The water demand shaping effects of new irrigation technology: evapotranspiration irrigation controllers in southern California, USA

T.W. Chesnutt
A&N Technical Services, Inc. 839 Second Street, Suite 5, Encinitas CA, 92024, USA
(E-mail: tom@antechserv.com)

Abstract The purpose of this work is a statistical analysis of the net change to water demand among customers who installed evapotranspiration irrigation controllers and customers given irrigation education in the Irvine Ranch Water District, California. This paper documents a statistical analysis of historical water demand to derive estimates of the net water savings from these interventions. This type of empirical investigation is important since California water agencies are considering multimillion dollar investments in this type of demand-side management. Thus, the predictable demand reduction and demand load-shaping are critical to rational economic investment decisions.

Keywords Demand management; irrigation technology; statistical intervention analysis; variance components

Approach
Weather-based evapotranspiration (ET) irrigation control has long been a tool of large agricultural operations, maximizing crop yields through pinpoint management of crop watering. The Residential Runoff Reduction (R3) Study was conducted to evaluate the applicability of ET technology for urban applications.

Historical water consumption records for a sample of participants and for a sample of nonparticipating customers were examined statistically. The hypothesis was that installation of new irrigation technology or better management of existing equipment would reduce the observed water consumption of customers participating in this program. This study empirically estimates the water savings that resulted from both types of interventions: (a) customers receiving both ET controllers and follow-up education and (b) customers receiving an education-only intervention.

Since installation of ET controllers required the voluntary agreement of the customer to participate, this sample of customers can be termed “self-selected.” Customers were randomly chosen to receive the education-only treatment. Both sets of residential customers were motivated by a water rate structure that combined a water budget and block rate pricing. While this analysis does quantitatively estimate the reduction of participants’ water consumption, one may not directly extrapolate this finding to nonparticipants. This is because self-selected participants can differ from customers that decided not to participate. Inference outside the sample of participants would require other formal methods of addressing selection – estimating the unknown regression functions, matching methods, use of a propensity score, some combination of these semiparametric approaches (see Rubin, 1973; Heckman, 1976; Rosenbaum and Rubin, 1984; Imbens, 2003). This paper does not attempt to provide a formal basis for this type of inference, limiting itself to within sample inference. The explanatory variables in these models include:

- harmonics to capture the seasonal shape of demand;
- weather conditions,
measures of air temperature,
measures of precipitation, contemporaneous and lagged;
• customer-specific mean water consumption; and
• “intervention” measures of the date of participation and the type of intervention.

Measures of customer characteristics (income, number of occupants, and other socioeco-
nomic measures) were not available for either participants or nonparticipants. As a result
we attempt to estimate no structural model.

Data and methods
Consumption records were compiled from the Irvine Ranch Water District (IRWD) cus-
tomer billing system for customers in the study areas. Billing histories were obtained from
meter reads between July 1997 and August 2002. It is important to note that a meter read
on August 1 will largely represent water consumption in July. Since the ET controllers
were installed in May and June of 2001, the derived sample will only contain slightly
more than one year of data for each participant. Table 1 presents descriptive statistics on
the sample.

The first major issue with using meter-read consumption data is the level and magni-
tude of noise in the data. The second major issue is that records of metered water con-
sumption can also embed non-ignorable meter mis-measurement. To keep either type of
data inconsistencies from corrupting statistical estimates of model parameters, this model-
ing effort employed a sophisticated range of outlier-detection methods and models.
These are described in the next section.

Daily weather measurements – daily precipitation, maximum air temperature, and
evapotranspiration – were collected from the CIMIS weather station located in Irvine.
The daily weather histories were collected as far back as were available (January 1,
1948) to provide the best possible estimates for “normal” weather through the year. Thus,
we have at least 54 observations upon which to judge what are “normal” rainfall and tem-
perature for January 1st of any given year.

Robust regression techniques were used to detect which observations are potentially
data quality errors. This methodology determines the relative level of inconsistency of
each observation with a given model form. A measure is constructed to depict the level
of inconsistency between zero and one; this measure is then used as a weight in sub-
sequent regressions. Less consistent observations are down-weighted. Other model-based
outlier diagnostics were also employed to screen the data for any egregious data quality
issues.

Table 1 Descriptive statistics for single family residential sample

<table>
<thead>
<tr>
<th></th>
<th>Site 1001</th>
<th>Site 1004</th>
<th>Site 1005</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ET controller participant</td>
<td>Non-participant</td>
<td>Control</td>
</tr>
<tr>
<td>Number of usable accounts</td>
<td>97</td>
<td>213</td>
<td>264</td>
</tr>
<tr>
<td>Pre-period July 1997–May 2001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean use (gpd)</td>
<td>375</td>
<td>371</td>
<td>405</td>
</tr>
<tr>
<td>No. of observations</td>
<td>4,504</td>
<td>9,860</td>
<td>12,452</td>
</tr>
<tr>
<td>Post-period June 2001 –August 2002</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean use (gpd)</td>
<td>366</td>
<td>379</td>
<td>427</td>
</tr>
<tr>
<td>No. of observations</td>
<td>1,358</td>
<td>2,982</td>
<td>3,694</td>
</tr>
</tbody>
</table>
 Specification

A model of water demand

The model for customer water demand seeks to separate several important driving forces. In the short run, changes in weather can make demand increase or decrease in a given year. These models are estimated at a household level and, as such, should be interpreted as a condensation of many types of relationships—meteorological, physical, behavioural, managerial, legal, and chronological. Nonetheless, these models depict key short-run and long-run relationships and should serve as a solid point of departure for improved quantification of these linkages.

Systematic effects

This section specifies a water demand function that has several unique features. First, it models seasonal and climatic effects as continuous (as opposed to discrete monthly, semi-annual, or annual) functions of time. Thus, the seasonal component in the water demand model can be specified on a continuous basis, then aggregated to a level comparable to measured water use (e.g. monthly). Second, the climatic component is specified in different form as a similar continuous function of time. The weather measures are thereby made independent of the seasonal component. Third, the model permits interactions of the seasonal component and the climatic component. Thus, the season-specific response of water demand can be specific to the season of the year. The general form of the model is:

\[
\text{Use} = \mu_i + S_t + W_t + E_{i,t}
\]

where,
- \( \text{Use} \): is the quantity of water demand within time \( t \),
- \( \mu_i \): represents mean water consumption per meter \( i \),
- \( S_t \): is a seasonal component,
- \( W_t \): is the weather component, and
- \( E_{i,t} \): is the effect of the landscape interventions for meter \( i \) at time period \( t \).

Seasonal component. A monthly seasonal component can be formed using monthly dummy variables to represent a seasonal step function. Equivalently, one may form a combination of sine and cosine terms in a Fourier series to define the seasonal component as a continuous function of time. The use of a harmonic representation for a seasonal component in a regression context dates back to Hanan (1960). Jorgenson (1964) extended these results to include least squares estimation of both trend and seasonal components. The following harmonics are defined for a given day \( T \), ignoring the slight complication of leap years:

\[
S_t = \sum_{j=1}^{6} \left[ \beta_{ij} \cdot \sin \left( \frac{2\pi j T}{365} \right) + \beta_{ij} \cdot \cos \left( \frac{2\pi j T}{365} \right) \right] = Z' \beta
\]

where,
- \( T \): (1,…,365) and
- \( j \): represents the frequency of each harmonic.

Because the lower frequencies tend to explain most of the seasonal fluctuation, the higher frequencies can often be omitted with little predictive loss. To compute the seasonal component one simply sums the multiplication of the seasonal coefficient with its respective value. This number will explain how demand changes due to seasonal fluctuation.
Weather component. The model incorporates two types of weather measures into the weather component – maximum daily air temperature and rainfall. The measures of temperature and rainfall are then logarithmically transformed to yield:

\[ R_t = \ln \left( 1 + \sum_{i=T}^{T_d} \ln(1 + \text{Rain}_i) \right) \quad A_t = \ln \left( \sum_{i=T}^{T_d} \frac{\text{AirTemp}_i}{d} \right) \]

where, \(d\): is the number of days in the time period. For monthly aggregations, \(d\) takes on the values 31, 30, or 28, ignoring leap years; for daily models, \(d\) takes on the value of one.

Because weather exhibits strong seasonal patterns, climatic measures are strongly correlated with the seasonal measures. In addition, the occurrence of rainfall can reduce expected air temperatures. To obtain valid estimates of a constant seasonal effect, the seasonal component is removed from the weather measures by construction.

Specifically, the weather measures are constructed as a departure from their “normal” or expected value at a given time of the year. The expected value for rainfall during the year, for example, is derived from regression against the seasonal harmonics. The expected value of the weather measures is subtracted from the original weather measures:

\[ W_t = (R_t - \bar{R})(\beta_E + (A_t - \bar{A}) \cdot \beta_A) \]

The weather measures in this deviation-from-mean form are thereby separated from the constant seasonal effect. Thus, the seasonal component of the model captures all constant seasonal effects, as it should, even if these constant effects are due to normal weather conditions. The remaining weather measures capture the effect of weather departing from its normal pattern.

The model can also specify a richer texture in the temporal effect of weather than the usual fixed contemporaneous effect. Seasonally-varying weather effects can be created by interacting the weather measures with the harmonic terms. In addition, the measures can be constructed to detect lagged effects of weather, such as the effect of rainfall one month ago on this month’s water demand.

Effect of landscape interventions. Information was compiled on the timing and location of each ET controller installation and education-only customer participation. The account numbers from these data were matched to meter consumption histories going back to 1997. All raw meter reads were converted to average daily consumption by dividing by the number of days in the read cycle. Using these data, relatively simple “intervention analysis” models (a term coined by Box and Tiao, 1975) were statistically estimated where, in this case, the intervention is participation in the ET controller program (ET controller installation coupled with landscape education) or participation in the landscape education program. The form of the intervention is:

\[ E_{it} = I_{ET} \cdot \hat{\beta}_{ET} + I_{Ed} \cdot \hat{\beta}_{Ed} \]

The indicator variable \(I_{ET}\) takes on the value one to indicate the participation in the ET controller program and is zero otherwise. The indicator variable \(I_{Ed}\) takes on the value one if a household agreed to participate in the education-only program and is zero otherwise. The parameter \(\hat{\beta}_{ET}\) represents the mean effect of installing an ET controller and is expected to be negative (installing an ET controller by educated customers reduces water consumption). The parameter \(\hat{\beta}_{Ed}\) has a similar interpretation for the education-only participants.
This formulation also permits formal testing of the hypothesis that landscape interventions can affect the seasonal shape of water consumption within the year. Since numerous studies have identified a tendency of customers to irrigate more than ET requirements in the fall and somewhat less in the spring, it will be informative to examine the effect of ET controllers designed to irrigate in accord with ET requirements.

The formal test is enacted by interacting the participation indicators with the sine and cosine harmonics. The model was specified as a variance components model with an individual household component and a random component. The model was estimated using maximum likelihood methods (details can be found in the full report, see acknowledgements).

**Estimation results**

**Estimated single family residential water demand model**

Table 2 presents the estimation results for the model of single family water demand in the R3 study sites. This sample represents water consumption among 1,525 single family households between June 1997 and July 2002. This sample contains 97 ET controller/education participants (in Site 1001) and 192 education-only participants (in Site 1005).

The constant term (1) describes the mean intercept for this equation (a separate intercept is estimated for each of the 1,525 households but these are not displayed in Table 2 for reasons of brevity). The independent variables 2 to 8, made up of the sines and cosines of the Fourier series described in Equation 2, are used to depict the seasonal shape of water demand. The predicted seasonal effect (that is, $Z\beta_S$) is the shape of demand in a normal weather year. This seasonal shape is important in that it represents...
the point of departure for the estimated weather effects (expressed as departure from normal). We will also test to see if the landscape interventions have any effect on this seasonal shape.

The estimated weather effect is specified in “departure-from-normal” form. Variable 11 is the departure of monthly temperature from the average temperature for that month in the season. (Average seasonal temperature is derived from a regression of daily temperature on the seasonal harmonics.) Rainfall is treated in an analogous fashion (Variable 14). One month lagged rainfall deviation is also included in the model (Variable 15). The reader should also note that the contemporaneous weather effect is interacted with the harmonics to capture any seasonal shape to both the rainfall (Variables 12 and 13) and the temperature (Variables 9 and 10) elasticities. Thus, departures of temperature from normal produce the largest percentage effect in the spring growing season. Similarly, an inch of rainfall produces a larger effect upon demand in the summer than in the winter.

The effect of the landscape conservation program interventions is captured in the following rows. The parameter on the indicator for ET controllers/education (16) suggests that the mean change in water consumption is 41.2 gpd while the education only participants (19) saved approximately 25.6 gpd. The model cannot say whether education-only participants saved this water through improved irrigation management or by also reducing indoor water consumption. Since the sample includes only one year of post-intervention date, the model cannot say how persistent either effect will be in future years (Table 2).

How ET controllers affect peak demand

The question of how these programs affected the seasonal shape of water demand can be interpreted from the remaining interactive effects – the indicators interacted with the first sine and cosine harmonics. For example, the seasonal shape of demand can be derived before and after ET controller/education participation:

\[
S_t = Z\hat{\beta}_0 + 45.4\sin_{t} - 89.1\cos_{t} + 3.6\sin_{2} + 1.1\cos_{2} + \ldots + 3.4\cos_{4}
\]

\[
S'_t = Z\hat{\beta}_0 + 39I_{ET}\sin_{t} - 6.4I_{ET}\cos_{t}
\]

When the pre/post seasonal patterns are combined with their pre/post mean water consumption, the following before and after picture can be seen throughout the year.

In Figure 1, several observations should be made. First, the difference between the two horizontal lines corresponds to the estimated mean reduction of approximately 41 gpd. Second, the assumption of a constant 41 gallon per day effect does not hold true throughout the year. The reduction is barely noticeable in the spring growing season and is much larger in the fall.

The reduction in peak demand – though dependent upon how the seasonal peak is defined – is greater than the average reduction. The estimated peak day demand, occurring on August 8, is reduced by approximately 51 gallons. This “load-shaping” effect of the ET controller intervention can translate into an additional benefit to water agencies. The benefits from peak reduction derive from the avoided costs of those water system costs driven by peak load and not average load – the costs for new treatment, conveyance, and distribution all contain cost components driven by peak capacity requirements.

Figure 2 plots the corresponding estimates for the Education-only intervention. The reduction in average demand is less, approximately 25 gpd. The effect upon the estimated seasonal shape of demand is much more muted. In fact, the change to the estimated
seasonal shape of demand induced by the education-only intervention is not significantly different from zero at classical levels of significance.

Conclusions
This paper documents the shape of water savings achieved by the landscape interventions of ET controllers and/or education. Households participating in these programs saved significant amounts of water. The education-only program showed less water savings than the ET controller/education program, but were still significant. The ET controller/education program changed both the level and shape of water demand. The peak reduction effect of the ET controller/education program provides greater benefits to the water utility in terms of avoided peak capacity costs.
Acknowledgements
The entire study from which this paper was derived assesses the effect of ET controller technology on urban runoff (volume and quality) in addition to water savings. It can be found on the World Wide Web: Residential Runoff Reduction (R3) Study, Irvine Ranch Water District, 2003 [Available online at: www.mwdoc.com/WaterUse/R3-PDFs/runoff-table-of-contents.htm].

References
Heckman, J.J. (1976). The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. *Annals of Economic and Social Measurement, 5*, 475–492.