mean of estimated savings for the sample under each parameter set was calculated. This gives an idea of how sensitive the matching process is to changes in the parameters. These estimates are visible below in Figure 2.

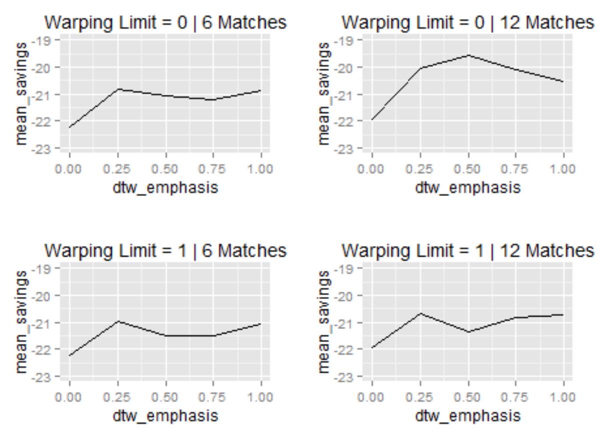

Figure 2: The charts display the sensitivity of the meta-estimate results under various values of the DTW EMPHASIS parameter. Each chart in turn uses a different warping limit or number of control account matches.

Table 2 shows the values of the matching procedure parameters based on the results from the sensitivity analysis, as well as required minimum observation period lengths and matching pool sizes.

3.6 Combining the Estimates

Monthly estimated water savings attributable to turf removal are obtained from each of the Bayesian STS models, yielding a total of 10759 impact estimates for 545 households. Furthermore, a credible interval can be calculated for each of these estimates. The aggregation of these estimates can be seen as a meta-analysis. Before a meta-analysis is conducted, a robust regression is performed using the same continuous moderator variables as the meta-model to remove large outliers. The robust method, Least Trimmed Squares is used with default settings as implemented by the `ltsReg` function in the `robustbase` package. After removing outliers, a random effects model to determine an overall meta-estimate for water savings is fitted. The meta analysis is done using the `metafor` package. Details on the technique

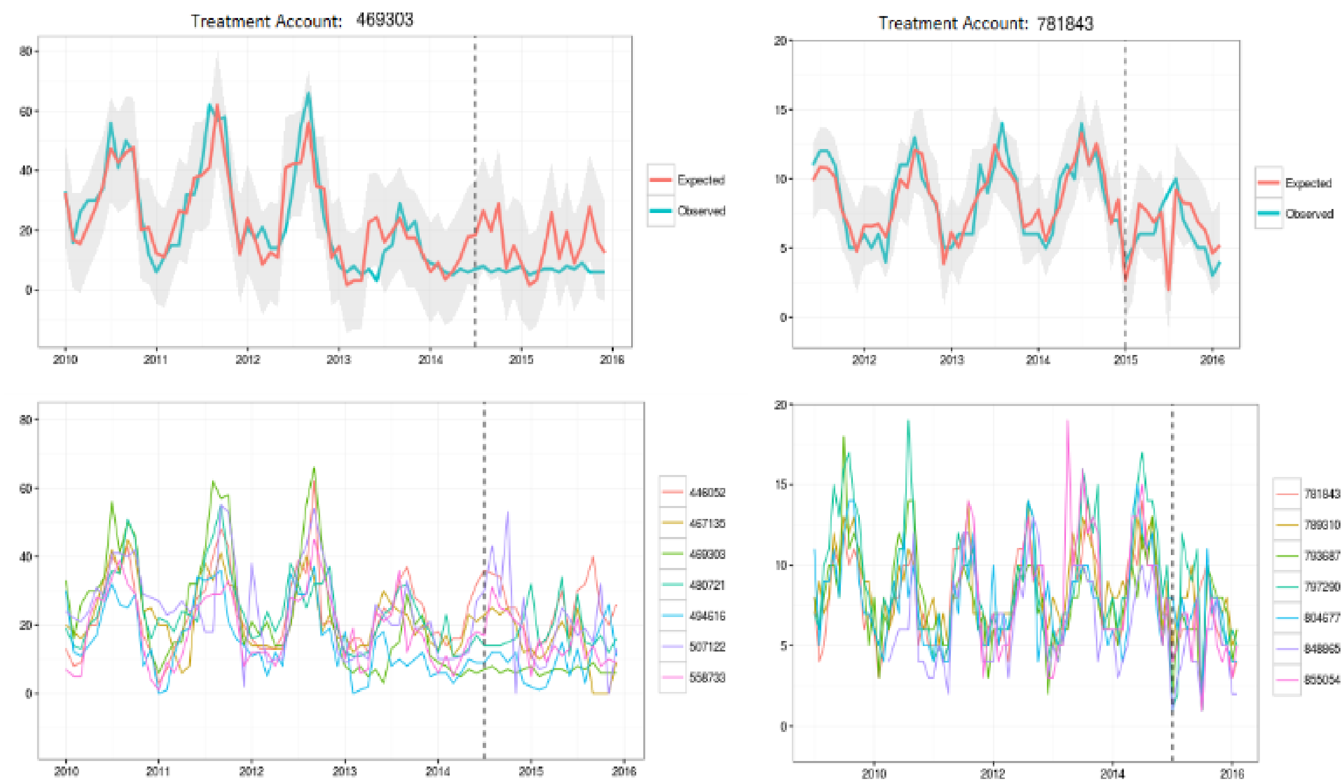

Figure 1: The first row shows the expected and observed usage patterns for two participating rebate accounts, where the difference between expected and observed after removal (dashed) is the estimated savings. The account on the left shows a visible reduction in usage compared to the counterfactual, while the right side has more ambiguous results. The bottom row shows the raw time series of water usage for the treatment and corresponding matched controls.

Table 2: Key Parameter choices in the modeling process.

Parameter	Value	Description
Min. Months Post-Period	12	Require at least 12 months since the rebate took place.
Min. Months Pre-Period	24	Require at least 24 months before the rebate for accurate matching.
Zip Sample Size	500	Randomly sample a maximum of 500 control accounts within the zip code as possible matches.
Min. Matching Series	100	Require a pool of at least 100 possible matches within the zip code.
Warping Limit	1	The size of the Sakoe-Chiba band limiting how much the time series are allowed to warp.
DTW Emphasis	0.7	Controls the trade-off between the DTW distance and Pearson correlation.
Number of Matches	6	The number of control accounts to match with and pass into the STS model.

and the software are available in Viechtbauer and others (2010).

4. RESULTS

The meta-analysis we conduct to aggregate the results from the Bayesian STS model estimates of the water savings from the ith turf-removing household at time t is a mixed effects model with the following fixed effects structure:

$$\begin{aligned} \mu \text{ gpsf}_{i,t} &= \alpha_i + \beta_0 + \beta_1 \times \text{HH Size}_{i,t} \\ &+ \beta_2 \times \text{Rebate Area Ratio}_{i,t} \\ &+ \beta_3 \times sin(2\pi/12Month_{i,t}) \\ &+ \beta_4 \times cos(2\pi/12Month_{i,t}) \\ &+ \beta_5 \times sin(4\pi/12Month_{i,t}) \\ &+ \beta_6 \times cos(4\pi/12Month_{i,t}) \\ &+ \beta_7 \times ln(\text{Rebate Quantity}_{i,t}) \\ &+ \beta_8 \times ln(\text{Irr Area Sf}_{i,t}) \\ &+ \beta_9 \times \text{Evapotranspiration}_{i,t} + \varepsilon_{i,t}. \end{aligned} \tag{7}$$

where μ gpsf is the monthly savings in gallons per square foot. The trigonometric terms in the model account for seasonality. Month, in this model, is a unique number for each of the months in the study and runs from $1, \ldots, 51$.

Table 3 contains the fixed effects estimates of the fitted model. Examining the effect of household size, we see that the more people there are in a household, the lower the impact of turf removal per square foot. This is likely because indoor water usage is larger in larger households, diminishing the potential savings from outdoor water usage relative to a similarly sized house with fewer inhabitants. Rebate area ratio has a large negative coefficient, meaning that the larger the share of the household's irrigable area that is removed, the greater the savings. Three of the trigonometric effects are significant, and are used by the model to capture general seasonal trends in water savings. The positive coefficient of `ln(Rebate Instance Quantity)` means that per foot savings are smaller as the amount of turf removed increases, possibly because watering efficiency increases with larger gardens and lawns. In contrast, the greater the irrigable area in total, the larger the savings. This effect can be similar to the household effect. The larger the irrigable area of a household, the larger outdoor watering's share of water use, and thus the greater the impact of turf removal on household water use per square foot of property. Lastly the evapotranspiration (ET) coefficient is negative, indicating greater savings with increased ET.

Table 3: Fixed effect estimates for the meta-model of turf removal water savings.

Variable	Estimate	SE	t-stat	p-value
Intercept	-0.57	0.67	-0.84	0.40
HH Size	0.12	0.03	3.48	0.00
Rebate Area Ratio	-3.66	0.57	-6.45	0.00
Month Sin 2	0.43	0.03	15.49	0.00
Month Cos 2	0.24	0.05	4.52	0.00
Month Sin 4	0.13	0.02	5.57	0.00
Month Cos 4	0.03	0.03	1.10	0.27
ln(Rebate Instance Quantity)	2.08	0.22	9.32	0.00
ln(Irr Area Sf)	-1.77	0.22	-7.89	0.00
Evapotranspiration	-0.08	0.02	-3.61	0.00

The first analysis we conduct is a comparison of average household savings by year. We do this for the sample in this study by using the model to predict the household savings given their moderator variables. Predicted savings are then grouped by household and year and averaged. The resulting savings estimates give an impression of the distributions of savings outcomes that would be expected by an analyst or policy-maker on this population. We see that annual savings were about 20 gallons per square foot. However, by aggregating the monthly savings to an annual level, we loose important details about the savings patterns.

A more nuanced approach is to use the model to predict the monthly savings. Overlaying the predictions are quantiles ranging from 5% to 95%. The savings pattern illustrated in Figure 4 is highly intuitive. The highest savings are in the months of July, August and September, reaching a monthly average of -2.7 gallons per square square foot less water use. During the months of January, February, and March, the reduction is much smaller but still valuable at -1.5 gallons per square foot.

4.1 Time-Series vs. Traditional Matching

One remaining question of interest is whether time series matching on historical usage produces comparable results to traditional matching on static attributes. In order to address this question, the mean distance from each treatment account to its matched control accounts was compared to the mean distance from each treatment to its potential controls that were not matched.

Distance was calculated by standardizing the covariates for household size and irrigable area within each zip code and customer class. The mean euclidean distance was then calculated between the treatment and each of the matched and unmatched groups. The results of this calculation are

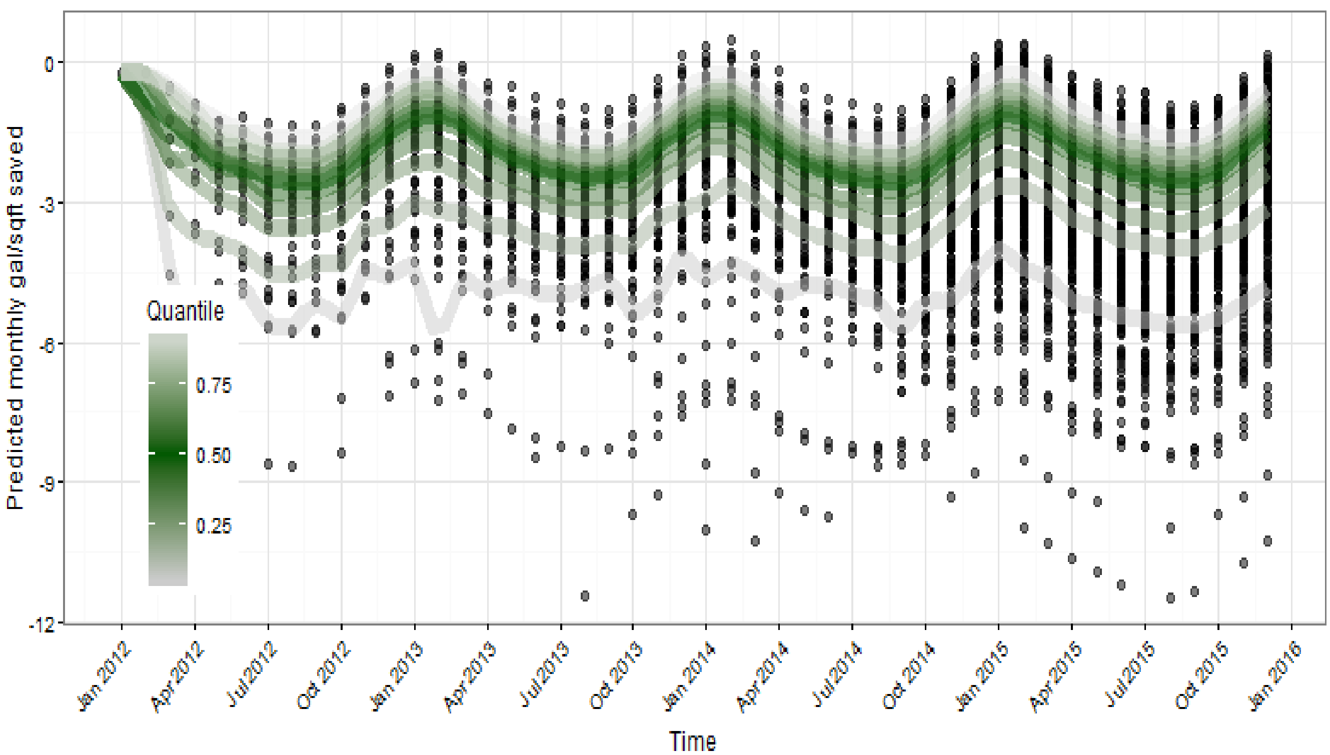

Figure 4: Predicted monthly savings for each household in the data set. The dark green line corresponds to median savings. Seasonal variation leads to swings in average savings from -1.5 to -2.7 gallons per square foot.

visible in Figure 5. One can see that matching on usage patterns tends to result, on average, in matches that are also similar in their household size and irrigable area. However, this was not universally true and manual inspection revealed a large variation even among the matched control accounts. This aligns with the intuition that static covariates do not capture all aspects of water usage, and that dissimilar accounts may have very similar water usage patterns.

5. CONCLUSIONS

This methodology enables estimation of the water savings associated with turf removal using very minimal data by requiring only observational water use over time and a bare minimum of contextual customer attribute data. Many other approaches rely on extensive lists of covariates that are at best proxies for water use behavior. This work matches on observed behavior directly and thereby attempts to incorporate the complexities of individual customer conservation behavior, resulting in estimates of 24.6 gallons saved per year per square foot of turf removed. Boostrapped standard errors of those predicted water savings are .11 gallons per year per square foot of turf removed. Those water savings are stable across district and vary sinusoidally over time highlighting the structural water savings of turf market transformation for regional and statewide water reliability initiatives. At $2 paid per square foot turf removed and assuming a hyperbolic discount rate of five percent over a landscape conversion lifespan of thirty years, that translates into a present value of $1422 plus or minus seven dollars per acre foot of water saved.

Still, these results should be considered an early data point measuring the effects of the generational shift away from water intensive lawns as the default landscaping. Landscape conversions can involve up to a two year period for new drought tolerant plants to establish and thus these results may need to be reassessed in the future. In addition, the turf rebate program has some uncertainty regarding the exact timing of turf removal introducing additional variation into these estimates. Furthermore, this study lacks data on whether artificial turf or California native or other non-turf landscaping were implemented after the rebate. Fortunately the simple data requirements of this method make it easy to redeploy on regularly updated customer use, rebate, customer survey and other creative data sources such as aerial remote sensing. This is the approach being pioneered by the California Data Collaborative utilities in this study and others as they centralize water use data. It enables water managers to measure the water savings with turf removal over time and adaptively manage this historic investment in turf removal.

Measuring savings at the household level also allows water managers to target educational materials on efficient watering practices to customers that have seen dis-savings in the post rebate period compared to their expected counterfactual water use. Finally, the approach can be used to evaluate the water savings associated with other conservation rebates, other customer-level demand management interventions, and potentially other natural resource conservation programs in energy or natural gas. As the old adage

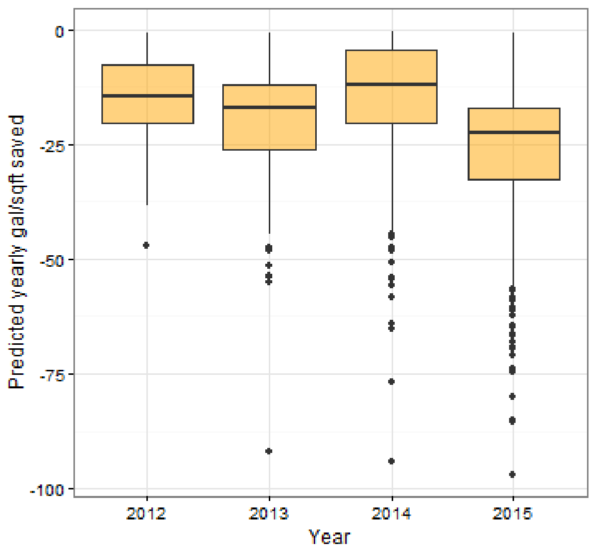

Figure 3: Average yearly savings for each household over 5 years.

goes, "you cannot manage what you cannot measure" and such rigorous impact evaluations can help California's public managers navigate the uncertain future we face with climate change.

6. ACKNOWLEDGEMENTS

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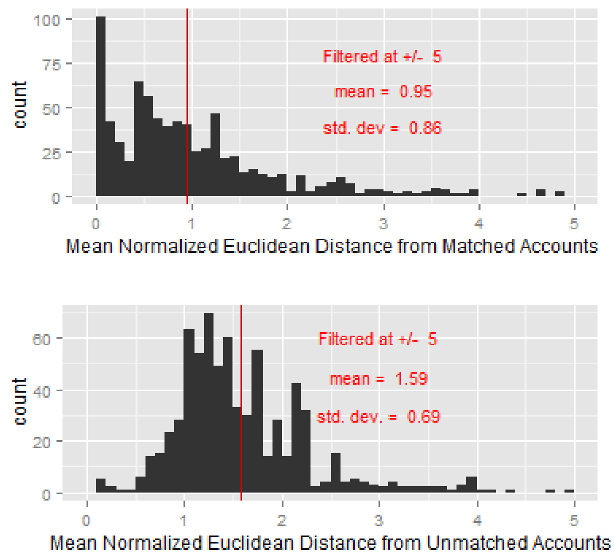

Figure 5: The top histogram shows the distribution of mean distances between treatments and their matched controls with similar historical usage. The bottom shows the distances between treatments and the unmatched accounts with more dissimilar usage patterns. On average, accounts with similar usage tend to be more similar in household size and irrigable area than those with very different usage patterns.

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