M.CUBED
POLICY ANALYSIS FOR THE PUBLIC AND PRIVATE SECTORS

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DATE: July 15, 2015
TO: Water Supply Advisory Committee
FR: David Mitchell
RE: Summary of Econometric Analysis of Demand and Forecast

Introduction

This memorandum provides an overview of the data, methods, and results of an econometric analysis and forecast of Santa Cruz water demand. The resulting forecast from this analysis replaces the interim demand forecast previously developed by M.Cubed (M.Cubed 2015a, M.Cubed 2015b). A full report documenting the work conducted by M.Cubed will be available in August.

Project Objective and Approach

The project objective is the development of statistically-based models of water demand that will be used to support WSAC deliberations as well as the 2015 UWMP being developed by the Water Department. Demand forecasts based on these models cover the period 2020-2035.

The general approach is to statistically estimate class-level conditional expectation functions of water demand using historical data on class water use, weather, water price, household income, conservation, and other economic variables determining water demand. The result for each customer class is a monthly model of average water use per housing unit (for single- and multi-family residential classes), service (for business, municipal, and irrigation classes), or acre (for golf courses), which can then be combined with forecasts of housing units, services, and acres, to forecast future water demands. The conditional expectation functions are used with forecasts of future conservation, water rates, household income, unemployment, and other economic factors to predict the trajectory of average water use over the forecast period. This represents a key departure from the 2010 UWMP forecast methodology, which relied on static average use estimates to forecast future demands.

Summary of Demand Forecast

The customer class demand forecasts are shown in Table 1. The production forecast shown at the bottom of the table is the sum of the class demands and miscellaneous uses and system losses. Class demands have been adjusted for the effects of plumbing codes and Program A conservation. Miscellaneous uses and system losses are estimated to average 7.5% of total production, based on historical rates of system losses.

Despite a projected 18% increase in service area population by 2035, total production is forecast to remain below 2013 production and stay within the neighborhood of 3,200 MG (rounded) through 2035. This is primarily due to future effects of plumbing codes, conservation, and rate increases, reduced demand by Pasatiempo golf course, and minimal growth in industrial water use.

A comparison of the new and interim production forecasts is provided in Table 2. Despite being independently derived and based on different data and methods, the two production forecasts are nearly identical, differing by no more than a few percent. As will be shown later, the econometric analysis generally corroborates the assumptions of price and income response used to develop the interim forecast, so perhaps it is not too surprising the forecasts are so similar.

Table 1. Forecasted Demand by Customer Class (Million Gallons)

YEAR	**2013**	**2020**	**2025**	**2030**	**2035**
	Actual	Forecast	Forecast	Forecast	Forecast
Single Family	1,233	1,180	1,175	1,172	1,177
Multi Family	705	662	626	625	625
Business	628	579	566	565	567
Industrial	56	57	59	61	62
Municipal	63	47	46	44	43
Irrigation	123	119	133	143	153
Golf	108	58	50	42	40
UC	182	196	234	271	308
TOTAL DEMAND	**3,100**	**2,897**	**2,889**	**2,923**	**2,974**
MISC/LOSS	251	235	234	237	241
TOTAL PRODUCTION	**3,352**	**3,132**	**3,123**	**3,160**	**3,215**
ROUNDED	**3,400**	**3,100**	**3,100**	**3,200**	**3,200**

Table 2. Econometric and Interim Production Forecasts (million gallons)

YEAR	**2020**	**2025**	**2030**	**2035**
	Forecast	Forecast	Forecast	Forecast
Unrounded				
Econometric	3,132	3,123	3,160	3,215
Interim	3,236	3,213	3,218	3,169
Rounded				
Econometric	3,100	3,100	3,200	3,200
Interim	3,200	3,200	3,200	3,200

Econometric Models of Average Demand

The class-level models of average demand builds on similar models of water demand developed for the California Urban Water Conservation Council (Western Policy Research, 2011), Bay Area Water Supply and Conservation Agency (Western Policy Research, 2014), California Water Services Company (A&N Technical Services, 2014, M.Cubed 2015), and Contra Costa Water District (M.Cubed 2014).

The models have several useful features. First, climate and weather effects on demand are decomposed into two distinct components. The climate component measures the seasonal load shape of monthly demand under normal weather conditions. The weather component measures the effect on demand when weather departs from normal conditions. The seasonal and weather components are interacted to get season-specific weather effects. This is useful since the response to weather is expected to vary by season. For example, the effect of above normal rainfall on demand in winter, when outdoor water uses are lower, is generally found to be lower than its effect in spring or fall, when outdoor water uses are higher. Second, prior to model estimation, monthly water use is adjusted for historical conservation from plumbing codes. This helps to address the confounding effect of conservation on the estimation of other demand parameters like price, employment, and income. Third, the model includes economic parameters (e.g. price, household income, unemployment) known to influence urban water demand (Renzetti, 2002; Billings and Jones, 1996). Fourth, the model includes drought policy parameters to measure the effect of drought restrictions on demand. Thus, expected demand can be expressed conditional on season, weather, conservation, economic conditions, and drought stage.

The model of expected demand is stated as:

$$ln(\tilde{y}_{it}) = \mu_i + \beta_S Season_t + \beta_W Weather_t + \beta_E Economic_{it} + \beta_D Drought_t + \varepsilon_{it} \quad (1)$$

Where:

$\tilde{y}_{it}$ average use in month t for service region i adjusted to remove the effects of water savings due to plumbing codes and appliance standards

μ_i model intercept for service region i

$\beta_S Season_t$ seasonal component of average use in month t

$\beta_W Weather_t$ weather component of average use in month t

$\beta_E Economic_{it}$ economic component of average use in month t

$\beta_D Drought_t$ drought component of average use in month t

ε_{it} stochastic component (error term)

Seasonal Component

The seasonal component is specified using eleven monthly indicator variables. The monthly indicator variables take the value of one if t = j, and zero otherwise.

$$\beta_S Season_t = \sum_{j=2}^{12} \beta_j \, month_{jt} \tag{2}$$

The eleven monthly parameters plus the model intercept describe the seasonal load shape of average demand. A seasonal index of monthly demand, where January has an index value of one, is easily constructed as shown in Table 3. The eleven seasonal parameters are seen to scale monthly demand relative to January demand.

Table 3. Seasonal Index of Monthly Average Demand

Month	Seasonal Index	Month	Seasonal Index
Jan	1	Jul	e^{β_7}
Feb	e^{β_2}	Aug	e^{β_8}
Mar	e^{β_3}	Sep	e^{β_9}
Apr	e^{β_4}	Oct	$e^{\beta_{10}}$
May	e^{β_5}	Nov	$e^{\beta_{11}}$
Jun	e^{β_6}	Dec	$e^{\beta_{12}}$

Weather Component

The weather component is comprised of weather measures (monthly rainfall, average daily maximum air temperature, monthly ETo) that are transformed logarithmically with their monthly average subtracted away. In the case of rainfall, both contemporaneous and lagged measures are included in the model.

$$\beta_W Weather_t = \beta_{w1} dlR_t + \beta_{w2} dlR_{t-1} + \beta_{w3} dlR_{t-2} + \beta_{w4} dlT_t \ (or\ dlET_t) \tag{3}$$

Where[1]

$$dlR_t = ln(Rain_t + 1) - \overline{ln(Rain_t + 1)} \tag{4}$$

$$dlT_t = ln(Temp_t) - \overline{ln(Temp_t)} \tag{5}$$

$$dlET_t = ln(ET_t) - \overline{ln(ET_t)} \tag{6}$$

For the residential and business customer classes, average daily maximum air temperature is used rather an ET. For the golf, irrigation, and municipal categories, which have greater landscape water uses, ET is used.

During model estimation, the weather component is interacted with seasonal indicators to estimate separate seasonal weather effects for fall-winter (Nov-Mar), spring (Apr-Jun), and summer-fall (Jul-Oct).[2]

[1] One is added to monthly rain totals to ensure the rainfall measure is defined in months in which total rainfall is zero.
[2] The seasonal construct follows the CUWCC's GPCD weather normalization methodology (Western Policy Research, 2011).

Weather normalization of historical demands can be done in two ways. The first way is to use the predicted model values assuming average weather. In this case the model's weather component simply falls away and we are left with:

$$Weather\ Normalized\ \tilde{y}_{it} = exp(\mu_i + \beta_S Season_t + \beta_E Economic_{it}) \quad (7)$$

The second approach is to rescale observed water use using the estimated weather effects. The ratio of observed to weather normalized demand is

$$WeatherEffect_t = exp\big(\beta_{w1} dlR_t + \beta_{w2} dlR_{t-1} + \beta_{w3} dlR_{t-2} + \beta_{w4} dlT_t\ (or\ dlET_t)\big) \quad (8)$$

Weather normalized observed demand is then given by

$$Weather\ Normalized\ \tilde{y}_{it} = \frac{\tilde{y}_{it}}{WeatherEffect_t} \quad (9)$$

Economic Component

The economic component consists of economic variables that influence average water demand, including water price, household income, vacancy rate, and unemployment rate. The economic variables are logarithmically transformed prior to model estimation. The vacancy rate and unemployment rate variables are expressed as departures from their long-run average values.

$$\beta_E Economic_{it} = \beta_{E1} lPrice_{it} + \beta_{E2} lInc_{it} + \beta_{E3} dlVac_t + \beta_{E4} dlUnempl_t \quad (10)$$

Where

$$lPrice_{it} = ln(marginal\ price)\ in\ service\ region\ i, period\ t \quad (11)$$

$$lInc_{it} = ln(median\ household\ income)\ in\ service\ region\ i, period\ t \quad (12)$$

$$dlVac_t = ln(housing\ vacancy\ rate) - \overline{ln(housing\ vacancy\ rate)} \quad (13)$$

$$dlUnempl_t = \ln(unemployment\ rate) - \overline{\ln(unemployment\ rate)} \quad (14)$$

Each customer class model uses a restricted form of equation 10, as shown in Table 4. These restrictions are guided both by economic theory and model diagnostics. For the single family model, the primary economic drivers are marginal water price and household income. For the multi-family model, vacancy rate replaces household income. For the business and municipal class models, marginal price and unemployment measures are used. For golf and irrigation, only marginal price is included in the models.

Table 4. Economic Variable Restrictions in Customer Class Models

Customer Class Model	Economic Variable Restrictions
Single Family	$\beta_{E3} = \beta_{E4} = 0$
Multi Family	$\beta_{E2} = \beta_{E4} = 0$
Business, Municipal	$\beta_{E2} = \beta_{E3} = 0$
Golf, Irrigation	$\beta_{E2} = \beta_{E3} = \beta_{E4} = 0$

Drought Component

The model's drought component consists of three indicator variables for stage 1, 2, and 3 drought restrictions. The indicator variable takes the value of one in months that the drought stage was active and zero otherwise.

Data for Model Estimation

Datasets for monthly consumption, weather variables, economic variables, and plumbing code/conservation variables were developed to estimate the models. These datasets were constructed as follows.

Consumption Data

The models were estimated with monthly consumption data for the period January 2000 to November 2014. Class-level aggregated meter read data were obtained from the Water Department. The Water Department data were bifurcated between Inside City and Outside City accounts, and contained aggregated data from both bi-monthly and monthly meter read cycles. Before the data could be used for model estimation, it had to be transformed into estimated aggregate monthly consumption. For any read month t, data from bi-monthly meter reads was allocated approximately 25% to month t-2, 50% to month t-1, and 25% to month t. Thus for data from meters read in March, approximately 25% of the consumption was allocated to January, 50% to February, and 25% to March. For data from monthly meter reads, consumption was allocated approximately 50% to month t-1 and 50% to month t. Thus for data from meters read in March, approximately 50% was allocated to February and 50% to March. The allocations are based on the approximate share of total consumption days in each month represented in the aggregated meter read data. The percentages cited above are only approximate values. To do the actual allocations, seasonal weights were applied to each month to account for the seasonal shape of consumption.

Estimated monthly consumption was then divided by the number of housing units (for single-family and multi-family customer classes), services (for business, municipal, and irrigation classes), or acres (for golf courses) to get average monthly water use per housing unit, service, or acre.

Monthly conservation from plumbing codes was then added onto estimated average monthly consumption to remove the effects of plumbing code savings from consumption. Monthly plumbing code savings for the estimation period were estimated with the Alliance for Water Efficiency's Water Conservation Tracking Tool.

Weather Data

The weather variables were constructed from monthly data on precipitation, ETo, and average maximum air temperature from October 1990 to April 2015 taken from CIMIS Station 104 (De Laveaga), which situated within Santa Cruz city limits.

Economic Data

The economic data came from multiple sources. The water rate data set was constructed with Water Department records of water rates for each customer class. Annual unemployment rates in Santa Cruz for the period 1990 to 2014 come from the California Employment Development Department. Median and per capita income estimates for Inside City and Outside City customers come from Decennial Census and American Community Survey data. The income data cover estimation years 2000 and 2005-2013. Values for other years were imputed. Average annual residential vacancy rates for City of Santa Cruz for the years 1991-2014 are taken from the California Department of Finance (DOF E-8).

Estimation Results

The average demand models were estimated with R version 3.2 statistical software. Robust regression methods were applied to down-weight outlier consumption data. For customer classes that had both Inside City and Outside City customers (e.g. residential, business, irrigation, and golf) fixed effects models were estimated so that the data could be pooled. Estimation results as summarized by adjusted R-squared are shown in Table 5. Across all classes, the models explain 90% to 96% of the observed variation in the data. All statistically significant model coefficients have the expected signs and magnitudes. Estimation results for each customer class are provided in Attachment 1.

Table 5. Average Demand Model Estimation, Adjusted R-Square

Customer Class	Number of Observations	Adjusted R-Square
Single Family	358	0.917
Multi Family	351	0.900
Business	353	0.942
Municipal	177	0.951
Irrigation	358	0.916
Golf	352	0.957

The estimated price elasticities derived from the econometric models are shown in Table 6. Inside and Outside City customers face different rates and so the models were first estimated to detect if price response was statistically different in the two regions. It was for the single family and golf classes, but not for the multi-family, business, and irrigation classes. The municipal class is Inside City only. Single family customers in the Outside City part of the service area were found to be slightly less price responsive than Inside City customers.

The estimated price response for single family is only about half as large as the interim forecast assumed: -0.11 versus -0.24. However, the estimated price responses for multi-family and business are identical to what was assumed in the interim forecast: -0.12 for multi-family and -0.10 for business. The estimated income elasticity for the single family customer class is 0.23, which is also very close to the 0.25 assumption used in the interim forecast.

Irrigation demands are seen to be more price responsive than residential and business demands, which is expected. The Pasatiempo golf course is an exception to this general finding. Its price response was not statistically different from zero. Perhaps this is because it is a top tier course and has a substantially higher willingness to pay for water than other irrigators.

Table 6. Estimate Price Elasticity by Customer Class

Class	**Inside City**	**Outside City**
Single Family [1/]	-0.11	-0.10
Multi Family	-0.12	
Business	-0.10	
Municipal	-0.24	NA
Irrigation	-0.54	
Golf	-0.34	0.00 [2/]

1/ Weighted average of estimate summer and winter elasticities
2/ Outside city elasticity for golf not statistically different from zero.

Estimated drought responses by customer class and stage are summarized in Table 7.

Table 7. Average Change in Demand Attributable to Drought Stage

Class	**Stage 1**	**Stage 2**	**Stage 3**
Single Family	-5%	-7%	-35%
Multi Family	0%	-3%	-17%
Business	0%	0%	-12%
Municipal	0%	-10%	-46%
Irrigation	0%	-22%	-60%
Golf	0%	0%	-31%

<u>Forecasted Average Demand</u>

Class forecasts of average demand are shown in Table 8. These forecasts are based on the rate and income growth assumptions developed for the interim demand forecast and have been adjusted for plumbing code and Program A water savings. They presume normal weather and economic conditions.

Table 8. Forecasted Average Demand by Customer Class (CCF/Year)

YEAR		**2013**	**2020**	**2025**	**2030**	**2035**
	Per	Actual	Forecast	Forecast	Forecast	Forecast
Single Family	Housing Unit	89	81	79	77	76
Multi Family	Housing Unit	54	47	43	41	39
Business	Service	445	405	391	382	372
Municipal	Service	323	289	282	272	263
Irrigation	Service	339	255	255	233	219
Golf	Acre	740	654	615	565	537

Population and Housing Unit Forecasts

The population and housing unit forecasts are anchored on the AMBAG 2014 Regional Growth Forecast (AMBAG 2014). Forecasted population and total housing units for Inside City and Outside City are shown in Tables 9 and 10.

Table 9. Inside City Population and Housing Unit Forecasts

	2010 1/	**2020**	**2025**	**2030**	**2035**
City Total Population 2/	59,946	66,860	70,058	73,375	76,692
UCSC 3/	7,331	8,845	9,602	10,359	11,116
City	52,615	58,015	60,456	63,016	65,576
In households 4/	50,711	55,916	58,268	60,736	63,203
In group qtrs	1,904	2,099	2,188	2,280	2,373
Household size 5/	2.34	2.38	2.41	2.42	2.44
City Housing Units					
Total 6/	22,913	24,854	25,580	26,594	27,429
Occupied 7/	21,657	23,492	24,177	25,136	25,925
Vacancy rate 8/	5.5%	5.5%	5.5%	5.5%	5.5%

Notes

1/ Actual per 2010 Census.

2/ AMBAG 2014 Regional Growth Forecast (adopted June 11, 2014).

3/ 2020-35 forecast based on projected UCSC enrollment through 2035 and historical and projected share of students living on campus.

4/ 2020-35 forecast based on 2010 ratio of population in households to total population.

5/ 2020-35 forecast assumes household size increases at same rate as forecast for AMBAG region

6/ Occupied housing divided by one minus vacancy rate.

7/ Population in households divided by household size.

8/ 2020-35 vacancy rate assumed to equal 2010 census estimate.

Table 10. Outside City Population and Housing Unit Forecasts

	2010 1/	2020	2025	2030	2035
Population 2/	31,342	32,543	33,562	34,614	35,698
In households 3/	30,678	31,853	32,851	33,880	34,941
In group qtrs.	665	690	712	734	757
Household size 4/	2.39	2.43	2.46	2.46	2.48
Housing Units					
Total 5/	14,323	14,630	14,902	15,329	15,669
Occupied 6/	12,856	13,132	13,376	13,759	14,064
Vacancy rate 7/	10.2%	10.2%	10.2%	10.2%	10.2%

Notes

1/ Actual per 2010 Census.

2/ 2020 and 2035 Water Dept. forecast. 2025 and 2030 interpolated.

3/ 2020-35 forecast based on 2010 ratio of population in households to total population.

4/ 2020-35 forecast assumes household size increases at same rate as forecast for AMBAG region

5/ Occupied housing divided by one minus vacancy rate.

6/ Population in households divided by household size.

7/ 2020-35 vacancy rate assumed to equal 2010 census estimate.

These forecasts are used to project Inside City and Outside City single- and multi-family housing units with active water services. These forecasts are shown in Tables 11 and 12. The Inside City forecast calibrates exactly to the forecast of total occupied housing units in Table 9. This is not the case for the Outside City forecast. There is a discrepancy between Water Department data on housing units in 2014 with active water service and the forecast of occupied housing units in Table 10. The Water Department's estimate is higher by several hundred housing units. This issue is still under review and has not been resolved. For now, the forecast of Outside City housing units with active services is anchored to the Water Department's estimate of housing units, with growth in total units pegged to the growth in housing units in Table 10.

The disaggregation of total housing units into single- and multi-family housing units starts with the Water Department's 2014 estimates. Single-family housing units are then increased at their historical growth rate. In the case of Inside City single-family housing, growth is capped at 1,000 units based on the General Plan's estimate of potential for new single family housing.[3] No cap is applied to the Outside City forecast. Multi-family units are then the difference between the forecast of total units and single-family units. For the Inside City service area, three-fourths of the gain in housing units is multi-family. For the Outside City service area, multi-family units comprise a little less than half of the gain.

[3] The General Plan, which extends to 2030, identified a potential for 840 new single family units. This was increased to 1000 units since this forecast runs to 2035.

Table 11. Inside City Forecast of Housing Units with Active Water Services

	2014 1/	2020	2025	2030	2035	Gain From 2014	% of Gain
Single Family 2/	12,246	12,534	12,780	13,030	13,246	1,000	24%
Multi Family 3/	9,583	10,958	11,398	12,106	12,679	3,096	76%
Total	21,829	23,492	24,177	25,136	25,925	4,096	100%

Notes

1/ Actual per Water Department billing records.

2/ 2020-35 forecast assumes up to 1,000 new units by 2035

3/ 2020-35 forecast equals the difference between total and single family forecasted units.

Table 12. Outside City Forecast of Housing Units with Active Water Services

	2014 1/	2020	2025	2030	2035	Gain From 2014	% of Gain
Single Family 2/	6,743	6,922	7,074	7,230	7,390	647	52%
Multi Family 3/	7,901	7,910	8,033	8,310	8,495	594	48%
Total	14,644	14,832	15,107	15,540	15,884	1,240	100%

Notes

1/ Actual per Water Department billing records.

2/ 2020-35 forecast assumes single family units added at historical rate.

3/ 2020-35 forecast equals the difference between total and single family forecasted units.

<u>Business, Municipal, and Irrigation Services Forecasts</u>

Historically, the ratio of business demand to residential demand has been very stable at about 0.315. This ratio is used with the forecast of residential demand and average business demand per service to forecast the growth in business services. The number of new business services is added so that the ratio of business demand to residential demand is maintained at 0.315. This results in a gain of 150 new business services between 2013 and 2035. As a check on the forecast, it is noted that over the 18 year period 1996-2013, there was a gain of 120 business services. Extending this rate of growth to 22 years to match the length of our forecast would results in 147 new services, which is very close to the forecast of 150 new services for the 22 year period 2013 to 2035.

Based on discussions with Water Department Staff, not growth in municipal services is anticipated over the forecast horizon.

Growth in irrigation services is related to the growth in multi-family and business services. On average, 0.6 irrigation services have been added for the addition of a new multi-family or business service. This ratio is used with the forecast of multi-family and business services to project new irrigation services over the forecast horizon.

The forecasts of business, municipal, and irrigation services are presented in Table 13.

Table 13. Business, Municipal, and Irrigation Services Forecasts

	2013 [1/]	**2020**	**2025**	**2030**	**2035**	**Gain From 2013**
Business [2/]	1,889	1,910	1,935	1,980	2,039	150
Municipal [3/]	218	218	218	218	218	0
Irrigation	452	624	696	820	931	479

Notes

1/ Actual per Water Department billing records.

2/ Based on ratio of business to residential demand.

3/ Based on historical rate of gain in irrigation services per gain in multi-family and business services.

Golf Course Acreage Forecast

No change in irrigated acreage is forecast for the DeLaveaga golf course. This is not the case for Pasatiempo. Interviews with Pasatiempo staff indicate it has plans to reduce its reliance of City water starting this year. It expects to irrigate not more than 40 acres with City water by 2020 and not more than 20 acres by 2030. It currently irrigates about 67.5 acres with City water. The forecast of golf course acreage irrigated with City water is given in Table 14.

Table 14. Golf Course City Water Irrigated Acreage Forecasts

	2013 [1/]	**2020**	**2025**	**2030**	**2035**	**Gain From 2013**
DeLaveaga	78.9	78.9	78.9	78.9	78.9	0
Pasatiempo [2/]	67.5	40	30	20	20	-47.5

Notes

1/ Actual per Water Department billing records.

2/ Per communication with Pasatiempo staff.

<u>Industrial Demand Forecast</u>

There is a strong relationship between Santa Cruz County manufacturing employment and industrial water demand. This relationship is illustrated in Figure 1. Prior to the recession, industrial demand averaged approximately 11.9 CCF per job. Immediately after the recession this increased to about 38.3 CCF per job. We use the pre-recession rate with a forecast of manufacturing employment in Santa Cruz County to project future industrial water demand. The pre-recession rather than the post-recession rate of water use per job is used because it is thought to better reflect the long-term rate under normal economic conditions. The Caltrans forecast of manufacturing employment for Santa Cruz County is used to forecast industrial water use. The California Employment Development Department also has a forecast of manufacturing employment, but this forecast extends only to 2022. The two forecasts are consistent, as shown in Table 15.

Figure 1

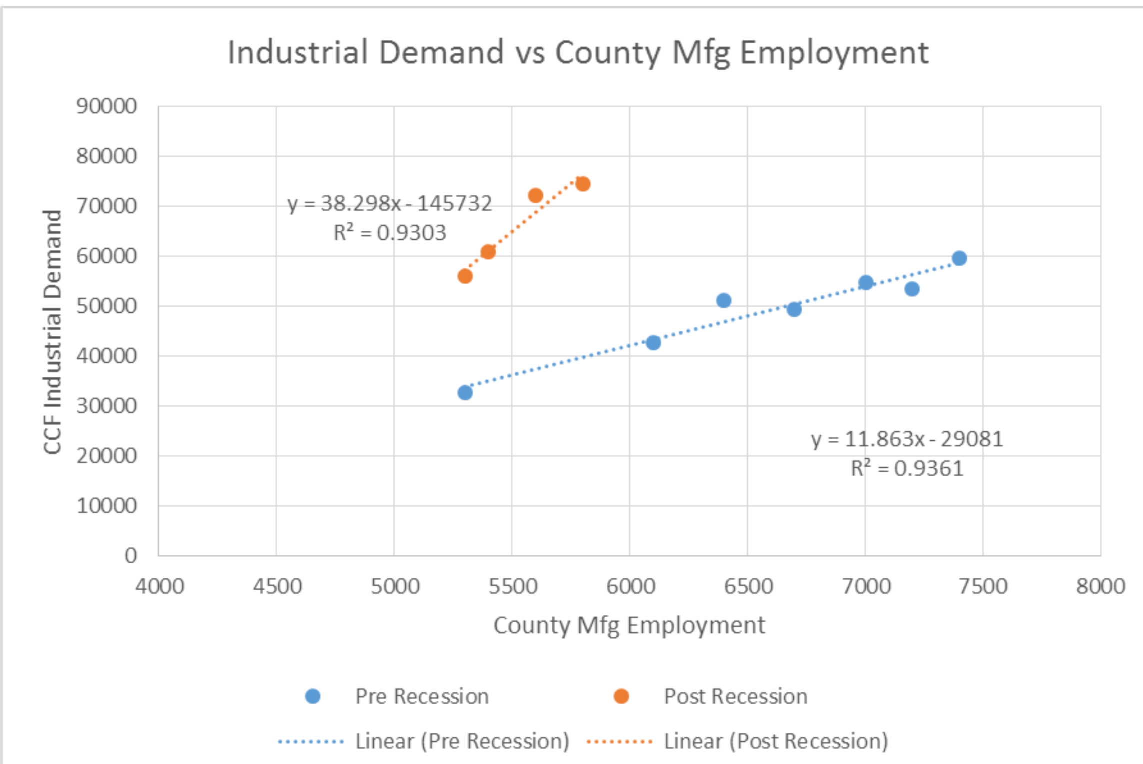

Table 15. Industrial Water Demand Forecast

	2013 1/	2020	2022	2025	2030	2035
Mfg Employment Forecast						
EDD	5,800		6,000			
Cal Trans		5,900		6,200	6,400	6,500
Industrial Water Demand						
CCF 2/	74,451	75,641		79,211	81,591	82,781
MG	56	57		59	61	62

Notes
1/ Actual per Water Department billing records.
2/ Based on 11.9 CCF per manufacturing job.

UC Demand Forecast

The forecast of UC demand is the same as in the interim demand forecast.

Summary of Demand Forecast

Table 16 provides a summary of the class demand forecasts.

Table 16. Summary of Demand Forecast

YEAR		**2020**	**2025**	**2030**	**2035**
		Forecast	Forecast	Forecast	Forecast
Service Units	**Units**				
SFR	Housing Units	19,456	19,854	20,260	20,636
MFR	Housing Units	18,867	19,430	20,416	21,174
BUS	Services	1,910	1,935	1,980	2,039
IND	NA	NA	NA	NA	NA
MUN	Services	218	218	218	218
IRR	Services	624	696	820	931
GOLF	Acres	119	109	99	99
UC	NA	NA	NA	NA	NA
Avg Demand	**Units**				
SFR	CCF	81.1	79.1	77.3	76.2
MFR	CCF	46.9	43.1	40.9	39.5
BUS	CCF	405.3	391.4	381.6	371.6
IND	NA	NA	NA	NA	NA
MUN	CCF	288.7	282.5	272.5	262.8
IRR	CCF	254.9	255.1	232.5	219.2
GOLF	CCF	654.0	614.9	565.3	536.9
UC	NA	NA	NA	NA	NA
Annual Demand	**Units**				
SFR	MG	1,180	1,175	1,172	1,177
MFR	MG	662	626	625	625
BUS	MG	579	566	565	567
IND	MG	57	59	61	62
MUN	MG	47	46	44	43
IRR	MG	119	133	143	153
GOLF	MG	58	50	42	40
UC	MG	196	234	271	308
Total Demand	**MG**	**2,897**	**2,889**	**2,923**	**2,974**
MISC/LOSS	MG	235	234	237	241
Total Production	**MG**	**3,132**	**3,123**	**3,160**	**3,215**
Rounded	**MG**	**3,100**	**3,100**	**3,200**	**3,200**

References

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Attachment 1: Model Estimation Results

Single Family Customer Class Model

	Dependent variable:
	ln.adj.use
geooutside	0.061 (0.018)***
fmonthFeb	-0.013 (0.010)
fmonthMar	0.014 (0.015)
fmonthApr	0.159 (0.015)***
fmonthMay	0.451 (0.021)***
fmonthJun	0.564 (0.021)***
fmonthJul	0.632 (0.022)***
fmonthAug	0.615 (0.023)***
fmonthSep	0.550 (0.018)***
fmonthOct	0.360 (0.017)***
fmonthNov	0.143 (0.014)***
fmonthDec	0.053 (0.009)***
temp.nov.mar	0.203 (0.091)**
temp.apr.jun	0.422 (0.204)**
temp.jul.oct	0.636 (0.191)***
rain.nov.mar	-0.016 (0.009)*
rain.apr.jun	-0.069 (0.014)***
rain.jul.oct	-0.040 (0.020)**
ln.rain.dev.lag1	-0.034 (0.006)***
ln.rain.dev.lag2	-0.026 (0.007)***
ln.price.winter	-0.075 (0.010)***
ln.price.summer	-0.139 (0.017)***
ln.hh.inc	0.228 (0.076)***
drght.stage1	-0.051 (0.019)***
drght.stage2	-0.071 (0.017)***
drght.stage3	-0.431 (0.019)***
geooutside:ln.price.summer	0.020 (0.009)**
Constant	-0.605 (0.845)
Observations	358
R2	0.923
Adjusted R2	0.917
Residual Std. Error	0.064 (df = 330)
F Statistic	147.089*** (df = 27; 330)
Note:	*p<0.1; **p<0.05; ***p<0.01

Multi Family Customer Class Model

	Dependent variable:
	ln.adj.use
geooutside	0.055 (0.012)***
fmonthFeb	0.009 (0.014)
fmonthMar	-0.006 (0.014)
fmonthApr	0.031 (0.014)**
fmonthMay	0.141 (0.013)***
fmonthJun	0.185 (0.012)***
fmonthJul	0.194 (0.015)***
fmonthAug	0.189 (0.013)***
fmonthSep	0.150 (0.012)***
fmonthOct	0.111 (0.011)***
fmonthNov	0.033 (0.015)**
fmonthDec	-0.001 (0.013)
temp.nov.mar	0.100 (0.066)
temp.apr.jun	0.338 (0.099)***
temp.jul.oct	-0.037 (0.089)
rain.nov.mar	0.001 (0.005)
rain.apr.jun	-0.020 (0.009)**
rain.jul.oct	-0.018 (0.008)**
ln.price	-0.124 (0.029)***
ln.vac.cap.dev	-0.164 (0.058)***
drght.stage1	-0.009 (0.010)
drght.stage2	-0.028 (0.008)***
drght.stage3	-0.192 (0.010)***
geooutside:fmonthFeb	-0.030 (0.017)*
geooutside:fmonthMar	0.002 (0.021)
geooutside:fmonthApr	0.051 (0.017)***
geooutside:fmonthMay	0.018 (0.016)
geooutside:fmonthJun	0.022 (0.018)
geooutside:fmonthJul	0.044 (0.017)***
geooutside:fmonthAug	0.031 (0.016)**
geooutside:fmonthSep	0.057 (0.018)***
geooutside:fmonthOct	0.017 (0.014)
geooutside:fmonthNov	0.041 (0.016)**
geooutside:fmonthDec	0.033 (0.014)**
Constant	1.726 (0.035)***
Observations	351
R2	0.909
Adjusted R2	0.900
Residual Std. Error	0.035 (df = 316)
F Statistic	93.266*** (df = 34; 316)
Note:	*p<0.1; **p<0.05; ***p<0.01

Business Customer Class Model

	Dependent variable:
	ln.adj.use
geooutside	0.486 (0.048)***
fmonthFeb	0.033 (0.017)*
fmonthMar	0.048 (0.017)***
fmonthApr	0.116 (0.015)***
fmonthMay	0.250 (0.016)***
fmonthJun	0.330 (0.015)***
fmonthJul	0.396 (0.017)***
fmonthAug	0.380 (0.018)***
fmonthSep	0.273 (0.015)***
fmonthOct	0.172 (0.014)***
fmonthNov	0.044 (0.020)**
fmonthDec	-0.005 (0.020)
temp.nov.mar	0.243 (0.103)**
temp.apr.jun	0.400 (0.193)**
temp.jul.oct	-0.135 (0.121)
rain.nov.mar	0.001 (0.007)
rain.apr.jun	-0.034 (0.013)***
rain.jul.oct	-0.028 (0.010)***
rain.lag1.apr.jun	-0.017 (0.008)**
ln.price	-0.099 (0.017)***
ln.unemp.rate.dev.city	-0.160 (0.011)***
drght.stage3	-0.123 (0.008)***
geooutside:fmonthFeb	-0.037 (0.021)*
geooutside:fmonthMar	-0.021 (0.026)
geooutside:fmonthApr	0.010 (0.020)
geooutside:fmonthMay	-0.037 (0.022)*
geooutside:fmonthJun	-0.031 (0.023)
geooutside:fmonthJul	-0.064 (0.022)***
geooutside:fmonthAug	-0.067 (0.024)***
geooutside:fmonthSep	0.007 (0.024)
geooutside:fmonthOct	0.018 (0.020)
geooutside:fmonthNov	0.062 (0.025)**
geooutside:fmonthDec	0.040 (0.022)*
geooutside:ln.price	-0.163 (0.028)***
geooutside:drght.stage3	-0.068 (0.011)***
Constant	3.488 (0.023)***
Observations	353
R2	0.948
Adjusted R2	0.942
Residual Std. Error	0.047 (df = 317)
F Statistic	163.460*** (df = 35; 317)

Municipal Customer Class Model

	Dependent variable: ln.use
fmonthFeb	-0.025 (0.040)
fmonthMar	0.101 (0.057)*
fmonthApr	0.767 (0.052)***
fmonthMay	1.214 (0.049)***
fmonthJun	1.424 (0.046)***
fmonthJul	1.553 (0.040)***
fmonthAug	1.579 (0.041)***
fmonthSep	1.360 (0.045)***
fmonthOct	1.061 (0.042)***
fmonthNov	0.521 (0.039)***
fmonthDec	0.087 (0.034)**
eto.nov.mar	0.516 (0.138)***
eto.apr.jun	0.804 (0.242)***
eto.jul.oct	0.357 (0.107)***
rain.nov.mar	0.037 (0.036)
rain.apr.jun	-0.147 (0.050)***
rain.jul.oct	0.006 (0.038)
ln.rain.dev.lag1	-0.097 (0.019)***
ln.rain.dev.lag2	-0.063 (0.019)***
ln.price	-0.237 (0.063)***
ln.unemp.rate.dev.city	-0.142 (0.046)***
drght.stage2	-0.108 (0.034)***
drght.stage3	-0.621 (0.035)***
Constant	2.645 (0.076)***
Observations	177
R2	0.957
Adjusted R2	0.951
Residual Std. Error	0.137 (df = 153)
F Statistic	149.772*** (df = 23; 153)
Note:	*p<0.1; **p<0.05; ***p<0.01

Irrigation Customer Class Model

	Dependent variable: ln.use
geooutside	0.150 (0.034)***
fmonthFeb	0.058 (0.039)
fmonthMar	0.380 (0.076)***
fmonthApr	1.256 (0.069)***
fmonthMay	1.697 (0.052)***
fmonthJun	1.938 (0.045)***
fmonthJul	2.028 (0.046)***
fmonthAug	1.992 (0.046)***
fmonthSep	1.920 (0.048)***
fmonthOct	1.614 (0.049)***
fmonthNov	1.073 (0.043)***
fmonthDec	0.479 (0.053)***
eto.nov.mar	0.509 (0.207)**
eto.apr.jun	0.660 (0.243)***
eto.jul.oct	0.163 (0.184)
rain.nov.mar	-0.044 (0.049)
rain.apr.jun	-0.116 (0.065)*
rain.jul.oct	-0.085 (0.040)**
ln.rain.dev.lag1	-0.166 (0.025)***
ln.rain.dev.lag2	-0.090 (0.021)***
ln.price	-0.545 (0.069)***
drght.stage1	-0.077 (0.048)
drght.stage2	-0.250 (0.044)***
drght.stage3	-0.930 (0.081)***
Constant	2.681 (0.080)***
Observations	358
R2	0.922
Adjusted R2	0.916
Residual Std. Error	0.216 (df = 333)
F Statistic	164.036*** (df = 24; 333)
Note:	*p<0.1; **p<0.05; ***p<0.01

Golf Customer Class Model

	Dependent variable:
	ln.use
geooutside	0.783 (0.163)***
fmonthFeb	-0.255 (0.136)*
fmonthMar	0.082 (0.124)
fmonthApr	2.781 (0.227)***
fmonthMay	4.094 (0.180)***
fmonthJun	4.765 (0.165)***
fmonthJul	4.950 (0.167)***
fmonthAug	5.034 (0.166)***
fmonthSep	4.814 (0.162)***
fmonthOct	4.387 (0.162)***
fmonthNov	3.058 (0.129)***
fmonthDec	0.696 (0.262)***
eto.nov.mar	0.626 (0.357)*
eto.apr.jun	0.352 (0.487)
eto.jul.oct	0.767 (0.232)***
rain.nov.mar	-0.155 (0.087)*
rain.apr.jun	-0.519 (0.139)***
rain.jul.oct	-0.036 (0.056)
ln.rain.dev.lag1	-0.613 (0.056)***
ln.rain.dev.lag2	-0.092 (0.037)**
ln.price.summer	-0.338 (0.098)***
drght.stage3	-0.368 (0.071)***
geooutside:fmonthFeb	0.399 (0.216)*
geooutside:fmonthMar	0.207 (0.240)
geooutside:fmonthApr	-0.451 (0.278)
geooutside:fmonthMay	-0.880 (0.252)***
geooutside:fmonthJun	-1.080 (0.237)***
geooutside:fmonthJul	-1.102 (0.240)***
geooutside:fmonthAug	-1.109 (0.232)***
geooutside:fmonthSep	-1.098 (0.235)***
geooutside:fmonthOct	-0.986 (0.230)***
geooutside:fmonthNov	-0.443 (0.192)**
geooutside:fmonthDec	0.634 (0.310)**
geooutside:ln.price.summer	0.376 (0.126)***
Constant	0.344 (0.110)***
Observations	352
R2	0.957
Adjusted R2	0.953
Residual Std. Error	0.368 (df = 317)
F Statistic	209.736*** (df = 34; 317)
Note:	*p<0.1; **p<0.05; ***p<0.01