Water Demand Forecasting in the Puget Sound Region:
Short and Long-term Models

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Abstract

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Water demand forecasting has become an essential ingredient in effective water resources planning and management. Water forecasts, together with an evaluation of existing supplies, provide valuable triggers in determining when, or if, new sources of water must be developed. In the Puget Sound area, this emphasis on accurate water forecasts is particularly important. There is an increased need for water demand forecasts as water rights conflicts continue, the area's population grows, the need for instream flows is more accurately quantified, and additional uses and needs of water are identified.

Forecasting provides a simulated, though rarely perfect, view of the future. Forecasting water demand is inherently challenging, as the factors that most directly affect water demand are difficult to predict. However, effective water resource planning can account for economic, social, environmental, and political impacts on water demand. Though water demand models assume various forms, models developed in this research address integrated approaches to both short-term (up to six months) and long-term (decades into the future) models. These models developed six-month demand forecasts including National Centers for Environmental Predictions (NCEP) climate variability for the Seattle, Tacoma, and Everett regions. This research also considers, if modeled successfully, that a spatially disaggregated model based on per capita, economic, and climate variables could provide utilities the ability to micromanage water use, identify specific problem areas, and negotiate urban development based on resource supply. Three methods in modeling highly disaggregated water use databases are presented in support of establishing a renewed framework for a Seattle long-term water demand model. Finally, this research also considers definite applications of the models presented and future investigations that would strengthen the existing study.

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Chapter 1. Introduction

Early settlers in the United States found that "everywhere one turned, one saw water, cheap water, inexhaustible water, and when there were more virgin rivers and aquifers to tap, the illusion was temporarily real" (Reisner, 1993). Where adequate rainfall, snowmelt, and groundwater met the needs of a young nation, this vision was accurate. However, as settlers overwhelmed the west, they encountered an environment that was more hostile and extreme than the east and where climate variability resulted in decade-long droughts. The history of water resources in the west from the early to mid-twentieth century is a tale of the development of dams and supply systems. These systems were constructed to protect growing agricultural and municipal interests from the devastating impacts of droughts. During this time, supply capacity was constructed for both current and anticipated demands, and there was little evaluation of the potential negative impact of providing water for all demands.

Today, water demand forecasting has become an essential ingredient in effective water resources planning and management. Water forecasts, together with an evaluation of existing supplies, provide valuable triggers in determining when, or if, new sources of water must be developed. However, the cost of securing new water supplies has grown dramatically. The recognition of the negative impacts of water withdrawals on the aquatic ecosystem has also grown. The importance of accurate estimates of future water demands and their role in public planning is now well recognized.

In the Puget Sound area, this emphasis on accurate water forecasts is particularly important. Though the region continues to grow in population, water demand within the region has shifted. There is an increased need for water demand forecasts as water rights conflicts continue, the area's population grows, the need for instream flows is more accurately quantified, and additional uses and needs of water are identified. Though municipal water supply plans from the 1970s and 1980s anticipated dramatic increases in water demands in the region, demand has decreased in average per capita consumption and in total municipal and industrial demand in the region. In the winter of 2003, the region experienced the water demands similar to those in the mid-1970s of Seattle Public Utilities. This is a result of successful conservation programming and a change in the regional attitude toward water use.

Forecasting provides a simulated, though rarely perfect, view of the future. However, accurate forecasts of demands and estimates that anticipate future water use patterns rather than simply extending old patterns, extremely valuable in estimating regional needs for water. These demand forecasts can contribute to identifying appropriate management alternatives in balancing supply and demand. Water resource planning must account for economic, social, environmental, and political impacts on water demand (Kindler and Russell, 1983). Forecasting water demand is inherently challenging, as the factors that most directly affect water demand are difficult to predict. Viewed in its simplest form, future water demands are a function of a region's population, the growth or decline of its industrial activity, technological changes, code changes, water pricing, and changes in outdoor water use associated with weather and landscaping choices. Unforeseen events significantly impact these factors.

For example, changes in international trade policy may affect regional water demand. A change in timber policy may increase the price of timber in the United States, making it less competitive on the global market. This could result in the closure of a large industrial mill and the elimination of its water demand. Water saving technology in household or industrial equipment, such as dishwashers, washing machines, or toilets can also markedly change water use. Forecasting such broad impacts and technological changes is difficult. Figure 1 presents forecasts of water demand made by the City of Seattle in 1968 and in 1980. In contrast with actual demands, forecasts have significantly overestimated future demands. These results indicate that poor model inputs can result in very poor output. During the 1970s and 1980s the region was expected to grow dramatically and regional resource managers were eager to meet these demands.

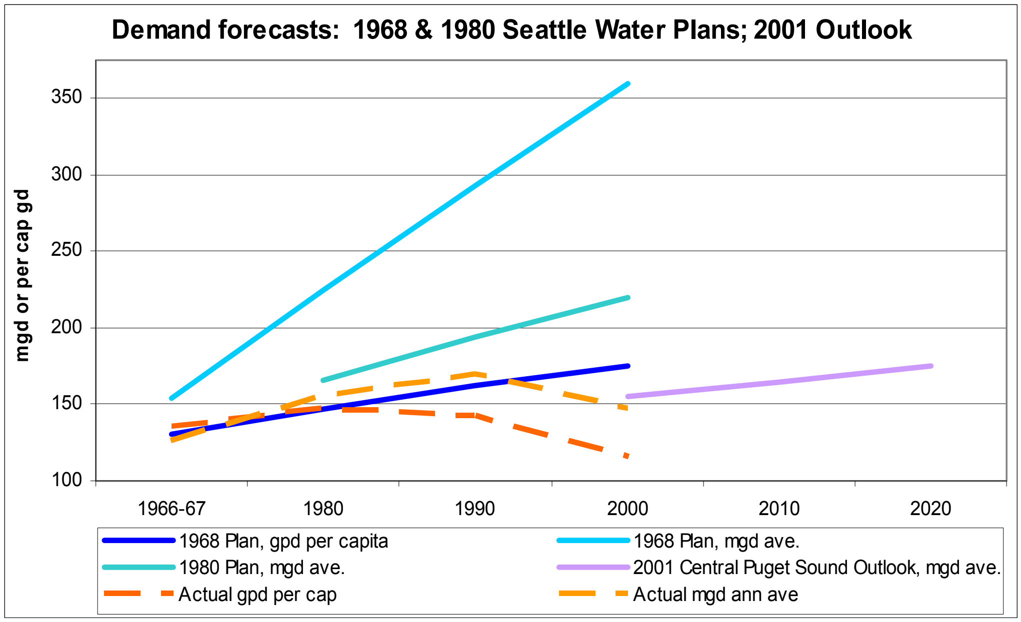

Figure 1. Graphical representation of Seattle water demand forecasts vs. actual demand, according to the 1968 and 1980 water plan documents.

Water demand models assume various forms. Models can be aggregated into simple and pliable models or disaggregated by region, population, or location. Models also vary in the timeframe of the data included and the breadth of the processes modeled. This thesis addresses both short-term (up to six months) and long-term (decades into the future) water demand forecasts in the Puget Sound region. The thesis will illustrate the history and future of forecasting models and their value.

The original scope of this research included a long-term, spatially distributed water demands for the city of Seattle. If modeled successfully, a spatially disaggregated model based on per capita, economic, climate, as well as spatial variables would provide utilities the ability to micromanage water use, identify specific problem areas, and negotiate urban development based on resource supply within the city. In addition, this project sought to develop six-month demand forecasts including National Centers for Environmental Predictions (NCEP) climate variability for the Seattle, Tacoma, and Everett regions.

Both the long- and short-term demand models developed in this research were created through multiple regression analysis, a common approach to modeling water demands. Water demand forecasting requires extensive data. The work presented here represents not only modeling successes and difficulties, but also the recruitment and creation of databases critical to these attempts. While this research may not pioneer a new effort in water resources research, as regional utilities already use models similar to those presented here, the research acknowledges a need for improved models using more effective model variables, and increased model accuracy created by personnel outside the utility.

This thesis presents the data, methods, results, and applications of demand forecasting models for the Puget Sound. These models are valuable in creating accurate regional supply and demand estimations, infrastructure claims, and conservation strategies. The improved accuracy and independent variable inclusion will provide more accurate estimations of regional demand. This study also provides an opportunity to expand on regional forecasting techniques, question and validate the philosophy behind forecasting, and make recommendations for future regional demand forecasting efforts.

The demands on water resources in many regions of the world exceed supplies. As resource managers and modelers, the task is not to accommodate or stifle these growing needs, but to design a system that can accommodate these changes in the future. This is only possible with a demand forecasting model that effectively incorporates changes in the social, economic, and environmental features in predictions of future water consumption in a growing region.

Chapter 2. The Creation, Value, and Limits of Demand Forecasting

> A common characteristic of water resources planning is its failure to anticipate change.
>
> -Sewell, 1978

Because it is difficult to anticipate change in human and natural systems, resource engineers have developed predictive models that guide our management of water supply and demand. Predictive models have become commonplace in all phases of planning, providing resource managers guidance for the various possible futures (Law and Kelton, 2000). Both skeptics and supporters of the science of forecasting question the philosophy, value, and application of forecast methods. With models as our most current and reliable tools to forecasting future climate and water resources, resource management often depends on them. This chapter addresses the philosophy of forecasting, how forecasts are created, and their value and limitations of forecasts in water resource planning.

The Philosophy of Demand Forecasting

> Caswell (1976)[1] addressed the fundamental duality of model as scientific theory versus model as engineering practice by differentiating the theoretical component from the operational component of a model. He distinguished two general purposes for which models are constructed: understanding (which he equated with theoretical models) and prediction (Rykiel, 1996).

According to Caswell and Rykiel, the success of simulation models results in both an improved understanding of the modeled system and a useful predictive tool. Similarly, Pace suggests the "interaction of prediction with … understanding" results in successful model construction (2001). While confident in his convictions, Pace also notes that no singular philosophy guides simulation science. Though predictive models are key

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[1] From Rykiel (1996): Caswell, H. 1976. The validation problem. *Systems Analysis and Simulation in Ecology*. Vol. IV. B. Patten, ed. New York, NY: Academic Press.

components in the sustainability of natural resources, there is no science or philosophy that absolutely guides model creation and implementation. Perhaps the philosophies that guide model use and the perspectives of several simulation scientists will provide a platform for understanding the purpose of forecast models.

The philosophies of Caswell, Rykiel, and Pace suggest that the pursuit of forecasting in research areas such as aquatic sciences will improve our understanding of forecast modeling. For example, understanding the variables within forecast models enhances the foundation for simulation science. Pace aptly characterizes the driving forces of simulation science:

> First, there is little doubt that human-driven changes in aquatic systems will require increased efforts in scientific analysis and predictive management in the future. Second, predictive approaches can be guides for research programs helping to keep attention focused on ultimate objectives and not small problems. Third, if aquatic scientists take the mandate for prediction seriously, there should be sufficient dissatisfaction with our current abilities to foster new and creative approaches (2001).

Pace suggests that the debate in simulation science is not necessarily over the philosophy of modeling or whether forecasting is worthwhile research, but rather, whether the models are appropriately validated and verified as effective predictive techniques. Rykiel (1996) and others argue that the value of simulation and forecast models is not necessarily determined by an abstract philosophy, but by the validation process that complements the models. Simulation models are used in all sectors of science and are critical components of short- and long-term natural resource management, despite the inherent unpredictability of the natural world. The goal is to create a predictive model that appropriately captures the uncertainty of the future and guides decision making. In reference to this challenge, Rykiel writes:

> The crux of the matter is deciding (1) if the model is acceptable for its intended use, i.e., whether the model mimics the real world well enough for its stated purpose (Giere, 1991)[2], and, (2) how much confidence to place in inferences about the real system that are based on model results (Curry et al., 1989)[3]. The former is validation, the latter is scientific hypothesis testing (1996).

For decades scientists and engineers have struggled with defining the terms and applying the processes of validation, verification, and calibration. Though never perfectly defined, these processes are reviewed in subsequent sections of this paper with regard to the models generated for the Puget Sound region.

Because of diverse applications of forecast models, researchers will likely never agree on the philosophy that guides simulation science. In general, however, simulation research, particularly in the management of natural resources, should have a positive impact on environmental management, as increased foresight should help us manage resources appropriately (Pace, 2001). Though agreement may not exist on how models should be validated or what model component is most critical, resource managers will continue to depend on forecast modeling in resource planning.

Forecast Methodology

Successful water demand forecasting is shaped by many components, including an understanding of what influences water demand, the availability of essential data, the stability of demand and its influences in the past, and how these influences may change in the future. Collecting data and deciding on the format of analysis are critical to the development of a reliable and credible model. A review of the traditional methods of water demand forecasting is presented.

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[2]From Rykiel (1996): Giere, R.N. 1991. *Understanding Scientific Reasoning*. New York, NY: Harcourt Brace Jovanovich College Publishers.
[3]From Rykiel (1996): Curry, G.L., Deurmeyer, B.L. and Feldman, R.M. 1989. *Discrete Simulation*. Oakland, CA: Holden-Day Publishing.

Bauman et al. (1998) suggest that the evaluation of a proper forecasting method include the following "correlates of accuracy"[4]:

- Is the chosen scope appropriate?
- Is there adequate disaggregation of the data?
- Do the model and assumptions (elasticities) reflect expectations?
- Does the model make use of the resources available?
- Is the model simple yet effective?
- Are the model and its assumptions robust?

These are important criteria as they apply to both the input data and the results of the forecast model. Consideration of these "correlates of accuracy" will likely ensure an effective water demand model.

Forecast models are primarily dependent on the data available and the models' intended use. The complexity of a model hinges on the level of detail in the data required by the model. However, a more complex model is not always more appropriate. A common philosophy in forecast modeling is the Principle of Parsimony or Occam's Razor, "if a simple process suffices, use it" (AWWA, 2001). If data are limited, a complex model of forecasting is not justified. The most common type of water demand model statistically relates future water demand to a series of explanatory variables. Once the appropriate data have been gathered, a forecast method and time-step must be chosen to complete model calibration and verification process. Explanatory variables help to calibrate the model by relating historical water demand values to a number of independent variables. Once a model has been calibrated, this model can be used to predict future water demand values.

Water demand models can have various time-steps: long (annual or decadal), medium (monthly to annual), or short term (hourly, daily, or weekly) (AWWA, 1996). For the purposes of this study, we focus on long- and short-term models. Long-term models

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[4] From Bauman et al. (1998): Ascher, W. 1978. *Forecasting Methods: An Appraisal for Policy-Makers and Planners*. Baltimore, MD: Johns Hopkins University Press.

usually focus on forecasts for 10 or more years into the future. These models help managers determine long-term infrastructure or supply changes while considering variables such as changes in population, price structure, or climate change. While these forecasts are critical to future management, such forecasts are often highly uncertain. Of course, the greater the forecast time (i.e., 30 years, 40 years), the less accurate the forecast or predictive variables tend to be. Unlike the long-term vision of the decadal model, the short-term model typically investigates periods of less than one year. These models may be used to examine the impacts of climate variability and planned seasonal operations or financial changes. Short-term models are often quite accurate, but may be plagued by unexpected changes in weather or sociologic factors. In both long- and short-term models, factors that influence water are similar. These factors are also referred to as explanatory variables and include population, the economy, technology, climate, water price, and conservation programming (AWWA, 1996). Further evidence of the impact of these factors is included in Chapters 3 and 4, as several such factors are included in the short- and long-term models for the Puget Sound region.

Two of the most common models for forecasting water demands are based on “per capita consumption” and econometric considerations. The per capita consumption method calculates the total water demand per person per year and applies a forecasted population factor to project future consumption per person. Although simple, this method is often sufficient for calculating demands and impacts on water supply. In contrast, econometric models use factors such as billing rates and personal income as variables for calculating water demands. As one of the most commonly referenced models in the field of water demand forecasting, the US Army Corps IWR-MAIN system incorporates both per capita and econometric features (USACOE, 1988).

The IWR-MAIN model disaggregates users of water into individual water use sectors to allow detailed analysis of water uses with similar characteristics. This technique has proven useful for over 30 years (Boland, 1997). The water users, or classes, include residential, commercial, industrial, and unaccounted-for or public water demand. Within each of these classes, water demand is separated into additional classes characterized by residential or commercial type. For example, single family (i.e., one household) water demand may be separate from multifamily (i.e., apartment building) water demand, and commercial water demand can be separated into a number of groups based on SIC (Standard Industrial Classification) code (Boland, 1997). This approach is often considered the most accurate method of determining future water demands. Chapter 4 describes the long-term model created for the Seattle residential water demands, based partially on the IWR-MAIN framework. In contrast, a more simplistic, short-term model using an expanded per capita approach is discussed in Chapter 3.

Model Applications

Water demand forecasts are used in many areas of utility planning. From small utility models to long-term interstate resource management, reliable forecasts are critical components of water planning and policy. To be reliable, water demand forecasts must include social, economic, and environmental factors. The use of such forecasts has become standard, particularly when considering new water resource supplies. Water demand forecasts are essential to many planning activities including expansion, expanding existing distribution systems, preparing contingency plans for droughts, evaluating conservation methods, performing sensitivity analysis using different assumptions about the explanatory variables, and assessing utility revenues (USACOE, 1988). In addition to these applications, forecasts also play an important role in cases related to climate change and the Endangered Species Act (ESA). As climate research and water allocations debates over instream habitat and other regulatory requirements continue, demand forecasts will be critical to providing information about the future of regional water resource demands and how they should be distributed.

Water demand forecasts are essential to current planning in the Puget Sound. Utilities are currently concerned with new supply developments, privatization, and the potential impacts of climate change on water demand. The issue of climate change and water resources has been addressed by water resources and climate research for years (Weiss, 1990; Boland, 1997; JISAO/SMA CIG, 2003 and in press). This research raises concerns about decreasing snow pack and subsequent decreases in summer streamflow, preserving water resources for the future, and changes in water demand due to warmer, drier summers. Research in the Bull Run watershed serving Portland, Oregon suggests that by the year 2040, 18% of the impact of climate change will be caused by changes on water demands (Palmer and Hahn, 2003). Though the impacts of climate change in the Puget Sound region are less understood, the short-term demand model development, discussed in Chapter 3, demonstrates the clear link between climate and water demand (see Figure 3) in the Seattle region. Changes in demand because of climate change may affect the way utilities proceed with supply development and conservation programming. Other water resource issues that would benefit from water demand forecasts include water conflicts throughout the West. For example, California continues to struggle with limited state resources, a contract battle over the Colorado River and growing urban populations, demand forecasts are germane to decisions about water transfers, contract battles, and new techniques in water conservation in agriculture.

Though water demand forecasts are rarely used as the only determining factor in resource planning, forecasts can prevent utilities from making needless investments and policy errors in development (AWWA, 1996). Forecasts also provide an opportunity to organize important utility information and demand data. Finally, with increasing acclaim and accuracy, demand forecasting may guide communities toward a more sustainable future in water resources.

Limitations and Uncertainty in Forecast Modeling

Though the capabilities of forecast modeling are many, they do not, unfortunately, eliminate the inherent challenges of simulation science. These challenges include modeling a complex natural environment, uncertainty in future sociologic variables, compounded uncertainty from other forecast variables (e.g., climate), inherent uncertainty in data analysis, and difficulties in model validation.

Uncertainty is a feature in the human environment, as in the natural environment. Our inability to predict future sociologic or economic variables that will affect water demand is definitely a limiting factor in simulating future demands (Ng and Kuczera, 1993). Though resource agencies (e.g., Puget Sound Regional Council, PSRC) create forecasts of future social and economic conditions, these predictions contain variables with significant uncertainty, adding error to the water demand forecast analysis. This is also true for climate forecasts. The use of forecasted climate variables in water demand models helps to model water demand under a variety of climate change scenarios. With regard to such models, Boland states "the range of predicted outcomes reflects at least a portion of the range of uncertainty regarding future weather" (1997). There is a considerable degree of uncertainty associated with climate forecasts. Uncertainties in climate, social, and economic variables are often the result of an inaccurate understanding or downscale of a climate model, as well as unexpected changes in the social and economic structure as a result of cultural trends. These uncertainties are often unpreventable and when combined may result in a model limited by both known and unknown errors and assumptions. Measuring model skill and error may help quantify this uncertainty; however, these measures will not necessarily identify the specific causes of, or solutions to, model inaccuracy.

Once researchers have selected a forecast methodology and model, progress is often hindered by difficulties with model verification, validation, and calibration. Rykiel claims that when validating a model, three prior specifications are necessary: The purpose of the model, the criteria the model must meet to be acceptable, and the context of operation (Rykiel, 1996). If these three areas are not clarified before model execution, the verification and validation of a model can limit model implementation. Rykiel's concerns are rooted in the possibility of using models that are faulty despite their appearance as capable or correct. On this issue, Rykiel notes that fellow researcher B. van Fraassen has argued “that the goal of scientific theories is not truth (because that is unobtainable) but empirical adequacy” (1996). Rykiel argues that verification for “empirical adequacy” can be quite difficult because of undetectable errors in the data and the unpredictable nature of future conditions.

Despite these limitations, forecast models provide a glimpse of the future of water resources. Though these glimpses are uncertain and limited, the option of not including the forecast is less appealing than recognizing model errors. With this need for guidance in mind, the following chapters present two water demand models. Chapter three includes short-term water demand forecasts for Seattle and other Puget Sound regions. These forecasts provide planning assistance through the incorporation of climate variability forecasts and other valuable explanatory variables.

Chapter 3. Short-term Water Demands

Short-term demand projections help water managers make more informed water management decisions to balance the needs of water supply, residential and industrial demands, and instream flows for fish and other habitat. Short-term demands aid utilities in planning and managing water demands for near-term events (Jain and Ormsbee, 2002). For the purposes of this thesis, the near term is defined as a period within the next six months. Short-term forecasting can also help managers make decisions during unexpected climate conditions, emergencies, or unanticipated financial change. Short-term forecasting models are typically based upon recent trends and actual conditions. For water demands, factors considered the most influential include recent water demands, forecasted climate, seasonal considerations, and water management policies. Demand models consider these factors and also incorporate population growth, water rate changes, and regional conservation efforts. Despite potential errors in its narrow perspective on daily weather or human behavior, short-term method of modeling water demands play an important role in seasonal water resource management techniques (Bauman et al., 1998; Billings and Jones, 1996).

The short-term demand models described in this thesis were developed to meet several needs: to provide regional utilities improved foresight in system operations, to investigate water demands during the drought conditions of 2003, and to contrast the framework for developing such demands to the techniques used for long-term demands. The goal of the short-term demand forecasting model for the Puget Sound region is to predict demands during 2003 and early 2004, using 20 different climate (temperature and precipitation) ensembles.

Seattle Public Utilities (SPU) developed a weekly model for measuring demand variability relative to weather for a reliability study during 1994-1996, but like other short-term models developed after this study, this model is no longer used. Current short-term demand modeling at SPU provides forecasts on an hourly or daily time step using a neural network modeling system. This model can be aggregated to a weekly time-step for operational planning, but it is commonly used on a shorter time-step (Kersnar, 2003). According to SPU model operators, these forecasts are very accurate and are used in regular management and system operations. Because of the short foresight of these forecasts, they do not incorporate climate variability and are unable to accurately forecast demand beyond a single day or operating period (She, 2003). The response from SPU managers to adopting a short-term weekly water demand model has been positive, as they recognize the potential impact of this effort on seasonal management of the system (SPU, 2003). This chapter will discuss methods and development of new short-term models for Seattle, Tacoma, and Everett, using data provided by Seattle Public Utilities, Tacoma Water, and the City of Everett.

Defining the Short-term Model Structure

Though there are several methods for creating short-term demand models. The short-term model used for all three systems (Seattle, Tacoma, Everett) in this research is a weekly time-step, multiple regression model run calibrated for four independent seasons. The format of the regression model is log linear, shown in Equation 1 below. Coefficients A through G are detailed in Table 2 below.

Equation 1.

$$\text{Water Demand} = \beta * \cdot A^{x_1} \cdot B^{x_2} \cdot C^{x_3} \cdot D^{x_4} \cdot E^{x_5} \cdot F^{x_6} \cdot G^{x_7}$$

Take the natural log of both sides:

$$\text{Ln(Water Demand)} = \beta* + x_1 \cdot \text{Ln}(A) + x_2 \cdot \text{Ln}(B) + x_3 \cdot \text{Ln}(C) + x_4 \cdot \text{Ln}(D) + x_5 \cdot \text{Ln}(E) + x_6 \cdot \text{Ln}(F) + x_7 \cdot \text{Ln}(G)$$

*The value of the intercept is derived in the regression analysis

The short-term demand model is a function of a number of independent variables. Table 1 identifies the variables used in the short-term demand model.

Table 1. Short-term model variables.

Dependent variable	System (SPU)-wide weekly averages
Independent variables	A. Temperature (average weekly max) (Tmax)
	B. Precipitation (weekly average)
	C. Winter water use
	D. System user population**
	E. Water rate/price***
	F. Temperature (max) (one-week **lag**)
	G. System-wide weekly average (one-week **lag**)

**Information for this variable was only available for the Seattle model.
***Water rates varied seasonally. Off-peak rates applied to September-May (1989-1994) and October-May (1995-2003); on-peak (2nd block) rates were applied to June-August (1989-1994) and June-September (1995-2003).

The seasons used in the model were selected to mimic the drawdown and refill time-periods utilized by SPU (Table 2) and are generally appropriate for Tacoma and Everett (Figure 2).

Table 2. Short-term model seasons defined.

Summer	June – August
Spring	March – June
Fall	September – October
Winter	November – February

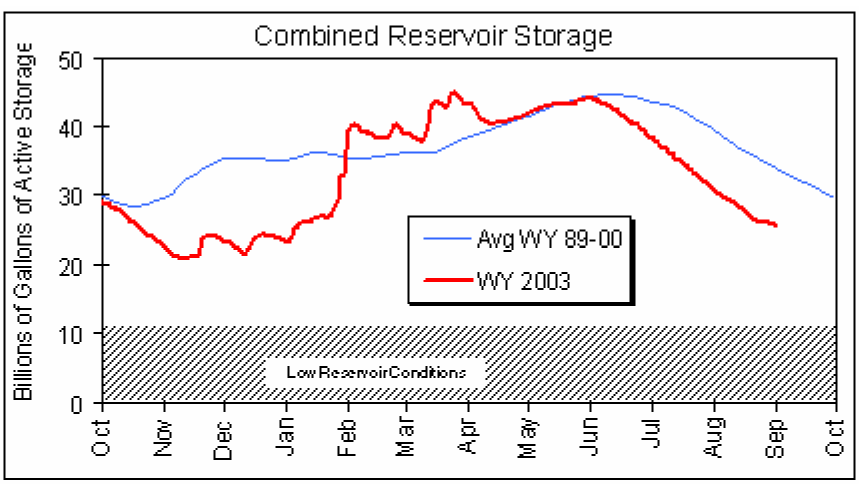

Figure 2. Combine Reservoir Storage, Seattle Public Utilities, August 2003.

A primary goal of the short-term model is to capture both the seasonal patterns of water demand and the weekly variability that is associated with climate. Jain and Ormsbee (2002) suggest that daily time-step models are likely to be highly inaccurate because of the unpredictability and variability of various parameters. Daily models can also be less appropriate for management decisions that are made less frequently. In contrast, weekly models provide strong seasonal signals without the extremes represented by daily values. Data used to calibrate and validate these models include the period from January 1989-September 2003. Data for 1992 in the Seattle model were removed from analysis because of water curtailments and restrictions instated by SPU during the 1992 drought.

Determination of the independent variables used in the model (Table 1) was completed based on recommendations from published demand models (USACOE, 1988; SPU, 2003), natural indicators and predictors of water demand (e.g., climate variables), as well as through trial-and-error of regression analyses. Because weather conditions affect outdoor water use, such conditions were captured using maximum daily temperature and precipitation. It is evident these climate factors are primary drivers of water demand in this region (Figure 3). In addition to climate variables, service area population and water rate are common to most water demand models and are critical components in determination of future use.

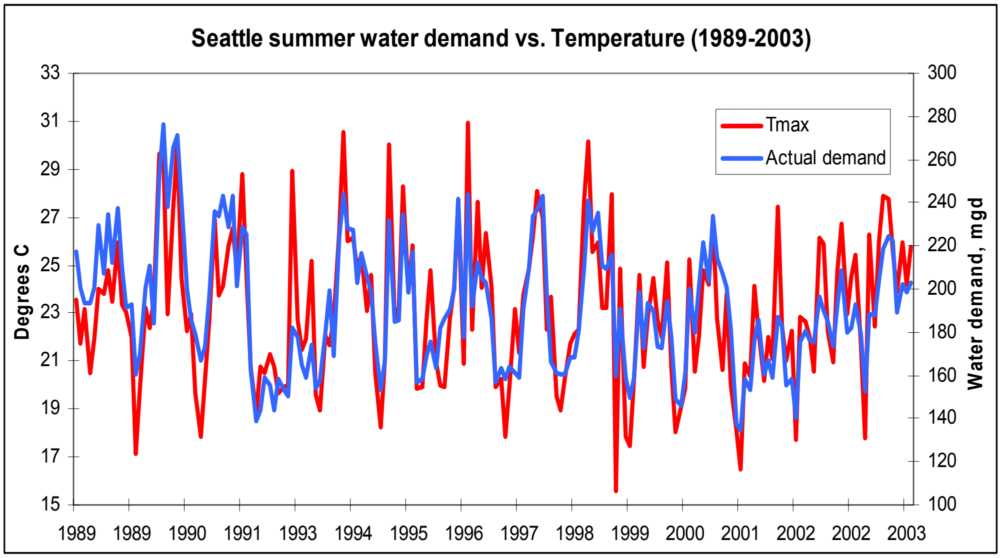

Figure 3. Seattle summer water demand plotted against the average weekly maximum temperature (Tmax) for 1983 through 2003. Summer months are June through August.

The lagged variables of Tmax and system-wide weekly average water use were used as additional predictive variables. These are lagged by one week, as we assume that water use is dictated not only by the current week, but also by the temperature and water use that occurred in the prior week.

The winter water use term is used to represent "base" demand. In the Puget Sound region, winter water use does not include watering lawns, flushing Green Lake, regular washing of cars, or the watering of public and private parks. The base demand provides a foundation on which to forecast other seasonal water use. In addition, changes in winter water demand are a good estimate of indoor water conservation (Weber, 1993). Winter demands for the SPU water users are shown in Figure 4 below.

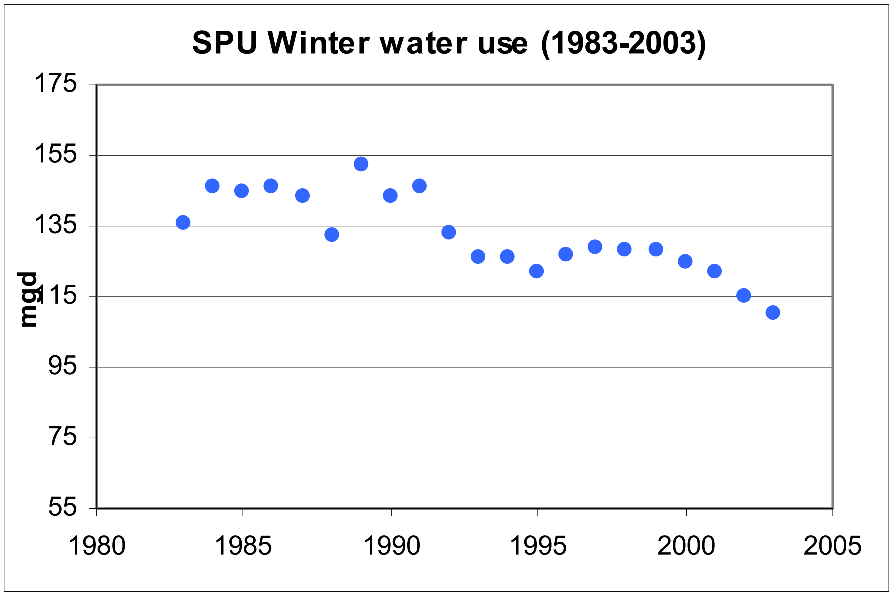

Figure 4. Annual average SPU winter (Nov.-Feb.) water demand.

This figure demonstrates the effects of natural and programmed conservation on Seattle's average winter water demand (November-February) (AWWA, 2001). "Naturally occurring conservation" includes the impacts of SPU's conservation programs and plumbing code and/or fixture changes. "Programmed conservation" represents the power of curtailments during droughts (i.e. 1987 and 1992) and mandatory reductions in water use. Curtailments during droughts are reflected in the sharp drops in consumption in Figure 4 during those periods. Plumbing code savings today are primarily continued savings from the 1993 plumbing code changes. These changes are assumed to continue through 2020 (Forum Outlook, 2001). Plumbing code savings commonly occur as water savings from changes in piping or other infrastructure implemented by the city or managing utility. Plumbing code changes can also include changes in construction code and the required installation of low water use fixtures, such as toilets. SPU also encourages customers to conserve on a regular basis. Some studies indicate that because of customer conservation and fixture changes, post-drought winter water demand per household remained more than 10 gpd (gallons per day) lower than pre-drought demands for five to nine years (Weber, 1993). Seattle is currently committed to 1% decrease in demand per year for the next decade, potentially affecting 42% of the area's population. Reductions in demand are evident in Figure 4, despite population growth in the service area. Similar attempts to improve conservation in the Tacoma and Everett regions are underway (Outlook 2001: Section 8; Appendix B). The Outlook 2001, produced by the Central Puget Sound Regional Water Suppliers Forum, indicates a 4.4% increase in demand, despite a 27% anticipated increase in regional population. The baseline winter water demand should, over time, reflect these changes though the extent to which conservation will be effective is uncertain. Eventually demands are expected to harden forcing conservation to reach a maximum; at this point demands will likely stabilize or increase merely due to population. It is unclear at this time when or the extent to which demand hardening will occur.

Sources of Data for Short-Term Model

The primary sources of data for creating the short-term demand forecasting models are the regional utilities. Bruce Flory from SPU provided a majority of the supporting SPU data. Ron Knoll from Tacoma and Souheil Nasar from Everett provided data from their respective utilities. These data include the system-wide water use database for at least 1990 through September, 2003, the rate and billing history from 1990 through January, 2004, and the number of system users from 1980 through 2003 (SPU only). The SPU water consumption data includes the city of Seattle, as well as purveyors outside Seattle. These data represent the total water diversions from the Tolt and Cedar Rivers, total production from Highline wells, and changes in distribution reservoir storage (Flory, 2003). Both Tacoma and Everett demand data include residential demand and industrial demand. The climate variables of average weekly maximum temperatures and weekly precipitation values were collected from the Seattle-Tacoma International Airport weather site (COOP ID 457473). These data were collected on the National Climate Data Center (NCDC) website from the National Oceanic and Atmospheric Administration (NOAA) database.

Model Calibration and Validation

The short-term demand models were calibrated using data for each season from 1989-1998 for the Seattle, Tacoma, and Everett regions. Figures 5 and 6 illustrate examples of the calibration of the model, while Figures 7 and 8 provide examples of the validation of the model. The calibration of the summer and fall seasons demonstrates the correlation between the historic and modeled values for the Seattle region, while the validation illustrates how well the model actually forecasts demands. Validation of the model was completed with a weekly forecast using data from 1999-2003. These analyses produced the following relationships and coefficients to be applied to Equation 1 (above) in creating weekly as well as four six-month forecasts. See Appendix A for results of the Seattle models not included here, and Appendix B for results from the Tacoma and Everett regions.

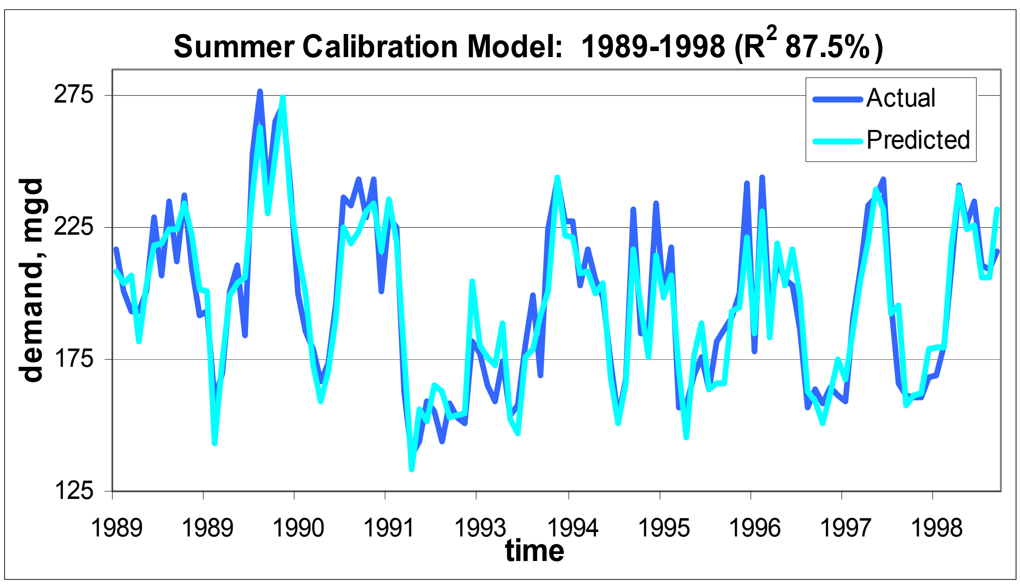

Figure 5. Seattle's summer water demand (system-wide) model calibration: actual (historic) versus predicted model.

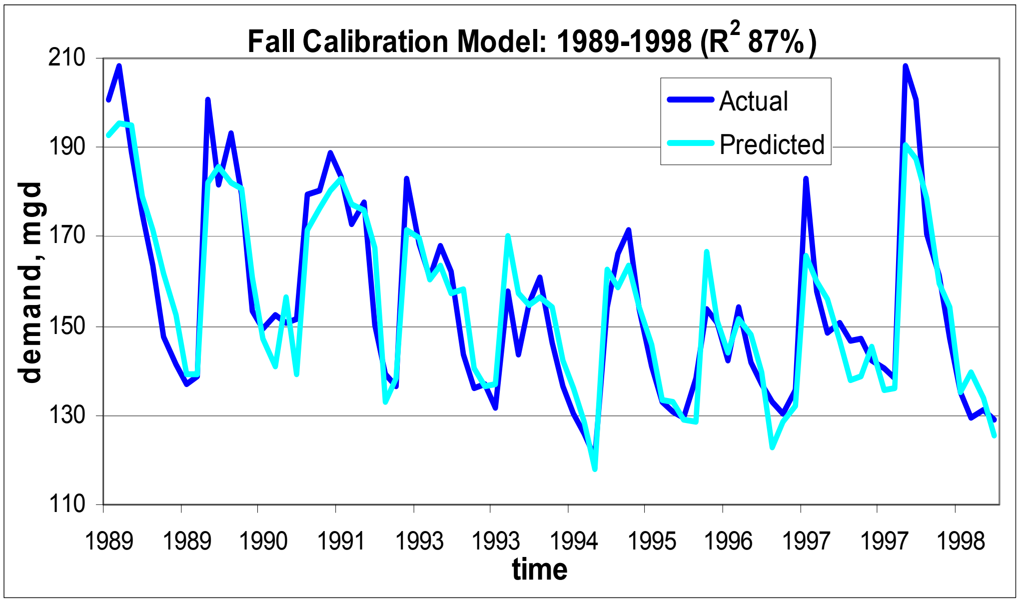

Figure 6. Seattle's fall water demand (system-wide) model calibration: actual (historic) versus predicted model.

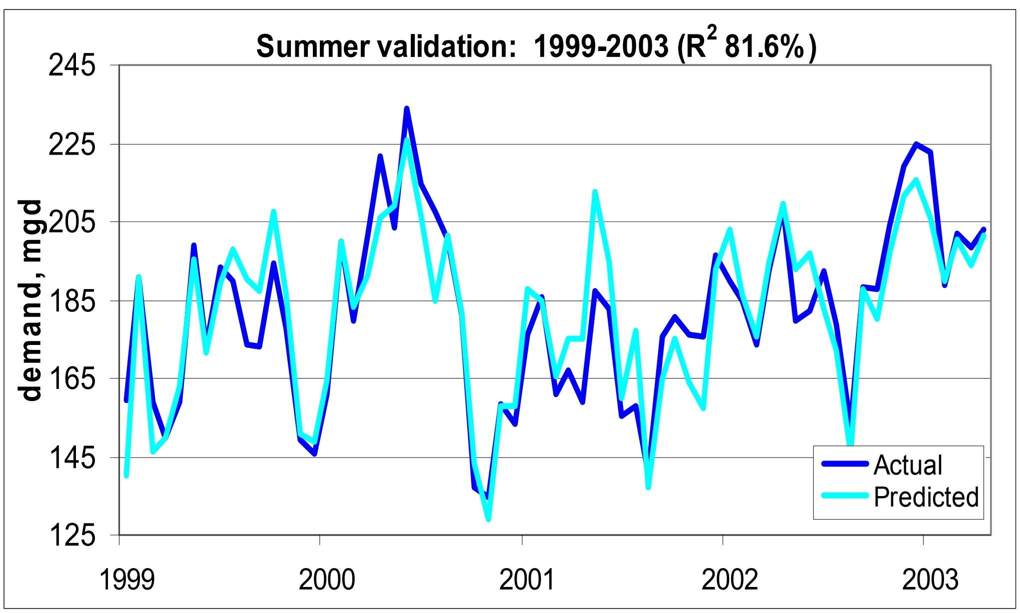

Figure 7. Summer water demand (system-wide) model validation: actual (historic) versus predicted model for the Seattle region.

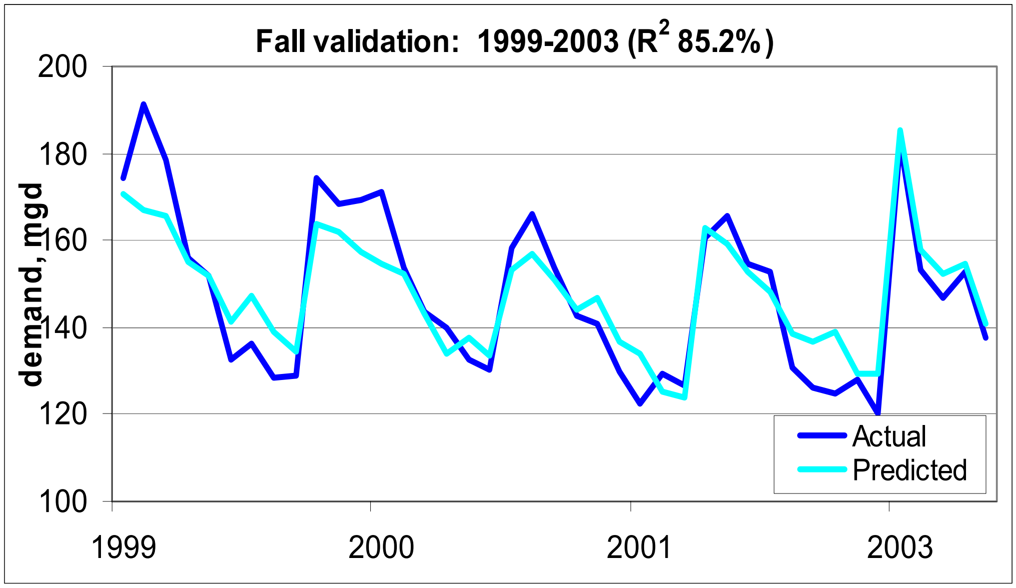

Figure 8. Fall water demand (system-wide) model validation: actual (historic) versus predicted model for the Seattle region.

The calibration of the summer and fall models reveals a model that is highly accurate for at least the model years of 1989-1998. In addition, the validation figures confirm that the model performs well.

Seventy percent of the data, years 1989-1998, were used for the calibration of Seattle's short-term model. Validation was performed using data from 1999-2003. Further analysis of the calibration process for the Seattle model reveals that coefficient values were robust and varied little during critical seasons, such as summer, regardless of the years chosen for calibration. Discussion of the Tacoma and Everett models and coefficients can be found in Appendix B.

Table 3. Short-term model variables and associated coefficients for Seattle region.

	SPRING	Value	SUMMER	Value	FALL	Value	WINTER	Value
β	Intercept	-4.418	Intercept	-16.14	Intercept	0.592	Intercept	3.852
A	Tmax	0.161	Tmax	0.673	Tmax	0.185	Tmax	-0.033
B	Precip, mm	-0.036	Precip, mm	-0.149	Precip, mm	-0.066	Precip, mm	-0.018
C	wh20	0.310	wh20	0.313	wh20	0.295	wh20	0.247
D	Pop.	0.309	Pop.	1.164	Pop.	0.000	Pop.	-0.227
E	$	-0.037	$	-0.112	$	0.000	$	0.017
F	Tmax, lagged	-0.013	Tmax, lagged	-0.119	Tmax, lagged	-0.077	Tmax, lagged	-0.035
G	H2O, lagged	0.648	H2O, lagged	0.412	H2O, lagged	0.557	H2O, lagged	0.658

An example of the final regression equation is demonstrated by the Seattle region's spring season model:

Equation 2.

$$\mathrm{Ln}(\text{Spring Water Demand}) = -4.418 + .161\cdot A - .0356\cdot B + .310\cdot C + .309\cdot D - .0375\cdot E - .0135\cdot F + .648\cdot G$$

The coefficients in Table 3 represent elasticities that measure "the effect of a change in an independent variable on the dependent variable" (AWWA, 1996). A positive elasticity means that as the value of that variable increases, so does water demand; a negative elasticity indicates that as the variable increases, water demand decreases. For example, Seattle's water price elasticity is greatest in winter and lowest in summer (Table 3). During the summer price plays an important role. The decrease in price elasticity during warmer periods indicates that as price increases, water use decreases. The price elasticity of -.112 during the summer indicates that a 1 percent increase in price will help decrease water use by 11.2%. Other coefficients, such as Tmax, also respond differently during different seasons. The positive value of the coefficient suggests that as the temperature increases, so does water demand. The value of the coefficient decreases as the seasons cool, suggesting that the variable is more influential during summer than winter. There is an equal but opposite reaction in water demand to the precipitation coefficient, which gets increasingly negative as the seasons warm (as precipitation increases, water demand decreases).

The high p-values[5] observed in the fall calibration regression indicated that the population (p-value: .63) and water price (p-value: .93) variables should be removed; therefore their value is set to zero when forecasts are completed. Clearly, each coefficient plays a unique and important role in controlling water demand.

Model Application: Six Month Forecast Variables and Results

Using the multivariate regression model developed during the calibration of regional water demands, four six-month forecasts were created. These time periods were chosen as the appropriate windows to provide information necessary to water supply planning during the typical refill and drawdown period (June-November). In order to complete these forecasts, the model required the actual and forecasted values of each explanatory variable (Table 3).

If the six-month forecast extended beyond December 2003, several assumptions were made with regard to changes in water pricing, population, and winter water demand. For the Seattle model, a 1% increase in the service population was initiated in January 2004, as well as a 1% decrease in the winter water use variable and an SPU approved increase in the price of water. The population increase of 1% is an estimate that concurs with SPU and other regional documentation[6]. A 1% decrease in demand is calculated for the winter

[5] P-values are commonly defined as: "The probability that a variate would assume a value greater than or equal to the observed value strictly by chance" (Wolfram Research, 2003).

[6] The 2001 Puget Sound Regional Water Supply Outlook suggests a 27% increase in population from 2000 through 2020. This is an increase of approximately 1.35% each year. Recent reports by the PSRC also indicate our regional growth rate, averaged over the last 5-years, in 2002 to be 1.6% (PSRC, 2003). In addition, documents from the Cascade Water Alliance (Loranger, 2003) suggested a use of 1% annual growth in reference to regional supply models. The use of 1% is an approximation which is substantiated by the aforementioned estimates of other models, though it may be an underestimate. Since this increase only occurs for one month (January, 2004) of the forecasted data, the possible underestimation is of small concern.

water demand variable in January based on the conservation goals of SPU's 10-year (2000-2010) Conservation Program (SPU, 2001). Similar information regarding population and conservation programming for the Tacoma and Everett regions was unavailable. To establish a trend for future base water demands in these regions, the future winter water demand variable was altered to reflect a running average of the previous five years' base water demand. Winter water demand for 2003 was then multiplied by this final average factor.[7] Though this method is somewhat arbitrary, it attempts to find a trend, if any, in the winter water demand in Tacoma and Everett during recent years. Rates for the Tacoma and Everett models increased based on the utilities projections for January 2004.

A critical component of the six-month water demand forecasts is the forecasted climate information needed to project demands. Using 20 different NCEP forecasts in a climate ensemble, the Tmax and precipitation variables were derived. These data were provided by doctoral candidate Michael Miller of the University of Washington. The NCEP forecasts are developed with the Global Spectral Model (GSM) and consist of six-month predictions of temperature, precipitation, and barometric pressure.

Miller and Palmer characterize the climate forecast as follows: "GSM forecasts use current ocean and atmospheric conditions to produce meteorological data at a spatial resolution of 1.9º for time-steps between 5 and 15 minutes. Every month, twenty six-month forecasts are produced. Each of the twenty is created with slightly different assumptions about the initial conditions of the ocean and atmosphere. NCEP also uses the GSM to produce ten hindcasts for each year from 1979 to 1999. A hindcast attempts

[7] For example: Winter water demand in 1998 is 75mgd, 78mgd in 1999, 82mgd in 2000, 74mgd in 2001, 78mgd in 2002, and 76mgd in 2003. The difference between 1998 and 1999 is a factor of 1.04, 1.05 between 2000 and 1999, .90 between 2001 and 2000, 1.05 between 2001 and 2002, and a factor of .97 separates 2002 and 2003. An average of these factors is: 1.0044. Therefore the factor of change between the winter water demand in 2003 and 2004 is assumed to be 1.0044; therefore the winter water demand in 2004 is 76.34mgd.

to replicate past conditions by varying the initial conditions of the ocean and atmosphere" (Miller and Palmer, 2003).

The large spatial resolution of the GSM requires the model to be corrected to mimic the smaller basins represented in these demand forecasting models. This is accomplished with a comparison of the hindcasts to the historic meteorological data. Furthermore, cumulative distribution functions (cdfs) for each data set are compared, and the bias within the GSM model is calculated. The cdfs are then used to change the GSM meteorological forecast data into appropriate values for the weather station (SeaTac) (Miller and Palmer, 2003). The result of this downscaling and bias correction process is 20 forecasts of temperature and precipitation.

As noted, there are 20 climate-variable scenarios; the model generates a forecast for each one. The model produces 20 possible demand forecasts for each of the four six-month forecasts: May-October 2003; July 2003-January 2004; August 2003-February 2004; October 2003-March 2004. Figures 9-12, below, illustrate the range covered by the forecasts relative to the actual demand (red) for the same time period. In addition, a forecast using the average temperatures from 1983-2002 is displayed in the green line. The black line, displayed in the April forecast, illustrates a forecast using the actual temperature and precipitation data for the forecasted period, 2003.

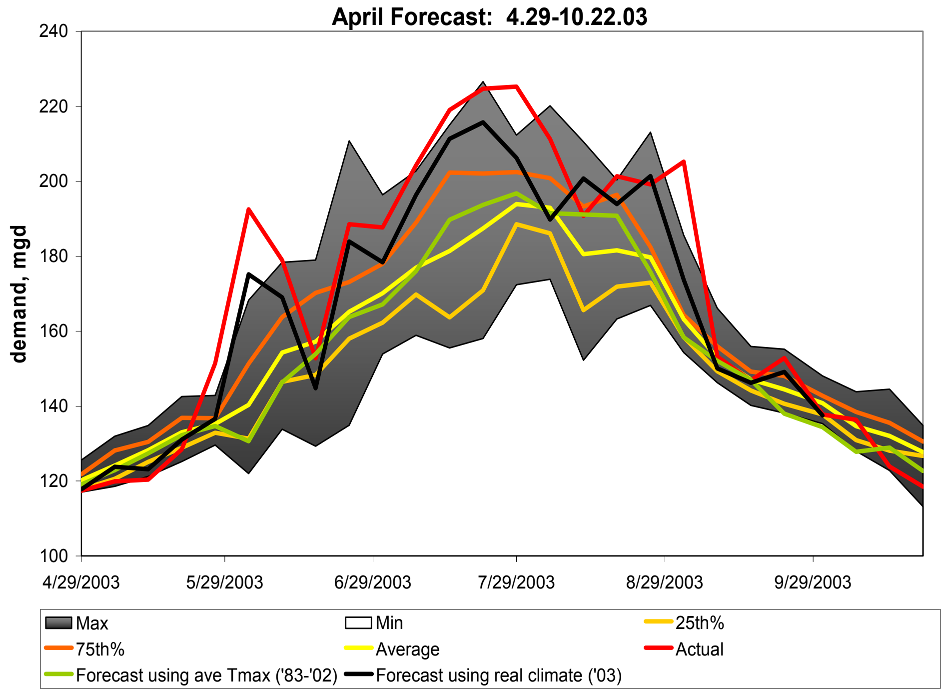

Figure 9. Seattle demand forecast for the weeks of April 29 through October 22, 2003.

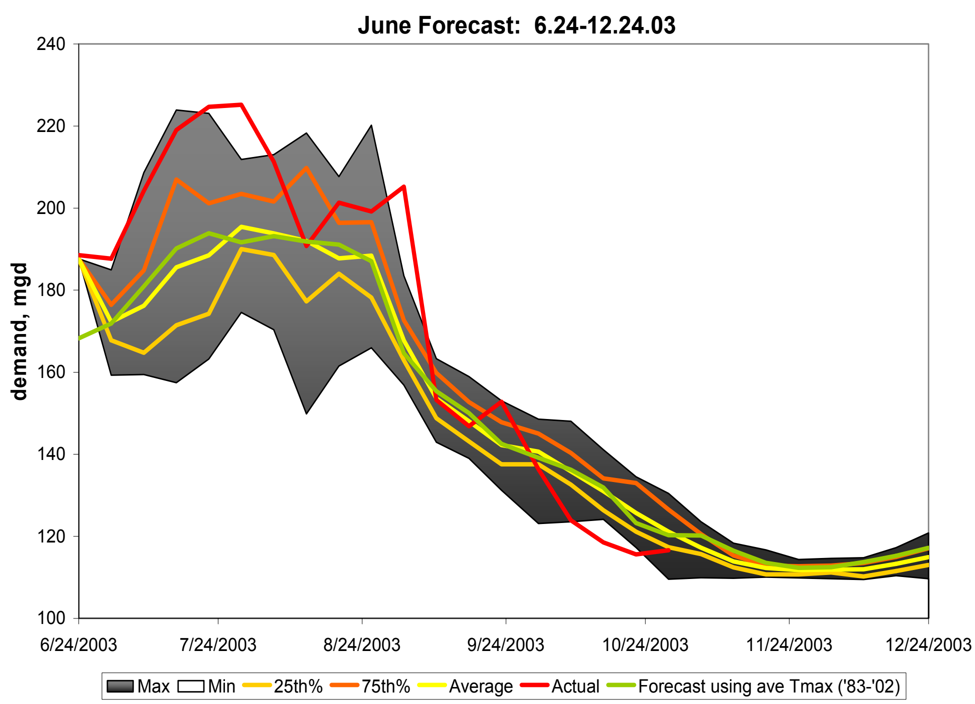

Figure 10. Seattle demand forecast for the weeks of July 29, 2003 through January 21, 2004.

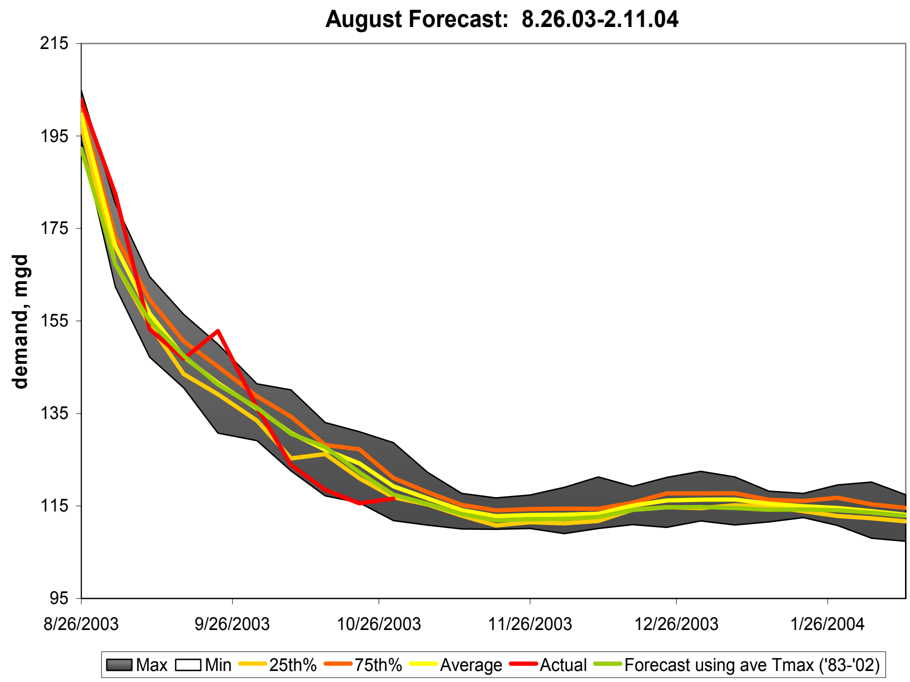

Figure 11. Seattle demand forecast for the weeks of August 26, 2003 through February 18, 2004.

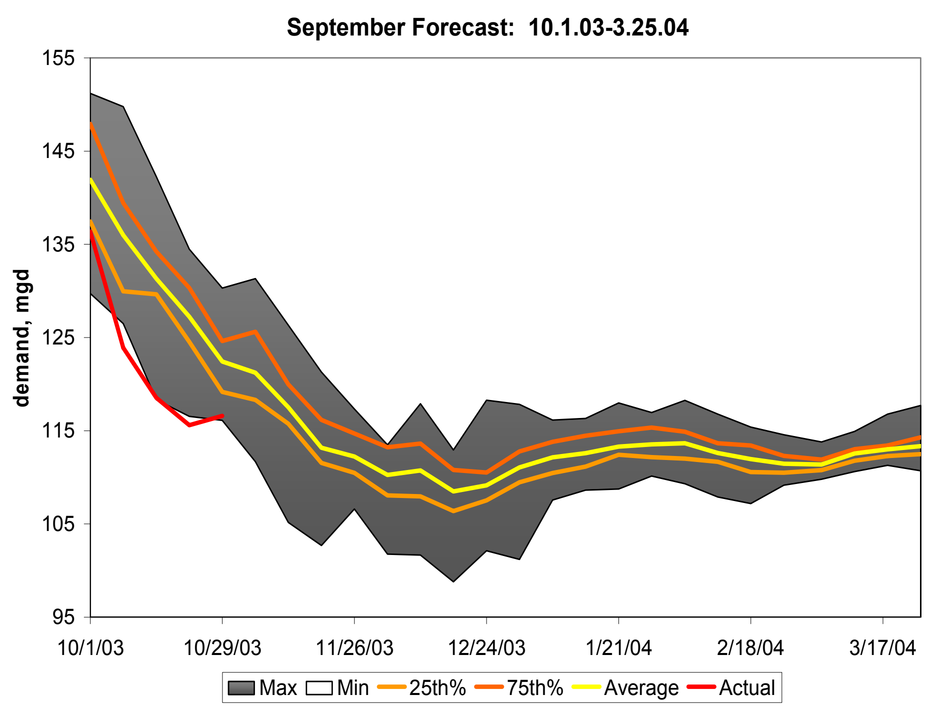

Figure 12. Seattle demand forecast for the weeks of October 1, 2003 through March 25, 2004.

The actual data represented in the April, June, and August forecast figures indicate that 2003 was an outlier. As the driest (least amount of precipitation) summer on record for the Seattle region, water demand reached unexpected peaks during unexpected weeks. This was particularly true for the first weeks of June, where 90 degree temperatures resulted in peak water use. Figure 13 aptly displays the high temperatures experienced during the summer of 2003. Because the forecast models were calibrated using data from 1989-1998, they did not capture the extreme heat of recent summers. As a result, the models were unable to account for extreme summer use. In contrast, days of record high rainfall occurred in mid-October, causing a significant drop in water demand, slightly beyond the scope of the September forecast. When calibrated and validated under less extreme conditions, the models perform more accurately.

Error in the 2003 forecasts is also a result of poor NCEP forecasts. Due to the unexpected heat during 2003, the NECP climate forecasts used in the April, June, and August water demand forecasts underestimate the temperature during the 2003 summer. Though NCEP forecasts are very valuable to water resource forecast models, there are periods during the year when climatologists have found NCEP forcasts more accurate. For example, Barnston et al. (1999) found NCEP predictions most accurate for December, January, February, and March, particularly during El Niño years. Local climatology during spring 2003 indicated a medium-sized El Niño in the Pacific Northwest; this signal has dissipated by the fall of 2003. The Barston et al. study also indicates that the predictive skill of NCEP forecasts of summer climate is definitely weaker than other seasons. The gap between the average NCEP temperatures for the April forecast and the real temperatures is shown in Figure 14. Due to the outlying temperatures and drought during 2003, it is unlikely that the results of forecasts during this year indicate the true value of the short-term model.

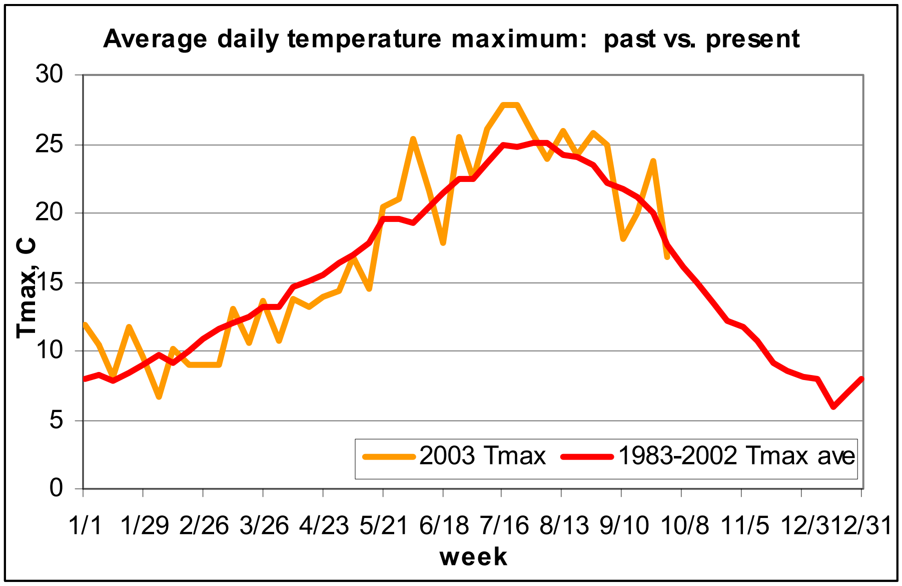

Figure 13. Actual 2003 Tmax plotted against the Tmax average from 1983-2002. Data is from the NCDC SeaTac site.

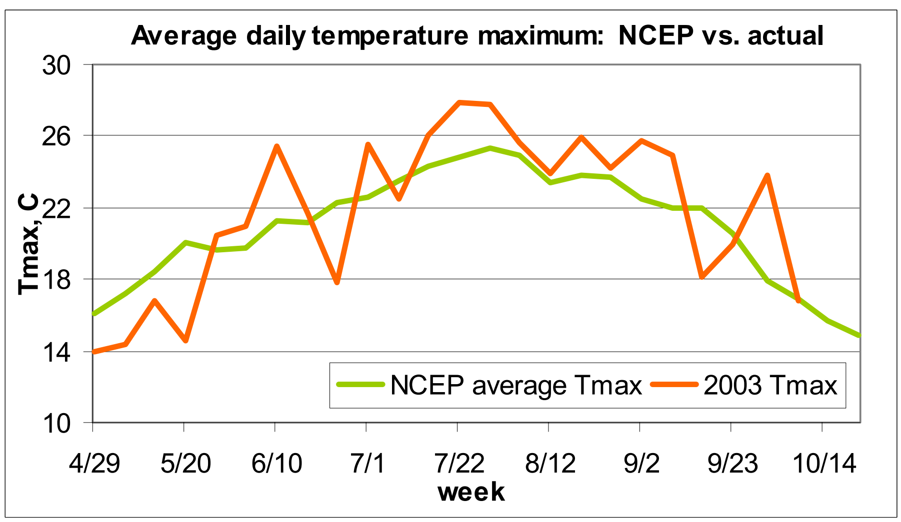

Figure 14. Actual 2003 Tmax plotted against the average NCEP Tmax forecast for the April forecast.

To demonstrate the ability of the forecast to appropriately capture the shape of water demands during the April forecast, a three-week moving average of the April forecast was also generated. These averages were calculated to smooth the data, remove the noise created in a weekly model, and illustrate the ability of the model to present forecasts during less extreme conditions. Shown in Figure 15 are the smoothed curves for the NCEP forecasts and actual data during the April forecast. The root mean squared error (RMSE) for the three-week moving average April forecast is also included in Figure 21.

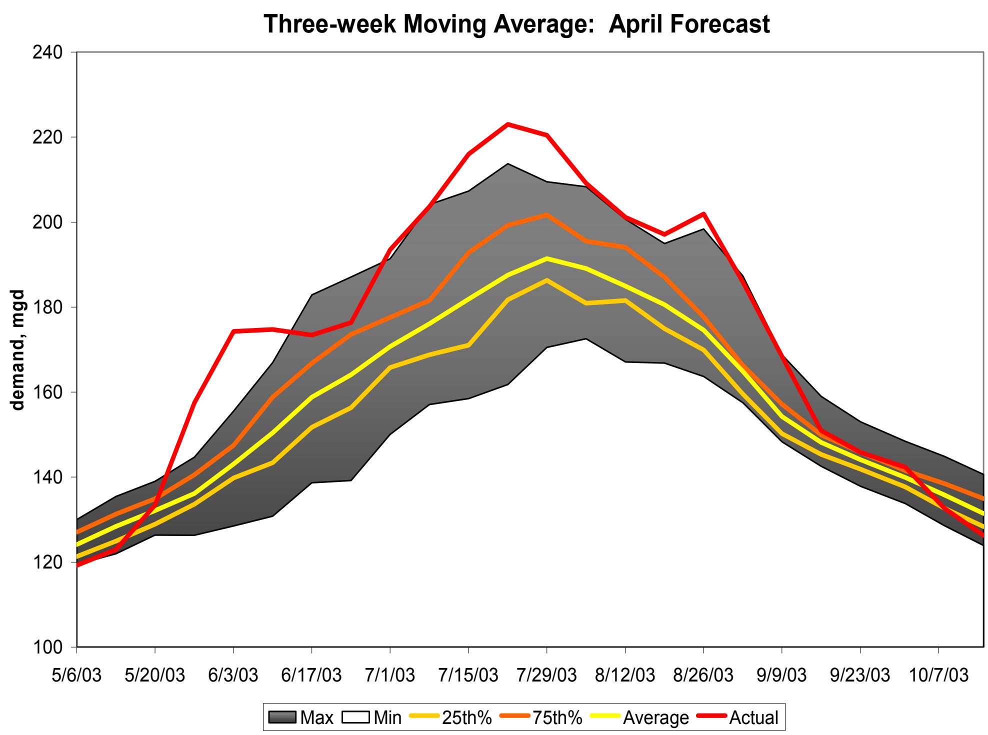

Figure 15. The three-week moving average of Seattle's demand forecast for April 29, 2003 through October 22, 2003.

Short-term Model Hindcasts (1982-1999)

Inaccuracies in the forecast model during 2003 raise concerns about the applicability of the short-term model. While the forecasts capture the general trend of demand during the spring and summer of 2003, the estimate of the total water demanded during this period was significantly less than that which occurred.

To estimate the accuracy of the short-term model, the model was tested using the NCEP climate hindcasts and regional data for 1989-1999. Unlike current NCEP climate forecasts, which include 20 different climate ensembles, NCEP hindcasts only include 10 scenarios. Population, rate, and water demand data were all collected from SPU databases. The short-term demand hindcasts are compared to the actual demand during different seasons of the 1989-1999 record. Because the primary concern is predicting summer demands during the utility's primary drawdown period (Figure 2), the hindcasts are for the April (May-October) forecast period.

Using the 1989-1999 hindcast results for the April forecast period, Table 4 includes the RMSE (root-mean-squared-error) and R^2 values for the total water demands of the average short-term hindcast versus the actual demand during May-October.

Table 4. Summary statistics for 1989-1999 hindcasts.

Year	RMSE	R^2 (%)
1989	16.65	64
1990	24.19	69
1991	22.26	54
1992	38.58	36
1993	22.74	31
1994	17.17	77
1995	29.76	21
1996	18.78	73
1997	21.69	58
1998	16.50	81
1999	20.43	54

The RMSE of the April hindcasts indicate that the model performs fairly well; however, many years did not reveal correlations that matched the accuracy of the 2003 short-term model calibrations. This is particularly true for years when SPU instituted mandatory curtailments (1991-1992). Erratic water demands due to curtailments and changing water demand behavior during the early 1990s is evident in the R^2 values in Table 4. Clearly the model is incapable of modeling curtailments and these are removed from the calibration displayed in Figure 16. An R^2 value of 76% in Figure 17 also illustrates the ability of the short-term model to forecast total seasonal water demand. The ability of the short-term model to forecast total seasonal demand is helpful in determining utility operations for the critical draw-down and refill periods (i.e. summer and fall).

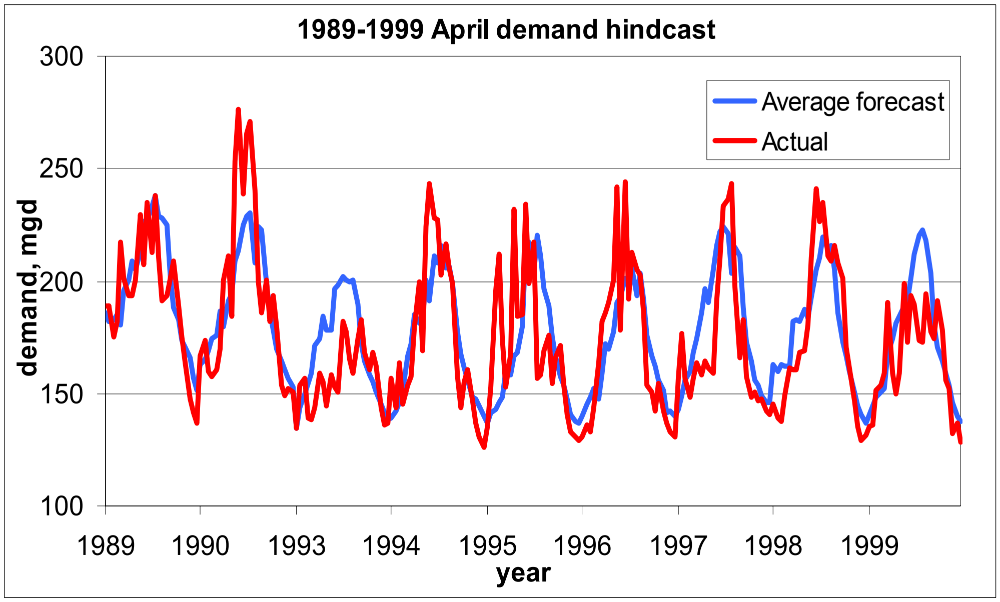

Figure 16. Calibration of April demand hindcast for each year during 1989-1999.

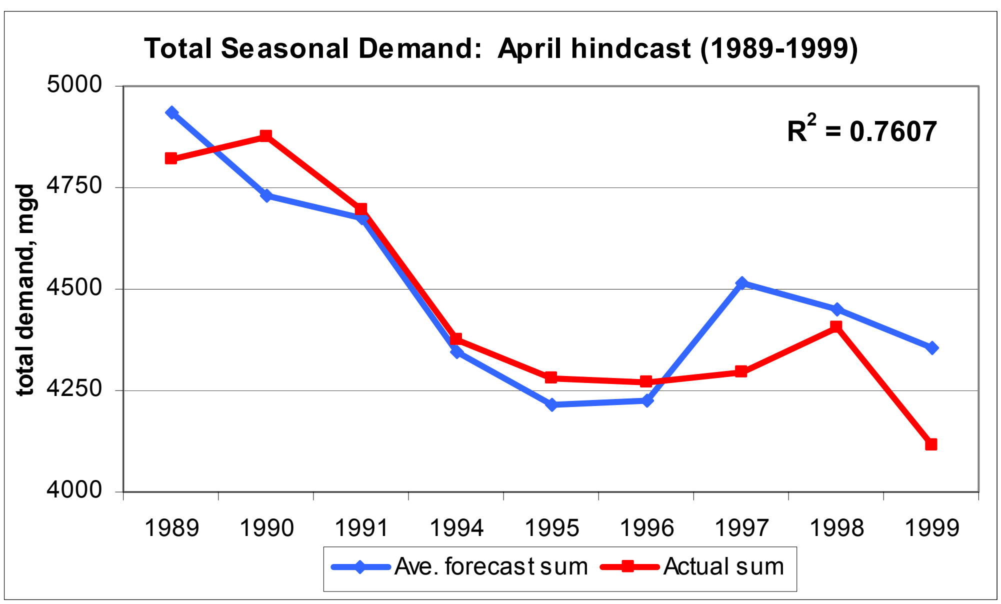

Figure 17. Total hindcasted water demand for May-October for 1989-1999.

As demonstrated by Table 4 and Figures 16 and 17, model calibrations for the 1989-1999 April hindcasts do not reveal consistently accurate demand predictions. Because temperature and precipitation are critical explanatory variables in the short-term model, the hindcast calibrations question the ability of the NCEP climate hindcasts. The NCEP climate hindcasts during 1989-1999 are illustrated in Figures 18 and 19. Both figures compare actual conditions to the average NCEP climate hindcast (temperature and precipitation). These comparisons reveal the "average" ability of NCEP climate hindcasts. It is evident that while NCEP climate hindcasts can predict temperature and precipitation with some accuracy, the hindcasts do not capture conditions that exceed average expectations.

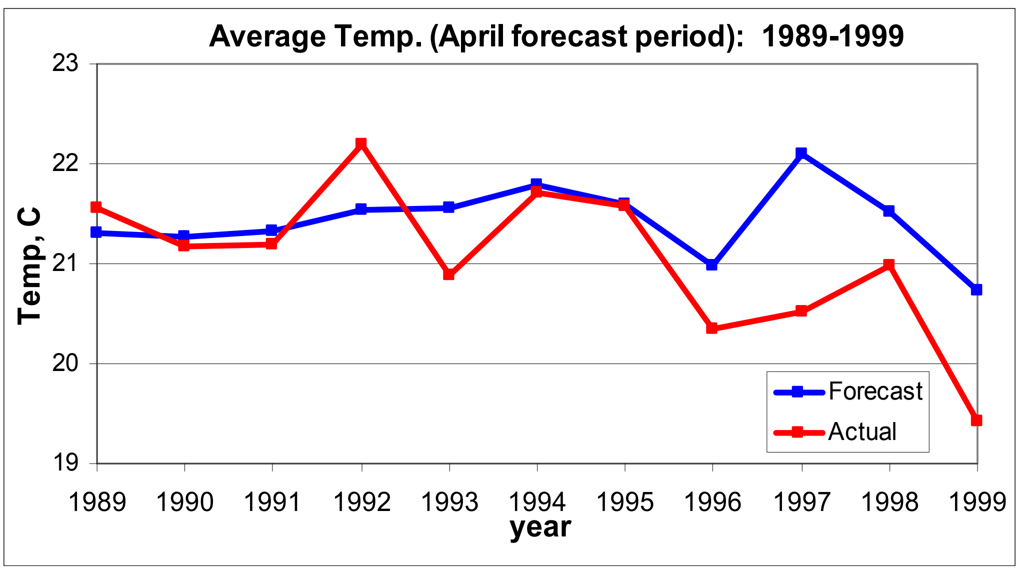

Figure 18. Actual average temperature during May-October, 1989-1999 compared to average NCEP temperature hindcast.

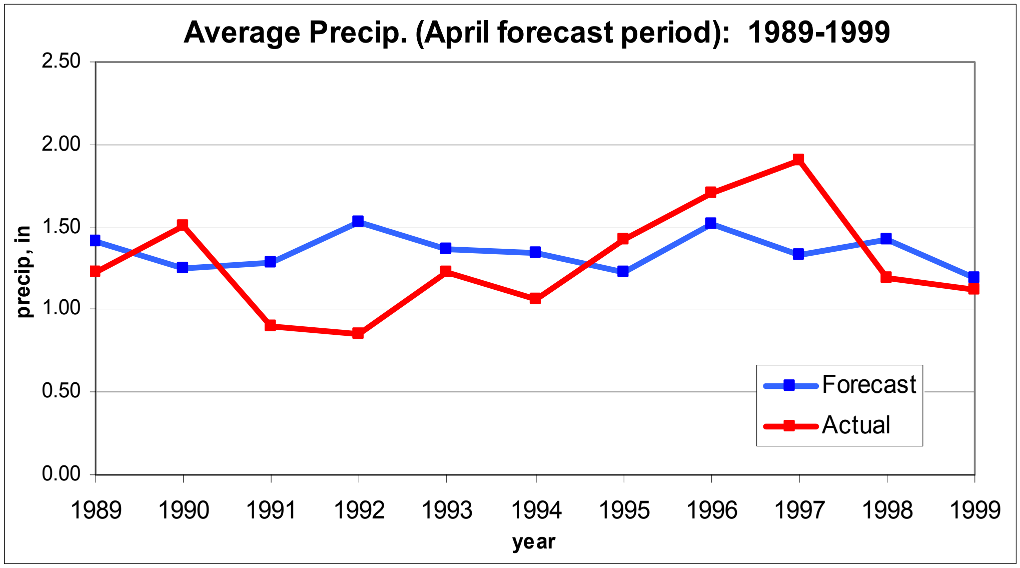

Figure 19. Actual average precipitation during May-October, 1989-1999 compared to average NCEP precipitation hindcast.

The inability of the NCEP climate hindcasts to capture extreme climate conditions is particularly evident and troubling during hot and dry conditions. Demand forecast models are predominantly used during drought conditions, when resource managers most need assistance for planning resource supply and demand. The poor performance of the NCEP hindcasts indicates that the short-term demand model may be unable to forecast or hindcast demand accurately given the tendency of the climate forecasts to be simply average. The NCEP hindcasts are not, however, an absolute indication of the accuracy of future climate forecasts. The results of the NCEP hindcasts appear worse than the NCEP climate forecasts used in the 2003 demand model (Figures 9-12). The culprit of the error in the 2003 demand forecasts seems to be the unexpected hot and dry conditions during the summer of 2003. Continued research in downscaling techniques and the applications of NCEP climate forecasts will help improve the reliability of the climate data as well as the models (e.g., demand forecasting) they are used in. In estimating the skill and error in the 2003 demand forecasts, a unique skill metric, as well as the RMSE were examined.

Skill and Error in Six-month Short-term Model Forecasts

Alan Hamlet (2003) developed a unique skill metric for water resource-related forecasts. Hamlet has attempted to create a skill metric that adequately ranks forecasts in the context of water resource management. Hamlet's revised metric, an expansion of more common skill metrics found in text such as Wilkes' (1966) *Introduction to Numerical Analysis*, is designed to reward data accuracy and punish spread in forecasts. This skill metric should indicate the value of forecasts in water resource management scenarios, as it provides an opportunity to compare forecasts to one another. This may help resource managers choose forecast and management techniques based on the level of skill displayed by the forecast. The metric takes the following form:

Equation 3.

$$\text{Skill} = 1 - \left[\sum(\textit{forecast} - \textit{observed})^2/\text{N} \,/\, \sum(\textit{historical} - \textit{observed})^2/\text{M}\right]$$

Where the *forecast* data represent the six-month forecast period, *historical* represents the weeks of years 1984 through 2002 (excluding 1992), *observed* are the actual demand values during the forecasted period, N is the number of ensembles in the forecast, and M is the number of years of historical observation for each week. The metric represents the skill of the forecast during each week of the forecasted period.

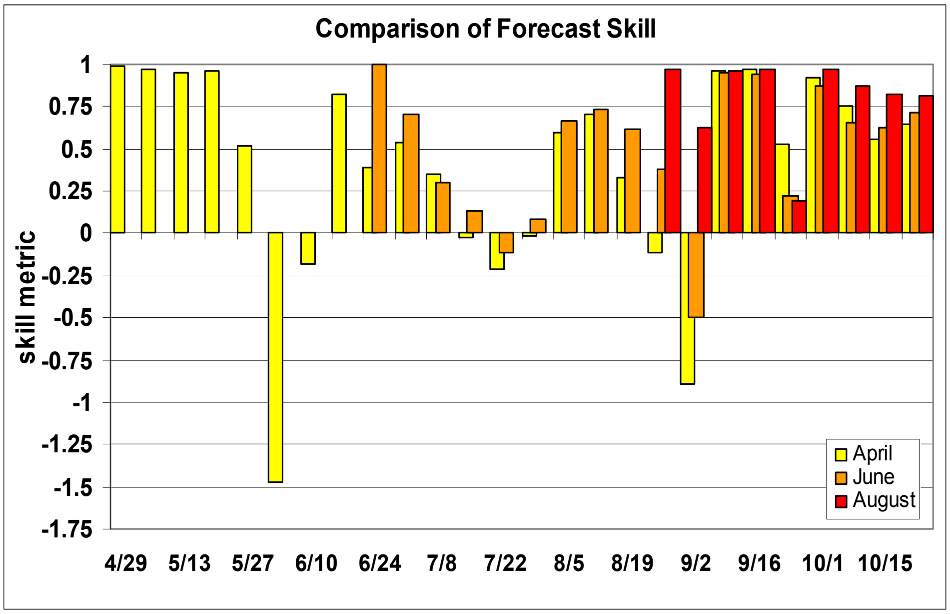

Figure 20. Skill metrics for the April, June, and August forecasts. Maximum skill possible is 1, minimum skill possible is infinite.

This metric illustrates the general improvement of forecasts over the forecasting periods (e.g., June's forecast has higher skill than April). Naturally the forecasts should improve as the forecasted period increases its proximity to the present. Figure 20 confirms this expectation while illustrating the power of unexpected climatology (e.g., first and third weeks of September) and poor NCEP forecasts. The metric is quite effective during outlier years, such as 2003, because the metric truly rewards the forecast for identifying an outlying period. The metric is less valuable during average years as the denominator in Equation 3 approaches zero. This skill metric would be more effective if comparing different types of forecast models. A more common test of skill is the root mean squared error (RMSE), shown below in Figure 21.

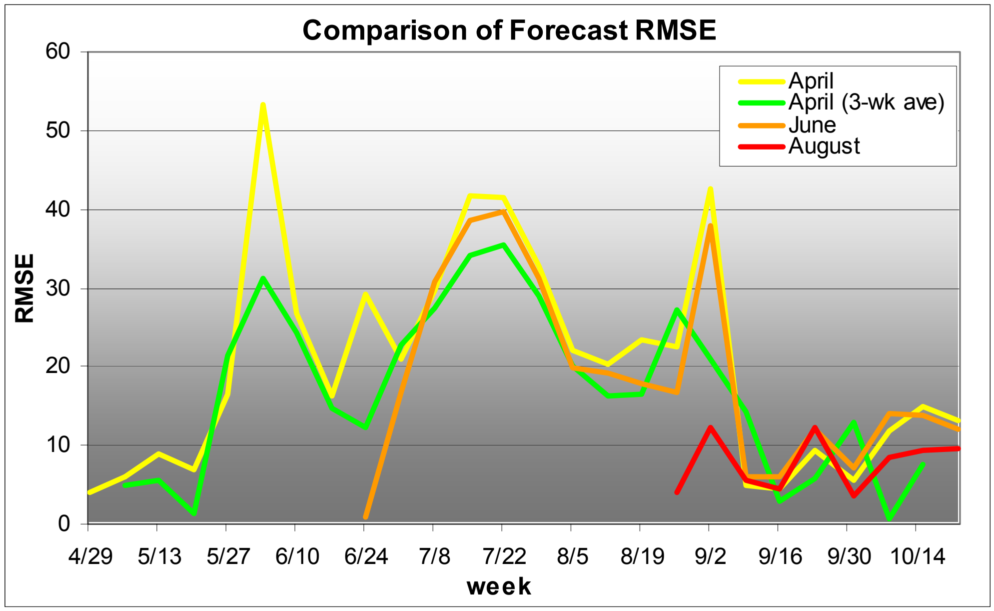

Figure 21. A comparison of the root mean squared errors of the April, June, and August forecasts.

Similar to the skill metric, the RMSE function tracks error in the forecasts over time. As in the Hamlet skill metric, error is greatest during the summer period, and clearly decreases as the fall season approaches.

Forecasts are not perfect, despite the expectations of resource researchers and managers. Opportunities for error in the modeling process are many. These include error in the original datasets, the process of aggregating data, the creation of the calibration models, the forecasted climatology data, and the error associated with the process of creating the forecasts. While some of this error may be attributed to data entry and calculations, some is also the result of computational mistakes in data collection by external agencies (e.g., water or met station records) or the inaccuracy of downscaled global climate models. Though it is difficult to assess the errors in demand forecasting, the skill and RMSE metrics help quantify the error in the forecasts. Though error is inevitable in forecast modeling, the cost of water management without benefit of any short-range water demand forecast may be even more damaging. Sewell has been correct in the past regarding water managers' inability to anticipate change. Such inability should not continue given the accessibility of water resource data, statistical techniques, and advancements in climate change research.

Using the Short-term Model Forecasts

Forecasted water demand is helpful for several reasons. The development of coefficients allows us to make forecasts regularly that are useful for additional water resource planning models for the Puget Sound region. The CRYSTAL (Cascade Regional Yield Simulation and Analysis) model, also developed as a PRISM (Puget Sound Regional Synthesis Model) project, attempts to simulate both the supply and demand of water in the Puget Sound region. The model focuses on water supply and instream flows for Seattle, Tacoma, and Everett. The primary objective of the model is to demonstrate the "value and opportunities of a regional approach to water management" (TAG, 2002). In order to accomplish this objective, the model must also acknowledge urban water demands by regional users. In order to make forecasts of future water supply and instream flow needs, the model requires demands for the forecasted period. Therefore, the demand forecasts developed for Seattle, Tacoma, and Everett are supplied to the CRYSTAL model to help develop more comprehensive regional water resource plans.

The demands for Seattle are supplied to a new optimization model of the Seattle system. This model attempts to set instream flows and user demand as the primary objectives given the forecasted streamflow for the next six months. Using the demands forecasted in this project and separately forecasted streamflows for the region, the optimization model determines if or when the region will have sufficient water supply to support demands. Finally, the short-term demand forecasts require regular attention and variable updates. While this requires additional work on behalf of the researcher or modeler, it assures the model will be updated and validated regularly, a practice less common to long-term forecast models.

Though the short-term water demand forecasting model only supports six-month forecasts, these are critical indicators of what resource managers may see in the coming season. This is chiefly relevant to climate variability or unexpected changes in regional supply or demand. Jain and Ormsbee (2002) agree that short-term demand models are critical components of optimization strategies, drought management, conservation improvements, and so on. In succeeding chapters, additional water demand forecast models with longer planning capacities will address long-term regional infrastructure needs, land use changes, and climate change impacts.

Chapter 4. Long-term Water Demands

The future ain't what it used to be.
-Yogi Berra

Water resource engineers commonly use the past as a guide to the future, planning as if events that have not occurred are unlikely to occur. However, the future's uncertainty has required planners to predict water demand two or three decades into the future. Past, long-term forecasts have allowed resource managers to be generous in their estimates of water demand. Long-term water demand modeling is a difficult task; it requires robust data sets and consideration of uncertain climate, economic, and cultural conditions. Therefore, water resource managers felt the professional responsibility to generate demands that were unlikely to be exceeded. For example, during the post-World War II years, resource mangers and planners typically chose the largest feasible project. While population and the economy grew, such decisions were justifiable (DeKay, 1985). Now, however, we find population growth more stable, water use decreasing, and significant environmental considerations. These changes have caused many water resource managers to rethink long-term demand planning.

Long-term models are helpful for supply planning, reservoir or urban infrastructure changes (i.e., water mains, transfer pipes, etc.), extended conservation programming or plumbing code changes, and regional urban planning and development. Unlike short-term models, long-term water demand models do not contribute to near-term or seasonal operations' policies regarding drought, instream flows, or climate variability. Instead, long-term models provide extended foresight for resource mangers to address overall system capacity and management (Bauman et al., 1998). Using various methods and databases from urban planning, regional surveys, and local utilities, efforts to renew a long term model for the Seattle region are both intriguing and challenging. In the following chapter the purpose, design, and challenges of long-term water demand models are discussed. This discussion reveals long-term models as critical components to regional water resource stability. In addition this chapter addresses the process of creating a framework for various types of long-term models as well as the difficulties in modeling complex databases. The research presented in this chapter will be used to develop an improved long-term water demand model for the Seattle region. This model will include a more disaggregated database based on spatial or land-use related variables. In addition, this research will help build a water resources component into a highly disaggregated urban transportation and planning simulation model, UrbanSim.

Possible Long-term Forecast Methodologies and Principal Components

Chapter 2 addressed several methods for forecasting demands, such as per capita, econometric, extrapolation or other integrated models (AWWA, 1996; 2001). Though these methods were not specifically linked to long-term forecasts in Chapter 2, most of these methods are, in fact, used with decadal models. The method chosen depends on the quantity and quality of data available, the capability of the forecasters (AWWA, 1996), and forecast goals. A brief summary of several methods addressed by the American Water Works Association (1996; 2001) are included here.

The per capita method is the most common for developing water demand forecasts. Most utilities' models use the per capita methodology as their foundation for developing their own forecast models. Per capita models are developed using utility and survey data of water use per person or household. Other variable information depends on survey detail and the number of respondents. Using current and historical demands, per capita consumption is estimated and multiplied by forecasted population to determine future water demand totals. Depending on the desired detail, the utility may include a number of urban sectors (i.e., residential, commercial, industrial) or land-use types.

For decades utilities relied on the simple method of extrapolation. Like the per capita model, data requirements are limited to current and historical demand data, population, and population forecasts. The data are plotted in a scatter plot as annual or monthly consumption; a trend line is drawn to determine the slope of the line and potential correlation between the variables of population and demand. The line is projected or extrapolated to develop longer-term relationship using the given slope. Essentially, the rate of increase in demand in the past is simply applied to the future.

Econometric models attempt to determine the variables most responsible for water demand. Econometric models are dependent on economic variables related to water demand and are often calculated using a multivariable regression (as in the short-term model, Chapter 3). Econometric variables include employment, water price, and household income. Similar to the subject specific data required by the econometric model, land use models focus on elements related to land use and water demands. This may include land use type (residential vs. commercial), policies related to urban development, or characteristics of a particular type of land use. Often variables from econometric and land use models are incorporated into an integrated model, a data intensive and diverse method.

Multivariate, integrated models include information from all sectors: social, economic, environmental, and spatial. The short-term model, presented previously, demonstrates the importance of several independent variables: winter water demand, temperature, precipitation, water price, and other system-wide variables. A long-term model often uses additional household characteristics such as income, size (number of people), house age, housing density (number per acre), etc. (PMCL, 2003). These variables are more likely to change on an annual or decadal basis, whereas the short-term model accounts for data variation within a shorter time-frame. Most long-term water demand models refer to a handful of standard model variables from the most influential categories: population, economy, technology, climate, water price, conservation, housing characteristics, and land-use (AWWA, 1996). In designing a long-term model for the Seattle region, many of these variables were included. Defining the long-term forecast variables, determining the level of disaggregation, and identifying data sources are the first and most critical elements of long-term model design.

Defining the Long-term Model: Data Sources, Aggregation, and Challenges

Water demand research suggests that a model is only as valuable as the data available. Unlike many short-term models, long-term models include diverse data with different time-steps and levels of detail. Data used in long-term models are collected by public utilities, regional research councils, land-use and planning studies, tax records, and climate databases. The level of detail and diversity of data may vary (Weber, 1993; AWWA, 2001); this presents a challenge for identifying the utility of data.

In addition to the historical data needed to create a long-term demand forecast model, the projection of water demand ten to thirty years into the future also requires knowledge about changes in the model's independent variables. Social and economic projections for some variables may be available through regional demographic research councils; however, this detail has a limited accuracy given the uncertainty of the forecasts. Projected climate variables used in a long-term, decadal model can be accessed through climate change research, similar to NCDC (National Climatic Data Centers) data used in the short-term demand model. Like forecasted social and economic data, climate forecasts are equally uncertain. The uncertainty in independent variables of long-term demand models is inevitable. However, long-term models can be successfully generated if the data are retrieved from reliable sources and error is both acknowledged and quantified.

IWR-MAIN's first recommendation for preparing a long-term forecast is to determine the "optimal disaggregation of the residential section…". Determining the level of data disaggregation in the forecast is a primary yet challenging first step in model design. While it is common to aggregate water demand data for the sake of simplicity, research also supports disaggregated methods for their ability to improve the quality and accountability of the forecast (Bauman et al., 1998). Truly disaggregated models can predict water demand by customer type, location, season, or other variables. A disaggregated model based on per capita, economic, as well as spatial variables can provide utilities with the ability to micromanage water use, identify specific problem areas, and mitigate urban development based on resource supply within urban areas.

In the late 1970s, the Seattle Water Department (SWD) used data from several classes (i.e., residential, commercial, industrial) in each of 120 geographic subareas within their service area to develop a multivariate regression model. Because the model included region specific detail, each subarea's forecast "reflected the specific characteristics of that subarea in terms of prices, incomes, water pressure, and the number of users in each sector" (DeKay, 1985). As a result, SWD was able to develop a system hydraulic model to help plan for improvements and identify points of vulnerability. Though the benefits of a disaggregated model are many, arguments against highly disaggregated models are also prevalent.

In reference to the highly disaggregated IWR-MAIN study by Boland and Dziegieleski (1989), Wilson and Luke (1990) refer to the results as "flawed" and "easily misused." A common concern regarding disaggregated models is that they are difficult to use due to the complexities in the databases. Though Wilson and Luke are primarily critical of specific results in Boland and Dziegieleski's study, they are also discouraged by the model's limited documentation and explanation of many model details, from coefficients to sector specific output. Though these arguments are valid, the opportunity to analyze the major and minor components of water demand is rare. Disaggregated models allow resource managers to examine specific controls on water demand, make detailed decisions about sector changes, and consider the individual pieces of a complicated system of resource demand. If created properly, disaggregated water demand models provide a unique perspective on urban water demand. Several approaches in this thesis, both disaggregated and aggregated, are used to evaluate a long-term model for the Seattle region.

Seattle Public Utilities Long-term Demand Model

Seattle Public Utilities (SPU), like most water utilities throughout the country, uses demand forecasting to provide essential information in balancing future supply and demand. Seattle's first quantitative estimates began in the 1940s. Simplistic per capita models grew into slightly more complicated multivariate models which were modified in the late 1980s and early 1990s to create an econometric model.

SPU's integrated-econometric water demand forecast model is organized by sectors/classes within retail and wholesale sectors. SPU's model uses the aforementioned multivariable regression approach with three to seven independent variables, depending on the forecasted class, as well as a conservation variable that dictates the most recent system-wide savings method. The independent variables include household type/size (single vs. multifamily), employment by sector, real household income, summer water price, winter water price, sewer price, precipitation, and temperature. The econometric model includes rate-induced conservation. Other forms of conservation (i.e., programmatic, plumbing code, etc.) are estimated separately and then subtracted from the total retail demand calculated by the model. To identify distinct differences in water use among their jurisdictions, SPU initially emphasized geographic disaggregation as a priority for the model. One model identifies 77 separate forecasts in the entire SPU demand forecasting model. These forecasts account for each customer class (single-family, duplex, multifamily, small commercial, large commercial, industrial, irrigation, government/education) in 28 different areas, inside and outside Seattle's city limits in addition to the demand of 26 purveyors. The independent variables, customer classes, and overall SPU modeling approach are detailed in the table and figure below.

Table 5. SPU explanatory variables and customer classes used in long-term demand forecast models (SPU).

Explanatory Variables	Customer Class						
	Single family/dupl	Multi-family	Small Comcl.	Large Comcl.	Indust.	Irrig.	Govt/ Educatn
Number of Households*	X	X					
Number of Employees*			X	X	X	X	X
Summer Water Price**	X	X	X	X	X	X	X
Winter Water Price**	X	X	X	X	X		X
Sewer Price**	X	X	X	X			X
Real Income**	X	X					
Precipitation***	X					X	
Temperature***	X	X	X	X		X	X
Price Elasticities#	-0.16 / -	-0.10	-0.18	-0.19	-0.14	-0.54	-.10

* The model actually calculates consumption per meter and then multiplies by the number of meters. The number of meters is a function of the number of households or employees in that class.
** Equations contain lagged values of these variables.
*** Weather variables are used in estimating the model but not in forecasting.
\# Price elasticities are weighted averages of long run summer and winter elasticities

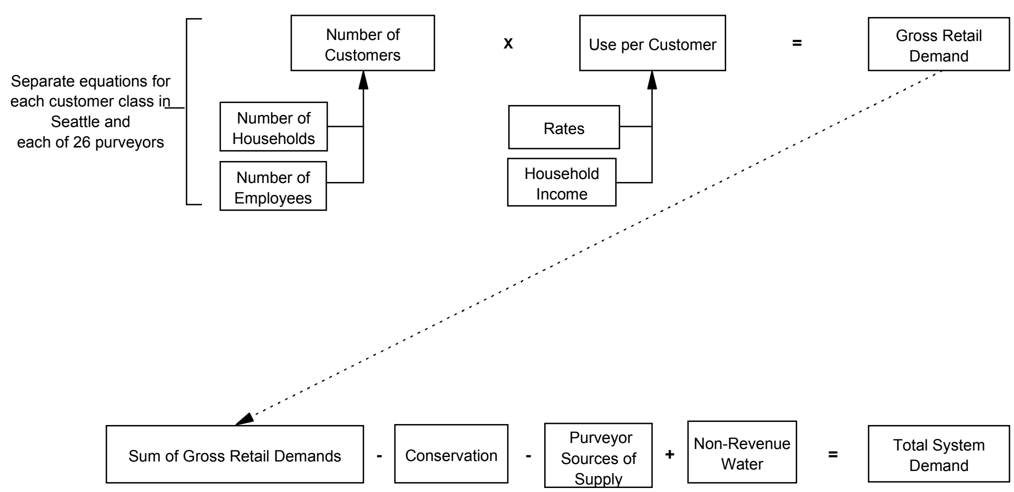

Figure 22. SPU depiction of long-term forecasting process.

Currently, SPU uses a specialized econometric approach to demand forecasting. This econometric model allows modification of the type, number, and parameters of determinants and assessment of which determinants are most significant. As in the short-term model described in Chapter 3, Seattle also uses a multivariate technique which employs a linear relationship between multiple variables (SPU). The most recent documentation of the Seattle model from an April 2001 "Long Range Water Demand Forecast and Yield Estimates" identifies the sources of data and provides assumptions used in the long-term forecast. SPU receives demographic growth information from PSRC's (Puget Sound Regional Council) forecast of households and employment, household incomes are prepared by Seattle City Light and include long range economic and demographic forecasts, and water and sewer rates are extracted from a 1996 SPU rate study. The forecast also includes current and projected SPU conservation programs. The "10% in 10 years" program (2000-2010) is used in a per capita forecast for all Seattle customers; after 2010, wholesale customers will implement new conservation techniques and retail customers are expected to participate in an additional conservation package in 2020. Using an econometric-per capita combined model, SPU's April 2001 forecast estimates demands for Seattle retail customers, current purveyors, and new purveyors from 1990-2020.

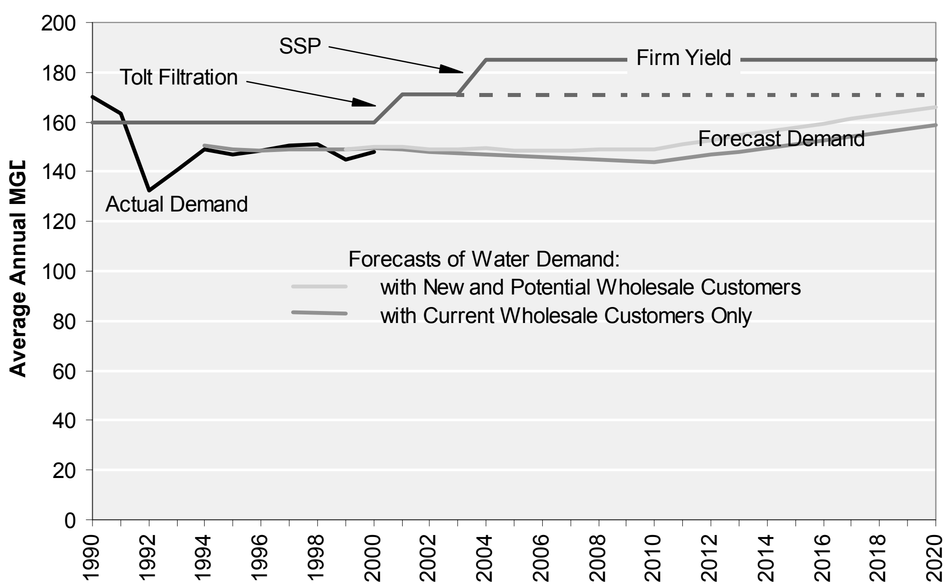

Figure 23. April 2001 SPU long-term water demand forecast.

The 2001 Central Puget Sound Regional Water Supply Outlook also provides similar water demand forecasts for the region. Though the Outlook initially recruited individual forecasts from over 150 regional utilities, the variability in the utilities' forecasts resulted in limited reliability of the combined model. The Outlook acknowledges the model's poor accountability for details regarding changes and/or development in smaller regions. Obviously a large scale regional demand forecasting model cannot explain changes on any small scale.

In general, forecasting models like those of the Outlook and SPU are designed to provide long-term forecasts through simple econometric or per capita methods, using aggregated data through time-series or cross-sectional conditions[8]. While highly aggregated modeling systems may be easier to work with due to the limited number of variables, they are inconsistent and less detailed in their analysis; this leaves significant room for improvement.

Revising the Seattle Long-term Model: Goals and Expectations

The SPU water demand model forecasts deliver confident forecasts despite documentation that reveals limited detail about the forecast methodology. One of the proposed goals of the SPU model was to geographically disaggregate water use data. Though the model divides the forecast into specific sectors based on customer class, the level of disaggregation is difficult to detect based on simplified results and restricted documentation of forecast results and methodology. Given the limited number of effectively disaggregated water demand models in the Seattle region and the potential of this type of model, the goal of this thesis is to build a framework for a highly disaggregated long-term water demand model. Using databases and resources from the City of Seattle, SPU, PSRC, and the University of Washington's Urban Simulation

[8] Time series data provide water data variables as part of historical records over a period of days, weeks, months, etc. Cross-sectional data uses one time step to describe specific conditions of water use.

research group, the model framework is a first step in gathering and organizing appropriate data in an urban planning model.

Researchers at the University of Washington have created "a software-based simulation model for integrated planning and analysis of urban development, incorporating the interactions between land use, transportation, and public policy" (UrbanSim, 2003). The model is intended for Urban Planning Commissions as well as other urban groups interested in the interface between travel models and new land use forecasting and analysis (UrbanSim, 2003). UrbanSim is a complex model that incorporates land-use and governmental policies with personal choices such as employment, household location, and method of transportation. UrbanSim is a detailed and dynamic model; however, in spite of the dynamic processes, UrbanSim neglects climate and natural resources. The model does not include regional temperature or precipitation. Similarly, UrbanSim does not identify changes in many natural resources, including water. A primary goal of the long-term Seattle water demand model was to work with UrbanSim to incorporate water resources into the model. Though a simple, aggregated water resource model may suffice for UrbanSim, a more effective model should utilize the abundant data and model disaggregation available in the UrbanSim framework. Methods for accomplishing this will be discussed.

The long-term Seattle water demand research process includes database collection, organization, and analysis; experimentation with model methodology; and collaboration with urban planning and research efforts. Through these processes, it became clear that while the need for a disaggregated water demand model for the Seattle region was well-established, research progress was not being made. Prior to this research study it is not clear that an effort to bring together many databases and resources to create the framework for a disaggregated Seattle water demand model had been attempted. While the original goal of the research was to create a tangible framework for developing and implementing a water demand model that included detailed economic, social, and environmental characteristics, the actual research process of this thesis identified the more practical terms of this goal. Practically, the long-term model research identified databases and techniques that may be employed in the design of a disaggregated long-term demand model for the Seattle region. This research was completed through experimentation with various water demand, social survey, and land-use databases. This experimentation helped determine the potential value of disaggregated water demand forecasts. While the results of these efforts are mixed, this research initiated the difficult tasks of database recruitment, joint resource planning, and initial disaggregated regression analysis.

Revised Seattle Long-term Model: Data Sources

The data sources critical to the development of a comprehensive demand model include information from the economic, social, environmental, and water utility sectors. Because the development of the model is dependent on the availability of water demand data, this research effort started with SPU. SPU provided two large water demand databases. One water demand database is organized by billing period for each SPU customer across all user sectors; the other is seasonal water data for each customer account. The seasons include averages for summer, May 16-September 15; spring/fall, September 16-November 15 and March 16-May 15; and winter December 16-March 15. The detailed billing data included residential classes of single and multifamily residences; industrial and commercial classes; fire service; and irrigation services. The classes were separated and single family residential customers became the primary sector for research. Climate data (temperature and precipitation) used during long-term model research was extracted from the SeaTac weather station. The same data are used in the short-term model (Chapter 3). Various social, economic, and land-use databases were gathered directly from PSRC and UrbanSim's regional databases from PSRC and tax related databases.

Similar to the water databases, the Parcel Index Number (PIN) tax based databases also presented detailed land-use information. This database included nearly 200,000 household accounts containing information about lot size, house size, house age, and other parcel related characteristics. Additional household information was recovered from PSRC general and household surveys. Though PSRC household surveys provide very specific details, they are far more limited in both number of households and years surveyed. The general PSRC databases are primarily linked to census data. These data cover many years and a large geographical area and can be difficult to use in a model requiring specific household information. Though data mining is time intensive and often difficult, these data searches are critical to recovery of important model resources.

Each database contributed to some aspect of the modeling exercise. These methods included highly disaggregated database organization as well as annual citywide census information. Though several different databases were utilized in many model attempts, only three methods are detailed in this thesis. Method I utilizes a geographic distribution of water demand to identify regional trends in demand, Method II incorporates a PSRC household survey with specific household water demand, and Method III integrates parcel-based information with household water demand. These methods helped to evaluate the value of various databases, determine the potential significance of disaggregated water demand models, and assess the future of research in this area of water resource management.

Revised Seattle Long-term Model: Select Methodology

METHOD I: SPATIAL DISAGGREGATION OF SEASONAL WATER DEMAND

Method I: Purpose

Because of data limitations and concerns about data base reliability, only residential users were selected to be modeled. These data were disaggregated spatially by imposing geographic divisions among SPU customers. The purpose of this method is to examine water use based on the customer's distance from an urban center in Seattle. This method makes several assumptions about SPU customers' water use; for example, dividing the city geographically assumes that users at the same distance from the center of the city use water equally because they have similar households, yard areas, housing density, or lifestyle. Dividing the database geographically provided simplification of the SPU customer database, and allowed investigation of possible geographic trends in water use. Displayed in Figure 24, the sectors are divided into rings, each with a different radius, or distance from the city center. The city center is defined as two locations in downtown Seattle, including SPU's downtown headquarters.

This method of analysis could be useful to long-term management of the SPU system. The simplification of household water use by geographic region may help the utility identify regional changes in seasonal water use or conservation when considering infrastructure, water distribution, or urban planning changes. In addition, geographic trends in water demand could help utilities identify target areas for conservation campaigns. Method I also provided the first stage in identifying useful explanatory variables and determining to what extent urban location affects water demand.

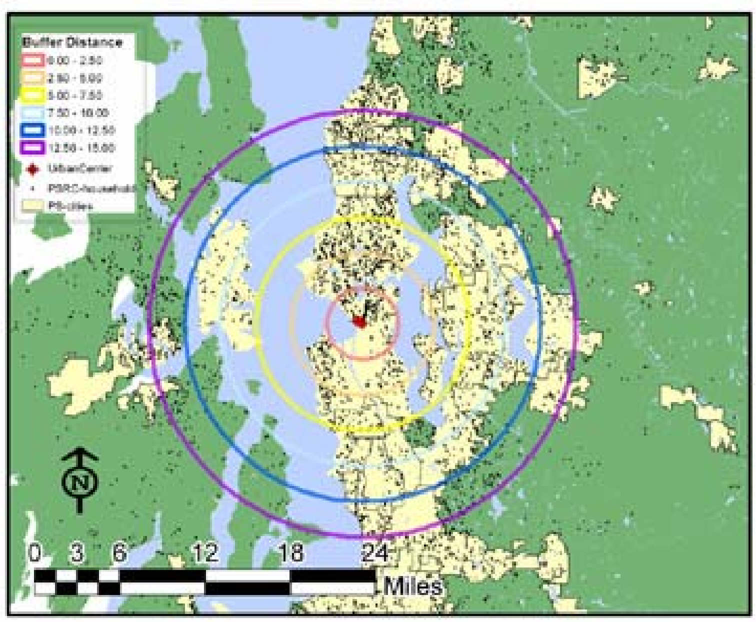

Figure 24. Spatial disaggregation of SPU residential customers in Puget Sound area. Distances in figure legend are in miles (e.g., 0.00-2.50 miles from city center).

Method I: Data

The variables included in the spatial analysis of Method I are seasonal household water use, average household income, average number of people per household, seasonal water price, average parcel area, seasonal average of monthly temperature maximum, and average seasonal precipitation. The dependent variable data, seasonal household water use, were acquired from SPU. Water prices (rates) were acquired from the utility. Household information, such as average size and annual income, was gathered from annual PSRC assessments while parcels were plotted and their area calculated using a parcel database from the Washington State Geospatial Data Archive (WAGDA). Climate data (temperature and precipitation) were obtained from NCDC's SeaTac weather station. All data were constrained to the SPU seasonal wateruse database time period of 1991-2002.

Data were aggregated into annual seasonal (summer, winter, spring-fall) averages. The households were sorted by parcel index number (PIN), plotted on an ArcGIS map, separated based on their distance from the center of Seattle (2.5 mile rings), and then sorted by year. The household water use data were then averaged for each year (1991-2002). In the five spatial rings or sectors the number of households varies for each sector.

Table 6. Geographic distribution of SPU residential customers in Figure 24 from seasonal water use database.

Distance from city center	Approx. number of SPU customers
0-2.5 miles	15,000
2.5-5	51,000
5-7.5	60,000
7.5-10	17,000
10-12.5	7,000

Method I: Methodology, Results, & Discussion

Using annual averages for each season in each of five spatial sectors, a linear regression was performed for each season, using 12 years of data of the aforementioned independent variable data. The format of the linear regression model, the regression variables, and an example of the data used for the summer season are noted below.

Equation 4.

Average seasonal household water demand = $\beta^* + x_1 \cdot A + x_2 \cdot B + x_3 \cdot C + x_4 \cdot D + x_5 \cdot E + x_6 \cdot F + x_7 \cdot G + x_8 \cdot H$

*The value of the intercept is derived in the regression analysis.

Table 7. Geographic distribution regression method variables.

Dependent variable	Average annual household water demand/season
Independent variables	A. Temperature (average seasonal max) (Tmax)
	B. Average temperature (average seasonal)
	C. Precipitation (seasonal average)
	D. Precipitation (seasonal cumulative)
	E. Water rate/price**
	F. Average household income
	G. Average number of people/household
	H. Average parcel area

**Water rates varied seasonally; the spring-fall season was taken as an average of the two off-peak rates.

Table 8. Example of data used in the 0-2.5 mile region during the summer season.

year	Tmax, F	Ave. temp, F	Ave precip., in	Ave. cumulative precip., in	Rate	LN(income)	Hshld size	Parcel area
1991	73.97	64.10	1.25	2.45	$0.93	10.83	2.40	7031.64
1992	76.63	66.17	0.90	2.70	$1.16	10.92	2.38	7025.89
1993	70.73	62.43	1.30	1.46	$1.12	10.78	2.42	7020.00
1994	75.03	65.27	0.61	2.27	$1.34	10.90	2.42	7007.52
1995	73.53	64.23	1.54	4.06	$1.33	11.01	2.42	6982.16
1996	75.17	64.97	0.89	3.94	$1.41	11.06	2.39	6954.83
1997	72.93	63.90	1.37	5.88	$1.44	10.96	2.39	6922.73
1998	74.23	64.77	0.62	1.48	$1.50	10.92	2.40	6902.55
1999	70.27	61.80	1.32	2.27	$1.60	10.88	2.37	6888.98
2000	71.90	62.80	0.72	1.68	$1.88	10.88	2.37	6888.41
2001	70.27	61.63	2.13	4.18	$2.16	10.88	2.37	6716.13
2002	73.37	63.77	0.80	1.10	$2.56	10.88	2.37	6694.27

Regressions were devised for each season in each geographic region (Figure 24). Though the regressions could include any of the independent variables specified in Table 7, most seasons and regions included four or five of the eight variables. Regression analysis revealed several variables as less significant and/or demonstrated collinearity with other variables. Though not all regional regressions performed well, several regressions produced R^2 values over 80%. A few examples of these calibrations are shown in Figures 25 and 26.

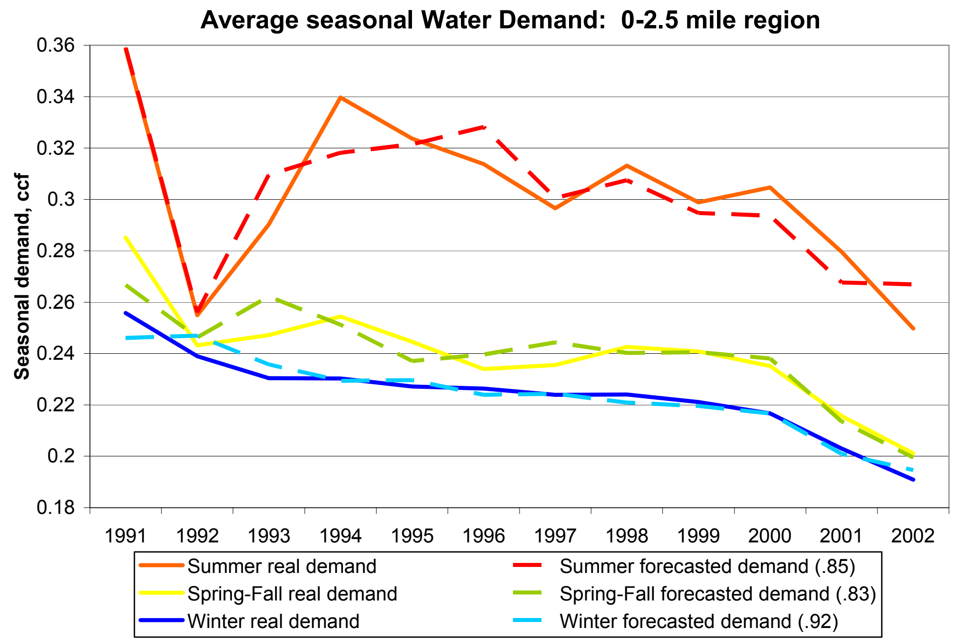

Figure 25. Calibration model for the average seasonal water demand for Seattle region 0-2.5 miles. R^2 values for each season are noted in parentheses.

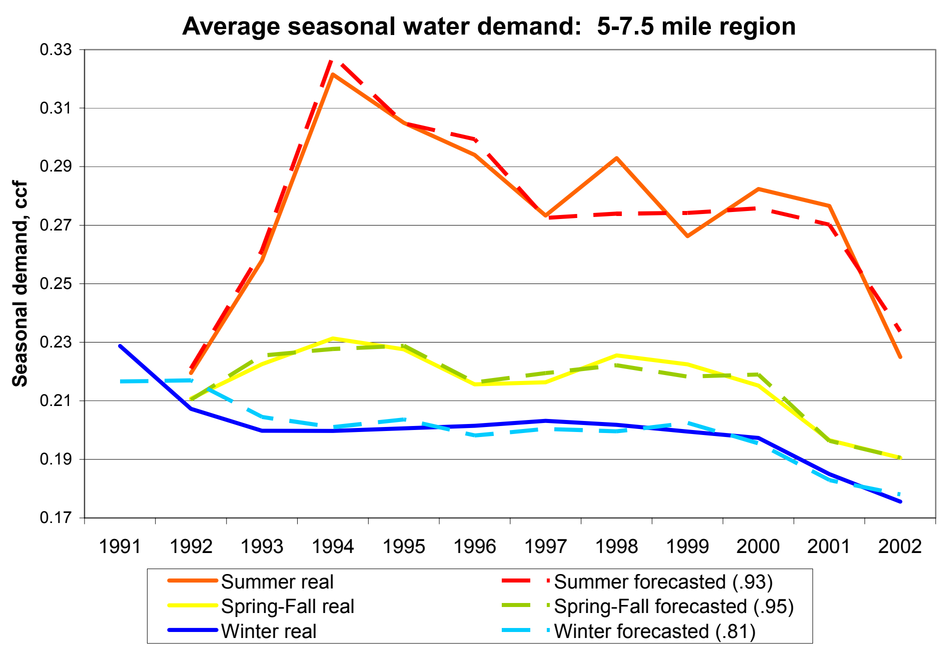

Figure 26. Calibration model for the average seasonal water demand for Seattle region 5-7.5 miles. R^2 values for each season are noted in parentheses.

These calibrations indicate the model performs well in certain regions and can help provide guidance regarding the need for and location of new supplies. It is likely, however, that the model performs well because of the highly aggregated data. Though this model allows the organization and display of a large and disaggregated database, regressions over only 12 years of annual averages are likely to produce high correlations but not necessarily powerful relationships. The adjusted R^2 (typically .66-.76)[9] and p-values (several above .50) indicate model limitations. Though seasonal averages of water use and other data are indeed representative of thousands of households, the annual averages of independent variable data (Table 7) eliminates the variability associated with these households. The results of Method I indicate that it is easier to detect a trend in averages than in the original and highly disaggregated data.

In an attempt to better utilize the disaggregated, household database, analysis was also done using individual household water use data but annual averages for each household's explanatory variables. Therefore the database included thousands of individual households with differing water demands, but similar explanatory variables. This regression analysis performed poorly during calibration (low R^2 and adjusted R^2 values and high p-values). These results are a product of the model's inability to find correlations between independent households' water use despite their similar size, income, etc. The highly disaggregated model demonstrates the high variance between individual household water use. Though less statistically robust due to lower significance values and potential collinearity between independent variables, the original aggregated model calibration captures regional annual seasonal averages more effectively.

With the exception of higher water use in the 10-12.5 mile region and the increased parcel area in the 5-7.5 mile region, the regions in Figure 24 are surprisingly similar.

[9] The adjusted R^2 value accounts for the degrees of freedom in the model and is adjusted based on the number of potentially unnecessary determinant (independent) variables in the regression (Based on its mathematical origin, R^2 values will always increase as the number of determinants increases, despite what is actually statistically valuable to the correlation.) (Devore, 1987).

Differences between water use or parcel size may be the result of a few outlying points or increased lawn size and watering; therefore no specific conclusions can be drawn from these minor differences. Unfortunately due to disaggregated data averages, Method I does not illustrate dramatic trends or the potential for evaluating future trends in Seattle's regional water use. While the original purpose of the long-term model analysis was to consider possible methods for evaluating and forecasting highly disaggregated water use, this method, though spatially disaggregated, does not ultimately meet this standard as Method I does not successfully utilize disaggregated data throughout the analysis. Method I does however identify potentially useful databases and strategies for future research in spatially disaggregated water demand data.

METHOD II: PSRC WAVE-SURVEY AND MATCHING SEASONAL WATER DEMAND

Method II: Purpose

Method II continues to explore modeling spatially disaggregated water demand. The value of specific household data in development of a regression-based demand model ranges from potential long-term system management to specific investigations of system failures in certain regions. Though Method I illustrated a potentially useful approach to data disaggregation, the poor performance of the model using water use averages and regional generalizations for independent household data did not support the value of the approach. Like Method I, Method II uses SPU's seasonal water use database but incorporates household-specific information based on a ten-year PSRC survey. The Wave survey may help determine long-term trends in households' income or size that could be used in a long-term forecast model.

Method II: Data

The water demand data (SPU seasonal, residential only), parcel area, water rates, and climate data are the same data used in Method I. The household data (income and number of people per household) was gathered from the PSRC "Wave survey" from 1989-1999 (except 1995 and 1998). The Wave survey documents PSRC's survey of household characteristics (i.e. size, income, number of cars, etc.) from hundreds of residents in the Puget Sound region over a 10-year period. The survey was acquired with PSRC permission from the Univeristy of Washington's UrbanSim research group.

Method II uses household specific information about wateruse and household characteristics. To integrate the Wave survey and SPU seasonal water use databases, the accounts were matched based on address; this significantly limited the number of households available for evaluation. Though hundreds of households were surveyed throughout the Puget Sound, only a select number within the SPU service region and/or were surveyed consistently throughout the PSRC survey period. A total 385 accounts were included in the joint wave survey and SPU databases.

Method II: Methodology, Results, & Discussion

A linear regression was performed using the PSRC Wave survey and SPU water demand accounts were used in linear regression analysis. Variables for Method II are specified in Table 9. Analogous to the short-term demand model, this method also uses winter water demand as an independent variable for the summer-fall seasons. Unlike the annual system-wide average winter demand in the short-term model (Chapter 3), winter water demand in Method II is taken as the actual household winter water demand for each year.

Equation 5.

Average seasonal household water demand = $\beta^* + x_1 \cdot A + x_2 \cdot B + x_3 \cdot C + x_4 \cdot D + x_5 \cdot E + x_6 \cdot F + x_7 \cdot G$

*The value of the intercept is derived in the regression analysis.

Table 9. PSRC wave survey regression method variables.

Dependent variable	Household water demand/season
Independent variables	A. Temperature (average seasonal max) (Tmax)
	B. Precipitation (seasonal average)
	C. Water rate/price**
	D. Actual annual household income
	E. Actual number of people/household
	F. Average parcel area
	G. Actual winter water use$^+$

**Water rates varied seasonally; the spring-fall season was taken as an average of the two off-peak rates.
$^+$Winter water use was used as an independent variable in the summer, spring-fall, and summer and spring-fall regressions. It was withheld from the regressions for all seasons and the winter season alone.

A sample of the model database used in Method II is illustrated in Table 10.

Table 10. Sample section of the database used in Method II.

Address	Year	Water use, ccf	Tmax, F	Ave precip., in	Rate	Std. Income	Hshld. size	Parcel area	Winter water use
CONFIDENTIAL		summer							
	1992	0.18	76.63	0.90	2.23	3	2	7025.9	0.17
	1992	0.20	76.63	0.90	2.23	4	5	7025.9	0.19
	1992	0.12	76.63	0.90	2.23	8	3	7025.9	0.12
	...	spring-fall							
	1992	0.16	62.12	2.52	0.96	3	2	7025.9	0.17
	1992	0.19	62.12	2.52	0.96	4	5	7025.9	0.19
	1992	0.13	62.12	2.52	0.96	8	3	7025.9	0.12
	...	winter							
	1992	0.17	49.07	5.00	0.93	3	2	7025.9	N/A
	1992	0.19	49.07	5.00	0.93	4	5	7025.9	N/A
	1992	0.12	49.07	5.00	0.93	8	3	7025.9	N/A

Characterized only by season, the calibration of the summer, spring-fall, and winter season regression models in Method II yields mixed results. These are summarized in Table 11. The R^2 values were low for most seasons; the summer and spring-fall combined season as well as the spring-fall season have stronger R^2 values as they benefit most from the explanatory variable of winter water demand. The winter regression performed most poorly due to the lack of strong explanatory variables. The significance (p-values) of the independent variables did not support strong correlations between the actual and predicted household water demand. In addition, the coefficients derived during the regression analysis do not indicate a strong relationship between the explanatory and independent variables. Many of the coefficients had very small and/or illogical values.

Table 11. Summary statistics for Method II regression analysis.

Season	R^2	RMSE
ALL	0.148	0.163
Summer	0.368	0.155
Spring-Fall	0.764	0.080
Winter	0.196	0.138
Summer and Spring-Fall	0.528	0.126

Though the statistical analysis of Method II is not encouraging, Method II provides an opportunity to analyze water demand by household. Despite the potentially helpful PSRC Wave survey, prediction of such disaggregated water demand clearly needs a more substantial and consistent database. This method, like Method I, provides knowledge about the effectiveness of data disaggregation and the needs for future forecast methods. According to these methods, household-specific data are important to the pursuit of truly disaggregated models. In addition, these data must include several years and be consistent in representing information throughout that time.

METHOD III: PIN DATABASE MATCHED TO MONTHLY WATER DEMAND

Method III Purpose:

Method III utilizes the SPU monthly billing database for residential household water use and the parcel index number (PIN) database from the UrbanSim research group. Using monthly water use information and parcel-based characteristics (i.e., lot size, built square-feet, number of residences per parcel, land value, house age, etc.) as well as climate data, Method III examines the relationship between water use and parcel characteristics related to urban development. The monthly database and PIN database provide an opportunity to examine household water use and the affects of parcel and household features. Trends in water use based on lot size and house-age may provide insight into the effectiveness of plumbing code versus volunteer conservation, or how future zoning regulations (regarding lot size) might affect water use.

Method III Data:

The PIN database includes public information collected through tax records; this includes the parcel's census block, city, county, land use type, number of residential units, lot area, built square feet, value of parcel improvements, land value, and year the parcel structure was built. The SPU database records bi-monthly water bills for every SPU customer from 1992-2003 (received from Tiva Brown). In addition to the water use and parcel information, Method III also incorporates climate data, including average monthly temperature maximum and cumulative monthly precipitation from NCDC's SeaTac weather station.

Due to the size (1+ gigabytes) of these databases, steps were taken to simplify them. Residential water use was sorted from the overall SPU water use database and the PIN and SPU databases were matched based on date and PIN id numbers. The two databases were combined with the associated climate data and parcels with one residential unit were selected. Though the database still included millions of accounts over the 12 year period (1992-2003), it contained only single family residences.

Seven independent variables were selected for model construction: lot area, built square feet, value of parcel improvements, land value, year the parcel structure was built, maximum monthly temperature, and cumulative precipitation. To remove outlying values that skewed initial model regressiosns, all water use values equal to zero were removed. In addition, values for each account in the aforementioned variables, as well as monthly water demand, were standardized[10]. The standardized variables were limited to a range of three standard deviations and outliers were removed. Remaining outliers are evidence of inevitable error often associated with extremely large database calculations. Most outlying values are the result of unusually high or low water use in a short time period for one account, mismatched database entries, or error in the calculation or input of the original water use data. With the remaining outliers in mind, the joint database was separated based on season: November-February (winter), March-May (spring), June-August (summer), and September-October (fall).

Method III: Methodology, Results, & Discussion

The evaluation of Method III includes experimentation with database consistency, linear versus log-linear regressions, and the determination of the most influential parcel characteristics.

To ensure the stability of each database, several linear regressions were performed for each season. Once the summary statistics (i.e., R^2 and adjusted R^2 values) of the linear regressions were consistent between sample sizes, the natural log of each variable (Table 12) was calculated for use in a final log linear model (Equation 6).

Equation 6.

Monthly water demand/household = $\beta * \cdot A^{x_1} \cdot B^{x_2} \cdot C^{x_3} \cdot D^{x_4} \cdot E^{x_5} \cdot F^{x_6} \cdot G^{x_7}$

Take the natural log of both sides:

Ln(Monthly water demand/household) = β* + $x_1 \cdot$Ln(A) + $x_2 \cdot$Ln(B) + $x_3 \cdot$Ln(C) + $x_4 \cdot$Ln(D) + $x_5 \cdot$Ln(E) + $x_6 \cdot$Ln(F) + $x_7 \cdot$Ln(G)

*The value of the intercept is derived in the regression analysis

[10] Standardized value $= (\chi - \mu)/\sigma$ where χ is the original value, μ is the mean of the original values, and σ is the standard deviation.

Table 12. PIN and SPU monthly billing regression method.

Dependent variable	Monthly water demand/household
Independent variables	A. Lot area
	B. Value of parcel improvements
	C. Land value
	D. Year parcel structure was built
	E. Tmax (average monthly max)
	F. Cumulative precipitation (monthly)
	G. Built square feet

Using the significance tests, R^2 values, and collinearity diagnostics, four to five variables were selected for each seasonal regression model (Table 13).

Table 13. Summary statistics of seasonal log-linear models using PIN and SPU monthly billing databases.

Season	R	R^2	Adj. R^2	Ind. Variables	Coefficient value
Winter (4 months)	0.261	0.068	0.068	Built sq. ft.	0.286
				Land value	-0.074
				Lot area	0.056
				Cum. Precip.	-0.023
				Intercept	1.121
Spring (3 months)	0.256	0.065	0.065	Built sq. ft.	0.278
				Land value	-0.081
				Tmax	0.169
				Lot area	0.048
				Intercept	0.730
Summer (3 months)	0.340	0.115	0.115	Built sq. ft.	0.295
				Lot area	0.137
				Improve. Value	0.045
				Tmax	0.810
				Intercept	-3.613
Fall (2 months)	0.357	0.127	0.127	Built sq. ft.	0.343
				Lot area	0.135
				Year built	-0.518
				Tmax	0.586
				Intercept	1.321

Log-linear regressions for each of the four seasons resulted in consistently low R^2 values. This is a result of weak correlation between the independent and explanatory variables and extremely diverse and disaggregated databases. These disaggregated databases, unlike those of Methods I and II, include millions of accounts over 12 years. Due to large databases and poor correlations log-linear modeling on the household level does not produce accurate water use predictions. This does not suggest that Method III is not a useful indicator of valuable parcel characteristics. Aggregated results of this method be captured the value of this method more precisely (Figures 27-30).

Using the seasonal coefficients noted in Table 13, predicted water demand was calculated for each household account and time period. The total water demanded for each year (1992-2003) during each season was then calculated. Unlike previous methods, the figures below do not represented calibrations of regression analysis. Instead, the predicted annual and actual annual totals for each season are displayed in Figures 27-30. Note high winter water demand in Figure 27 does not reflect the system-wide demand lows observed during the analysis of the short-term water demand model. The sum of winter water demands is greatest because the winter season represents four months, spring and summer are each three months, and fall represents only two months.

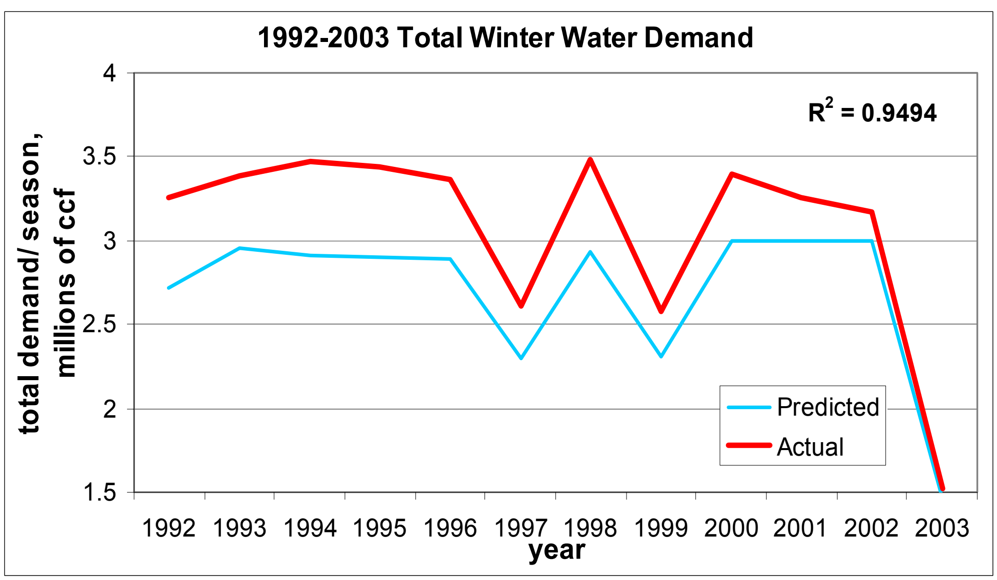

Figure 27. Total annual winter (November-February) water demanded by Seattle SPU residential customers, 1992-2003.

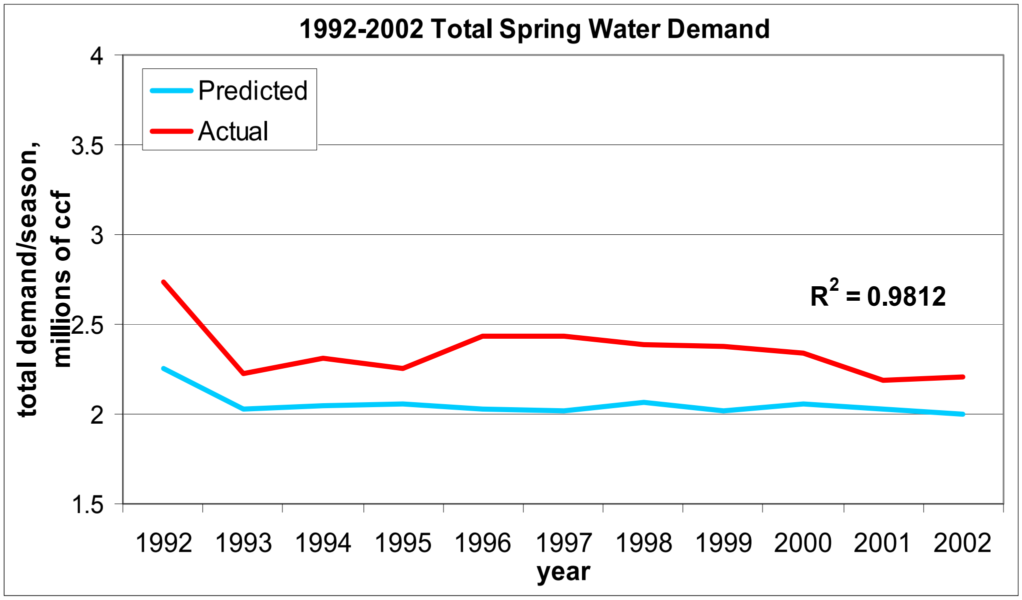

Figure 28. Total annual spring (March-May) water demanded by Seattle SPU residential customers, 1992-2002.

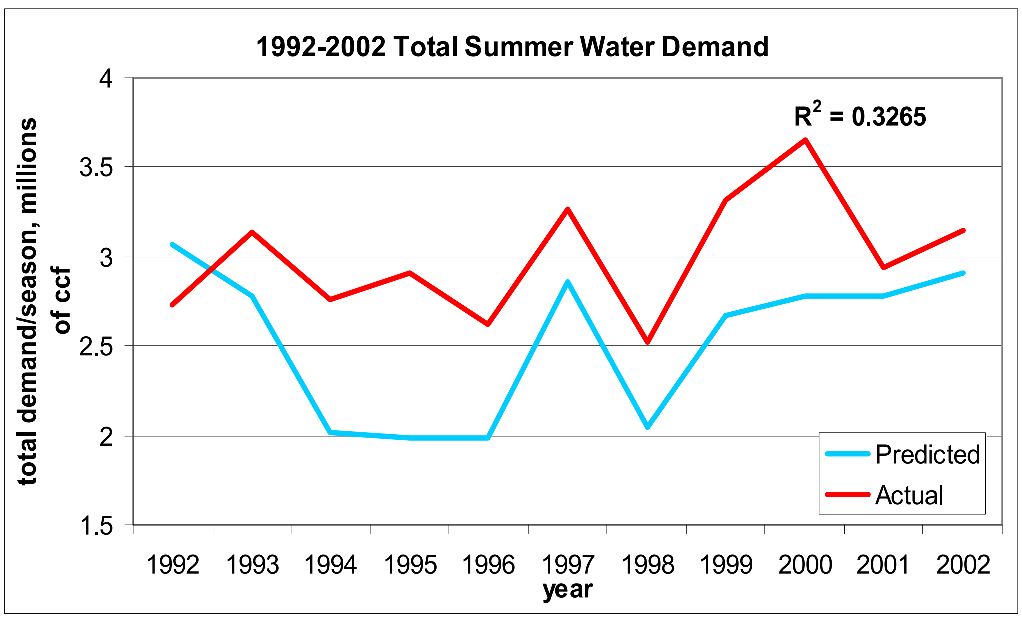

Figure 29. Total annual summer (June-August) water demanded by Seattle SPU residential customers, 1992-2002.

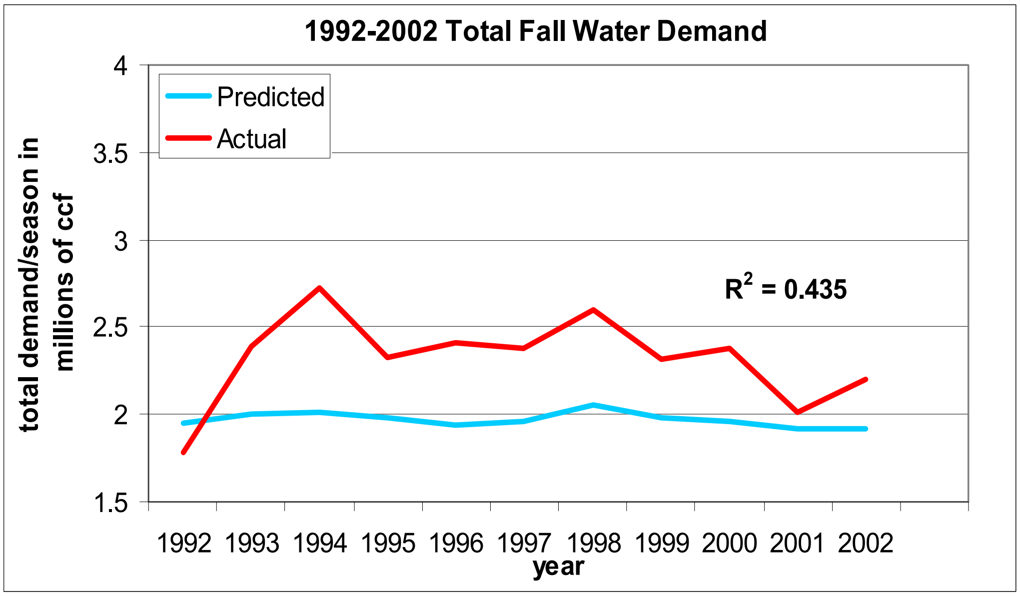

Figure 30. Total annual fall (September-October) water demanded by Seattle SPU residential customers, 1992-2002.

Figures 27-30 indicate a better correlation between total seasonal water demands than intra-seasonal monthly demands. These improved correlations are the result of decreased variability in the seasonal sums. The limited number of data points (12) represented by the sum totals for each season eliminates the unpredictable and sometimes erratic household water use between different months and seasons. Figures 27-30 reveal the hidden benefits of Method III's household regression model. The ability of the model to capture the shape and trend of seasonal water demand based on individual household assessments is important. These seasonal totals do limit the specificity of the disaggregated log-linear model but allow managers to gain appropriate estimates of the total water supply needed for each season. The predicted water demand is consistently below the actual water demand. This is a result of prevalent outliers in the combined database. Outlying values that represent inaccurate water demand draw the predicted seasonal totals down for each year. Future research with more effective database sorting techniques will help identify and remove such outlying values.

Several of the explanatory PIN database variables in Method III are useful predictors of water demand. Most independent variables/determinants were logically introduced to the model depending on season; spring, summer, and fall season models include temperature, while winter incorporates cumulative precipitation. Two variables common to all four seasons are built square feet (the number of square footage that contains a structure on the parcel) and total parcel lot area. Although no specific research has been completed with these variables, these determinants are the most prevalent variables in Method III and represent consistent generalizations about each account's indoor and outdoor water use. Namely, lot size is an indicator of outdoor water use (with a smaller coefficient value during wetter seasons, Table 13) and built square footage indicates the size of the house and indoor water use. As discussed earlier, research to determine trends in lot size relative to house age ("year built") or water use relative to improvement value may provide insight to new construction trends, successes in water conservation due to changes in urban planning (e.g., zoning), or the effectiveness of new household water-related infrastructure or appliances.

Poor performance of the model on the household level should not determine the long-term effectiveness of Method III. Though the research goal for this thesis seeks to create a highly disaggregated water demand model, Method III fully incorporates the household-specific, spatially disaggregated water data with a more traditional long-term model approach. Long-term water demand models, as shown in the SPU forecasts (Figure 23) are often generalizations of water demand, or sum totals of the demand anticipated for a certain user group during an entire year. Method III is capable of performing the same task, but employs specific user data over distinct time periods to more accurately represent water demands. A challenge to maintaining this new method is retaining accurate water demand databases. While a method of extrapolation may be easiest for predicting future seasonal water demand totals, this is less accurate than specific household estimates of future demand. The benefit of using PIN database variables is that these variables are easy to predict, therefore simplifying data needs for long-term demand forecasts.

Revised Seattle Long-term Model Conclusions

The recruitment, organization, and manipulation of SPU, PSRC, and urban planning databases were critical to the revised methods for Seattle's long-term demand model. Previous research in Puget Sound demand forecasting has not attempted the difficult task of joining such large and detailed databases. This research effort contributed significantly to the knowledge and availability of water demand data and determinant relationships. In addition, these methods introduced the possibility of using highly disaggregated data to create more accurate and realistic long-term residential water demand models.

The spatially disaggregated water use in Method I was not entirely successful due to the aggregation of annual water use data. This effort did, however, initiate the idea of geographic sectors of water demand. To capture more realistic distributions of water demand, future research using the geographic distribution of water demand might be more accurate if regions are based on pressure zones or transportation analysis zones. Methods II and III use the household-specific approach to estimate water demands. The benefits of these approaches are numerous; they are accurate representations of diverse water needs and provide resource managers with more information about seasonal or regional water demands. Future work using these methodologies should include the regular recruitment of user-specific water demand data, experimentation with specific parcel-based variables and water use (e.g., are higher improvement values representative of lower indoor water use?), and regional assessments of water demand according to neighborhoods or residence type.

Research for the revised long-term water demand model for the Seattle region suggests that highly disaggregated water demands cannot be used effectively unless properly preprocessed. In addition, disaggregated water demand models need several determinants, representative of social, economic, and environmental factors. Though statistical correlations between highly disaggregated predicted water demand and actual demand may be weaker than typical expectations of forecast or regression models, disaggregated water demands, by region, season, or customer are critical components to more precise forecast models. As urban demands on water increase with growing populations, environmental needs, and climate change impacts, more diverse and precise water demand models will be increasingly useful to water resource managers.

Chapter 5. Conclusions and Recommendations

> Water is like the blood in our veins.
> -Levi Eshkol, Isreali Prime Minister, 1962

> And it never failed that during the dry years the people forgot about the rich years, and during the wet years they lost all memory of the dry years. It was always that way.
> - John Steinbeck, East of Eden

Due to increasing global populations, urban development, requirements for fish flows, and hydrologic changes due to climate change, nearly 7 billion people in 60 countries could face challenges due to water scarcity by 2050 (Nature, 2003). While many developing countries confront serious difficulties due to water quality issues, the western U.S. must address the consequences of drought conditions and demands that exceed the water resources available. Like the blood in our veins, water is a necessity to all life forms and pursuits. Consequently, changing global and regional circumstances have increased the need for accurate predictions of both water supply and demand.

Nearly every decision we make is based on a forecast or prediction about some future condition. Demand forecasting is an essential part of water resource management decisions. Utility managers are responsible for answering dozens of questions related to water demands; including inquiries about seasonal patterns, regional supplies, supply development, climate variability and change impacts, financial impacts, and changes and consequences of conservation (AWWA, 1996). As our knowledge about current and future water demands improves, the ability of resource managers to make confident assessments about the impacts of climate change, demand management, changes in urban planning, and the outcome of long-term water resource conflicts improves.

This research explores the theory and history of water demand forecasting, short-term applications of water demand forecasts, and the value of highly disaggregated water demand model methodologies. Some of the conclusions drawn by these research efforts are noted below:

- Demand forecasting models are critical to successful resource management
  Research in water resource management has revealed the consequences of inaccurate water demand forecasting. Unexpected droughts, financial crises, over-use of resources, or unnecessary infrastructure development are the result of poor anticipation of water demands and inflexible resource management. Examples of this include the Klamath Basin water crisis in Oregon and California, the Lower Colorado water conflict, and many international water crises (e.g., Hermanus, South Africa).

- Models are created for both understanding and prediction
  Throughout the modeling process it is easy to be absorbed by the pressure for accurate forecasts. According to other simulation scientists, the value of forecast models is not only in the forecasts they create, but the process that creates them. Improved understandings of the determinants of water demand provide information about the relationship between key social, economic, and environmental variables and water consumption.

- Short-term models provide six-month forecasts of regional water demand
  Using NCEP climate forecasts, short-term water demand models for the Puget Sound region provide seasonal guidance for utility managers. According to the forecasts during 2003-2004, six-month forecasts for system-wide water demand are significantly affected by baseline demands (winter water demand) and climate factors such as temperature and precipitation. Forecast models for 2003 calibrated with R^2 values above 80% and were validated with R^2 of 60-85%. The six-month forecasts demonstrated improved skill and decreased RMSE over time. Demand hindcasts during 1989-1999 confirmed the capabilities of the short-term

model. Errors in the hindcast output are largely the result of inaccuracte NCEP climate hindcasts, unpredictable changes in the behavior of water users, and SPU curtailments.

Six-month forecasts are also an important part of general system models that incorporate multiple supplies and demands to help prepare resource managers and aid decision making processes. The short-term model will be used to generate on-going forecasts using updated NCEP climate forecast information. These forecasts will be used in Seattle operations models and future Puget Sound water resources research.

- <u>Disaggregated water demand models are complex systems that may result in more accurate and accountable long-term demand forecasting</u>
  The methods detailed in Chapter 4 indicate that while the value of disaggregated water demand data is often lost in its variability, such databases could be significant to the improvement of traditional and simplistic long-term demand models.

  Methods pursued in this study indicate that aggregated residential water demand data and household characteristics correlate well but do not adequately represent actual household water demands. In addition, while spatial disaggregation of water demands effectively separates data and may identify trends in water use based on land use or residential density, this method did not produce a robust model. The most effective method produced seasonal sums of total water demand based on the results of a highly disaggregated model. Method III utilizes highly disaggregated data but presents useful results for resource managers. Though data intensive, the right combination of land use, climate, and household related determinants, as well as careful aggregation of detailed data, results in a useful framework for continuing research in natural resource management and urban planning.

These conclusions also represent hopeful applications of the research completed in this thesis. An automated short-term forecasting model can be regularly updated with recalibrated coefficients, climate forecasts, and recent water demand data. Short-term forecasts can be used in decision support systems and models for the Puget Sound region. The long-term modeling efforts have not only identified key databases for future experimentation in disaggregated demand forecasting analysis, but with additional analysis can be incorporated into detailed Puget Sound urban planning simulation model.

These conclusions are not without a need for future research:

- Regular calibrations and experimentation with new variables is important for the on-going use of the short-term demand model. Consideration of different atmospheric variables, such as a clear-sky index, may be useful for certain seasons. In addition, future research on short-term demand modeling might include altering the time-step of the model or improving the metrics for model evaluation. Finally, future modeling efforts should include discussion with local utilities regarding changes in supply flows, resource distribution or financial policies, regional supply opportunities, community relations, and conservation.

- The disaggregated modeling efforts will be improved with closer examination of relationships between water use and specific urban planning or land use-related variables. In addition, future research should encourage the collection of both household and parcel-related information; this may occur as formal independent surveys or more detailed inquiries to existing agencies such as the PSRC. Improved availability of highly disaggregated data from all sectors, including household and parcel-based information related to geographic, social, economic, and environmental sectors, may improve the correlation between actual and predicted household water demands.

As in the short-term model research, future long-term model work should also consider local utility changes in supply flows, resource distribution or financial policies, regional supply opportunities, community relations, and extending conservation plans. While the modeling research accomplished in this study did not produce a model prepared for long-term water demand forecasts, further calibration and consideration of the aforementioned suggestions may lead to successful long-term forecasts for the Seattle region.

Determined to disprove Sewell's characterization of water resource planning as unable to anticipate change, this research creates new models and relationships for resource prediction and management. As we enter a new era of potential resource scarcity and increasing resource politics, flexible and inventive resource management will prove techniques such as demand forecasting critical to the preservation of our most treasured natural resources.

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Appendix A. Short-term Model: Seattle

Included are the remaining calibration and validation figures for the winter and spring seasons for the Seattle short-term model.

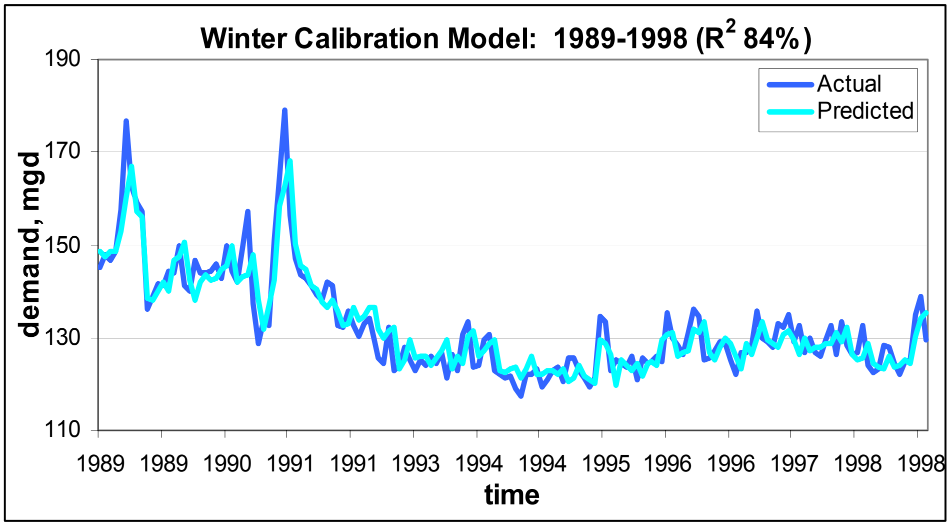

Figure 1A. Seattle's winter water demand (system-wide) model calibration: actual (historic) versus predicted model.

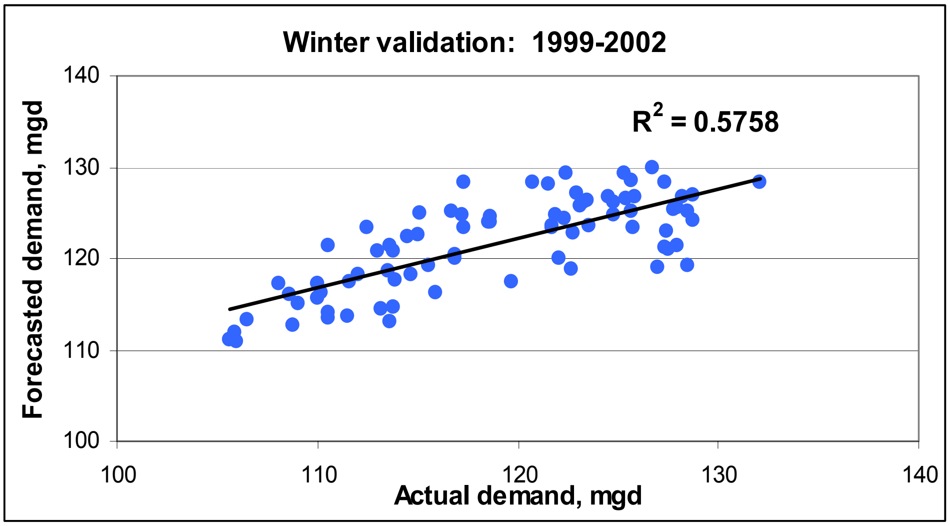

Figure 2A. Winter water demand (system-wide) model validation: actual (historic) versus predicted model for the Seattle region.

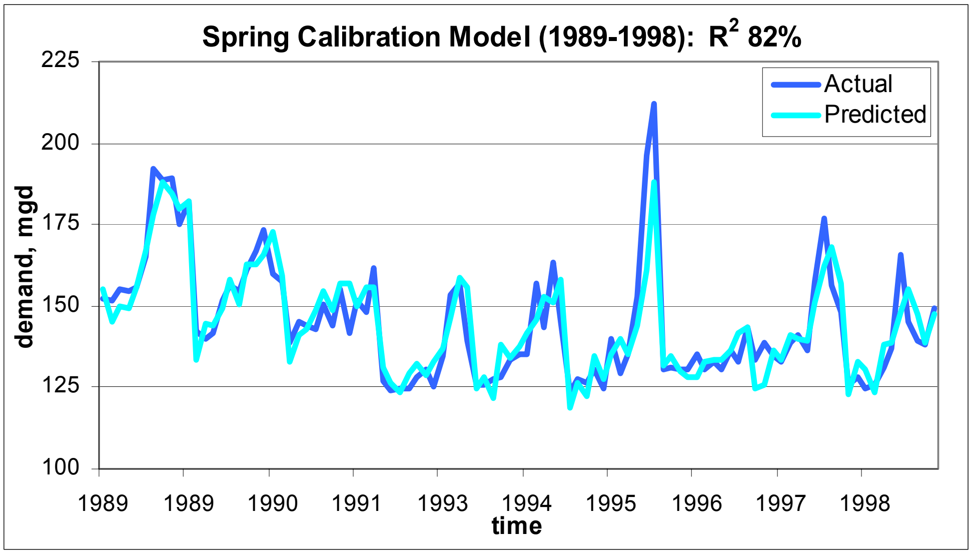

Figure 3A. Seattle's spring water demand (system-wide) model calibration: actual (historic) versus predicted model.

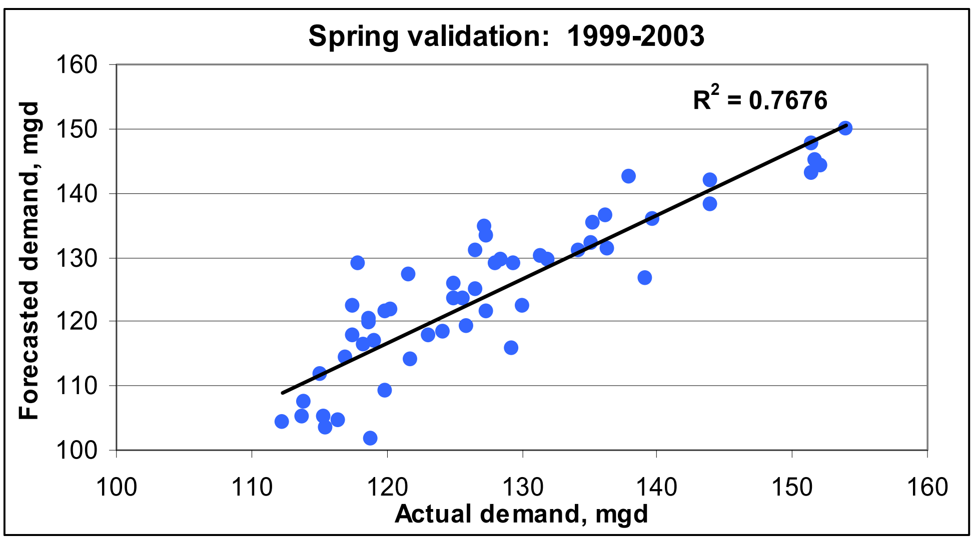

Figure 4A. Spring water demand (system-wide) model validation: actual (historic) versus predicted model for the Seattle region.

Appendix B. Short-term Model: Tacoma and Everett

Both the Tacoma and Everett models were designed to forecast only municipal water demand. Though industrial demands are a significant part of both utilities demands, they are far less variable and are much simpler to predict, as they are managed regularly. As in the Seattle model, the Tacoma and Everett models are based on a log linear regression over four seasons and similar independent variables.

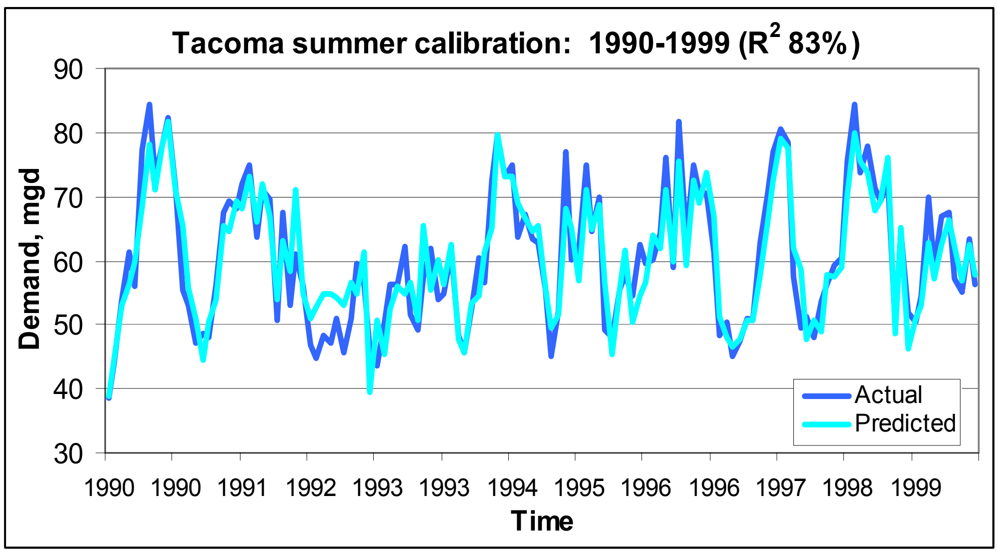

Figure 1B. Tacoma's summer water demand (system-wide) model calibration: actual (historic) versus predicted model.

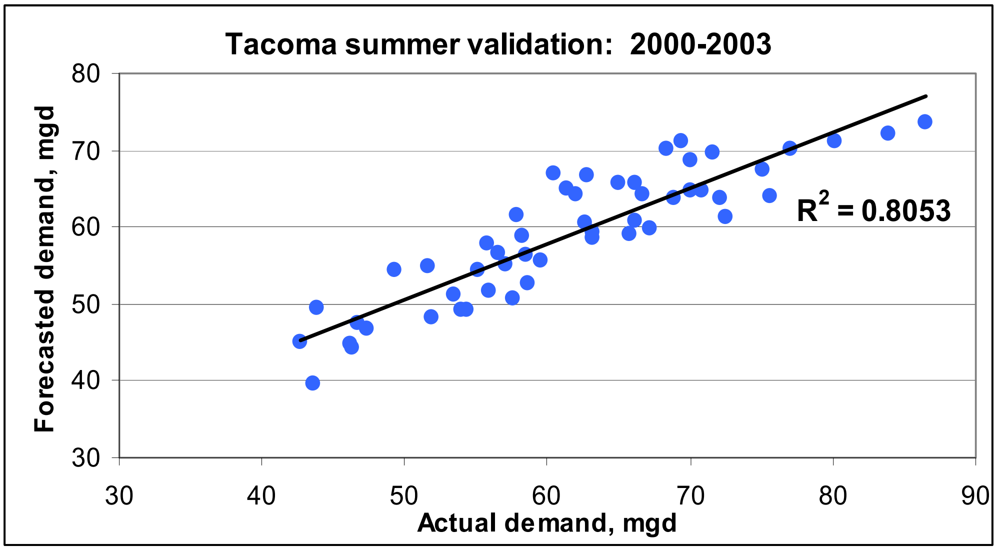

Figure 2B. Summer water demand (system-wide) model validation: actual (historic) versus predicted model for the Tacoma region.

The remaining seasons for the Tacoma model were calibrated and validated using similar techniques. The fall season was calibrated using 1990-1999, winter: 1992-2001, and spring was calibrated over all the data due to weak results of the selected years. The coefficients used for each season for the Tacoma model are displayed below.

Table 1B. Tacoma short-term model variables and coefficients.

Spring		Winter	
intercept	1.07773	intercept	0.0996
LnTmax	0.21332	add5LnTmax	-0.0266
add5LnPrecip	-0.0429	add5LnPrecip	-0.0119
LnTmaxlag	0.13467	add5LnTmaxlag	-0.0115
Ln$	-0.0201	Ln$	-0.0406
LnwH2O	0.46376	LnwH2O	0.23323
LnH2Olag	0.02703	LnH2Olag	0.76691

Fall		Summer	
intercept	-0.9113	intercept	0.7283
LnTmax	0.17118	LnTmax	0.6203
add5LnPrecip	-0.07	add5LnPrecip	-0.2139
Ln$	0.07595	LnTmaxlag	-0.2961
LnwH2O	0.70506	Ln$	0.0549
LnH2Olag	0.47363	LnwH2O	0.0346
		LnH2Olag	0.6393

Due to the consistent and large changes in the coefficients during the calibration tests, each season of the Everett model was calibrated over the entire record (1990-2003).

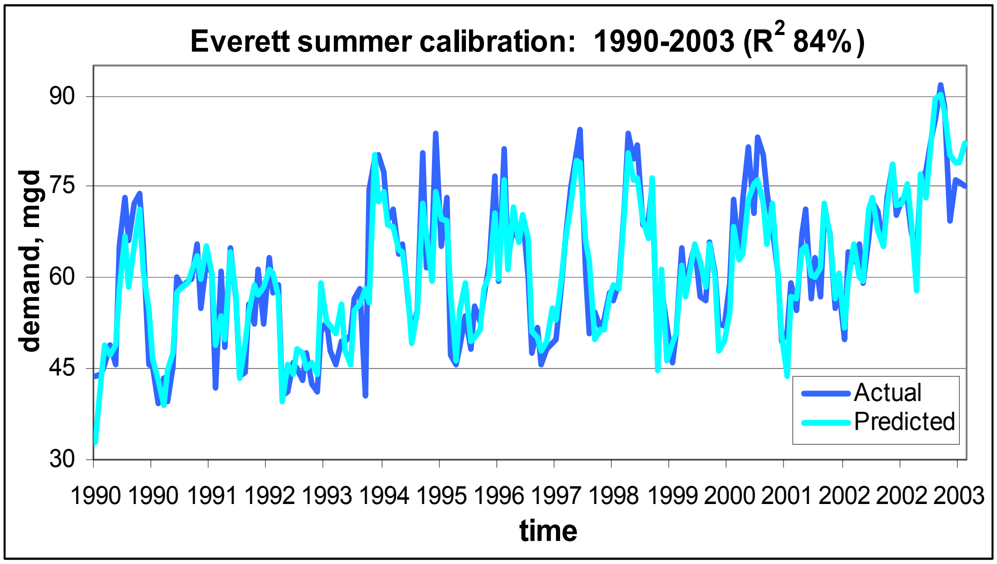

Figure 3B. Everett's summer water demand (system-wide) model calibration: actual (historic) versus predicted model.

Table 2B. Everett short-term model variables and coefficients.

Spring		Winter	
intercept	-0.322	intercept	0.6691
add5LnTmax	0.1064	LnTmax	-0.0553
add5LnPrecip	-0.087	add5LnPrecip	0.0135
add5LnTmaxlag	0.0193	LnTmaxlag	-0.01
Ln$	0.0818	Ln$	0.0798
LnwH2O	0.3818	LnwH2O	0.4145
LnH2Olag	0.663	LnH2Olag	0.4384

Fall		Summer	
intercept	-0.8332	intercept	-1.096
LnTmax	0.127	LnTmax	0.7302
add5LnPrecip	-0.0133	add5LnPrecip	-0.128
LnwH2O	0.5765	LnTmaxlag	-0.089
LnH2Olag	0.5704	Ln$	0.2108
		LnwH2O	0.4094
		LnH2Olag	0.4472