Valley Water

MEMORANDUM

FC 14 (08-21-19)

TO: Garth Hall, DOO

FROM: Neeta Bijoor, Ph.D.

SUBJECT: Request to post benchmark analysis of demand projection models on Valley Water website

DATE: April 13, 2020

Santa Clara Valley Water District (Valley Water) is responsible for supplying clean, safe water to all of Santa Clara County (County). To ensure Valley Water can provide a reliable water supply in the future, Valley Water is developing a water demand model to forecast the County's water demand and support Valley Water's water supply planning efforts. Valley Water has contracted with the consulting firm Hazen and Sawyer (Hazen) to assist with demand model development. As part of demand model development, Hazen completed a benchmark analysis of demand modeling approaches used by Valley Water's peer agencies. The benchmark analysis allows Valley Water to better understand the opportunities and constraints Valley Water may experience by using different modeling approaches. Hazen has summarized benchmark analysis findings in the attached technical memorandum, "Benchmark Analysis of Regional Demand Projection Models" (TM1). TM1 describes different approaches and required data for developing demand models. TM1 then describes the results of the benchmark analysis of demand modeling approaches used by the following eight water supply agencies:

- San Francisco Public Utilities Commission
- Bay Area Water Supply and Conservation Agency
- San Diego County Water Authority
- Metropolitan Water District of Southern California
- Tampa Bay Water
- Contra Costa Water District
- Sonoma County Water Agency
- Zone 7 Water Agency.

While the benchmark analysis found a great deal of variety in the modeling approaches that were employed, most agencies used a statistically-based approach often referred to as econometric modeling. TM1 concluded that Valley Water likely has considerable flexibility in choosing a demand modeling approach. The determination of which approach is best suited for Valley Water will depend on the availability and quality of historic County water use data.

RECOMMENDATION

TM1 provides a foundational understanding to demand modeling that will support Valley Water's ultimate model choice. Therefore, Valley Water staff recommend posting TM1 to the Valley Water website (https://www.valleywater.org/your-water/water-supply-planning) in order to share study findings with stakeholders. Stakeholders may also want to refer to TM1 as they develop their own demand models in preparation for their 2020 Urban Water Management Plans.

ATTACHMENT:

Attachment 1: “Benchmark Analysis of Regional Demand Projection Models” technical memorandum (TM1).

Sincerely,

Neeta Bijoor

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Neeta Bijoor, Ph.D.
Associate Water Resources Specialist
Water Supply Planning and Conservation

Cc: S. Greene, M. Richert, J. De La Piedra

December 9, 2019

To: Samantha Greene, Ph.D.

From: Jack Kiefer, Ph.D.
Luke Wang, PE

cc: Jerry De La Piedra, Metra Richert

QC: Marc Solomon, PE, BCEE, D.WRE

Technical Memorandum 1

Benchmark Analysis of Regional Demand Projection Models

Introduction

Santa Clara Valley Water District (Valley Water) is in the process of developing a new model to forecast total water demand in Santa Clara County. Demand projections from the model will be used to support several planning initiatives and documents including:

- The 2021 Urban Water Management Plan (UWMP);
- Monitoring of and updates to the Water Supply Master Plan;
- Inputs to Valley Water's water supply planning model; and
- Evaluating conservation programs and capital projects.

Valley Water manages a diverse portfolio of water supplies to provide water to Santa Clara County's independent well owners and thirteen retailers. The majority of Santa Clara County customers obtain their water directly from their retailer. As a result, each retailer develops their own water demand forecasts. These forecasts are useful and have been used to inform Valley Water's prior UWMPs. However, Valley Water is responsible for county-wide water resource planning activities (e.g. groundwater management, treated water production, potable reuse development, surface water infrastructure management and development, and active conservation program implementation) that are better served by a consistent modeling approach and assumptions across the service area. Valley Water has historically developed its own water demand forecast for the County using the IWR-MAIN model, which has provided a consistent platform and basis for disaggregating forecasts into geographic areas and sectors. The IWR-MAIN model has not been supported in nearly two decades, further motivating Valley Water's interest in evaluating a new demand model approach and platform.

The purpose of this Technical Memorandum (TM1) is to support the evaluation of a new demand model through a benchmarking analysis of the modeling approaches used by Valley Water's peer agencies. TM1 is organized by first reviewing a conceptual typology of demand forecasting elements, which is useful in characterizing and comparing the forecasting approaches among water supply utilities. The typology is supported with a detailed discussion of several quantitative methods often used to forecast demand. Given this background and framework, TM1 reviews the forecasting approaches employed by several regional water supply providers and wholesale agencies. These agencies include:

- San Francisco Public Utilities Commission
- Bay Area Water Supply and Conservation Agency
- San Diego County Water Authority
- Metropolitan Water District of Southern California
- Tampa Bay Water (FL)
- Contra Costa Water District
- Sonoma County Water Agency
- Zone 7 Water Agency

TM1 concludes with a summary of the benchmarking analysis which includes a characterization of Valley Water's prior forecast approach and the implications of the analysis on selection of a new forecast modeling approach.

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1. Typology for Demand Forecasting

This Section reviews a conceptual typology of demand forecasting elements, which is useful in characterizing and comparing the forecasting approaches between water supply utilities. The working typology of long-term forecasting approaches presented in this Section has been developed by Kiefer, Dzielgielewski, and Jones[1] and is summarized below and prior to describing the approaches used by Valley Water peer water providers. The intent of the typology is to add a structure around which the topic of water demand forecasting can be described and characterized. The typology is based on the review of several reports and studies developed by more than 100 water utilities and related water management agencies documenting long-term water demand forecasting efforts. The review provides a representative assessment of the prevailing design features of current forecast practices.

In general, most of the differences in how water demand forecasts are prepared relate to specific details about underlying assumptions. However, stepping back from these details, there appears to exist four main elements that can add structure for classifying the features of a long-term water demand forecast. The working typology suggests that a long-term forecast is generally describable as the intersection of four main elements identified in the following Figure 1.

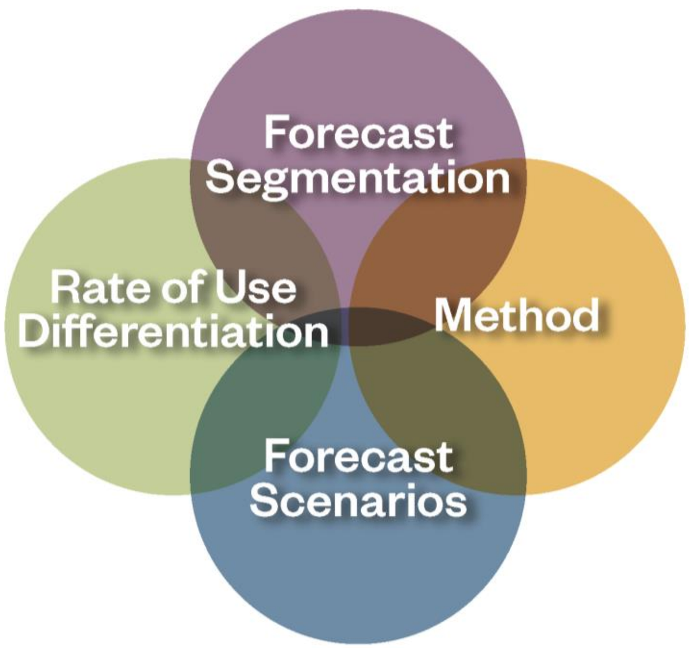

Figure 1: Long-term Water Demand Forecasting Typology as an Intersection of Four Main Descriptive Elements

[1] The typology is based on work that will appear in Kiefer, J., Dziegielewski, B., and C. Jones. [N.D. forthcoming]. *Long Term Water Demand Forecasting Practices for Water Resources and Infrastructure Planning.* Water Research Foundation, Denver, CO.

1.1 Forecast Segmentation

Forecast segmentation refers to whether and how a water demand forecast is broken down into component pieces. As shown in Figure 2, forecasts can be derived for the following dimensions:

- Groups of customers, such as billing classes or sectors defined by other criteria
- End uses of water, which define specific water using purposes[2]
- Geographical areas, which make up a current or future water service area
- Times of the year, such as seasons or months

For example, a forecast may provide monthly predictions of water use for six water user types, broken into indoor and outdoor components, for 10 water delivery zones. On the other hand, a forecast without segmentation might simply reflect a prediction of total production demands for a given utility.

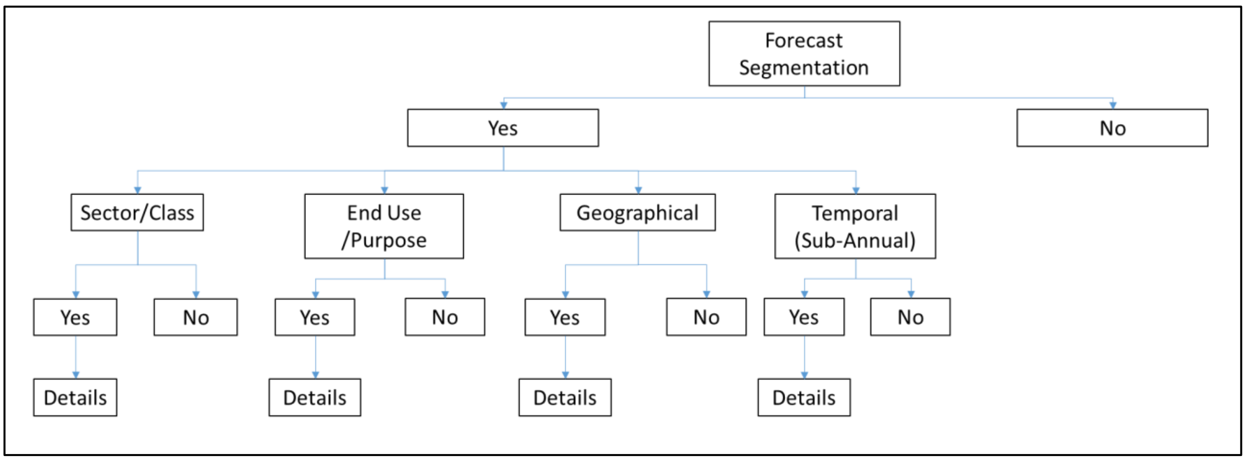

Figure 2: Typology Element Defining Forecast Segmentation

The review of forecasting literature suggests that, in practice, forecast segmentation can involve many combinations among these forecast dimensions, as well as a wide variety in how each is defined. For example, one utility may forecast water use for single family and multifamily water billing sectors, while another may forecast for a combined residential sector defined by land use zoning criteria. A utility may choose to forecast for residential end uses of water, but not at the end use level for commercial and industrial classes. Some utilities may forecast total production demands by month by pressure zone, and others may forecast by Census tract for multiple sectors for low, mid, and high water using seasons.

1.2 Rate of Use Differentiation

Rate of use differentiation refers to splitting a forecast into a subcomponent that reflects water using intensity (Figure 3). This implies that the forecast employs the use of one or more forecast "drivers". A

[2] Example end uses include irrigation, toilet flushing, showering, rinsing, etc. End uses are sometimes, but not always, tied to specific water fixtures.

driver is a count (N) of a variable that defines either scale or frequency, where for any given forecast dimension a prediction of water use (Q) is defined as:

$$Q \equiv N * \frac{Q}{N} \equiv N * q \quad (1)$$

Where simple conversion suggests the rate of use is q. Table 1 identifies several examples of driver variables and corresponding rate of use metrics that can be differentiated.

Table 1: Examples of Drivers and Rates of Use

Driver Unit (*N*)	Corresponding Rate of Use (*q*)
Population	Per capita use
Households	Per household
Acres	Per acre
Employees	Per employee
Square feet	Per square foot
Accounts	Per account
Meters	Per meter
Toilet flushes	Per flush
Wash loads	Per load

With the addition of this typology element, one can begin to envision how typology elements intersect to describe a forecast. For example, a utility may not segment its water demand forecast, but may derive the forecast as the product of projected population and per capita use. A utility may use households as the driver for a residential sector and employees as the driver of a commercial class. It is also possible that a utility differentiates the rate of use only for a subset of classes. These are the types of details that are often encountered when reviewing forecast documentation.

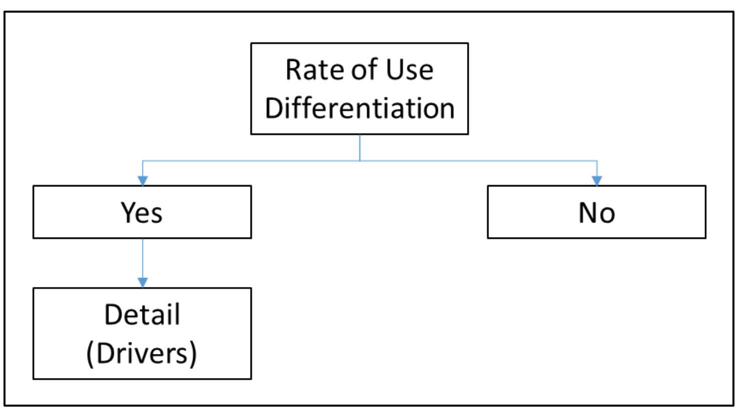

Figure 3: Differentiating Forecasted Rates of Water Use is Another Element of the Typology

1.3 Method

The "method" element of the working typology refers to how a forecast is calculated, i.e., the underlying arithmetic, and how information and assumptions about the future are connected to create a forecast. Forecast methods may consist of components from three different model types described in Table 2 below.

Table 2: Description of Forecast Methods/Models

Model Type	Description
Statistical	Consists of functional relationships estimated from observed historical data, which may define explanatory variables (i.e., covariates), or, alternatively, predict the future from past time series alone
Associative	Models connect (or associate) information to calculate forecasts without reference to statistical relationships estimated from historical data; they are functional or perform functions, but not statistical
Judgmental	Models that reflect forecast assumptions that are not immediately based on explicit statistical or associative calculations

The method element can also intersect other typology elements. Based on the review of utility forecasts, forecasts can be highly nuanced, employing multiple methods at the same time (which gives rise to the "combination" pathway in Figure 4). For example, a utility may predict water use per account in the single-family sector as a statistical function of price and income (sector segmentation, rate of use differentiation, statistical method, with covariates), meanwhile assuming the number of single-family accounts (drivers) and nonresidential sector demands change at a rate tied to population projections (associative). The same utility may assume that future demands for certain large users will stay constant (judgmental). Another utility may forecast total production demands by multiplying population (driver) projections by per capita usage (rates of use) that decline at a rate tied to estimates of future toilet flush volumes (associative) or assume future per capita usage rates reflect policy targets associated with conservation (judgmental) or engineering guidelines (judgmental).

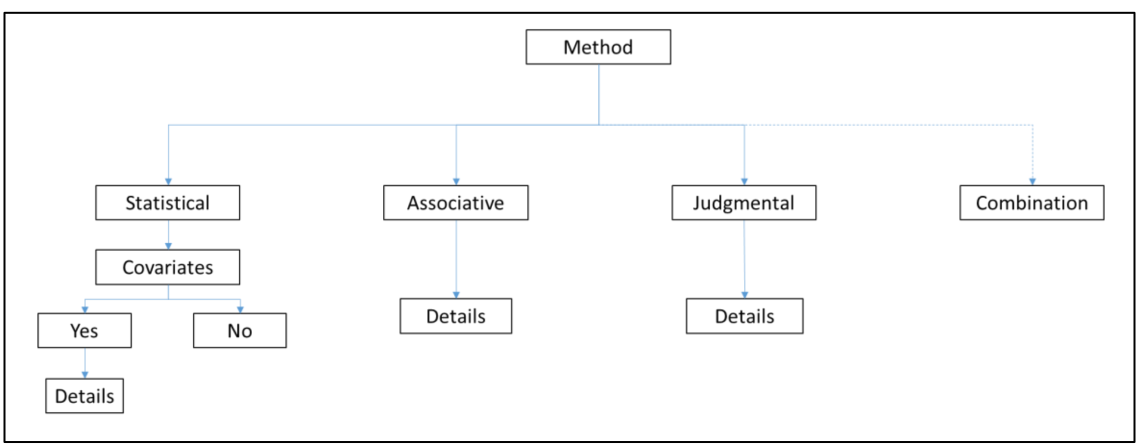

Figure 4: The Method element defines the basis of forecast calculations

1.4 Forecast Scenarios

The final element of the working typology defines whether and how alternative forecasts scenarios are calculated, as opposed to a single forecast scenario, which is assumed as given (Figure 5). Some examples of forecast scenarios include high and low growth scenarios, with and without conservation, hot/dry versus cool/wet weather conditions, and historical climate versus climate change. Scenarios can be introduced by varying any of the values of variables and assumptions comprising the method element of the typology and there are both qualitative and quantitative methods for creating and portraying the scenarios. Probabilistic simulation is one quantitative technique for generating many scenarios, encompassing hundreds or thousands of potential outcomes.

Although the calculations of alternative scenarios are highly dependent on features related to model method, they also can intersect with other typology elements. For example, rates of use may be treated as uncertain (i.e., allowed to vary), but driver counts may be portrayed as a single set of values, and vice versa. Some scenarios may assume development of additional geographic areas within the service area or different future land uses, different conservation scenarios may be applied to different sectors, and so on. The actual choice of forecast scenarios is often driven by planning objectives, reporting requirements, and the relative emphasis on addressing future uncertainties, which also reflect nuance and affect the details of any forecast.

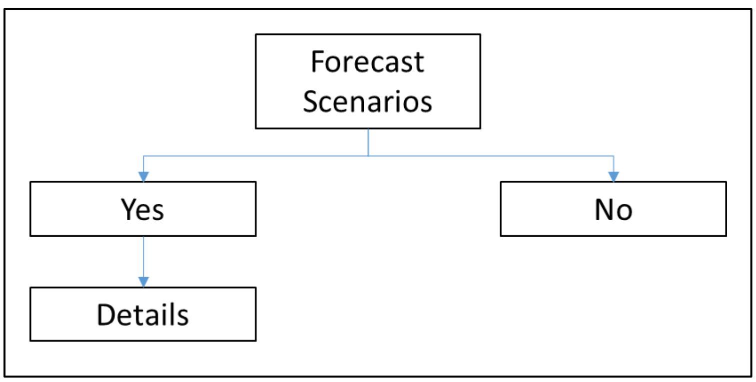

Figure 5: The Use of Alternative Forecast Scenarios is a Descriptive Element of the Typology

2. Spectrum of Associative and Statistical Modeling Methods

The range of associative and statistical water use modeling methods is well developed. Billings and Jones (2008), Donkor et al. (2014), Rinaudo (2015), and others have summarized differences in forecasting models, which differ mechanically in form and function, as well as in data requirements and skills/training needed for application. The sections below summarize several alternative model constructs, highlighting some of their best features and disadvantages. These generally reflect the menu of options available to Valley Water in terms of the method component of the forecasting typology, notwithstanding the ability to integrate multiple methods and many possible details about how they intersect with other typology elements, such as forecast segmentation and forecast scenarios.

2.1 Trend Extrapolation and Univariate Time Series Models

Trend extrapolation simply fits a trend line through an historical time series of observed water use values and uses this line to extrapolate future values. Trend lines are easily fit in spreadsheet programs, which also provide some options for fitting nonlinear curves. The underlying assumption of trend extrapolation is that water use can be explained by the passage of time and forecasts of future demand rely only on the value of a time counter or index.

Univariate time series models can be significantly more refined and statistically complex than simple trend extrapolation. As a class of models, they stem from the work of Box and Jenkins (1976). The time series literature is highly developed and specialized. In general, time series models can generally be described by the three component parts; Auto-Regressive, Integrated, and Moving Average (ARIMA). A purely auto-regressive (AR) model predicts water use using a statistical weighting of its past values. If considered necessary, adding a moving average (MA) component weighs past prediction errors of the AR component to improve predictions. If differencing of historical observations is necessary to make the original series stationary, the order of integration (I) reflects how many times the series must be differenced.

Trend extrapolation and univariate time series techniques forecast water demand as a function of its past values, so there are relatively low data requirements. Although these approaches are seldom used in a long-term forecasting context they are technically adaptable to any forecast horizon. Despite the relatively low data requirements, substantial technical training and expertise is necessary to identify the components of a univariate time series model. Furthermore, since these types of models do not directly define cause and effect relationships, additional qualitative judgments may be needed to explain predicted movements in time.

2.2 Fixed Unit Use Coefficient Models

Unit use coefficient models are closely related to the "rate of use differentiation" component of the working typology, in that, by design, they differentiate unit rates of use from the count of units that are assumed to drive water use. Typically, unit usage rates, such as water use per capita, water use per household, or water use per employee, are derived and then multiplied by projections of corresponding units to derive forecasts of water use.

The most basic application of fixed unit use methods utilizes a single rate of use metric and a single forecast driver, such as the traditional industry standard of multiplying an assumed per capita usage rate by projections of population. More robust applications disaggregate unit usage rates by customer class and/or geographic areas and/or seasonal time periods. A generic representation a fixed unit use coefficient model consisting of geographic (g), sectoral (s) and monthly (m) dimensions can be written as:

$$Q_t = \sum_{g}^{G} \sum_{s}^{S} \sum_{m}^{M} N_{g,s,m,t} * q_{g,s,m} \qquad \textbf{(2)}$$

Where the sums of the products of unit use coefficients (q) and driver units (N) calculate a forecast of total water use (Q) for future period t. Note that in this formulation, the unit use coefficients do not vary in future time periods (and, hence, do not take the index t).

Fixed unit use coefficient models are technically straightforward and do not require statistical rigor, as they rely on averages or other central tendency measures. These types of models characterize expected values, but do not attempt to explain variability in the data used to calculate averages or address observed variability in averages through time. Disaggregation of unit usage rates and relevant driver units into sectors, geographic areas, and time periods offers a mechanism to exploit underlying variability in water use to improve the quality of forecast information but comes with a corresponding increase in data requirements. Selection of unit usage rates will typically require judgments or statistical analyses to “normalize” for the effects of weather and other circumstances, if, in fact, historical data are used as a basis to derive the unit use coefficients. Mechanistically, future changes in the unit usage rates (for example, due to assumed changes in use caused by water efficiency improvements) may be integrated easily into the framework by permitting the coefficients to vary with time (t):

$$Q_t = \sum_{g}^{G} \sum_{s}^{S} \sum_{m}^{M} N_{g,s,m,t} * q_{g,s,m,t} \tag{3}$$

2.3 Regression and Econometric Models

Regression analysis and econometrics[3] are techniques for relating the values of 2 or more variables statistically. Regression models are estimated equations that predict how the value of a dependent variable (Y) changes in response to a change in the value of one or more independent variables (X).[4] Thus, regression models are designed to reflect a functional relationship that implies a causal connection between the dependent variable and a set of independent variables. Regression models are estimated from data measured in time or space, or across both dimensions. Ignoring the dimensions over which it is estimated, the classic linear regression model with one independent variable can be written as:

$$Y = \alpha + \beta X + \varepsilon \tag{4}$$

Where α denotes an "intercept" term that estimates the value of Y when X equals 0 and β is a regression parameter (or slope coefficient) that describes both the direction and degree that Y changes when X changes. The model error (or residual) term ε measures the difference between the predicted value of Y, given the value of X, and the true or observed value of Y.

If values of Y and X are transformed into natural logarithms prior to estimation, then this gives rise to the classic multiplicative (or Cobb-Douglas) formulation, where the value of the exponent β can be

[3] Generally speaking, econometric models are regression models that incorporate variables that have interest to economists (such as price and income, among others).

[4] Independent variables (X) are also referred to as covariates.

interpreted directly as an elasticity, which measures the percent change in Y stemming from a 1 percent change in X:[5]

$$Y = e^{\alpha} X^{\beta} e^{\varepsilon} \tag{5}$$

Multiple regression differs from the examples of simple single-variable regression as shown above only in that more than one independent or explanatory variable is specified in the regression model. The underlying principles and assumptions still apply, except only that more variables are used to explain changes in the dependent variable.

The literature on regression analysis is thorough, rich, and specialized and the span of technical details and sophistication varies widely. Estimation and interpretation of regression models for water demand forecasting requires academic training. A major appeal of using regression-based models is the ability to estimate cause-effect relationships that can be used to forecast future "what if" scenarios. However, this comes with additional analytical requirements, including ample historical data upon which to estimate model parameters. For example, estimating the influence of weather, price, income, and other factors on water use will require time-series and/or spatial observations of these factors paired with corresponding values of water use. Furthermore, in order to employ resulting models for forecasting, assumptions regarding future values of independent variables will be needed, and formal sources of projections for some variables may be hard to find. However, regression models permit forecasters and planners to estimate the sensitivity of forecasts to changes in assumptions about any of the factors that are specified.

2.4 End Use Accounting Models

End use models attempt either to build up estimates of demand from estimates of water use devoted to specific purposes or allocate estimates of water use into different purposes based on external sources of information.[6] Because of the intent that whole add up to the individual parts, these types of models are often called end use accounting models. In general, these models attempt to differentiate technology from behavior, which make them relatively powerful for evaluating the effects of changes in water efficiency. Figure 6 shows one such end use framework[7], which first specifies different discrete levels of mechanical efficiency for a given end use and the percentage of the total stock of a given end use that corresponds to each efficiency level.

[5] Note that the term *e* in Equation 5 represents the base of the natural logarithm.

[6] The Residential End Uses of Water Study Update (DeOreo et al. 2016) and its predecessor study (Mayer et al. 1999) are often used external sources that provide assumptions for allocating residential use into end use components.

[7] The general framework shown in Figure 6was originally employed within the IWR-MAIN Water Demand Management Suite Conservation Manager. This "bottom-up" framework, which is not inherent to all end use models, also recognizes the average frequency or intensity of end use events and the proportion of water users that have the particular end use, which generally describes the behavioral aspects of the system.

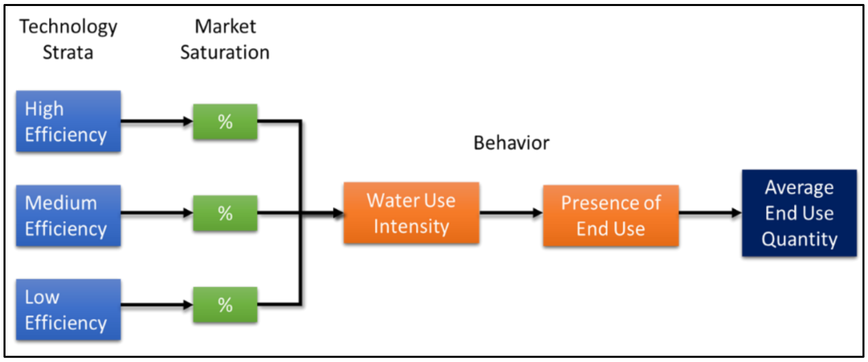

Figure 6: Example Elements of Water End Use Framework

The elegance of the end use approach stems from the ability to compartmentalize how changes in consumption can occur through time. One difficulty with end use models is that end use models do not easily capture time series and geographical variability in water use that stem from factors other than water efficiency (such as weather and economic activity). Another difficulty is the wide range of process use and fixtures employed in the nonresidential sectors (such as cooling, rinsing, and specialized water processes), where less has been formalized in terms of mechanical efficiency levels and variability in water using behaviors, both of which may be influenced by the demand for goods and services that use water as a direct or indirect input. These difficulties often lead to the need to initially calibrate end use estimates to fixed unit usage estimates and to specify “catch-all” end use categories (such as “outdoor-other” or “non-residential other”) in order to balance the accounting.

2.5 Hybrid and Other Model Types

There are other types of forecasting models that can be found in the literature, which distinguish themselves in certain ways from the types discussed above. For example, there are econometric methods that exploit the power of ARIMA techniques, and time series methods that can be extended to use information on independent variables (e.g. transfer function models). There are also machine learning techniques, such as application of artificial neural networks (ANN), which mine data in search of patterns that can be learned for predictive purposes. For the most part computational intelligence models have been used in the context of short-term forecasting, with emphasis on comparing predictive performance with other types of models.

There is a wide range of hybrid models used for long-term water demand forecasting, which reflects the nuance and creativity found in creating forecasts. It is not uncommon to see various blends of coefficient, end use, and regression models used together, and with different degrees of modeling sophistication and complexity. It is fairly common practice to complement econometric forecast models with end use-based models to adjust econometric forecasts for the effects of passive water savings. There are other examples that integrate input from independent or external sources to formulate custom forecasting equations. For example, New York City’s current demand forecast model can adjust simple per capita use projections using climatic terms estimated via regression and a water efficiency index estimated separately with the aid of tax appraiser data (Kenniff and Kiefer 2014). Similarly, the "variable flow factor" model used by Seattle Public Utilities employs literature-based price and income elasticity estimates along with water conservation assumptions (Flory 2012). These examples can be defined as *modified forecast factor models* that can be written in generalized form as:

$$Y_F = Y_B * \prod_{j}^{J} \left(\frac{X_{j,F}}{X_{j,B}} \right)^{\beta_j} \qquad (6)$$

Where like equation (5), Y is the dependent variable that is being forecasted based on the values of j independent variables X and estimated elasticities (β) that define the response of Y to the specified set of independent variables. The index B represents a base or starting value and the index F denotes a different future value. In this formulation, the forecasted value of Y is a multiplicative product (or scaling) of its base value, which is determined by the ratio change in the values of independent variables from their respective base values and their corresponding elasticities.[8] Modified forecast factor models can be considered hybrid models to the extent that they use externally derived sources for statistical response parameters or use limited or partial local data to make statistical inferences about different and broader populations.

The principal advantage of hybrid models is that they attempt to overcome data constraints by making appropriate use of available knowledge bases and a mix of desired features of associative and statistical modeling methods. However, use of external information, such as assumed elasticities, requires some judgments on applicability and credible sources, and mixing of models in multiple forecasting steps can complicate the formulation of scenarios or related assessments of statistical confidence.

3. Forecasting Approaches Employed by Selected Bay Area Providers

This section presents a review of water demand forecasting approaches used by selected water providers in the Bay Area. The approaches used by each agency are evaluated with respect to the four primary elements of the typology discussed above, including some additional detail on models used and sources of projection data. The assessments are based on available information from recent Urban Water Management Plans, related water supply planning documents that describe forecasting processes, and in some cases direct experience of the study team in implementing these processes. It is important to caution that these summaries represent interpretations of the written documentation and there can be some uncertainty in these interpretations.

3.1 San Francisco Public Utilities Commission

The San Francisco Public Utilities Commission (SFPUC) is a retailer and wholesaler that provides water partly or entirely within San Francisco, San Mateo, Santa Clara, Alameda, San Joaquin and Tuolumne Counties. The retail service area is home to a population of about 850,000, whereas the broader wholesale

[8] In the forecasting context F usually identifies the forecast year.

service area is estimated to have a population of about 1.8 million. SFPUC currently sources its water from the Hetch Hetchy system, as well as from local watersheds in the East Bay and on the Peninsula.

Table 3 summarizes elements of SFPUC forecast. The forecast is segmented into three primary sectors (not counting line items for estimated losses). The forecast differentiates between single- and multifamily residential households and combines nonresidential users into a commercial and industrial (CI) sector. The forecasting method is primarily econometric prior to utilizing an end use model to estimate conservation scenarios. The conservation model is a customized version of the Alliance for Water Efficiency Water Conservation Tracking Tool. SFPUC forecasts employ auxiliary judgments about growth in the Multifamily sector and future demands from suburban and wholesale customer groups/geographic areas.

The specification of variables within the econometric models differs by sector. The dataset used to estimate the econometric models included data from water providers outside of SFPUC to increase sample size and variability within the modeling data. Weather and income variables are used to normalize the starting point of the forecast to account for cooler and wetter conditions, as well lower incomes than in the recent past. Projections of forecast drivers are taken from San Francisco Planning Department estimates and median income projections reflect ABAG estimates. Price projections are derived from SFPUC's Division of finance and adjusted for an assumed 2 percent annual rate of inflation. The effects of price are assumed to capture passive water efficiency. The initial passive savings estimates are added back into the retail forecast prior to applying the conservation model in order not to double count and to provide an explicit accounting of the estimated amount of water conserved by both passive and active measures.

Table 3: SFPUC Forecast Summary

Agency and Categorization and Population Served	Retail (0.85 M served) and Wholesale (~1.8 M served)
Sources for Model Input	• San Francisco Planning Dept. (drivers) • ABAG (median income growth) • SPUC Division of Finance
Documents Used in Forecast Review	SFPUC 2015 UWMP

Typology	Approach	Details
Forecast Segmentation	Segmented by sectors, geography, time	Sectors/Land Uses • Single-family Residential (SFR) • Multifamily Residential (MFR) • Commercial & Industrial (CI) • Retail Water Losses • Wholesale Water Losses Geographic • In City service • Suburban retail • 26 Wholesale customers Temporal • Annual

Typology	Approach	Details
Rate of Use Differentiation	Differentiated	Drivers • Accounts/Households units (SFR) • Employees (CI)
Method	Statistical (Econometric) + Associative (End Use) + Judgmental	Modeled Variables (estimated elasticities) • Price (SFR: -0.24, MFR: -0.17, CI: -0.15) • Median Income (SFR: 1.02) • Summer Avg. Max Temperature (SFR: 0.11, CI: 0.48) • Annual Precipitation (SFR: -0.09, CI: -0.04) Other Assumptions • MFR escalation based on projected MFR household growth • Suburban retail demand held constant • Wholesale demand held constant at contractual obligations
Forecast Scenarios	Explicit Scenarios	• With passive conservation • With passive and active conservation

3.2 Bay Area Water Supply and Conservation Agency

The Bay Area Water Supply and Conservation Agency (BAWSCA) represents the water supply planning interests of 24 municipalities/districts and 2 private utility companies (26 total member agencies) in Alameda, San Mateo and Santa Clara Counties. BAWSCA does not own or operate any water related infrastructure but can acquire water for its agencies and plays an important role in communicating their interests to larger organizations such as SFPUC and Valley Water. BAWSCA member agencies receive most of their supply from SFPUC, with the remainder derived from other local and regional sources including local, non-SFPUC owned surface water (e.g. Bear Gulch Reservoir); local groundwater on the Peninsula; groundwater in Santa Clara County managed by Valley Water; and treated surface water in Santa Clara County delivered from Valley Water.

Since BAWSCA is a representative agency there is not a requirement to submit an Urban Water Management Plan with forecasts of demands. However, BAWSCA does regularly coordinate with their member agencies to develop demand forecasts as well as provide in-depth detail on their current usage and conservation measures.

BAWSCA integrates econometric and end use-base models for preparation of annual demand forecasts for 3 user sectors across their 26 member agencies (Table 4). Water production per capita is forecasted using an econometric model for the first few years of the forecast horizon, which is then transitioned into an end-use framework for later years of the forecast. The forecasts are generated and contained within the Demand Side Management Least Cost Planning Decision Support System (DSS Model).[9] Past estimates of water savings from the DSS Model were added back to historical production data prior to development

[9] The DSS Model is proprietary and sold with "subscription" fees to Maddaus Water Management.

of the econometric model and short-term econometric forecasts. The DSS Model was then calibrated to weather-normalized econometric model forecasts.

The DSS Model initially allocates water use per capita (residential sectors) and water use per employee (nonresidential sector) into end use components based on estimates of indoor/outdoor splits and literature-based estimates of the distribution of indoor and outdoor use across specific end uses. The effects of passive and active water efficiency measures are then estimated at an end use level. Thus, population and employment projections drive the forecasts across retail areas, whereas the effects of efficiency influence the projections of use per capita and per employee.

Table 4: BAWSCA Forecast Summary

Agency and Categorization and Population Served	Representative Agency (~1.8 M served)
Sources for Model Input	• Plan Bay Area - ABAG Projections 2013 • Member agency 2010 UWMPs • California Department of Finance • United States Census Bureau • Member agency specific planning documents
Documents Used in Forecast Review	Regional Water Demand and Conservation Projections

Typology	Approach	Details
Forecast Segmentation	Segmented by sectors, geography, time	Sectors/Land Uses • Single-family Residential • Multifamily Residential • Nonresidential Geographic • 26 member agencies Temporal • Annual
Rate of Use Differentiation	Differentiated	Drivers • Population • Employees
Method	First 7 forecast years: Statistical (Econometric; production per capita) Remaining Forecast Years: Associative (End Use) + Judgmental	Modeled Variables (estimated elasticities) • Price (-0.168) • Unemployment Rate (-0.051) • Seasonality • Avg. Max Temperature Deviation (w/Seasonal Interactions) • Annual Precipitation Deviation (w/Seasonal Interactions) • Agency unique intercept (fixed effects) • Agency unique trend terms End Use Model • Residential and Nonresidential end uses allocated according to WaterRF research

Typology	Approach	Details
Forecast Scenarios	Explicit Scenarios	• Before passive savings • With passive conservation • With passive and active conservation

4. Forecasting Approaches Employed by Peer Wholesale Agencies

This section presents a review of water demand forecasting approaches used by peer wholesale water providers, three of these wholesalers also reside in the Bay Area. As in the prior section, the four primary elements of the water demand forecasting typology are used as a basis for summarizing available documentation on forecasting methodologies employed, and that there can be some uncertainty in the interpretation of the available documentation.

4.1 San Diego County Water Authority

The San Diego County Water Authority (SDCWA) provides wholesale water deliveries to 24 member retail water agencies in San Diego County at the southern tip of California and serves approximately 3.3 million people over an area of about 950,000 acres. The SDCWA service areas covers about 1,500 square miles and is comprised of a mixture of dense urban areas and rural, predominantly agricultural, areas. The characteristics of individual member agencies vary considerably in terms of size, climate, and water customer base. About 80 percent of the region's water supply is imported from the Colorado River and Northern California. SDCWA is a member agency of the Metropolitan Water District of Southern California (MWD), which is the SDCWA's largest supplier. The remaining water comes from local supply sources including groundwater, local surface water, recycled water, and conservation. SDCWA also has a 30-year Water Purchase Agreement with Poseidon Water for the purchase of up to 56,000 acre-feet of desalinated seawater per year, which is equivalent to almost 8 percent of the region's projected water demand in 2020.

Table 5 summarizes the features of SDCWA's forecast. The SDCWA forecast model is called CWA-MAIN,[10] due to its consistency with the spatially and sectorally disaggregated forecasting framework embodied in the original IWR-MAIN forecasting software tool.[11] SDCWA's production forecast is segmented into 4 retail sectors (including metered Ag). Line items for losses and unclassified use are added to the retail forecasts to generate forecasts of production demands. Forecasts are generated using a corresponding set of 4 econometric models estimated using historical data from member retail agencies. Sectoral models are estimated using a two-step procedure. First, sectoral model includes a socioeconomic component that is common to all retail agencies, with controls for historical watering restrictions and the effects of cyclical economic effects. Next, estimated responses to weather and seasonality are estimated uniquely for each member agency because of the influence of micro-climates within the region. The two-step process effectively creates a unique model for each retail agency and sector. Finally, the modeled

[10] The acronym MAIN, in both CWA-MAIN and IWR-MAIN refers to Municipal and Industrial Needs.

[11] Note that the SDCWA forecast is not contained or generated within IWR-MAIN but rather within various relational databases and spreadsheets.

demands are calibrated over a multiyear period by month to derive normalized starting values for the forecast.

The San Diego Association of Governments (SANDAG) is the primary source of both historical and projected values of model variables (e.g., median income, housing density, persons per household, and employment mix) and forecast drivers (i.e., households, employment, and irrigated acres). SANDAG socioeconomic forecasts are the "official" source of baseline projections. SDCWA's sectoral forecasts are generated by month, but usually aggregated up to annual values for reporting purposes. The baseline forecast scenario does not include estimates of impacts from future passive or active water conservation efforts, nor reductions in use from water supply shortage restrictions. Estimates of future conservation are estimated using the Alliance for Water Efficiency Water Conservation Tracking Tool and are treated as one of several supply sources that are used to evaluate how forecasted demands will be met. Climate change scenarios are selected from a range of downscaled climate projections and implemented using the climatic components of the sectoral models.

Table 5: SDCWA Forecast Summary

Agency and Categorization and Population Served	Wholesale (~3.3 M served)
Sources for Model Input	• San Diego Association of Governments (SANDAG) • SDCWA assessments of crop types and requirements
Documents Used in Forecast Review	• Water Demand Model and Forecast Update 2015 (report Prepared by Hazen and Sawyer) • 2015 UWMP

Typology	Approach	Details
Forecast Segmentation	Segmented by sectors, geography, time	Sectors/Land Uses • Single-family Residential • Multifamily Residential • Nonresidential • Agricultural • Unclassified • Losses Geographic • 24 member agencies (including Pendleton Military Reservation) Temporal • Annual • Monthly
Rate of Use Differentiation	Differentiated	Drivers • Households • Employees • Irrigated acres
Method	Statistical (Econometric) + Judgmental + Associative (End Use)	Modeled Variables (estimated elasticities) • Price (SFR: -0.23, MFR: -0.14, NR: -0.17 to -0.34, AG: -0.61) • Median Household Income (SFR: 0.54, MFR: 0.07) • Persons per Household (SFR: 0.44, MFR: 0.56) • Housing Density (SFR: -0.31, MFR: -0.30)

Typology	Approach	Details
		• USD Economic Index • Watering Restrictions • Employment Mix • Employment Density • Normal Avg. Max Temperature • Avg. Max Temperature Deviation • Normal Precipitation • Precipitation Deviation • Crop type distribution • Crop ET requirements
Method (continued)		Notes • Pendleton demands provided externally to model • Price elasticities for the single-family, multifamily, and nonresidential sectors are reduced by 20 percent in early years of the forecast horizon
Forecast Scenarios	Explicit Scenarios	• Climate Change • Single hot/dry year • Consecutive hot/dry years • w/Conservation

4.2 Metropolitan Water District of Southern California

The majority of Southern California's population is served by the Metropolitan Water District of Southern California (MWD). The district is a wholesaler that supplies its 26 member agencies over a service area of 5200 square miles in Los Angeles, Orange, Riverside, San Diego and Ventura counties. Although the MWD service area only covers 14 percent of the area of these counties, it supplies 85 percent of the population. About half of the of MWD's supplies come from local surface water, groundwater basins and the L.A. Aqueduct. The other half of the district's supply comes from the Bay-Delta system through the State Water Project and the Colorado River. Metropolitan has several projects within each of its member agencies exploring local supply sources including desalination, groundwater recovery, and water recycling.

MWD's demand forecast takes a broad perspective, estimating "total demand" on MWD to include Retail Municipal and Industrial (M&I), Seawater Barrier, Groundwater Replenishment, and Retail Agriculture demands (Table 6). Retail M&I demand forecasts are generated from a set of 3 econometric models estimated for the single-family residential, multifamily residential, and composite commercial, industrial, institutional (CII) sectors, respectively. M&I forecasts are further segmented by County and member agency and both the econometric modeling and projections use an annual time step. The specification of model variables differs across econometric models, including the definition of the variable capturing the influence of price. The models are estimated from historical data collected from MWD member agencies and their respective retailers.

Prior to model estimation, estimates of past water conservation savings generated from MWD's Conservation Savings Model were added to the observed historical consumption data. The Conservation Savings Model is an end use model designed to estimate the effects of code-based and active efficiency measures over time. Projections of per household demand for the residential sectors and per employee demand for the CII sector are multiplied by projections of households and employees, respectively, to obtain baseline "pre-conservation" forecasts in volumetric terms. The Southern California and San Diego County Associations of Government (SCAG and SANDAG) are the primary source of projection data for model inputs and forecast drivers. The "pre-conservation" forecasts deduct estimated savings from the Conservation model to produce "post-conservation" forecasts, which reflect the remainder of Retail demands that are expected to be met through other supply sources. The models are calibrated to reproduce 2013 "post-conservation" demands by MWD member agency and sector.

Table 6: MWD Forecast Summary

Agency and Categorization and Population Served	Wholesale (~19 M served)
Sources for Model Input	• San Diego Association of Governments (SANDAG) • Southern California Association of Governments (SCAG)
Documents Used in Forecast Review	• 2015 IRP Technical Appendices • 2015 UWMP

Typology	Approach	Details
Forecast Segmentation	Segmented by sectors, geography, time	<u>Sectors/Land Uses</u> • Retail M&I (Single-family Residential, Multifamily Residential, Commercial, Industrial, Institutional (CII), Unmetered) • Retail Agriculture* • Seawater Barrier* • Groundwater Replenishment* <u>Geographic</u> • 26 member agencies • 6 Counties <u>Temporal</u> • Annual ** Prepared by member agencies and groundwater management districts*
Rate of Use Differentiation	Differentiated	<u>Drivers</u> • Households • Employees
Method	Statistical (Econometric) + Judgmental + Associative (End Use)	<u>Modeled Variables (estimated elasticities)</u> • Average Price (SFR: 0 to -0.50) • Median Tier Price (MFR: -0.11, NR: -0.43) • Median Household Income (SFR: 0.29, MFR: 0.17) • Persons per Household (SFR: 0.10, MFR: 0.14) • Median Lot Size (SFR: 0.69, MFR: 0.16) • Share of Employment in Manufacturing • Avg. Max Temperature (SFR, CII only) • Annual Precipitation (SFR only) • Annual Cooling Degree Days (CII only) <u>Notes</u>

Typology	Approach	Details
		• Reported SFR price elasticity implied range from interaction with lot size variable • Estimated price elasticities reduced by 33 percent in early part of forecast horizon
Forecast Scenarios	Explicit Scenarios	• Single dry year • Multiple dry years • With conservation

4.3 Tampa Bay Water

Tampa Bay Water (TBW) is a wholesale water provider to more than 2.5 million people in the Tampa Bay region. Residential demands account for nearly 75 percent of billed water consumption, with the remainder associated with the needs of commercial businesses and industry. Tampa Bay Water's water demand is comprised of demands from six member governments, or members, across a three-county area. These member demands are satisfied through bulk deliveries of water from Tampa Bay Water at 15 points of potable water connection. Members then use these bulk deliveries to satisfy retail demand for individually billed water accounts. In addition, some members resell water on a wholesale basis to other local utilities. Members provide water to customers located within seven geographical planning units known as Water Demand Planning Areas (WDPAs). The region's water is blended from three different sources: groundwater, surface water and desalinated seawater. TBW's water supply facilities include a 120 million gallons per day (mgd) surface water treatment plant, a 25 mgd Tampa Bay Seawater Desalination Plant, a 15.5 billion gallon reservoir, and 120 mgd of permitted capacity from groundwater.

TBW's forecast is based on a set of three econometric models, which project monthly unit usage rates for the single-family, multifamily, and nonresidential sectors, respectively (Table 7). The sectoral water use models were estimated from data at a Census Tract scale and were subsequently calibrated to and applied at the WDPA level. Parcel-level data on water use were aggregated up to tract level for modeling and provided key information on specific attributes, such as housing density, year built, and business type. Model calibrations were designed to reproduce recent 3-year average demands by sector and WDPA. Forecast drivers include housing units for the residential sectors and building square footage for the nonresidential sector. For the forecast, future nonresidential square footage is assumed to follow employment projections, which were available for the region.

Average efficiency of toilet fixtures was taken as an indicator of general trends in baseline and future water efficiency. Water efficiency factors were based on changes in average flush volume estimates derived from a fixture stock model. The efficiency index was used as an explanatory variable in the econometric models alongside other variables, allowing direct estimation and projections of passive efficiency using the index as a proxy. The use of the efficiency index variable permits direct development of baseline and passive efficiency forecast scenarios using the econometric model. In addition, future values of model inputs are generated using Monte Carlo simulation and assumptions about input distributions, which produce a probabilistic forecast interval for sector and total production demands.

In general, projections of model inputs required derivation from several sources, since there is no metropolitan planning organization to rely upon. The main sources for assumptions include the University of Florida and Moody's Economy.com, which provides county-level projections for several socioeconomic and demographic metrics for purchase or via paid subscription.

Table 7: TBW Forecast Summary

Agency and Categorization and Population Served	Wholesale (~2.5 M served)
Sources for Model Input	• University of Florida Bureau of Economic and Business Research (BEBR) • Moody's
Documents Used in Forecast Review	• Personal communication • Long-Term Demand Forecast Model Redevelopment and Base-Period 2014-2016 Forecasts (Hazen and Sawyer, forthcoming)

Typology	Approach	Details
Forecast Segmentation	Segmented by sectors, geography, time	Sectors/Land Uses • Single-family Residential (SFR) • Multifamily Residential (MFR) • Nonresidential (NR) • Member Wholesale • Unbilled Geographic • 7 Water Demand Planning Areas (WDPAs) Temporal • Annual • Monthly
Rate of Use Differentiation	Differentiated	Drivers • Households • Square footage / employees
Method	Statistical (Econometric) + Judgmental	Modeled Variables (estimated elasticities) • Price • Median Household Income • Persons per Household • Housing Density • Fraction Accounts with Reclaimed Water (SFR and NR only) • Passive Efficiency Index • Share of NR Sq. Footage among 10 Industry Classes • Seasonality • Avg. Max Temperature Departure from Normal • Monthly Precipitation Departure from Normal
Forecast Scenarios	Explicit Scenarios	• Baseline • With passive savings • Probabilistic

4.4 Contra Costa Water District

Contra Costa Water District (CCWD) is both a water retailer and wholesaler, providing water to approximately 500,000 people in central and eastern Contra Costa County California. Retail customers for treated water reside in the communities of Clayton, Clyde, Concord, Pacheco, Port Costa and parts of Martinez, Pleasant Hill and Walnut Creek. CCWD provides treated water on a wholesale basis to the City of Antioch, the Golden State Water Company in Bay Point, and a portion of the City of Brentwood, and untreated water to the cities of Antioch, Martinez, and Pittsburg, and Diablo Water District. The District obtains its water supply exclusively from the Sacramento-San Joaquin Delta (Delta), distributing water through the Contra Costa Canal. CCWD has four untreated water storage reservoirs and operates three water treatment plants. The distribution system for treated water also relies on treated water storage reservoirs, pump stations, and pipelines.

The description of CCWD's forecasting approach was based on review of CCWD's recent UWMP, as well as documentation obtained from a chapter of CCWD's Future Water Supply Study (marked as Draft Final). The model used to project municipal demands within the treated water service area and municipalities is reported to include the effects of "influence factors". These factors include unemployment rate, per capita income, and weather. Population projections are utilized, which implies that the influence factors are used to estimate per capita use. The effects of weather are estimated on monthly data, though all forecasts are provided on an annual basis. Future use in unincorporated areas are assumed to change proportionally with future population. Industrial use projections are based primarily on assumptions utilizing available information and are held constant over the forecast period, except for an allowance for future industrial expansion. Untreated irrigation demands, evaporative losses, and conveyance losses are held constant at calculated levels. The forecasts do not include the effects of water savings from passive and active programs, which are considered as sources of supply.

Table 8: CCWD Forecast Summary

Agency and Categorization and Population Served	Total system (500,000; ~200,000 retail)
Sources for Model Input	• Planning documents of member municipalities • California Department of Transportation • Association of Bay Area Governments (ABAG)
Documents Used in Forecast Review	• 2015 Urban Water Management Plan • Future Water Supply Study – Final Draft (Chapter 4)

Typology	Approach	Details
Forecast Segmentation	Segmented by sectors, geography, time	Sectors/Land Uses • Municipal • Industrial • Untreated water irrigation demands Geographic • Treated Water Service Area • 6 municipalities • Unincorporated areas Temporal • Annual
Rate of Use Differentiation	Differentiated (implied for municipal users in the treated water service area, municipalities, and unincorporated areas)	Drivers • Population
Method	Statistical (Econometric) + Judgmental	Modeled Variables • Unemployment rate • Per capita income • Precipitation • Avg. Max. Daily Temperature
Forecast Scenarios	Explicit Scenarios	• Normal weather • Dry weather (reported)

4.5 Sonoma County Water Agency

Sonoma County Water Agency (SCWA) is a wholesale water provider that serves a large area of Sonoma County and the eastern portion of Marin County. The Agency is responsible for supplying 14 municipalities and in 2015 served an estimated a population of 614,196 people. SCWA supply is almost entirely surface water from the Russian River treated for potable use. SCWA can use groundwater from the Santa Rosa Plain to augment surface water when necessary. The agency has obligations to adjust flowrates in the Russian River to help rehabilitation efforts of threatened salmon species. Projected demand for 2040 exceeds the agency's maximum allocations, and, as a result, SCWA is seeking larger allocations and more storage space in Lakes Mendocino and Sonoma, which are operated in coordination with the U.S. Army Corps of Engineers.

Table 9 provides a summary of SCWA's water demand forecast features. SCWA employs a judgmental water demand forecasting method in that the agency compiles demand forecasts of the agencies to which it provides wholesale water. These demands are segmented as "sales to other agencies," and are net demands on SCWA, counting the effects of any water conservation and recycled water projects, as well as system losses. There is some indication that the 14 agencies served by SCWA use consistent forecasting and conservation assessment methodologies, such as the Demand Side Management Least Cost Planning Decision Support System (DSS Model).

SCWA's forecast contains 8 other categories, although current forecasts are non-zero only for Agricultural Irrigation (which is constant over the forecast horizon), "Retail demand for use by agencies that are primarily wholesalers", and Losses. For the "Retail demand for use by agencies that are primarily wholesalers" category, SCWA forecasts water use based on estimated rates of population growth. Losses reflect SCWA's estimates of transmission losses and are top of any losses estimated by SCWA's retailers.

Table 9: SCWA Forecast Summary

Agency and Categorization and Population Served	Wholesale (~0.6 M served)
Sources for Model Input	• Forecasts embed assumptions used by Agency customers, including conservation • Association of Bay Area Governments (ABAG)
Documents Used in Forecast Review	• 2015 UWMP

Typology	Approach	Details
Forecast Segmentation	Segmented by category, geography, time	Forecast Categories • Sales to other agencies • Transfers to other agencies • Exchanges to other agencies • Groundwater recharge • Saline water intrusion barrier • Agricultural irrigation • Wetlands or wildlife habitat • Retail demand for use by agencies that are primarily wholesalers with a small volume of retail sales • Losses Geographic • 8 Water Contractors • 5 Other Transmission System Customers • 1 Municipal Water District • Collection of Other small users Temporal • Annual
Rate of Use Differentiation	Not differentiated	N/A
Method	Judgmental + Associative	• Sales to other agencies compiled as sum of demand forecasts provided by Contractor and District UWMPs • Retail demand for use by agencies that are primarily wholesalers based on population growth
Forecast Scenarios	None	N/A

4.6 Zone 7 Water Agency

Zone 7 Water Agency (Zone 7) is a wholesaler that serves a population of about 240,000 people served by four water retailers including the cities of Pleasanton and Livermore, California Water Service Company-Livermore, and Dublin San Ramon Services District. Zone 7 also provides untreated water for agricultural irrigation of 3,500 acres. Zone 7 derives the majority of its water from the State Water Project (around 80 percent) and operates four wellfields primarily for backup supply during droughts. During wet years, Zone 7 uses a portion of its State Water Project water, along with local surface runoff water to recharge the region's groundwater basin. Zone 7 also has groundwater-banking rights in Kern County, which can be drawn upon during drought.

As indicated in Table 10, Forecasts for Zone 7's water retailers are based on each retailer's own forecasting methodologies. Zone 7 aggregates the forecasts of its retailers into a "Sales to other agencies" category and does not report the forecasts of retailers individually. Zone 7 derives forecasts for a small set of 6 retail customers, which is held constant over the forecast horizon. Water for groundwater recharge, groundwater banking, and surface storage are counted in the categorization of demands. Zone 7's forecasts contain separate line items for losses associated with storage and transmission.

Table 10: Zone 7 Forecast Summary

Agency and Categorization and Population Served	Wholesale (~0.24 M served)
Sources for Model Input	• Forecasts embed assumptions used by Agency customers, including conservation
Documents Used in Forecast Review	• 2015 UWMP

Typology	Approach	Details
Forecast Segmentation	Segmented by category, geography, time	Forecast Categories • Sales to other agencies • Agricultural irrigation • Retail demand for use by agencies that are primarily wholesalers with a small volume of retail sales (Direct Retail) • Groundwater recharge • Other-Groundwater Banking • Other-Surface Water Storage • Losses-Storage • Losses-Transmission • Potable water • Raw water Geographic • Service area wide Temporal • Annual
Rate of Use Differentiation	Not differentiated	N/A

Typology	Approach	Details
Method	Judgmental	• Forecast compiled as sum of demand forecasts provided by Contractor and District UWMPs
Forecast Scenarios	None	N/A

5. Summary of Benchmarking Analysis

The review of water demand forecasting methodologies employed by selected Bay Area water providers and other wholesale water agencies shows a diversity of practices, and, as indicated in the typology of forecasting approaches, a significant amount of nuance in application. Statistical (econometric) models tend to be developed in cases where ample historical data permits and when there is interest in explaining variability. Several estimated elasticities for economic and demographic variables are available from those agencies reviewed, as well as from the literature, but their values vary due to several factors.

End use models tend to be employed when water conservation alternatives are being evaluated for implementation and to account for the effects of passive measures so they can be deducted off of future "baseline" demands. The Alliance for Water Efficiency Water Conservation Tracking tool and the Demand Side Management Least Cost Planning Decision Support System (DSS Model) were referenced frequently in the reviewed documentation. These models tend to focus on allocating per unit (e.g., per capita) rates of water use into end use components using the findings of available end use research, but do not technically represent "bottom up" approaches that attempt to model individual end uses separately to arrive at a total rate of consumption.

Econometric and end use models are often used together to generate "with conservation" forecast scenarios. The types of forecast scenarios that are generated tend to be limited to those associated with climate and water conservation, though some models can generate several other scenarios based on socioeconomic model parameters. For the California agencies reviewed, the scenarios that are implemented tend to be tied to UWMP requirements.

Differentiation of unit rates of water usage from volumetric totals is common, and with population, housing, and employment often used as forecast drivers. These drivers represent unit counts that are generally more likely to be forecasted by regional and metropolitan planning agencies, such as ABAG. Typically, forecasts are segmented into annual time steps for reporting purposes, and in some cases the annual values reflect sums of monthly forecast values. Geographical disaggregation of demand forecasts is common, generally revolving around jurisdictions or planning areas served by the water agency.

There seems to be a distinct divergence in forecasting approaches used by water wholesalers. There are those who model and forecast the demands of water retailers and those who take the forecasts of water retailers directly as input into the preparation of their forecasts. The former seems more applicable to cases where institutional arrangements are clear cut (such as when a single regional wholesaler serves a defined geographic region) and/or when routine data collection mechanisms with retailers have been in place for some time. The latter case could be viewed as an efficient use of available information, particularly for periodic reporting requirements (such as UWMPs in California).

With a few exceptions (e.g. BAWSCA and SCWA), most water supply utilities did not explicitly identify a modeling platform or tool for developing their demand forecasts. Based on Hazen and Sawyer's experience on the subject, most utilities that employ associative and statistical modeling methods fit their forecast equations in statistical modeling packages, such as R, MATLAB, or SAS.[12] However, these statistical modeling packages are usually not the application used to calculate the forecasts themselves. When conducting forecast exercises (e.g. conducting scenario analysis), utilities often house their forecast equations in a spreadsheet, GIS application, relational database, or dashboard application in order to streamline alteration of model parameters and conditions.

5.1 Characterization of Valley Water's Prior Forecast Approach

Valley Water's 2015 Urban Water Management Plan (UWMP) describes the features of Valley Water's water demand forecast methodology. Valley Water's forecast is segmented by its 13 water retailers and is reported in five-year increments. Additional line items include forecasts for agricultural groundwater pumping, independent groundwater pumping, raw water, and losses, which, except for losses, are assumed constant over the forecast horizon. The forecast is reported in terms of annual totals but can be post-processed into months. Forecasts prepared by Valley Water's retailers are compiled and aggregated to calculate the forecast, which generally classifies the forecast as judgmental within the demand forecasting typology. There are no explicit additional forecast scenarios reported in Valley Water's 2015 UWMP, and the forecasts generated by the retailers embed (to the extent they were evaluated) any estimated effects from water conservation and recycled water. The 2015 UWMP does, however, provide a discussion on some of the forecasting uncertainties that may ultimately influence the accuracy of the forecast, such as rate of rebound from past drought management actions, the potential for future water use mandates, economic development patterns, and climate change. Though the 2015 UWMP did not review any explicit scenarios, Valley Water actively conducts internal scenario analysis as part of their planning activities, which includes the most recent "trending scenario" used to inform the most recent Water Supply Master Plan.

Though the forecasts reported in Valley Water's 2015 UWMP are generally based directly on the forecasts prepared by water retailers, Valley Water prepared its own county-wide forecast segmented by service area, independent pumpers, and agriculture for water supply planning purposes using the IWR-MAIN Water Demand Management Suite's Forecast Manager module. Fundamental inputs for IWR-MAIN include selection of a base year, designation of geographic areas (i.e., service areas), and definition of sectors. For this effort, a base year (2013) was selected, 12 retailers were defined as study areas[13], and 7 sectors were classified (single-family, multifamily, commercial, industrial, institutional, irrigation, and other). Historical estimates and projections for housing and jobs were consolidated from the Association of Bay Area Governments (ABAG) and US Census data at the Census tract level and then aggregated geographically by retailer. Using ABAG rates of change in housing and jobs, growth factors were calculated and applied by retailer and water use sector to generate retail forecasts county-wide and by retailer. Although considerable judgment was involved in defining the forecast factors, this secondary approach employed by Valley Water can be classified as an associative model, in that future changes in consumption are associated with projected rates of change in housing and employment. Implicitly, this

[12] Excel can potentially be used in simple cases.

[13] Stanford was not explicitly modeled in the prior forecast.

technique equates to an application of a fixed coefficient model, which was generalized earlier in Equation (2).

5.2 Benchmarking Implications for Valley Water

Overall the implication of this review is that there is considerable “freedom of choice” for Valley Water in terms of adopting a forecasting methodology or forecasting model. A reasonable assumption is that Valley Water can continue to compile forecasts from its current retailers, similar to SCWA and Zone 7, and/or generate independent forecasts using its own water demand analysis, which, at least for the its 2015 UWMP, was based on a set of fixed demand factors and assumptions about regional growth in housing and jobs. The ability to collect enough historical water use and socioeconomic data across retail members will determine the degree to which Valley Water should pursue development of its own statistical models, and will influence the relative ability to create statistical models by sector, as well as the independent variables that can be specified. Because of uncertainty in terms of the quality of available water use data and socioeconomic, demographic, and climatic information that can be linked to these data, the modified forecast factor approach (generalized in equation 6 above) should be considered a strong candidate in terms of general model requirements.

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