Effects of Urban Development and Climate on Water Demands and Curtailments

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Abstract

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Water demand forecasts play a crucial role in management of municipal water resources. An accurate forecast indicates the quantity of water needed for the future; however, demand forecasting is an evolving art, and there is no single forecast method that is appropriate for all settings. Many forecasting methods have evolved to address demography, the economy, and social attitudes of a region. Methods for forecasting water demands have been evolving since the mid-1960s. Prior to that, water demand was modeled as a rudimentary function of the number of residential and industrial water users. Water demand models are useful as both descriptive and predictive tools. Utilities commonly develop water demand models to infer demand patterns and characteristics associated with their customer base. Understanding customer characteristics can provide valuable insight into consumer response to demand management techniques, such as changes in price or rate structures, implementation of water conservation programs, or response to drought curtailments. The ability to predict customer response to demand-side changes increases the tools available to water resources managers and decreases the uncertainty associated with making management decisions. As a predictive tool, forecasts provide municipalities estimates of short and long-term demands. Accurate forecasts help ensure that an appropriate amount of water supply is available when it is needed and that it will be provided reliably.

This research improves the understanding of some key factors that determine water consumption, and investigates how changes in climate and regional growth patterns influence residential water consumption. This research also investigates customer response to demand management techniques and quantifies the effectiveness of one common technique, water curtailments, among different customer groups. This dissertation provides engineers and planners methods for developing detailed and potentially more accurate forecasts of long-term water demands, as well as highlighting how the built environment and climate change influence residential water demands and curtailment effectiveness.

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Chapter 1: Introduction

Water is essential for life. Humans require approximately 2500 cubic feet (ft^3) of water per year, or about 50 gallons per capita per day (gpcd), to meet standard needs (drinking water, sanitation services, bathing, and cooking), with minimal hardships (Gleick 1996). Gleick estimates that just over 1750 ft^3 (36 gpcd) of water is required to meet the most fundamental human requirements (1996). In the United States public water use totaled 44.2 Bgal/d in 2005, constituting about 13% of all freshwater withdrawals and averaging 100 gpcd for domestic uses (USGS 2005). These 2005 consumption rates are greater than those in any other nation, at twice the domestic average usage of European countries.

Approximately half of municipal water demands are classified as 'luxury' usage, such as outdoor yard watering, filling swimming pools, operating evaporative coolers, and sanitation and cleaning water consumption above the basic requirements. These activities are responsible for much of the variability of water demands between different regions, the magnitude to which climate drives seasonal water use, and the differences between customer groups and development patterns. The key to understanding emerging patterns of water demand is the relationship between our water use above basic needs and the social characteristics that define user response.

Water supply has been relatively abundant for most cities within the United States, the exception being water availability during drought. Until the 1980's, high per capita residential water consumption led to greater revenues for water utilities, as many supply systems were designed with large capacities relative to their demands. High per capita water use was commonly overlooked, if not directly encouraged or subsidized. By the beginning of the

1980's, the posture on water consumption changed. Despite its small proportion of total fresh water consumption (less than 15% of national freshwater withdrawals), domestic water demands will become increasingly difficult to meet in some urban areas, especially in times of drought, as urban populations rapidly grow. Metropolitan areas continue to expand and attract larger populations, a phenomenon described as a movement toward urbanity (Nelson 2009). This shift requires water managers of metropolitan systems to extend existing water resources, as new supply source development is expensive and requires significant time and planning efforts. Recent projections of growth for the Puget Sound Region, in Washington State, serve as a prime example of this phenomenon, where a combined increase of approximately 1.7 million new residents for Kitsap, Snohomish, Pierce, and King Counties (Figure 1) over the next 40 years will likely increase demands above current supply capacity. The relationship between water demands, development patterns, and shifts in demographics must be improved if forecasts of water demand are used in water supply decision making.

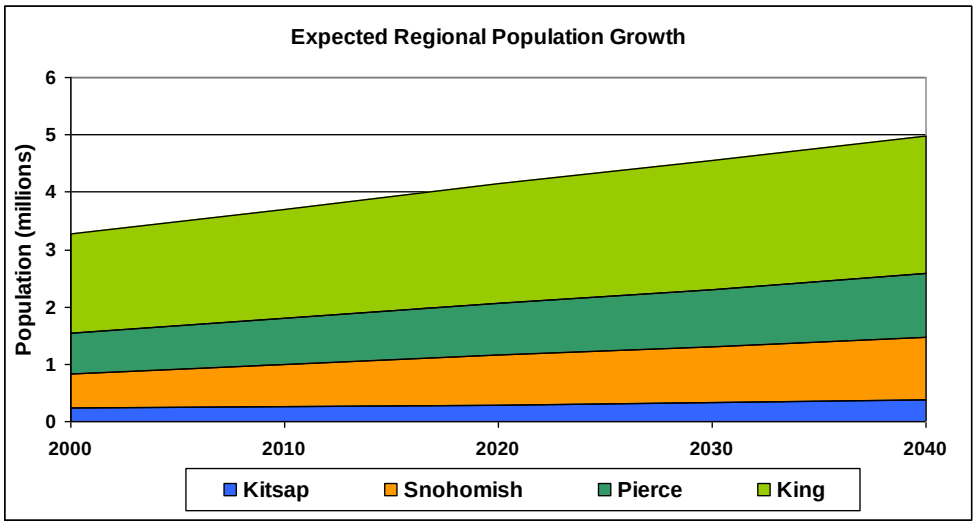

Figure 1: Projected Population for Puget Sound Region

Water supply challenges posed by urbanization are compounded by the societal movement in many of the basins providing water for urban centers in the Western United States toward a "closed" status, with little or no streamflow available for allocation to new or expanded uses (above that which has been committed to either human uses or ecological purposes) (Figure 2). Gleick and Palaniappan (2010) describe this situation with the concept of "peak water". When a region extracts more water from a watershed than is naturally replenished, peak renewable water is said to be reached. The Colorado River Basin in the US and the Yellow River in China are two major watersheds that are currently approaching peak water. Gleick and Palaniappan (2010) suggest the United States has reached peak water, as total withdrawals have remained constant or below historic peak water withdrawals reached during the late 1970's (Figure 3).

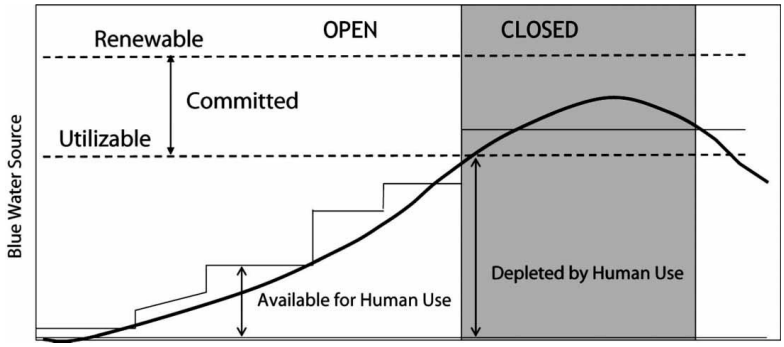

Figure 2: A River Basin Moving From Open to Closed Status (Taken from Falkenmark and Molden, 2008)

This does not suggest that the United States is threatened by mass water shortages, but rather that we are becoming more efficient with total water use and actively changing the American economic landscape that has driven water demands in the past (less water intense industry, and potentially more efficient agriculture). Domestic use and withdrawals have also stabilized for many utilities since the early 1980's due to a shift toward more aggressive water pricing, changes in national fixture efficiency standards, and implementation of active

conservation programs. Utilities and their customers are becoming more aware and concerned about their water resources.

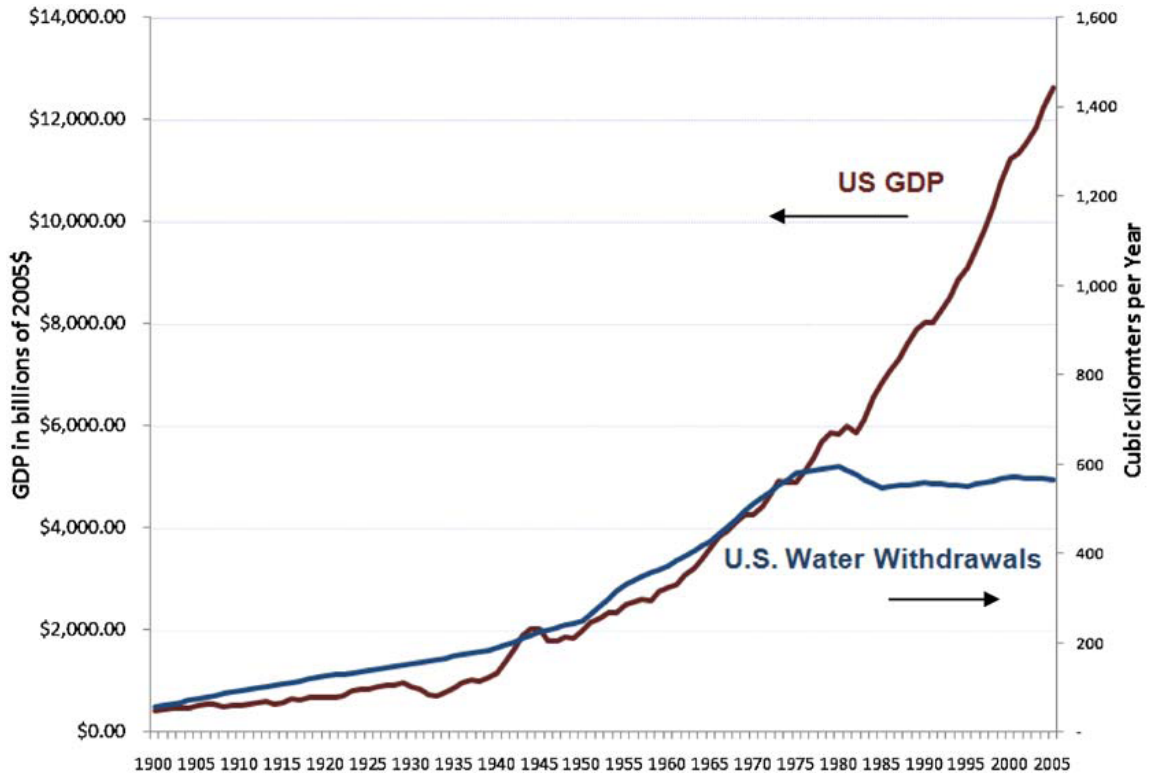

Figure 3: US gross domestic product (GDP) in 2005 dollars from 1900 to 2005 (left axis) plotted with total water withdrawals for all purposes in cubic kilometers per year (right axis). Data on GDP come from the US Bureau of Economic Analysis; data on water use c comes from the US Geological Survey (taken from Gleick and Palaniappan 2010)

Largely responsible for this shift is a renewed sense of conservation ethic, increased water prices, changes in water pricing rate structures, implementation of water metering devices, general knowledge of actual water use, the occurrence of droughts due to over tapped resources in the West and Southwest, and the specter of climate change. In response to an expensive alternative (development of additional supply), water resource managers have implemented conservation efforts such as indoor fixture retrofit programs, outdoor watering education campaigns, and technology investments to extend existing supplies. These practices, however, lead to demand hardening. Lund (1995) defines demand hardening as the reduction of the

effectiveness of short-term water conservation measures within a given sector of use after the long-term implementation of conservation practices and efficiency gains. A similar, yet broader interpretation is that water demand hardening occurs when the returns on investment in water use efficiency exponentially decrease as efficiency increases. Technological advancements, behavioral changes, and water pricing are the primary drivers of increased water use efficiency. Most utilities attempt efficiency gains from the implementation of lower cost, higher pay-off programs, such as reducing system leakage, introducing water metering, or increasing prices. Other alternatives include implementation of xeriscaping (landscape) policy, toilet retrofit programs, clothes washer rebates, and outdoor watering education programs. As these options are exhausted, further reductions become increasingly expensive. For most water systems in the United States, demand hardening will continue for the next decade as inefficient fixtures are replaced in older homes. The rate at which this occurs and the point at which per capita demands stabilize is an important question that remains to be answered.

The evolution of water demands within urban and suburban areas is a complex process involving population growth, changing urban landscapes, demand hardening, and water demand management practices. This dissertation develops predictive methods that incorporate the societal factors that influence these trade-offs. Accurate estimates of water demand are required for sound water infrastructure investments. Three fundamental challenges within water demand modeling are addressed:

1. Estimation of water demands at local spatial scales using detailed demographic information,
2. How to incorporate urban development, climate variability and climate change into future water demand projections, and

3. Quantifying customer response to water curtailments.

Accurately forecasting water demands in changing urban environments requires an approach that incorporates the spatial and temporal variability of urban and suburban space, as water use patterns may differ substantially as lot sizes decrease and building characteristics change. Changing land use and urban form are important components in determining future water demands. Variables that capture these changes are not commonly employed in water demand modeling, namely because of a paucity of data availability for model calibration and a lack of forecasts for these variables (such as estimates of future housing density, lot sizes, and structure age). Much of the data available for analyzing the relationship between changing urban patterns and water demands comes from decennial censuses, a relatively coarse temporal snapshot of urban data. Forecasts of any of these variables are rare and usually based on industry "rule of thumb" estimates as opposed to actual projections.

The increased popularity of Geographic Information System (GIS) and the ability to warehouse, retrieve, and analyze these data has significantly contributed to increasing our understanding. For instance, King County, Washington, maintains a geo-database that contains up-to-date information on every parcel within county boundaries. The City of Seattle (within King County) has begun including in GIS maps the building footprint within the individual parcels. The ability to obtain building statistics or summarize building characteristics by parcel or a user specified sub-region facilitates the use of this information in water demand modeling. Urban simulation models have recently been developed to create forecasts of the variables needed to drive a water demand model. "UrbanSim", a parcel based urban simulation model operates at individual parcel resolution and uses parcel characteristics and census data to project future changes in urban development. Using models like UrbanSim for regional planning is

becoming more common, yet using estimates from these models in the water resources realm is not yet fully realized despite the wealth of information urban simulation models can provide about the future.

The effects of climate change add an additional layer of uncertainty to water demand modeling. Water demand and wastewater baseflow forecasts have typically not considered the potential influence of climate change (Boland 1997; Lettenmaier et al. 1999). With respect to demand, warming will increase evapotranspiration rates and potentially increase the number of growing days, directly affecting the amount of water required for lawn watering and other outdoor water uses (Tebaldi et al. 2006, Hamlet et al. 2007). In the Pacific Northwest, anticipated climate change will decrease late spring and summer reservoir inflows due to loss of and earlier melt of snowpack (Mote et al. 2003) and increase summer stream temperatures, requiring higher environmental flows (Vano et al. 2010, Traynham et al 2010, and Battin et al. 2006). Climate change may also increase drought severity, drought length, and water demand during drought periods (Meehl and Tebaldi 2004). In general, the amount of water available during summer and fall months will decrease while demands are likely to increase. Many western US utilities could face serious challenges in meeting summer water demands. In addition to these challenges, utilities may face increasing extremes in precipitation magnitude, hindering their capability to convey and treat wastewater efficiently and effectively in combined systems.

The purpose of this dissertation is to illustrate how population growth, land use, climate change, and conservation will affect future water demands and curtailment effectiveness within the Puget Sound region. This dissertation consists of three chapters that add to the science of water demand management and forecasting. Chapter 2, ‘Developing a Spatially and Temporally

Disaggregate Water Demand Model', describes the development of a water demand model that incorporates both spatial and temporal variability in the parameter estimates. This chapter has been published in the Journal of Water Resource Planning and Management (Polebitski and Palmer 2010). Chapter 3, 'Evaluating Water Demands Incorporating Climate Change and Transitions in the Urban Environment', uses the water demand model developed in Chapter 2 to estimate future water demands for the Puget Sound Region of Washington State under different growth scenarios and climate change. This chapter is currently in press in the Journal of Water Resource Planning and Management (Polebitski and Palmer 2010b). Chapter 4, 'Analysis of Changing Water Curtailment Responses within Single Family Residences', examines customer response to water curtailments and the impact future development patterns have on curtailment response. This chapter will be submitted to the Journal of Water Resource Planning and Management. Finally, Chapter 5, 'Conclusions', summarizes Chapters 2-4 and concludes this dissertation. Together, these chapters are intended to provide water managers new tools that aid in predicting water demands and develop a better understanding their customer base.

Chapter 2: Developing a Spatially and Temporally Disaggregate Water Demand Model

Introduction

Identifying the drivers of urban water demand has been an area of active research since the 1960's, with most efforts using population, demographic differences, and price as explanatory variables to describe water consumption for different user groups (Howe and Linaweaver 1967; Foster and Beattie 1979; Murdock et al. 1991; Lyman 1992; Nieswiadomy 1992; Arbues et al. 2003). Short-term operation and long-term planning of water resources are two of the most important reasons for forecasting water demand. This study focuses on long-term demand forecasting, but has relevance and application to short-term operation and planning. Population growth is typically the major explanatory variable for long-term water consumption, though conservation efforts by utilities and national plumbing code changes in past decades have played important roles in decreasing residential per capita consumption. Seasonal water demand and variations in annual water demand are driven by local weather conditions, due to outdoor water use in urban and suburban regions.

Increasing growth in urban and suburban regions across the United States can strain the ability of utilities to provide water reliably. In many situations, new water supplies are being proposed, and in others, managers are relying on conservation, improved efficiency, and water reuse programs to meet increasing demands. In addition, the potential impacts of climate change may also pose serious challenges in meeting summer water demands. Water demand forecasts have typically not considered the potential impacts of climate change on water demand (Boland 1997; Lettenmaier et al. 1999). Climate change will impact water supply by decreasing reservoir inflows for many mountainous western states due to shifted spring streamflows, decreasing summer streamflows, and loss of snowpack (Mote et al. 2003). Changing temperature and

precipitation patterns will also alter water use patterns. Climate change may also affect the possibility of increased drought severity, drought length, and water demand (Meehl and Tebaldi 2004).

Accurate estimates of water demand are required as inputs for sound decisions concerning supply system development and expansion, the staging of such projects, and the establishment of water rates. Upgrading and maintaining existing supply systems, enhancing conservation programs, implementing land use policy, and initiating water reuse projects provides a means to delay, and possibly eliminate, the need for new water resource development projects (EPA 2002). Effective planning and targeting of these efforts requires in-depth knowledge of the customer base, including water conservation and water efficiency (DeOreo 2001).

Water demand research typically focuses on a micro level (specific use within a household) or at an aggregate level (water use within a city or region). Little research has examined water use at the multi-house or census tract level, the appropriate level for many water planning decisions. This paper uses census tract data to examine spatial patterns in water use within the study region. The spatial scale of a census tract has many desirable properties, including the availability of data, appropriate frequency of observation, and a spatial resolution similar to many types of demographic data. Using census tracts as a spatial unit provides detailed information concerning water consumption patterns useful to planners and engineers for evaluating conservation programs and land use policy. Utilities interested in spatial pricing schemes may also find this approach useful. Lastly, census tract level data provides valuable information on wastewater baseflows not commonly monitored or available for some utilities.

This research utilizes regression methods specific to panel data to develop relationships between the dependent and independent variables. A panel of data is defined as a dataset that contains repeated observations of subjects over multiple time periods. For this work, the subjects are census tracts, the repeated observations are changes in bi-monthly residential per capita water consumption, demographic, economic, and weather, within each census tract over 12 years. Several studies have utilized panel data approaches, though cross-sectional analysis of water demand is the investigative tool for a majority of studies (Arbues 2003). If used properly, panel data approaches can provide more efficient and consistent estimates of model coefficients than cross-sectional ordinary least squares (OLS) techniques. Panel data approaches incorporate both temporal and subject-based variability into coefficient estimates, generating better parameter estimates than typical regression approaches and more accurate water demand estimates within individual census tracts. Brief descriptions of the differences between each regression technique are provided in Table 1. A more detailed explanation is found in the methods section of this paper. Disadvantages of using these methods include extensive data requirements and variable attrition (loss of subjects over time). Improvement in database technology, data accessibility, computing power, and spatial tools make employing large demographic and economic datasets less daunting.

Table 1: Regression Method Definitions

Regression Method	*Definition*
Pooled Data	Variability between census tracts not explicitly accounted for
Fixed Effects	Fixed parameters assigned to each census tract to account for variability
Random Effects	Census tract variability treated as random variable

Literature Review of Past Studies Using Panel Data

Statistical techniques used in panel data analysis have not been used as widely as other methods to estimate water demand, primarily due to the lack of demographic and water consumption data needed to create a panel dataset. The most common approaches are cross-sectional or pooled cross-sectional time-series approaches, most relying on OLS regression techniques, and artificial neural networks (Howe and Linaweaver 1967; Foster and Beattie 1979; Lyman 1992; Nieswiadomy 1992; Adamowski 2008). Nieswiadomy and Molina (1989) created a panel dataset to examine price effects of increasing and decreasing block rate structures on summer water use. Investigation of water demand price sensitivity was explored using "instrumental variables" and two-stage least squares estimation. Residences selected for this study were assumed to have no temporal change in demographics. Schneider and Whitlatch (1991) utilized panel-data techniques to investigate elasticities of demand variables in communities surrounding Columbus, Ohio using annual consumption data. The panel dataset was found to be a rich source of information for each sector despite the coarse nature of both the temporal (annual consumption data) and spatial (community) dimensions. Schneider and Whitlatch found that OLS, combined with cross-sectional dummy variables (fixed effects), to be an effective means of controlling for the variability exhibited spatially between communities, though a partial adjustments model utilizing generalized least squares (GLS) was the recommended model. Schneider and Whitlatch did not incorporate temperature as a variable; instead, precipitation was used to describe inter-annual variability in water demands within the communities.

Högland (1999) used panel-data methods to study price effects on water demand and revenue in 282 communities in Sweden. Though Högland acknowledged that the household

level may be more appropriate when studying price effects, he noted that many studies at community or utility levels yielded accurate household demands. Lack of data typically prevents analysis at the household level. Högland examined price effects through five static models and one dynamic model. Högland found the fixed effects model preferable to the GLS model, but that the fixed effects model explained only small portions of variation due to the homogeneity of his data. Högland concluded that the OLS and between effects (controls for omitted variables that change over time but are constant between subjects) models yielded the most reliable results. In the analysis, Högland did not include climatic effects on water demand because the temporal scale was not sub-annual, and did not differentiate between residential sectors due to lack of water consumption data.

Nauges and Thomas (2000) created a panel dataset from 116 communities in eastern France using six years of annual data. Nauges and Thomas estimated four regression models: OLS, a fixed effects model, a random effects model using GLS, and an Instrumental Variables approach suggested by Breusch, Mizon, and Schmidt (1989). The Instrumental Variables model was preferred to the "fixed effects" model because of the ability to incorporate time-varying and invariant effects, and to resolve the problem of endogeneity (independent variable is correlated with error term) that is commonly associated with the price variable.

A recent paper by Kenney et al. (2008) utilized a very disaggregate panel dataset (10,000 households examined over seven years at a monthly time-steps) to examine price structure and water use restrictions on water consumption. Fixed effects accounted for the spatial variability in demographics between homes. That study found response to price differed between restriction periods and by income level. The study was unable to incorporate many demographic variables due to time invariance. Instead, elasticities were determined for different water using groups

based on demographics. Other recent studies have utilized dynamic panel methods for coefficient estimation, but these methods remain relatively new to the field (Arbues et al. 2003; Arbues et al. 2004; and Martinez-Espiñeira 2002).

Few water demand studies determine elasticities for variables on a seasonal basis, despite the fact that large and important differences may exist (Lyman 1992, Baumann et al. 1997). No water demand studies were found that used panel data techniques to examine highly disaggregated spatial and temporal scales (i.e. sub-community and sub-annual resolution).

Description of Data

The independent variable, single-family per capita consumption, is derived from water consumption data provided by Seattle Public Utilities (SPU). SPU provided single-family account data with a census tract identifier for location purposes, the date of the meter reading, number of billed days since the last meter reading, and the total consumption in hundreds of cubic feet for the years 1991-2005. SPU bills on a bi-monthly basis for most accounts. A simple algorithm was used to remove the lag between the bill period and the meter read date using the assumption that water is consumed evenly over the bill period, which is likely not the case. Figure 4 represents the overall process. Parcel consumption data are first filtered by sector to extract out single family accounts. Next, for each day of the year, starting in 1991 and going through 2005, all parcel records with that day of the year bill date are selected (Step 1). These data are disaggregated uniformly by the number of bill days within the bill period for each parcel (Step 2). This step creates a daily consumption record for each parcel. Next, consumption from parcels located within the same census tract boundaries are summed to generate daily census tract water consumption numbers (Step 3).

Lastly, the daily consumption within each census tract is summed to a bi-monthly period. The bi-monthly period is selected as there is a lack of knowledge of the daily patterns of use for each account given that the data originated as bi-monthly consumption. To create single-family per capita demand, water consumption within each census tract is divided by its single family population for each bi-monthly period.

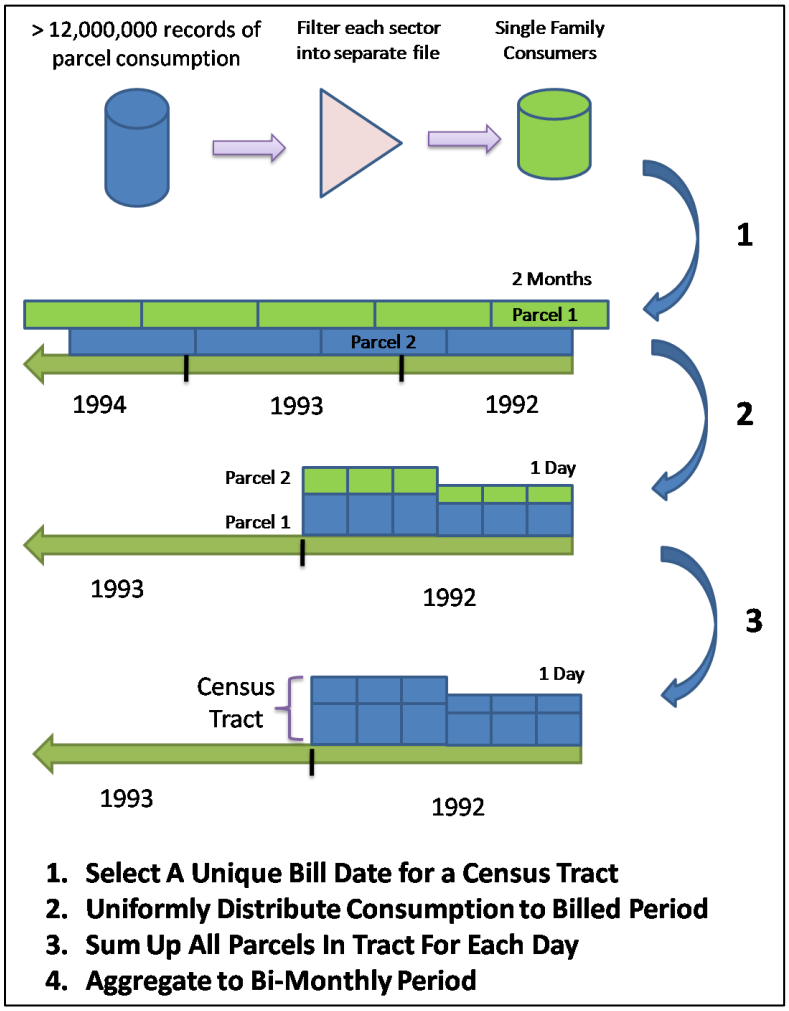

Figure 4: Water Demand Data Processing

After the algorithm is executed for each account within an individual census tract, consumption is summed within each bi-monthly period. The bi-monthly period is selected as there is a lack of knowledge of the daily patterns of use for each account given that the data

originated as bi-monthly consumption. To create single-family per capita demand, water consumption within each census tract is divided by its single family population for each bi-monthly period.

Table 2 contains a complete list of the independent variables used in the single family models. Demographic data used in this research originate from the Puget Sound Regional Council (PSRC) and the 1990 and 2000 Census. Yearly estimates of single-family population and households are used for each census tract.

Table 2: List of Single-Family Variables (natural log of each variable is used)

Variables	Definition (each variable calculated for each Census Tract)	Units
Density	Total Single-Family Homes per Acre	Units/acre
Built ft^2	Median Single-Family Structures Square Feet	Ft^2
Lot Size	Mean Single-Family Parcel Lot Size	Ft^2
House Hold Size	Average Number of Residents in a Household	Persons/Unit
Post-1992	Number of Homes built after 1992	Units
Income	Average Per Capita Income (2000 dollars)	Dollars/Person
Price	Average Price of Water (2000 dollars)	Dollars/100 Ft^3 Water
Max Temp	Average Maximum Daily Temperature	Degrees Celsius
Precip	Cumulative Precipitation	Inches
Policy	Dummy Variables for two drought periods	N/A

A density variable for single-family homes is created by dividing the number of occupied single-family homes by the total acreage of a census tract. Average income within each census tract is developed from 1990 and 2000 census estimates, and the yearly trends in income for the City of Seattle are imposed on each census tract. The median and average built square feet and the mean lot size of parcels within a census tract were computed from tax assessor records for

each year. These data were also used to determine the number of homes built after 1992 within each census tract.

Water pricing data and tariff structures are supplied by SPU. SPU bills residential customers for both a fixed cost and a metered rate. The fixed rate is based on the size of the connection for each residence. The metered rate varies seasonally and has a block-rate structure for summer periods. During summer periods, an increasing block rate structure has been in place since 1992, though the third block has been in place only since 2001. There is no block rate during the winter (Figure 5).

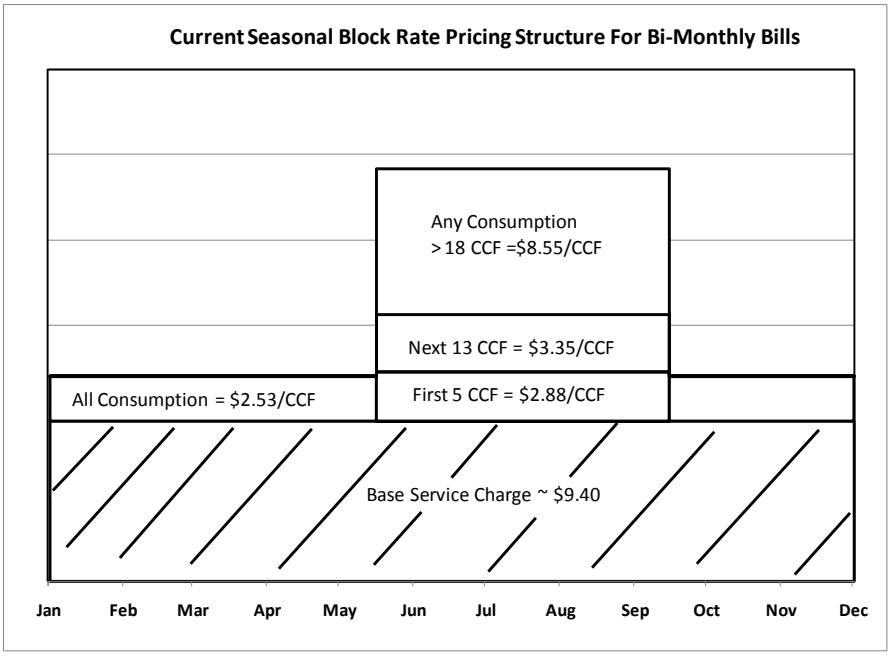

Figure 5: Seattle Water Pricing Structure, Spring 2008

There has been much debate regarding price variables in demand modeling. An excellent summary of price variable specification is found in Arbues et al. (2003). Modeling response to block rate price structures proves to be especially difficult. One acceptable approach is to use the average price of water sold to account for the block rate. This study makes use of an average

price specification where the water bill is based on the average per capita consumption per bi-monthly billing period for each census tract. The computed price of water for each census tract is based on the block rate structure. This specification overestimates the overall effect of price on consumption for most census tracts during winter periods because it is per capita and typically households have more than a single resident. This results in the fixed charge portion of the bill being counted twice. For census tracts with large consumptions, the price effect will be slightly underestimated as these tracts may enter the third block of consumption for a household.

Climatic data come from the National Climatic Data Center. The meteorological station used in this analysis is located at the SeaTac International Airport and is representative of the climate of Seattle. An average of maximum daily temperature for each bi-monthly period is used as the temperature variable. The precipitation value used is the cumulative precipitation for the bi-monthly periods.

Data Exploration

In 2006, the average daily consumption of the City of Seattle was approximately 60 million gallons per day (MGD), sixty-percent of which was residential consumption. According to the Residential End Uses of Water Study (REUWS) conducted by AWWARF, in conjunction with Seattle Public Utilities, Seattle residents consume on average 57 gallons per day for indoor uses, or approximately 457 cubic feet per bi-monthly period (DeOreo et al. 2001). Single-family usage comprises approximately forty percent of total consumption for the city and is seasonally variable. Figure 6 plots an average of annual total consumption divided into winter and summer usage for each census tract, with the size of the circle representing total consumption relative to other tracts. For most census tracts, outdoor usage is highly seasonal, driven primarily by weather as with most major mid-latitude cities.

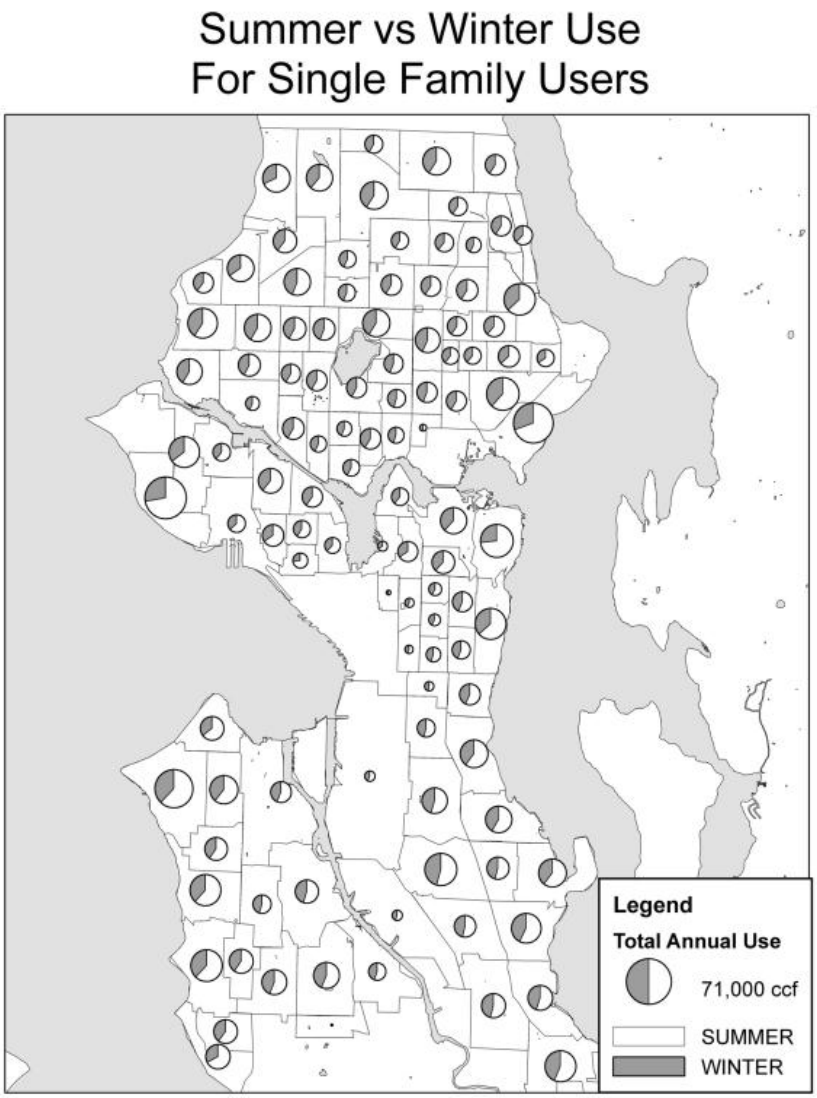

Figure 6: Average Winter and Summer Single-Family Usage

Figure 7 illustrates this observation, where residential per capita consumption (gray lines) in the July-August period for each census tract are standardized (mean subtracted and divided by the standard deviation) and plotted against time. The solid line corresponds to the mean standardized per capita residential demand and the dashed lines represent the standardized temperature and precipitation variables. Subject specific variability over time is small when the tracts are standardized and closely mimics the temperature signal. This suggests that, over the

observed time period, temperature and precipitation define water use patterns for each census tract during summer months.

Seasonal peaking is spatially variable and dependent on demographic characteristics. This study refers to the seasonal peaking factor as the ratio of average summer demand to average winter demands within a census tract. There is considerable spatial variation in single-family seasonal peaking factors (Figure 8).

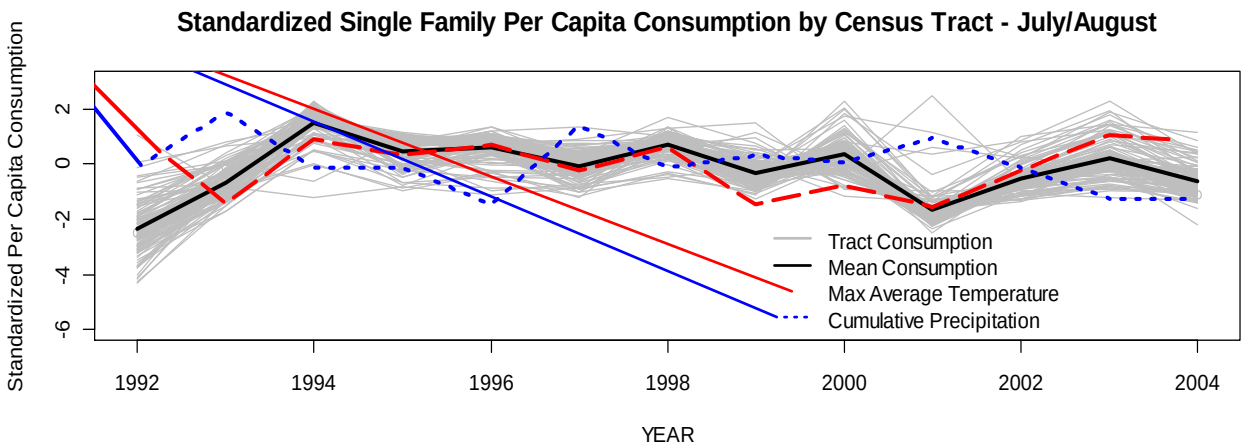

Figure 7: Standardized Single-Family Water Use for July-August

There is good correlation between both income and seasonal peaking factors and lot value and seasonal peaking factors (Figure 9). Not all individual households with large incomes use more water for sprinkling and other outdoor activities. There is less variability in the higher income ranges, suggesting more affluent areas typically have more consistent and higher outdoor water use in the summer periods. Higher income neighborhoods, particularly those with large peaking factors, have the highest summer usage. Areas with higher annual consumption also tend to exhibit higher seasonal peaking factors, though exceptions exist.

In the past fifteen years, Seattle has implemented water use curtailments twice within the study period (there were also major water use curtailments in the fall of 1987). The first

curtailment period, the summer of 1992, involved mandatory water use restrictions for all sectors within the City of Seattle.

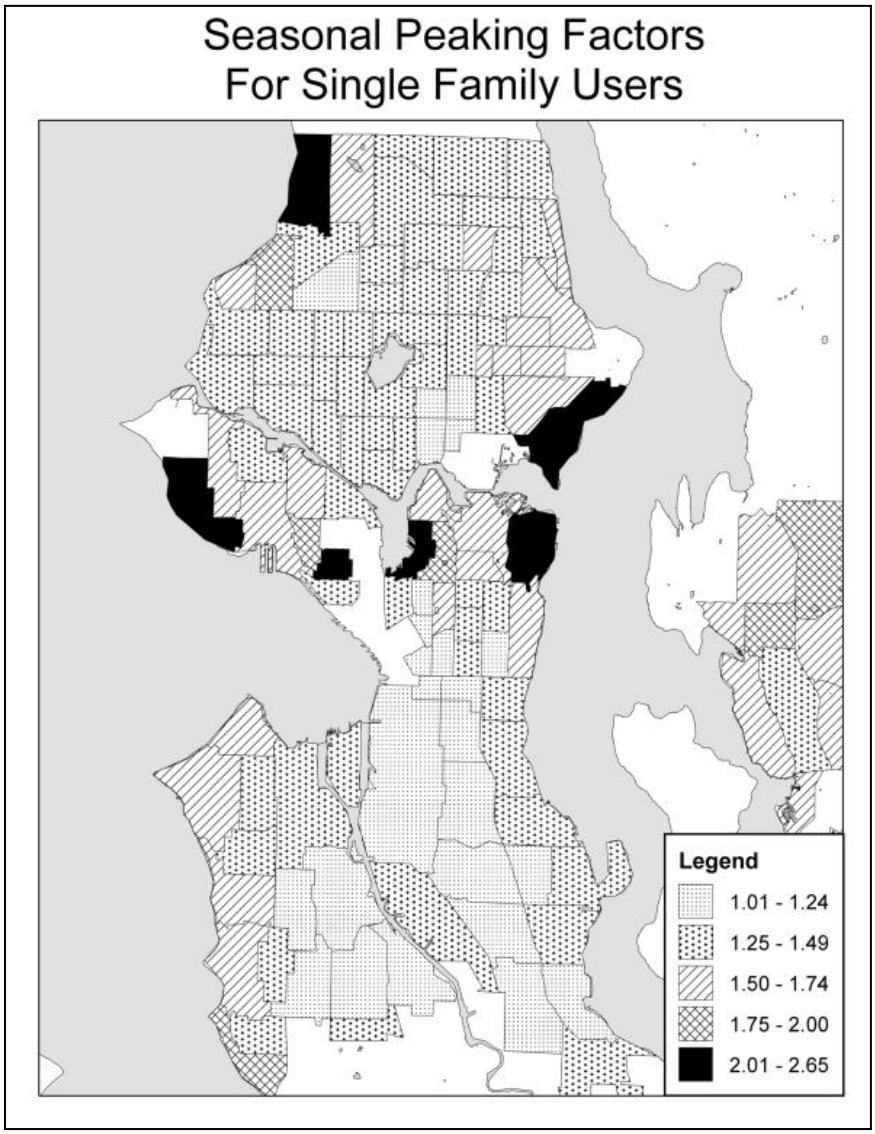

Figure 8: Single-Family Seasonal Peaking Factors by Census Tract for Seattle

The mandatory curtailments were issued due to low snowpack accumulation during the winter months, little precipitation in the spring, and a hot summer. A second curtailment event occurred in 2001, when below average precipitation during the winter and spring resulted in an abnormally low snowpack. The 2001 curtailments were voluntary restrictions, but were effective

at reducing demand. The mandatory and voluntary curtailments reduced water use in the summer periods by one-half and one-quarter of average consumption respectively.

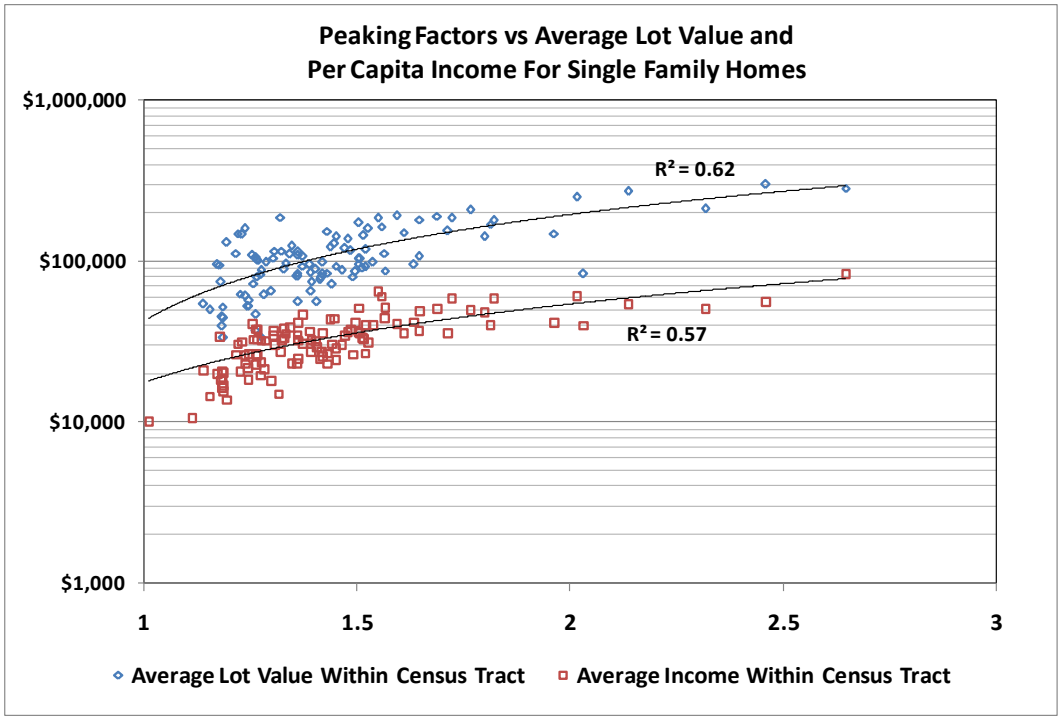

Figure 9: Peaking Factor versus Average per Capita Income and Lot Value for Single-Family Homes

Reduction in winter is a result of programmatic and passive conservation actions, most noticeably in the years post-1999. This reduction is the result of changes in plumbing codes impacting water use in new development, increase in public awareness of water related issues, and the activities of Seattle's conservation program.

Model Structure and Estimation

This study makes use of three linear regression models (pooled, fixed, and random effects) with a unique approach, that being incorporation of panel methods to capture subject and time variability. Detailed description and derivation of the mathematical formulation for panel and longitudinal studies are presented elsewhere (Frees 2004; Wooldridge 2002). Only a brief description of the pooled, fixed, and random effects models are provided here.

Pooled regression (OLS) is commonly expressed as $y_i = \alpha + \boldsymbol{x}_i'\boldsymbol{\beta} + \boldsymbol{e}_i$, where y_i is the dependent variable of interest, $\boldsymbol{x}_i'$ are the observed values of the independent terms, $\boldsymbol{\beta}$ are the regression coefficients, α is the intercept and $\boldsymbol{e}_i$ is the error term. The least squares estimates, $\hat{\boldsymbol{\beta}}$, are chosen to minimize the residual sum of squares.

A fixed effects approach consists of the same basic form, but, in estimating the regression coefficients, the intercept is allowed to vary between subjects. This allows variation in the intercepts but consistent coefficients in all other variables across the model domain. The varying intercepts account for subject heterogeneity that is not accounted for within the other population parameters. The basic fixed effects model is represented mathematically as, $y_{it} = \alpha_i + \boldsymbol{x}_{it}'\boldsymbol{\beta} + \boldsymbol{e}_{it}$, where y_{it} is the independent variable or expected response (Ey_{it}), α_i is a subject specific parameter, $\boldsymbol{x}_{it}'\boldsymbol{\beta}$ are matrices of the dependent variables and the population parameter, and $\boldsymbol{e}_{it}$ is the error term. Because the fixed effects model separates subject-specific effects from the error term, estimates of variability are more accurate (Frees 2004). The random effects model, or error components model, is a special case of the mixed linear model. The random effects model takes the same form as above but the subject term is assumed to be a random variable and not an unknown constant value. All three models utilize a (natural) log-log approach between the dependent and independent variables. The estimated coefficients of the log-log models are the elasticities.

The dependent variable for this study is bi-monthly single-family per capita water demand within individual census tracts. The independent variables in this study are density of single-family units, average household size, median parcel built square feet, mean parcel lot size, average annual income, average bi-monthly price of water, bi-monthly average maximum daily

temperature, bi-monthly cumulative precipitation, the number of homes built post 1992, and two water-use restriction variables incorporated only during the summers of 1992 and 2001 (Table 2).

The three regression models are developed for each bi-monthly period, with variables selected based upon significance and appropriateness. Possible unaccounted for variables are lot value, lawn size, and the average age of householder, along with other possible demographic indicators of water use. R, a statistical software package, and other subpackages are used for the analysis (Croissant and Millo 2007).

Results

Estimates of elasticities for each variable are presented in Table 3. The fixed effects model, random effects model, and a pooled model are estimated over the period October 1991-December 2003 using the panel dataset for each bi-monthly period. Variables with statistically significant values ($P<0.05$) are denoted with asterisks.

To determine whether panel data methods are an improvement over pooling the data (that is, the subjects exhibit variability not captured by a single intercept), a pooling test (partial F-test) is performed between the fixed effects model and the pooled model. The null hypothesis is that all intercepts between census tracts are equal. In all single-family models, the F-statistic is well beyond the range of accepting the null hypothesis, therefore the fixed effects and random effects models are an improvement upon pooling the data and allowing only a single intercept. The heterogeneity among census tracts is better captured through varied intercepts. Next, a Hausman Test is performed to indicate the presence of persistent effects by comparing the random effects model with the fixed effects model. Under the null hypothesis, if there are no omitted variables, the random effects model would be more efficient. If variables are omitted,

then the fixed effects model is a more appropriate approach because it yields unbiased and consistent estimates. The test statistic rejects the null hypothesis and confirms the presence of persistent subject-specific characteristics, indicating that the fixed effects method is more suitable for this dataset. Despite the results of the Hausman test, random effects models are still estimated for this study, as there is concern that fixed effects may bias the estimates if variables are changing slowly over time (Pluemper and Troeger 2004).

Price

Each estimated model suggests price elasticities differ by bi-monthly period. The estimated price elasticities are negative, with greater absolute value of the elasticities occurring in the summer periods. The variation in the price elasticities between summer and winter bi-monthly periods agrees with results from Lyman (1992), who found peak prices to be more elastic than off-peak prices. The values for price elasticity are similar for all models, with particularly good agreement in the two summer periods. Price elasticity is highest for May-June period. The May-June period is also a transition period for local climate, as temperatures increase and evapotranspiration rates begin to exceed rainfall. The average price elasticity for the models in the winter months was -0.23 with a range of -0.14 to -0.31 between the three models. The average price elasticity for the summer months was -0.45, with a range of -0.27 to -0.7 between the three models.

Income, Density, Lot Size, and Structure Size

For all models, income has little effect on water consumption patterns during winter, but does have significant impacts on summer demands. This suggests that income level does not contribute to spatial variability of indoor residential per capita use. Indoor usage is better attributed to other variables such as the built square feet of a residence, density and residents within a household. During summer months, income level does play a significant role in

explaining water demand. This suggests that households with higher income tend to consume more water for outdoor purposes.

The fixed effects models indicate density to be an important explanatory variable, whereas the pooled and random effects model estimates of single-family residence density contribute minor or no role in determining water consumption across residences. Conversely, the estimates of lot size and built square feet are important explanatory variables for both the pooled and random effects models but not for the fixed effects model. The differences between the fixed effects model and the others are most likely due to the assigning of intercepts to each subject. By allowing each subject a different intercept, the fixed effects model may mask the variability that is otherwise explained by the spatially heterogeneous variables. The values of these variables do not change rapidly (mean lot size and built square feet) so it is possible that the fixed effects models may bias their coefficients.

The pooled and random effects models suggest larger homes tend to consume more water, regardless of income levels. This is expected as increasing house size typically results in more bathrooms and higher chances of leaks. The random effects and pooled models suggest that lot size is an important explanatory variable for summer months whereas the fixed effects model suggests a positive, though statistically insignificant, influence of lot size on water demand.

Household Size

For all three models, the elasticity for household size is negative. Both the random and fixed effects models estimate similar elasticities for household size. The pooled-OLS model, with the exception of July-August, shows a smaller response to household size. In general, as household size increases, the models suggest a per capita savings, though total household

consumption increases. This is likely due to tasks that require water but are executed more efficiently. For base demands, this may be fuller dishwashers and laundry machines, whereas for irrigation and outdoor usage per capita savings stem from similar outdoor water use as compared with other single-family homes, but split between more individuals. There is a discontinuity to this relationship, as census tracts that have less than an average of 2.5 residents per household have considerable variability in per capita demand. Changing growth patterns in urban areas will affect household sizes. An understanding of how household size will change is needed to determine whether this results in savings or increased usage.

Table 3: Coefficients From Regression

Variable	Model	Jan-Feb	Mar-Apr	May-Jun	Jul-Aug	Sep-Oct	Nov-Dec
Density	Pooled	-0.009*	-0.013*	-0.020*	0.001	-0.020*	-0.018*
	Fixed	-0.731*	-0.776*	-0.740*	-0.772*	-0.793*	-0.821*
	Random	-0.056*	-0.073*	-0.102*	-0.076*	-0.092*	-0.052*
Built ft^2	Pooled	0.213*	0.261*	0.434*	0.619*	0.439*	0.245*
	Fixed	-0.191*	-0.075	-0.138	0.060	-0.281*	-0.122
	Random	0.175*	0.255*	0.211*	0.521*	0.307*	0.222*
Lot Size	Pooled	0.000	0.000	0.113*	0.253*	0.082*	0.000
	Fixed	0.000	0.000	0.068	0.052	0.069	0.000
	Random	0.000	0.000	0.114*	0.185*	0.066*	0.000
Household Size	Pooled	-0.291*	-0.375*	-0.556*	-0.704*	-0.487*	-0.296*
	Fixed	-0.798*	-0.715*	-0.820*	-0.779*	-0.814*	-0.661*
	Random	-0.629*	-0.659*	-0.721*	-0.789*	-0.753*	-0.513*
Income	Pooled	0.000	0.026*	0.169*	0.160*	0.144*	0.048*
	Fixed	-0.004	-0.040*	0.340*	0.175*	0.139*	0.019
	Random	-0.007	-0.011	0.288*	0.191*	0.156*	0.038*
Price	Pooled	-0.235*	-0.282*	-0.620*	-0.388*	-0.341*	-0.306*
	Fixed	-0.138*	-0.157*	-0.693*	-0.350*	-0.270*	-0.231*
	Random	-0.180*	-0.217*	-0.692*	-0.390*	-0.304*	-0.283*
Max Temp	Pooled	0.000	0.000	0.010	1.105*	0.471*	0.000
	Fixed	0.000	0.000	0.082*	1.077*	0.412*	0.000
	Random	0.000	0.000	0.042	1.121*	0.424*	0.000
Precip	Pooled	0.028*	-0.068*	-0.232*	-0.013*	0.001	-0.026*
	Fixed	0.033*	-0.069*	-0.245*	-0.018*	0.002	-0.022*
	Random	0.034*	-0.069*	-0.245*	-0.013*	0.005	-0.023*
Post 1992	Pooled	0.000	0.006*	0.014*	0.000	0.008*	0.008*
	Fixed	-0.008*	0.005	0.004	-0.002	0.006	0.017*
	Random	-0.014*	-0.004	-0.002	-0.011*	-0.010*	0.006
Voluntary Restriction	Pooled	0.000	0.000	-0.073*	-0.149*	-0.099*	0.000
	Fixed	0.000	0.000	-0.076*	-0.134*	-0.087*	0.000
	Random	0.000	0.000	-0.078*	-0.149*	-0.096*	0.000
Mandatory Restrictions	Pooled	0.000	0.000	-0.452*	-0.413*	-0.201*	0.000
	Fixed	0.000	0.000	-0.486*	-0.410*	-0.208*	0.000
	Random	0.000	0.000	-0.4848	-0.418*	-0.212*	0.000

Policy and Climate

All models estimate similar elasticities for the two water-use restriction variables (1992 and 2001, the drought years). The different models also estimate similar elasticities for climatic variables, maximum temperature, and precipitation. All models estimate similar temperature elasticities, which are largest for the July-August summer period and influence early fall consumption (September-October). For July and August, a 10% increase in maximum average monthly temperature results in a 10% increase in water consumption for all models, i.e. an increase of 3º C results in an additional 100 ft^3 of consumption per capita per bi-monthly period, while in September and October a 10% increase in temperature would likely result in only a 4% increase in total water consumption. Conversely, precipitation is important in the early summer months (May and June), where a 10% increase in cumulative monthly precipitation results in a 2.5% decrease in total water usage. Precipitation impacts to water demands in the July-August period are comparatively minor. This may well be due to the general lack of precipitation during these months. Precipitation elasticities were significant for the three winter months, a surprising result. Although the elasticities for these months are small, precipitation amounts in these months may reflect some general statement about climate effects on water use during those years. The models might be improved by removing winter month climatic variables from the estimation.

Homes Built Post 1992

Large differences in the estimated elasticities exist between models for the number of households built post-1992. The random effects model consistently estimates newer homes consuming less water while the pooled-OLS and fixed effects model do not have consistent results. Instead, these models estimate increases in consumption during summer and winter months with increasing new-development. The random effects model finds the post-1992

variable to have significant explanatory power in three of the six periods and a tendency to decrease per capita consumption. The post-1992 variable is significant in four periods for the pooled-OLS model and in two periods for the fixed effects model, and estimates increases in per capita consumption with increasing new-development.

The lack of consistent statistical significance and direction of the elasticities suggests weak correlation. Of the three models, the random effects model provides the most realistic value of savings, approximately a 1%-2% reduction in per capita demand in 2000 solely from newer homes. Other approaches to modeling passive conservation may provide better results and could be used either in the model specification or in post-processing of demands. Further research improving estimates of passive conservation is needed.

Calibration and Verification

In general, there are minor differences between the coefficients of the fixed, pooled-OLS, and random effects models for income, price, policy, and the climatic variables (Table 3). Additionally, the variables with significant explanatory power are the same for each regression method across bi-monthly periods. As explained earlier, the different coefficient estimates of density and other structure-related variables are likely due to differences in the estimated intercept values.

In modeling total single-family consumption for Seattle over the calibration period of late 1991- 2003, all models perform well (Figure 10). At the census tract level, models differ on their ability to estimate water demand. To compare the performance of the models at the census tract level, the root mean square error (RMSE) for each census tract for each period is calculated. The calculated RMSE values are then divided by the average observed consumption for each tract

and period forming a fraction of error for water demand estimates. Mathematically, this is expressed as: $RMSE = \left(\frac{\sqrt{\sum_{i=1}^{n} (x_{1,i} - x_{2,i})^2}}{n} \right) * \frac{1}{x}$

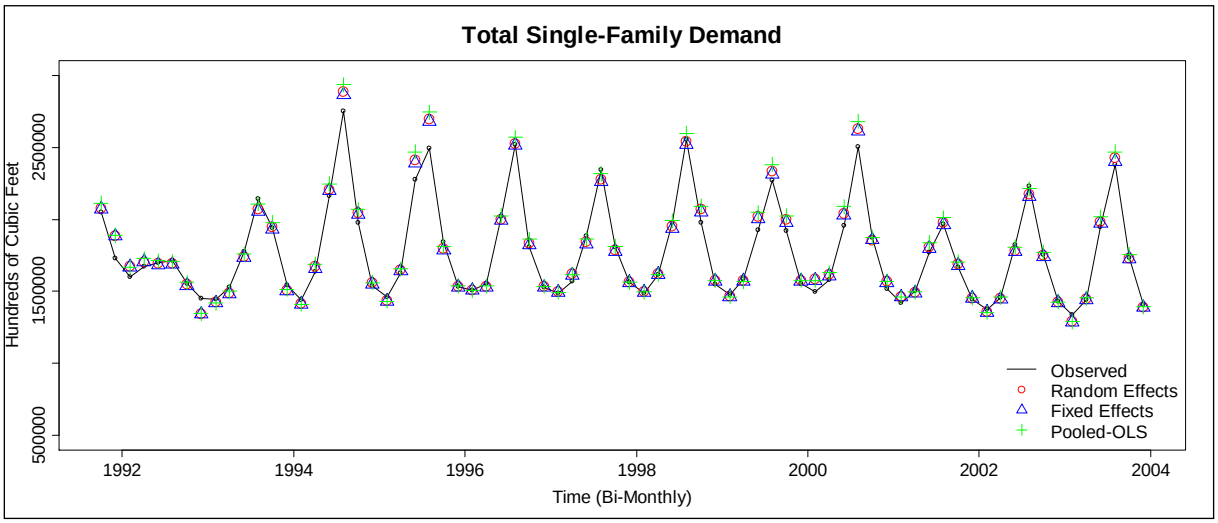

Figure 10: Comparison of Regression Model Estimates of Total Single-Family Bi-Monthly Water Demand

The results are displayed as boxplots in Figure 11. The winter periods are modeled well (Jan-Feb, Mar-Apr, and Nov-Dec), though the fixed effects model performs consistently better than the random and pooled-OLS models for each period. The average RMSEs for the winter periods are 7% for both the pooled-OLS and random effects models and 4% for the fixed effects model. The models capture summer water demands well but show the same differences in performance between the fixed effects model (6%) and the others (~10%). The distribution of model error was generally consistent between the random effects and pooled-OLS models for both summer and winter months whereas the distribution of error for the fixed effects model tended to show lower variance.

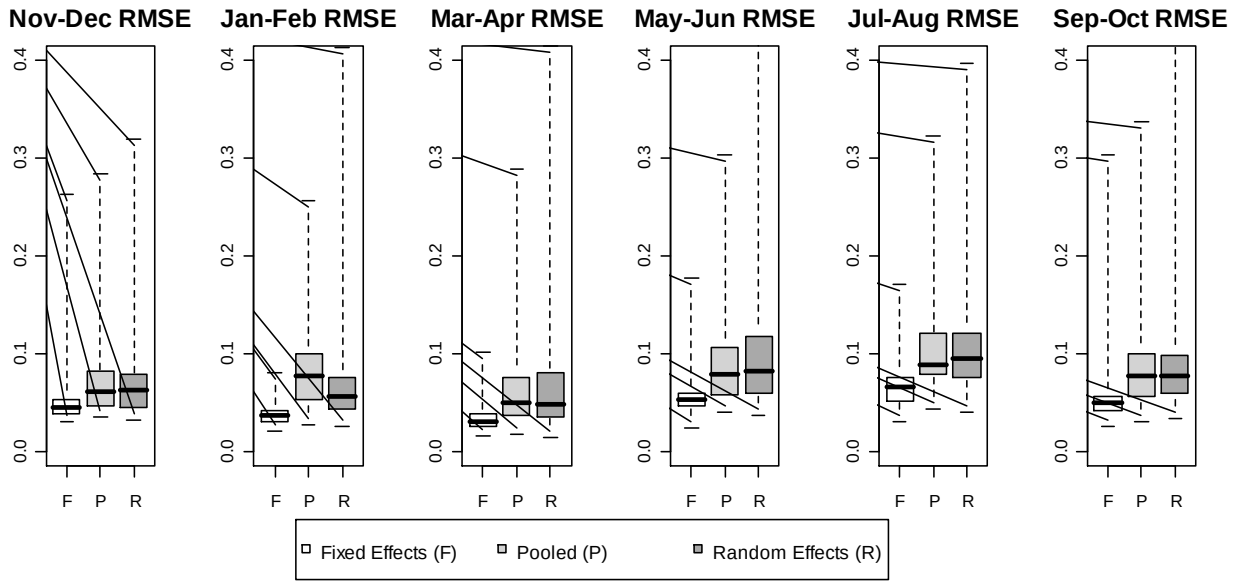

Figure 11: Boxplots of Root Mean Square Error by Census Tract for Single-Family Sector (Calibration Period 1992-2003)

To verify these models, the water consumption for the period of 2004-2005 is estimated. This period was not used in the calibration/estimation process. Figure 12 presents boxplots of RMSE for each period for the three models. The pooled-OLS and random effects water demand models have similar winter RMSE (~7%) but slightly higher summer RMSE (~12%) for the two year period compared with the calibration period. The fixed effects model does not perform as well over the verification period, with the average summer and winter RMSE being twice those for the calibration period (~10%).

The three models perform well in replicating demand for individual census tracts. There are advantages to each model. By ignoring tract variability, the pooled model may be biased due to omitted variables within the error term, though coefficient estimates are similar to those determined by the random effects model. The fixed effects model provided low RMSE across all census tracts within the model domain, but is not easily used to forecast demand outside the model domain. Improvements are needed in relating demographic characteristics to the fixed

effects. Even if many suspected omitted variables (type of vegetation, number of bathrooms, age of householder, presence of pools, etc.) are included, there may be enough differences spatially between neighborhoods that fixed effects or random effects could still yield improved parameter estimates over simply pooling the data.

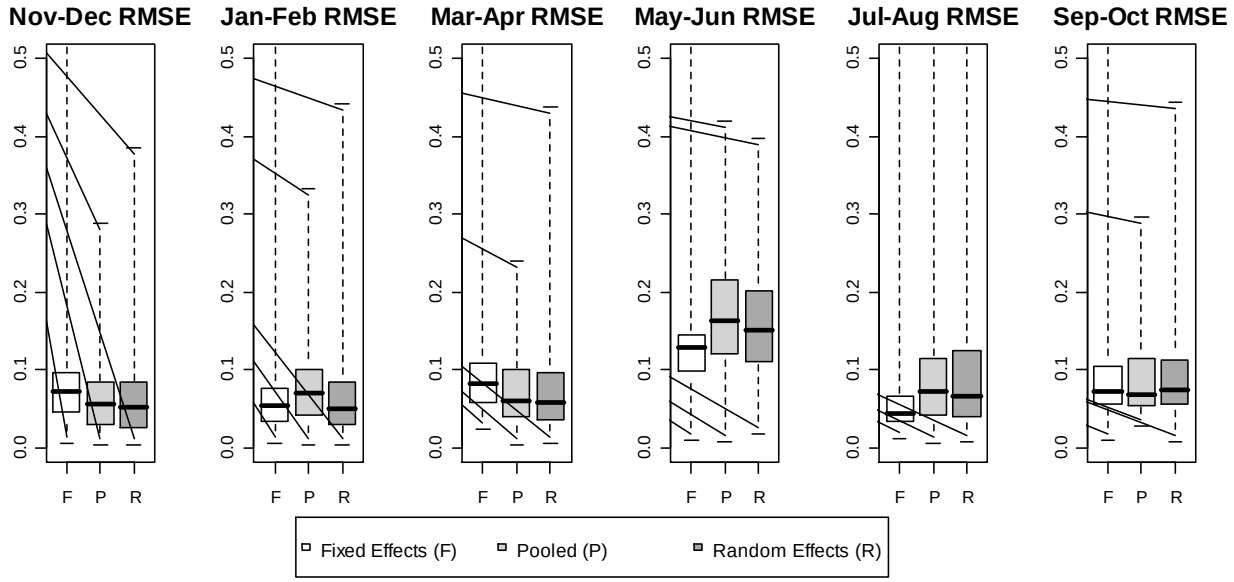

Figure 12: Boxplots of Root Mean Square Error by Census Tract for Single-Family Sector (Verification Period 2004-2005)

Although this approach provided insight into the factors impacting water use, many questions remained unanswered. A more accurate estimate of the role of water conservation is needed to improve overall model performance when projecting over long periods. In addition, accurate estimates of elasticities and water demand are important to utilities that encounter future water supply challenges. This has implications for current water demand forecasting methods because most rely upon elasticities from the literature, rather than deriving them for specific regions. Because econometric modeling of water demand can be time consuming and data intensive, simpler and more straightforward approaches are commonly used. While these methods do not pose the same challenges as spatially explicit models and their results can be more easily communicated to stakeholders and utilities, they do require accurate elasticities as

assumptions. Fixed and random effects methods, coupled with disaggregate demographics and water consumption, can deliver elasticities that incorporate dynamic relationships between the dependent and independent variables. These models can even account for subject heterogeneity and omitted variables.

The results of this modeling approach and the data described here will be used in Chapter 2 to forecast water demands for the Puget Sound area by integrating them into urban growth models (UrbanSim). These results will provide insight into questions important for insight on the influence of growth within and around national metropolitan areas on single-family water demands and infrastructure expansion in the region.

Chapter 3: Evaluating Water Demands Incorporating Climate Change and Transitions in the Urban Environment

Introduction

More than 60% of the population within the United States lives within incorporated local political boundaries, with most residing in large metropolitan areas. As of 2006, the 361 designated metropolitan areas in the United States contained over 83% of the nation's population. Growth in the urban population sector is forecasted to continue. In 2007, the 50 fastest growing metropolitan areas were concentrated in the South and in the West, two areas historically concerned with water availability (Bernstein 2007). Among the fastest growing metropolitan areas, the Atlanta area has gained nearly a million residents between 2000 and 2009. Likewise, the population in Houston has increased by 250,000 residents since July of 2000. In some regions, this has strained the ability of water utilities to meet increased demands, particularly in times of drought. Although metropolitan areas like Atlanta are experiencing increases in total water demands that are directly tied to growth, other metropolitan areas are experiencing decreases in both total consumption and per capita demands. In Seattle, total water demands have declined over the last 20 years despite increasing population and urbanization within the region.

Accurate projections of future population growth and development are essential to forecasting future water use. The current urban landscape is a critical factor in determining how water demands and the base flow of wastewater will change in the future. For example, many customers in aging housing stock typically use appliances and fixtures that are inefficient by today's construction standards. Passive conservation (the replacement of fixtures and appliances due to new development or redevelopment) can significantly affect indoor per capita consumption within residential and commercial sectors (DeOreo et. al. 2001, Vickers 2001, US

GAO 2000). The rate of home improvement and remodeling of commercial premises is an important factor in determining savings from passive conservation.

Despite having one of the nation's lowest outdoor watering rates, the average single-family home within Seattle still consumes approximately 1.4 times more water during summer months compared to winter months (Polebitski and Palmer 2010, Mayer et. al. 1999). Changing development patterns and urban densification, (the conversion of large, single family lots into smaller townhomes with little or no yard space) can have significant influence on water demands. Outdoor water use is the single most important driver in single-family water demands during summer months. Urban populations shifting from aging single-family homes to newer condominiums or smaller residential units may further reduce water consumption as many units have small gardens and yards relative to existing single-family homes.

Forecasting changes in demographic parameters that influence urban water use accurately requires an appropriate analytical framework and supporting data (Baumann et al. 1998, Mays et al. 1992). Common forecast methods include scenario-based approaches, probabilistic methods/sensitivity analyses (such as Monte Carlo methods) and contingency trees (Whitford 1972, Baumann et. al. 1998). These methods generate a distribution of potential water demands given changes in price, income, density, and occasionally variables as detailed as lot size, built square footage of residential units, and the rate of new construction. These methods can be effective if data are available, model parameters are properly calculated, and engineering judgment is applied. Less complicated and more commonly applied methods, such as unit-use methods or variable flow factor models do not consider changes in many of the demographic variables listed in Table 4. These methods often cannot address the fundamental driving factors impacting demand.

Using a deterministic model can provide an objective means to forecasting socio-demographic variables and limits the number of scenarios. Using output from an urban simulation model integrates results of scenarios reflecting urban planning constraints and management tools, such as the location of urban growth boundaries, changes in transportation networks, and new land use policies.

This research identifies the benefits of coupling water demand models to urban simulation models. Output from an urban simulation model, UrbanSim, (Waddell et. al. 2002) is used as input to a previously developed multiple regression water demand model (Polebitski and Palmer 2010). The model estimates water demands using several variables and generates water demands using terms sensitive to temperature and precipitation changes, longer-term changes in socio-economic variables, and price of water.

Background

Study Region

This study describes an application in the Puget Sound Region (PSR) of Washington State, USA. The Puget Sound Region is defined as the combined areas of King, Snohomish, Pierce, and Kitsap counties. These counties span roughly 6,300 square miles, and include the cities of Seattle, Everett, Tacoma, and Bellevue (Figure 13). The domain for this study is a subset of this planning region and is divided into over 600 census tracts and 800 Traffic Analysis Zones (TAZ). For many analyses that include demographic information, census tracts provide data appropriate for decision making and planning within cities and urban areas.

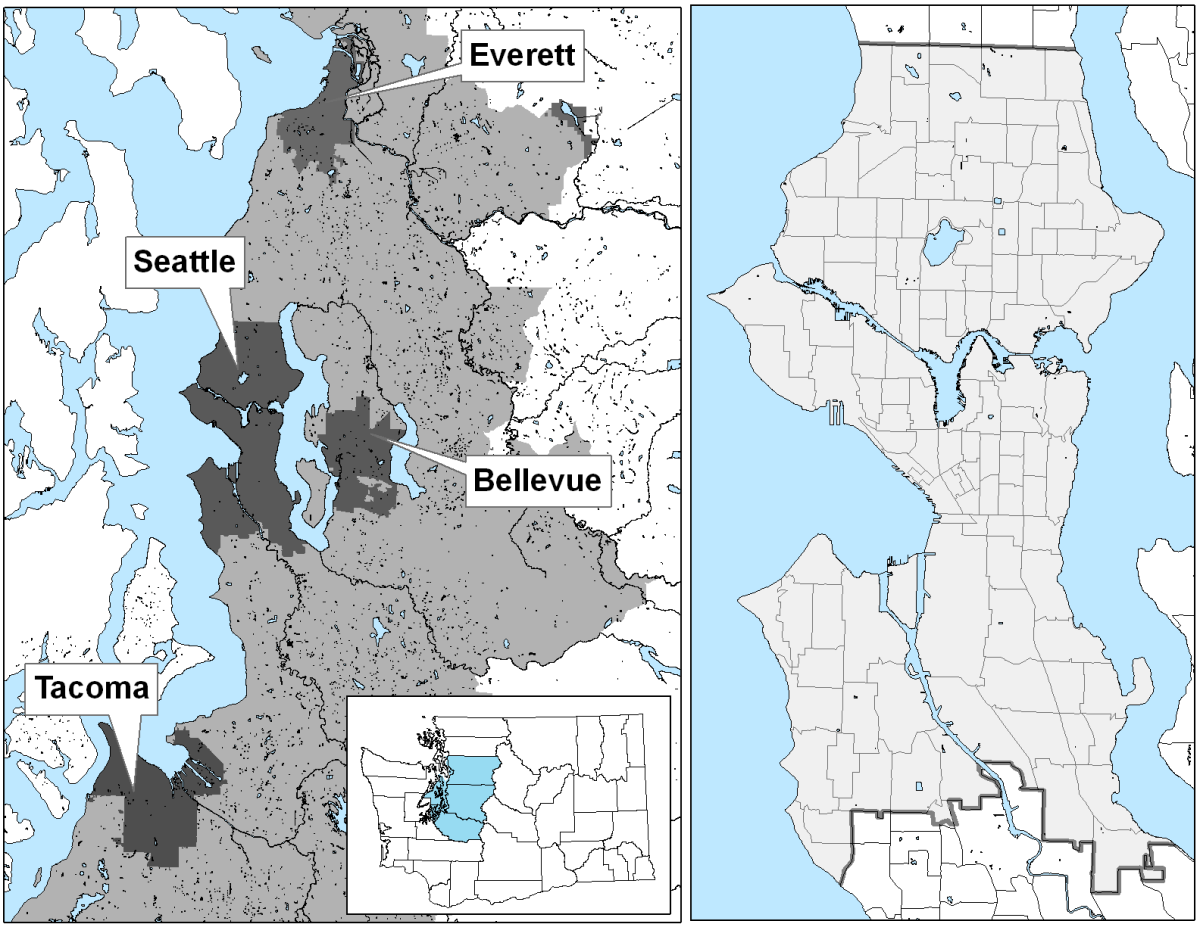

Figure 13: Study Domain (Left Pane) and Census Tracts Within Seattle City Limits (Right)

The PSR has experienced significant growth during the past decade, with a 10% change in population from 2000 to 2008 (357,000 additional residents). This rate of growth is slower but similar to that which occurred in the 1990's when 525,000 residents were added to the region (a twenty percent increase in population). In 2000, two-thirds of the population resided within incorporated areas; in 1990, that ratio was 50%. The growth in the first decade of the 21st century continues the migration to incorporated areas, with growth concentrated primarily in existing dense urban areas but some new growth in the urban fringe (PSRC 2008). Development of condominiums and increasing redevelopment of single-family lots into multiple townhome style single-family homes creates additional residential space inside Seattle. The

development along the urban fringe has increased the density of housing, but large lots and residences are still common.

Population within the region is projected to continue to increase, with an additional 1.7 million residents, or one million households from 2000 to 2040 (PSRC 2006). Most population increases are in the one and two resident households, suggesting large increases in multifamily populations and townhomes (Figure 14). This estimate agrees with the current trends of growth in the major urban areas (Seattle, Tacoma, Bellevue, and Everett) and is an important factor in future urban development patterns.

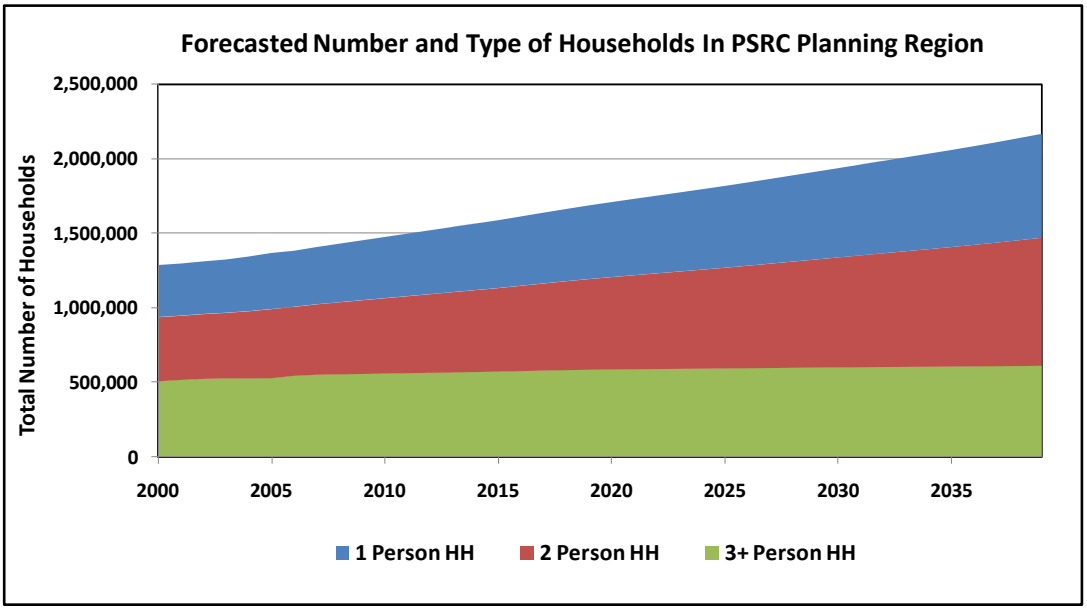

Figure 14: Changes in Number of Households and Household Size

The study region's climate is considered Mediterranean, having warm, dry summers and rainy, cool winters. Average maximum daily summer temperatures in the bi-monthly period of May-June are 67° F and 75° F in the July-August period. Average total summer precipitation during June, July, and August is approximately 3 inches. The importance of snowpack on

streamflows and its impacts on hydropower production, water supply, recreation and aquatic ecosystems has sparked active research into the impacts of climate change within the region. Warming in the Puget Sound over the past 30 years has been greater than increases in average global temperature (Mote 2003a). This has reduced snowpack levels in the later part of the century compared with those measured in the 1940's, 1950's and 1960's (Mote 2003b). Further warming will likely shift the hydrologic regime, with spring flows occurring earlier in the year. This presents a serious challenge for many local utilities as they rely on snowpack melt water to fill water supply reservoirs during spring and support summer supplies.

None of the reservoirs in the Puget Sound Region are over-year storage reservoirs, making supply especially susceptible to drought conditions if low winter snowpack conditions are followed by minimal summer and fall precipitation. Seattle Public Utilities has issued water curtailments twice in the past two decades (1992 and 2001). In 1992 and 2001, water demands were reduced in the summer periods by one-half and one-quarter of average consumption, respectively.

Historic Water Demands

Seattle has experienced decreasing total and per capita residential demands over the past two decades due to an active conservation program, responses to price increases (particularly for wastewater), increasing fixture efficiency from new development and redevelopment, and two curtailment periods that have had long lasting impacts on the perception of water use in the region. In Seattle, single-family outdoor water use is still a large portion of the water consumed annually, despite some of the lowest per capita outdoor watering rates in the nation (Mayer et al. 1999).

Figure 15 plots the distribution of peak factor (the ratio of summer demand to winter demand) by sector for census tracts within the City of Seattle. Commercial and single-family residential sectors have strong seasonality, with summer months having median values of 1.4 times that of winter usage, and for some census tracts more than twice winter base demands. The skew of the single-family and commercial water demand peaking factors indicates a tendency towards increased water use in the summer months and is an indication of increased outdoor water use not present in the winter months. This seasonal variability presents challenges when modeling, but plays an important role in overall water use for a region and could influence demand management strategies. The multi-family sector has water demands with considerably less seasonality due to less green space for outdoor watering. This is particularly important for determining future demands, as the multi-family sector will likely see large growth rates.

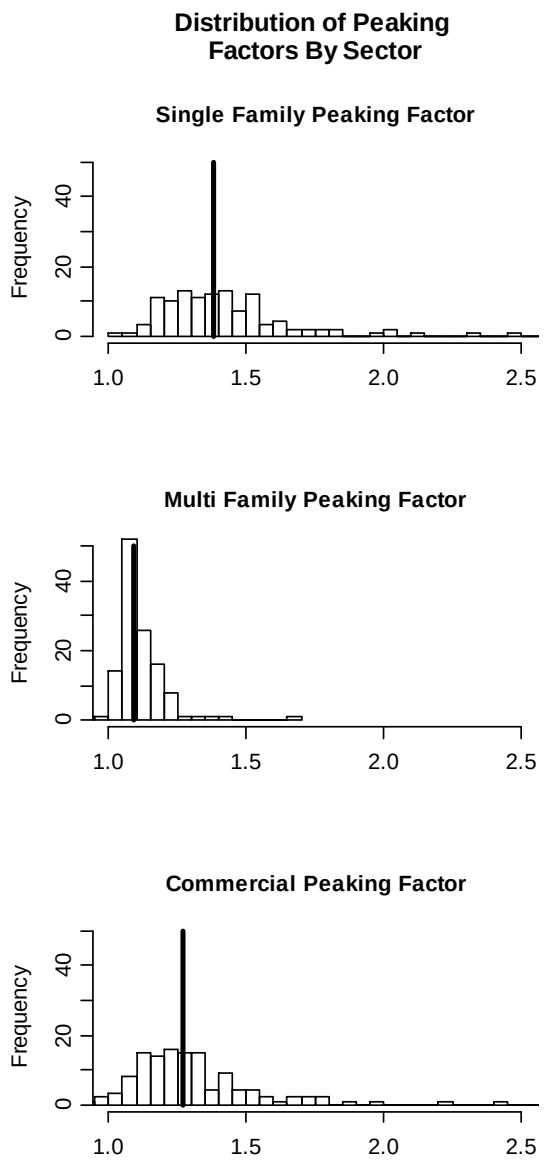

Figure 15: Histograms of Census Tract Peaking Factors By Sector

Methods

Scenarios

This research investigates the influence of urban development, policy changes, and climate change on water demand using four modeling scenarios. These scenarios present the water demand model's sensitivity to urban growth, land use change, policy implementation, and climate change. Forecasts of regional water demand are created using the water demand models and data generated from UrbanSim (Waddell 2002, Waddell et. al 2003) that are described below. Understanding the elasticity of water demands in each scenario is important for weighing policy decisions, evaluating supply expansion options, and planning for future climate change. The forecast period for each scenario begins in 2001 and ends in 2030. Table 4 contains a summary of which variables change or are constant in a given scenario.

First, a Baseline Scenario with constant socio-demographic variables and changing population is created. The Baseline Scenario provides a useful comparison point for other scenarios. To create the Baseline Scenario, per capita consumption within each TAZ is computed using 2001 demographics. These per capita estimates are multiplied by 2030 population estimates to create a forecast of 2030 regional water demands. In the Baseline Scenario, the variability of demands across a region are accounted for and future changes in demographics are assumed to be minimal. This is the most often applied approach in water demand modeling, as many models use per capita values to estimate demands for specific regions but do not update the per capita demands given changing development patterns.

The next scenario, Scenario 1, uses future projections of socio-demographic variables from UrbanSim as the forcings for the water demand model. In a dynamic planning environment, the status quo does not imply an alternative for which there is no change, but rather

the likely future conditions when no actions are taken. Scenario 1 serves this purpose as changes in demographics and building characteristics and stock are reflected within the water demand forecast. Relative pricing of water (constant dollars) is held constant at 2001 values and pricing rates and patterns are assumed to be similar to Seattle's pricing policy for the planning region. Temperature and precipitation are also held at constant 2001 values.

Scenario 2 uses the same output from UrbanSim and includes an aggressive water pricing policy. Pricing begins at 2001 values and increases in real terms at 2% per year through 2030. This results in approximate doubling of the real costs of water over a 30 year period (181%). The current block rate structure implemented by the City of Seattle is used for the region. Temperature and precipitation are held at constant 2001 values.

Whereas in the other scenarios temperature and precipitation values are held constant to highlight changes in other variables, Scenario 3 includes changes in temperature and precipitation between 2001 and the periods of 2030, 2060, and 2090. Relative pricing of water (constant dollars) is held constant at 2001 values and pricing rates and patterns are assumed to be similar to Seattle's pricing policy for the planning region. A discussion of the method used for creating the projections of temperature and precipitation is found below.

UrbanSim

UrbanSim generates detailed spatial resolution (parcel level data), that are aggregated to a spatial unit called a Traffic Analysis Zone (TAZ) for use in the water demand models. TAZs are similar in size to census tracts and are commonly used for planning purposes in the Puget Sound Region. The use of a disaggregated urban simulation model provides a unique opportunity to incorporate forecasts of many important variables into water demand models and provides water

resources planners a new perspective in evaluating how changing urban landscapes impact overall demands.

As residential density increases in urban areas, the characteristics of new development and redevelopment play a pivotal role in water consumption. The advent of the townhome provides an example of increasing density influencing urban water usage. Summer per capita demands decrease overall due to decreasing yard and garden space when compared with existing residential lots. Increasing housing density and reduced lot sizes are indicators of this development pattern. In addition, there are also reductions in per capita consumption derived from fixtures that are more efficient and appliances that occur in new development and remodels. Many forecasting techniques do not incorporate changing building characteristics, density, or land use, as data availability restricts examination of their impacts on past and present demand. UrbanSim is a useful tool to estimate how current and future planning will affect development, and consequently, water demands.

UrbanSim is an open source, spatially (parcel based computations) and temporally (annual time steps) disaggregate urban simulation model that operates within the Open Platform for Urban Simulation (OPUS) framework. The software and corresponding documentation are freely available at www.urbansim.org. UrbanSim calculates changes in household location and type, employment location and type, land pricing, and real estate development. Using the OPUS framework, external models, such as travel demand models, land use models and, in this research, water demand models can be coupled with UrbanSim. The functional forms of core components within UrbanSim are multinomial logit or multiple regression models that simulate changes in real estate price, resident mobility, and employment choice within the modeled

region. UrbanSim has been implemented in eight major cities within the United States and is being actively used within the Puget Sound Region for planning.

Using a longitudinal comparison, Waddell (2002) examined simulation results for two periods (1980 and 1994) for the Eugene-Springfield area in Oregon. Over the 14-year simulation period, UrbanSim yielded encouraging results, with correlation between simulated and observed values in TAZs of roughly 0.9 for employment, population, nonresidential square feet, housing units, and land value. Using a more stringent method of comparison (the difference between observed and simulated by zone), for approximately 57% of the simulated area, UrbanSim correctly predicted the number of households in a TAZ within an error range of less than 50 households.

For this study, outputs from recent simulations of the Puget Sound Region are used. The period of investigation is 2000-2030 and incorporates annual changes in urban characteristics, water pricing, and climate variables. Output for each of the relevant variables (Table 4) was extracted from a MySQL database of the most current research run. These variables are calculated on an annual time-step for each parcel within the study region. The parcel results are aggregated to a TAZ spatial resolution for use in the water demand model. Currently, water consumption does not drive changes within UrbanSim, though an infrastructure component is in development to account for this feedback.

Water Demand Model

The water demand model used in this study originates from previous work by Polebitski and Palmer (2010), which focused on water demands for single-family residences. The demand model is a multiple regression model capable of forecasting water demands at small spatial scales. The single-family model uses several explanatory variables to forecast single-family

water consumption (Table 4). The regression model was estimated using a panel dataset of water demands and demographic variables for census tracts within the City of Seattle over the period October 1991- December 2003, and verified over the 2004-2005 period. The billing data used for calibration and verification were provided by the City of Bellevue and the City of Seattle. The billing data comes from individual parcel accounts aggregated to a spatial resolution of census tract.

Polebitski and Palmer (2010) established that water demands within small spatial resolutions (census tracts) could be predicted with good accuracy using panel data regression methods. The elasticity estimates of price and income variables were within current and past literature ranges (Table 4) and incorporate the temporal and spatial variation found in water demands across planning regions. These elasticities are appropriate for use in forecasts where changes in development type and land use are expected. Other variables not commonly included in water demand models, such as built square feet of a residence, housing density, lot size, building age, and the number of people per household were found to be significant in explaining spatial and temporal variation in water demands. Lot size, density, and building size significantly influence water demand patterns and were identified as variables that should be incorporated in water demand models, as urban patterns are likely to change for many regions.

Table 4: List of Single-Family Variables (used as natural logarithms)

Variables	Definition	Units	Winter	Summer	Baseline	Scenario 1	Scenario 2	Scenario 3
Density	Total Single-Family Homes per Acre	Units/acre	-0.06	-0.09	constant	***variable***	***variable***	***variable***
Built ft^2	Mean Single-Family Structures Square Feet	Ft^2	0.22	0.35	constant	***variable***	***variable***	***variable***
Lot Size	Mean Single-Family Parcel Lot Size	Ft^2	0	0.12	constant	***variable***	***variable***	***variable***
House Hold Size	Average Number of Residents in a Household	Persons/Unit	-0.6	-0.75	constant	***variable***	***variable***	***variable***
Post-1992 Homes	Number of Homes built after 1992	Units	-0.004	-0.008	constant	***variable***	***variable***	***variable***
Income	Average Per Capita Income (2000 dollars)	Dollars/Person	0.01	0.21	constant	***variable***	***variable***	***variable***
Price	Average Price of Water (2000 dollars)	Dollars/100 Ft^3 Water	-0.23	-0.46	constant	constant	***variable***	constant
Max Temperature	Average Maximum Daily Temperature	Degrees Celsius	0	0.53	constant	constant	constant	***variable***
Precipitation	Cumulative Precipitation	Inches	-0.02	-0.09	constant	constant	constant	***variable***

Climate Change Data

This study uses downscaled climate data from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project Phase 3 (CMIP3) multi-model dataset. Well-established downscaling methodologies were used to derive values for temperature and rainfall for the region for future periods (Maurer 2007, Wood et al. 2002, 2004). These procedures were used in a regional study supported by a large number of state and local governments (including King, Pierce, and Snohomish Counties, the cities of Seattle, Bellevue, Tacoma, and Everett, along with local utilities). During the study the downscaling technique was closely examined and widely vetted.

Average monthly temperature and cumulative monthly precipitation data for the 1/8th degree spatial cells containing the City of Seattle were extracted from the CMIP3 data for 16 different GCMs and the A2 emission scenario (the highest emissions scenario). The A2 emission scenario is one of the warmest overall and is used to demonstrate the potential impacts of climate change relative to the constant climate in Scenario 1 and 2. Figure 16 plots the projected changes in temperature and precipitation in the summer months (June, July, August, and September).

The average temperature and cumulative precipitation values for the two decades surrounding the base year (2001) are representative of historic climate for the region. A twenty-one year average centered on the year of interest is used to generate the bi-monthly temperature and precipitation data required by the water demand model. Average maximum bi-monthly temperatures were scaled using a relationship developed between historic temperatures and average maximum temperature for each bi-monthly period. This assumes that maximum

temperatures will change in the same proportions as the projected average bi-monthly temperatures.

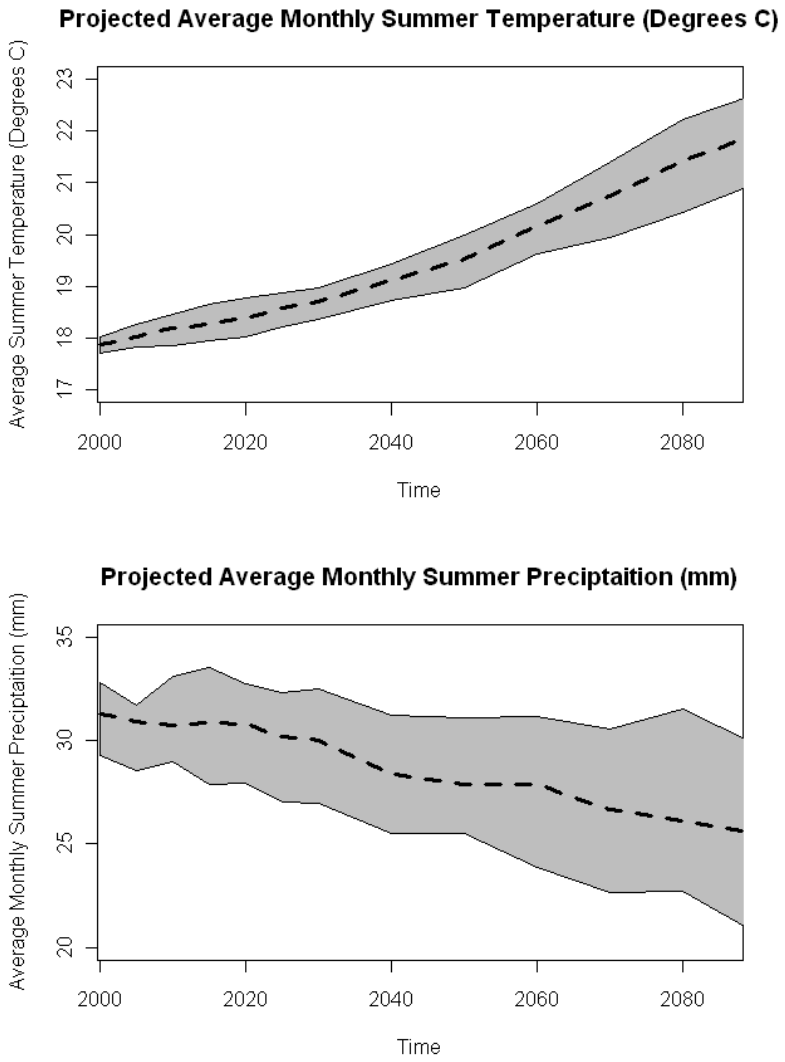

Figure 16: Projected Climate Variables for Summer Months (JJAS). The dark dashed line represents the GCM ensmeble mean, the gray area surrounding this line represents the twenty-fifth and seventy-fifth percentile values.

Results

In the first comparison, the differences between the Baseline Scenario and Scenario 1 are examined. The Baseline Scenario predicts 4% more total annual single-family demand (or 8 MGD) than Scenario 1. The forecasted changes in single-family household water demands for

2030 are presented in Table 5 for each scenario. In Scenario 1, the average household summer month consumption for the region decreases from 229 gallons per household per day (gphd) in 2001 to 218 gphd in in 2030. In winter months, the regional average shifts from 155 gphd in 2001 to 148 gphd in 2030. In the Baseline Scenario and Scenario 1, growth in population within the Puget Sound Region drives the increase in total demands in 2030. In Scenario 1, total single-family consumption during summer and winter months increase by almost 17% in the region relative to 2001 totals, despite the decreases in both summer and winter per capita demands.

Table 5: Average Regional Single Family Household Consumption

Scenario	Winter (gpdh)	Summer (gpdh)	Total (MGD)
2001 Demands	155	229	166
Baseline	155	229	203
Scenario 1	148	218	195
Scenario 2	135	161	157
Scenario 3 -2030	146	244	208
Scenario 3 - 2060	147	260	217
Scenario 3 - 2090	146	272	223

Figure 17 presents the difference in total annual consumption for Scenario 1 between 2001 and 2030. In Scenario 1, most zones increase total consumption between 2001 and 2030, though a few remain relatively unchanged. The projected increase in regional population creates higher total demands despite other factors that lower per capita demand. Total growth in consumption is largest in the areas east and south of Seattle. The cities of Puyallup, Federal Way, Tukwila, West Seattle and White Center, Kirkland, Redmond, Sammamish Plateau, Northern Seattle, Mountlake Terrace, and Edmonds represent areas with the largest net gains in total water consumption, an indicator of heavy growth and densification.

The change in total annual demands by TAZ between the Baseline Scenario and Scenario 1 are quite different. Figure 18 presents the difference in total annual demand between the

Baseline Scenario and Scenario 1. The left pane plots areas where Scenario 1 predicts higher water usage in 2030 compared with the Baseline Scenario. The right pane of Figure 18 displays areas where decreases in total annual water demands are predicted relative to the Baseline Scenario forecast for 2030.

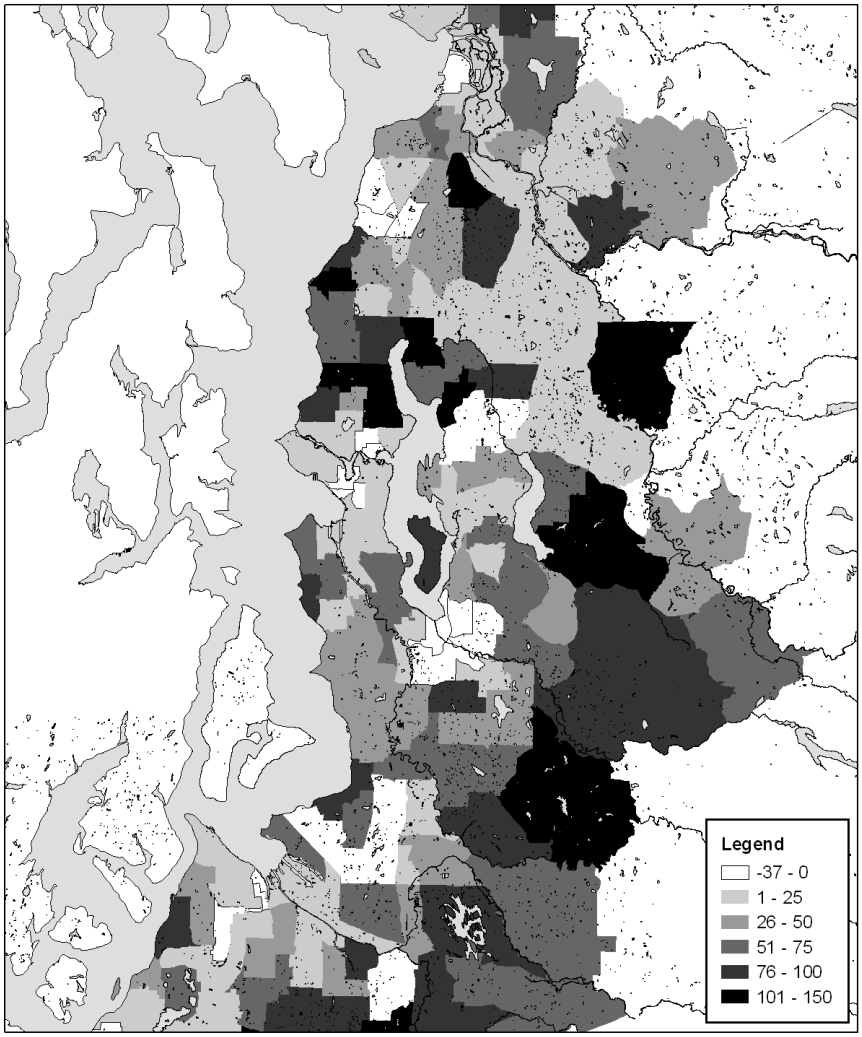

Figure 17: Change in Total Annual Demand (2001 vs. 2030) (MG)

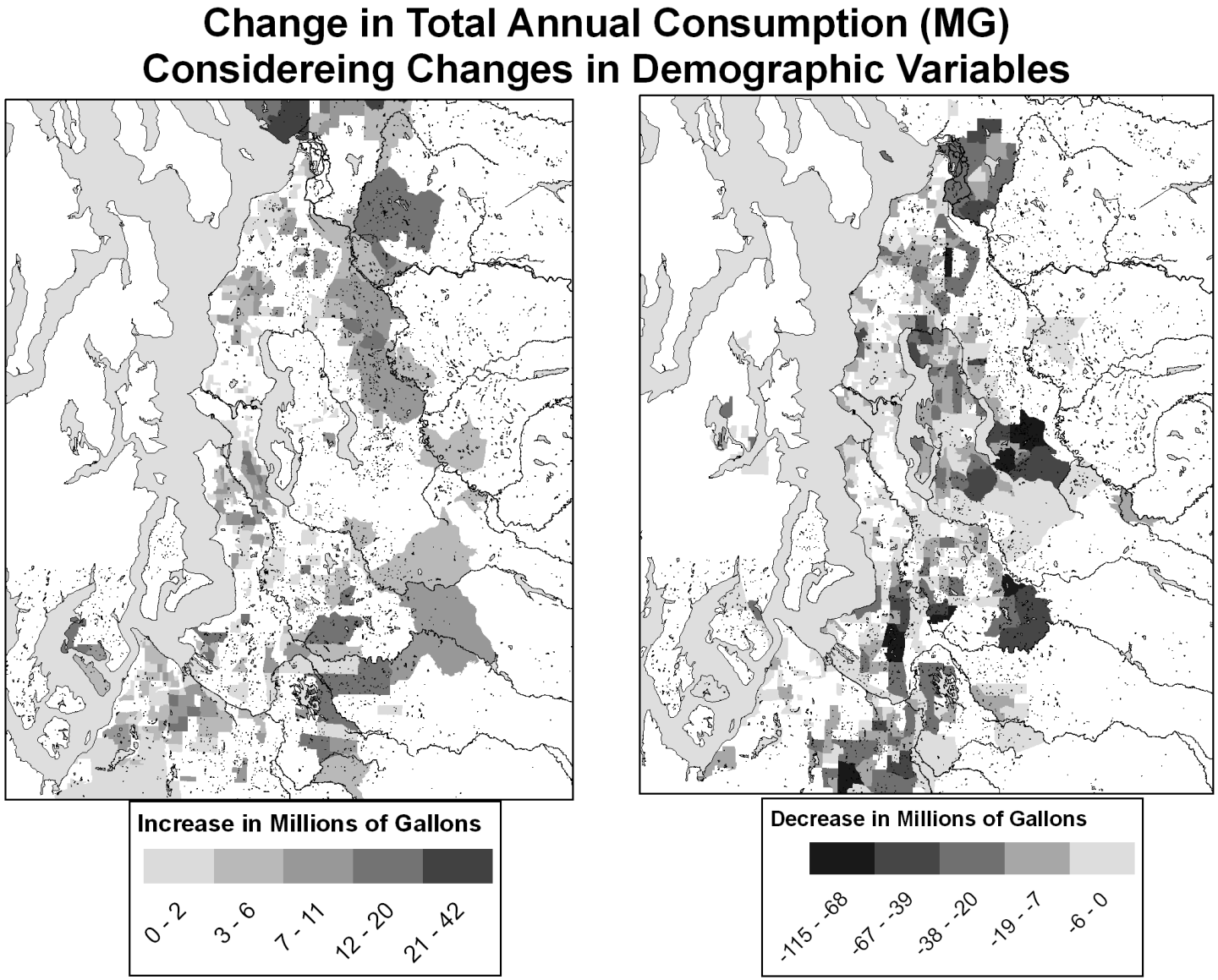

Figure 18: Difference in Total Annual Consumption between the Baseline Scenario and Scenario 1 in 2030

The Baseline Scenario, which neglects changes in demographic variables, produces significant overestimation of demands in the suburban areas east of Seattle and south along the industrial corridor, as well as in the suburbs an exurban area of Everett, south Tacoma and south Puyallup relative to Scenario 1. The primary reasons for over predicition are:

1. Increasing density and slightly reduced lot sizes,
2. Increasing household size and decreasing per capita income, and
3. Smaller homes containing more efficient fixtures.

For many of these regions, the overestimation of demands are manifested in the summer period (Figure 19). Scenario 1 indicates overall savings in summer water consumption relative to the Baseline Scenario as changes in building characteristics and demographics creates a denser suburban area, which is neglected by the Baseline Scenario. The current housing trend within many of the urban areas is the redevelopment of existing large homes into subdivided lots with residences smaller in size and containing more efficient fixtures than existing homes. Scenario 1 suggests continuation of this trend in the suburban areas as these regions densify.

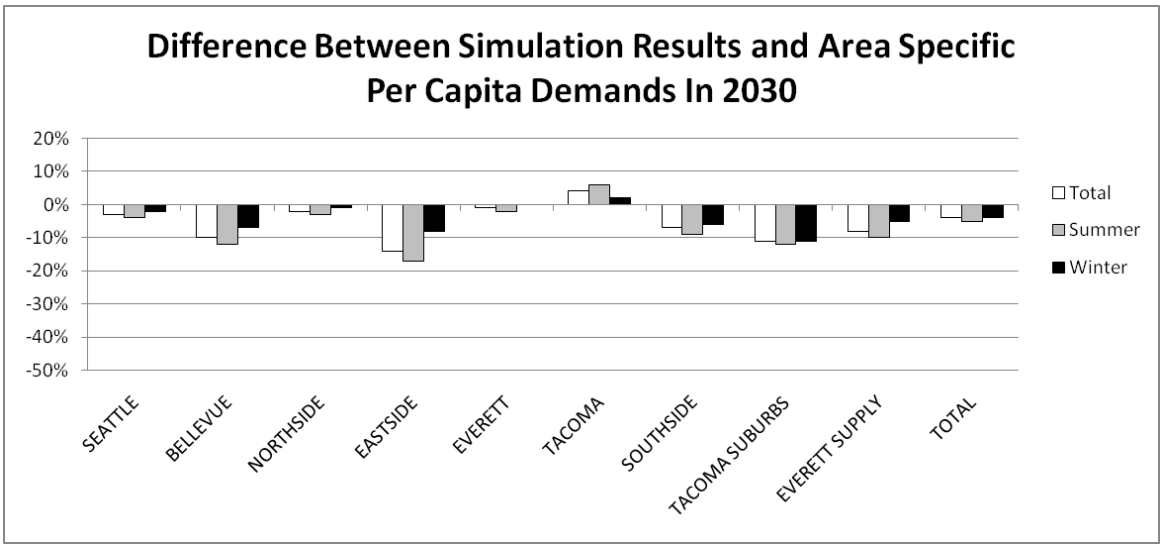

Figure 19: Percent Difference Between Simulation Estimates and Area Specific Per Capita Water Demand Calculation

The estimated water demands in Bellevue and the surrounding suburbs, an area with larger lots and homes relative to Seattle illustrate this effect. Scenario 1 suggests decreasing per capita consumption during winter months and decreasing peak factors (summer use relative to winter use). UrbanSim forecasts decreases in residential built square feet of new development and redevelopment, and increases in residential density. The change of these two variables coupled with an increasing number of homes built post-1992 and increasing residents per household results in decreasing indoor and outdoor demands.

Scenario 1 forecasts increasing demands relative to the Baseline Scenario in the southern portions of Seattle, in the suburbs located directly north of Seattle, and throughout much of the City of Tacoma. For these regions, smaller families (decreasing residents per household) increase the per capita consumption within each TAZ, while increases in income offset the increases in density. In Tacoma, winter per capita consumption increases throughout the city, though peak factors remain similar to 2001 values. Scenario 1 forecasts increasing total demand relative to the Baseline Scenario due to increasing winter per capita consumption. The increase in water usage in Tacoma for Scenario 1 relative to the Baseline Scenario stems from fewer residents per household in 2030 and increasing income, despite decreasing built square feet and increasing density of single-family homes.

In Scenario 1, many of the rural areas located on the urban fringe increase per capita consumption during summer months relative to the Baseline Scenario. Increased development of large homes is primarily responsible. There is uncertainty in the water demand model predictions for this portion of the study region, as many of the homes located in areas that are more rural are self-supplied water users, i.e. have wells that provide drinking and irrigation needs. Calibration of the regression model was accomplished with the use of single-family water

consumption data of metered customers belonging to the Seattle Utility District. Model predictions for rural households not connected to public water supplies are not included as part of this study.

Scenario 2 extends Scenario 1 by introducing an aggressive water pricing policy. The forecast period begins in 2001 and ends in 2030. Pricing begins at 2001 values and increases in real terms at 2% per year through 2030. This results in an approximate doubling of the real costs of water over a 30 year period (181%). The current block rate structure implemented by the City of Seattle is used for the region. Temperature and precipition are held at constant, 2001 values. Scenario 2 is compared with the Baseline Scenario to examine the impacts of increased water pricing and changes in demographics.

The influence of pricing on household demands is substantial (Table 5). Whereas Scenario 1 indicates modest regional decreases in winter household usage, large reductions are seen under increased pricing regimes. The average winter consumption is reduced by 20 gpdh relative to the Baseline Scenario. Summer usage redutions are also significant, with average summer use reduced by nearly 70 gpdh..

The decreases in both winter and summer demands result in 2030 total water usage that is less than 2001 demands. Much of this is due to the large savings in summer demands, as summer prices are higher than winter prices and demand elasticity to pricing changes for summer months is nearly 3 times that of winter pricing elasticity. The largest reductions in water use tend to be outside of the City of Seattle, demonstrated by reductions in many of the cities that are east of Lake Washington and those directly south and north of Seattle. All of these cities are sensitive to the price of water. Many of these areas tend to have higher per capita summer water

consumption, making them more responsive to pricing policy than other zones located within the planning region.

This pricing policy is a substantial change from current policy and would likely meet with significant resistance. It would be difficult to achieve these reductions, as response to price tends to diminish with greater rates. However, Scenario 2 does illustrate the pricing necessary to drive summer demands near those observed in winter months.

In Scenario 3, the impacts of climate change are compared against the Baseline Scenario. The forecast period is 2001- 2030. Pricing is held constant at 2001 values and pricing rates and patterns are assumed to be similar to Seattle's pricing policy for the planning region. Temperature and precipition values from an ensemble of general circulation models (GCM) are used to evaluate the impacts of climate change on water demand. A moving twenty-one year average is calculated using 32 GCMs over the period 1990-2100. This moving average characterizes the general trends from the GCMs rather than focusing on specific annual events. A scaling factor is used to convert monthly average temperatures into average maximum temperature. The ensemble average is used as the temperature forcing for the water demand model for the years 2001, 2030, 2060, and 2090. Figure 16 provides an example of the degree to which temperature and precipitation are forecasted to change in summer months (June, July, August, and September). The ensemble average temperature of 32 GCMs and the twenty-fifth and seventy-fifth percentiles for the summer months are presented for the years 2000-2090. Though there is considerable variability between the individual members of the ensemble, as depicted by the gray area, the consensus is an upward departure from current climate and historic climatology for the Seattle region.

Changes in household demand between the Baseline Scenario and Scenario 3 with 2030 temperatures are modest, with 25 more gpdh being used to water during summer months. The increase in temperatures for the 2030 period creates additional demands that eliminate regional savings seen in Scenario 1 (Table 5). Projected warming over the next 25-30 years is likely to influence summer water demands as much as changes in urban density, changes to residential structures, and conservation. This supports the results of other studies (Boland 1997). Continuation of current pricing policy and conservation programs may offset increases in summer demands through 2030.

Under 2060 warming conditions, a different picture emerges. The impacts of increasing temperatures and decreasing summer precipitation drive per capita demands futher outside of the savings seen under Scenario 1. Total demands in 2060 are 22 MGD higher than Scenario 1, and 9 MGD higher than those in Scenario 3 using 2030 temperature and precipitation values. The additional demands would occur solely in summer months, putting additional stress on water resources during a time of year that water is often needed to sustain biological communities in river systems. In 2090, single family demands grow to 223 MGD, 28 MGD higher than Scenario 1 demands and 20 MGD greater than the Baseline Scenario. This increase is nearly equal to the decreases seen by 2030 under an aggressive pricing policy. Pricing, enhanced conservation measures, and smart growth policies are three useful adaptation strategies to deal with climate change.

Changes in demographics and built environment simulated by UrbanSim will be used in Chapter 4 to examine changes in single-family curtailment effectiveness. Understanding the drivers of water demands and willingness to ration water under curtailment policies will aid water managers in decision making during drought conditions.

Chapter 4: Analysis of Changing Water Curtailment Responses within Single Family Residences

Introduction

Water resource managers plan for extreme meteorological and hydrological events. Meteorological drought is responsible for the majority of the municipal water supply shortages in the United States. Extended periods of below normal precipitation and above normal temperatures (either within a year or over multiple years) can have serious impacts on water supply and water demands. Climate change may result in increased drought severity and length (Meehl and Tebaldi 2004, Tebaldi et al. 2006, Sheffield and Wood 2008, Overpeck and Udall 2010), and, in turn, higher water demands or longer periods of curtailment.

Drought events represent the 'worst case scenario' that has been observed and serve as a benchmark upon which managers craft future adaptation and management plans. Unfortunately drought, as with most extreme events, is inherently difficult to predict. The lack of predictability of drought and its uncertain onset has led to the development of demand-side management techniques that can be used in real-time by managers to guarantee adequate water supply to their entire customer base.

In addition to challenges in predicting drought, predicting customer response to drought is difficult because of the paucity of past events experienced by specific utilities in similar situations. Changes over time in demographics and the built environment further complicate the ability to forecast demands, as does the uncertainties with projecting those changes forward. In the domestic and commercial sectors, demand hardening results from increases in efficiency in indoor and outdoor water consumption (Howe and Goemans 2007).

Demand hardening, the reduction in the effect of water rationing methods, and other short-term response mechanisms complicates drought management. As the cost of providing new increments of safe and reliable water has increased over time, water managers are focusing more attention on how best to estimate future water demands and determining which actions, when implemented, effectively manage demand.

This chapter evaluates the response of single-family residents to mandatory and voluntary water use restrictions during two drought events (1992, and 2001), in Seattle, Washington. This study begins by analyzing the difference in customer response under different water use restrictions by comparing the differences in water usage during the two drought events. Next, the study focuses on prediction of customer response given voluntary water use restrictions (2001 drought event). A hierarchical clustering analysis of single-family water usage and demographic variables is used to identify different customer response groups. Predictive relationships between curtailment effectiveness and variables identified as important factors from the clustering analysis are developed that describe user group response using spatial regression techniques. Lastly, customer response to curtailments is explored to determine potential change under future development patterns using output from an urban simulation model as input to the regression model developed in this research.

Background

In the United States, per capita domestic usage is approximately 100 gallons per day (USGS 2005). This is twice the domestic average usage of European countries and dramatically larger than that used in developing countries (Gleick 2010). Outdoor watering, inefficient appliances, street cleaning, swimming pools, and the maintenance and flushing of distribution systems are all partially responsible for increasing per capita water use. These

activities are responsible for the majority of variability in water demands between different regions, the magnitude to which climate drives seasonal water use, and the differences between customer groups and development patterns. Because of this, domestic water demands in the United States are highly seasonal (Mayer and DeOreo 1999) and, in most metropolitan regions, are correlated with temperature and precipitation (Balling and Gober 2007, Balling et al 2008, Polebitski and Palmer 2010). Polebitski and Palmer (2010) determined seasonal peaking (ratio of average summer demand to average winter demand) to be spatially variable within small domains (within city or region) and highly dependent on demographic and urban characteristics. They found explained variance of R^2=0.62, and R^2=0.57 between income and seasonal peaking factors and house "lot value" and seasonal peaking factors in census tracts within the City of Seattle. Wentz and Gober (2007) found single family demand to be spatially variable in Phoenix and dependent on similar variables (household size, lot size, presence of pools, and landscaping type). Balling et al. (2008) note that many census tracts (one-third of the census tracts examined) within Phoenix were not sensitive to variations in climate and those tracts most sensitive to climate variation had higher percentages of pools, higher incomes, and larger lot sizes.

In Seattle, the average peaking factor for single-family homes is approximately 140% (that is, there is 40% more water usage in the summer than in winter months). The highest peaking factors were found in neighborhoods with the highest median income and land value. Seattle has lower seasonal peaking factors than the national average, with cities in southern California, the Southwest, and the Southeast having some of the highest summer outdoor water usage (Mayer and DeOreo 1999; Balling et al 2008).

Despite Seattle's lower than average summer water consumption, summer demands can influence water supply. Seattle's climate regime is a "Mediterranean climate," with warm and generally dry summers and wet, cool winters. There is virtually no "over-year" storage in the two major reservoirs that serve Seattle , thus water supply is dependent on 1) spring snowpack melt to provide water through the summer and 2) the return of fall rains to dampen demand and refill the reservoirs. Recent studies project further tightening of water availability under climate change scenarios. Decreasing snowpack (Mote et al 2005, Mote 2006), changing seasonality of flows (Wiley and Palmer. 2008, Vano et al. 2010, Traynham et al. 2010), increasing stream temperatures (Battin et al. 2007) and increasing frequency of heat waves (Meehl et al. 2004; Tebaldi et al. 2006) will bring new challenges in meeting summer water demands.

Seattle's population increased by nearly 40,000 residents between 2000 and 2009 (PSRC 2009), a 7% gain, predominantly in the multifamily housing sector. This is slightly less than nearby incorporated area growth, where increases of 10% occurred over the same period. Much of the new development within Seattle is in the form of multifamily units (condominiums) and redevelopment of single-family lots into multiple townhome style single-family homes. This trend has decreased lot size and yard size and increased the number of households. The Puget Sound Regional Council (PSRC) estimates future growth within Seattle to be primarily in the multifamily sector, with total multifamily households doubling by 2040. This is consistent with the current landscape and trends. The PSRC projects single-family homes to increase, but only by 7.5% over the same period.

It is uncertain how changes in population will impact future water demands. Polebitski and Palmer (2010) coupled a water demand model with an urban simulation model

to examine the influence of changing urban landscapes on water demands. They found that changes in density, lot size, employment (income) and household size are important factors in determining demand and that future per capita demands would likely decrease if the projected changes from the urban simulation model were realized. An important implication of their research is the potential change in response to water reductions under various rationing schemes. This is timely given the continued population growth within Seattle despite the recent (2007-2010) economic downturn.

Four drought events have been experienced in the region in the last 25 years (1987,1992, 2001, and 2005). Water restrictions were implemented in three of these drought years (1987, 1992, and 2001). During the droughts in 1992 and 2001, mandatory and voluntary water curtailments were imposed. In 1992, Seattle implemented mandatory water use restrictions following a low snowpack accumulation during the winter months, below average precipitation in the spring, and low reservoir storage. In 2001, voluntary water use curtailments were implemented when below average precipitation during the winter and spring resulted in an abnormally low snowpack. Unlike other regions (Kenney et al 2008), these periods were not accompanied by price increases to deter water usage, instead media outlets, educational campaigns, and utility enforcements served as the primary mode for response. Both the mandatory and voluntary curtailments were effective in reducing demands.

Figure 20 presents boxplots of average single-family per capita water use within census block groups for each drought year and the average usage in surrounding years. Water reductions in 1992 were significant, with a majority of customers (more than 75%)

reducing usage well below even the most efficient users (25th percentile) during average years.

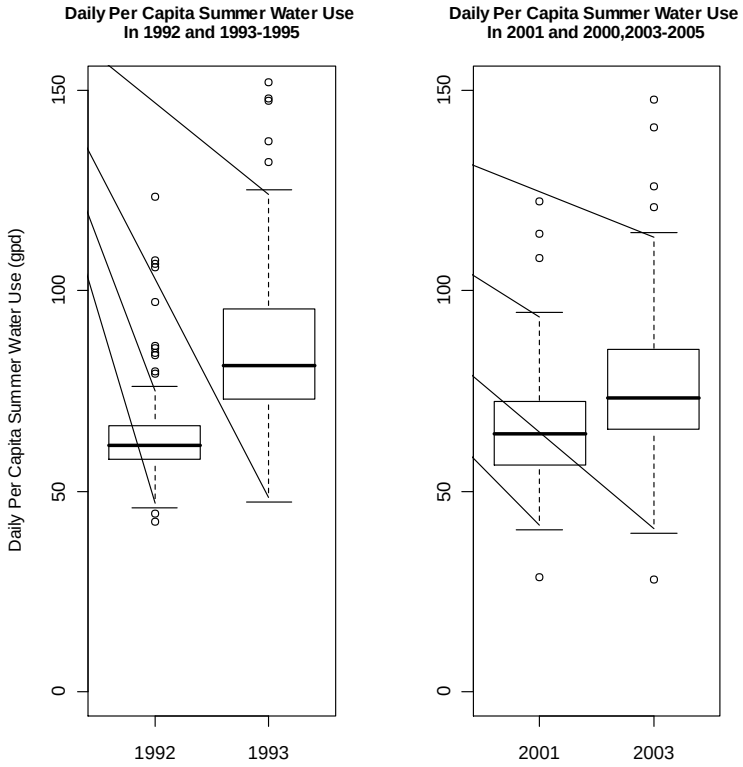

Figure 20: Boxplots of Response to Curtailments

The voluntary curtailments of 2001 were effective, but shift in customer response was not as great as the mandatory curtailments elicited in 1992. Figure 20 plots the response of single-family customers across the study domain. The largest per capita reductions occurred in census tracts with high water usage. The "high water usage" neighborhoods typically had larger lots, larger yards, higher household incomes and predominately single family dwellings. Kenney et al. (2008) found residential water users with large summer consumption were less responsive to pricing policies during restriction years than other users

despite being more influenced by price during non-restriction years. They also found middle and high water consumers respond similarly to restrictions (approximately 12% reductions from restrictions alone) compared with low water consumers (6.5% reductions due to restrictions). In Seattle, the top 20% water consumers reduced consumption under voluntary restrictions by 15% compared with 11% reductions from the remaining customer base. With mandatory restrictions, water use was reduced by over 30% of average water usage for the top 20% of water users, and by 23% for the remaining customer base. Total water reductions were 28% of normal year water consumption for single-family users in 1992, or about 8 million gallons per day (MGD) saved. These reductions are purely due to restrictions being implemented as no pricing changes were implemented during either drought.

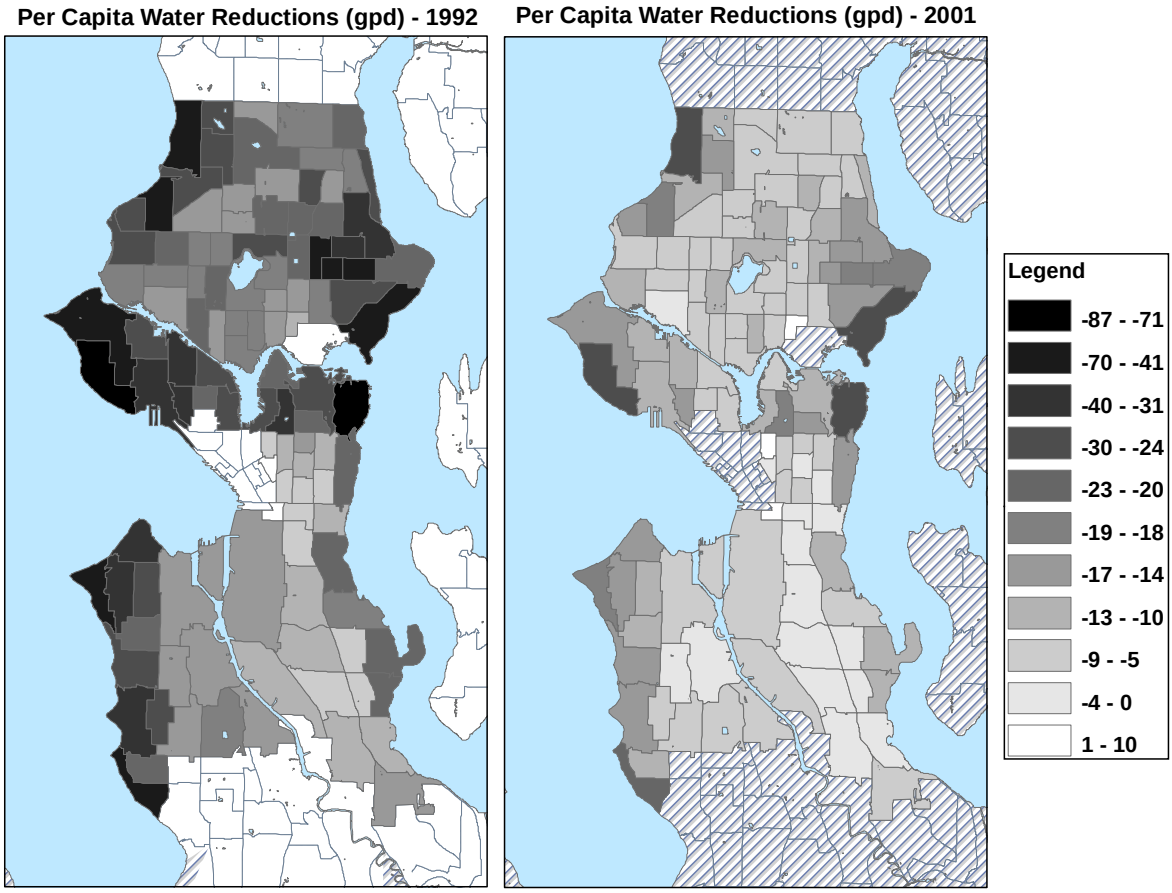

Figure 21: Average Per Capita Water Reductions

Water reductions under mandatory curtailment policies are similar to those found by Kenney et al. (2004), where reductions in water use under mandatory restriction ranged from 13 to 55% for cities in Colorado. They found voluntary water use restrictions to be less effective, where savings ranged from 7 to 12 percent. The voluntary curtailments issued during the drought of 2001 in Seattle appear to be similar in effectiveness, as the average percent savings across all block groups relative to other summers is 12 percent, or about 4 MGD.

Methods

This paper uses k-means clustering and regression analysis to investigate customer response to water curtailments issues during the summer of 2001. K-means clustering provides a simple means to group like customers. Classifying customers into groups with similar traits and curtailment response is useful for determining effective education campaigns, policy enforcement, and changes to revenue. Next, ordinary least squares regression and spatial lag regression models are developed. Regression analysis is a good supplement to k-means clustering, as clustering does not develop a continuous or causal relationship that can be used predicatively given changes in built environment.

Data

Single-family water consumption is derived from parcel based billing records provided by Seattle Public Utilities (SPU). Metered water usage for single-family homes is billed on a non-uniform bi-monthly basis. To assign water usage to a given month, a time-shifting process similar to the method employed by Polebitski and Palmer (2010) is used. The bill date and the number of days within the billing period are used to identify the dates of water usage. The total water usage is then applied uniformly over the billing period. This

algorithm is applied for each single-family account and for each bill period. After the algorithm is executed, consumption is summed by block group and bi-monthly period. The bi-monthly period is selected as there is uncertainty concerning the daily patterns of use for each account given that the data originated as bi-monthly consumption.

Demographic data are from the 2000 US Census datasets at the block group level. Single-family households are defined as detached, single residential dwellings within the city limits. This criterion is used to select for single family population, total single family units, single family income, and education levels from the 2000 Census data. In the cluster analysis, percent education represents the percent of the population over 18 with some college education. Lot size, yard size, and total built square footage of a single-family residence are computed using parcel GIS layers available from the City of Seattle. To compute yard size, building footprints are subtracted from the parcels they reside within. The yard size for each parcel is then averaged within a block group. Parcel records available from the King County Assessor's Office are used to identify the built square feet for each single-family parcel within the study region.

Projections of changes in urban development are from UrbanSim, an open source, spatially (parcel based computations) and temporally (annual time-step) disaggregate urban simulation model. UrbanSim utilizes a series of internal multinomial logit and regression models, along with a macroeconomic forcing, to estimate changes in household location and type, employment location and type, land pricing, and real estate development (Waddell 2004, 2006). Documentation and model code for UrbanSim are available at www.UrbanSim.org. UrbanSim has been implemented in eight major cities within the United States and is being actively used within the Puget Sound Region for planning.

Polebitski and Palmer (2010) forced a regional water demand model with output from UrbanSim to examine the influence of changing urban patterns on water demands. They found changing development patterns decreased per capita consumptions in winter and summer months, regionally though certain areas (new suburban regions) did increase per capita demands with growth.

For this study, outputs from recent simulations of the Puget Sound Region are used. The periods of investigation are 2000 and 2030. Because the spatial units differ between UrbanSim (TAZ) and the census data (block groups), the ratio of income, lot size, built square feet, and household size in 2030 and 2000 are calculated and multiplied by the values for the year 2000 to create a 2030 estimate of change within each block group.

Data based upon location within a city contain spatial correlations, as neighboring units tend to share some characteristics with other nearby spatial units, a phenomenon known as "the first law of geography" (Tobler 1970). Clustering methods and spatial regression are techniques that provide objective means for analyzing spatially correlated data. Spatial regression accounts for bias when the response of the dependent variable (in this case water reductions) exhibit spatial patterns or are spatially correlated to an extent such that ordinary least squares regression estimates become biased. The small spatial scale of a census block group (there are over 500 spatial units for the study region) increases the likelihood of spatial correlation, as neighborhoods within a city tend to share similar demographic and socioeconomic characteristics.

K-Means Clustering Analysis

K-means clustering is a commonly employed statistical method to group data into user specified clusters. The clusters are created to minimize the within-cluster sum of

squares. The k-means clustering technique is used here to identify customer classes that have similar demographic characteristics and water reductions. Eight variables are analyzed and grouped in five clusters (Table 8). The R statistics software package (R Core Development Team 2008) is used to process the data. R provides a clustering routine (Maechler and Rousseeuw 2005) for determining k mean cluster groups based on research by Hartigan and Wong (1979). The analysis identifies like groups based on variables historically important in determining water demands and curtailment effectiveness, such as lot size, living space, income, and education.

Spatial Regression

Regression models are created to describe user response to water curtailments. We focus on the voluntary curtailment of the 2001 drought, as insufficient demographic data exists to develop a model of customer response for the mandatory curtailments issued during the 1992 drought. Four variables were initially chosen (Table 6) as predicators. Each variable is correlated with water reductions (Figure 22), though the variables themselves are highly correlated with one-another (Table 6).

Table 6: Correlation Matrix of Predictor Variables

Variable	Lot Size	Built Sq Ft	Household Size	Income
Lot Size	1.00	0.41	-0.05	0.22
Built Sq Ft	0.41	1.00	0.01	0.63
Household Size	-0.05	0.01	1.00	-0.15
Income	0.22	0.63	-0.15	1.00

In ordinary least squares regression (OLS), highly correlated predictor variables create multicollinearity. This inflates the standard error of coefficient estimates, making prediction of future values volatile. Many methods are available to remedy multicollinearity,

including removing variables, standardizing variables, or increasing the sample size. Another method, principal component analysis, provides a robust means to create uncorrelated variables. Principal component analysis transforms correlated predictor variables into a smaller set of uncorrelated variables, called principal components. These principal components are linearly independent weighted averages of the predictor variables. The weights, or loadings, reflect the importance of each variable within a principal component. The magnitude of a variables loading reflects the importance of the variable in describing that particular mode of variance. Each principal component describes an independent mode of variability within the data set. For instance, lot size, living space, and income are highly correlated variables; a single principal component will describe their correlated variability across space. Table 7 presents the weights, or loadings, of the first four principal components. Each variable was standardized prior to determining the principal components to resolve scaling issues.

The first principal component loads lot size, living space, and income with similar magnitude and in a negative direction, whereas the second principal component is heavily weighted by the residents within a household. The third and fourth principal components are not used in the analysis as they explain little variability. The first and second principal components are used as the predictor variables in the OLS regression model and the spatial lag models discussed below.

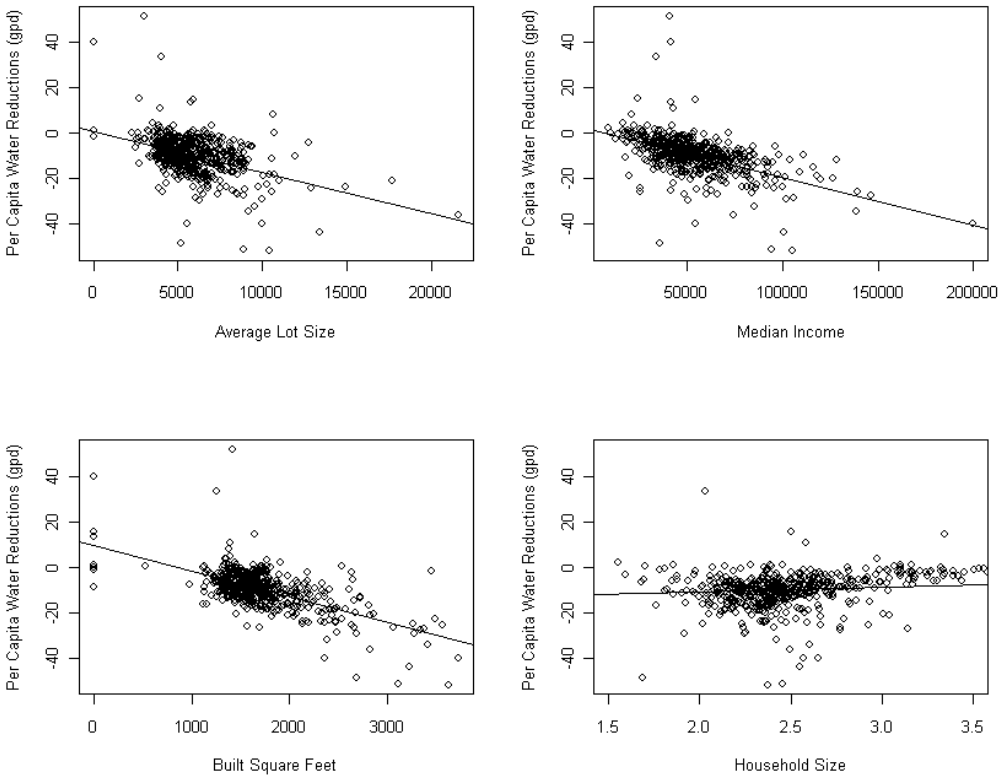

Figure 22: Per Capita Water Reductions vs. Predictor Variables

Ordinary least squares regression (OLS) takes the form of y = BX + e, where y is the dependent variable (water reduction), X represents the independent variables (principal components of lot size, living space, income, and residents per household), B contains the model coefficients that minimize the squared error between the fitted and the observed values, and e contains the residual error from the fitted values of the estimated linear model. OLS becomes biased if the dependent observations are correlated spatially. Moran's I test determines whether the residuals are spatially autocorrelated. If spatial autocorrelation exists, spatial OLS regression techniques are preferred as they provide better estimates of model standard error. Moran's I test indicated the presence of spatial autocorrelation in the dependent variable, consequently two spatial regression models were examined.

Table 7: Loadings By Principal Component

Variable	PC1	PC2	PC3	PC4
Lot Size	-0.46	0.16	-0.84	-0.25
Built Sq Ft	-0.64	0.18	0.17	0.72
Household Size	0.13	0.96	0.16	-0.17
Income	-0.60	-0.11	0.50	-0.62

Two spatial regression methods are commonly employed to account for spatial error and autocorrelation: spatial error models and spatial lag models. Spatial regression models incorporate additional terms to account for correlation with neighboring spatial units. A spatial lag model is defined as y = pWy +BX +e, where the new term W and p represent a weights matrix and spatial correlation, respectively. The weights matrix contains the spatial information needed to determine neighboring units for each block group, and p represents the amount of spatial correlation a unit has with its neighbors. The spatial lag model proved to be the best model to as it had a higher R^2 value, lower log likelihood, and removed spatial autocorrelation from the model residuals.

To estimate changes in lot size, living space, income, and family size for 2030, output from UrbanSim for each block group were generated. Each variable was standardized, then the principal components were developed using the standardized variables and the loading matrix in Table 7. This generates values of PC1 and PC2 that are processed through the regression models to develop water reductions capturing demographic and physical changes simulated by UrbanSim for 2030.

Results

Clustering Analysis

Table 1 presents the results from the clustering analysis. The largest per capita reductions (Cluster Group 3) occur within census block groups with the largest yards/lot sizes, largest

homes, highest household incomes, and highest rates of college education. The smallest reductions (Cluster Group 4) are in block groups with the smallest lot sizes/yards, smallest living spaces, highest residents per household, lowest household income, and lowest level of college education. Cluster Group 1, Cluster Group 2, and Cluster Group 5 represent block groups that fall in between these ranges. Cluster Group 5 shares similar traits with Cluster Group 4 in that reductions are small relative to other clusters. Residences are similar size to those in Cluster Group 4 though the lot size and yard size are larger, and resident income and family size are slightly larger. Cluster Group 1 and Cluster Group 2 are more similar to each other than to Cluster Groups 3-5. Reductions are larger relative to groups four and five. These cluster groups have larger lots, yards, and living spaces relative to Cluster Group 4 and 5, as well as higher family income and college education levels.

Table 8: Results from K-Mean Clustering Analysis

Cluster	Per Capita Reductions (gpd)	Lot Size (ft^2)	Living Space (ft^2)	Residents Per Household	Income	Yard Size (ft^2)	Houses Built Post-1994	Percent College Education
1	-12.40	6042	1758	2.38	63792	4262	13.4	81%
2	-16.95	6449	2144	2.38	86754	4456	11.8	88%
3	-23.89	7329	2989	2.68	137015	5038	8.8	96%
4	-7.38	5397	1535	2.72	31015	3858	13.8	62%
5	-9.08	5876	1587	2.53	47478	4211	13.3	72%

In general, the wealthiest neighborhoods responded with the largest reductions in demand, though the majority of block groups reduce water usage during voluntary curtailments. The percent change in water usage relative to average years is against plotted median income in Figure 23. Water usage during a curtailment period generally decreases with increasing household income. Not only do the wealthiest neighborhoods respond with the greatest per capita reductions, percent-wise they tend to respond more than other block groups.

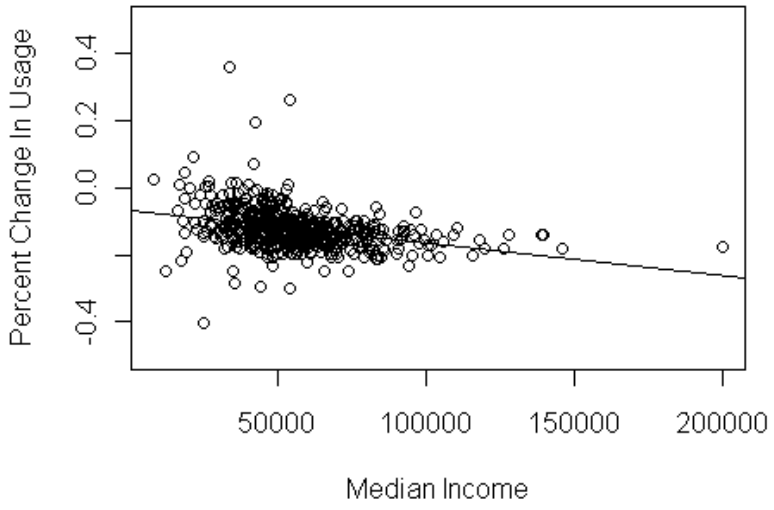

Figure 23: Percent Change In Usage (2001 relative to 2000,2003-2005) vs. Median Income

Regression Analysis

Table 9 contains estimates for the OLS and spatial lag regression models. Both regressions are highly significant ($p < 0.001$) as are the model coefficients ($p < 0.001$). Both models have similar coefficient values, though the spatial lag model has a higher R^2, indicating that the spatial weight matrix and autocorrelation value improves model estimates. The coefficients below suggest water reductions are influenced heavily by changes in PC1. The loadings in Table 2 suggest lot size, living space, and income are the most influential variables in PC1, thus water consumption during a curtailment period is primarily a function of income and physical property characteristics. Household size plays a lesser role, as it weakly influences PC1, and though dominant in PC2, PC2 contributes a third of the overall value of water reduction (1.17 and 0.94 versus 3.96 and 3.16).

Income and property characteristics are the dominating factors during curtailment periods as larger lots typically use high amounts of water for outdoor watering. Outdoor irrigation is a nonessential use of water, and offers an opportunity to decrease water use

significantly during voluntary curtailment periods. Most indoor water use is considered "essential" with few alternatives available for reductions, although some are available (washing clothes less often, repairing leaks, using dish washers only when full, etc.). Increases in the number of people per home (family size) tend to decrease the ability for a household to reduce water use during a curtailment period. This furthers the argument that the majority of water reductions stem from outdoor water use, as Polebitski and Palmer (2010), among many other studies (Högland et al. 1999, Arbués et al. 2003, Wentz and Gober 2007), have found per capita water consumption to decrease with increasing family size, mainly due to economies of scale from fuller washers, dishwashing machines, and less outdoor watering per person. Here, water reductions become less effective with larger families, as indoor water use is dominated by already in-place fixtures, that are expensive to modify or replace, and behavior that is hard to change. The results from the regression model agree with the k-means clustering analysis, where the largest reductions occur in block groups with large lots, large homes, and large household incomes. The model explains half of the variability of the curtailment response ($R^2 = 0.52$), which is an improvement relative to other models attempting the same, though does indicate other variables may be missing that could improve overall predicative ability.

Table 9: Estimated Regression Models

Model	Constant	PC1	PC2	Spatial Weight	R^2
OLS	-10.96	3.96	1.17	NA	0.47
Spatial Lag Model	-7.34	3.16	0.94	0.33	0.52

The effect changes in the urban environment and demographics have on water curtailment effectiveness were also evaluated. Figure 24 presents the change in water

reduction between 2030 and 2000. Negative values indicate additional reductions (blue), while positive values (red) indicate decreased response. Much of the area is lightly shaded, indicating little change in water reduction response. Areas of enhanced curtailment response are located in the eastern regions of Seattle whereas reductions in curtailment effectiveness are located in the western regions of Seattle.

Along the eastern portions of Seattle, the increase in curtailment effectiveness results from decreasing family size. Decreases in lot size and built square feet are forecasted for many of the block groups in this region of Seattle, which increases curtailment effectiveness. This suggests that the changes in household size are large enough that development of smaller homes will still result in larger per capita savings relative to current estimated curtailment savings. UrbanSim's forecast is consistent with current trends in the region, where much of the development in the central and southern parts of the city are new townhomes and condominiums that have smaller lots, living spaces and smaller families. Decreases in curtailment effectiveness in the western parts of Seattle are similarly driven by changes in household size. Forecasts of increasing family size in many of these block groups results in decreasing curtailment effectiveness. Increases in living space and lot size for these block groups are modulated by increases in household size.

These results are surprising as much of the variability of water demand in a block group is explained by the features of the surrounding built environment. Relative to lot size and built square feet, changes in household size are of greater magnitude and likely occur more rapidly. Development of new or redevelopment of existing structures in the single family sector would likely be slow in such a dense, developed region, especially when the majority of growth is forecasted to come in the form of multifamily structures.

What does this mean for total water curtailment effectiveness in the future? In Seattle, reductions across space are variable (Figure 24), but taken as a whole do not result in net increases or decreases in per capita effectiveness despite relatively large gains in single-family population (15 percent increase in single-family population). Work by Polebitski and Palmer (2010) project about a 3 million gallon per day increase in single-family water consumption between 2000 and 2030 during summer months. Net reduction from voluntary curtailments in 2000 was approximately 3.7 MGD, in 2030 it is projected to be 4.4 MGD. When taken as a percent of total single-family MGD these translate into ~16 percent reductions of summer demand in 2000 and a 17 percent reduction in 2030. This will be of concern to planners if 1) gains in water reduction are anticipated from continued densification of metropolitan centers, or 2) a doubling of multifamily residents occur. Base load for water demand will increase but system wide curtailment will decrease as indoor water usage is the primary component of multifamily water consumption and is relatively inelastic to curtailment policies.

These results suggest that the number of residents within a home is likely to be the most important factor in determining future curtailment effectiveness, though changes in lot size, built square feet of a residence, and income should be incorporated into curtailment response models, as some regions may have emerging development patterns that differ significantly from Seattle. From a planning point of view, much of Seattle is 'built out', meaning no new development of vacant tracts of land compared to other regions of Puget Sound where new suburbs and exurbs continue to be created. Changes in curtailment effectiveness in suburban areas may differ significantly than areas with dense development.

Increasing household size hardens demand as less per capita water is used outdoors for irrigating. Decreasing household size increases per capita curtailment effectiveness, even in regions with new and more water-efficient development patterns, as outdoor water use is still a significant portion of summer consumption.

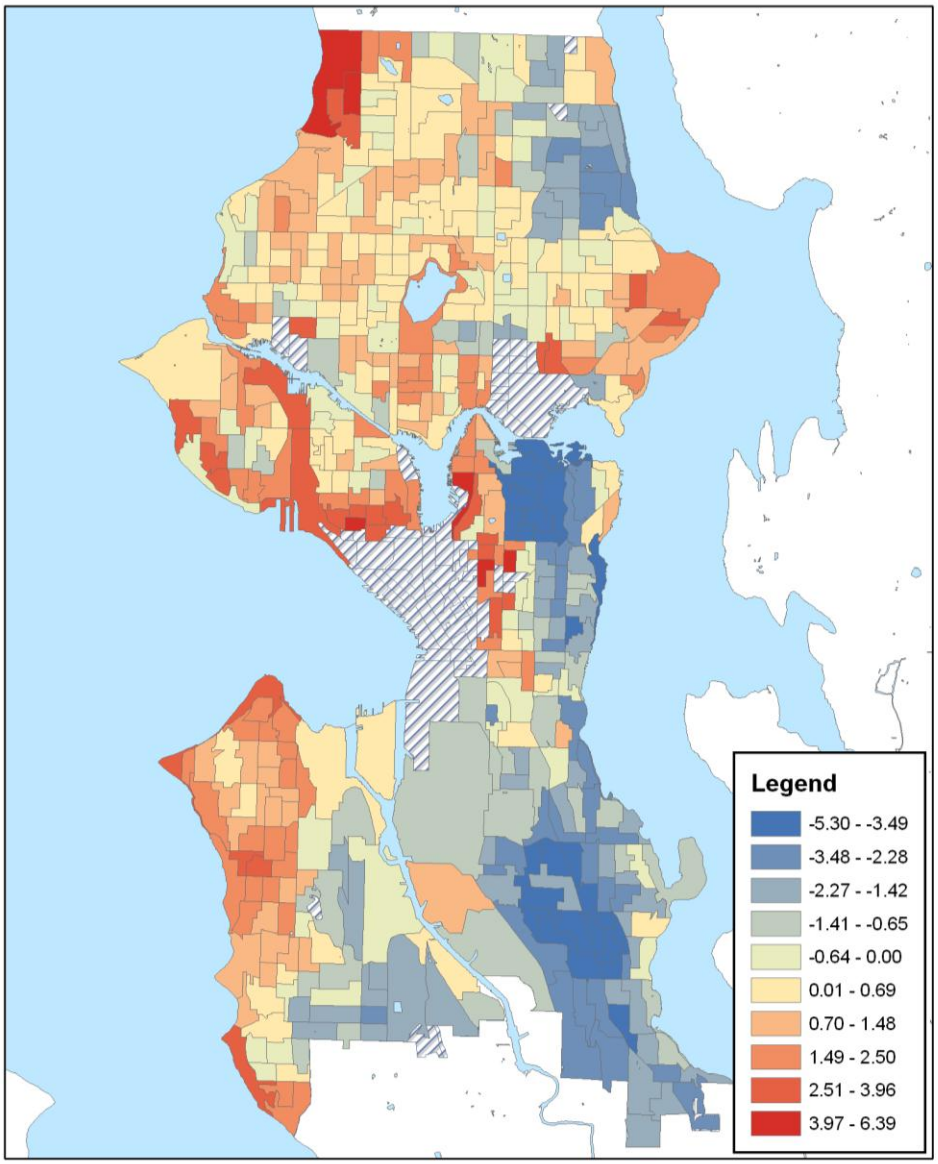

Figure 24: Change in Water Reduction between 2000 and 2030 (gpd)

Chapter 5: Conclusions

Methods that address three fundamental challenges associated with water demand modeling have been developed. These are:

1. incorporating urban change in modeling efforts,
2. accounting for climate variability and change, and
3. quantifying customer response to water curtailments.

Chapter 2 explores the spatially and temporally disaggregated aspects of water demand. The data used, and the models estimated with these data, are novel in that both data and model are at a greater level of resolution than typically used in water demand forecasting. Water demand within small geographic regions was found to be highly variable. Census tracts, as the forecasting unit, provide utility management staff with greater insights on where water is demanded and how specific demographics influence both temporal and spatial consumption. Pooled-Ordinary Least Squares, fixed effects, and random effects regression models were estimated separately for the single-family sector using over 100 census tracts and 12 years of data, including demographic, weather, economic, and bi-monthly water consumption. Fixed and random effects methods work well for modeling spatial (geographic) water consumption heterogeneity.

Panel-based regression methods produced accurate forecasts of per capita water demand for single-family residential consumption within individual census tracts and replicated total single-family consumption within the study area. Elasticity estimates for the models are consistent with current and past literature, although the elasticities estimated using random and fixed effects methods provide less biased results. Water demand was more elastic to price and income effects in summer months than in winter months for single-family

homes. Lot size, density, and building size influence water demand patterns and should be included as variables in water demand models give that urban patterns are likely to change for many regions. The elasticities developed from this analysis incorporate temporal and spatial variation in residential water demand patterns and include estimates of variables that have not commonly been incorporated into panel datasets. These elasticities are appropriate for use in forecasts where changes in development type and land use are expected. This is important, as many urban areas are experiencing changes in dwelling size, building density, and demographics.

The use of highly disaggregated data to forecast water demands is now possible, principally due to the availability of billing data in electronic formats, GIS tools that allow rapid manipulation of this data in a spatial framework, and inexpensive high-speed computing. Such water demand estimates allow the visualization and evaluation of demand information that was not previously possible.

Chapter 3 focuses on the influence of urban growth, land use, water pricing policy and climate change on single-family residential water demands; a deterministic urban simulation model is used to forecast water demands. The technique was applied to the Puget Sound Region, Washington State, using four scenarios for the 2000-2030 time period. Scenario 1 results in average household reductions of 7 gallons per day per household (gpdh) during winter months and 11 gpdh in summer months compared with the Baseline Scenario. Winter (or indoor) water demands, and subsequently wastewater baseflows, decrease per household but increase in total under all three scenarios due to population growth. Summer demands experience a similar decrease in per capita water demands relative to the Baseline Scenario but an overall increase in regional total demands.

Scenario 1 demonstrates the importance of incorporating urban growth and development in determining water demands for single-family homes. Omitting these variables from a water demand model could result in significant bias when projecting future demands for a sub-region, though total regional demands may be similar. Urban and suburban areas are complex and evolve over time. Assuming that important variables are static (such as income, density, or building age distribution) will likely result in added bias to future projections.

Scenario 2 and Scenario 3 strongly influenced summer demands. The increasing step water pricing policy (Scenario 2) decreases demands whereas the increasing temperatures from global warming (Scenario 3) increase summer demands. Under aggressive pricing policy, summer demands were close to winter demand levels for much of the region. Anticipated climate warming increased summer usage by as much as 20 MGD relative to the Baseline Scenario of 203 MGD and 28 MGD relative to Scenario 1. The increases in summer water consumption due to climate warming may be ameliorated by aggressive pricing policies and continuation or enhancement of conservation programs.

Chapter 3 provides insight into the influence of growth within and around national metropolitan areas on single-family water demands. Housing density, which may prove to be a key to understanding the overall impacts of climate change on water demand is currently absent from many demand forecast models. Increasing unit density within metropolitan regions will reduce peak summer demands as available yard space decreases. Increased development of ex-urban areas may increase overall demands due to an increasing number of large yards. This has implications for regional planning and adaptation to climate change as

landscaping restrictions or code changes for new development may offset some potential increases in summer water demands for rapidly growing suburban regions.

The inclusion of water conservation programs is essential in accurate water demand forecasting because of their effects on future water use. The age of residential homes and business structures is important when calculating conservation savings, as newer homes and businesses, due to code changes in the early 1990's, have fixtures that are more efficient. Urban simulation models permit estimating how fixture replacement rates may change under different growth scenarios and may be useful in estimating the penetration rate and water savings given any new changes in standards.

Chapter 4 investigates customer response to demand management strategies, specifically the use of water curtailments/rationing. Mandatory and voluntary water curtailments without a water pricing component were effective in reducing per capita demands by 27 and 12 percent during the period issued. K-means clustering was used to group like customers together by identifying clusters with similar traits and water reductions. Cluster analysis provides a simple and efficient method for identifying like customers and their response to water curtailments within metered regions. Ordinary least squares and spatial lag regression models were estimated using the first and second principal components of household income, lot size, living space, and family size. Larger values of income, lot size, and living space enhanced water reductions while larger family size tended to reduce the effectiveness of curtailments. Output from UrbanSim was used to quantify the changes to Seattle's built environment and demographics between 2000 and 2030. Forecasted values of lot size, household size, income and residence built square feet were processed through the regression models to investigate changes in curtailment effectiveness.

Increasing household size hardened demands (decreased curtailment effectiveness) while decreasing household size increased per capita curtailment effectiveness. These results suggest that changes in the number of residents within a home is likely to be the most important factor in determining future curtailment effectiveness and should be of concern to planners if 1) gains in water reduction are anticipated from continued densification of metropolitan centers, or 2) a doubling of multifamily residents occur. Overall curtailment effectiveness did not change significantly, with net reductions from voluntary curtailments changing by less than 1 MGD, or approximately 1% of total single family MGD consumption.

Three fundamental challenges within water demand modeling have been addressed:

1. Estimation of water demands at local spatial scales using detailed demographic information,
2. How to incorporate urban development, climate variability and climate change into future water demand projections, and
3. Quantifying customer response to water curtailments.

This dissertation provides water managers with new tools to aid in predicting water demands and developing a better understanding of their customer base.

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