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Tacoma Water – Rates and Financial Planning

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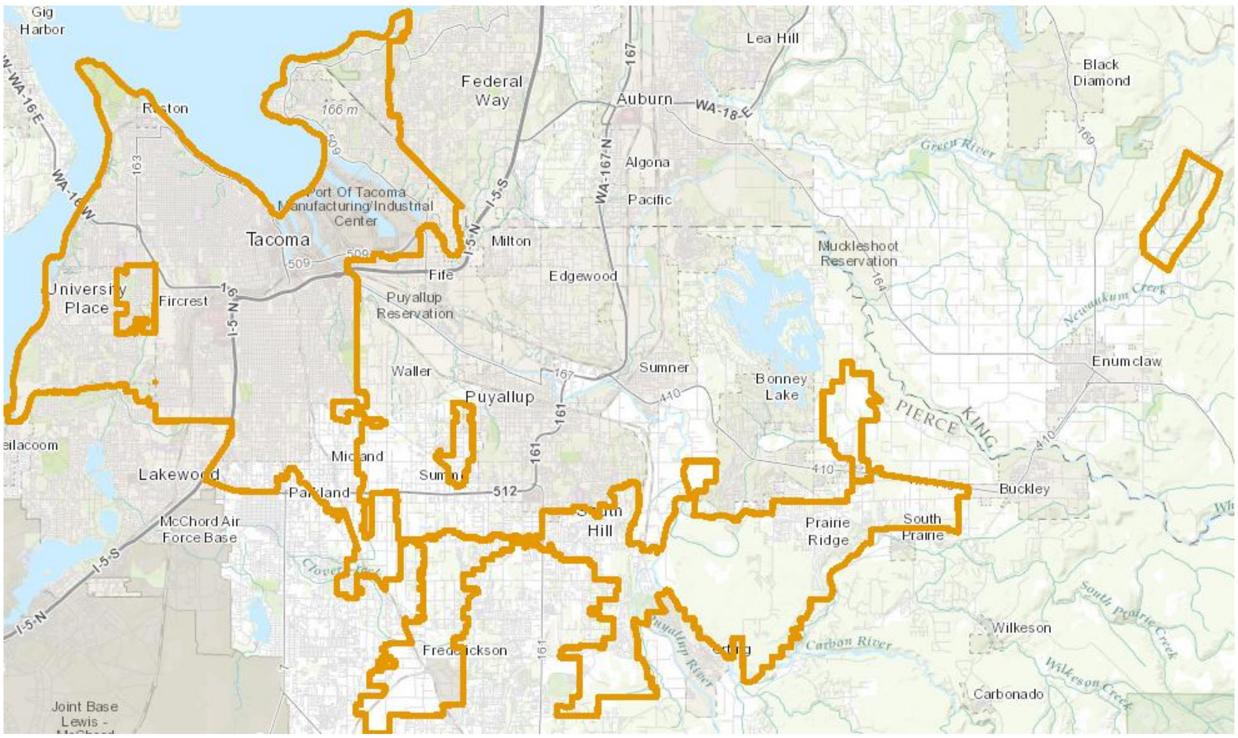
Introduction

Tacoma Water is a medium-sized water utility serving a population of approximately 320,000 (2014). Tacoma Water was established in 1913 and uses the Green River and in-town wells for its main sources of supply. Average day demand for Tacoma Water (2014) was 51.98 mgd with a peak day demand of 80.82 mgd. Commercial and industrial customers constitute 50% (2014) of Tacoma Water's billed demand, compared to 43% for residential and 7% for wholesale customers. As can be seen in the retail service area map below, Tacoma Water serves the entirety of the customer base within the Tacoma city limits, and the service area extends into many jurisdictions within Pierce County:

Figure 1: Tacoma Water Service Territory



To better serve our customers through the enhancement of the long-run system planning and short-run financial planning, Tacoma Water developed these forecasts with two distinct objectives in mind, each of which was addressed by a separate model that was developed with a slightly different methodology: (1) The Short-Term Forecast focuses on revenue-generating demand and accounts to project revenue for a 10-year planning horizon, which informs the establishment of the revenue requirement, and aids in conducting the cost of service analysis and rate design efforts. (2) The Long-Term Forecast examines potential source-of-supply constraints and wholesale/large volume customer contracting demand risks when used in conjunction with the Tacoma Water Supply group's Source-of-Supply Model.

In the past Tacoma Water has commissioned external consultants to forecast demands to aid in revenue projections and supply risk management. First, the results were delivered in the form of a "black box" which left staff unable to interpret the accuracy, assumptions, results, or repeat model runs. Second, the inability to reproduce the results with differing scenarios, up-to-date data, or tamper with data left forecasts dated. Third, the forecasts also lacked probabilistic bands around the most-likely scenario to aid in financial or source-of-supply risk management, which is the primary purpose of this tool. Finally, the methods, model, assumptions, and results were not always comprehensively documented.

In order to address internal objectives for the demand forecast tool, and ultimately provide a model suitable for internal applications, we successfully completed two distinct probabilistic forecasts which address Tacoma Water's financial and strategic needs. Both forecasts have been designed with four key features to satisfy the forecasting objectives described above:

First, Tacoma Water's forecasts need to be transparent at each step in the process. Transparency allows access to the process and results in a meaningful and actionable way for the various stakeholders. We have worked with Asset and Information Management to establish a customer database which contains all of the billing data necessary for future forecasting efforts with all of the data available on BlueWave. We included Supply Engineering throughout the Long-term Forecast's process to ensure that the timestamp and output were useable. We informed neighborhood councils, the Public Utility Board, and City Councils about the budget and rates which were results of the Short-term forecast. There were also check-ins with management, staff, colleagues, and consultants for brainstorming and firming up methodologies. We are also linking the results of both forecasts to the Water Rates and Financial Planning SharePoint site. Each of the examples discussed above enhanced transparency in meaningful ways that have not been done prior to this forecasting effort.

Second, we have focused on documenting the process at each decision point and produced two omnibus reports: (1) This report, which discusses every decision, the results, and improvements for the forecasting effort, and (2) the user manual to allow others the ability to repeat each step. These documents are more thorough than previous efforts and have been more inclusive in the drafting process to ensure they are targeting a wide enough audience.

Third, we have made the models repeatable. Repeatability allows for scenario testing such as, estimating various population, conservation, customer accounts, or weather scenarios. The capability to change variables and assumptions on the fly or in "real-time" allows for a flexibility that has not been previously accessible to Tacoma Water. We have already used the Long-term Forecast's flexibility to estimate lost revenue in 1992 and track 2015 daily demands as well as estimate demands in 2035 under 2003 weather. This capability highlights the importance of this effort and the way in which it was conducted.

Finally, the forecast results are probabilistic[1]. Prior to this forecasting effort all prior forecasts provided single answers to the future, and in some cases High/Medium/Low. Since demands are built on historical data the future will, more than likely, not match exactly (and in some cases diverge significantly), thus there was no way to know how far demands could deviate given various weather scenarios or population assumptions, i.e. how likely once scenario was compared to the next. Probability is not just an important feature of scenario building, but for risk management. Probabilistic results allow for managers and expert staff to asses potential future risks and determine the right level of risk appetite Tacoma Water should endure when setting rates, budgeting, determining levels of supply guarantee, or real-time supply management.

[1] Probability is how likely an event is to occur

Short-Term Forecast

The short-term forecast uses historical billed demand and revenue data at the rate category level to produce a 10-year forecast. The demand data used for the regression models were from 2004 (the year of SAP's implementation) to 2013. We also examined billed demand data prior to SAP for anomalies and shifts between accounts and demands. Weather data was analyzed from 1964 to 2013 to improve the probabilistic forecast, and customer accounts from 2000 to 2013 to address various longer-term patterns exhibited in some rate categories.

To have a useable forecast we must (1) regress historical data to build a model, (2) forecast independent variables, and (3) adjust forecasted results to produce a revenue-generating demand forecast for the COSA model and rate design.

The historical demand data, which derives from SAP, is a mix of monthly and bi-monthly billed demands and contract months billed (accounts). The ultimate goal for the short-term forecast is to aid in budgeting and rate-setting for the utility. The budget and rate-setting model and results are expressed in annual terms, however forecasting water demands, which are heavily reliant on day-to-day weather patterns, at an annual level yields poor results as demands are closely linked to daily weather events and monthly weather patterns.

We chose a monthly time-step for the short-term forecast because it was the most granular time-step available. Using monthly data allows for some sensitivity to weather and follows our billing cycle – which is the intended goal of the short-term forecast; to ultimately project revenues for the upcoming biennium and 10-year financial planning time horizon. This is an important distinction between long-term and short-term forecasts, as we are not concerned about supply constraints or excess capacity but revenue and the ability to finance our future obligations and operations.

Application of the Short-term Forecast: Financial Management

Tacoma Water has a biennial budget and rate process which utilizes the results of the short-term forecast's billed demands and customer accounts. The forecasted demands and accounts are used to determine "revenue under existing rates", which are the revenues Tacoma Water would receive without increasing rates. The difference between revenue under existing rates less expenses determines how much additional, if any, revenue is needed. For more details on the financial model and rate setting process please see the Tacoma Water Rate Report document.

Data used to inform the Short-Term Forecast

Water demands are sensitive to weather, economic factors, and time. We have tested variations of temperature, precipitation, socio-economic metrics, and time indicator variables. Below in Table 1 we examine each of the variables and their significance.

Table 1: Short-Term Regression Variables

Variable	Description
Average Max Temperature	Daily maximum temperatures which have been averaged.
Four Day Heat [Summed Binary]	The number of days where daily maximum temperatures was over 77 degrees for four days
Recession [Binary]	The Great Recession occurring
Seasonal Billing	Billing anomaly in December/January with late bills
Month [Binary]	An indicator variable per month of the year
Peak Temperature	The highest temperature of the month
Go Live! [Binary]	Billing issues during the initial phases of implementing SAP's billing system
Days of Rain [Summed Binary]	The number of days of rain
Sinosoidal Temp and Rain	A continuous series of quadratics based on temperature and rainfall patterns
Weather	An interaction variable that examines the total monthly temperature divided by the number of days above 77 degrees divided by the monthly total rainfall divided by the days of rainfall.

Independent Variable Forecasting

After constructing regression models for each rate category we then developed a forecast for each independent variable in order to forecast billed demands from 2014-2024. In developing a retail demand forecast we forecasted each independent variable that contributes to the regression.

Weather

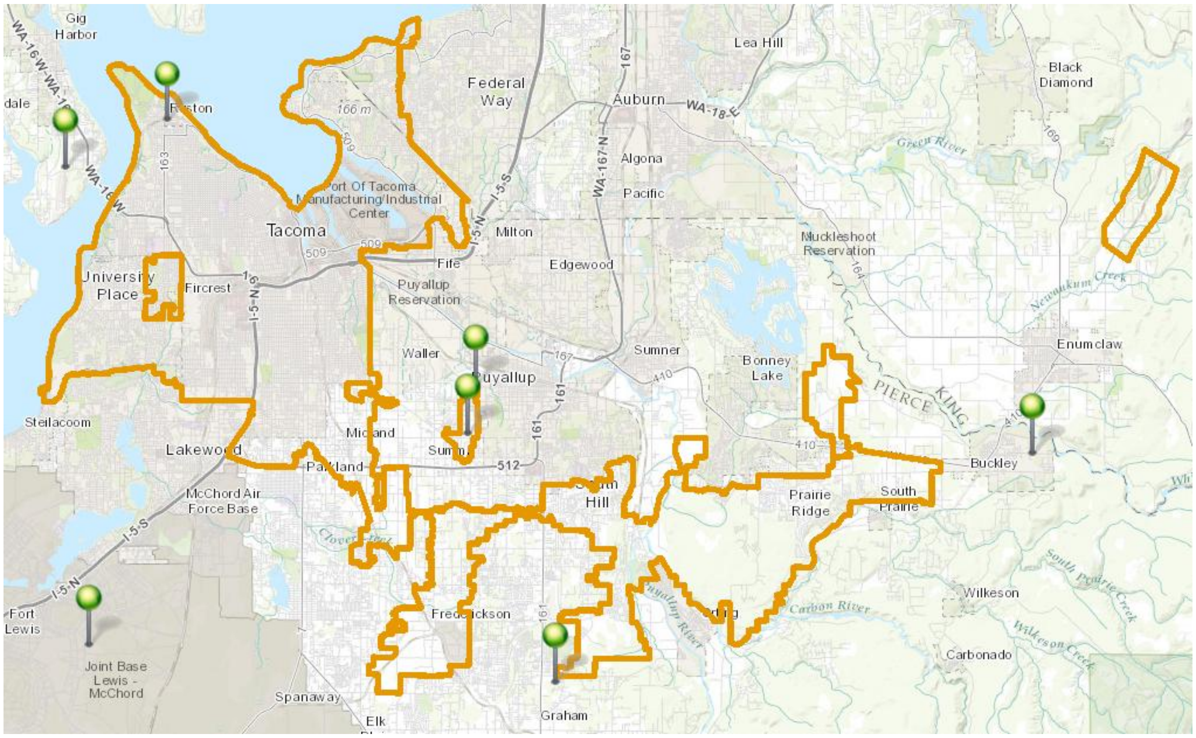
Temperature and rainfall are assumed to have probabilistic outcomes around each time step, e.g. the average monthly temperature for June is 50% of the time between 64 and 74 degrees with a median of 70 degrees but has been as high as 86.82 degrees. See Table 2 below for more probabilistic examples:

Table 2 Daily Averaged Maximum Temperature by Month (F) Probability Distribution

	1%	5%	25%	MLF	75%	95%	99%
Jan	31.92	35.20	41.16	47.32	49.79	54.68	57.52
Feb	36.73	40.46	45.42	50.03	52.60	57.75	60.15
Mar	42.25	44.82	49.20	54.32	56.64	63.08	65.89
Apr	47.68	49.52	53.27	59.00	61.82	69.59	73.92
May	53.23	55.20	59.19	65.81	69.19	78.21	82.24
Jun	57.85	59.89	64.55	70.28	74.67	83.14	86.82
Jul	63.51	66.26	70.76	77.57	80.73	87.65	90.95
Aug	64.05	66.62	71.54	77.00	80.91	87.48	90.38
Sep	59.14	61.41	65.59	71.06	75.22	81.50	84.87
Oct	50.67	52.69	56.47	60.11	63.56	68.76	72.02
Nov	38.07	41.62	47.37	51.94	53.78	58.31	60.87
Dec	29.21	34.27	41.20	45.47	48.94	53.83	56.27

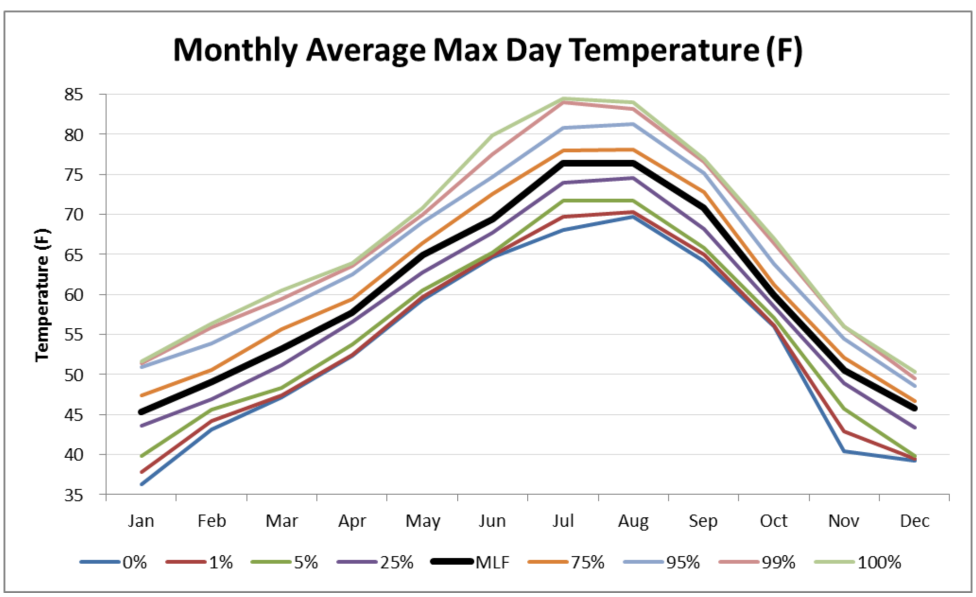
The probabilities are created from daily weather data located in our service territory from 1964 to 2013. The year 1964 was chosen as a starting point because of the increased accuracy of the weather data. The locations of the weather stations and Tacoma Water's service territory are highlighted in the Figure below:

Figure 2: Weather Station Locations Relative to Tacoma Water Service Territory



The data was collected from seven sites in or around the Tacoma Water service territory. The sites were averaged to provide one system-wide data point each for daily minimum temperature, daily maximum temperature, and total daily precipitation. The data is provided by NOAA and Washington State University. The sites were chosen for the completeness of the data, and the relative location to our service territory. Each dataset was scrubbed and tested for outliers or divergent trends. The results of scrubbing the data and creating probabilistic curves based on the historic data are found in the Figure below:

Figure 3: Maximum Monthly Averaged Temperature (F)



We averaged the daily maximum temperatures into a monthly figure which we call "Monthly Average Max Day Temperature". The monthly average max day temperature has a low of 35 degrees F and high at approximately 85. The maximum temperatures fluctuate with a typical range of ± 6 degrees from the 50th percentile.

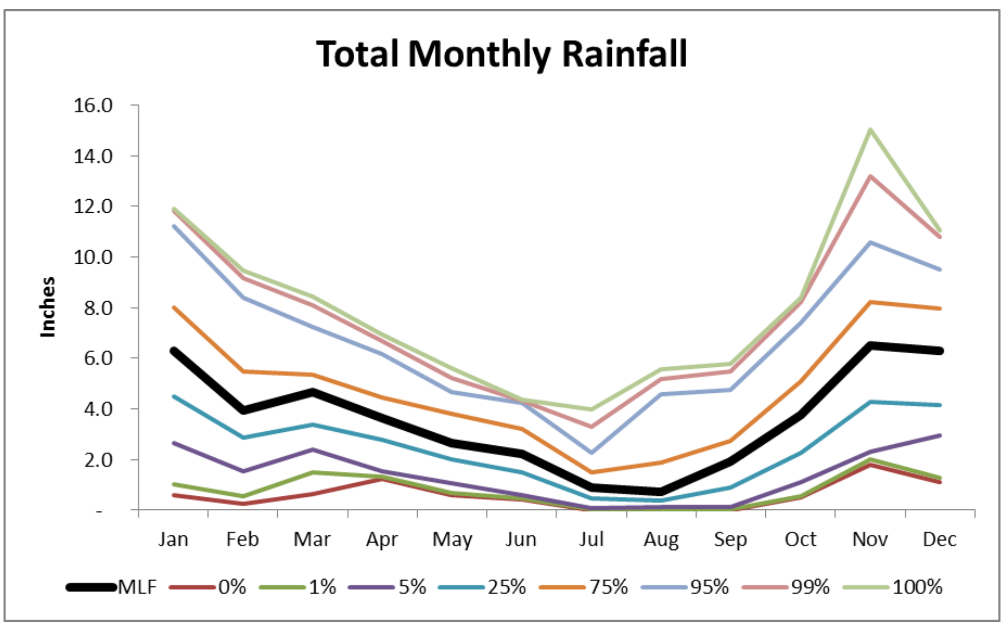
Rainfall was also collected daily from 1964-2014. The rainfall was then summed for total precipitation as can be seen in Table 3 below:

Table 3: Total Summed Daily Precipitation (in.) by Month Distribution

	1%	5%	25%	MLF	75%	95%	99%
Jan	1.02	2.63	4.53	5.19	8.07	11.27	11.84
Feb	0.55	1.54	2.86	2.90	5.40	8.40	9.19
Mar	1.47	2.40	3.35	4.43	5.27	7.11	7.52
Apr	1.34	1.54	2.73	3.02	4.46	6.18	6.70
May	0.70	1.08	1.97	2.67	3.85	4.69	5.25
Jun	0.47	0.67	1.54	1.47	3.25	4.23	4.33
Jul	0.02	0.06	0.45	0.64	1.52	2.28	3.30
Aug	0.00	0.11	0.36	0.87	1.90	4.58	5.17
Sep	0.03	0.10	0.86	1.94	2.77	4.76	5.47
Oct	0.57	1.09	2.25	3.46	5.07	7.44	8.21
Nov	2.00	2.30	4.22	5.82	8.25	10.60	13.25
Dec	1.29	2.93	4.12	4.40	7.99	9.51	10.79

We can see that the median (MLF) total rainfall for each month has a low of 0.50 inches and a high above 5.0 inches. We can see the table's results graphically in Figure 12 below:

Figure 4: Total Monthly Precipitation (in.)



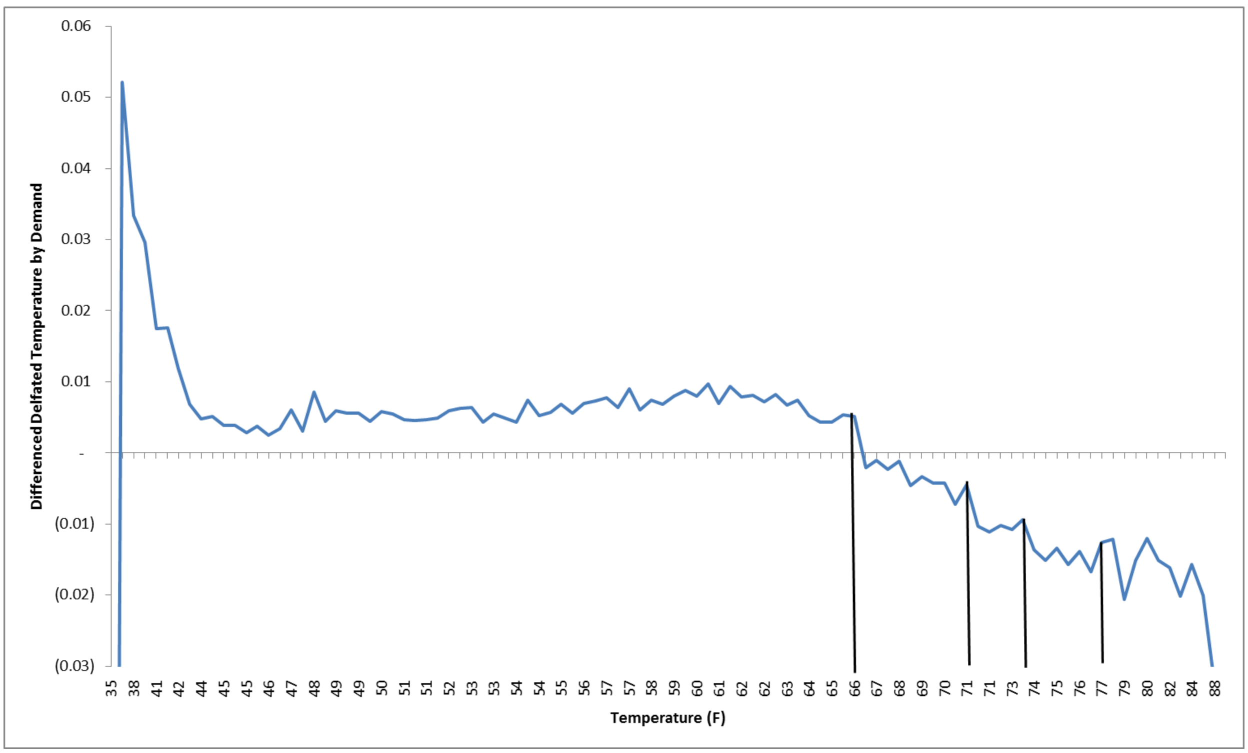
Monthly Total Precipitation by Probability of Occurrence (inches)

The Total Monthly Precipitation has a low of 0 inches of rain per month and a high of approximately 15 total inches per month based on historical data (1964-2014). The average monthly total precipitation fluctuates with a typical range of $\pm$3.7 inches from the 50th percentile, with a lower bound of zero.

In addition to the weather data we can construct indicator variables to aid in the analysis and regression, for example, measuring multiple days of rainfall for a monthly statistic. The “number of days of rain” variable measured how many days of rain occurred in a month. This informs the model whether the rain was spread out over a week or a single event. Below are indicator or interaction variables which aid in our analysis of weather’s effects on demand.

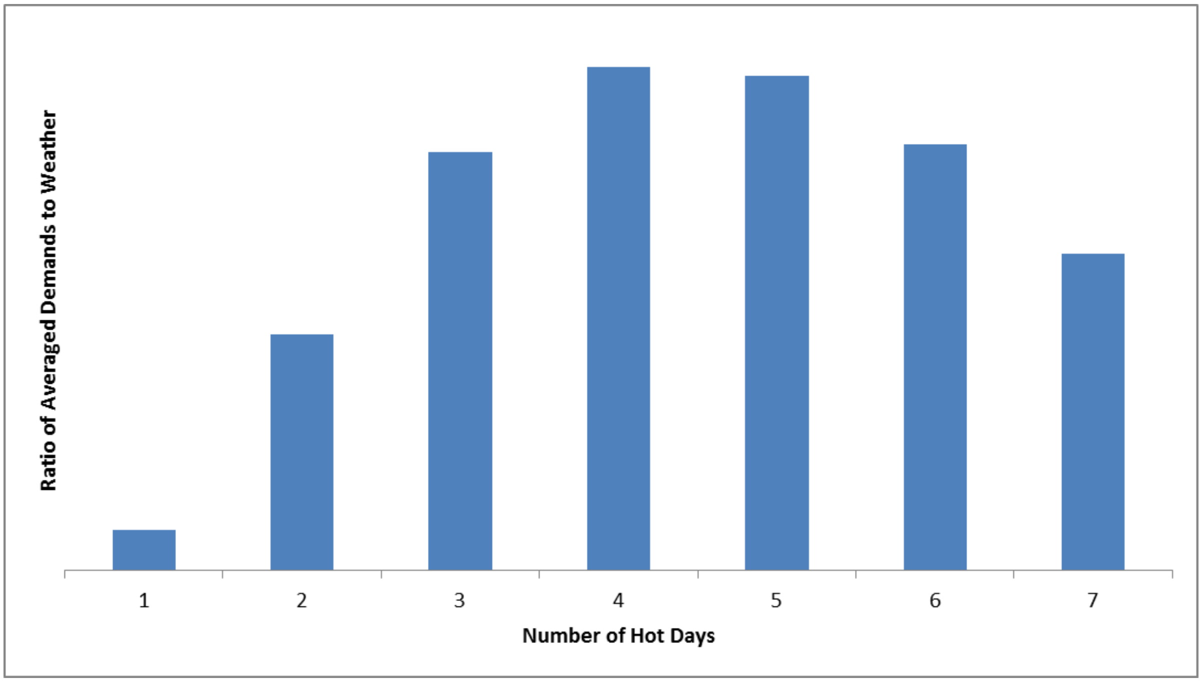
We constructed a temperature variable called “FourDayHeat” the variable counts the total number of consecutive days in which temperature were over 77 degrees Fahrenheit. This theory was constructed after examining how demand is influenced at various temperatures as seen in the Figure below:

Figure 5: Pent Up Demand



This “pent up demand” was tested at 66, 71, 74, and 77. Another interesting phenomena we see occurring in the data is the hyperbolic switch at colder temperatures, which we believe is due to increased leaks with frozen pipes. To generate the FourDayHeat variable we wanted to see if customers exhibited “pent up demand” and what day it peaked if the temperature was 77 degrees or more for extended periods of time. We tested the 77 degrees at various time periods as seen in the Figure below:

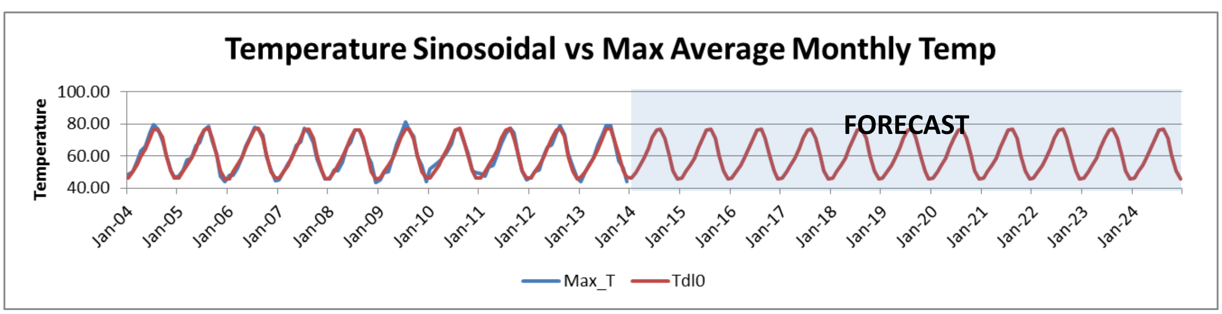
Figure 6: Pent up Demand by Day When Temperature is Above 77 Degrees



The Figure clearly shows that pent up demand is highest by the 4th consecutive day, interestingly it drops off precipitously after the 5th day, which may be a sign that if it too warm for too long people do not water nearly as much. This may be due to two causes: First, the customer base may water by the fourth day and then feel the need to not water on consecutive days after that, i.e. they have saturated the ground thoroughly and may not need to water for the remainder of the week. Alternatively, the customer may choose to "give up" on their lawn and gardens if weather is too hot and dry for too long. Separating these two outcomes would be difficult without more data.

We have also created two sinusoidal (Fourier Series) models which replicate seasonal changes in temperature and rainfall and their influence on demand. An example of this model is in the Figure Below:

Figure 7: Fourier Temperature Model



The Fourier model replicates temperature and is easy to forecast forward using sine and cosine variables.

We have also created several indicator variables which are either events which cause permanent shifts in demand or recurring shifts in demands. These variables include the months of the year, the Great Recession (January 2009 onward), GoLive (2004), and seasonal billing (Nov-Jan each year).

Customer Accounts

Customer accounts are important to forecasting both demand and revenue. Tacoma Water has various customers segmented into "Rate Categories". Each rate category attempts to contain only homogeneous (similar) customers by demand characteristic. For purposes of creating rates and estimating revenue each Rate Category is separately forecasted. The rate categories are also split between accounts which are located inside the City of Tacoma (Inside City) and those outside the City of Tacoma (Outside City). For simplicity the rate category labels are shortened to match their codes within SAP which is where the billing information and rates are ultimately tested and implemented. The comprehensive list of rate categories and their codes can be seen in the Table below:

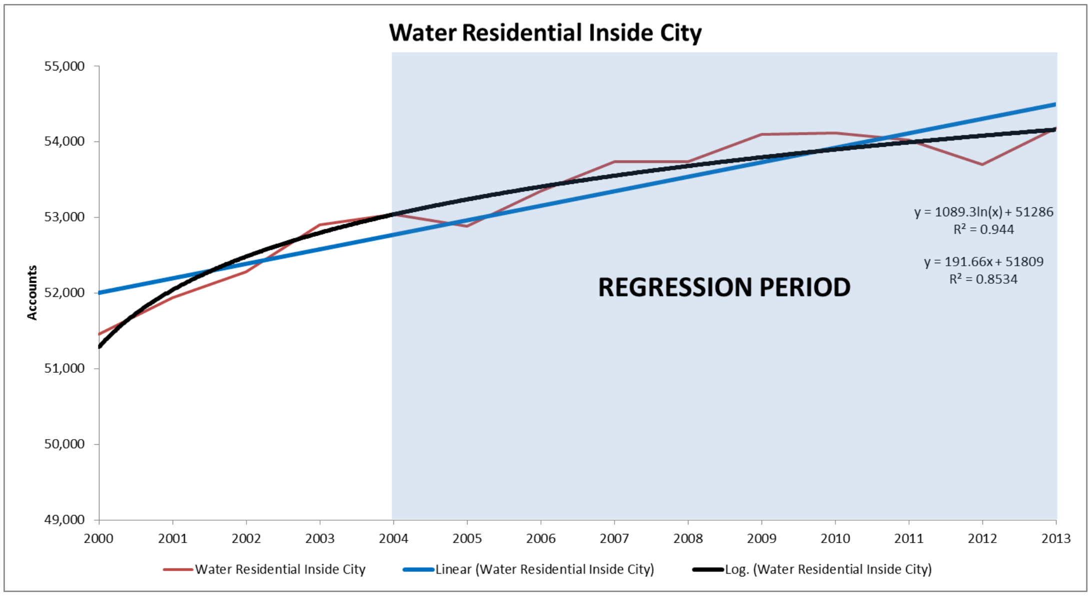
Table 4: Rate Category Key

Category	Description	Key
Residential Single Family Inside City	Single unit dwelling	WT_R_SI
Residential Single Family Outside City	Single unit dwelling	WT_R_SO
Residential Multi-Living Unit Inside City	Condos, Apartments, row houses	WT_R_MLUI
Residential Multi-Living Unit Outside City	Condos, Apartments, row houses	WT_R_MLUO
Commercial General Service Inside City	Single and multi-unit commercial buildings	WT_C_GSI
Commercial General Service Outside City	Single and multi-unit commercial buildings	WT_C_GSO
Irrigation Inside City	Commercial and Residential Irrigation	WT_IRI
Irrigation Outside City	Commercial and Residential Irrigation	WT_IRO
Private Fire Protection Inside City	Private fire sprinkler systems	WT_FRI
Private Fire Protection Outside City	Private fire sprinkler systems	WT_FRO
Wholesale	Other utilities	Wholesale
Pulpmill	WestRock a paper & pulp mill located in Tacoma	Pulpmill
Large Volume Commercial	Commercial customers who consume more than 65,000 CCF per year	Large Volume

Rate Category accounts were forecasted using various lines of best fit and expert knowledge. Below are the models, methods, and results of each forecast.

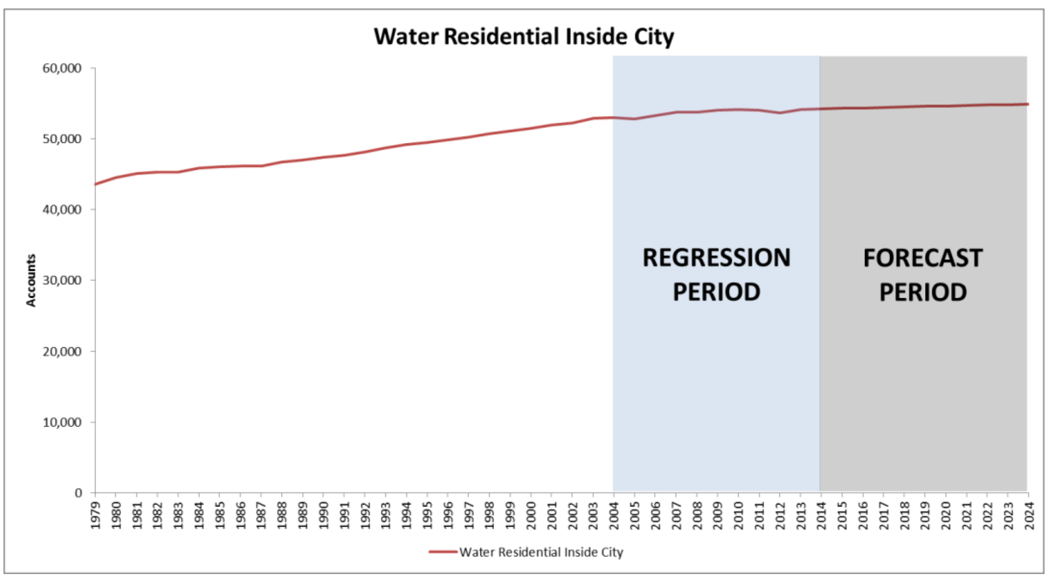
Residential Single Family Inside City (56% of average total accounts (2004-2013)) grew by 2.2% from 2004 to 2013 or 0.21% per year. Much of the growth during this period occurred in the boom years between 2000 and 2004. In recent years it has slowed considerably as there is virtually no growth from 2008-2013. Because the City of Tacoma is built out and growth in new housing is unlikely to continue at its strong pace during the Housing Boom a logarithmic model was chosen, the model also fits the data better than a linear growth assumption seen in the Figure below:

Figure 8: Residential Single Family Inside City – Historical and Fitted Account Growth



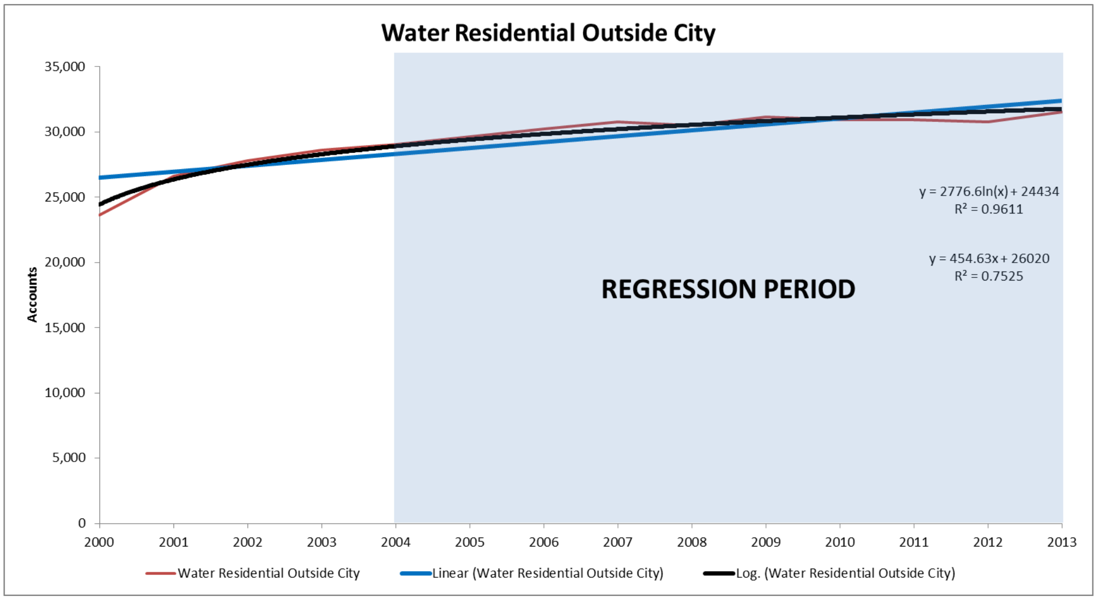
We estimate Residential Single Family Inside City account growth to total 1.3% over the next ten years or 0.12% per year. The results of this forecast, and some additional historical context, can be seen in the Figure below:

Figure 9: Water Residential Inside City – Historical and Forecasted Accounts



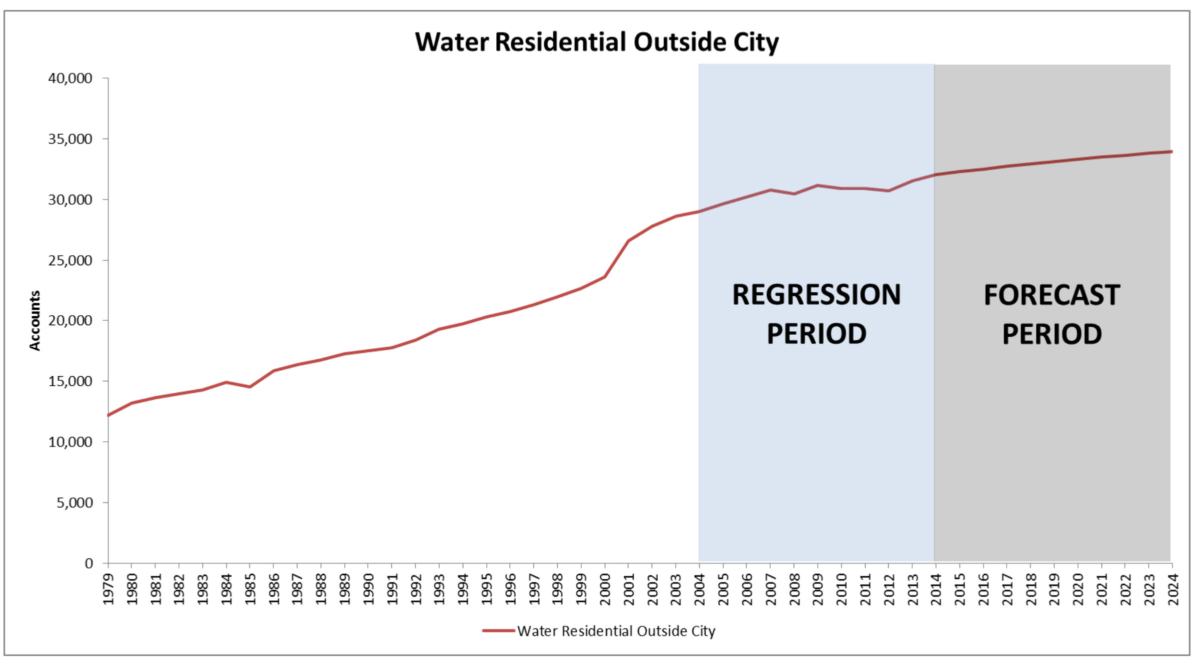
Residential Single Family Outside City (32% of average total accounts (2004-2013)) grew by 8.6% from 2004 to 2013 or 0.83% per year. We chose to use a logarithmic trend line because of the better fit and the longer term slower growth projections as foreclosed homes would be utilized before building new properties[2] as seen in the Figure below:

Figure 10: Residential Single Family Outside City – Historical and Fitted Account Growth



We expect account growth to total 5.9% over the next ten years or 0.52% per year. The results of which can be seen in the figure below:

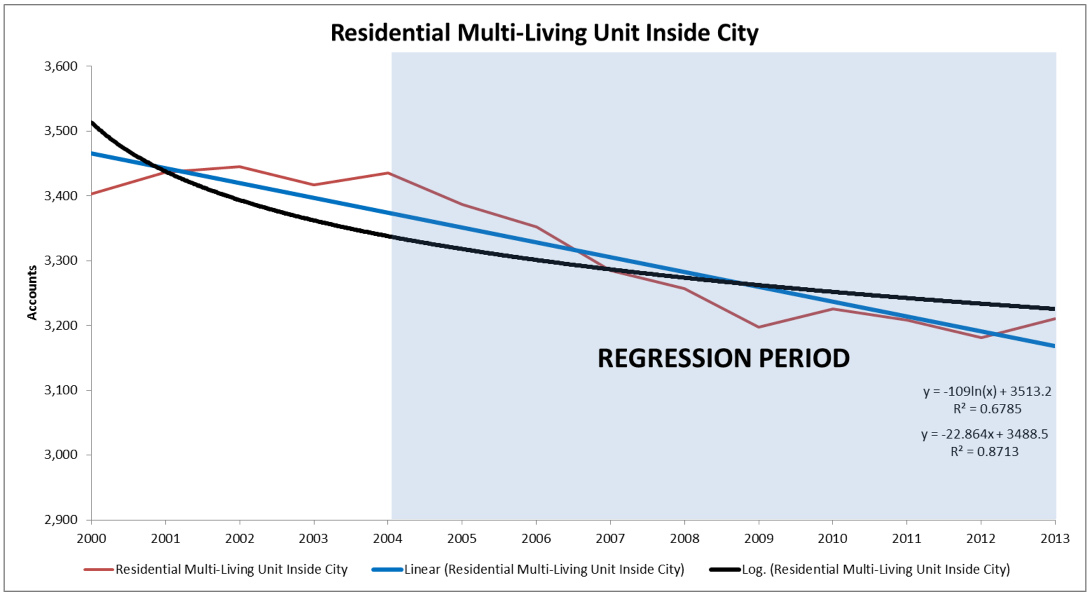
Figure 11: Water Residential Outside City – Historical and Forecasted Accounts



[2] As per the September 2015 Puget Sound Economic Forecaster by Dick Conway and Doug Pederson.

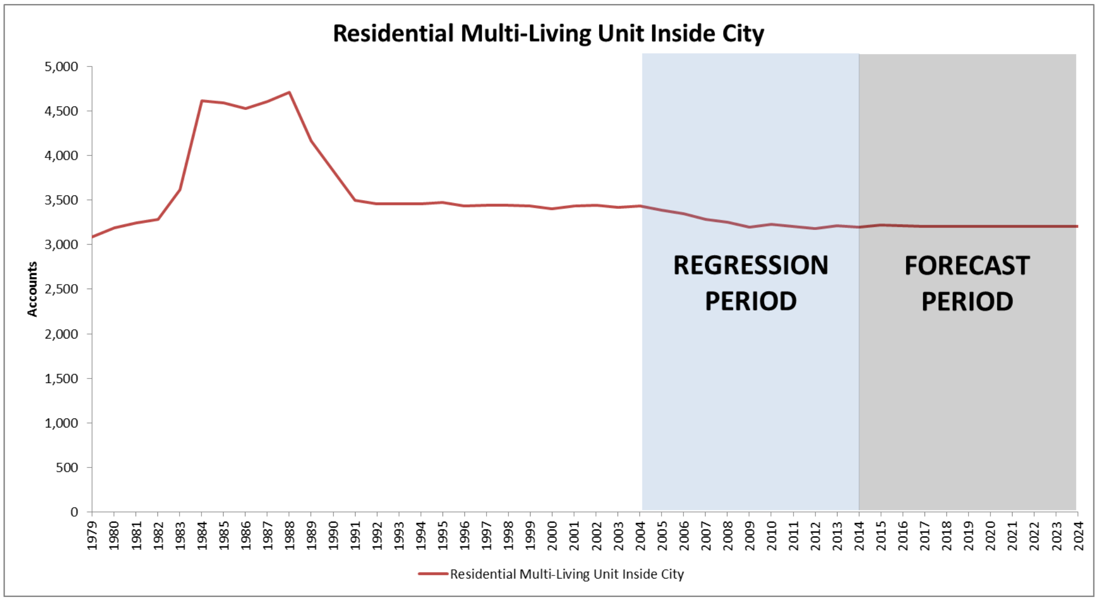
Multi-Living Unit Inside City (3% of average total accounts (2004-2013)) declined 6.5% between 2004 and 2013 or 0.67% decline per year. We used a logarithmic model for this class despite having a worse fit to the historical data this is because we do not expect year-over-year declines in multi-living units to continue as we know Point Ruston and downtown Tacoma are in the process of building more condominium and apartment buildings.

Figure 12: Multi-Family Inside City – Historical and Fitted Account Growth



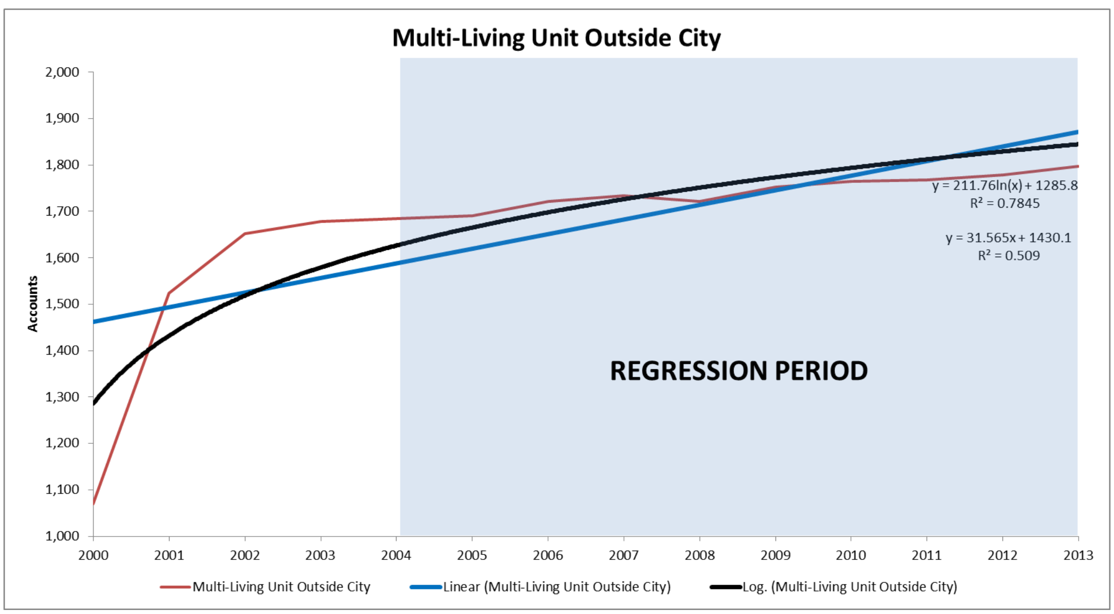
We expect account growth to total 0.3% over the next ten years or 0.03% per year. This is because Multi-Living Units accounts experienced most of their declines between 2000 and 2009 and a flattening afterwards, and, as discussed earlier, we expect inside city multi-living units to increase with the additional condominiums and high-rises being built. We have chosen to use the 2010 to 2013 period for the logarithmic model. Notably, in the 1980's, outside of the *Regression Period,* is a substantial abnormality which, despite internal interviews and examination of data, has yet to be explained as can be seen in the Figure below:

Figure 13: Water Residential Multi-Living Units Inside City – Historical and Forecasted Accounts



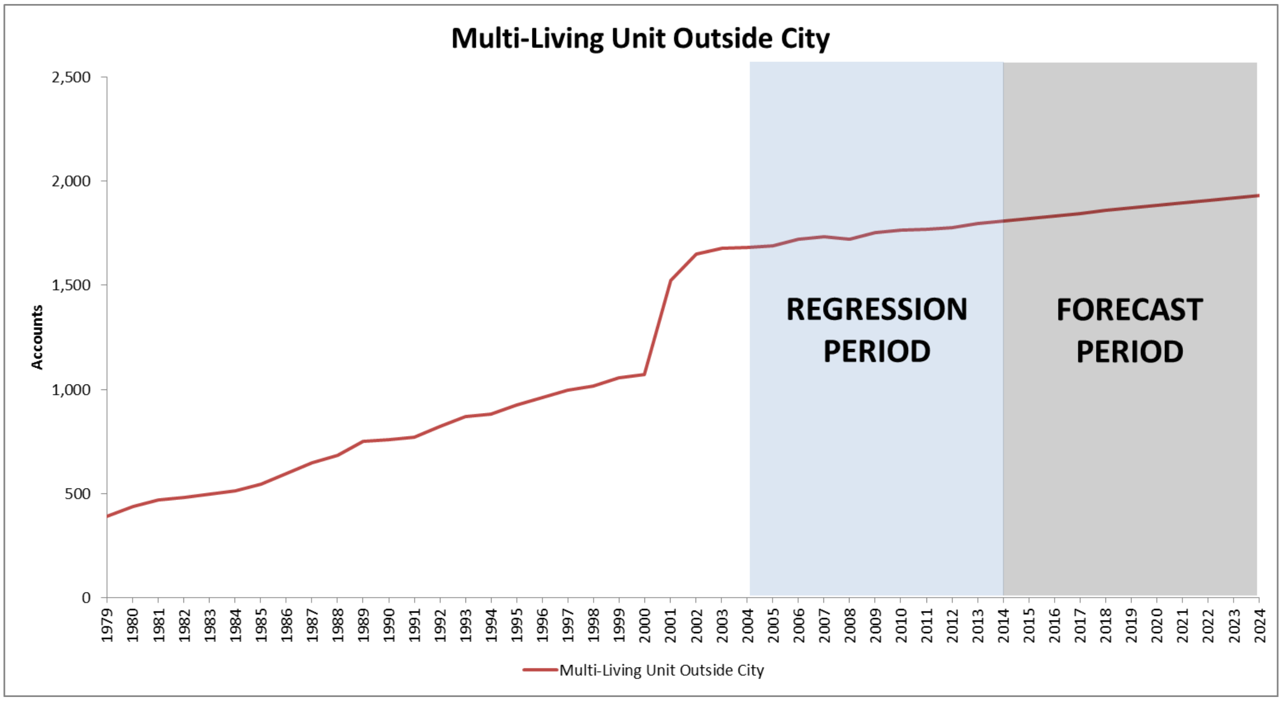
Multi-Living Unit Outside City (2% of average total accounts (2004-2013)) grew 6.8% between 2004 and 2013 or 0.66% per year. Because no trend line fit the data well for 2000-2013 we examined a smaller time frame, 2004-2013, and the linear trend line fit the data well and was used. The model results are seen in the Figure below:

Figure 14: Multi-Living Unit Outside City – Historical and Fitted Account Growth



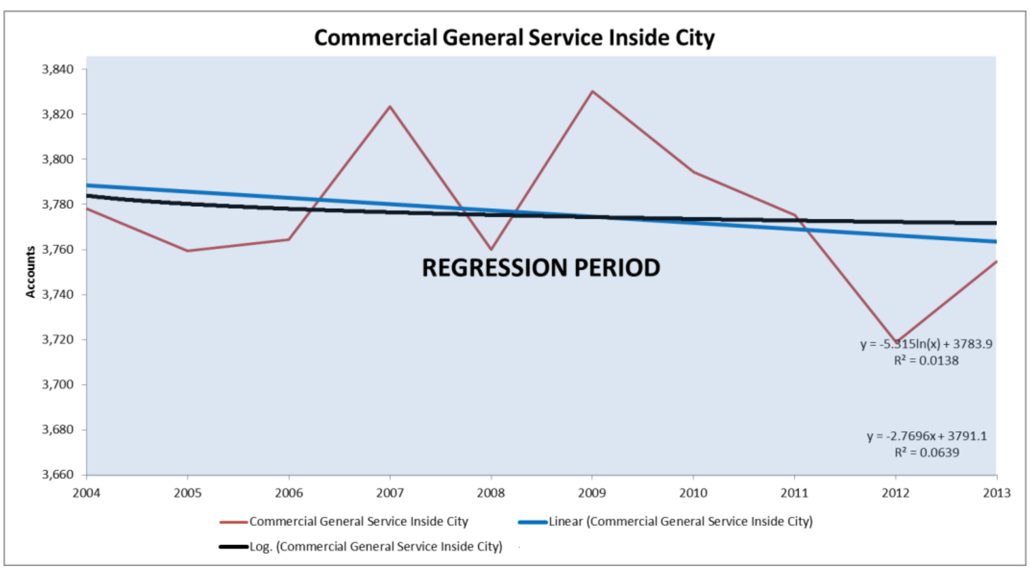
We expect account growth to total 6.8% over the next ten years. The substantial increase in accounts in the early 00's was due to service area assumptions seen in the figure below:

Figure 15: Multi-Living Unit Outside City – Historical and Forecasted Accounts



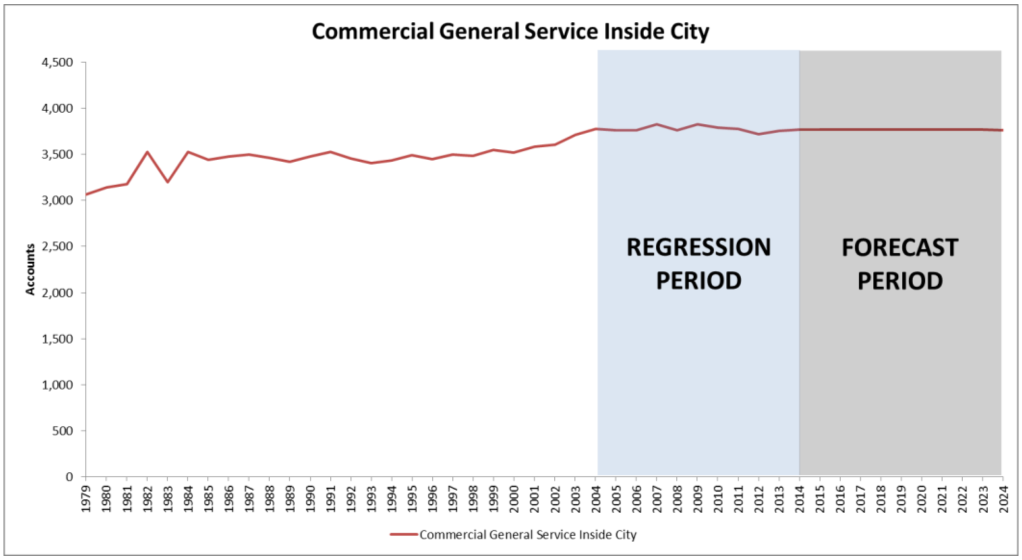
Commercial General Service Inside City (4% of average total accounts (2004-2013)) declined by 0.6% from 2004 to 2013 or a decline of 0.06% per year. Trend lines using data from 2000 to 2013 estimated account growth, but we decided that this was not what the recent trend showed, so we have shortened the model period to 2004 to 2013 as seen in the Figure below:

Figure 16: Commercial General Inside City – Account Growth



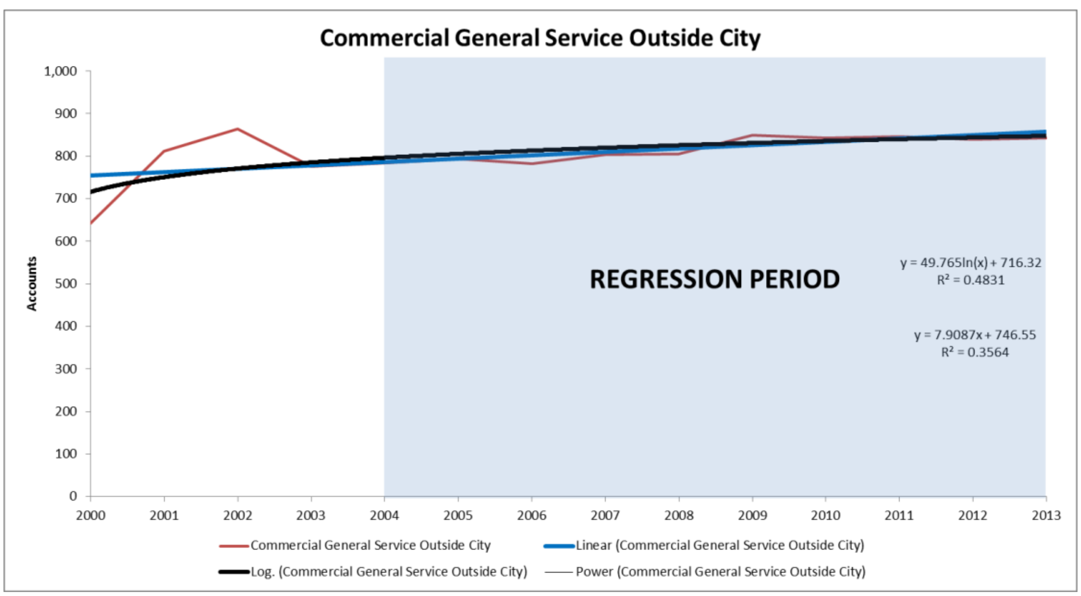
We estimate accounts to decline by -0.1% over the next ten years or 0.01% per year. From 2007 to 2011 we saw declines in active accounts, a trend that stabilized in 2012 and 2013. Because of the large swings in 2007, 2009, and the trough in 2012 we feel the model should represent the slight decline in accounts, but also project a flatter curve going out for the forecast as we do not know if the downward trend will be maintained in the long-run as seen in the Figure below:

Figure 17: Commercial General Inside City – Historical and Forecasted Accounts



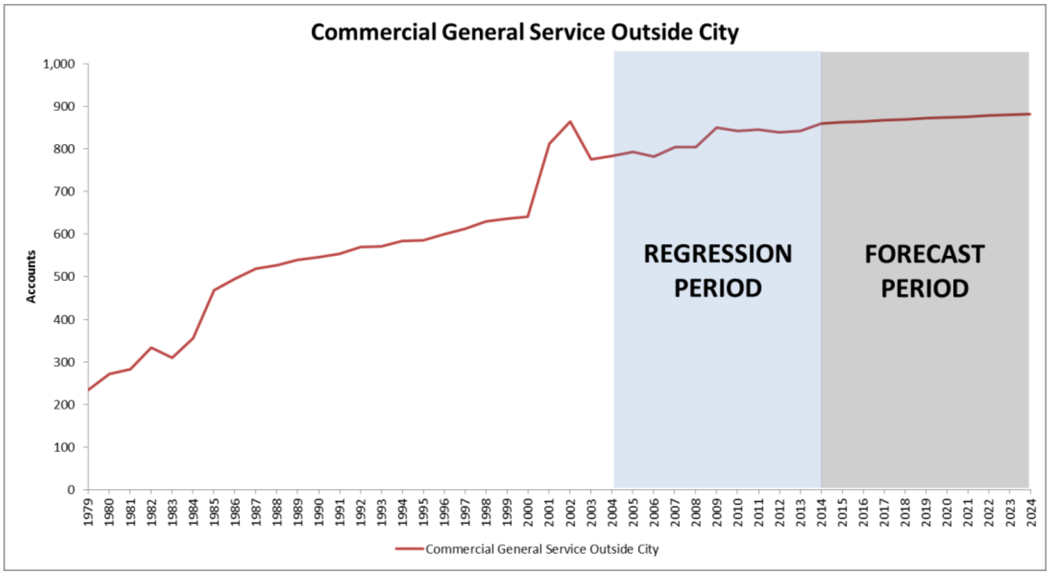
Commercial General Service Outside City (1% of average total accounts (2004-2013)) experienced growth of 7.5% from 2004 to 2013 or 0.72% per year. We believe the logarithmic model better explains the growth in the class better than a linear model because of the sizable increase of 50 accounts in one year (2009). When we remove this growth in accounts the line of best-fit is increasing as can be seen in the Figure below:

Figure 18: Commercial General Outside City – Account Growth



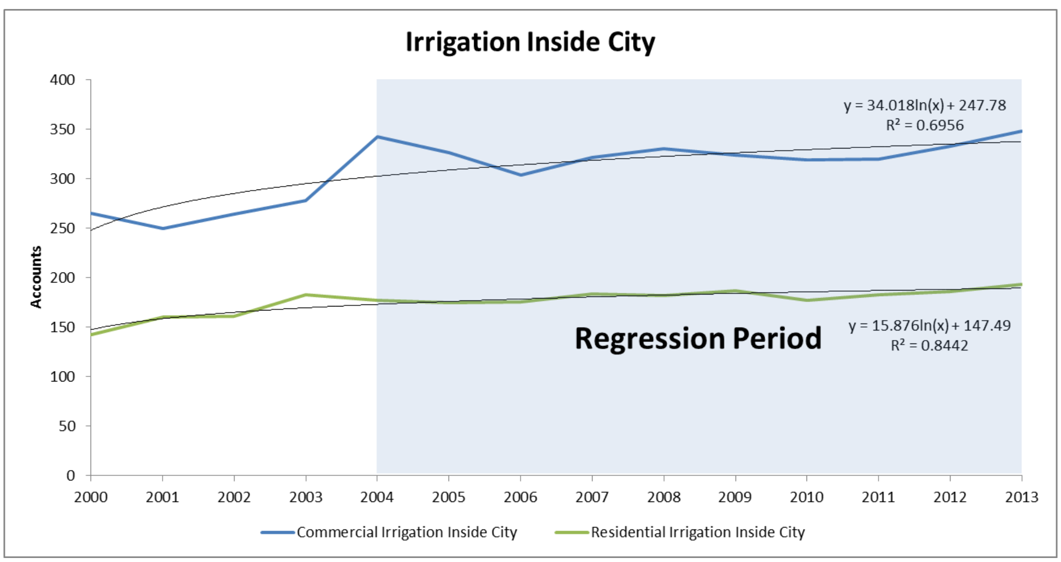
We expect total Commercial General Outside City accounts to increase by 2.6% over the next ten years or 0.23%. The sharp drop during 2003 was due to data quality abnormalities discovered during the SAP implementation. Interestingly, 50 accounts were removed between 2002 and 2003 and another approximately 50 accounts (different companies) were added in 2009 which can be seen in the Figure below:

Figure 19: Commercial General Outside City – Historical and Forecasted Accounts



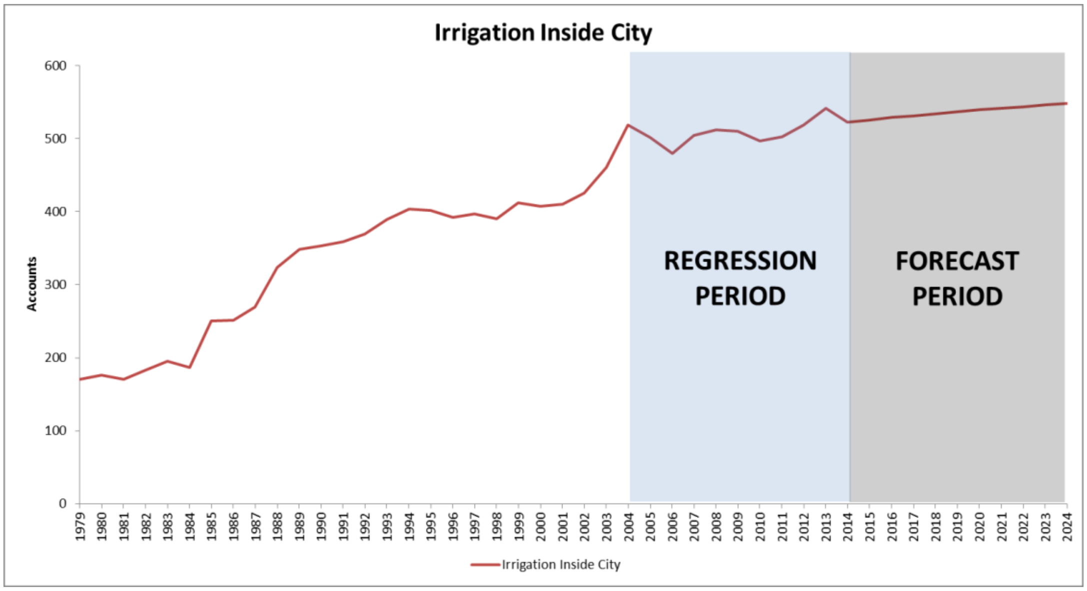
Irrigation Inside City (1% of average total accounts (2004-2013)) increased by 4.3% from 2004 to 2013 or by 0.42% per year. The overall model is the total of residential and commercial irrigation accounts. Both rate categories use logarithmic models which fit the data well as shown in the Figure below:

Figure 20: Parks and Irrigation Inside City – Account Growth



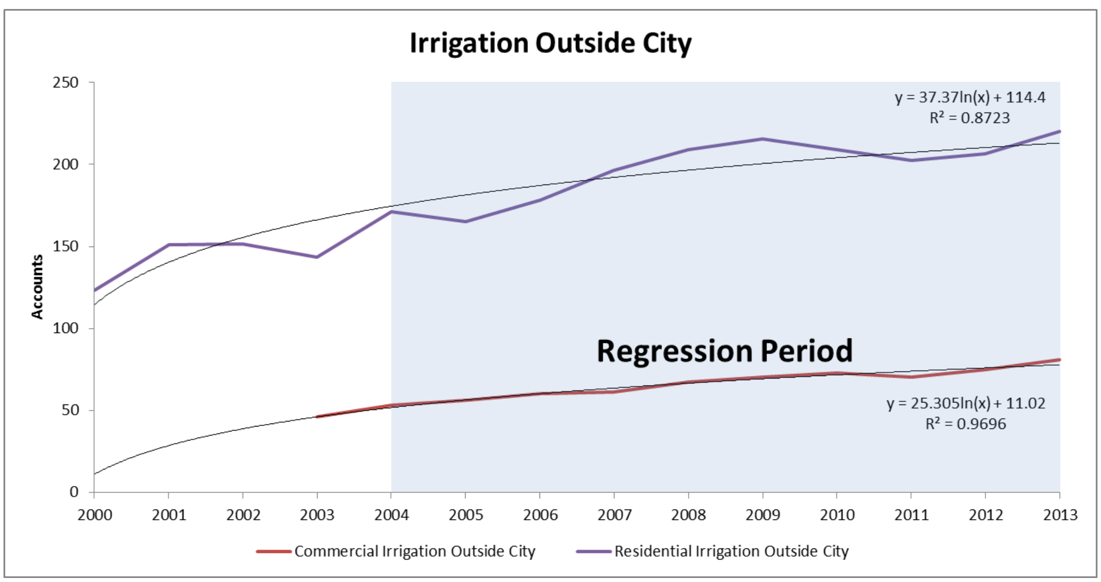
We estimate account growth to total 4.9% over the next ten years or 0.43% per year. This estimate continues the historical trend for the forecast period as seen in the Figure below:

Figure 21: Irrigation Inside City – Historical and Forecasted Accounts



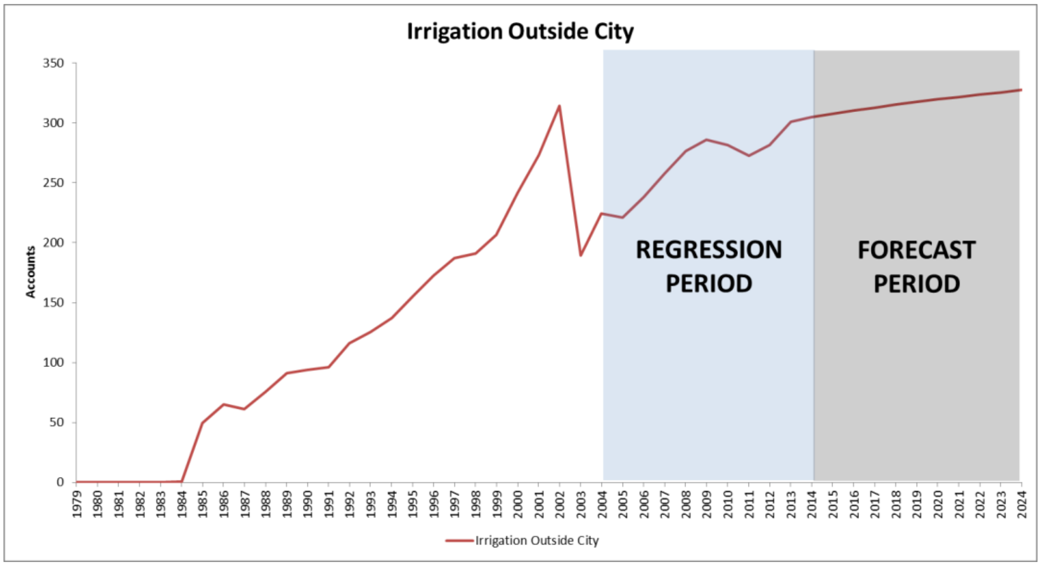
Irrigation Outside City (1% of average total accounts (2004-2013)) increased by 34% from 2004 to 2013 or by 2.98% per year – most of this growth is attributed to Residential Irrigation accounts. Commercial Irrigation Outside City only utilized 2003-2013 data to avoid the large shift in accounts that occurred between 2000 and 2003.

Figure 22: Parks and Irrigation Outside City – Account Growth



We expect account growth to increase by 7.4% over the next ten years or by 0.65%. The 2001 boom and corresponding decline in 2003 are due to SAP implementation quality control and checks, because irrigation customers are tax exempt there was a concerted effort to examine each account in the class this led to a sizable reduction in accounts in the irrigation classes. These customers were either moved to residential or commercial classes as seen in the Figure below:

Figure 23: Irrigation Outside City – Historical and Forecasted Accounts

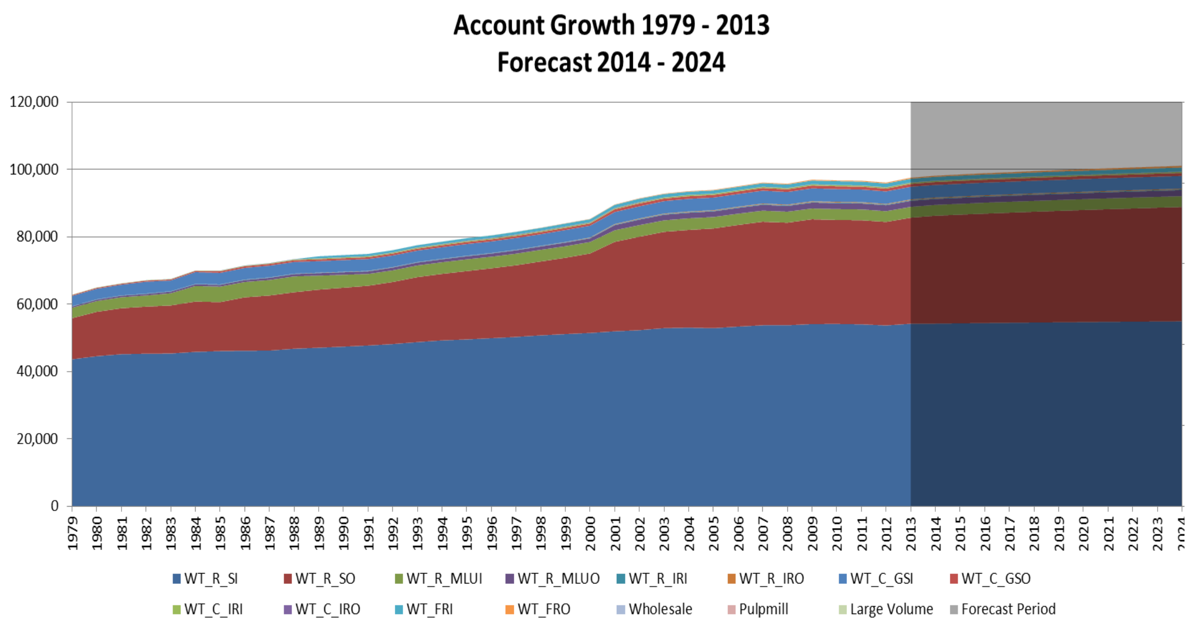


We expect growth to occur mainly in outside city areas, continuing the historic trends for each category. One area we may expect more growth to occur, which is not represented in these forecasts, is in Tehaleh. Tehaleh would increase nearly all outside city forecasted rate categories (commercial, irrigation, and residential). We have spoken to Tehaleh about the potential households and the expansion plans and feel the developers are overly optimistic (as seen in the Figure below) as we have observed a lack of new houses. Therefore we have, as a general rule, aired on the side of caution to project lower growth or omit potential areas of known growth like Tehaleh. This conservatism is also seen in our choice of logarithmic models for many of the rate categories because this seems to match the historical data better than simplistic linear models.

Figure 24: Empty Tehaleh Main Street

After forecast all of the various rate categories we see that overall account growth between 2004 and 2013 was 3.9% or 0.39%. We expect accounts to grow by 2.9% from 2014 to 2024 or 0.26% per year as shown in the Figure below:

Figure 25: Customer Account Growth 1979-2013 and Forecasted period 2014-2024



Demand Regression Models

The next step in our process to forecast rate category demands for rate setting and financial planning is to develop models for each rate category with variables that express a high level of correlation and to incorporate the forecasted accounts.

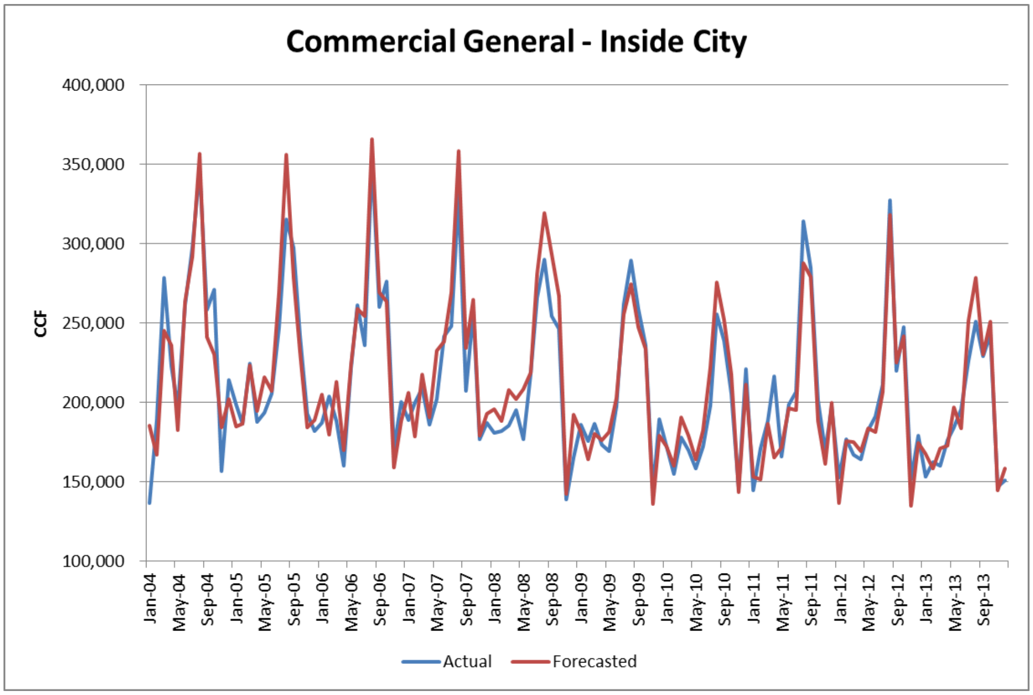
To create the various regression models we will utilize the weather and account data in the prior sections. These various regression models will be used to forecast per account demands and ultimately estimate future revenues in order to inform Tacoma Water's budget and rates. We used nine years of billed rate category specific data (2004-2013).

The rate classes chosen for regressions are: Commercial General, Residential Single Family, Parks and Irrigation, and Residential Multi-Living Units. These are subdivided into inside the City of Tacoma (Inside City) and outside the City of Tacoma (Outside City). This level of detail avoids many of the errors and major billing irregularities found in some of the smaller jurisdictional classes found outside of the City of Tacoma (Fircrest, University Place, Lakewood, and Puyallup). However, in order to project *revenue-generating* demands we will, after the forecast is complete, apportion the Outside City demands back to their jurisdictions using recent historical demands (more on this in the Post-Modeling section below). In addition to the regressed demands we also forecasted Commercial Large Volume, Private Fire (accounts), RockTenn, and Wholesale using various methods such as dialogue with the customer or following multi-year trends.

In order to isolate the underlying factors behind changes in demand over time, the rate class specific demands are expressed as demand per account prior to being regressed.

To decide if the model has a "good fit" to the historical data we have chosen to use the Mean Absolute Percentage Error (MAPE). This is a statistical measure of the overall error in the model results when compared to the historical data. Below are the various regression results, their MAPE scores, and corresponding form of the model.

Figure 26: Regression Results - Commercial General Inside City – Demand



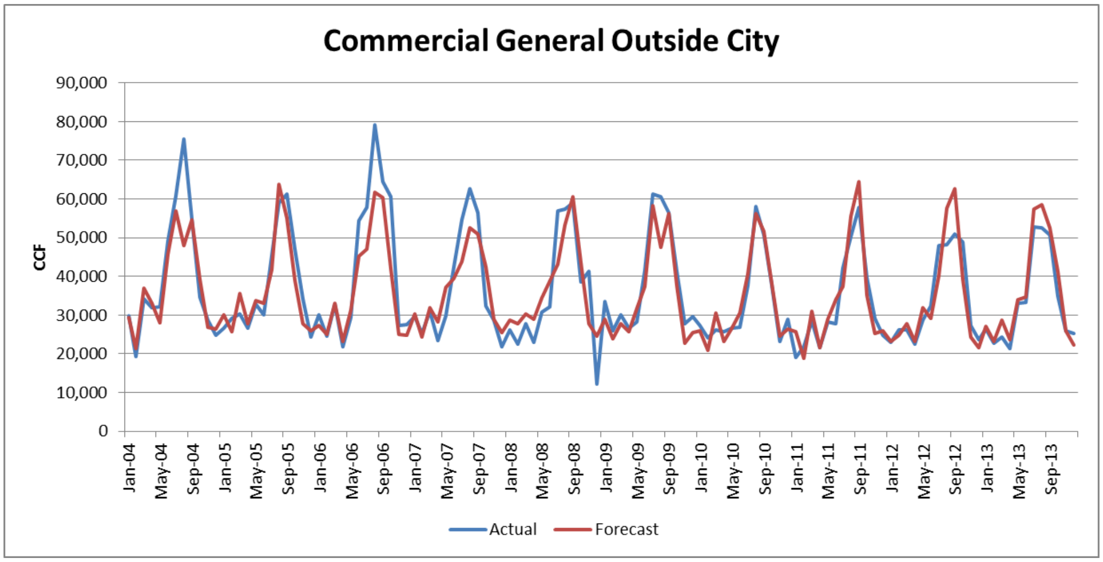
Commercial General Inside City (10.3% of average total demand (2004-2013)) matches the historical data well with MAPE of $\pm$6%. With the highest error occurring in 2008, despite having a recession dummy variable, there seems to be a larger decrease in demand in this year which can be seen in the winter and summer periods of the regression model. The peak-month to base demand ratio is 1.66x. This is a rather surprising result, as we have typically assumed the commercial class to not exhibit a strong seasonal pattern. The reason for this high peak/base ratio is because of the heterogeneity in the class and lack of sub-metering for irrigation purposes. It is recommended to sub-meter commercial customers which exhibit seasonal irrigation demand patterns. The model is shown below:

Equation 1: Commercial General Inside City

$$\frac{Demand_t}{Accounts_t} = \beta_0 + MaxTemp_t + FourDayHeat_t - Recession_t + Seasonal\ Billing_t + Months_t$$

Where demand per account is defined by: The intercept (β_0). MaxTemp is the averaged max day temperatures for the month ($MaxTemp$). FourDayHeat is the number of four consecutive hot days of temperature over 77 degrees there were in the month ($FourDayHeat$). Recession is the Great Recession occurring from January 2009 onward ($Recession$). Seasonal Billing is the billing department's end of year catch up on bills from November through January ($Seasonal\ Billing$). The variable Months are the months that were significant for this model ($Months$).

Figure 27: Regression Results – Commercial General Outside City - Demand



The regression results for Commercial General Outside City (2.0% of average total demand (2004-2013)) exhibit a lot of volatility due to several factors: (1) The Great Recession (2009-2013), even though this is controlled for by an indicator variable, it cannot capture the complexity of the largest economic downturn since the Great Depression which effects each customer differently and at different times which can be seen in the over estimation of demands for relatively warm summers (2012 and 2013). (2) Heavy demand customers which were either removed from the class (and added to the Large Volume Commercial class such as Frederickson Power) or added to the class (such as University of Puget Sound, St. Joseph Medical, Tacoma General, and Atlas Foundry) caused shocks [sudden changes in demand that are either temporary or permanent]. We controlled for the entrance and removal of customers from the class with indicator variables, but this, much like (1) cannot capture the entirety of the shock[3]. (3) The heterogeneity (customers not being homogeneous, i.e. of the same type) of the class as we are regressing demands from very different customers (restaurants, warehouses, water parks, office buildings, and schools) which can only be improved with customer segmentation into new rate categories. The MAPE score is $\pm$11%. The high peak month to base of 2.14x again highlights the mixture of various companies and their applications of water and can be only remedied by segmenting the class. The model is shown below:

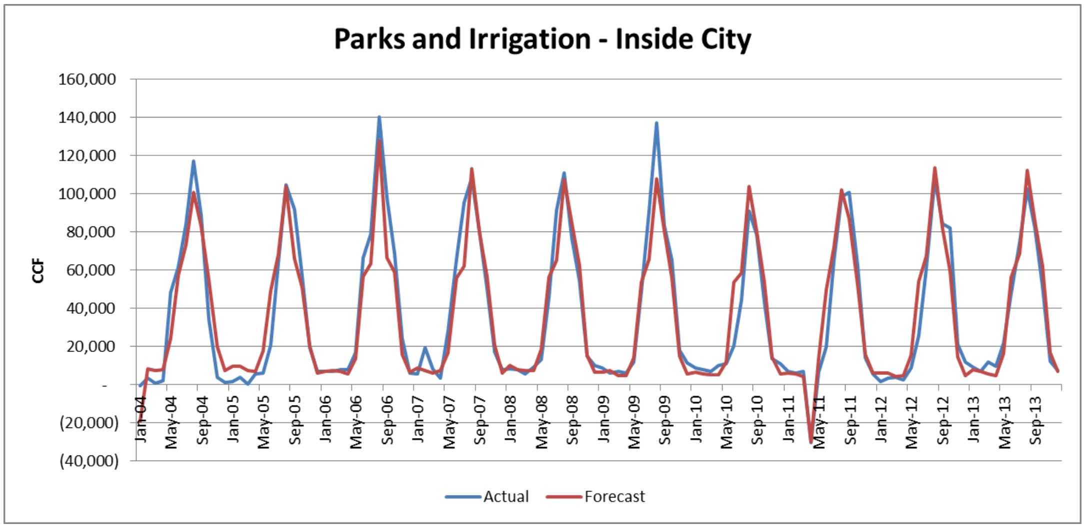
Equation 2: Commercial General Outside City

$$\frac{Demand_t}{Accounts_t} = \beta_0 + PeakTemp_t - DaysofRain_t + GoLive_t - Recession_t + Months_t + Weather_t$$

Where demand per account is defined by: The intercept (β_0). PeakTemp is the max day temperature for the month ($PeakTemp$). DaysofRain is the number of days of rainfall which occurred in the month ($DaysofRain$). GoLive is the billing reversals and errors which occurred during the process to bring SAP online ($GoLive$). Recession is the Great Recession occurring from January 2009 onward ($Recession$). Months are the months in the year that were significant for this model ($Months$). Weather is the interaction model variable for temperature and rainfall in a month ($Weather$).

[3] This will be an area we explore further in later forecasting efforts.

Figure 28: Parks and Irrigation Inside City – Demand



Parks and Irrigation Inside City (1.7% of average total demand (2004-2013)) has a MAPE score of $\pm$39% with 2004 results included but a 28% when removed. Because the class is so small relative to other customer classes the 2004 SAP implementation[4] which contained reversals and billing errors have an acute negative effect on the regression results. To improve regression results it is recommended to move towards daily demand recording and a thorough examination of the customers within the class. As expected the peak month to base ratio is extremely high at 8.56x. The model is shown below:

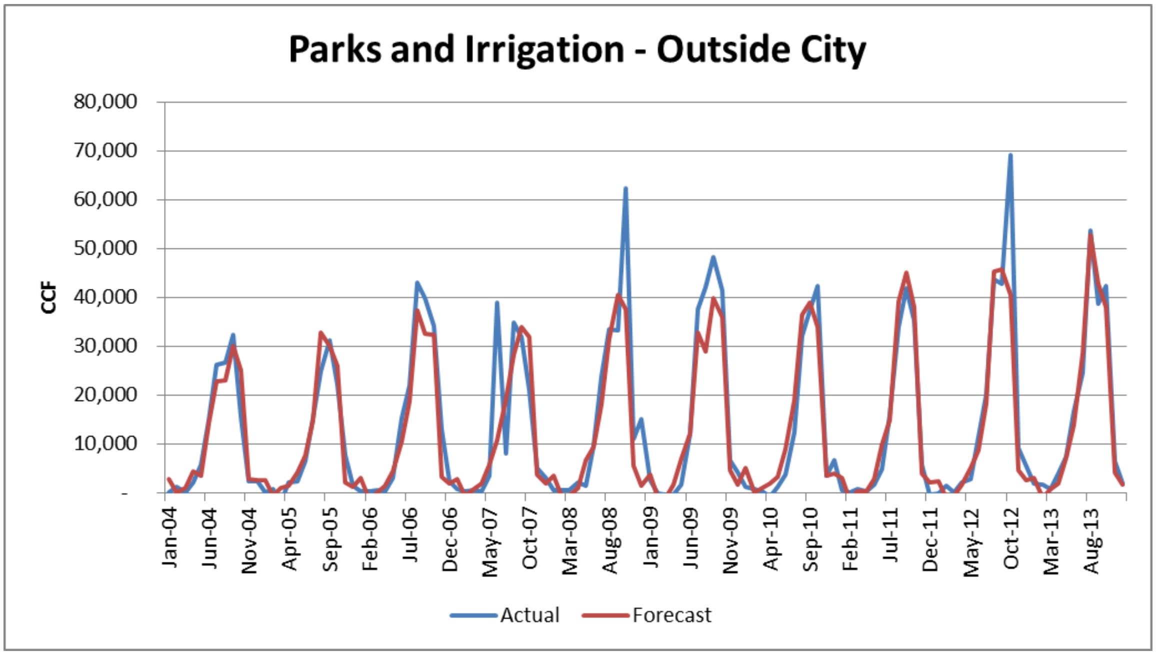
Equation 3: Parks and Irrigation Inside City

$$\frac{Demand_t}{Accounts_t} = -\beta_0 + MajorReveral_t - Recession_t + Months_t + Tdl0_t + Pdl0_t$$

Where demand per account is defined by: The intercept (β_0). MajorReversal is major billing corrections across several accounts in 2004 and 2011 ($MajorReversal$). Recession is the Great Recession occurring from January 2009 onward ($Recession$). Months are the months in the year that were significant for this model ($Months$). Tdl0 is the sinusoidal model of temperature ($Tdl0$). Pdl0 is the sinusoidal model of rainfall ($Pdl0$).

[4] SAP Implementation occurred on November 2003. From 11/2003 to 12/2004 there were numerous reversals and billing errors in certain classes. Some customers were not billed for several months. Also during this time and until February 2008 reversals in revenue and demand occurred.

Figure 29: Parks and Irrigation Outside City – Demand



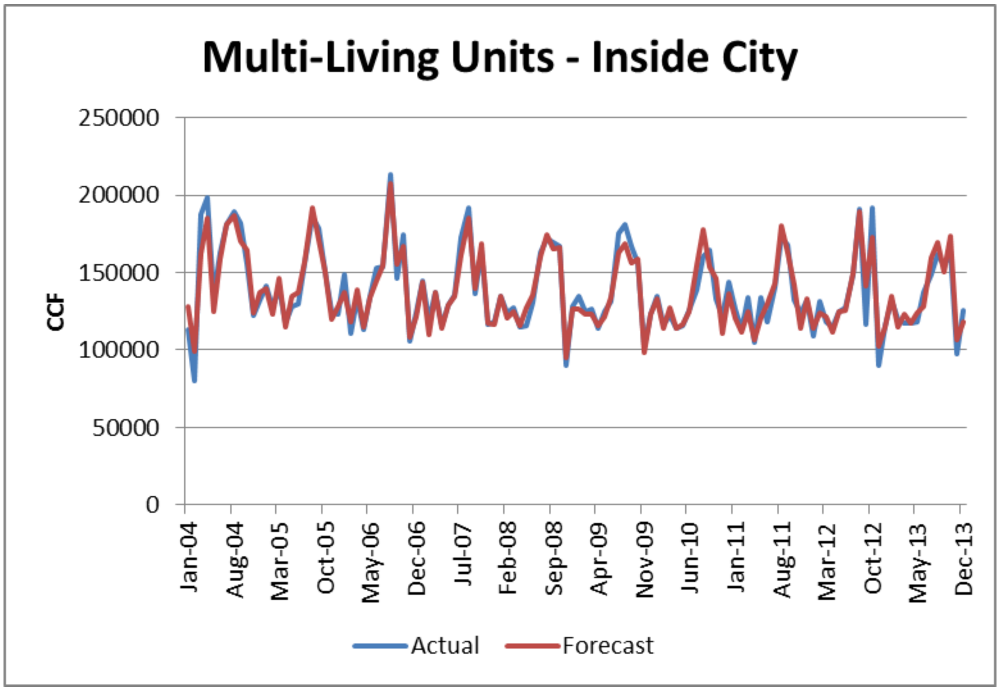
Parks and Irrigation – Outside City (0.7% of average total demand (2004-2013)) is very difficult to accurately regress. The same issues that applied to P&I – Inside City apply here. The MAPE for Parks and Irrigation – Outside City is $\pm$84%. We can see the peak in 2008 and 2012 being substantially under predicted – highlighting the need for daily demand records to better understand the correlation between weather and irrigation demands. As expected the peak-month to base demand is extremely high at 9.95x. The model is shown below:

Equation 4: Parks and Irrigation Outside City

$$\frac{Demand_t}{Accounts_t} = \beta_0 + MaxTemp_t + Seasonal\ Billing_t + Months_t + Weather_t - Pdl0_t$$

Where demand per account is defined by: The intercept (β_0). MaxTemp is the averaged max day temperatures for the month ($MaxTemp$). Seasonal Billing is the billing department's end of year catch up on bills from November through January ($Seasonal\ Billing$). Months are the months in the year that were significant for this model ($Months$).Weather is the interaction model variable with temperature and rainfall in a month ($Weather$). Pdl0 is a sinusoidal model constructing rainfall ($Pdl0$).

Figure 30: Multi-Living Units Inside City – Demand



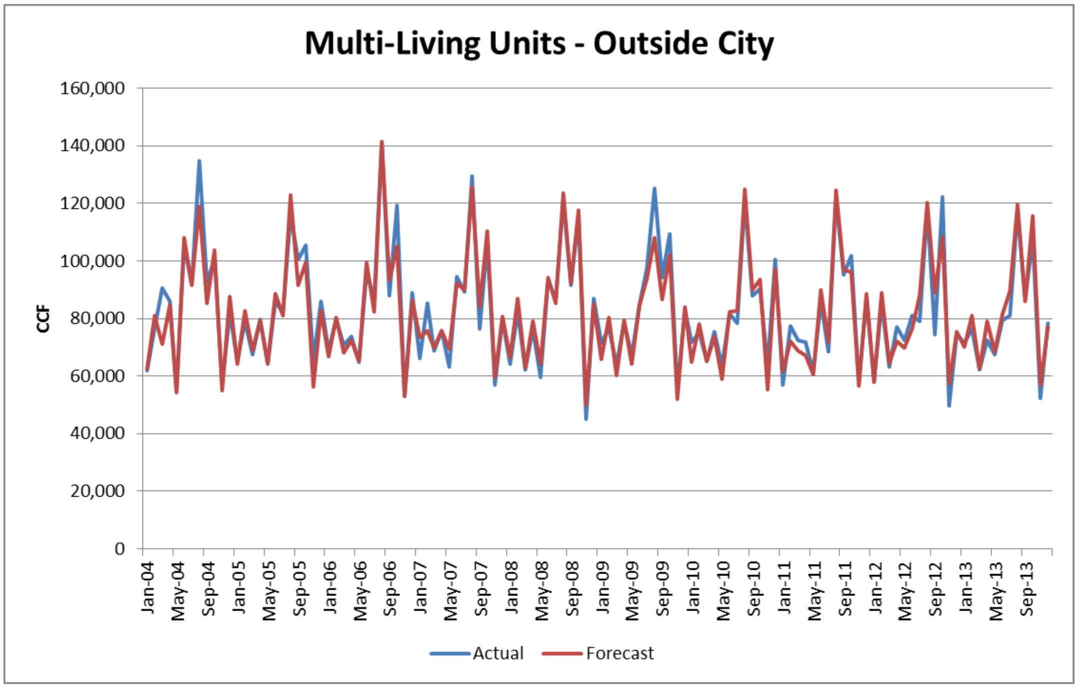
Multi-Living Units – Inside City (6.8% of average total demand (2004-2013)) fits the data well with a MAPE of $\pm$4%. The seasonality (peak season to off-peak is 1.45x) exhibited in the class is due to duplex, triplex, etc. units which have lawns or gardening. It is recommended that these customers either be moved into the Residential Single Family class or into a new class altogether. This would allow for apartment buildings and high-rise condominiums to be singled out, removing the seasonal shape. The model is shown below:

Equation 5: Multi-Living Units Inside City

$$\frac{Demand_t}{Accounts_t} = \beta_0 + FourDayHeat_t + DaysofRain_t + PeakTemp_t + GoLive_t + Seasonal\ Billing_t - Recession_t + Months_t$$

Where demand per account is defined by: The intercept (β_0). FourDayHeat is the number of four consecutive hot days of temperature over 77 degrees there were in the month ($FourDayHeat$). DaysofRain is the number of days of rainfall which occurred in the month ($DaysofRain$). PeakTemp is the max day temperature for the month ($PeakTemp$). GoLive is the billing reversals and errors which occurred during the process to bring SAP online ($GoLive$). Seasonal Billing is the billing department's end of year catch up on bills from November through January ($Seasonal\ Billing$). Recession is the Great Recession occurring from January 2009 onward ($Recession$). Months are the months in the year that were significant for this model ($Months$).

Figure 31: Multi-Living Units Outside City – Demand



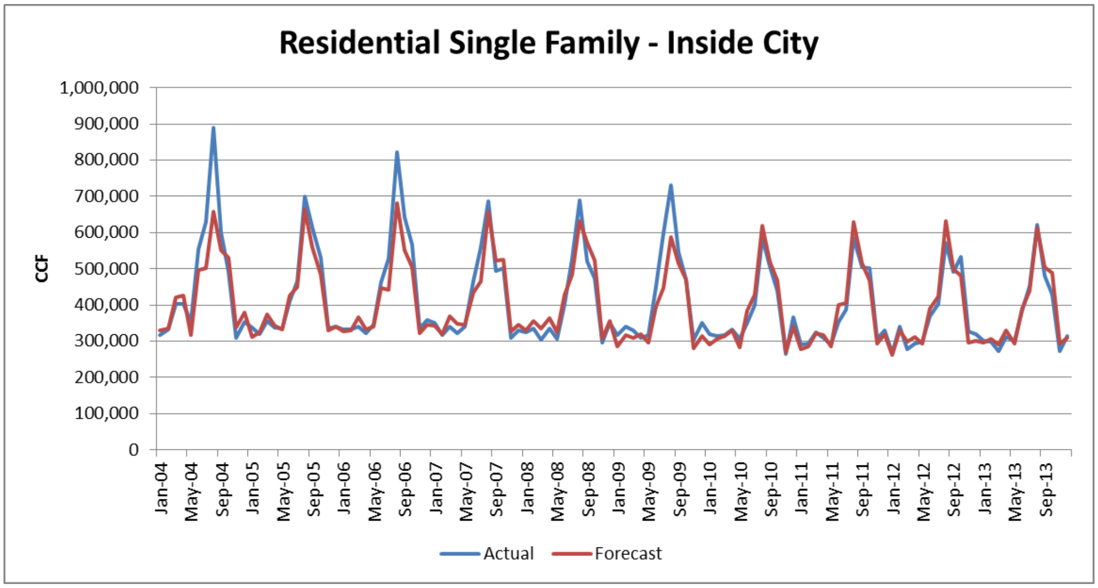
Multi-Living Units – Outside City (4.0% of average total demand (2004-2013)) fits the data well with a MAPE of $\pm$4%. The seasonality (peak month to base demand is 1.71x) exhibited in the class is due to the same class structures discussed above (Multi-Living Units – Inside City). It is recommended to move towards homogeneous rate categories. The model is shown below:

Equation 6: Multi-Living Units Outside City

$$\frac{Demand_t}{Accounts_t} = \beta_0 + FourDayHeat_t + Recession_t + PeakTemp_t + GoLive_t + Months_t$$

Where demand per account is defined by: The intercept (β_0). FourDayHeat is the number of four consecutive hot days of temperature over 77 degrees there were in the month ($FourDayHeat$). Recession is the Great Recession occurring from January 2009 onward ($Recession$). PeakTemp is the max day temperature for the month ($PeakTemp$). GoLive is the billing reversals and errors which occurred during the process to bring SAP online ($GoLive$). Months are the months in the year that were significant for this model ($Months$).

Figure 32: Residential Single Family Inside City – Demand



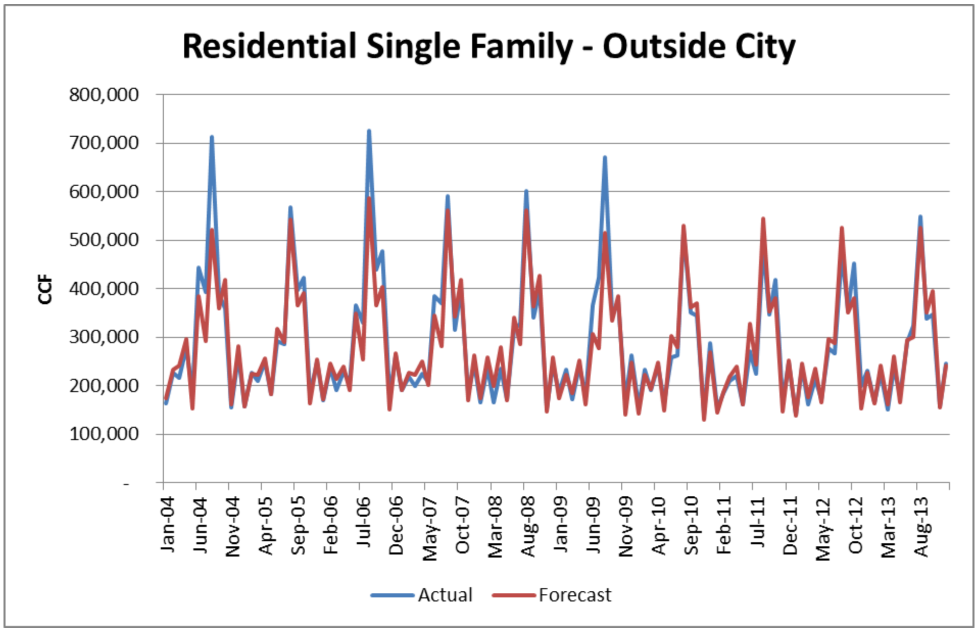
Residential Single Family – Inside City (20.0% of average total demand (2004-2013)) fits the data well with a MAPE of $\pm$6%. There is a clear under-estimation of 2004, 2006, and 2009 all of which were hot/dry summers. The peak month to base demand ratio is 2.06x as expected from a single family houses which each have their own lawns to irrigate. We recommend daily demand data from a sample population of inside city households to improve the relationship between customer water demands and weather patterns. The model is shown below:

Equation 7: Residential Single Family Inside City

$$\frac{Demand_t}{Accounts_t} = \beta_0 + MaxTemp_t - Recession_t + Weather_t + GoLive_t + Months_t$$

Where demand per account is defined by: The intercept (β_0). MaxTemp is the averaged max day temperatures for the month ($MaxTemp$). Recession is the Great Recession occurring from January 2009 onward ($Recession$). Weather is the interaction variable examining temperature and rainfall in a month ($Weather$). GoLive is the billing reversals and errors which occurred during the process to bring SAP online ($GoLive$). Months are the months in the year that were significant for this model ($Months$).

Figure 33: Residential Single Family Outside City – Demand



Residential Single Family – Outside City (14.0% of average total demand (2004-2013)) fits the data well with a MAPE of $\pm$6%. Similar to Residential Single Family – Inside City hot/dry summers are under forecasted. However, because of larger parcel sizes the peak month to base demand ratio is substantively higher for this class at 2.7x. We recommend a sample size of outside city customers be equipped with daily meter reading units to improve regression relationships with water demand and daily weather patterns. The model is shown below:

Equation 8: Residential Single Family Outside City

$$\frac{Demand_t}{Accounts_t} = \beta_0 - DaysofRain_t - Recession_t + GoLive_t + Months_t + Tdl0_t$$

Where demand per account is defined by: The intercept (β_0). DaysofRain is the number of days of rainfall which occurred in the month ($DaysofRain$). Recession is the Great Recession occurring from January 2009 onward ($Recession$). GoLive is the billing reversals and errors which occurred during the process to bring SAP online ($GoLive$). Months are the months in the year that were significant for this model ($Months$). Tdl0 is the sinusoidal model of temperature ($Tdl0$).

Conservation

Conservation is an important aspect of understanding the historical downward trend in water demands and, for our purposes, understanding what is most likely to occur in the future. In the last forecasting effort (2012) nationwide conservation estimates were applied to each rate category as a percentage of the overall downward trend. However, with the release of Tacoma Water specific data the Residential classes could be more thoroughly examined.

Tacoma Water participated in an “End Use Study” in 2010 being researched by the consulting firm Aquacraft and being funded by the Water Research Foundation. The goal of the project was to conduct a survey on single family residential indoor applications (fixtures such as sinks, washers, showers, etc.) and outside irrigation applications. In addition to the survey, Aquacraft data logged a statistically significant sampling of customers to estimate average household use in various utilities' service territories. The methodology and results were incorporated into both the Short-Term Forecast and Long-Term Forecast.

Tacoma Water has used the results in a novel way to estimate conservation during a historical period and, using the theory of "conservation saturation,"[5] constructed logarithmic curves to model the approach of water-using fixtures to their current technological limitations across the service territory. The two studies used were 1999 (Tacoma Water did not participate) and 2010 (Tacoma Water did participate). Because many of the utilities that participated in both studies had similar indoor demand profiles to Tacoma Water's, it was possible to extrapolate Tacoma Water's conservation trends from this data. The Table below depicts the 2010 Aquacraft study of average daily water demand from each type of fixture analyzed, and compares them to the same averages reported by Tacoma Water.

Table 5: Aquacraft 2010 Study: Average Daily Water Use by Fixture per Household

	Average Daily Use (gpdph)										
	Sink	Toilet	Shower	Bath	Leak	Washer	Dishwasher	Other	Indoor	Outdoor	Total
2010 Study Average	26.35	33.08	28.08	3.62	17.04	22.76	1.58	5.18	137.69	94.00	231.69
2010 Tacoma Water	25.10	34.70	25.9	3.10	13.50	22.90	2.00	0.40	127.60	56.29	183.89
% Difference	-4.74%	4.90%	-7.76%	-14.36%	-20.77%	0.62%	26.58%	-92.28%	-7.33%	-40.12%	-20.63%

Tacoma Water single family residential indoor consumptions is 7.33% less than the average of sampled utility respondents. This difference is reduced to a 4% difference when the "Other" category[6] is removed. The End Use Study and our own analysis concluded that this is within the margin of error and therefore not statistically significant, which means that we can assume that Tacoma Water's single family customers are the same as the other customers in this study for purposes of extrapolating results for use in the demand forecast. On the other hand, outdoor usage *is* statistically significant compared to the average of other utility respondents – Tacoma Water's single family residential average for outdoor use is 40% less than the average for the rest of the study participants, at 56 gpdh. The Table below depicts the 1999 Aquacraft study of average daily water demand from each type of fixture, and compares them to the extrapolated Tacoma Water demands by fixture.

Table 6: Aquacraft 1999 Study: Average Daily Water Use by Fixture per Household and Extrapolated Tacoma Water Demands

	Average Daily Use (gpdph)										
	Sink	Toilet	Shower	Bath	Leak	Washer	Dishwasher	Other	Indoor	Outdoor	Total
1999 Estimate Tacoma Water	25.50	47.45	28.68	4.47	17.42	40.51	4.06	0.65	168.83	94.00	262.83
2010 Tacoma Water	25.10	34.70	25.9	3.10	13.50	22.90	2.00	0.40	127.60	56.29	183.89
% Decline	-1.57%	- 26.86%	-9.68%	- 30.65 %	- 22.51%	- 43.47%	-50.78%	- 38.41 %	- 24.42%	-40.12%	- 30.03%

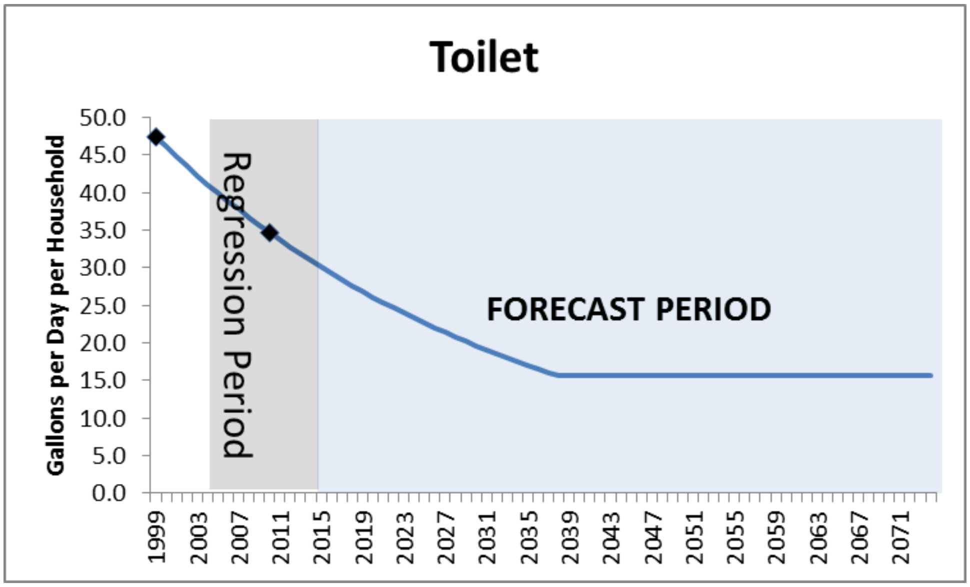
After establishing each estimated fixture's use per household per day we forecasted using a logarithmic model to the current technological conservation limitation of the fixture (1 gal. flush toilets for example), i.e. 100% saturation point of the fixture. Below are individual forecasts for toilets, showers, washers, dishwashers, and

[5] http://sustainablecities.usc.edu/research/Chapter%208.%20The%20Future%20Conservation%20Potential%20of%20BMPs%2012%2019%20p.pdf

[6] The "Other" category includes all use that could not be easily explained by the defined fixtures or outdoor use. Some anecdotal evidence of this could be home brewing beer, indoor gardens, or indoor pools/hot tubs.

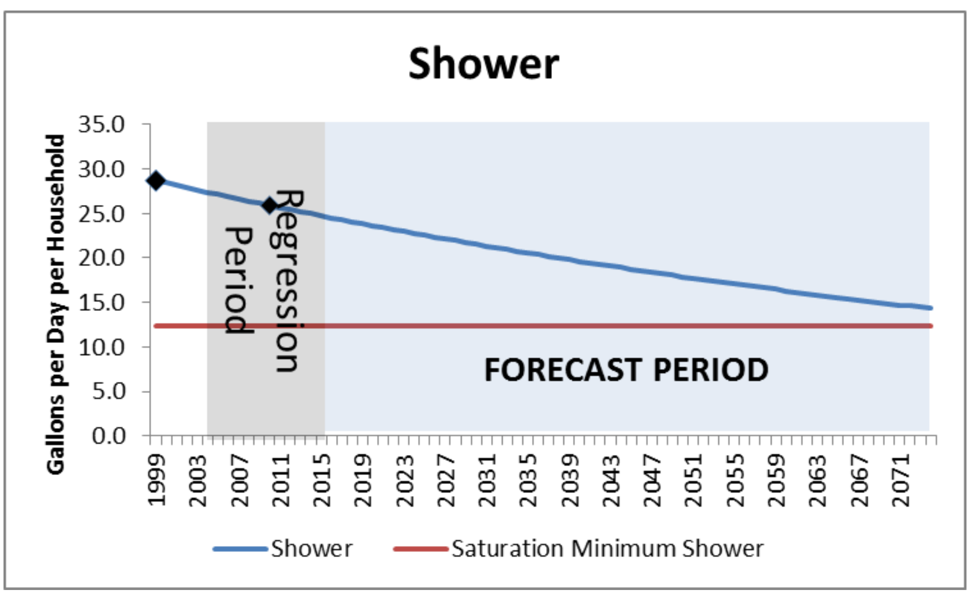
outdoor applications. The remaining categories are not forecasted due to declines in load that were either statistically insignificant between the two studies (sink and bath) or there were difficulties in reliably measuring application specific-loads (leaks and other). The forecasted conservation results displayed in the figures below highlight the 1999 extrapolated demand data, the 2010 actual demand data, the Forecast Period (2014-2074, because this data will also be used in the Long-term Forecast), and the Regression Period (2004-2013).

Figure 34: Household Gallons per Day Use by Fixture - Toilet



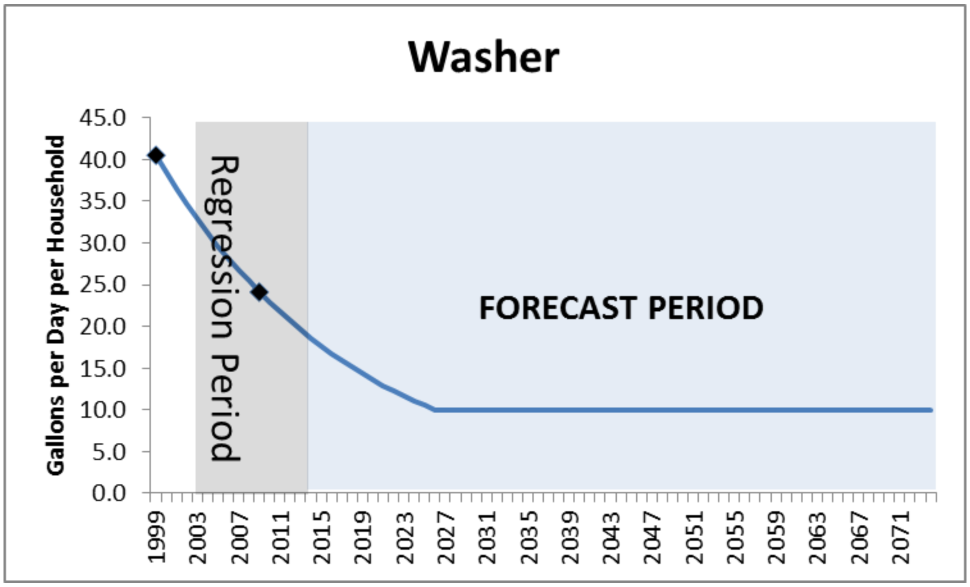
Toilet fixture water use is expected to decline by 25% between 2014 and 2024. Maximum saturation of this technology is achieved in 2038.

Figure 35: Household Gallons per Day Use by Fixture - Shower



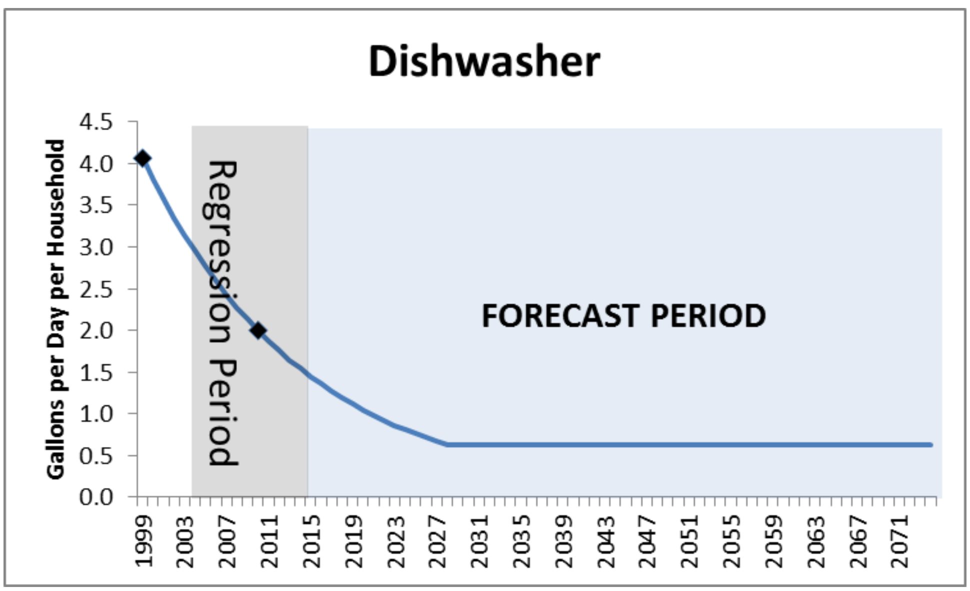
Shower fixture water use is expected to decline by 9% between 2014 and 2024. Maximum saturation (red line to show the maximum conservation reached) of this technology is achieved in 2092.

Figure 36: Household Gallons per Day Use by Fixture - Washer



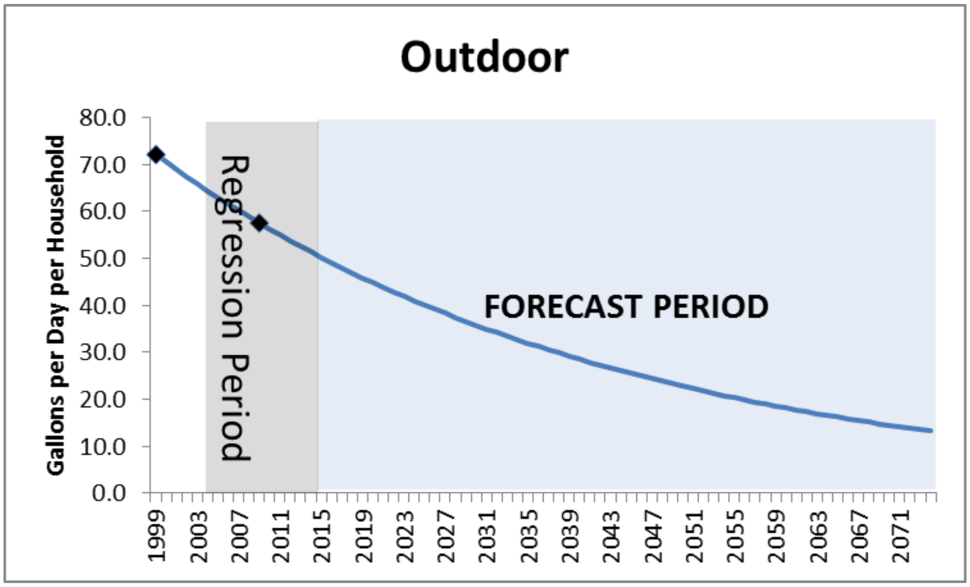
Washer fixture water use is expected to decline by 43% between 2014 and 2024. Maximum saturation of this technology is achieved in 2025.

Figure 37: Household Gallons per Day Use by Fixture - Dishwasher



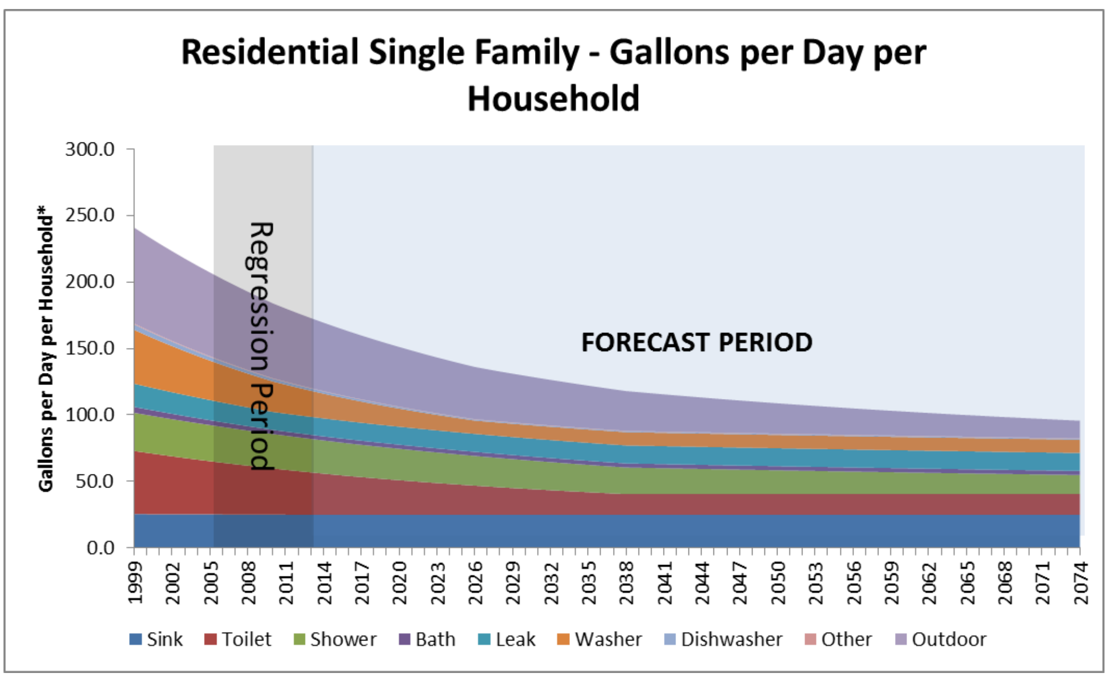
Dishwasher fixture water use is expected to decline by 48% between 2014 and 2024. Maximum saturation of this technology is achieved in 2028.

Figure 38: Household Gallons per Day Use by Fixture - Outdoor



Outdoor demand was assumed to have a lower limit of zero, because outdoor lawn irrigation is typically an elective use (non-essential). We must note that this is a strong assumption, but we have no way of knowing the lower limit each customer's outdoor water preference would be over time. This theoretical zero limit is reached in 2322, far beyond the horizon under consideration in this demand forecast.

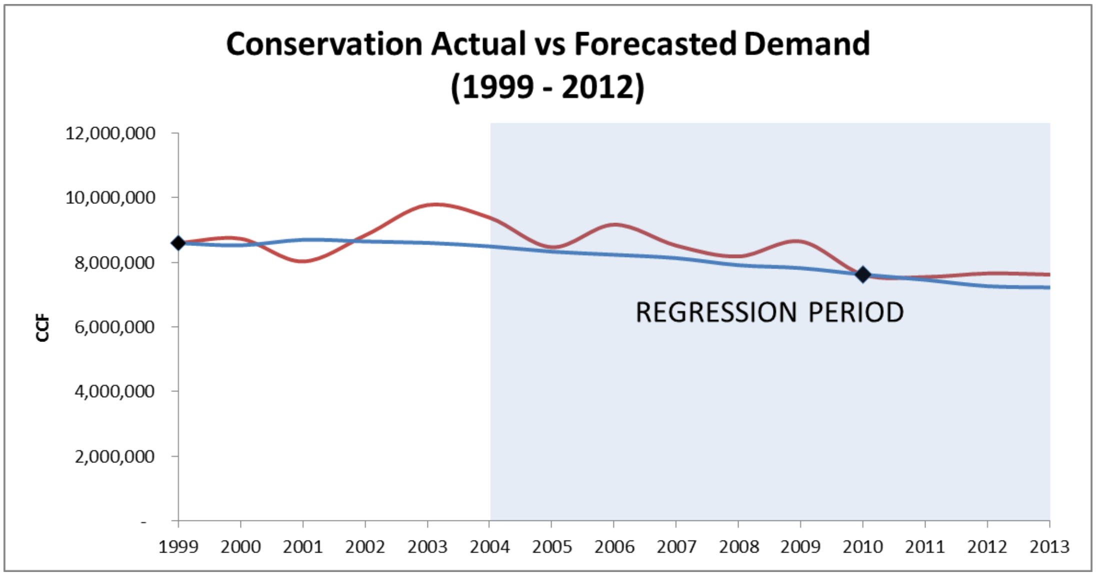
Figure 39: Summary of Gallons per Day per Household by Fixture



*Outdoor application is a seasonal metric and not indicative of everyday use. However, for comparison purposes this has been made into a daily figure.

We have assumed that conservation is not probabilistic but deterministic for this forecasting effort. We do not realistically know what the upper and lower bounds for conservation are based on one study, nor do we have enough data to create unbiased variables. That is to say that our forecasted conservation assumptions represent our most-likely estimate. We are, however, confident the forecasted residential demands between 1999 and 2013 track the data well as seen in the Figure below:

Figure 40: Residential Conservation Historical and Forecasted Demands



The forecasted conservation line has a MAPE (Mean Absolute Percentage Error) of 4.98%. We also note that the line travels on the lower end of demands because 2010 was a cold/wet year in which the demand was taken. Therefore, the conservation curve is not representative of a typical year we would see under more normal weather circumstances. The lower trend line means we are not fully capturing how our residential customers behave in a given year. We recommend pursuing more surveys and data logging events which we will discuss further in the conclusions.

Historical and MLF Demands for Regressed Customer Classes

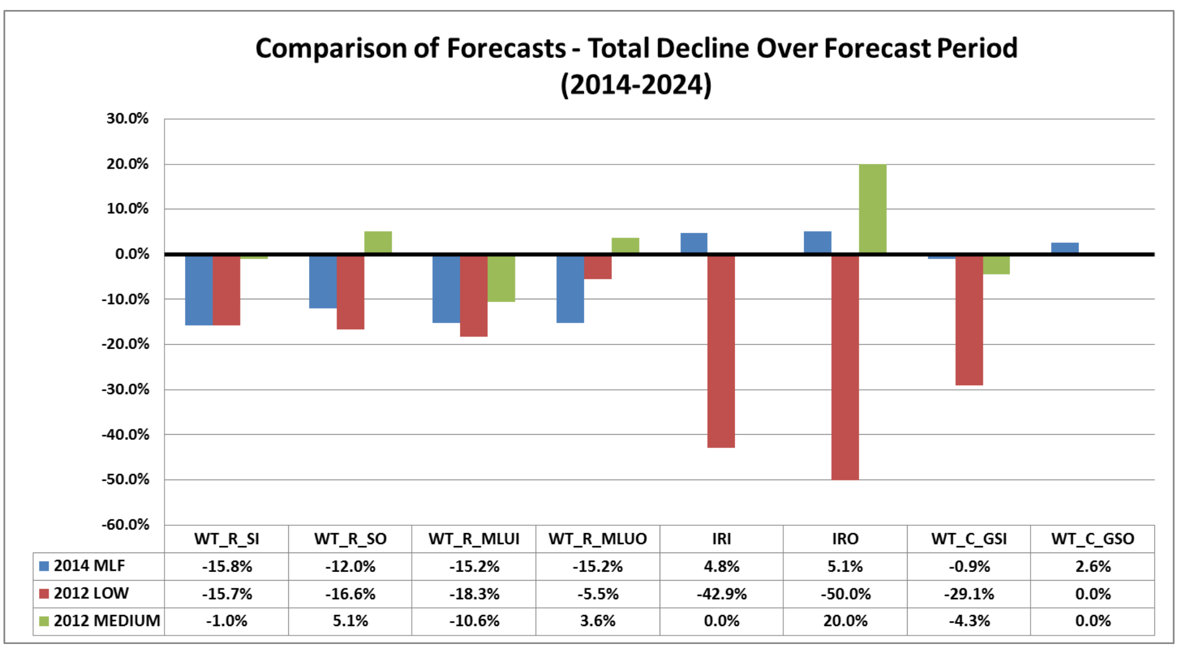
After incorporating conservation and account growth the Most Likely Forecast (MLF) demands show an overall decline of 10.6% from 2014-2024 (see below). The main causes of decline are tied to residential conservation (single-family and multi-family). We predict that overall retail demands will decline by approximately 1% per year over the 10-year period. Highlighted below in the Table are the regression results:

Table 7: Historical and Forecasted Retail Billed MLF Demand (MGD)

	Single-Family Inside	Single-Family Outside	Multi-Family Inside	Multi-Family Outside	Irrigation Inside	Irrigation Outside	Commercial General Inside	Commercial General Outside	Total	
2004	11.56	7.63	3.79	2.14	0.38	0.26	5.75	1.47	32.97	Historical
2005	10.42	7.01	3.49	2.04	0.78	0.23	5.48	1.38	30.83	
2006	11.04	7.82	3.51	2.11	1.08	0.36	5.58	1.05	32.54	
2007	10.28	7.24	3.44	2.03	1.00	0.31	5.40	0.90	30.61	
2008	9.96	6.87	3.35	2.02	0.92	0.40	5.12	0.88	29.52	
2009	10.37	7.41	3.40	2.06	1.01	0.40	5.06	0.95	30.68	
2010	9.22	6.45	3.26	2.00	0.71	0.29	4.65	0.81	27.39	
2011	9.18	6.34	3.28	1.96	0.74	0.29	5.04	0.80	27.63	
2012	9.21	6.53	3.23	1.96	0.85	0.43	4.86	0.83	27.91	
2013	9.09	6.58	3.27	1.95	0.90	0.41	4.67	0.83	27.69	
2014	8.56	6.29	3.12	1.89	0.87	0.36	4.88	0.85	26.83	Forecasted MLF
2015	8.40	6.22	3.07	1.85	0.88	0.36	4.84	0.85	26.47	
2016	8.25	6.14	3.04	1.82	0.89	0.36	4.84	0.86	26.20	
2017	8.11	6.06	2.96	1.79	0.89	0.36	4.84	0.86	25.88	
2018	7.97	5.98	2.92	1.78	0.90	0.37	4.84	0.86	25.62	
2019	7.83	5.91	2.88	1.74	0.90	0.37	4.84	0.86	25.33	
2020	7.70	5.83	2.82	1.71	0.91	0.37	4.84	0.86	25.05	
2021	7.57	5.76	2.78	1.68	0.91	0.38	4.84	0.87	24.78	
2022	7.44	5.69	2.74	1.65	0.91	0.38	4.84	0.87	24.52	
2023	7.32	5.61	2.69	1.63	0.92	0.38	4.84	0.87	24.26	
2024	7.20	5.54	2.65	1.60	0.92	0.38	4.84	0.87	24.02	

The majority of the observed and forecasted declines in demand are felt in the residential class. We can see irrigation, both inside and outside the Tacoma city limits, experiencing strong growth. Commercial General Inside and Outside are expected to be nearly flat. Many of our forecasted results are similar to the 2012 forecast with some notable exceptions (irrigation and commercial general) – the shift in results is shown in the Figure below:

Figure 41: Forecast Comparison 2012 Medium and Low Scenarios vs MLF 2014



The prior external forecast did not examine account level details and overlooked accounts which caused significant differences in demand between one year and the next. Below are some factors which caused such dramatic shifts in commercial and irrigation between the 2012 forecast and the 2014 forecast:

Table 8: Differences between 2012 and 2014 Irrigation and Commercial Forecasts

Category	Effect on Forecast
Smaller data set (2004-2010 vs 2004-2013)	The shorter timeframe emphasized the decline in irrigation demands between 2009 and 2010. Actual demand nearly recovered in irrigation by 2013.
Metro Parks inter-rate category shifts	Between 2008 and 2012 Metro Parks was moved between Commercial (Off-Peak Season) and Irrigation (Peak Season). Our forecast accounted for this and included Metro Parks Demand into Irrigation for the entire historical period, as their demands going forward will be in this class.
The Great Recession	The “Low 2012” forecast continued the Great Recession forward until 2014. The “Medium 2012” forecast zeroed out the Great Recession in the forecast period. The “2014 MLF” carried the Great Recession forward for the whole period as a permanent shock.

Non-Regression Demands & Combined Forecast Results

After forecasting retail demands for the rate categories listed above using regression results, we applied alternative methodologies to forecast rate categories for which conventional regression-based forecasting is inappropriate. These rate categories are large volume, wholesale, the pulp mill (currently West Rock), and private fire.

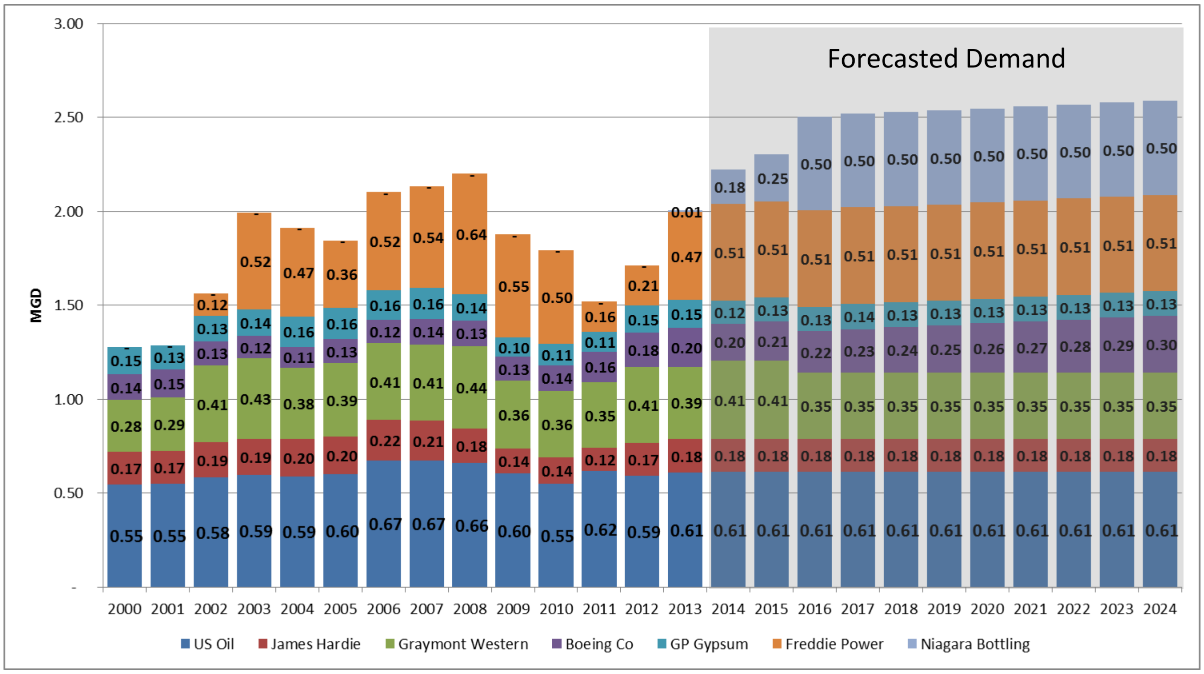
Tacoma Water has seven customers in its Large Volume Commercial customer class. In order to be included in this class, a customer must use more than 65,000 CCF per year, or approximately 133,000 gallons per day. Presently, the customers included in this rate category are:

Table 9: Large Volume Customer Profile

Large Volume Customer	Water Use Application	2013 Demand (MGD, ADD)
US Oil	Cooling process	0.61
James Hardie	Industrial process (Cement) & Cooling Process	0.18
Graymont Western	Industrial process (Quicklime) & Cooling Process	0.39
Boeing Company	Industrial (Cleaning) & Cooling Process	0.20
GP Gypsum	Industrial process (Drywall) & Cooling Process	0.15
Frederickson Power	Industrial process (Gas-fired combined cycle steam)	0.47
Niagara Bottling	Product (bottled water)	0.01

As can be seen in the Table above, these customers each use water differently in their respective production processes. As a rate class we estimate an increase of 16.37% (2014-2024) or an additional 0.36mgd which is largely attributed to forecasted growth as communicated by Boeing. Figure 29 below shows historical demand by these customers going back to 2000, and forecasted demand from 2014-2024.

Figure 42: Large Volume Historical and Forecasted Demands (MGD)



We see a slight overall increase due mainly to demand growth at Boeing and the introduction of Niagara Bottling to the Frederickson area of the service territory. However, these gains are dampened by Graymont Western, which is expecting to achieve a 15% reduction in demand by year 2016. This decline in demand was estimated after dialogue with the customer about a new tailings pond. Both Boeing and Niagara's growth estimates are based on conversations with the customers.

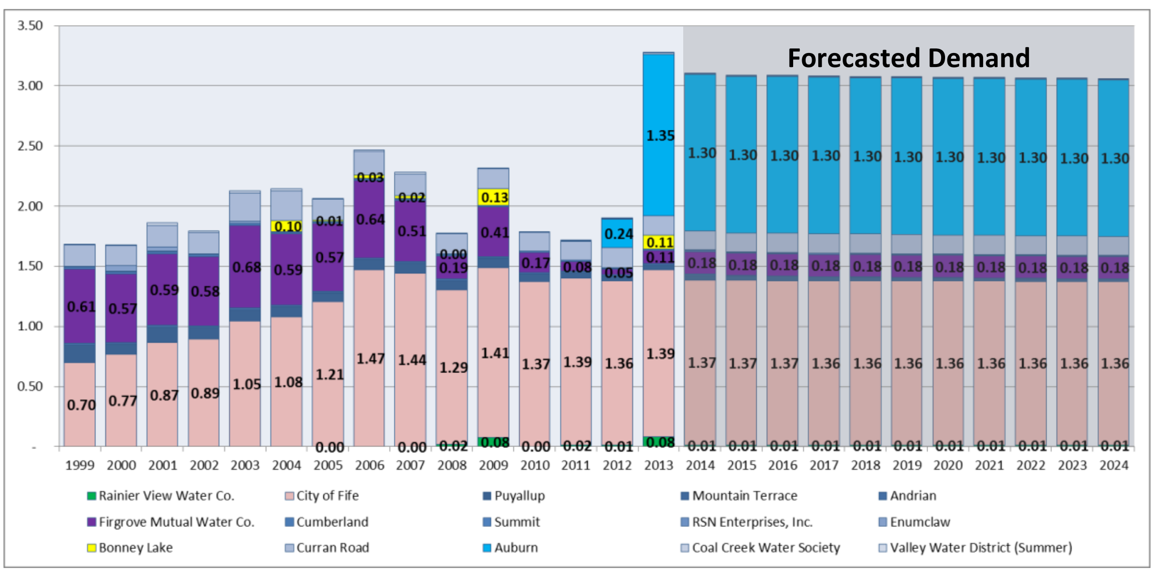
In addition to large volume commercial demands, Tacoma Water provides wholesale service to a number of other utilities, which are shown in Table 8 below. These customers vary in size and use water very differently depending on the configuration of their own systems, and it is for this reason that their demands were forecasted from results gleaned in conversations with utility management or independently forecasted by Tacoma Water using historical data.

Table 10: Wholesale Customer Demand

Wholesale Customer	2013 Average Day Demand (MGD, ADD)	2013 Peak Season Demand (MGD, Jun-Sep)
City of Fife	1.39	1.92
City of Auburn	1.35	1.77
Firgrove Mutual Water Company	0.11	0.04
Curran Road	0.16	0.21
City of Bonney Lake	0.11	0.29
Rainier View Water Company	0.08	0.15
Cumberland	0.01	0.01
City of Puyallup	0.04	0.06
Summit	-	-
Mountain Terrace	<0.01	<0.01
RSN Enterprises, Inc.	<0.01	0.01
Coal Creek Water Society	0.01	0.01
Andrain	0.01	0.02
City of Enumclaw	<0.01	<0.01
Valley Water District	<0.01	<0.01

In total, we estimate a decrease of -1.43% (2014-2024) or a loss of 0.04 mgd, for the wholesale class – a relatively flat growth rate. This is predicated on an assumption that pricing continues as is – success in selling market-based water may result in increases in demand from what is shown in Figure below:

Figure 43: Wholesale Historical and Forecasted Demands (MGD)



Rainier View and Bonney Lake only utilize the system during hot/dry summers (2009 and 2013), because this is the Most Likely Forecast we have ignored them. The additional 0.05mgd of demand from Auburn in 2013 was due to a facility failure and was not assumed to carry into the future. The Cities of Fife and Auburn are Tacoma Water's largest wholesale customers, representing 83% of Tacoma Water's wholesale deliveries. Fife's "Holt

Well" is assumed to not be built, and Auburn is expected to use a similar amount of water in the future to what they have been using.

Demand from the Pulp mill (WestRock), which is in its own customer class by contract, was projected for 2014 and held constant for the remainder of the forecast period based on feedback from WestRock staff. Private Fire (an insignificant amount of demand) was held constant for all of the forecasted years. The forecast historical and forecasted results are shown below:

Table 11: Wholesale, Private Fire, Large Volume, and Pulp Mill Demand Forecasts (MGD)

	Private Fire	Wholsale	Pulpmill	Large Volume	Total
2004	0.04	3.37	16.49	1.75	21.65
2005	0.04	3.25	14.91	2.32	20.52
2006	0.02	2.85	13.75	3.15	19.77
2007	0.07	2.26	14.98	2.79	20.09
2008	0.06	1.78	15.94	2.71	20.48
2009	0.03	2.31	15.14	2.44	19.93
2010	0.04	1.79	15.83	2.46	20.12
2011	0.03	1.72	16.01	1.81	19.56
2012	0.02	1.96	16.06	1.68	19.71
2013	0.02	3.33	16.02	1.92	21.29
2014	0.03	2.97	16.07	2.22	21.28
2015	0.03	2.95	16.07	2.30	21.34
2016	0.03	2.95	16.07	2.50	21.54
2017	0.03	2.94	16.07	2.51	21.55
2018	0.03	2.94	16.07	2.52	21.56
2019	0.03	2.94	16.07	2.53	21.56
2020	0.03	2.93	16.07	2.54	21.57
2021	0.03	2.93	16.07	2.55	21.58
2022	0.03	2.93	16.07	2.56	21.59
2023	0.03	2.93	16.07	2.57	21.59
2024	0.03	2.92	16.07	2.58	21.60

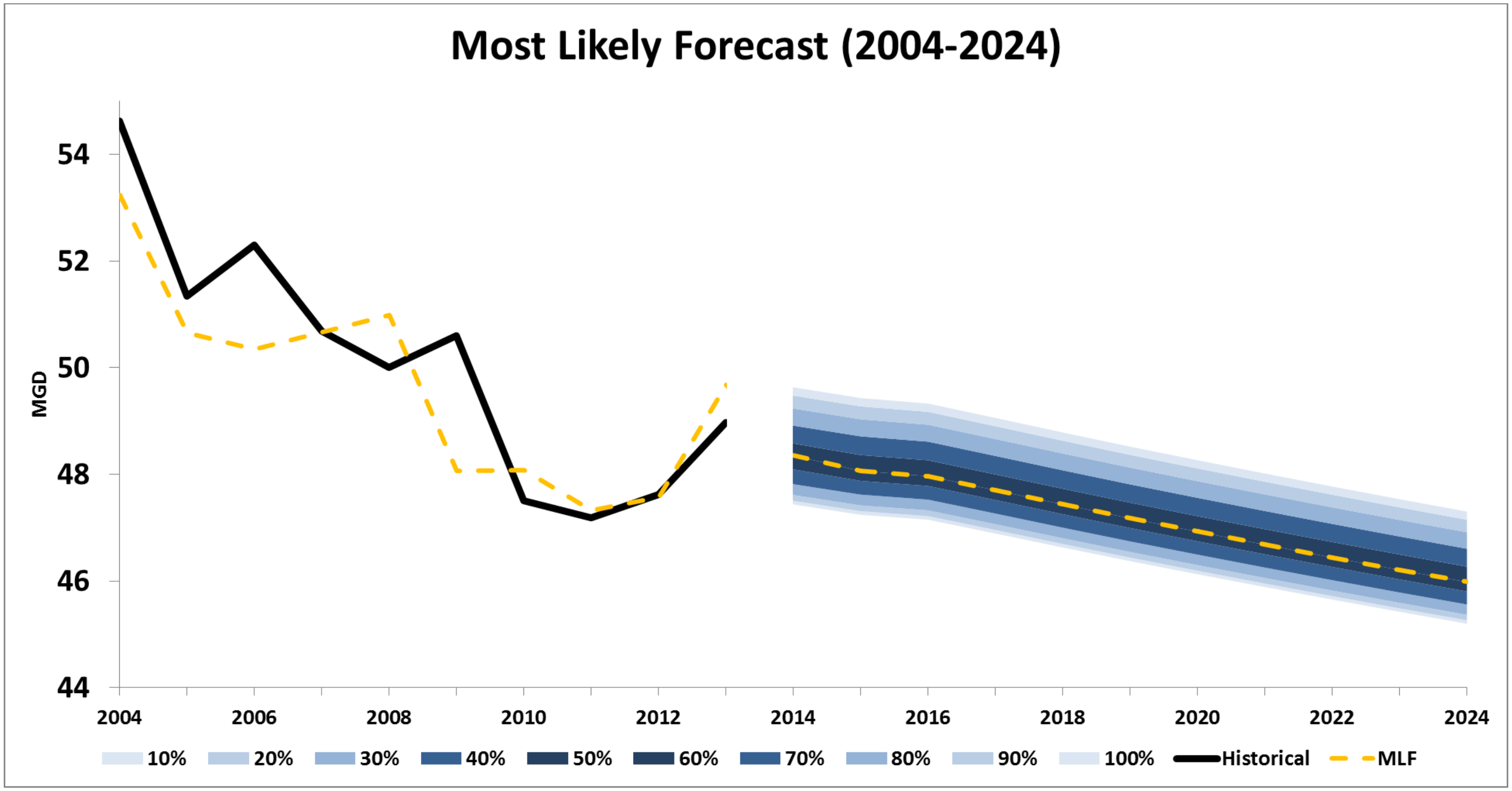
We have forecasted per account demands for all customer rate categories, projected probabilistic weather patterns through 2024, constructed regression models for 12 different rate categories, forecasted each category through 2024 with those regressions, and applied conservation to Residential Single-Family and Multi-Living Unit categories. The results of the most-likely forecast and recent historical demands are seen in the Table below:

Table 12: Short-Term Forecasted Demands (MGD)

Year	Residential Single-Family - Inside City	Residential Single-Family - Outside City	Multi-Living Unit - Inside City	Multi-Living Unit - Outside City	Parks and Irrigation - Inside City	Parks and Irrigation - Outside City	Commercial General Services - Inside City	Commercial General Services - Outside City	Private Fire	Wholesale	Pulpmill	Large Volume	Total	
2004	11.56	7.63	3.79	2.14	0.38	0.26	5.75	1.47	0.04	3.37	16.49	1.75	54.63	**HISTORICAL**
2005	10.42	7.01	3.49	2.04	0.78	0.23	5.48	1.38	0.04	3.25	14.91	2.32	51.34	
2006	11.04	7.82	3.51	2.11	1.08	0.36	5.58	1.05	0.02	2.85	13.75	3.15	52.31	
2007	10.28	7.24	3.44	2.03	1.00	0.31	5.40	0.90	0.07	2.26	14.98	2.79	50.69	
2008	9.96	6.87	3.35	2.02	0.92	0.40	5.12	0.88	0.06	1.78	15.94	2.71	50.01	
2009	10.37	7.41	3.40	2.06	1.01	0.40	5.06	0.95	0.03	2.31	15.14	2.44	50.60	
2010	9.22	6.45	3.26	2.00	0.71	0.29	4.65	0.81	0.04	1.79	15.83	2.46	47.51	
2011	9.18	6.34	3.28	1.96	0.74	0.29	5.04	0.80	0.03	1.72	16.01	1.81	47.19	
2012	9.21	6.53	3.23	1.96	0.85	0.43	4.86	0.83	0.02	1.96	16.06	1.68	47.62	
2013	9.09	6.58	3.27	1.95	0.90	0.41	4.67	0.83	0.02	3.33	16.02	1.92	48.98	
2014	8.56	6.29	3.08	1.89	0.87	0.37	4.88	0.83	0.03	2.97	16.07	2.22	48.06	**FORECAST**
2015	8.40	6.22	3.04	1.85	0.88	0.37	4.84	0.83	0.03	2.95	16.07	2.30	47.77	
2016	8.25	6.14	2.98	1.82	0.88	0.37	4.84	0.83	0.03	2.95	16.07	2.50	47.65	
2017	8.11	6.06	2.93	1.79	0.89	0.37	4.84	0.84	0.03	2.94	16.07	2.51	47.38	
2018	7.97	5.98	2.88	1.76	0.89	0.38	4.84	0.84	0.03	2.94	16.07	2.52	47.09	
2019	7.83	5.91	2.83	1.73	0.90	0.38	4.84	0.84	0.03	2.94	16.07	2.53	46.82	
2020	7.70	5.83	2.78	1.70	0.90	0.38	4.84	0.84	0.03	2.93	16.07	2.54	46.55	
2021	7.57	5.76	2.74	1.67	0.91	0.38	4.84	0.84	0.03	2.93	16.07	2.55	46.29	
2022	7.44	5.69	2.69	1.65	0.91	0.39	4.84	0.85	0.03	2.93	16.07	2.56	46.04	
2023	7.32	5.61	2.65	1.62	0.91	0.39	4.84	0.85	0.03	2.93	16.07	2.57	45.79	
2024	7.20	5.54	2.61	1.60	0.92	0.39	4.84	0.85	0.03	2.92	16.07	2.58	45.55	
% Forecast Decline (2014-2024)	**-15.82%**	**-11.96%**	**-15.20%**	**-15.20%**	**4.80%**	**5.14%**	**-0.94%**	**2.56%**	**0.00%**	**-1.43%**	**0.00%**	**16.37%**	**-5.21%**	
Forecast Decline (MGD) (2014-2024)	**(1.35)**	**(0.75)**	**(0.47)**	**(0.29)**	**0.04**	**0.02**	**(0.05)**	**0.02**	**-**	**(0.04)**	**-**	**0.36**	**(2.50)**	

We expect a total decline of 2.50 MGD or 5.2% from 2014-2024. We will experience the highest customer growth in outside city rate categories. The probabilistic results are in the Figure below:

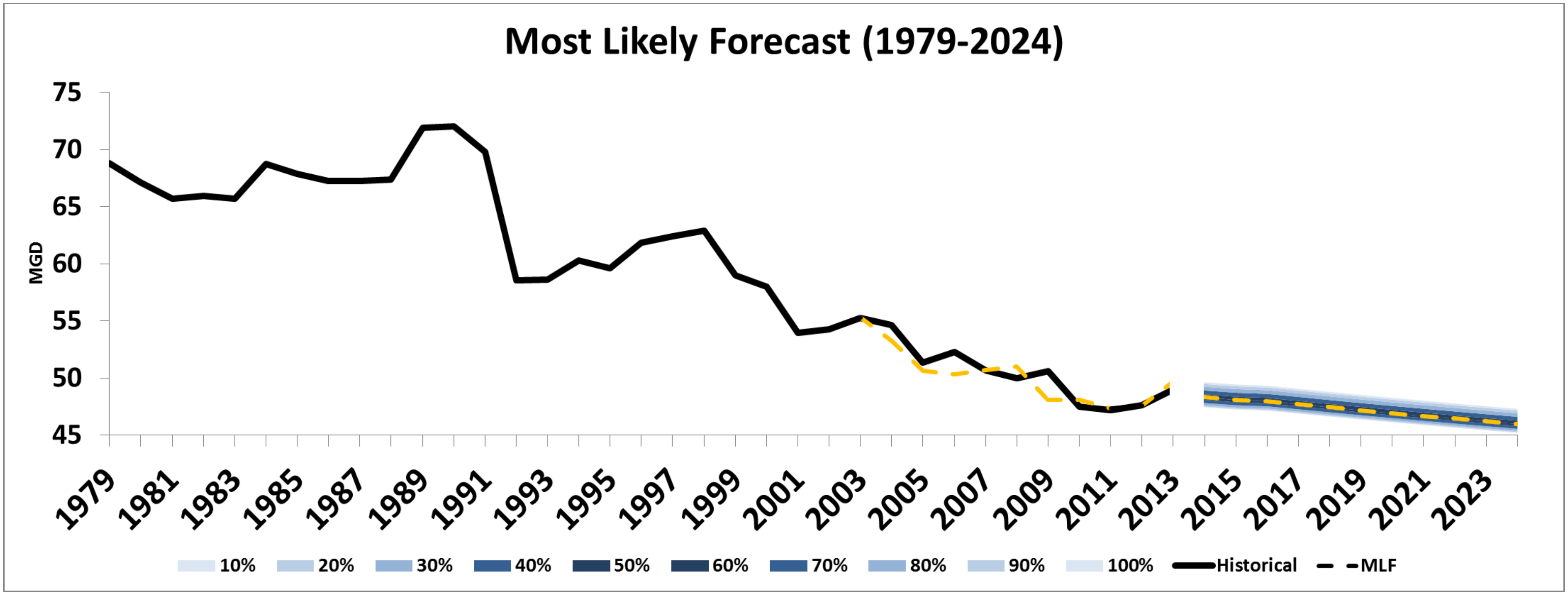
Figure 44: Short-Term Most Likely Forecast (2004-2024)



Over the next ten years, we expect demands to decline between 3.7% and 8.0% from 2013 levels, with a most-likely forecasted decline of 5.2%. This probabilistic range is due to variations in precipitation and temperature as discussed above. The distribution of the weather-based probabilities around the most-likely forecast is not symmetrical – demand is clearly more sensitive to hotter and drier conditions during the summer months than it is to cooler and wetter conditions in the winter. These asymmetric results are in line with basic water application and literature. We can clearly see that in the last two years demands have been on the higher end of the scale with both summers being hot and dry, coming off the lows of 2010 and 2011 which were both uncharacteristically cold and wet for the summer season. We should also note that much of the significant declines between

2004 and 2014 are due in large part to large volume customers and commercial customers closing down or reducing their take. In the Figure below we see the same chart but with a longer historical period back to 1979:

Figure 45: Short-Term Most Likely Forecast (1979-2024)



When displayed with a long-term historical perspective we can clearly see the major declines and the forecast continuing the downward trend. At this stage in the process we have forecasted all rate categories needed for COSA and rate design. However, there are some important steps between the forecast and COSA/Rate Design. We must adjust demand and accounts in order to produce *revenue-generating* demand and *revenue-generating* accounts as described below in "Ex Post Modeling – Revenue Generating & Jurisdiction Breakout" – otherwise we would over-estimate forecasted revenues. Also, we must separate rate categories into the various jurisdictions, e.g. Outside City splitting into Puyallup, University Place, Lakewood, Fircrest, and Outside City (Unincorporated Pierce and King counties, Ruston, etc.).

Post Forecast Modeling – Revenue Generating & Jurisdiction Breakout

Tacoma Water has noted a difference between the theoretical revenue and actual billed revenue, which must be accounted for when projecting demands for financial purposes. Theoretical revenue is what one would expect to achieve given the projected demand and account information. Actual revenue is what we actually will report in our financial results. These do not ever match exactly. There are various reasons why this difference exists: (1) Meter shut offs or partial year customers and (2) how taxes are charged in SAP vs how we recover them through rates. Below are the average adjustments to the variable demands and the contract months billed by overall rate category:

Table 13: Average Revenue Generating Adjustments by Rate Category

Rate Category	Average Adjustment Variable Demand	Average Adjustment Contract Months Billed
Residential	-1.02%	-0.14%
Commercial	-0.64%	-0.10%
Large Volume	-0.27%	0.56%
Private Fire	N/A	-0.56%
Parks & Irrigation	-0.13%	2.08%
Wholesale	-5.47%	-3.03%

(1) Partial year customers such as Parks and Irrigation class customers, we believe, are shutting off their meters seasonally and incurring a second meter charge upon turning the meter back on, which results in revenues that are higher than one would expect based on the account data.

(2) Wholesale variable demand revenue is adjusted downward by 5% because we include the State Public Utility Tax in the wholesale rate. We then back the tax out, in the interest of transparency, as a separate line item on the bill.

After calculating what adjustments must take place for the rate class we begin to break apart Outside City customers into three sub-categories based on their rate category: (1) Outside City (unincorporated Pierce County, and City of Ruston), (2) City of Fircrest, and (3) University Place, Lakewood, and Puyallup. The rate class categories are created by examining historical proportions of accounts by meter size by jurisdiction compared to the total Outside City rate class. In the Table below we have these breakouts listed:

Table 14: Annual Jurisdictional Allocation of Demands

Rate Class Category	2010	2011	2012	2013
Outside City	73.6%	73.4%	73.3%	73.7%
Fircrest	0.2%	0.2%	0.2%	0.2%
Lakewood, University Place, and Puyallup	26.3%	26.4%	26.5%	26.1%
Total	100.0%	100.0%	100.0%	100.0%

As we can see with the table the jurisdictional allocation of demands does not change drastically from one year to the next. An average was taken for the purposes of allocating demands and customer

Long-Term Forecast

The long-term forecast is a 60-year forecast of daily demands that is meant to provide decision-makers with a tool that can help with supply planning and management, and inform long-term water supply agreement development. Because this application is different from near-term financial planning, the methodology used to develop the forecast is also different, including the nature of the historical data used to conduct the initial regression analysis, the nature of our analysis of conservation efforts, the projection of weather variability into the future, and the format of the forecast results. Ultimately, the forecast results will need to work in concert with the utility's yield and hydraulic modelling work so that utility managers and planners can understand the manner in which supply constraints might materialize in the future. Because these constraints might materialize in many different ways, the long-term forecast was developed with the capability to forecast demands at daily, weekly, monthly, or annual levels of resolution.

Data used to inform the Long-Term Forecast

The long-term forecast uses much of the same data as the short-term forecast, however there is typically less processing and averaging, because the data is analyzed and reported as a daily figure. The daily information allows for Tacoma Water to link daily weather patterns or events with daily system-wide demand. We have also gathered census household counts from the 2001 Pierce County Coordinated Water System Plan (PCCWSP 2001) instead of using the 2010 estimated US census block[7] data. The PCCWSP 2001 was chosen because this option was expedient, and at the time we did not have access to block group census data[8] (more on this below). The PCCWSP 2001 had households and accounts by jurisdiction. The numbers of households were linked to accounts information (single-family households to single-family accounts) and this ratio was forecasted into the future.

We have also used our conservation, large volume, wholesale, and Pulp mill assumptions from the short-term forecast for the long-term forecast's post-modeling process.

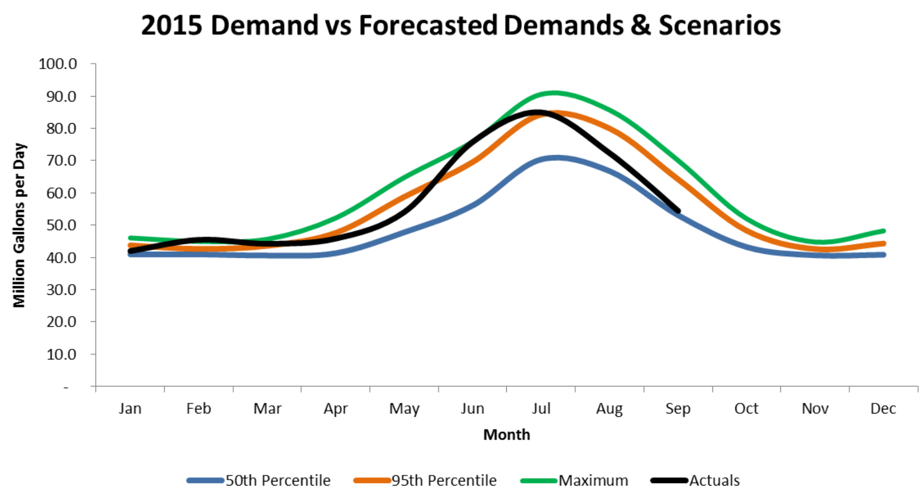
[7] A census block is the smallest geographic unit used by the United States Census Bureau for tabulation of 100-percent data (data collected from all houses, rather than a sample of houses). The number of blocks in the United States, including Puerto Rico, for the 2010 Census was 11,155,486.

[8] This, however should change now that Tacoma Water's ESRI ArcMap GIS software has been populated with the census information and our service territory.

Application of the Long-term Forecast: Supply and Infrastructure Management

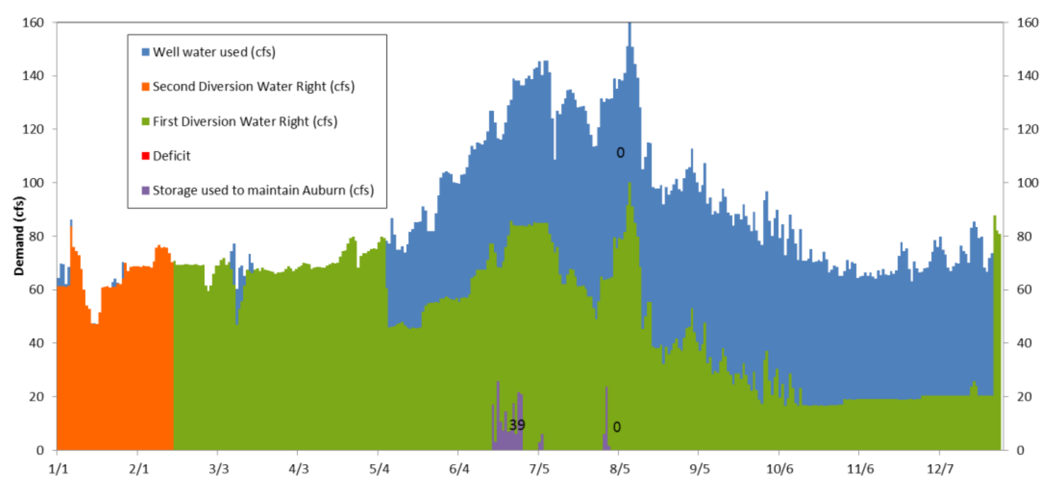
The long-term forecast is meant to be used for supply and infrastructure management. Tacoma Water's Supply group has been utilizing the results of the long-term forecast to monitor demands against expectations in real-time, as shown in the Figure below:

Figure 46: Actual and Forecasted Demand Scenarios for 2015



By tracking demand in real-time it offers engineers and management the tools necessary to make supply management decisions concerning the use of storage, wells, surface water, or purchasing water via wholesale. The probabilistic nature of the forecast also allows for setting targets during voluntary/mandatory curtailment and scenario testing as seen in the Figure below:

Figure 47: Supply Shortage Model



The Figure above was developed by the Supply group to analyze each category of supply (e.g. wells and surface water) to monitor the potential shortages which is predicated on the long-term forecast's 95th percentile demand shape. The scenario development and usage of probabilities is still in its infancy for

Tacoma Water and we can expect to develop a fully functioning supply model which will, instead of single scenario testing, the model will be capable of testing all probabilities and incorporate historical yield data.

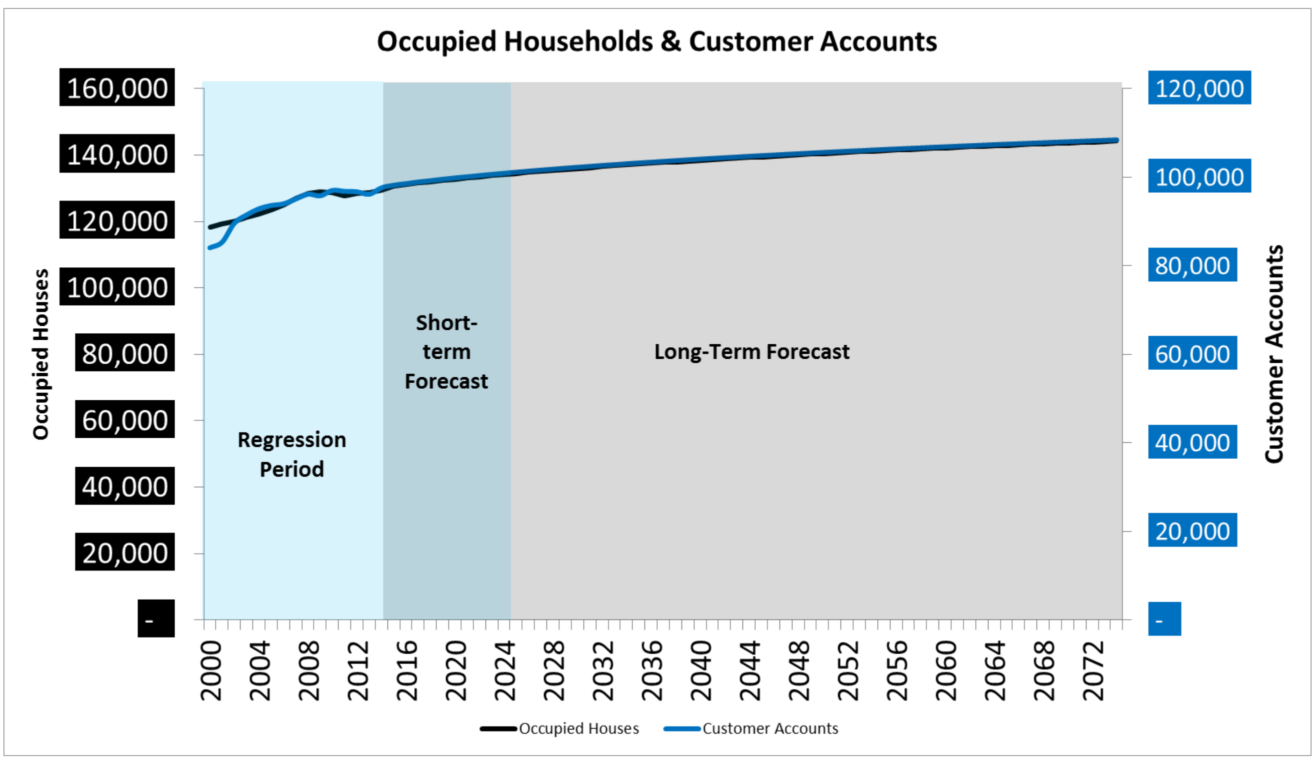
Occupied House Growth

We chose to forecast occupied household growth in the Tacoma Water service territory instead of using accounts. There are several reasons for this choice: (1) Census block data is very accurate during census years (100% accuracy). (2) Accessibility of data and forecasts once Tacoma Water ESRI GIS is operational will be easy and defensible. And (3) Accounts makes no distinction between occupied parcels and unoccupied parcels – only that a bill was sent to the owner.

One consideration was to use weighted accounts by meter size, however this would overly complicate the forecast as we would have to group various meter sizes and forecast each group. Additionally, we would also be making a very large assumption that all 2" meters consume proportionally more water than a 1.5" meter or a 5/8th inch meter – and after careful study we know this to not be the case.

Households were forecasted using the published figures in the 2001 Peirce County Coordinated Water System Plan and anchored to account growth expectations from the short-term forecast. After extending the short-term forecast account growth model to match the Long-term Forecast time horizon (60 years) we can see the logarithmic formulae at work as the model growth slows as time progresses. We then estimate household growth using the same growth assumptions as Seen in the Figure below:

Figure 48 Occupied Households & Customer Accounts



We held the ratio of houses to accounts (1.33) because this ratio was closely held for 14 of the 15 years of data. Buildout figures for Tacoma Water's service territory derive from the Pierce County Coordinated Water System Plan and Regional Supplement 2001. We have assumed that occupied housing is increasing at a decreasing rate as buildable land is developed and build out is reached. The buildout figures derive from the Pierce County Coordinated Water System Plan and Regional Supplement 2001 document. The buildout for Tacoma Water's service territory was modeled as follows:

Table 15: Tacoma Water Occupied Household Buildout

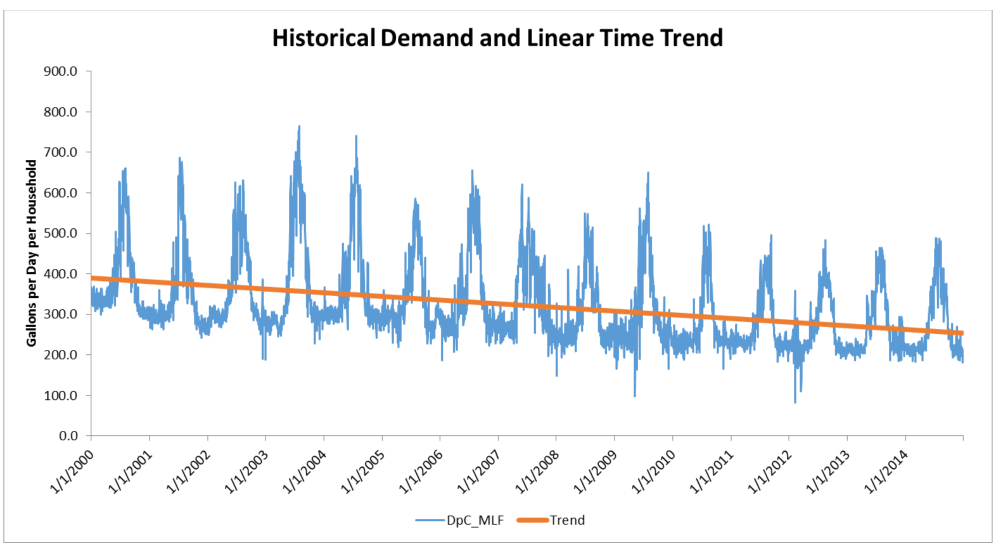
	2000	2074	Percent Change	Year over Year Percent Change	Buildout
Service Territory	118,304	144,359	22%	0.26%	167,395

Per Household Demand Regression Model

An econometric regression model was developed based on historical demand, temperature, and precipitation data. Like the short-term forecast, demands are expressed as *per household* demands in order to isolate the underlying factors influencing demand. The estimation of this model used ten years of daily data (2004-2014).

Prior to the regression model we needed to make demand stationary, i.e. the daily demand data does not deviate or move randomly over time (the DOW Jones Industrial Index is considered a random walk for example). Stationarity[9] is a central tenant of econometrics and time series forecasting. The time trend can be seen in the Figure below:

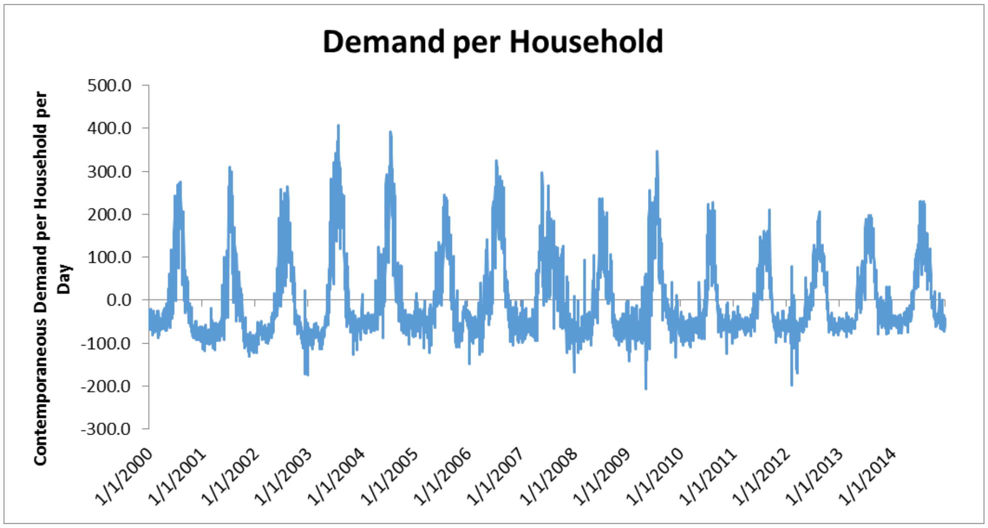
Figure 49: Historical Demand and Linear Time Trend



[9] Testing for stationarity involves testing what econometricians and statisticians call "unit roots" or "unit root testing" uses the Augmented Dickey-Fuller Test (ADF). We achieved an I(0) with the time trend and control for population growth, meaning the demand is stationary and we did not need to difference the demand data.

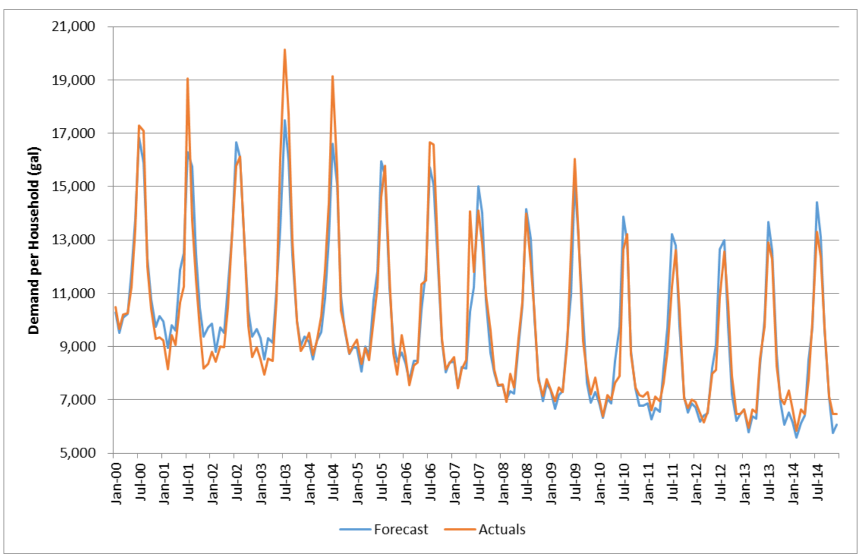
By removing the time trend and converting demands into demand per household we have a stationary time series model that measures the contemporaneous[10] demand per household as seen in the Figure below:

Figure 50: Stationary Demand per Household



The contemporaneous demand is stationary and ready for the regression. We have chosen to show the regression results in a monthly time step for visual simplicity as seen in the Figure below:

Figure 51: Estimated Demand per Household vs Historical Demand per Household (GAL)



The regression closely tracks historical demand with a daily MAPE of 8.2%, a monthly MAPE of 4.2%, and an annual MAPE of 2.4%. The model examined per household demand as a function of weather

[10] Contemporaneous meaning that we are measuring the change in demand at a point in time to a change in one of the variables (such as temperature) at the same point in time without the influence of the downward demand trend or other influences like growing population.

(temperature and rainfall), seasonal variables, indicator variables, time trend, but did not include the pulp mill or any conservation assumptions as seen in the Equation below:

Equation 9: Long-term Forecast Model

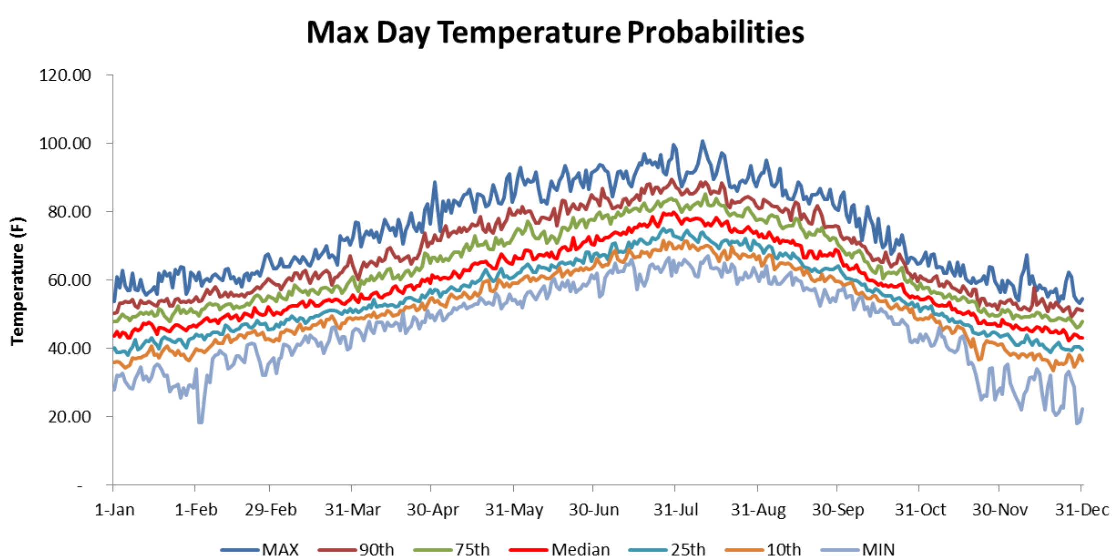
$$\frac{Demand_t}{Household_t} = \beta_0 - MaxtTemp_t + MinTemp_t + MaxTemp_t^2 - MinTemp_t^2 + MinMax_t - Rain_t + Day_t + Week_t + Month_t - Holiday_t - Recession_t + Large\ Volume_t + Trend_t$$

The forecast will require some post-regression modeling such as probabilistic weather, including short-term forecasting assumptions from the Pulp Mill (West Rock), Large Volume Commercial, and Wholesale customers, and Residential conservation.

Weather

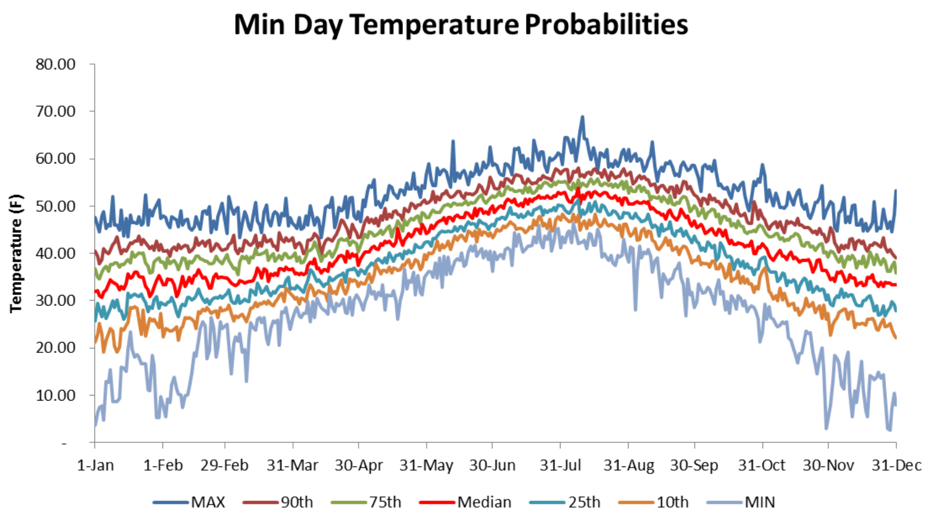
The long-term forecast utilizes the same 51 years of historical daily weather data consisting of max day temperate, min day temperature, and rainfall as the short-term forecast. However, because the forecast is in a daily time step there is little processing of the weather data which needs to occur. Each data series were analyzed in periods of 365 days (ignoring leap years) to generate the probabilities necessary for supply planning and wholesale market-based agreements as seen in the Figure below:

Figure 52: Max Day Temperature Probabilities



The max day temperatures have a wide range, approximately 20 degrees difference, throughout the fall and spring periods, but increases to a 30 degree spread during summer. We can see the lowest recorded (MIN) max day temperatures have a much larger spread than the other percentiles during the November – February time period. The winter divergence is also seen more clearly in minimum daily temperatures seen in the Figure below:

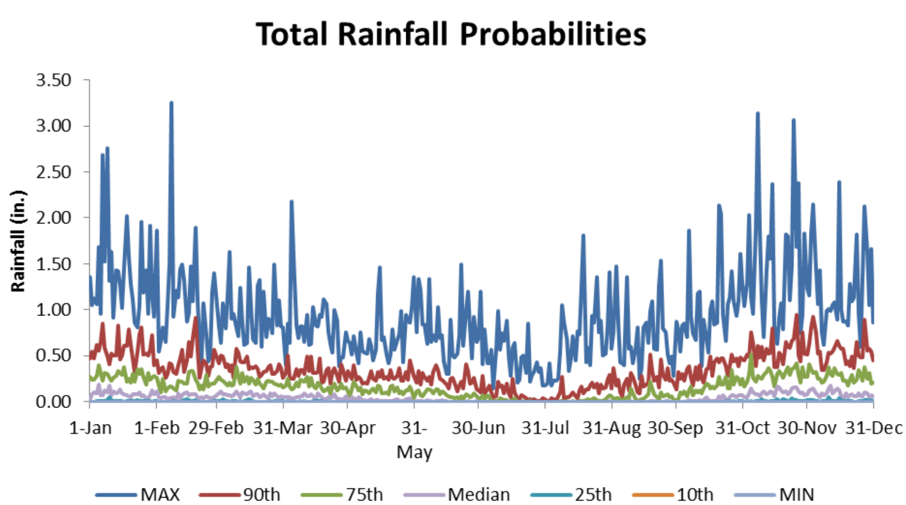
Figure 53: Min Day Temperature Probabilities



Min day temperature data has a wider dispersion during winter (approximately 40 degrees). However, during the summer the spread diminishes to a mere 20 degrees between the highest recorded min day temperature and the lowest min day temperature.

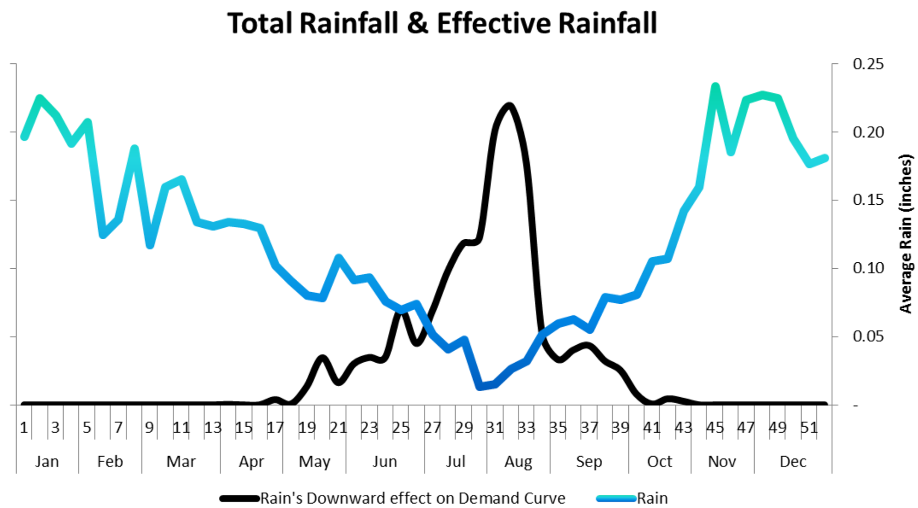
Rainfall was also analyzed in terms of probabilities as shown in the Figure below:

Figure 54: Total Rainfall Probabilities



The rainfall results are interesting, as the median rainfall for the winter, spring, and fall is slightly above 0, however the maximum rainfall ranges from 0.5 inches of rain to a torrential downpour of over 3.0 inches of rain per day. Rainfall is expected to have a negative influence on demand, i.e. the more it rains the less demand there is. However, this is only the case during the summer period as rainfall only changes outdoor irrigation application behaviors. Through hypothesis testing and model building we examined the effect rainfall had on demand at a weekly time step compared to when there was no rainfall. The results show there is a strong correlation between declines in demand and rainfall as the Figure below highlights:

Figure 55: Average Total Weekly Rainfall & Effective Rainfall

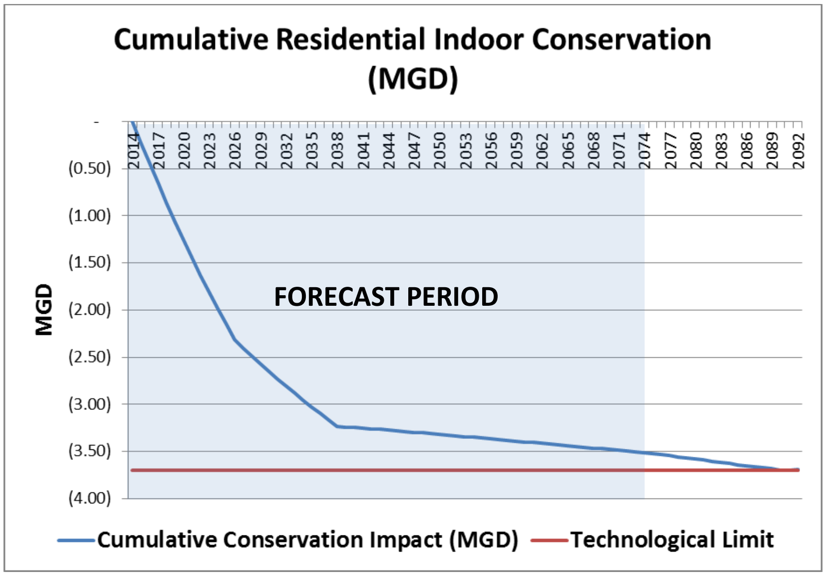


Interestingly there is little to no influence during the off-peak season (October through April), but between May and late September there is a quadratic-like shape which peaks in late July and early August. With these results we zeroed out all rainfall data between October 1st to April 30th and only left the rain that was within the May through September time period. We may need to examine cloud cover as well, as there may be times when there is significant cloud cover but no rainfall, or a weather prediction of rainfall, but no rain actually occurs (a false positive) as either of these events may also lead to declines in demand which are currently not captured in our analysis.

Post Regression Modeling – Conservation

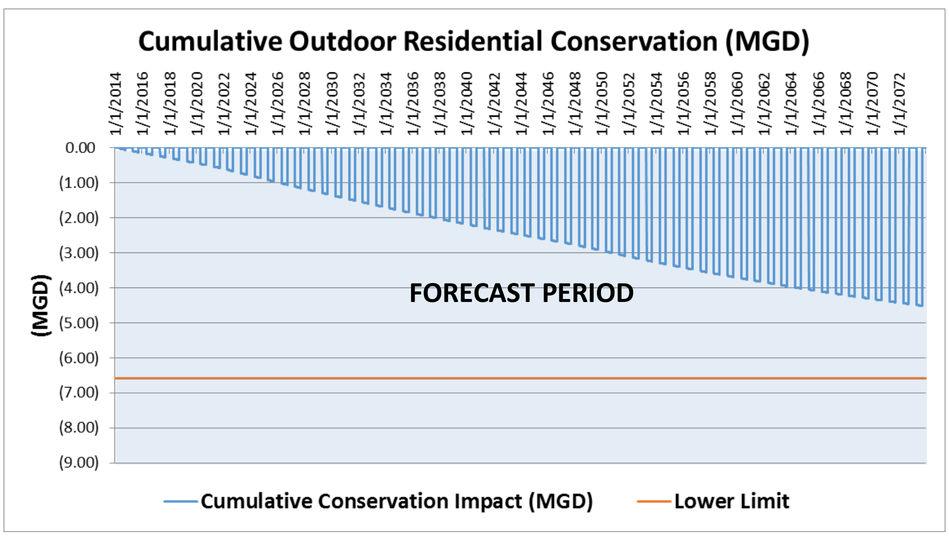
Conservation data derives from the 2010 End Use Study as per the short-term forecast. However, the data was converted from annual figures to daily figures. Indoor conservation by fixture was summed as the Figure below shows:

Figure 56: Indoor Residential Conserved Demand (MGD)



Indoor conservation starts with 0.0 mgd conservation in January 1st 2014 to 3.5 mgd conservation by December 31st 2073. The current technology saturation limits are reached by 2092 for indoor fixtures, with a reduction of 3.70 MGD.

Figure 57: Outdoor Residential Conserved Demand (MGD)



Outdoor conservation decline starts with 0.0 MGD conservation in January 1st 2014 to -4.63 MGD by December 31st 2073. Outdoor conservation is assumed to be 100% elective with a zero limit for water use. The theoretical limit of zero is reached in 2322 with a cumulative -6.58 MGD applied to system-wide demands. The 6.58 MGD, again, only represents the estimated conservation achieved from Residential customers. The current short-term and long-term forecasts contain no assumptions for Commercial General Service, Irrigation, or other rate categories. There is a real need to begin collecting data from daily meter reading data and regularly scheduled customer surveys.

Post Regression Modeling – Wholesale, Large Volume, & Pulp Mill

Wholesale and Large Volume rate categories were forecasted in the short-term demand forecast and were incorporated into the long-term forecast. However, the forecasted demands were held constant past 2024. To incorporate the rate categories into the long-term forecast we differenced the annual forecasted demands of each rate category and made these into daily demand figures. This was the best option available given that large volume and some wholesale customers are not tracked daily[11]. Tacoma Water was in the process of installing either SCADA or AMI technology on all wholesale customers, this will help modeling efforts and forecasting efforts for the class in future forecast efforts.

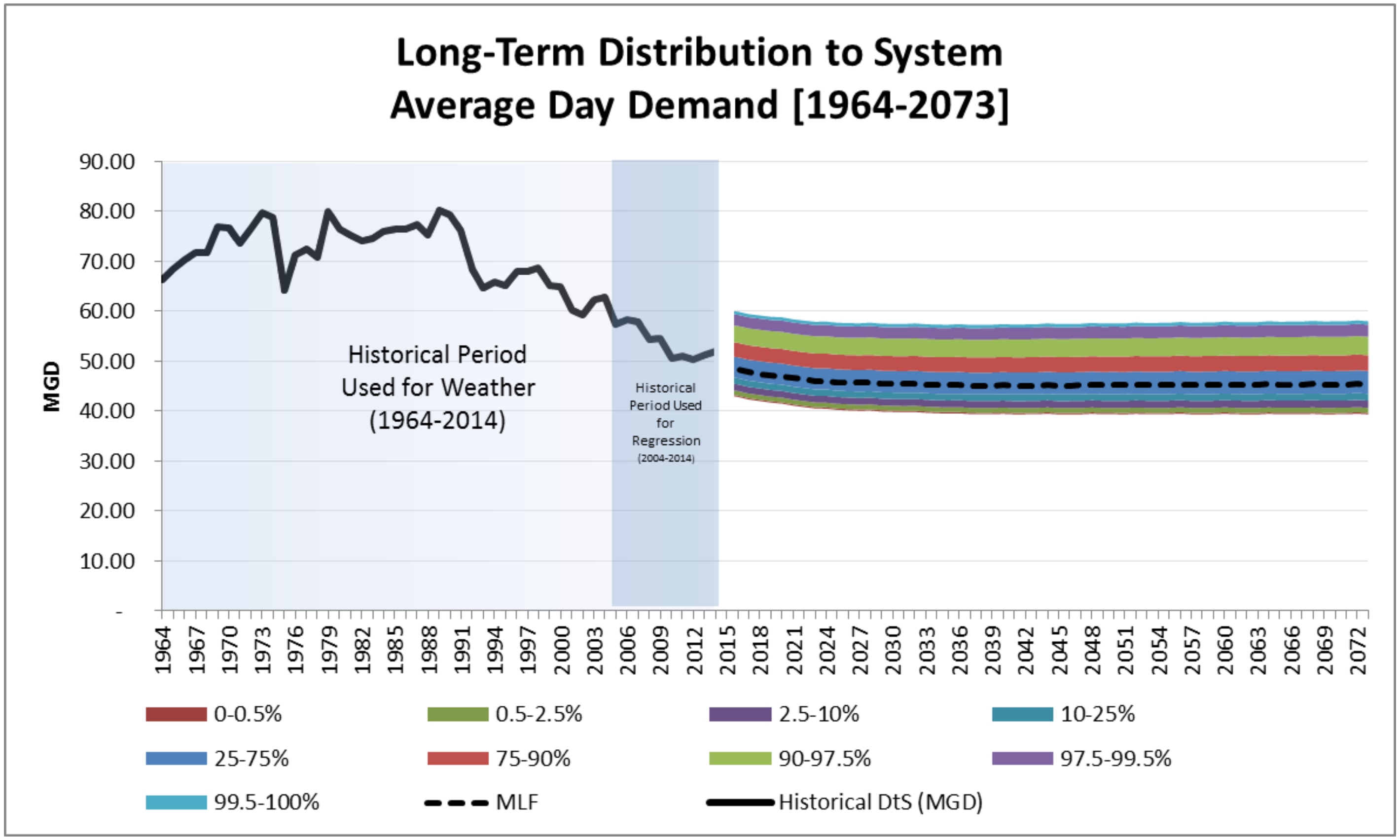
The Pulp Mill was also added in the post-processing phase. This was simply applying the Short-Term Forecast where we estimated 16.07 MGD. The long-term forecast made no additional assumptions and held the 16.07 MGD constant through the forecast.

[11] There are some wholesale customers who were connected to AMR, however these customers had serious data deficiencies due to technology persistent data failures. We decided to treat the class in the same manner rather than differing methodologies for individual customers when their forecasted change is small relative to the system-wide demand.

Historical and MLF Demands

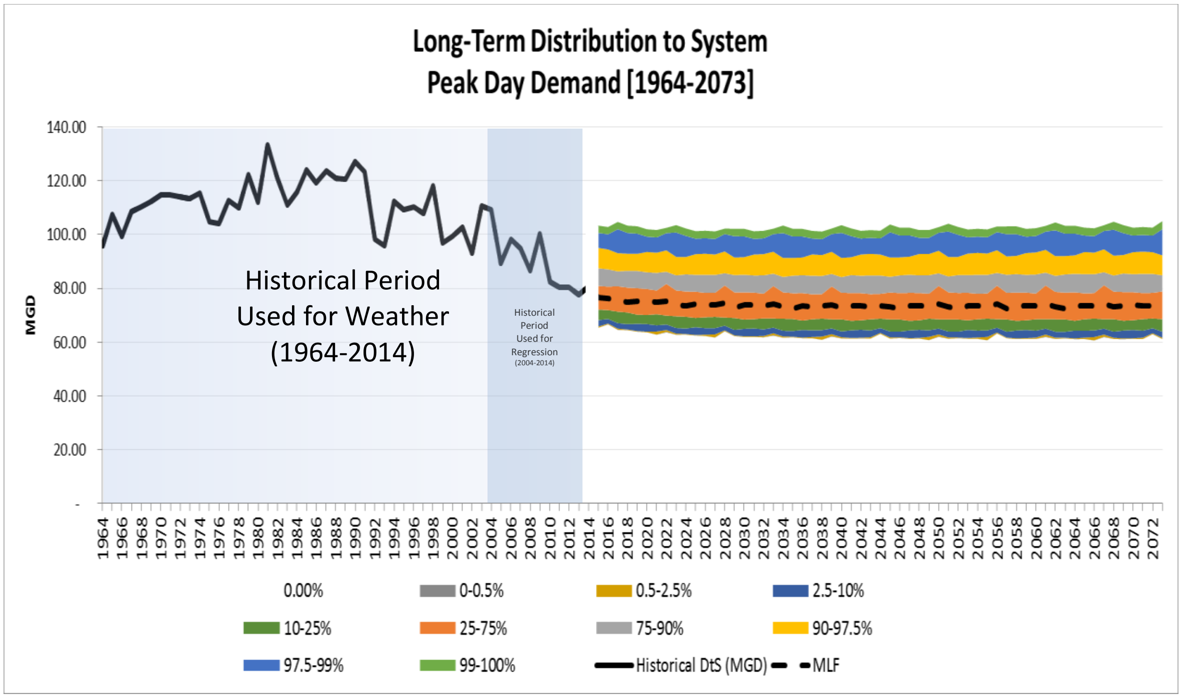
After combining all of the forecast modeling and post-forecast modeling we ran a macro for each year of historical weather data we collected (51 in total), this process created 51 daily forecasts which we did a final processing step to examine the various percentiles based on the 51 differing forecasts. The percentiles generated Most-Likely Long-Term Forecast Figure below:

Figure 58 Long-term MLF Historical and Forecasted Average Day Demands – 1964-2072



The Long-term Most Likely Forecast average day demand shows a decline of 12.7% from 2015-2073. We predict that overall distribution to system demands will decline by 0.23% per year, on average over the forecast period. There is significant upside to our forecasted demands based on the nature of water demand's correlation with hot temperatures as we can see in the peak-day demand forecast in the Figure below:

Figure 59: Long-Term MLF Forecast Peak Day Demand (1964-2073)



We can see from 1964 to 2014 there is extreme volatility between years as we measure peak-day demands. The gyrations from year to the next of the forecast line are due to the time indicator variables. These variables inevitably set a constant floor for which demand is set, for example Monday increases demand by 1.4 gallons per household whereas the first week in the year decreases demand per household by 20 gallons. These are static effects placed on demand, however from one year to the next the last day of July may fall on a Monday rather than a Tuesday which changes the "floor" at which demand can be influenced by weather.

We estimate that peak day demands will decrease between 6.4% or increase by 1.6% from 2015 to 2072 with a median decline of 4.4% in peak-day demand or 0.08% per year. The demand bands (seen in Figure 38) skew higher because of the exponential effect of high temperature and no rainfall on demand.

Conclusions

Tacoma Water has taken well established econometric forecasting methodologies and yielded two similar yet distinct forecasts to aid in financial and supply planning. The Short-Term forecast has been fully incorporated into the rate setting and financial model for budgeting and adopted rates for our retail population of 320,000. The Long-term forecast has been utilized during the 2015 drought for supply planning, backcasting, and estimating the effects of voluntary curtailment messaging on demand.

The results show the downward trend continuing well beyond the 2024 end-date of the short-term forecast and well into 2035 in the long-term forecast. We expect billed demands to decline between 8% and 3% with a most-likely decline of 5.2% by 2024. However we expect system-wide demands to decline by 23% or increase by 12% with a most-likely decline of 12% by 2073.

We plan to rerun the short-term forecast every biennium as the forecast is directly linked to budgeting and Cost of Service Analysis (COSA). The long-term forecast will be rerun annually to track overall shifts in system-wide demand, major developments (recessions, new large volume customers, or droughts), and for aiding efforts in the Supply group to begin managing Tacoma Water's Supply/Demand balance in a probabilistic manner. These probabilistic models will examine inflow data to the Howard Hanson Dam and ultimately the Green River (Tacoma Water's main source of supply) and various well capacities located throughout Tacoma Water's system.

To improve the both forecasting efforts we plan on installing smart meter technology to collect daily read data. The improvements may not be in time for the 2017/2018 biennial budget and COSA, but in later iterations this is a real possibility. This will allow for more accurate modeling for conservation (in various rate categories), and the daily data will also allow for wholesale and large volume forecasting that aligns with the long-term forecast's daily time-step.

We have automated the collection of billed data to a SQL server; this is a vast improvement in time management and quality control compared to the methods used above in the short-term forecast. However, there are still many internal Tacoma Public Utility practices that must be changed to improve the data quality such as: stopping the adjustments of demand in reversed bills, smoothing artificial increases in demand due to billing backlogs (November – January timeframe), and creating a systematic way to deal with or prevent incorrect or incomplete data ("Z'ed" out addresses, missing meter sizes, etc.). We would also like to move towards true monthly meter reads or have customers remain on the same meter reading schedule instead of moving between monthly and bi-monthly schedules and back again.

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