SUPPORTING THE IMPLEMENTATION OF EFFECTIVE URBAN WATER CONSERVATION AND DEMAND MANAGEMENT STRATEGIES

by

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Abstract

There is an urgent need to ensure the sustainability of urban water resources. In the face of growing challenges including urbanization, climate change, and increased competition for available resources, new and innovative water management strategies are required. The conventional approach to sustainable urban water management typically focusses on the supply dimension; however, this has proven to be largely inadequate and many are calling for a new approach to addressing this issue. The aim of this thesis is to examine how the water meter data management and analysis systems might be improved to better support water conservation efforts by exploring the literature and carrying out a case study of the City of Vancouver. Literature covering the field of urban water demand modeling as well as conservation interventions and their use in reducing potable water demand were reviewed within the context of the changing understanding of urban water resource sustainability and its dimensions. A case study of the City of Vancouver parks system then explored how existing water meter data could be leveraged to support conservation efforts. The results found that while there have been substantial efforts undertaken to characterize and understand the factors that influence water demand, behaviour and social factors remain largely unaccounted for which are vital dimensions to include in the development of solutions. The case study findings demonstrated that the analysis of existing data can be successful in understanding conservation strategy options, which can be a useful entry point in addressing this highly complex problem. Across the literature and case study the findings highlight the gap in knowledge around water use and behaviour that is evident when the focus is on sustainability. Future work is recommended to incorporate a wide range of influencing factors that go beyond the conventional supply oriented paradigm.

Lay Summary

There is an urgent need to ensure the sustainability of urban water resources. The aim of this thesis is to examine how the water meter data management and analysis systems might be improved to better support water conservation efforts by exploring the literature and carrying out a case study of the City of Vancouver. The results found that while there have been substantial efforts undertaken to characterize and understand the factors that influence water demand, behaviour and social/cultural factors remain largely unaccounted for. The case study findings demonstrated that the analysis of existing data can be successful in understanding conservation strategy options, which can be a useful entry point in addressing the complexity of the problem and suitable solutions.

Preface

I was the lead researcher for all aspects of this thesis including literature reviews and discussion as well as the identification and design of the research program, research methods development, data analysis, as well as manuscript composition for the case study.

A version of Chapter 4 has been published in July 2017 in the Journal – American Water Works Association.

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I would like to acknowledge that UBC and the City of Vancouver are situated on the unceded traditional territory of the Musqueam, Squamish and Tsleil-Waututh peoples.

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CoV – City of Vancouver

ICI – Industrial, Commercial, and Institutional

SEQREUS - South East Queensland Residential End Use Study

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1 Introduction

The sustainable management of water resources is becoming increasingly challenging as climate change, urbanization, industrialization, and changing socio-economic conditions all contribute to the growing stress on fresh water availability (Alcamo et al., 2007; Brown et al., 2009; Pahl-Wostl, 2007; Vörösmarty et al., 2000). This context has also led to growing competition between stakeholders for the remaining resources, especially in urban areas (Mitchell, 2006). In the face of these mounting challenges to sustainability of water resources, it is argued that there is a need for new and innovative water management strategies, partly because in their opinion, as stated by Wong et al. (2008), “the conventional urban water management approach is highly unsuited to addressing current and future sustainability issues” (p.1).

The conventional approach to urban water management typically places the supply of water as its primary goal, meaning the focus is “on finding new sources of supply to address perceived new demands” (Gleick, 2000, p.127). While this approach has proven to be largely inadequate, some authors have found what they consider to be a continued but significant reluctance to change (Lach et al., 2005; Mitchell, 2006; Wong & Brown, 2008). Research indicates that some cities and water utilities are continuing to undertake water management strategies that are rooted in the conventional wisdom which do not address the mounting challenges they face (Lach et al., 2005; Wong & Brown, 2008). This may be partly attributed to the lack of consensus on what the objectives of a new approach to urban water management would be or what it should look like (Brown et al., 2009). In addition, from an operational perspective, urban water systems cannot be easily or rapidly retrofit, and many factors beyond the development of a new theoretical management strategy, that limit change (Marlow et al., 2013). Therefore, despite the growing understanding that a new approach to water management is needed, in the opinion of Brown and Farrelly (2009): “urban water management remains a complex and fragmented area relying on traditional, technical, linear management approaches” (p.839).

In recent literature however, several academic researchers are calling for a paradigm shift in the way urban water is addressed, in order to ensure the sustainability of water resources (Brown & Farrelly, 2009; Lach et al., 2005; Moglia et al., 2010; Pahl-Wostl, 2007). This push for changes to water management is not novel within the world of urban water management, and a historical analysis outlines a number of transitions that have occurred over time (Brown et al., 2009; Mitchell, 2006; Wong & Brown, 2009). These changes were motivated by changing socio-political issues, such as ensuring adequate access to clean water, protecting public heath from disease transmission, flood protection, etc. (Brown et al., 2009; Mitchell, 2006; Wong & Brown, 2009). Blake (1956), in his overview of the history of urban water supply development in the United States, describes the early drivers of the urban water systems improvements: first to fulfill the basic human need for water, as well as for fire suppression, then to mitigate the spread of disease, and for hygienic purposes. Lund (2015) furthers this point, stating that "Most fundamentally, societies manage water to improve public health and safety, support economic and recreational activities, and sustain a socially desired environment" (p.5906). In the same vein, Brown et al. (2009), characterized "six distinct, yet cumulative, transitional stages in the development of urban water management across Australian cities" (p.850), and identified the principal drivers for each stage that include access to water, public health protection, flood protection, environmental protection, natural resource limitations, and the last stage, climate change resilience and intergenerational equity (the yet unattained 'water sensitive city') (Brown et al., 2009).

Based on this final stage of urban water management drivers that incorporate sustainability dimensions, a reframing of the problem becomes necessary (Brown et al., 2009). Specifically, framing urban water sustainability as a wicked problem can be a useful lens through which to approach this issue (Lach et al., 2005). The idea of wicked problems was first formally described in the 1970s by Rittel and Webber, in their 1973 paper, *Planning Problems are Wicked*. Lach et al. (2005) later applied this understanding of wicked problems to water resource management specifically, however the wicked problem framing has been applied to a number of fields that include urban planning, forestry and economics (Allen & Gould, 1986; Batie, 2008; Rittel & Webber, 1973a).

In defining wicked problems it is useful to begin with the opposite - a tame problem, which is well defined, separate from other problems, with verifiable solutions (Head & Alford, 2013; Rittel & Webber, 1973b). Example of tame problems include mathematical equations or engineering problems (Head & Alford, 2013; Rittel & Webber, 1973a). In terms of water management, if viewed as a tame problem the issues focus around "not having water in the right places at the right times, in the right amount, and/or of sufficient quality" (Lach et al., 2005, p.3), an outlook that has supported the conventional supply paradigm that still dominates today (Lach et al., 2005; Wong & Brown, 2008).

Conversely, wicked problems "have multiple and conflicting criteria for defining solutions, solutions that create problems for others, and no rules for determining when problems can be said to be solved" (Lach et al., 2005, p.7) making them difficult to solve with conventional approaches. Wicked problems are unique in space and time, are continuously restructured, making them difficult to define and burdened with significant uncertainty (Head & Alford, 2013; Patterson & Williams, 1998; Reed & Kasprzyk, 2009; Rittel & Webber, 1973b). In addition, the root of wicked problems is their social dimension, which creates consequences that are difficult to predict, and unevenly distributed, which means that questions of equity and even morality become intertwined in solving them (Rittel & Webber, 1973b). Rittel and Webber (1973b) provide ten distinguishing properties of wicked problems each of which apply to urban water sustainability. Historically, urban water sustainability has been often characterized as a tame problem; framing the problem as wicked can ensure the range of relevant but previously overlooked characteristics of the problem are addressed (Lach et al., 2005; Wong & Brown, 2008). This wicked problem framing provides a basis for, what is identified by Pahl-Wostl et al. (2011), as a need for a substantial shift in the way in which water management is undertaken.

Within this context, the aim of this thesis is to examine how the water meter data management and analysis systems might be improved to better support water conservation efforts by exploring the literature and carrying out a case study of the City of Vancouver.

Before moving forward, it is important to describe the difference between water conservation and water demand management. Brooks (2006) defines water demand management as "any method that will accomplish one or more of the following:

(1) Reduce the quantity or quality of water required to accomplish a specific task.
(2) Adjust the nature of the task or the way it is undertaken so that it can be accomplished with less water or with lower quality water.
(3) Reduce the loss in quantity or quality of water as it flows from source through use to disposal.
(4) Shift the timing of use from peak to off-peak periods.
(5) Increase the ability of the water system to continue to serve society during times when water is in short supply." (p. 524).

Water conservation on the other hand is similar, but less broad, and is focussed on minimizing the volume of water used for a given end use while continuing to meet the desired objectives (Anderson, 2013).

Another important consideration is that the literature and case study in this thesis explore revealed quantitative water consumption data, as opposed to declared data. Revealed data has some advantages as it is easier to analyze and provides information on how people act and use water in the real world, as opposed to how they think they use water, which can be erroneous (Beal et al., 2013). A study by Beal et al. (2013) demonstrated that people's perceptions of their water consumption does not match well with their actually use. However, there are some disadvantages to using revealed data; no context or reasoning for consumption behaviour is provided and therefore the causation for trends is not evident. Furthermore, while analysis of data is easier with revealed quantitative data, the data sets themselves can be large enough and be challenging to manage.

2 of this thesis provides an overview of selected academic research on urban water demand modelling, and provides a discussion on their data requirements, utilization and drawbacks in the context of implementing demand management strategies. Demand modeling is the basis for water resource management, and the assessment of benefits and gaps of current modeling approaches can provide insight into what is required moving forward. The body of work examined in Chapter 2 provides an overview what influencing factors and dimensions of water use are being considered by existing models.

3 examines the effectiveness of various household level water conservation interventions through analysis of selected and representative academic studies and experiments. This chapter facilitates a better understanding of the relative effectiveness of household conservation strategies are in reducing water use compared to their historical baseline.

4 explores if improvements to the management and analysis of existing water meter data can be used to provide support conservation efforts. The work uses the City of Vancouver parks system as a case study. In general water system data is ill-suited for conservation analysis, and this case study looks at generating tailored data outputs that are a useful in the development on water conservation strategy development. Finally, 0 provides the conclusion of the thesis.

2 Overview of Selected Academic Research – Urban Water Demand Modelling

2.1 Introduction

Water utilities collect large volumes of data about their water systems, and through ongoing technological developments, the amount of data that can be made available has been growing rapidly along with significant improvements to the resolution of that data (Timmerman et al., 2010). This chapter is focussed on gaining an understanding of how residential urban water demand is being understood through modelling. It was anticipated that several established and commonly used demand models would emerge within the field, however it was quickly discovered that modelling techniques vary significantly in terms of specifics and objectives, which will be explored here.

There is a wealth of literature related to urban water demand modelling, and the aim was not to cover all of it, but to choose papers that represent the various approaches that are being used (Cominola et al., 2015; House-Peters & Chang, 2011). Urban water models are very technical in nature; however, the focus of this chapter is not on the specific technical aspects or developments of the water models (the back end), but on what is being modeled, the approach to modelling, the data is being used, and the objectives of the model.

To ensure that the body of literature was manageable for this topic, the scope of the literature was narrowed to papers that focus on residential water demand modeling. The specific papers for the reading list were primarily identified using a number of review papers that provided a thorough overview of papers in the field (Cominola et al., 2015; House-Peters & Chang, 2011). Additional papers were found through database keyword searches (using Google Scholar). The papers were vetted based on their relevance, as well as the number of citations. The aim of this chapter is to get a up-to-date understanding of the field, and therefore more recent papers were favored, which meant that a large number of the papers were identified through the Cominola et al. (2015) review.

This chapter begins with a brief introduction, followed by a section discussing temporal data resolution for model input. The following section deals with modelling approaches for residential water demand, split into two categories based on their objectives: descriptive models, and prescriptive models. Finally, a summary and brief discussion is presented.

2.2 Temporal Data Resolution

Data is the fundamental building block of any model, and the spatial and temporal resolution of the input data will dictate any potential outputs (Cominola et al., 2015). Water meter data is a frequent basis for urban water demand models, especially at the household level, but the temporal resolution of the data can vary significantly from monthly or quarterly meter readings, often associated with billing, or smart meter data that can log a meter readings at close to real time resolution (Cominola et al., 2015). Generally, meters that are read less frequently have lower precision and may be read by radio or even manually, whereas smart meters are more precise, and are combined with a data logger that automatically captures, collects and communicates the readings electronically (R. A. Stewart et al., 2005). In the review of smart meter data utilization for demand modeling, Cominola et al. (2015) separate temporal data resolution into two categories: high resolution (sub daily), and low resolution (daily or greater), which includes billing data.

Spatial resolution is also important (however most papers cited here are at the household level), as well as the measurement resolution of water meters themselves (in terms of measuring volume), but for many the papers discussed in this chapter, temporal resolution is of most concern (Cominola et al., 2015).

2.2.1 High Resolution Data

The studies that use high resolution (sub-daily) data tend to have similar objectives; namely to identify water end uses through the disaggregation and analysis of household level meter data (Cominola et al., 2015). For practical and economic reasons, much of the high resolution data collection on the household level is done using flowmeters, however alternative methods for characterizing end use have been developed (Cominola et al., 2015). As an example, Froehlich et al. (2011; 2009) aimed to identify household water consumption end uses using pressure sensors installed in a household with the capacity to measure one thousand samples per second.

The utilization of high resolution data allows for a much more refined analysis of household water demand (Cominola et al., 2015). However, the data collection requires expensive hardware that is not currently installed at the residential level in many municipalities, as well as significant resources put into the analysis of the data (Cominola et al., 2015; K. Nguyen et al., 2013). Because of this, several papers based their models on data collected as part of a handful of pilot projects (for example both the Willis et al. (2013) and Beal et al. (2011)), which could introduce geographic bias within the research in the field. Furthermore, throughout the literature related to this topic there is little discussion about the advantage of higher resolution data over lower resolution given the objectives of the research. There are vague mentions of the greater ability of high resolution data to characterize consumption, but a more in-depth analysis of the benefits in light of the significant resources needed to collect and analyze higher resolution data is lacking (Beal et al., 2011). The studies presented here tend to be focussed on the technical aspects of extracting information from the data.

2.2.2 Low Resolution Data

There are fewer studies concerned with using low resolution smart meter data, and the ones included here cover a diversity of objectives (Cominola et al., 2015). No explicit discussion of why there are significantly fewer recent articles interested in low resolution data was found. Many water utilities only have access to low resolution data, meaning that an exploration of the potential utilization of that data, in the opinion of the author, is potentially valuable.

There are some cases where low resolution billing data has been utilized as part of demand modeling. The temporal resolution for billing data is often monthly or even quarterly, and water meters tend to be less precise, however billing data is commonly generated in cities where households have water meters, and the lower resolution of the data means that analysis can be less resource intensive (Cominola et al., 2015). A number of studies use billing data in combination with other data sources to examine the influencing factors on residential water demand (Dziedzic et al., 2014; Kenney et al., 2008; Martinez-Espinera, 2002; Morales et al., 2011). Billing data is also commonly used for model calibration and validation.

2.2.3 Temporal Data Resolution Summary

There are advantages and disadvantages to both high and low resolution water data. High resolution data allows for more in depth analysis of water use, and can facilitate disaggregation to the activity or appliance level, which may be particularly useful to evaluate demand management strategies that upgrade or replace water using appliance, for example (Cominola et al., 2015). High resolution data requires significant infrastructure and resources to transform the data into useful information, however, and municipalities may not be equipped with meters capable of collecting this type of data (Cominola et al., 2015). On the other hand, lower resolution data, including billing data, is more readily available and easier to work with, but is limited in terms of its explanatory power (Cominola et al., 2015). There seems to be a lack of explicit strategic thinking about what data resolution and water monitoring is required to meet specific objectives in the literature (Timmerman et al., 2010). In many cases data has already been collected (often by pilot projects) and therefore the researchers have no influence on the data collection strategy (Timmerman et al., 2010). In these cases, the identification of the study objectives tends to come after the development of a water monitoring strategy which is evidenced by the studies that had access to higher resolution data, but did not need or use it in their work, as it was not required to meet their objectives (Anda et al., 2013; Olmstead et al., 2007). While higher resolution data allows for a much larger potential for analysis, in many cases it is aggregated to block of neighbourhood scale to protect the privacy of the households, which may defeat the purpose of such high resolution data, depending on the objectives of the study (Cominola et al., 2015; House-Peters & Chang, 2011).

The data resolution changes the decisions that can be made based on consumption data analysis. Low resolution data (daily, monthly, or annual data) is often aggregated and used to support municipal or district level decisions (Cominola et al., 2015). The effects of seasonality or economic variables have been historically studied using low resolution data, and decisions around water restriction policy or price and rate structure for water can be explored (Cominola et al., 2015). High resolution data (minute or hourly data), is used primarily to characterize household level consumption down to the end use, and can be used for decisions about conservation strategies (Cominola et al., 2015). Because high resolution data can distinguish between outdoor and indoor water consumption, as well as specific appliance water use, where to target conservation actions can be determine for example rebate programs for specific appliances, water restrictions for outdoor use, educational interventions, plumbing code changes, leak reduction programs, etc.

2.3 Urban Water Demand Models

Urban water models can be divided into two groups, descriptive models, that attempt to determine what has happened, by examining historical data, and prescriptive models that attempt to determine what should be done by providing actionable information about multiple futures, based on potential actions by decision makers. Prescriptive analysis requires a predictive model, which attempts to determine what could happen – essentially filling in missing data based on probabilities, but takes it one step further by incorporating actionable data and feedback. Both descriptive models and prescriptive models will be discussed in this chapter, and a summary of the studies included can be seen in Table 2.1.

2.3.1 Descriptive Models

Descriptive models attempt to determine what has happened, by identifying and characterizing the relationship between influencing factors using historical data. In short, descriptive models analyze historically observed behaviour pertaining to water use, either by disaggregating household level end use data, or by aggregating consumption patterns, depending on data availability (Cominola et al., 2015). This data is analyzed to understand the relationships between different factors and how they might influence future outcomes. Furthermore, descriptive models can be used to determine the relative influence of various drivers on residential water use.

There are number of examples of descriptive models in the literature, and a selected group will be presented here. The available literature that discusses or develops descriptive models tends to be focussed on the household level, with many using case study regions in Australia, which may introduce geographical bias to the results.

Several authors focussed their work on improving the characterization of residential water demand generally, without looking at specific factors that influence consumption (Cardell-Oliver, 2013; Cardell-Oliver & Peach, 2013; Gurung et al., 2015; Gurung et al., 2014). For example, two studies by Cardell-Oliver and Cardell-Oliver and Peach (2013; 2013) use an activity pattern model applied to smart meter data in order to identify and explain water use patterns at the household level. These studies attempt to describe water use behaviour through the identification and analysis of signature patterns from water using appliances. The findings may be useful in identifying household behaviours that could be the target of conservation efforts, but the transferability of these findings is potentially difficult, as water use behaviour can be based significantly on local conditions. Another example is from Gurung et al. (2014; 2015) who looked at different aspects of the water system and developed improved residential demand curves based on sub-household level smart meter data, to improve average day, peak day and mean day maximum calculations. Their study aimed to more accurately assess the status of the water supply system, and improve the system loss estimates by providing a model of the current system (Gurung et al., 2014). Despite the fact that high resolution sub-household level data was used in the development of the demand curves, they are only valid over the averaged study area, and the authors themselves discuss that lower resolution water demand data could have been obtained in lower resolution to achieve the save objective (Gurung et al., 2014).

Beal and Stewart (2014) also looked to determine the drivers of residential peak demand by disaggregating smart meter data using in order to determine peaking factors. The authors suggest that the findings are particularly useful for the design of water supply infrastructure such as pipe sizing, but there is no wider discussion of its usefulness (Beal & Stewart, 2014). The data for this project was generated from the South East Queensland Residential End Use Study (SEQREUS), which is the basis for a number of studies discussed in the present paper (Beal et al., 2010; Beal et al., 2011; Willis et al. 2013). Again looking to generally characterize water demand, Alvisi et al. (2007) developed a descriptive model of water demand in order to forecast water use, based on historical data. The goal of this model was to identify use patterns to facilitate better day-to-day management of water provision, and therefore the applicability of these findings to larger issues was not examined (Alvisi et al., 2007).

Table 2.1: Summary table of urban water demand models.

Study	Influencing Factors Considered	Data Considered
Alvisi et al. (2007)	Time of day; day of week; seasonality	Flow distribution data
Balling et al. (2008)	Weather; climate; house characteristics; income; demographics	Low resolution consumption data (billing data); weather data; land-use data; socio-demographic data
Beal et al. (2011)	Appliance efficiency; socio-demographics;	High resolution consumption data; socio-demographic data
Beal & Stewart (2014)	Household occupancy; family composition; household income; weather	High resolution consumption data; household demographics data; climate data
Boyle et al. (2011)	Customer type; outdoor water use	Low resolution consumption data (billing data)
Cardell-Oliver (2013) Cardell-Oliver & Peach (2013)	Time of day; day of week; seasonality	Medium resolution consumption data (1hr)
Dziedzic et al. (2014)	Customer type; house type; house characteristics	Low resolution consumption data (billing data); land-use data; demographic data
Fox et al. (2009)	Property characteristics	Daily water demand data; property physical characteristics data
Giacomoni & Berglund (2015)	Land-use; consumer behaviour; management decisions; rainfall/runoff; reservoir storage	Climate data; house physical characteristics; land-use data; population data
Gurung et al. (2014; 2015)	Indoor/outdoor water use; appliance efficiency; time of day	High resolution consumption data (5s)
Kenney et al. (2008)	Price; water restrictions; rebate programs; climate; weather; demographics	Low resolution consumption data (billing data); price data; weather data; conservation interventions data; household demographic data
Kowalski & Marshallsay (2003; 2005)	Time of day; socioeconomic status; household characteristics	Appliance data; housing characteristics data; land-use data; socio-economic data;
Makki et al. (2015)	Appliance efficiency; household demographics; socio-demographics	High resolution consumption data; appliance stock data; socio-demographic data; self-reported behavioural data
Martinez-Espiñeira (2002)	Price; billing; climate; sociodemographic characteristics	Monthly aggregate consumption data; tariff data; household demographics data
Mead & Aravinthan (2009)	Appliance efficiency; household characteristics	High resolution consumption data (10s)
Morales et al. (2011)	Land-use	Low resolution consumption data (billing data); land-use data
Olmstead et al. (2007)	Price structure; income; household/home characteristics; weather; city fixed effects; season	Household demand data (daily); daily weather data; household demographic data
Praskievcz & Chang (2009)	Weather; climate; seasonality	Low resolution consumption data (daily/monthly); daily weather data
Rosenberg (2010)	Price; rate structure; weather; household/house characteristics; water use behaviour; appliance efficiency	Large panel dataset of 126 parameters
Willis et al. (2013)	Region; socio-economic status; lot size; rainwater tank ownership; income; household characteristics; appliance efficiency	High resolution consumption data; self-reported household water use data

Several studies explore ways to disaggregate household level water end use data, to identify specific demand of activities and appliances (Kowalski & Marshallsay, 2003, 2005; Mead & Aravinthan, 2009). Kowalski and Marshallsay (2003, 2005) used flow characteristics to facilitate the disaggregation of water end use activities at the household level in order to model the effectiveness of conservation strategies at reducing water use in comparison to historical use. The authors developed the Identiflow disaggregation software, which uses specific appliance and activity parameters available from a previously developed database of parameters such as volume, flow rate, and time for a variety of end uses (toilet, shower, dishwasher, etc.), but is therefore limited to the identification of only those end uses available in the database (Kowalski & Marshallsay, 2003). Similarly, Mead and Aravinthan (2009) used a similar disaggregation software (Trace Wizard), developed by Aquacraft (2014) in order to identify and categorize water end use activities, information that is used to evaluate the performance of demand management programs. Trace Wizard identifies water use activities based on user input boundary conditions for end use events, and therefore shares a similar challenge to Identiflow, in that it cannot identify end uses that are not characterized by the user inputs (Aquacraft, 2014). Furthermore, for the Kowalski and Marshallsay (2003, 2005) and Mead and Aravinthan (2009) studies, disaggregation required significant resources, and an in-depth discussion of the benefits of this type of analysis in light of the required efforts is not undertaken.

There has also been research looking at the effects of price and rate structure on water demand (Cominola et al., 2015; Martinez-Espiñeira, 2002; Olmstead et al., 2007; Rosenberg, 2010). Two studies that utilized low resolution data were Olmstead et al. (2007) and Rosenberg (2010) who looked at the effects of price and tariff structure on residential water demand, with the goal of estimating water demand response. The overall aim of this work is to identify the potential of using water rates as a tool for managing demand, and to determine the elasticity of demand to price; utilities have historically considered demand to be inelastic (Olmstead et al., 2007; Rosenberg, 2010). Both studies identify varying elasticities for different rate structures, but used different approaches: Olmstead et al. (2007) developed a structural discrete/continuous choice model water demand model, that incorporates demographic factors, to calculate elasticities (based on data from a study by Mayer et al. (1999)), while Rosenberg (2010) used an existing model that takes into account investments in various water supply alternatives for cost minimization. Similarly, Martinez-Espiñeira (2002) looked at the price elasticity of water demand under different tariff structures, while using price, billing, climate and socio-demographic characteristics as explanatory factors. This study was undertaken for several municipalities in Northern Spain using monthly household level billing data, and a regression analysis was undertaken to determine the elasticities, but also the effects of the various explanatory factors on water use (Martinez-Espinera, 2002).

There are several studies that look specifically at socio-demographic factors in relation to water demand (Beal et al., 2011; Boyle et al., 2011; Cominola et al., 2015; Willis et al., 2013). Two studies, one by Willis et al. (2013) and the other by Beal et al. (2011), used comparative analysis to determine the influence of a number of socio-demographic factors on water end use in households. As part of the SEQREUS study, high resolution smart meter data was available, and household water use was disaggregated to the appliance level which was analyzed alongside demographic information gathered from questionnaire surveys of households (Beal et al., 2011; Willis et al., 2013). Ultimately, both studies were able to quantify the relative influence of factors such as household income, household size, and appliance efficiency, among others, on water demand (Beal et al., 2011; Willis et al., 2013). Similarly, Boyle et al. (2011)use data mining to analyze low resolution residential billing data to identify categories of customers based on their water use characteristics, and to inform policy decisions, facilitate comparative analysis, and develop conservation communications. The information about water use can be used to set rate structures, identify target audiences for tailored conservation strategies based on their specific use patterns, and distinguish users that disproportionately contribute to peak demand (Boyle et al., 2011).

Other examples of using socio-demographic data come from Dziedzic et al. (2014), who developed an integrated database of water consumption and demographic data, and used data mining techniques to define user clusters and characterize their water use patterns. And from Morales et al. (2011) who conducted a study looking to describe water use in the commercial, industrial and institutional sector using spatial, physical and economic property characteristics data. The Morales et al. (2011) study is not focussed on the residential sector, but was included here because it was the only study found that uses land use data and classification as a factor for describing water demand.

Psychographic factors, such as property characteristics, attitudes, and lifestyle, were considered by several studies (Cominola et al., 2015; Fox et al., 2009; Russell & Fielding, 2010). For example, Fox et al. (2009) attempted to classify properties in terms of water demand, based on physical characteristics including number of bedrooms, architectural type, and garden presence, to estimate water consumption for future developments. Fox et al. (2009) note however, that geographic variations between classified properties were identified, but not explored, indicating that additional factors not included in the study are likely influencing water use. Russell and Fielding (2010) on the other hand, looked studies focussed on the effects of behaviour on water consumption from a psychology perspective, and identified five broad drivers of conservation behaviour: attitudes, beliefs, habits/routines, personal capabilities, and contextual factors. The findings of the study indicate that there is a clear indication from previous research that attitudes and beliefs affect water use behaviour, but the correlation is not yet well established for the other drivers (Russell & Fielding, 2010). The psychological factors that drive water use have been studied from several perspectives, have considered a variety of behaviours, and can help in the identification of key drivers of water consumption, as well as the development of demand management strategies (Cominola et al., 2015). However, descriptive modeling remains the norm, because predicting the effectiveness of these strategies to reduce consumption is challenging as behavioural analysis tends to rely on self-reported data, or conservation intention data (Russell & Fielding, 2010).

Geo-spatial factors were considered by Balling et al. (2008) who determined the sensitivity of residential water demand to atmospheric conditions, and by Praskievcz and Chang (2009) who determined the effects of water variables on seasonal water use. Both studies were able to characterize the effects of the specific drivers of water demand examined (Balling et al., 2008; Praskievicz & Chang, 2009). Balling et al. (2008), analyzed water demand date alongside climate, land-use, and sociodemographic data to determine both temporal and spatial sensitivity to climate conditions. Praskievcz and Chang (2009) on the other hand, completed a statistical analysis of the influence of variable such as temperature, precipitation, daylight, wind speed, and cloud cover, among others, on water demand. They also developed a regression model which allowed them to determine how much of the water use variance could be accounted for by weather variables (Praskievicz & Chang, 2009).

There are also studies that consider a whole range of dimensions that affect residential demand (Cominola et al., 2015; Kenney et al., 2008; Makki et al., 2015). For example, Kenney et al. (2008) looked at factors such as price, weather, and climate, as well as water management programs such as watering restrictions and appliance efficiency improvements to determine their effects on household demand in Aurora, Colorado. The authors used regression analysis to model demand, and were able to uncover interactions and differences between factors acting on demand (Kenney et al., 2008). Another example is a study by Makki et al. (2015) who explored the main factors that influence residential water demand. The authors first identify the main drivers of household level indoor water consumption, using high resolution smart meter data, water end use disaggregation software, and multivariate analysis to develop a quantitative forecasting model to estimate consumption (Makki et al., 2015). This study is able to identify the key drivers and predictors of water consumption from six pre-defined categories, and develops a model capable of predicting the average household level consumption for each category, which can help to optimize demand management initiative by forecasting their effectiveness at reducing water demand (Makki et al., 2015). This study does develop a predictive model, but does not cross over in the prescriptive modelling (Makki et al., 2015).

Overall, descriptive models are useful to better understand the urban water system, and to gather information on how water is currently being used (Cominola et al., 2015). As seen here, a wide variety of factors that influence water demand are examined by researchers, however fully describing all of the variation seen in observed data has been challenging (Jorgensen et al., 2009). These descriptive studies can provide interesting insight into the drivers of water use, but do not give decision makers prescriptive information about how to proceed – which is the subject of the following section.

2.3.2 Prescriptive Models

Prescriptive models are used to develop information that decision makers can use to inform their actions, and suggest what ought to be done. Prescriptive modelling is a step beyond predictive modelling because in addition to predicting events, also suggests actions while demonstrating the implications of multiple options. Fundamentally, prescriptive models attempt to quantify the effects of future decisions, and therefore help to recommend actions to decision makers. There are fewer examples of prescriptive models in the urban water demand literature, potentially due to the increased complexity of developing such a model, and therefore only one study is included here.

A recent study that utilizes prescriptive modelling by Giacomoni and Berglund (2015) simulated land-use changes, consumer behaviours, management decisions, rainfall-runoff processes, and reservoir storage using an adaptive modelling framework in order to determine the effectiveness of adaptive water demand management strategies at reducing water use under historical and projected hydroclimate climate change scenarios. This study not only models the demand of individual users, but attempts to take into account the social interactions between water consumers (Giacomoni & Berglund, 2015). Giacomoni and Berglund (2015) present a comprehensive model in order to quantify the effects of multiple demand management strategies that are adaptively implemented based on reservoir storage level. Furthermore, they demonstrate the quantitative advantage of their adaptive management approach in terms of water demand reductions, in comparison with alternative conservation strategies (Giacomoni & Berglund, 2015). This study creates a framework of models, including a land use change model, hydrologic model, housing and population model, consumer model, reservoir model, and a policy maker model, which combined facilitate the simulation of the urban water resource system based on a large number of factors, that accounts for feedbacks and demands (Giacomoni & Berglund, 2015). The challenge with such a model framework however, is that the data and resource requirements far more intensive than for a single model, which may be prohibitive for many utilities (Giacomoni & Berglund, 2015).

2.4 Summary and Discussion

Much research has been undertaken looking to accurately identify and characterize the relationships and impacts of several influencing factors on residential water demand (Cominola et al., 2015). As evidenced by the wide range of factors examined across the papers included in this reading list, there is yet to be any consensus about which are the most important to consider – however consensus may not be possible given that many studies have different objectives, and this may not be an issue if the objectives are clear. The existing models and their results move the field closer to understanding which factors are the most influential in terms of water demand. Continued modelling work tested with real world data from a range of geographic locations will further help to identify the factors that matter most.

No study has yet to account for all the variation in water demand using the factors chosen, and the field seems to be adding additional factors as it grows (Jorgensen et al., 2009). Jorgensen et al. (2009)

describes that none of the studies included in their review of water models were able to account for all of the variation in water demand using the specific factors included in each study, leading to the conclusion that there are still individual variables or combinations of variables that remain to be described. In general, behavioural factors are challenging to characterize quantitatively and therefore are often not included in demand models but are identified as being consequential in terms of demand, which may account for some of the variation that is not accounted for in the models presented in this chapter (Russell & Fielding, 2010). The high resolution meter data used in several of the models does not directly include observed behaviour information, and tend to examine influence on behaviour through abstract constructs such as socio-demographic characteristics and climatic conditions. Moving forward, future work should consider a more direct measure of behaviour would be beneficial to better characterize its effects on water end use.

The finding that behaviour is an important explanatory factor for demand aligns with the emerging paradigm for urban water sustainability that highlights the importance of social factors. Wicked problems are inherently challenging because of behavioural/social dimensions, which affects both how the problem is perceived, as well as how solutions should be approached (Rittel & Webber, 1973). Without the behavioural component, water demand issues tend to be seen as an issue of limited supply, which can both be addressed through conventional engineering approaches, but does not tackle the underlying issues related to end use (Lach et al., 2005).

In addition, while the bulk of the recent research is interested in modeling high resolution data, there seems to be a lack of discussion about the overall objectives of demand modelling, and what is required in terms of data. In some studies, lower resolution data, which requires fewer resource and infrastructure, would have been sufficient to meet the study goals (Cominola et al., 2015). There also seems to be limited scrutiny pertaining to the resources required or the availability of data for a particular modeling approach, something which could potentially help practitioners when it comes to developing models. In a related point, there is minimal discussion of the practicalities, or even possibility of applying these modeling techniques to larger scales (Cominola et al., 2015). Fundamentally, it seems as if there is a strategic discussion that is lacking about how to optimize data collection considering what is needed in terms of model output (Timmerman et al., 2010). This may be the case because the studies included in this chapter tend to be academically focussed, and while they utilize water utility data, but there seems to be no input from the practitioners about what is needed (Timmerman et al., 2010).

Ultimately, there is significant work being undertaken looking at how to more accurately model residential water demand, and impressive advancements have been gained (Cominola et al., 2015). What is perhaps needed in future work is an expansion of dimensions beyond the norm to incorporate the wider dimensions implicit when the problem is framed as wicked, that includes behaviour, organizational characteristics across a multi-generational time frame (Brown et al., 2009).

3 Overview of Selected Academic Research - Effectiveness of Household Level Water Conservation Strategies

3.1 Introduction

This chapter is focussed on assessing academic work on the effectiveness of various residential water demand management strategies at reducing potable water use. The focus is on recent studies that used real observation data (as opposed to simulations or projections) that look at the effectiveness of interventions used to decrease household water use from historical averages. To gain an understanding from across the field, a wide variety of demand management strategies are represented here, and the interventions are divided into categories (financial, technological, educational, and regulatory).

The results of these many papers were generally inconsistent, with some authors conducting similar experiments in different geographical areas, but finding varying results (Inman & Jeffrey, 2006). Fundamentally, these inconsistencies may derive from the behavioural basis for a given strategy, which is tied to the local context (Inman & Jeffrey, 2006). The main challenge in this field, based on the literature examined in this chapter, seems to be in the generalization of findings.

The following sections will summarize several articles within each category separately, and end with a brief discussion of the main themes and points that were derived from the papers in that category. Table 3.1 provides an overview of the various studies (excluding the review articles), the interventions they examined, their effectiveness, and factors considered.

3.2 Review Articles

Two review articles looking at demand management provide some insight into intervention effectiveness in reducing household water use (Garcia-Valiñas et al., 2015; Inman & Jeffrey, 2006). Inman and Jeffrey

(2006) authored a review looking at various residential demand side management strategies and looked at quantitative studies that evaluated demand side management tools in five categories: financial, technological, educational, operational/maintenance, and regulatory/legislative. When the paper was written (in 2006), there was a need for a comprehensive and up to date synthesis of the work undertaken in this field, both through academic research as well as projects implemented by water institutions (Inman & Jeffrey, 2006). Inman and Jeffrey (2006) also attempted to identify factors that influence the success of these demand management tools on residential water consumption .

In terms of financial interventions for household conservation, Inman and Jeffrey (2006) separated the available studies into two categories: metering and pricing. The installation of water meters (in combination with the introduction of volumetric water pricing) was found to vary widely in terms of resulting in water savings, with some studies finding no significant effects on water use up to a 56% reduction in household consumption (Inman & Jeffrey, 2006). For those studies that saw a decline in water use, the reasons for the savings are often unclear as other factors related to metering also have an effect (such as changes to billing structure, or feedback mechanisms), and local conditions tended to be important (for example demographics, income, a focus on indoor or outdoor use, etc.) (Inman & Jeffrey, 2006).

Price was also found to have uncertain effectiveness at reducing consumption due to questions about the permanence of potential savings (many studies found that consumption rates returned to pre-intervention levels at some later point) (Inman & Jeffrey, 2006). Residential water demand tends to be relatively price inelastic as found by Inman and Jeffrey (2006), however elasticity was found in some cases and varied based on the type of tariff structure, regional differences, and/or income groups (Inman & Jeffrey, 2006). The price elasticity values are difficult to compare between studies because of these differences, and were not quantitatively summarized by the authors (Inman & Jeffrey, 2006). Two example studies included in

Table 3.1: Summary table of household water conservation intervention studies, their effectiveness, explanatory factors considered, and rebound effects. Some studies did not report percent water savings, and therefore their effectiveness is reported in the available format.

Study	Location	Category	Intervention(s)	Effectiveness	Explanatory Factors Considered	Rebound Effect
Harutyunyan (2015)	Armenia	Financial	Metering & Volumetric Pricing	-70% household reduction	Introduction of volumetric pricing, water payment enforcement, water rate changes	48% decrease after 8 years
Tanverakul & Lee (2015)	USA - CA	Financial	Metering & Volumetric Pricing	-15 to -31% household reduction	Introduction of volumetric pricing, ET, seasonality of water use	8-19% decrease after 3 months; 13-21% decrease after 6 months
Kenney et al. (2008)	USA - CO	Financial	Price Elasticity	-0.6 price elasticity	Rate structure, water restrictions, drought conditions, high/low users, weather, demographics	
Rinaudo et al. (2012)	France	Financial	Price Elasticity	-0.18 price elasticity	Water price, income, extreme climate events, presence of second home on property	
Yoo et al. (2014)	USA - AZ	Financial	Price Elasticity	-0.661 price elasticity	Water price, income, water efficient appliances, irrigation efficiency	-1.155 price elasticity after 8 years
Lee et al. (2011)	USA - FL	Tech.	Appliance incentive programs	Household reductions: -9% showerhead program; -1% toilet program; -6.5% clothes washer program	Voluntary appliance incentive programs, number of appliances, climate, high/low users, water restrictions, household demographics	-19.1% showerhead (after 4 years); -18% toilet (after 4 years); -14.7% clothes washer (after 3 years)
Willis et al. (2010)	Australia	Tech.	Alarming visual display	-27% shower use reduction	User consumption awareness, water use feedback	
Tsai et al. (2011)	USA - MA	Tech.	Various	Household reductions: -37 m3/year irrigation controller; -3.94 m3/year toilet rebate; -5.38 m3/year washing machine rebate; -4.93 m3/year audits + retrofit kit; -5.01 m3/year audit + retrofit + rebate	Irrigation efficiency, sample size	

Study	Location	Category	Intervention(s)	Effectiveness	Explanatory Factors Considered	Rebound Effect
Ferraro & Price (2013)	USA - GA	Educational	Norm-based messaging	Household reductions: Insignificant - T1 - technical advice -2.7% T2 - tech. advice + personal letter -4.8% T3 - tech. advice + personal letter + comparison	High/low users, seasonality, demographics, household composition	Ferraro et al. (2011): -2.7% (after 4 months) & insignificant (after 1 year) - T2 -4.8% (after 4 months), 2.6% (after 1 year), 1.3% (after 2 years) - T3 Bernedo et al. (2014): -1.26% (after 4 years), -1.43% after 6 years) - T3
Fielding et al. (2013)	Australia	Educational	Norm-based messaging	-11.3 L/capita/day (-8%)	Drought conditions, water restrictions	After 1 year, consumption returned to pre-intervention levels
Mini et al. (2014)	USA - CA	Regulatory	Water restrictions	Household reductions: insignificant - voluntary restrictions -19 to 23% mandatory restrictions (spring/summer)	Drought conditions, water restriction policy, income, lot size, climate, seasonality	
Kenney et al. (2004)	USA - CO	Regulatory	Water restrictions	Household reductions: -4 to 12% (insignificant) voluntary restrictions; -13 to 53% mandatory restrictions	Drought conditions, water restriction policy, population, water system, climate	
Ozan & Alsharif (2013)	USA - FL	Regulatory	Water restrictions	Household reductions: +15.8% Wet season; +9.1% Moderate season; +5.7 Dry season	Drought conditions, neighbourhood association rules, restriction policy, policy violation citations	

the review looked at the USA (Dalhuisen et al., 2003) and Australia (Dandy et al., 1997), and found drastically different price elasticities ranging from -0.005 to -0.28 for the USA (meaning a 10% increase in price would lead to a 0.5 to 2.8% decrease in water demand), and from -0.6 and -0.8 in Australia.

Inman and Jeffrey (2006) also looks at technological interventions which proved to be the most effective and reliable in terms of conservation. Programs targeting indoor use focus on water using appliances, and retrofit programs were found to decrease water consumption by 9-12%, while appliance replacement programs were more successful and reduced use by 35-50% (Inman & Jeffrey, 2006). However, there are cases where retrofit programs did not facilitate any water savings, for example Mayer et al. (2003). There were no studies assessing demand side management strategies focussed on outdoor water use included in the review, but there is the potential for savings as identified through qualitative research, highlighting the need for future work (Inman & Jeffrey, 2006).

Educational interventions were found to have a modest effect on residential water use based on the studies examined in the paper by Inman and Jeffrey (2006), however many studies identified challenges in separating the educational dimensions from other factors. Public education campaigns were found to achieve a water savings that ranged from 2 to 12%, however some were not successful at all, and in some cases few people were aware that and educational campaign even existed (Inman & Jeffrey, 2006).

Inman and Jeffrey (2006) looked at operation and maintenance interventions which tend to focus on minimizing losses and leaks in the system. These types of savings are difficult to separate from other factors; however, there are estimates that in some cases savings due to appliance replacement are partly due to significantly reduced losses from replacing older leaking appliances (Mayer et al., 2003; Mayer et al., 1999). There may be a large water savings potential in minimizing losses through leaks, and this approach is often regarded as more important than other demand management strategies, but there were no specific studies looking at leaks specifically included in the Inman and Jeffrey (2006) review.

Finally, Inman and Jeffrey (2006) reviewed regulatory and legislative interventions which vary widely in terms of their effectiveness at reducing water consumption and their specific policy characteristics. Some examples include: a combination of plumbing code upgrades and the inclusion of water efficiency labelling of appliance which realized a 5-10% water savings (White, 2001), or timing and frequency restrictions on certain water intensive activities (such as car-washing, and landscape irrigation), which realized a 25-35% savings (Kanakoudis, 2002; Renwick & Archibald, 1998). Inman and Jeffrey (2006) also discussed potential influences on the success of demand management interventions such as household occupancy, income, and offsetting behaviour based on knowledge of increased efficiency.

Overall, the Inman and Jeffrey (2006) highlighted the significant work still needed in the field, and the potential limitations of the current work. Fundamentally, the findings of many demand management studies tend to lack the ability to be useful in other regions or even neighbourhood, as local conditions and context are important influencing factors (Inman & Jeffrey, 2006). Furthermore, the permanence of many of these tools is questionable, and needs a closer look, as initial water savings does not necessarily translate into permanent conservation (Inman & Jeffrey, 2006).

A more recent review paper on the topic by Garcia-Valiñas et al. (2015) summarized the impacts of non-price demand side management strategies aimed at reducing domestic water consumption. Similar to the study by Inman and Jeffrey (2006), the Garcia-Valiñas et al. (2015) summarize the findings from various demand management studies, and organize them by category (technological tools, educational tools, informational tools (specifically labelling), and legislative tools), however in this paper they do not attempt to provide a comprehensive overview. After examining a number of studies in each category, the

Garcia-Valiñas et al. (2015) then discusses the advantages and disadvantages of non-price demand management strategies in comparison with price based tools. Garcia-Valiñas et al. (2015) suggest that while price based instruments tend to be more flexible (allowing users to choose how they consume), in addition to collecting revenue, while non-price tools tend to be more effective at reducing consumption (in the short term at least), and have more concrete results.

Garcia-Valiñas et al. (2015) provide more of a summary of several examples from the field, than a comprehensive review of works, and has significant overlap in terms of papers with the Inman and Jeffrey (2006) review, despite it being a more recent publication, the review does not offer a quantitative summary or synthesis of the findings.

3.2.1 Review Papers Summary

Both review papers included here provide a good basis of the work undertaken in the field of residential water demand management, but each has its drawbacks (Garcia-Valiñas et al., 2015; Inman & Jeffrey, 2006). The Inman and Jeffrey (2006) review was published a decade ago and significant research has been undertaken since, while the Garcia-Valiñas et al. (2015) summary is not comprehensive, and only includes a few examples papers for each of its categories (which themselves are not comprehensive). The reviews also categorize demand management strategies differently, and categorization itself is challenging as many strategies include interventions from multiple categories (Garcia-Valiñas et al., 2015; Inman & Jeffrey, 2006). Fundamentally, there is significant difficulty in comparing any strategies because, as is evident in both review papers, local factors and context are important factors in residential water demand, and studies looking at the same strategies have routinely found different results, which provides more evidence that behavioural factors may play a large role (Garcia-Valiñas et al., 2015; Inman & Jeffrey, 2006). Keeping these challenges in mind, there persists a gap in the literature for an up to date review paper on this topic, Inman and Jeffrey (2006) addressed the same gap in 2006, but since then there have been many significant advancements (technological and other) in terms of demand management strategies, and synthesizing the knowledge about what works, what doesn't work, and why or why not, is valuable to water utilities and municipalities that increasingly interested in water conservation.

3.3 Financial Interventions

Financial interventions aimed at conservation include both volumetric pricing and modifications to rate and price structures, both of which will be discussed in this section.

In terms of volumetric pricing, Harutyunyan (2015) studied the installation of municipal water meters along with the introduction of volumetric pricing in Armenia, and its effects on residential water demand. Armenia is an interesting case as residential water use was essentially unmetered at the beginning of the century, but is now moving rapidly toward universal metering (Harutyunyan, 2015). The aim of this study was to quantify the effects of the transition to volumetric water pricing on residential water demand (Harutyunyan, 2015).

Within the first year of implementation a significant decrease (70%) in normal residential consumption was observed, followed by a rebound effect over the following months (to 30% reduction from normal use) (Harutyunyan, 2015). The initial meter installation program was not coupled with a change in tariffs, but did mean that water bills were substantially lower than flat rate charges, likely accounting for the rebound effects ((Harutyunyan, 2015). Over the long-term however, residential water demand ultimately decreased from pre-metering levels by 48% (Harutyunyan, 2015). There are numerous factors that may account for the decline in water use over this study period including increased prices, but also improved leak detection, increases in fee collections, or the identification of water theft facilitated by move meter coverage, all of which make specific conclusions difficult (Harutyunyan, 2015).

Another study on volumetric pricing by Tanverakul and Lee (2015) examined the impact of water meter installation on previously unmetered houses, along with the transition from flat rate billing, to volumetric charges. Two groups of single-family homes in three cities in California were compared in the project: those where a meter was installed for the first time (the treatment group), and those that were already metered (the comparison group) (Tanverakul & Lee, 2015). The study found that in the period after new meters were installed, but before the first water bill water received by the household, the treatment group consumed between 15-31% more water than the comparison group (Tanverakul & Lee, 2015). After three months of metering and volumetric billing, a decrease in water use of between 8% and 19% in comparison to the initial use was observed for the treatment group (Tanverakul & Lee, 2015). A further drop in water consumption was observed after six months, with the treatment group decreasing consumption from 13-21%, compared to their pre-volumetric billing consumption (Tanverakul & Lee, 2015).

Similar to the study by Harutyunyan (2015), the research by Tanverakul and Lee (2015) quantifies the water saving potential of water meter installation, in combination with tariff changes. The Tanverakul and Lee (2015) study includes a comparison group, but not a control group of homes that either remained unmetered, or were newly metered homes that continued to be billed at a flat rate. A control group could have helped minimize the effect of factors on water use such as weather, climate, and behavioural changes based on the knowledge that they were part of a scientific study. Furthermore, the study did not discuss changes to household water bills after the introduction of volumetric pricing – which could provide insight in to potential behavioural changes (Tanverakul & Lee, 2015).

In terms of price, Kenney et al. (2008) reviewed a number of factors that affected residential water consumption during a drought period in Aurora, Colorado, and looked to isolate the impact of water restriction policies and price changes on water demand. In response to the severe drought that imposed significant water supply challenges, several demand management programs were put into place simultaneously (Kenney et al., 2008). The authors identify and address several of factors controlled by water utilities, (price and non-price strategies), and those that are not controlled by utilities (for example weather, and demographics) (Kenney et al., 2008).

The results from the Kenney et al. (2008) study found the price elasticity for residential water consumption was -0.6 (meaning for each 10% increase in price, demand is expected to decrease by 6%), but that elasticity dropped to -0.37 when water restrictions were in place. The households included in the study were divided into groups based on consumption levels, and price elasticities were found to vary between them (Kenney et al., 2008). High consuming households were the most price elastic (-0.75) during period of normal weather, but the least elastic (-0.24) during restriction periods (Kenney et al., 2008). Furthermore, it was found that price elasticities were much high during periods of drought (-1.11) in comparison to non-drought periods (-0.6) (Kenney et al., 2008). Based on these findings, Kenney et al. (2008) suggest that to decrease water demand, water restrictions are potentially more effective at reducing water consumption when targeting high water consuming households, while price modifications will be more effective if lower use households are the target. This study also quantified the influence of other price and non-price factors on residential demand, finding a variety of impacts to water consumption based on the model outputs (Kenney et al., 2008).

The findings of this study are useful for water utilities, as they provide information about how to address different use groups (high/low users). While this study is able to quantify household water demand sensitivity to price, the authors are not able to fully determine the reasons. In addition, the authors caution about applying the results of this study in other regions, as there are many local characteristics that influence the results (Kenney et al., 2008).

Similar price intervention study by Rinaudo et al. (2012) calculated the price elasticity of residential water demand both through observational data, but also estimated water demand under different price structures using a regional simulation model. Flat rate pricing, increasing block tariffs, and seasonal tariff structures were simulated for a region in southern France (Rinaudo et al., 2012). The study found price elasticity to be -0.18 (meaning a 10% increase in price would decrease water use by 1.8%), but that there are other significant determining factors on water use that include income, extreme climate events, and the presence of second homes on the property in question (Rinaudo et al., 2012). The simulation model results showed that increase the flat rate price of water from 0 to \$1 €/m^3 would result in a 3M m^3 reduction in residential water demand for the year (Rinaudo et al., 2012). The implementation of a seasonal rate structure would decrease water demand by 1.6M m^3 for the year, while an increasing block structure would decrease demand by between 2.3 and 3M m^3, depending on the specific structure and rates of the block system (Rinaudo et al., 2012). Rinaudo et al. (2012) also simulated the potential sales revenue and cost to consumers for each of the new rate structures considered.

The findings indicate that an increase in the flat rate price for water would be as (or more) effective as introducing a seasonal or increasing block rate structure for decreasing water use (Rinaudo et al., 2012). While Rinaudo et al. (2012) provide quantitative data on the potential water savings and revenue generation, they emphasize that social issues such as equity are vital when water utilities are looking to implement new pricing. The price elasticity results from this study are well within the range found in other work, but the simulation may be problematic because it assumes a static elasticity over time. Furthermore, the local context or the attitudes of individuals play an important role in determining water demand, and were not considered (Rinaudo et al., 2012).

Finally, Yoo et al. (2014) estimate the price elasticity of residential water demand, by attempting to isolate the effects of water rates from other factors affecting water use in Phoenix, Arizona. A simple two block seasonal water rate structure is in place in Phoenix (Yoo et al., 2014). Yoo et al. (2014) estimate the effects of price by creating models to describe demand as a function of price, climate, demographics, physical housing characteristics, and time. The results of this research are consistent with the findings of previous work in the literature, showing a short-term (2-year) price elasticity of -0.661 (meaning a 10% increase in price would mean a 6.61% decrease in water demand), and a long-term (8-year) price elasticity of -1.155 (Yoo et al., 2014). Yoo et al. (2014) also looked at the effect of income on water use, finding that households with higher income have higher water consumption, and that a 1% increase in income correlated to a 0.036% increase in water demand.

While the reason price elasticity increases over the long term is not addressed in depth in the paper by Yoo et al. (2014), some thoughts provided by other works are discussed. In brief, over the long term, households have more time to transition to more water efficient appliances and to landscaping that requires less irrigation, as well as individuals have more time to register the changes in water costs, and make connections and change activates and habits that are driving water use (Yoo et al., 2014).

3.3.1 Financial Interventions Summary

The studies looking at water metering and volumetric pricing as a way of managing residential demand, and found that significant water savings are possible; however, neither of the two papers (Harutyunyan, 2015; Tanverakul & Lee, 2015) outline a concrete explanation or discussion of why consumption decreased. Because these demand management strategies are an attempt to alter household water use behaviour, it would be valuable to determine what aspects of the intervention stimulated these changes. For example, there was no attempt from either study to separate the effects of implementing water meters (which may affect behaviour by providing actual water use data to households, by households knowing that their water use was being tracked, or by improving leak detection), from the effects of the introduction of volumetric pricing (which would likely change water bills – higher or lower – which can affect water use behaviour).

Furthermore, the longer-term effects of introducing metering to houses were not considered in a comprehensive way. To improve the understanding of demand, it may be useful for future work to determine if the behaviour change seen after the installation of water meters and the introduction of volumetric pricing continues, or wanes over time. Harutyunyan (2015) examined longer term effects on the country level and found that consumption rebounded post implementation, however the national water consumption may be subject to a number of other factors that influence water demand on that large scale (leaving room for further study on a smaller geographic scale). In addition, neither the Harutyunyan (2015) nor the Tanverakul and Lee (2015) studies considered the cost of installing meters on a large scale in comparison to the potential revenue generated.

In terms of price interventions, the determination of the price elasticity of water demand is based on estimates calculated through the development of demand models, however all three (Kenney et al., 2008; Rinaudo et al., 2012; Yoo et al., 2014) of the studies described in this chapter observation data from study areas that either underwent changes in price or rate structure, or compare regions with differing rate structures, as a basis for their estimates. Historical research looking at price elasticity concluded that water demand was relatively inelastic, however a growing pool of research, demonstrates that elasticity does exist, and attempt to describe the effects of changes in price (Inman & Jeffrey, 2006). The three representative studies presented here found elasticity values that fell within the range of what has historically been determined (Inman & Jeffrey, 2006; Kenney et al., 2008; Rinaudo et al., 2012; Yoo et al., 2014). Likely there will be no universally acceptable tariff structure, and each water utility will need to develop their own considering local contexts (Inman & Jeffrey, 2006). Furthermore, the persistence of the water savings under new price structures is vital in understanding the potential long term impacts of price changes, but was only examined by Yoo et al. (2014), which was consistent with other research in the field where few studies have a long term time scale.

In terms of behavioural changes, based on these findings, households react to changes in their water bills by decreasing their consumption (Inman & Jeffrey, 2006; Kenney et al., 2008; Rinaudo et al., 2012; Yoo et al., 2014). However, there are other factors that come into play, such as the billing frequency, how the household water use information is presented, and how well the rate structure and price are communicated to household, all of which can be influencing factors on demand, and warrant further analysis for future work (Fielding et al., 2013).

3.4 Technological Interventions

Technological interventions range from appliance level efficiency, water consumption displays, and irrigation timers, along with incentive programs to access these technologies (Inman & Jeffrey, 2006).

Starting with incentive programs for appliances, Lee et al. (2011) quantified the impacts of water-using appliance incentive programs on residential water demand in Miami-Dade Country, Florida over a four-year period. Three incentive programs were examined: a high efficiency showerhead exchange program, a high efficiency toilet rebate program, and a high efficiency clothes washer rebate program (Lee et al., 2011). Lee et al. (2011) found substantial residential water savings for all the incentive programs over the study period. The household level water savings for each program were found for the first year to be 9% for the showerhead exchange, 1% for the toilet rebate, and 6.5% for the clothes washer rebate (Lee et al., 2011). However, savings increased over time to 19.1% for the showerhead exchange after 4 years, 18% for the toilet rebate after 4 years, and 14.7% for the clothes water after 3 years (Lee et al., 2011). In general, the cumulative water savings increased over the study period, with the most savings being seen in the fourth year after implementation (Lee et al., 2011). Lee et al. (2011) suggest that the decreasing household consumption may be a result of increasing awareness of the benefits of conservation over time.

One limitation of the Lee et al. (2011) study was the control (water consumption of participating household in the year prior), and factors such as climate, the existence of mandatory outdoor water restrictions, and household demographics may change between years, and would affect household demand differently across the previous year and study year. These potential influencers were discussed as possible explanatory factors by the authors, but were not included in the quantification of the water savings, leaving room for future studies to look at those additional impacts more closely (Lee et al., 2011).

In terms of non-appliance technologies, a study by Willis et al. (2010) looks at the water use reduction from the installation of alarming visual display monitoring in residential showers in a sample of 151 Australian households. This research used smart water meters to continuously capture and communicate real-time water use data automatically at high resolution, as well as disaggregation software to isolate the water use attributed to specific activities or appliances (Willis et al., 2010). The intervention for this study was a water use monitor installed in the showers of participating households that gave real-time feedback on flow rate, shower duration, and temperature, but does not limit volume or flow rate (Willis et al., 2010). The shower monitor also provided audible feedback (an alarm), when consumption of a predetermined volume of water was exceeded (Willis et al., 2010). Willis et al. (2010) found that the installation of alarming visual displays in showers decreased shower event volume by 27% from the baseline, which translates to a potential city-wide water savings of 3% per year.

One potential source of bias in the study was that households who participated in the study, opted in, and were willing to have their water use monitored for two years, potentially indicating that they are more environmental or water conscious, and more willing to change their behaviour to conserve water (Willis et al., 2010). Furthermore, as Willis et al. (2010) point out, more research is needed to determine the permanence of those water savings because the water monitor can be easily ignored (the results showed that some study participants did ignore the alarm, and continued to shower), or even removed.

Another study by Tsai et al. (2011) looked at a series of technologies were examined in four controlled demand management experiments implemented in several towns in Massachusetts, USA. The interventions included weather-sensitive irrigation controller switches (for residential properties, and municipal sports fields), rainwater harvesting systems (for residential properties), two outreach programs – one was an indoor water audit and fixture retrofit kit, the other a rebate program for low flow toilets and washing machines - (aimed at residential properties), and another non-residential intervention that will not be summarized here (Tsai et al., 2011).

Tsai et al. (2011) found that for the residential weather-sensitive irrigation controller switches, no statistically significant difference in water demand between the control group and the treatment group was found after installation. However, the treatment group that installed the technology consumed an average of 37 m^3/year less than the control group (Tsai et al., 2011). In terms of rainwater harvesting systems, household water use was found to be unaffected by their installation, even though there were many anecdotal reports of rainwater being substituted for potable water by households throughout the study period (Tsai et al., 2011).

The outreach programs included free indoor water audits, retrofit kits, and a rebate program for toilets and washing machines (Tsai et al., 2011). The water savings for each program separately were found to range from 3.94 to 5.38 m^3/year for the toilet rebate and washing machine rebate, respectively (Tsai et al., 2011). Those household that took advantage of both programs saved an average of 4.58 m^3/year. The water audits and retrofit kits were found to decrease demand by an average of 4.93 m^3/year per household with the combination of the audits and retrofit kits with any rebate program saving an average of 5.01 m^3/year per household (Tsai et al., 2011). However, none of the water savings found for any of the programs was found to be statistically significant from the control (Tsai et al., 2011). The findings from this study lay some groundwork for further study of similar strategies, even though local context plays a vital role in the success of any technological tool, especially if it requires the purchase of new hardware (Tsai et al., 2011).

3.4.1 Technological Interventions Summary

These three studies were chosen because they represent various approaches to technological demand management, but also consider different variables (Lee et al., 2011; Tsai et al., 2011; Willis et al., 2010). Programs that facilitate the replacement or retrofit of older appliances to more water efficient technologies saw some water savings, however because the frequency of use is based on individual behaviour which may change, the results were not consistent (Lee et al., 2011; Tsai et al., 2011; Willis et al., 2010). Lee et al. (2011) found persistent water savings for rebate and retrofit programs, while Tsai et al. (2011) found no statistically significant difference in water use. On the one hand, the literature discusses the possibility of additional water savings coming from the replacement of older toilets and washing machines because leaks and faulty valves can be fixed (Jorgensen et al., 2009). On the other hand, offsetting behaviour, essentially because individuals are aware that their appliance is more water efficient, they may use it more, can result in the erosion of water savings, or even greater consumption that before the intervention (Inman & Jeffrey, 2006).

Aside from Lee et al. (2011) who looked at a four year time frame, the permanence of any water savings is questionable especially in light of the behavioural offsetting aspects of use. This is particularly pertinent in the alarming shower display study as that technology can be easily ignored or removed (Willis et al., 2010).

There is some discussion in the literature that knowing about high water efficient appliances is the root cause of the offsetting behaviour, and therefore if an individual does not know that their device is more efficient, offsetting behaviour is less significant (Campbell et al., 2004). Further study of this would be beneficial to better understand the specifics of offsetting behaviour, as well as the effeteness of various technologies, rebate programs, and regulations (Inman & Jeffrey, 2006).

Because these technological approaches to demand management are subject to individual behaviours and not just the technology itself, future work should make sure to consider and incorporate behavioural considerations into any strategy (Inman & Jeffrey, 2006). The utilization of technological tools to management water demand, coupled with other strategies, could be explored further, and may help to improve the effectiveness and longevity of conservation efforts aimed at reducing water consumption (Inman & Jeffrey, 2006).

3.5 Educational Interventions

Educational interventions aimed at changing behaviour through appeals to social norms or messaging has been of recent interest in the field (Bernedo et al., 2014; Ferraro & Price, 2013; Fielding et al., 2013). Ferraro and Price (2013) conducted a natural field experiment in Atlanta, Georgia to determine the influence of norm-based messaging on household water use. The study was conducted in 2007 but was not published in the Review of Economics and Statistics until 2013 (which is how subsequent studies based on this experiment were published first, for example Bernedo et al. (2014)). The project collected data on over 100,000 households, split into three treatment groups: Treatment 1 - a group that received technical advice, Treatment 2 - a group that received technical advice as well as an appeal to prosocial preferences including a personally addressed letter, and Treatment 3 - a group that received both technical advice and an appeal to prosocial preferences that included a social comparison to other households (Ferraro & Price, 2013). The information and advice was distributed by personalized mail to households (Ferraro & Price, 2013). Treatments 2 and 3 were found to be effective at reducing consumption, realizing a 2.7% and 4.8% water savings, respectively, however treatment 1 was below the policy relevant threshold, and therefore deemed to be indistinguishable from having no effect (Ferraro & Price, 2013). Furthermore, treatments 2 and 3 were found to be more effective at reducing water use in households that were higher than average water consumers (Ferraro & Price, 2013). Ferraro and Price (2013) provide evidence that indicated that the water savings for all treatments decay over time.

Another study based on the research described in the Ferraro and Price (2013) paper is by Ferraro et al. (2011), which looks at long term effects of the behavioural intervention strategy on residential water demand. The original study looked at demand for a period of 4 months after the treatment, whereas this work examined a two-year period (Ferraro et al., 2011). The results showed that for the Treatment 2 group, there was a 2.7% decrease in water use four months after the intervention, but after one year there was no significant difference between this group and the control in terms on water consumed (Ferraro et al., 2011). For the Treatment 3 group however, the initial 4.8% decline in water use four months after the intervention, decreased to 2.6% after one year, and 1.3% after two-year, but was significantly significant in all cases (Ferraro et al., 2011).

The implications of these findings of Ferraro et al. (2011) are that only the strong appeal to social norms that includes comparisons with neighbours has a lasting effect on water use, however the magnitude declines significantly. Overall, the continued significance of the decrease in water use for the Treatment 3 group is valuable, as the intervention has limited cost, and was only applied once (Ferraro et al., 2011).

A further study based on the work described in the previous paragraphs by Bernedo et al. (2014) looked at the long-term effectiveness of a one-time behavioural nudge provided to households during a drought period, with the aim of encouraging conservation behaviour and reducing water consumption. The goal of this study was to evaluate the sustained effect of a nudging intervention on the general population (Bernedo et al., 2014). The study only looked at houses that were treated with a strong social norm message (T3), meaning they were provided with a letter encouraging them to save water as members of society, along with a comparison of their water use with the median water use in Atlanta, as well as technical tips on how to save water in their home (Bernedo et al., 2014).

Bernedo et al. (2014) found that while the water savings realized by the initial study decreased by almost half after one year (from 5.62% to 2.95% compared to the control), after four to six years (depending on if the people in the house moved), the effects of that single intervention remain measurable and policy relevant (1.26% after four years and 1.43% after six years). These findings are at least in part validated by comparing water use in houses with occupants that remained the same between studies, with those that moved, where the treatment effects were not detectable (Bernedo et al., 2014).

Ultimately, like the original study by Ferraro and Price (2013), Bernedo et al. (2014) found that the greatest impact on water savings occurred during the first year after the treatment. This work shows that the long-term effects of this demand management project are being actively pursued, as many studies do not evaluate program results after the original work (Bernedo et al., 2014). The authors of this study found that the water savings may be more persistent than originally thought, but the effects do diminish over time (Bernedo et al., 2014). Furthermore, while significant decreases in water use were found four and six years after the treatment, the water use savings in the fifth year was not found to be significant in comparison with the control group (Bernedo et al., 2014). More experiments would help to validate these long-term findings. One potential issue with this work is that it took place six years after the original study, so while the effects of changes to households was considered, other changes in behaviour, living arrangement, or climactic conditions and events were not considered (Bernedo et al., 2014). In addition, questions remain about the applicability and result of such an approach outside of the study area (Bernedo et al., 2014).

A similar educational intervention, but looking at voluntary actions was studied by Fielding et al. (2013) who examined the long and short term effects of three interventions for 221 households in South East Queensland, Australia. The overall aim of the study was to provide information about conservation strategy effectiveness at reducing water consumption to policy-makers interested in developing demand management strategies (Fielding et al., 2013).

Fielding et al. (2013) split participating households split into four treatment groups: a control group, a group that received information about how to save water in their household, a group that received descriptive norm information (discussing how other similar households were conserving water, with information taken from a household water use survey) in addition to the water saving information, and a group that received household specific water end use feedback information, such as overall water use, and a water use breakdown by activity, in addition to the other information. Fielding et al. (2013) found that all three interventions were effective at reducing per capita household water consumption (11.3 L per capita per day on average), and that simply providing information about how to save water (the first group) was just as effective as the other treatments. After twelve months however, water consumption returned to pre-intervention levels for all intervention groups (Fielding et al., 2013).

Fielding et al. (2013) identified several limitations, and potential sources of bias in their work. The study area, South East Queensland, is not only extensively studied in relation to demand management, but also had experienced severe drought in the years leading up to the study (Fielding et al., 2013). Water restrictions addressing household water use were in place during the study period, and therefore participants were likely already engaged or familiar with water issues and conservation behaviour (Fielding et al., 2013). Furthermore, households who participated were chosen from among households that had previously been part of a water use study, meaning they may be more interested and motivated to conserve water than a typical household (Fielding et al., 2013). Overall, this means that the savings found in this study are likely overestimated in comparison with regions where water availability is less of a concern (Fielding et al., 2013).

3.5.1 Educational Interventions Summary

The educational interventions studies presented in this chapter address water use behaviour directly (Ferraro & Price, 2013; Fielding et al., 2013). This is not a rich area of literature, particularly in terms of studies that attempt to quantify the effects of educational interventions, especially as part of a control experiment. The papers chosen here represent only two experiments (Ferraro & Price, 2013; Fielding et al., 2013), however the study by Ferraro and Price (2013) was used as the basis for two subsequent studies looking at the longer-term effects of the intervention. All the studies showed that educational interventions can have decreasing residential water consumption, but that the persistence of these effects can be problematic and there is room for further study therefore, on longer-term interventions (Ferraro & Price, 2013; Fielding et al., 2013).

Local context plays a large role in both studies, as both study regions have a history of drought, and therefore the transferability of this work may be difficult, as differing values and beliefs will no doubt influence the success of educational treatments, and regions more vulnerable to drought likely have a higher value places on water resources (Fielding et al., 2013). The local context factor, coupled with the short-term effectiveness of these interventions (followed by a diminishing effect) in reducing consumption, may mean that this type of educational approach is best suited for emergency situations (such as a severe drought, or other water supply issue where a short-term decline in water use is needed) (Ferraro & Price, 2013; Fielding et al., 2013).

Furthermore, these experiments looked only at the effects of educational tools, however there is likely some value in coupling education with other demand management strategies such as water efficient appliance rebates, or retrofit options (among others). The social norm information provided to households encourages them to conserve water, and if they are compelled to act, the availability of water saving technologies and appliances is likely a factor in facilitating conservation (Ferraro & Price, 2013; Fielding et al., 2013).

3.6 Regulatory Interventions

Regulatory internventions generally include actions such as municipal level mandated water restrictions and irrigation policy (Kenney et al., 2004; Mini et al., 2014; Ozan & Alsharif, 2013). Looking at California, Mini et al. (2014) quantified the effectiveness of various demand management strategies targeting outdoor water use reductions, implemented in the City of Los Angeles, USA. Three levels of restrictions were implemented in response to the ongoing drought; first, voluntary conservation measures were put in place that asked household to reduce consumption by 10% (Mini et al., 2014). This was followed by mandatory restrictions limiting lawn irrigation in terms of frequency and duration, as well as prohibited water end uses such as car washing and irrigating during rain events (Mini et al., 2014). Finally, mandatory restrictions in combination with price incentives were implemented (two-tiered increasing block water rates), which expanded the prohibited activities and further limited irrigation (Mini et al., 2014).

Mini et al. (2014) used billing data (pro-rated to monthly values, aggregated to bi-monthly), climate data, and unemployment data to create a predictive model of residential water use. The results of this study found that the initial voluntary water restrictions did not have a significant effect on average household water use, but mandatory restrictions were effective at reducing water consumption (Mini et al., 2014). The highest water reductions were seen in the months after the final restrictions when modified water rates were introduced, corresponding to an average water savings of between 19% and 23% (Mini et al., 2014).

Mini et al. (2014) was not able to differentiate between the two phases of mandatory restrictions (without water price increases, and with increases to the tier 2 price), or separate between the effects of the price increase, and the restrictions themselves, leaving room for more research to be undertaken. A longer time scale for the study would have been useful to determine the ongoing effects of these efforts; however, the goal of these restrictions was conservation during a period of drought, and therefore the persistence of the reductions in water use was not a concern (Mini et al., 2014).

Also looking at water shortage conditions, Kenney et al. (2004) used the 2002 drought in Colorado, USA, to study a variety of voluntary and mandatory water restrictions focussed on lawn irrigation implemented by eight water utilities. The basic components of the outdoor water restrictions were similar across the water utilities included in the study, however the specifics differed (Kenney et al., 2004). Whether compliance water voluntary or mandatory was not the same across the various utilities, and lawn watering frequency, time of day and duration was restricted differently (Kenney et al., 2004). Some municipalities also instituted drought surcharges to water rates, and/or restrictions to car washing and the planting of new sod (Kenney et al., 2004). All the municipal water utilities in the study coupled educational materials with their restrictions (Kenney et al., 2004).

Kenney et al. (2004) used both the water consumption data from previous years during the same period, as well as water use estimates for consumption would have been without the restrictions based on the climate data, to calculate the effectiveness of the implemented restrictions at reducing water consumption. The findings showed that mandatory lawn watering restrictions facilitated significant water savings in all study regions, ranging from 13-53% based on comparisons with historical data, and 18-56% based on the predicted consumption output from the model (Kenney et al., 2004). Like other studies however, the voluntary water restrictions were found to be ineffective (some municipalities saw demand increase), however using predicted data, savings ranged from 4% to 12% (Kenney et al., 2004). The greatest water savings were found in those municipalities that implemented the strictest restrictions (Kenney et al., 2004).

Looking specifically at lawn watering, Ozan and Alsharif (2013) examined the effects of turfgrass irrigation restrictions on domestic water consumption in Tampa, USA. The authors highlight the challenges and potential conflicts in relation to lawn watering restrictions; the most common turfgrass used in residential properties in Florida requires irrigation 2-3 times per week, however municipal drought restrictions limit irrigation to once per week (Ozan & Alsharif, 2013). Ozan and Alsharif (2013) identify this as particularly problematic considering the rules imposed by many homeowner associations which mandate that residents must maintain healthy lawns. This study looked at the effectiveness of watering restrictions at reducing water consumption by considering water usage at the parcel level, key environmental factors such as climate, weather, and pool presence, and the enforcement of restrictions (Ozan & Alsharif, 2013).

Ozan and Alsharif (2013) focussed on periods of lawn watering restrictions that limited watering to once or twice a week in neighbourhoods that were subject to homeowner association rules and regulations. The results of the study showed that there was no significant difference between the limiting of lawn watering to one day per week or two days per week (Ozan & Alsharif, 2013). Those homes that received a citation for irrigation restriction violation in the past were shown to increase their consumption from between 8%

and 16% depending on the season (Ozan & Alsharif, 2013). Furthermore, homes that did not receive a violation saw a change in their consumption range from an increase of 15.5% to a decrease of 2.5% depending on the season, again for the transition from twice a week watering to once a week (Ozan & Alsharif, 2013).

On average, Ozan and Alsharif (2013) found that all regions increased their residential water consumption after the more stringent irrigation restrictions limiting watering to one day per week were put into place indicating that these homes, in general, did not comply with the more limited watering restrictions. Furthermore, those households that had been previously penalized for violations increased their consumption to a greater extent than those that did not when more stringent restrictions were put into place (Ozan & Alsharif, 2013). Based on these findings Ozan and Alsharif (2013) suggest that in the study area, households would prefer to pay the fine for violation than limit their water use, which calls into question the enforcement system that not only has a limited ability, but penalties for violations do not cover the costs of enforcement, making the system financially unsustainable.

Furthermore, as found by Ozan and Alsharif (2013), there is seems to be a greater importance put on lawn aesthetics and lawn health, as well as the homeowner association rules, than on water conservation during drought periods. Ozan and Alsharif (2013) discuss the ideological role of the lawn in many neighbourhoods, and the potential motivation of homeowners to avoid conflicts with their neighbours about their lawn, and foster solidarity through non-compliance with irrigation regulations.

3.6.1 Regulatory Interventions Summary

Fundamentally, the goal of the water restrictions discussed in these studies was short term reductions in water demand in the face of water supply shortages (Kenney et al., 2004). Therefore, there is less emphasis or examination of long term effects, and the design of these interventions does not tend to be focussed on the longer term. Mini et al. (2014) and Kenney et al. (2004) found that voluntary water restrictions had an insignificant effect on water demand. Furthermore, both studies found that mandatory restrictions could reduce water use, with more stringent restrictions leading to greater conservation (Kenney et al., 2004; Mini et al., 2014). These results are valuable to water utilities that can use this information to determine the severity of restrictions required during specific drought conditions.

However, all of the interventions presented in this literature aim to induce behavioural change, and as the Ozan and Alsharif (2013) study indicates, they may not realize water savings at all. Faced with two incompatible lawn regulations, the authors found that households tended to ignore the municipal regulations in favour of keeping their lawns healthy, and comply with their neighbourhood association rules (Ozan & Alsharif, 2013). This case demonstrates the wickedness of this type of problem, where seemingly simple measures are taken to reduce water use during a drought, can exacerbate the problem and increase consumption due to competing values, beliefs, and regulations (Rittel & Webber, 1973b). The effect of regulatory interventions may be bolstered by their combination with other demand management tools, such as norm-based educational messages, which proved to have an effect in other studies (Ferraro & Price, 2013).

4 Utilizing Existing Municipal Water Data to Support Conservation Efforts – A Case Study of the City of Vancouver's Parks System

4.1 Introduction

The sustainable management of water resources is becoming increasingly challenging as climate change, urbanization, and changing socio-economic conditions all contribute to the growing demand on fresh water availability (Alcamo et al., 2007; Brown et al., 2009; Pahl-Wostl, 2007; Vörösmarty et al., 2000). This is leading to growing competition between stakeholders for the remaining fresh water resources, especially in urban areas (Mitchell, 2006). Historically, water availability challenges have been addressed by increasing the supply, but the high costs and environmental impacts of water supply infrastructure has led to a push for demand management strategies, including conservation (Brown & Farrelly, 2009; Gleick, 2000; Mitchell, 2006). As a result, there is a growing need to review the data collection and analysis systems to ensure that they meet the information needs of demand management strategies (R. a. Stewart et al., 2010; van der Steen & Howe, 2009). The aim of this chapter is to describe and analyze how existing water meter data can be utilized to support demand management strategies, drawing on experiences from the City of Vancouver, B.C., Canada.

Existing research in this field covers a range of topics. In terms of data management and analysis generally, there has been substantial work looking into the preparation of data for analysis (Zhang et al., 2010), in addition to the development of the formal steps of the analysis process (Schutt & O'Neil, 2014). From the water data perspective, there has been an identification and scrutiny of the gap between water data that is generated and the production of useful information to support water utilities. To this end, Timmerman et al. (2010) suggest that the backbone of sustainable management of water resources requires data and information that is produced specifically for the end use application. Fletcher and Deletić (2008) go further by describing the specific data requirements for urban water management.

There has also been research looking at the analysis of water meter data to support conservation efforts. This area is wide ranging, covering the mining of water billing data to support conservation policy development or reduce residential demand (Boyer et al., 2016; C. E. Boyle et al., 2011), the disaggregation and analysis of high resolution smart meter data to model demand and help develop conservation strategies (Gurung et al., 2015; Liu et al., 2015; Makki et al., 2015; K. A. Nguyen et al., 2013), as well as assessing the effectiveness of various implemented water conservation efforts at reducing water consumption (C. E. Boyle et al., 2011; Cole & Stewart, 2013a; Martinez-Espinera, 2002; Mini et al., 2014). While the above-mentioned studies represent a larger substantial body of work, the existing research tends to be ultimately focussed on decreasing residential water consumption through behavioural change, with few studies examining other water end use groups (T. Boyle et al., 2013; Cole & Stewart, 2013a).

Following this introduction, Section 4.2 will provide a background of the case study, and describe the City of Vancouver's water supply system, as well as touch on water use in the parks system. Section 4.3 will outline the methods used in the research study, and Section 4.4 will detail the results. A discussion of the results in the context of relevant research in the field is provided in Section 4.5.

4.2 The City of Vancouver's Water Supply and Parks System

The City of Vancouver (CoV), which is situated by the Pacific Ocean in southwest Canada, has a current population of 650,000, and is expected to grow rapidly over the next quarter century (18% for the CoV; 36% for Metro Vancouver) (BC Stats, 2015; Metro Vancouver, 2015b). Water is supplied to the CoV by a regional authority (Metro Vancouver), who manages three mountain reservoirs fed by precipitation and snow melt (Metro Vancouver, 2011). The expected growth, coupled with predicted changes to the climate, is anticipated to put increasing pressure on the existing water supplies as demands increase

(Metro Vancouver, 2011). The seasonality of the precipitation pattern is a major challenge for the CoV because it is opposite to the consumption pattern, as illustrated in Figure 4.1.

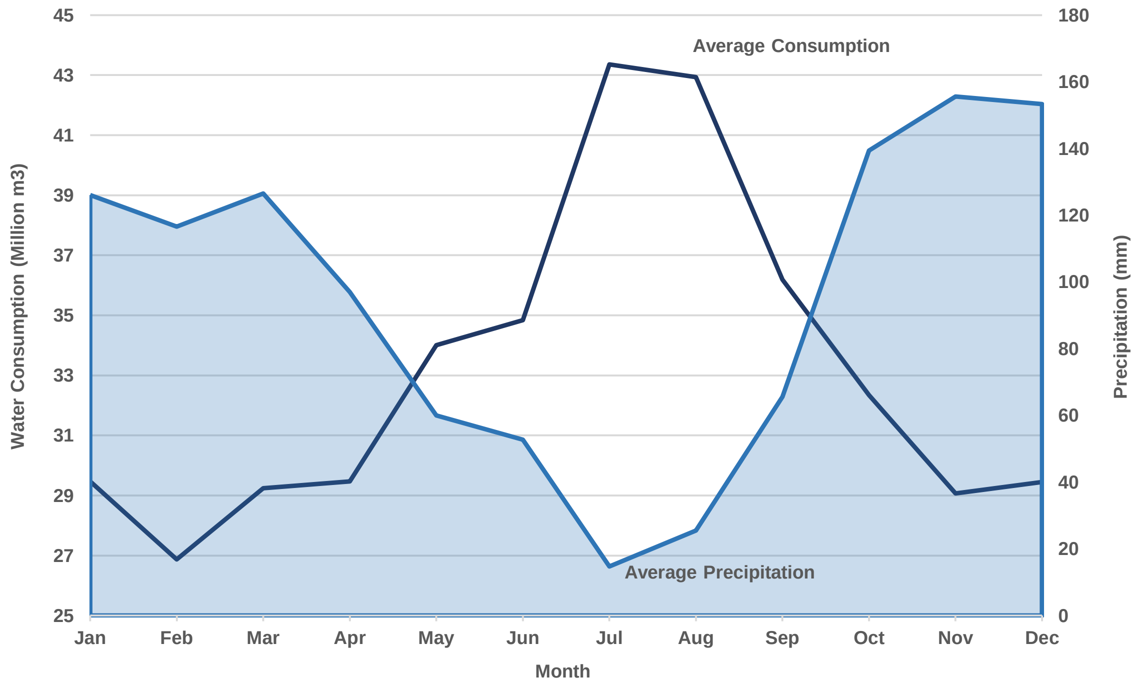
In light of the growing challenges involved in supplying sufficient amounts of water throughout the year, combined with an overall push to increase sustainability, the CoV set as a goal to reduce the per capita potable water consumption by 33% by 2020 from 2006 levels (City of Vancouver, 2012). Initial conservation strategies focussed on residential consumption, which resulted in a 17% decrease. Further reductions are needed to meet the target, which has prompted projects aimed at reducing water use in the industrial, commercial and institutional (ICI) sector as well as municipal use, including parks (City of Vancouver, 2015).

The parks system has an annual water consumption of just over 1.2 million m^3 but has only recently been included in conservation efforts. The system is comprised of 215 parks that use potable water for irrigation of vegetation and playing fields, top up of ponds and streams, water spray parks, as well as various indoor facilities. There are 196 water meters covering water use in 76 parks, which account for 72% of the estimated total consumption. Meters are manually read roughly every two months, and the data is uploaded to the CoV's digital meter account system.

4.3 Methods

I was hired by the City of Vancouver (CoV, May-August 2015) to help develop a conservation strategy for the park system. During this period, I set out to identify barriers to the development of conservation efforts and analyzed if the identified barriers could be overcome by improving components in the data analysis process. This was achieved through informal interviews and interactions with parks staff as well as through hands-on experience of the various data sets and systems used by CoV. I used a modified version of Schutt and O'Neil's data analysis process (2014) to aid the identification of barriers,

Figure 4.1: Average monthly water consumption (dark blue) and precipitation (light blue) for Metro Vancouver (2012-2014), highlighting the seasonality of each (Government of Canada, 2016; Metro Vancouver, 2015a)

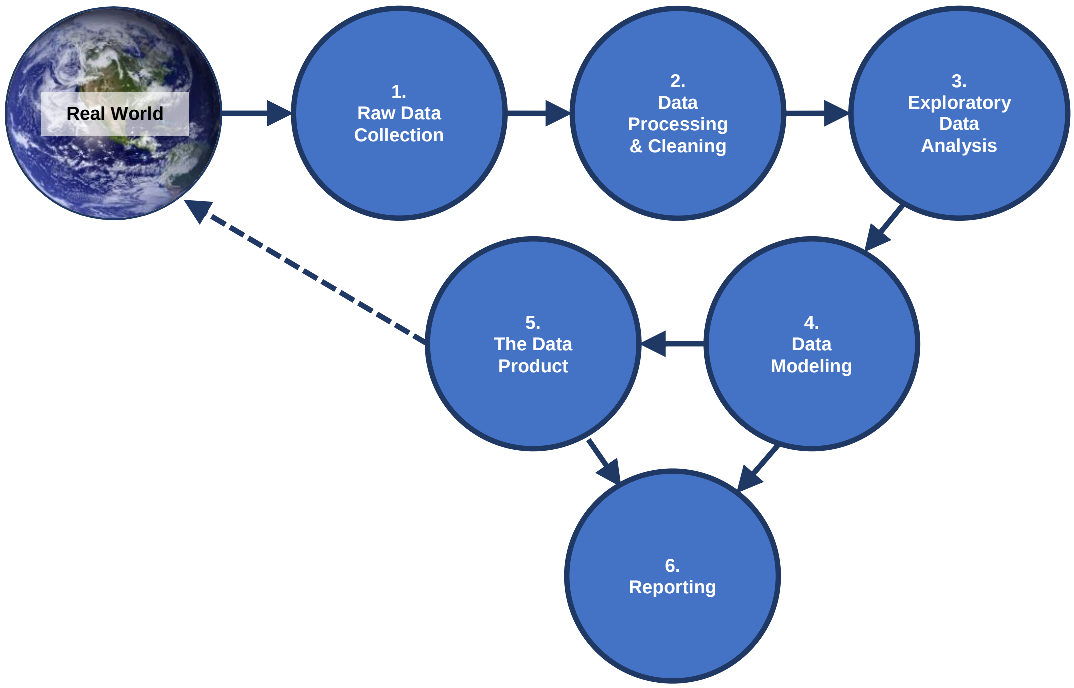


opportunities and improvements, focussing on Components #2, 3, 5 and 6 of the framework Figure 4.2: The data analysis process (modified from Schutt and O'Neil 2014). A summary of the components, the existing barriers in the current system, and the actions taken can be seen in Table 4.1: Data analysis process components, barriers, and actions.. Component #1 was not included because the focus of this study was to explore what information could be gleaned from data that already exists, and was readily available. Upgrades to data collection system are often resource intensive, especially on the municipal scale, and while high resolution data can provide the potential for more in-depth analysis of the data, this data will not be available to the CoV in the near future (Cominola et al., 2015).

4.3.1 Component #2: Data Processing and Cleaning

Existing data for the park system (2012-2016) was compiled from the COV's digital meter account system and daily consumption between readings was estimated using interpolation (assuming consistent consumption) using a computer program developed in R, a statistical programming language and environment (R Development Core Team, 2008). Because the meter reading dates were not uniform (the

Figure 4.2: The data analysis process (modified from Schutt and O'Neil 2014)



time between readings changes), the raw data was not comparable as is, neccessitating the need for processing in this way. An R program was written to determine the number of days between two meter readings, calculate the average daily consumption between those readings (assuming constant consumption for each day – the total consumption for that period of days was divided by the number of days), and output the daily values for each meter (Appendix A). Subsequently, two R programs were created to calculate the monthly and annual consumption for each park meter by summing the estimated daily values, and averages for 2012-2014 were calucated, serving as a basis for subsequent analsyis (Appendix A). Because the raw meter reading data is specific to the CoV digital database, and the output table and fields are not standardized across the industry, the specific data procressing steps are not generalizable – however the general process and calculations are transferable.

Table 4.1: Data analysis process components, barriers, and actions.

Component	**Identified barrier in current system**	**Action(s) taken in the present study**
1. Raw Data Collection Collection of raw data.	Raw data is low resolution, limiting analysis potential.	Not addressed. Upgrades to the data collection system are resource intensive, and thus this project focussed on using the existing data for analysis.
2. Data Processing and Cleaning Transformation of data into an organized dataset free of errors and suitable for analysis	The data in the meter account system did not allow for data processing, or even download of data in bulk. Data also contained errors, and incomplete fields which required cleaning.	Developed computer program in R to compile raw data, estimate daily values, and compute monthly and yearly values.
3. Exploratory Data Analysis Initial analysis of data to identify and summarize its principle characteristics	No exploratory analysis undertaken for conservation purposes	Exploratory analysis of processed data (summary statistics, histogram, time series plots)
4. Data Modeling Identification of relationships between variables	No formal modeling of meter data is currently undertaken.	N/A
5. The Data Product Software that analyses data, creating outputs that feed back in the real world	The current data management system has the ability to identify abnormally high or low water use, however the limits used to identify ‘normal’ consumption were ill suited for the parks due to the strong seasonality of water consumption in the system.	Normal consumption ranges for the summer and winter periods were calculated, and a computer program in R was developed and used to identify abnormal consumption.
6. Reporting Communication of the data and analysis findings in a format that supports strategy development	No formal reporting of meter data analysis was undertaken prior to the present project.	Time series plots, meter ranking, reports of abnormal consumption.

Data for 2015 was excluded because the region experienced a severe drought during that year, which meant it was an atypical year in terms of water consumption due to strict restrictions on water use. Data from 2016 was used to assess the effectiveness of implemented conservation strategies at reducing water consumption developed through the data analysis output. The processed dataset was cleaned by manually removing known backflow events which record artifically high water consumption.

The raw data for the park system water meters has several uncertainties. First, the meters are regularly checked and calibared by the CoV meter shop, however reading errors and hardware issues can lead to incorrect consumption values, for example not detecting low flows, or backflow events. In addition, there is poor meta-data available for the parks meters, specifically there is no good information on what a specific meter covers in terms of water consumption. This is an issue because a park may have only one meter, but only some of the water consumption in that park is measured by a meter. Finally, the low resolution meter data (one reading every ~2 months) means that the calculated daily and monthly consumption values assumer constant use between readings which is not necessarily the case.

4.3.2 Component #3: Exploratory Analysis

Summary statistics were calculated using the built-in function 'summary' in R which computes descriptive statistics including mean, median, max and min (Appendix A). A histogram including cumulative frequency of the 2012-2014 annual average water consumption for all park meters was created using the built-in function 'hist' (25 bins were used, each 500 m^3) (Appendix A). In addition, a program in R was created by the author to plot the times series data of individual park meters (Appendix A).

4.3.3 Component #5: The Data Product

The normal consumption range for individual meters as well as summary statistics were calculated for summer (June to September) and winter (October to May) using seasonal consumption values, summing daily values and averaging the summed seasonal consumption for 2012-2014. Limits for the normal seasonal consumption range were then calculated for each meter based on those consumption values as per Eq. 4.1 using a program created in R (Appendix A). A subsequent program was developed in R to calculate the normal consumption range for each meter and identify meters with consumption outside the range for a given reading (Appendix A). After each new meter reading, the new values were compared to the historical normal range.

$$L_s = \mu_s \pm (2 * \sigma_s) \qquad \text{(Eq. 4.1)}$$

L_s: High/Low limits for the normal consumption range for a specific meter and season (s)
μ_s: Seasonal consumption for a specific meter and season (s) averaged for 2012-2014
σ_s: Standard deviation of seasonal consumption for a specific meter and season (s)

Meters with consumption outside of the normal consumption range were then further analyzed to validate whether the deviation was in fact due to an unknown issue or operational change. Time series analysis using line charts created for each flagged meter in R (Appendix A) provided a historical indication of seasonal periodicity of averaged water consumption. This provided insight into whether the potentially abnormal consumption value aligned with historical seasonal trends (but perhaps with higher consumption than previously) or fell outside of that pattern (for example a spike in consumption during winter months). Qualitative factors such as operational and maintenance consumption (for example newly planted turf requiring increase irrigation frequency, or leaks) were vetted through internal information gathering from relevant personnel, or on-the-ground investigations.

4.3.4 Component #6: Reporting

A series of programs in R were developed to facilitate identification and reporting of information that, according to the analysis, had the potential to reduce or remove the identified barriers (Appendix A). These charts and tables are based on the processed and cleaned data and included time series charts of individual meters (created in R), a summary statistics table (created in R), historic ranked consumption charts of all meters (created in excel), and consumption outside of the normal range tables (created in R) and charts for individual meters (a specific program in R was created).

4.4 Results

4.4.1 Identification of Barriers and Actions

Table 4.1 describes the components in the data analysis process along, the barriers that were identified as well as actions taken to address these barriers.

4.4.2 Component Specific Results

Component #2: Data Processing and Cleaning

The data was processed and cleaned and the data for 2012 to 2016 was output in three tables containing data for each water meter (annual, monthly, and daily water consumption values). This data served as the basis for the subsequent analysis.

Component #3: Exploratory Data Analysis

Summary statistics for the 2012-2014 average water consumption across the park system is shown in Table 4.2. A histogram of the relative and cumulative frequency of the same data for all the park system meters was created (Figure 4.3). Both the summary statistics and the histogram reveal that the consumption is skewed. Most the water meters record annual consumption well under 12,000 m^3. An example of a time series plot for Bobolink Park can be seen in Figure 4.4, which clearly shows that water consumption is primarily occurring in the summer months, and has been increasing since 2012. These findings helped characterize water use across the system, and were used to categorize the meters based on consumption.

Table 4.2: Summary statistics for the averaged water consumption 2012-2014 for all park meters (m3/year).

Minimum	1^{st} Quartile	Median	Mean	3^{rd} Quartile	Maximum
0.0	99	1044	5,875	3,969	215,800

Figure 4.3: Histogram of the average 2012-2014 water consumption of individual park system meters – Vancouver, Canada (n=196).

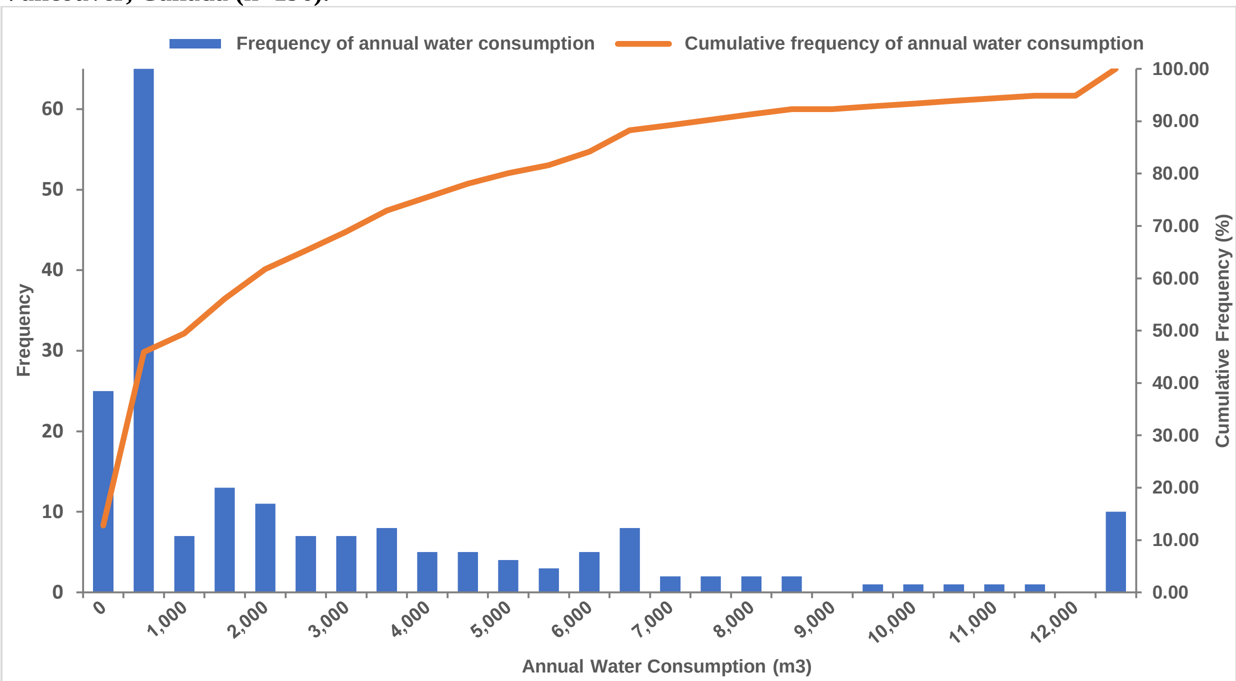
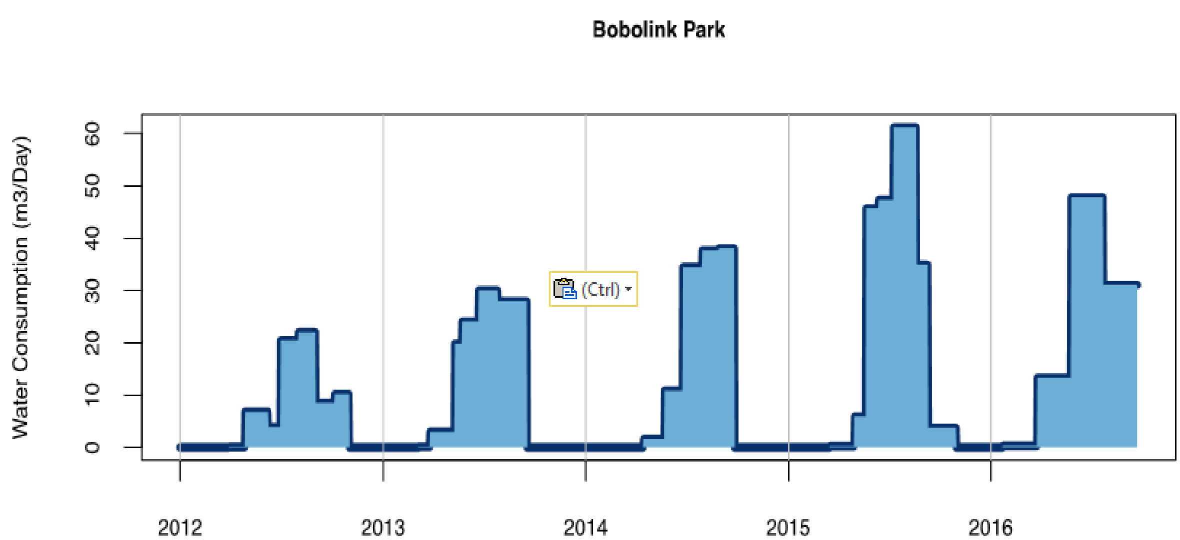


Figure 4.4: Historical daily water consumption and summary table for meters at Bobolink Park – Vancouver, Canada. This plot was generated from the R program developed specifically for this analysis.



Annual Data

	2011	2012	2013	2014	2015	2016
Water Consumption (m3)	5108	2272	3620	3820	5892	5526
Water Costs ($)	5499	2468	4050	4355	6665	6129

Component #5: The Data Product

The estimated normal consumption ranges for the summer and winter period for Bobolink Park (as an example) is shown in Figure 4.5 which shows the summer and winter water consumption and upper limits to the normal ranges. For both seasons the limit was exceeded for both 2015 and 2016 for the example park (Bobolink).

Component #6: Reporting

The histogram and summary statistics indicated that a handful of the highest consuming parks dominated overall consumption, which led me to create a plot that was designed to communicate this finding (

Figure 4.6). To further facilitate identification of outliers, the automated reporting was designed to include a time series plot for meters being flagged for unusual water consumption (an example plot can be seen in Figure 4.7).

Figure 4.5: Daily summer and winter water consumption (2011-2016) for Bobolink Park showing a time series plot of water consumption as well as the upper summer and winter limits of the normal seasonal consumption ranges.

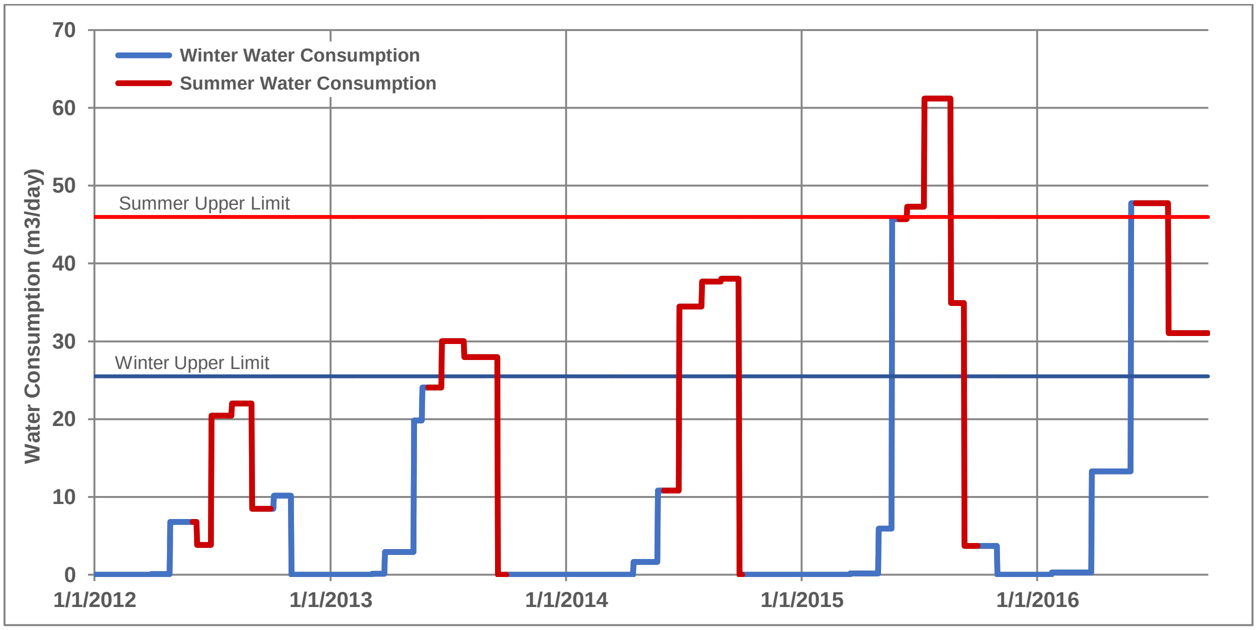


Figure 4.6: Plot of the actual and cumulative water consumption for all park meters showing each individual meter and 2012-2014 average annual consumption.

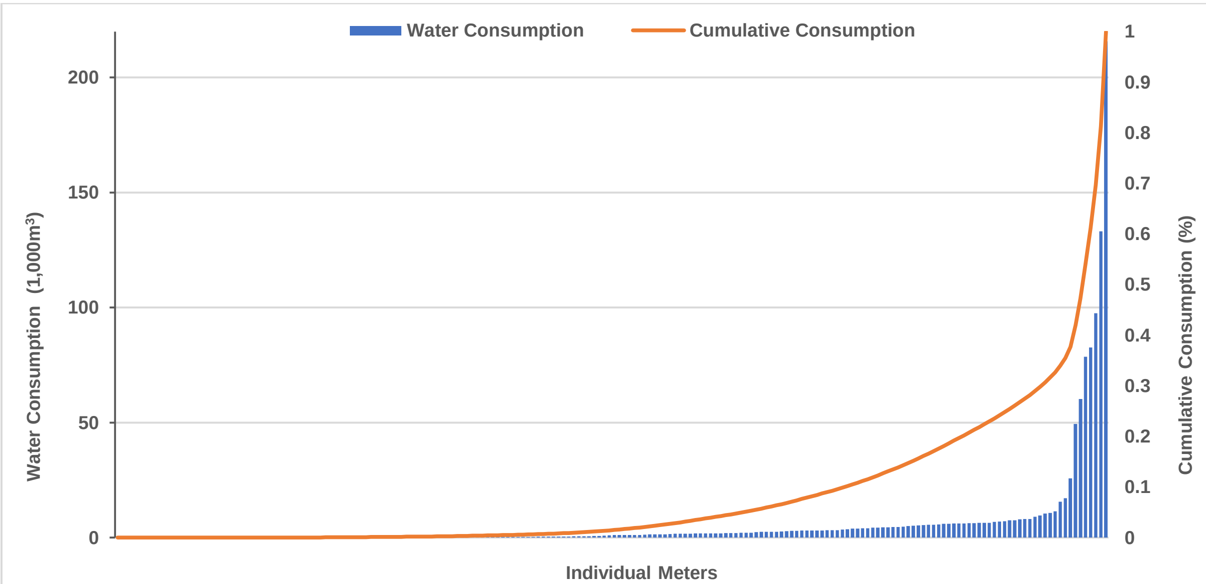
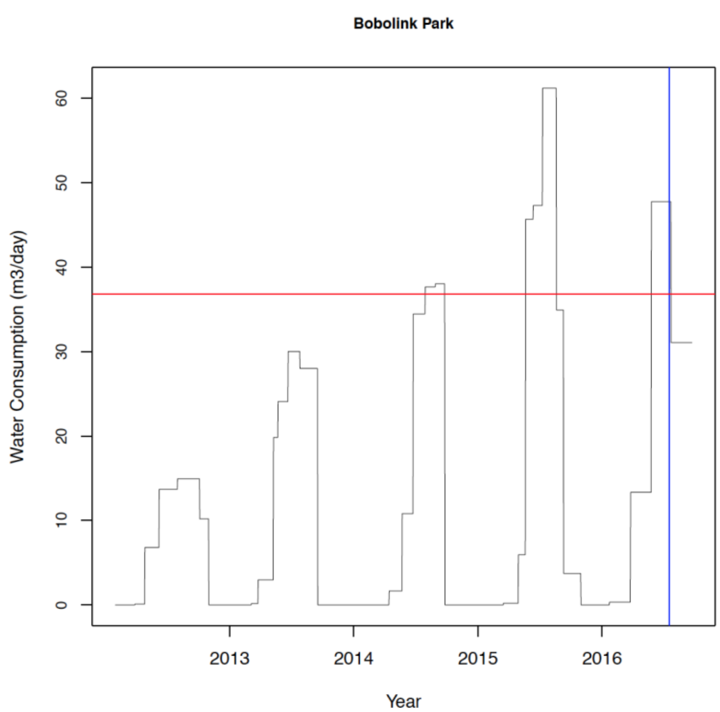


Figure 4.7: Daily consumption time series plot for Bobolink Parks, showing an example of consumption that exceeds the summer upper limit of the normal range; exceeded limit = red, meter read date = blue



4.5 Conclusion

In this study, I set out to explore how analysis of existing water data might be used to provide valuable information in support of conservation strategies. The CoV and Park Board have set ambitious water conservation targets that require effective interventions to achieve the water savings necessary. The improved data analysis outlined in this chapter supports efforts to meet these water use reduction targets by generating information from available data that is useful in improving the understanding of potential water conservation options.

Prior to the current study, the parks water meter data was not used in any systematic or routine analysis of water use. Meter data was used periodically to assess water use at various parks as part of ad-hoc conservation efforts; this single application was partly due to the accessibility and format of the data which was simple for a single meter, but ill-suited for wider analysis. The improvements to the meter data analysis outlined in this chapter provided a useful database of water consumption data for all the meters in the park system, which not only allow for analysis of single meter consumption, but also analysis of the park system water use as a whole. The data analysis process developed in this study has and will be used on an ongoing basis (meter data is analyzed after each meter read), and further improvements to the analysis continue.

In terms of improvements to the analysis of meter data, a number of authors discuss the need to bridge the gap between raw water data and the production of beneficial information that can be used to support demand management (Deletić & Fletcher, 2008; Timmerman et al., 2010). It is not uncommon for municipalities to collect significant volumes of data related to their water systems, but the data is often under-utilized. As for example pointed out by Timmerman (2015), a series of processing and analysis steps are required to tailor the usability of this type of data for conservation or demand management purposes. The present study address the gap between water data and information, with the intention of highlighting that conservation planning requires non-routine knowledge and information about water use.

In the case study presented in this paper, improvements to the processing and cleaning of raw data facilitated the exploratory analysis, which provided a better understanding of potential conservation strategies. Various conservation strategies were implemented targeting the largest users in the park system starting in 2016 and led to a 38% reduction in water use in the park system in comparison to the 2012-2014 baseline. This represents an absolute water savings of 460,000 m^3, which is equivalent to $455,000 in water cost savings. The top water consuming parks were identified through the exploratory analysis, and further investigated. The findings indicated that high use was related to once-through features with no recirculation, unregulated top-up of ponds and streams, operational scheduling of spray parks and other features that ran continuously though the summer season or inefficient irrigation systems. Measures were taken to address these high consumers included the installation of a float valve to regulate the top-up of a large lake and tie water input to the lake level, the installation of an activation button for a large once-though spray park that previously ran continuously, and addressing various once-through water features, systems and processes.

The data used in this case however has several challenges that limit the potential to define strategies moving forward. The lack of universal metering across the park system means that any data analysis can only be conducted on existing meter data, and there may be large water end uses that are not captured in the analysis and therefore not part of any conservation action. Furthermore, the low resolution of the data means that the ability to identify the reasons for observed trends through data analysis is limited; the causes of high water consumption may need to be explored either on the ground, or through other qualitative methods. The analysis also did not incorporate climate and weather variables which influence park water use, and only a few years of historical data (since 2012) are available which limits analysis.

The revealed data does provide a good indicator of how water is used across the system, but does not provide any qualitative insight into why trends and spikes in consumption have occurred.

Looking at exploratory data analysis of the raw data, it is often considered to be the lowest level of analysis and therefore at times overlooked. Schutt and O'Neil (2014) argue, however, that it is a key component of the process, which is supported by the findings of the present study. Exploratory data analysis provides an overview of water consumption across the system, and highlights use patterns, which can be used to identify areas where conservation can be most effective at reducing water consumption. For example, the overview and summary statistics of water consumption for individual meter data created for the CoV was used to identify how to strategically prioritize and target certain areas, in this case the small number of high use parks that dominate consumption in the city's park system. The identification of skewed consumption patterns and outliners made it possible to tailor conservation efforts by, for example, following up with time series plots of estimated daily water consumption. Unusual water consumption patterns can be indicators of losses (leaks), inefficient or modified water management, and other issues such as backflow events, which, can be systematically identified and, if addressed, can decrease water use. However, improving the identification and validation of unusual consumption would be beneficial moving forward. Utilizing autoregression in determining the normal consumption range could enhance the calculations, and more robust trend and time series analysis can provide additional explanatory information. Other authors have utilized exploratory analysis to support conservation efforts such as Boyle et al. (2011) who demonstrated how a range of techniques could be used to mine water billing data to support the development of management policies. Another example is Boyer et al. (2016) who used exploratory analysis to characterize residential irrigation demand.

In addition to the demonstrated value of exploratory data analysis, the importance of data processing and cleaning should not be underestimated. Real world data is often in formats that are ill-suited for analysis, and may be noisy, inconsistent and incomplete (Zhang et al., 2010). Data formatting can therefore be a significant barrier to further data analysis, as illustrated by the present study: the processing and cleaning of the data took a considerable amount of time, significantly more time and resources than the analysis. Successful implementation of a data processing strategy thus requires that sufficient resources be set aside for this step. Without usable data to support conservation efforts, analysis cannot be undertaken; therefore, the development of any strategy will not be based on observed trends. Concrete water use reductions that require a basis in reliable and readily available data.

This study further explored the benefits of lower resolution data. Several studies have been focussed on the development of sophisticated water data analysis, which includes, for example, the disaggregation of smart meter data (Nguyen et al., 2013), or descriptive demand modelling (Makki et al., 2015). The bulk of this research tends to focus on the utilization of data generated from more advanced metering technology such as smart meters which is not available in many municipalities (see Chapter 2) (Beal et al., 2013; Cole & Stewart, 2013b; Gurung et al., 2015; Liu et al., 2015). While higher resolution data can provide a more refined understanding of the water system, this study shows that the analysis of consumption data used for billing purposes has the potential to produce information to support the development of effective conservation strategies (Cominola et al., 2015). Other studies have demonstrated that consumption data used for billing purposes can be utilized to support management and policy decisions along with tailored customer communications as part of residential conservation efforts (Boyle et al., 2011), to estimate demand functions and the price elasticity of domestic water use (Martinez-Espinera, 2002), and to assess the effectiveness of summer water conservation measures in reducing water consumption at the household level (Mini et al., 2014), to name a few. The advantage of using consumption data used for billing purposes for analysis is that it is frequently available and accessible across metered water utilities, and is therefore a potential information source that does not require additional investment in data collection (Boyle et al., 2011). The objective of this thesis is not to argue that analysis of consumption data used for billing purposes is sufficient to address all the challenges to sustainable water management, but to highlight the potential value of that existing data.

Finally, this study intended to highlight the potential value of better utilizing existing data, as well as the potential water savings in smaller water sectors, such as municipal use. Because the costs associated with authorized but unbilled water consumption are indirectly paid by the municipality (which is the case for the CoV park system) there is a risk that this sector may be overlooked in the development of conservation strategies (Gonzalez-Gomez et al., 2011). Much of the demand management research targets residential water consumption due to the large share of water use in that sector (e.g. Boyle et al. 2011, Martinez-Espinera 2002, Mini et al. 2014), there are significant water savings possible for non-revenue unbilled but authorized consumption (Boyle et al., 2013; Cole & Stewart, 2013b).

This study has some limitations. The CoV case was limited to the parks sector, which is not necessarily representative of most water end use. Furthermore, the research findings, while they can identify areas where water conservation strategies should be focussed, do not provide information about how best to address identified issues or which actions will be the most effective in terms of conservation. Considering these limitations, future research could strengthen the findings by applying the same research methods and data analysis to other water end use groups such as the residential or ICI sectors. Further research could also look at the inclusion of climate and weather variables as part of the analysis, bring in alternative statistical criteria for identifying unusual water consumption patterns, or attempt to identify the causes of high water use through the data analysis process.

5 Conclusion

The development and implementation of water conservation strategies to address sustainability issues related to water resources in urban settings remains challenging. However, research is addressing this problem through novel and innovative approaches (see Chapter 2 & Chapter 3). The wicked water framing, coupled with new approaches such as the water sensitive city provide new ways to characterize and understand the challenges faced (Lach et al., 2005; Wong & Brown, 2009). Improvements to our knowledge of water demand and end uses provide even more information which serves as a basis for the development of solutions, and research looking at the effectiveness of conservation strategies at reducing water consumption can help with the selection and implementation process. In addition, formalizing data analysis and reporting to explicitly support conservation planning has been demonstrated to be vital as a basis for understanding conservation options (see Chapter 4).

Chapter 2 provided good insight in various approaches to modeling demand, but showed that no models had yet to account for all the variability, despite significant improvements. The demand models provide a basis to understanding the drivers of water use quantitatively and in relation to the chosen parameters which is an important basis for conservation and the sustainability of the water system, depending on their accuracy. Interest in urban water demand modelling stems from an understanding that water resource sustainability is about more than adequate supply, which means the problem framing and therefore modeling becomes more complex (Brown et al., 2009; Lach et al., 2005). The existing models aim to address some of this complexity, but are yet unable to fully account for the behavioural and social/cultural dimensions of demand – which are challenging to quantify (Jorgensen et al., 2009). Some of the findings from the household conservation interventions considered in Chapter 3 proved to be inefficient at decreasing demand, and future work may want to consider the behavioural or social context as a potential explanatory factor. An ongoing issue in the water conservation literature is that the effectiveness of interventions aimed at reducing water consumption seems to be challenging to generalize due to local factors and context – a characteristic of wicked problems (Inman & Jeffrey, 2006; Lach et al., 2005). While research in the field demonstrates that some interventions are more effective at reducing water consumption than others, more research into the reasons is warranted (Inman & Jeffrey, 2006).

Both the demand modeling and conservation intervention research aims to provide decision makers with data and information to support the development of conservation strategies to improve the sustainability of water resources (Cominola et al., 2015; Inman & Jeffrey, 2006). The case study presented in Chapter 4 aimed to address this directly by tailoring data analysis and reporting to that objective. The focus was on the parks sector which was chosen to minimize the behavioural dimensions of demand (and therefore complexity to some extent). Based on the case study findings, water data requirements to support conservation and sustainable demand management are outside of what is routinely available and meter data often requires significant resources for processing and cleaning (Timmerman, 2015).

In terms of the CoV case study (Chapter 4), the impact of behaviour is different than that associated with household studies that focus on consumer end use behaviour. Because the park system water use is under the control of the Park Board staff, the relevant behaviour is on the operational and planning side. Operations staff behaviour around setting irrigation scheduling, prioritizing leak repairs, or identifying and minimizing inefficient water end uses have an impact of consumption. On the planning side, the relevant behaviour it is the prioritization of water conservation projects among other projects, funding and staffing decisions, and political motivation (the Park Board is an elected body). This behaviour ties to how planners and staff value water and perceptions about the importance of water resources, and the understanding of water supply, demand and scarcity.

Looking to generalize the findings of the case study, it was found that the challenges of data availability and analysis are not unique to the City of Vancouver. A recent study of the University of British

Columbia's water data management strategy found that strategic data management practices were not well suited to support of non-routine (in this case non-operational) planning (Banks et al., 2017). Typically, as found by Banks et al. (2017) as well as other authors (Timmerman, 2015), significant volumes of data are collected on the water system including demand, but access to the data, and the format of the data were not conducive to the development of planning strategies related to water – a finding which was mirrored by the case study findings in Chapter 4.

Moving forward, future work should look to incorporate behavioural and social dimensions into water demand modelling. In terms of the tailored data analysis, further work needs to be done to incorporate quantitative influencing factors such as weather and climate, but also qualitative dimensions such as operational culture or the non-monetary value of water. The case study presented trends for water use, but did not incorporate analysis to evaluate the factors causing those changes, which is a logical next step moving forward.

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Appendices

Appendix A: R Scripts

R Script 1 – Monthly Consumption

This script reads the raw meter reading data outputs from the CoV data management system. Raw data is exported in files containing a single meter reading for each meter; the relevant fields are the meter reading date, the water consumption, and the number of days since the last meter reading. Meter data for 2012 was unavailable in the database, and had to be added separately from a previously exported file. This script compiles this data for each meter for all readings, determines the daily annual average by dividing the consumption since the last meter reading by the number of days, and outputs a table containing the daily values for all meters.

```
setwd(SET_WORKING_DIRECTORY)

years <- c(2013, 2014, 2015, 2016)
periods <- c(1:12)
combined_data <- matrix(NA, 0, 10)
colnames(combined_data) <- c("Account_Num", "Seq", "Meter_Name", "Date", "Type", "Meter_Reading", "PP_Reading",
"Consumption_UNITS", "Std_Units", "Name")
meter_names <- read.csv("Meter_Names.csv",header = TRUE, sep = ",")

for( y in 1:(length(years)) ){
for( p in 1:length(periods) ){

if( file.exists(RAW_DATA_FILE.txt) == FALSE ){ next } # This skips files that don't exist

con <- file(paste("RAW_DATA_FILE.txt, sep=""), open="rt", raw=TRUE)
text <- readLines(con, skipNul = TRUE)

separated <- strsplit(unlist(text), split = " ")
lines <- NULL

check.numeric <- function(N){ !length(grep("[^[:digit:]]", as.character(N)) }

for(l in 1:length(separated)){
	if(length(separated[[l]]) == 0){next
	}else if(check.numeric(separated[[l]][which(separated[[l]] != "")[1]]) == TRUE && separated[[l]][which(separated[[l]]
!= "")[1]] > 5000000){
	lines <- append(lines, l)
	}else {next}		}

data <- matrix(NA, length(lines), 10)

for(l in 1:length(lines) ){
	location <- which(separated[[lines[l]]] != "")
	temp <- list()
```

```
	for( p in 1:length(location) ){  temp[[p]] <- separated[[lines[l]]][location[p]] }

	data[l,1:3] <- as.numeric(unlist(temp[1:3]))
	data[l,4:5] <- unlist(temp[4:5])
	data[l,6:9] <- as.numeric(unlist(temp[6:9]))
	this <- if( typeof( as.character( meter_names$Tempest_Name[ which(meter_names$Tempest_Account ==
as.numeric(unlist(temp[1])) ) ] )) == "character"
					&& length( as.character( meter_names$Tempest_Name[
which(meter_names$Tempest_Account == as.numeric(unlist(temp[1])) ) ] ) ) == 0 ){ "Unknown"
}else{ as.character( meter_names$Tempest_Name[ which(meter_names$Tempest_Account == as.numeric(unlist(temp[1])) ) ] ) }
	if( length(this) == 2 ) { this <- this[2] }
	data[l,10] <- this
}
	combined_data <- rbind(combined_data, data)
	closeAllConnections()
}}

combined_data_sorted <- matrix(NA, dim(combined_data)[1], dim(combined_data)[2])
combined_data_sorted <- combined_data[order(combined_data[,1]),]

# ADD DATA FROM 2012 which is only available from a separate file.
data_2012 <- read.csv("2012_DATA_M_READS.csv",header = FALSE, sep = ",")
data_2012_UNITS <- read.csv("2012_DATA_UNITS.csv",header = FALSE, sep = ",")

dates_2012 <- c("12/1/3", "12/1/30", "12/2/29", "12/3/28", "12/4/26", "12/6/7", "12/7/31", "12/10/4", "12/10/31", "12/12/7")
data_2012[1,3:12] <- dates_2012
data_2012_UNITS[1,3:12] <- dates_2012

list_data <- matrix(NA, (dim(data_2012)[1] * (dim(data_2012)[2]-2)), dim(combined_data_sorted)[2] )
colnames(list_data) <- c("Account_Num", "Seq", "Meter_Name", "Date", "Type", "Meter_Reading", "PP_Reading",
	"Consumption_UNITS", "Std_Units", "Name")

for(a in 1:(dim(data_2012)[1]-1) ) {
for(b in 1:(dim(data_2012)[2]-2) ) {

	list_data[(b+((a-1)*10)), "Account_Num"] <-  as.numeric( as.character( data_2012[(a+1), 1] ) )
	list_data[(b+((a-1)*10)), "Meter_Reading"] <- as.numeric( as.character( data_2012[(a+1), (b+2)] ))
	list_data[(b+((a-1)*10)), "Consumption_UNITS"] <- as.numeric( as.character( data_2012_UNITS[(a+1), (b+2)] ))
	list_data[(b+((a-1)*10)), "Date"] <- data_2012[ 1, (b+2)]

	list_data[(b+((a-1)*10)), "Name"] <- as.character( meter_names[which( meter_names[,1] == as.numeric( as.character(
data_2012[(a+1), 1] ) ) ), 2] )
}}

# ADD TO combined_data_sorted ############################
combined_data_sorted <- rbind(combined_data_sorted, list_data)
combined_data_sorted <- combined_data_sorted[order(as.Date(combined_data_sorted[,4])),]
combined_data_sorted <- combined_data_sorted[order(combined_data_sorted[,1]),]

#Calucalte days per period, and consumption /day  ###########################################################

day_data <- matrix(NA, dim(combined_data_sorted)[1], 1)

for( i in 2:(dim(combined_data_sorted)[1]) ){
	temp_day <- as.Date(combined_data_sorted[i,"Date"])-as.Date(combined_data_sorted[i-1,"Date"])
	day_data[i,1] <- as.numeric(temp_day) }

combined_data_sorted <- cbind(combined_data_sorted, day_data)

cons_day_data <- matrix(NA, dim(combined_data_sorted)[1], 1)
```

```
for( i in 1:(dim(combined_data_sorted)[1]-1) ){
	temp_cons_day <- as.numeric(combined_data_sorted[i,"Consumption_UNITS"]) /
as.numeric(combined_data_sorted[i,11])
	cons_day_data[i,1] <- as.numeric(temp_cons_day)
}

combined_data_sorted <- cbind(combined_data_sorted, cons_day_data)
colnames(combined_data_sorted) <- c("Account_Num", "Seq", "Meter_Name", "Date", "Type", "Meter_Reading",
"PP_Reading", "Consumption_UNITS", "Std_Units", "Name", "Period_Days", "Consumption_Units_Day")

#Remove First Measurement of each meter (day period is unknown)
for( r in 1:(dim(combined_data_sorted)[1]-2) ) {
	if( is.na( combined_data_sorted[r,"Period_Days"]) == T){ next }
	if(  as.numeric( combined_data_sorted[r,"Period_Days"]) <= 0 ){
		combined_data_sorted[r,"Period_Days"] <- NA
		combined_data_sorted[r,"Consumption_Units_Day"] <- NA
	}}

write.csv(combined_data_sorted, file = "RAW_DATA_TEMPEST_ALL.csv")
#write.csv(combined_data_sorted, file = "RAW_DATA_TEMPEST_ALL_2012_2014.csv")
```

R Script 2 – Annual Consumption

This script reads the table of daily consumption values output from R Script 1, and calculates annual values for each meter.

```
setwd(SET_WORKING_DIRECTORY)
raw <- read.csv("DATA_FILE.csv",header = TRUE, sep = ",")
acc <- na.omit( unique(raw[,"Account_Num"]) )

all_cons <- list()
all_cost <- list()
all_names <- list()
all_acc <- list()

#Water Rates (winter, summer)
rates <- read.csv("Water_Rates.csv",header = TRUE, sep = ",")

for( a in 1:length(acc) ){
	#select data for one account
	a_data <- raw[ which( raw[,"Account_Num"] == acc[a] ), ]

	# Separate Date File into day/month/year
	dates <- read.csv("Dates_Future.csv",header = TRUE, sep = ",")
	data_dates <- matrix(NA, dim(dates)[1], 6)
	colnames(data_dates) <- c("Day", "Month", "Year", "Units/Day", "m3/Day", "Residential Costs (2016)")

	for(i in 1:dim(data_dates)[1] ){
		data_dates[i,1] <- as.numeric( unlist( strsplit( as.character(dates[i,1]), split = "[/]" ) )[2] )
		data_dates[i,2] <- as.numeric( unlist( strsplit( as.character(dates[i,1]), split = "[/]" ) )[1] )
		data_dates[i,3] <- as.numeric( unlist( strsplit( as.character(dates[i,1]), split = "[/]" ) )[3] )
	}

	#Match dates
	months <- c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec")
```

```
	for(i in 2:(dim(a_data)[1]-1) ){

	# INDEX FOR THE PERIOD IN QUESTION
		reading_date <- strsplit( as.character(a_data[i,"Date"]), split = "/" )
		month <- as.numeric( unlist(reading_date)[2])

		year <- which( data_dates[,3] == as.numeric(unlist(reading_date)[1] )+2000 )
		day <- year[ which( data_dates[year,"Day"] == as.numeric(unlist(reading_date)[3] ) ) ]
		index <- day[ which( data_dates[day,"Month"] == month ) ]

	# INDEX FOR THE START OF THE NEXT PERIOD
	if( i != length(a_data) ){
		reading_date1 <- strsplit( as.character(a_data[i+1,"Date"]), split = "/" )
		month1 <-		as.numeric( unlist(reading_date1)[2] )

		year1 <- which( data_dates[,3] == as.numeric(unlist(reading_date1)[1] )+2000 )
		day1 <- year1[ which( data_dates[year1,"Day"] == as.numeric(unlist(reading_date1)[3] ) ) ]
		index1 <- day1[ which( data_dates[day1,2] == month1 ) ]
	}}

#DAILY DATA CALCS
jan1 <- matrix(NA, 30, 6)
for( i in 1:30){
	jan1[i,] <- data_dates1[1,]
	jan1[i,1] <- i
	jan1[i,2] <- 1
	jan1[i,3] <- 2012 }

jan <- rbind(jan1, data_dates1)
daily_data <- jan
colnames(daily_data) <- c("Day", "Month", "Year", "Units/Day", "m3/Day", "Residential Costs (2016)")

# Calculate Annual Consumption
years <- unique(daily_data[,"Year"])
annual_data <- matrix(NA, 1, length(years))
colnames(annual_data) <- years
rownames(annual_data) <- "Water Consumption (m3)"

for(y in 1:length(years) ){ annual_data[1,y] <- sum( daily_data[which( daily_data[,"Year"] == years[y] ), "m3/Day"] ) }

# Calculate Annual Costs
years <- unique(daily_data[,"Year"])
annual_data1 <- matrix(NA, 1, length(years))
colnames(annual_data1) <- years
rownames(annual_data1) <- "Water Costs ($)"

for(y in 1:length(years) ){
	annual_data1[1,y] <- sum( daily_data[which( daily_data[,"Year"] == years[y] ), "Residential Costs (2016)"] ) }

all_cons[[a]] <- annual_data
all_cost[[a]] <- annual_data1
all_names[[a]] <- as.character( raw[ which( raw[,"Account_Num"] == acc[a] )[1], "Name" ] )
all_acc[[a]] <- acc[a]

}#Accounts FOR Loop end

# Put all the data into one spreadsheet and export
cons <- matrix(NA, length(all_cons), 7)
cost <- matrix(NA, length(all_cost), 7)

colnames(cons) <- c("Name", "Account_Num", "2012", "2013", "2014", "2015", "2016")
```

```
colnames(cost) <- c("Name", "Account_Num", "2012", "2013", "2014", "2015", "2016")

for( i in 1:length(all_cons) ){

	if( length( all_cons[[i]] ) != 5 ){
		z <- 5 - (length( all_cons[[i]] ) )
		temp <- NA
		temp[1:z] <- 0
		temp[(z+1):5] <- unlist( all_cons[[i]] ) }
	if( length( all_cons[[i]] ) == 5 ){  temp <- unlist( all_cons[[i]] ) }
	cons[i,3:7] <- temp
	cons[i,1] <- all_names[[i]]
	cons[i,2] <- all_acc[[i]]
}

for( i in 1:length(all_cost) ){
	if( length( all_cost[[i]] ) != 5 ){
		z <- 5 - (length( all_cost[[i]] ) )
		temp <- NA
		temp[1:z] <- 0
		temp[(z+1):5] <- unlist( all_cost[[i]] )
	}

	if( length( all_cost[[i]] ) == 5 ){  temp <- unlist( all_cost[[i]] ) }

	cost[i,3:7] <- temp
	cost[i,1] <- all_names[[i]]
	cost[i,2] <- all_acc[[i]]
}
write.csv(cons, file = "Annual_Consumption_All.csv" )
write.csv(cost, file = "Annual_Costs_All.csv" )
```

R Script 3 – Monthly Consumption

This script reads the table of daily consumption values output from R Script 1, and calculates monthly values for each meter.

```
setwd(SET_WORKING_DIRECTORY)

#Water Rates (winter, summer)
rates <- read.csv("Water_Rates.csv",header = TRUE, sep = ",")
raw <- read.csv("DAILY_DATA_FILE.csv",header = TRUE, sep = ",")
acc <- na.omit( unique(raw[,"Account_Num"]) )

# YEARS SET TO 6 (2012-2017)
year_1 <- 6
months <- c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec")
names_y <- "Park Name"
for( yr in 1:year_1 ){
	names_y <- append(names_y, paste("",months,"",years[yr],"", sep=""))
}

all_monthly <- matrix(NA, length(acc), (12*year_1)+1 )
colnames(all_monthly) <- names_y
rownames(all_monthly) <- acc

for( t in 1:length(acc) ){
```

```
#RAW DATA CALCS (isolate account data, from 'raw')
t1 <- raw[ which( raw[,"Account_Num"] == acc[t]), ]
raw_data <- matrix(NA, dim(t1)[1], 11)
colnames(raw_data) <- c("Year", "Period", "Date", "Reading", "Consumption", "Measured In", "Consumption Billed", "Days",
"Units/Day", "Type", "Notes")

for(a in 1:dim(t1)[1] ) {
        raw_data[a,"Year"] <- as.numeric( unlist( strsplit( as.character(t1[a,"Date"]), split = "[/]" ) )[1] ) + 2000
        raw_data[a,"Date"] <- as.character( t1[a,"Date"] )
        raw_data[a,"Reading"] <- t1[a,"Meter_Reading"]
        raw_data[a,"Units/Day"] <- t1[a,"Consumption_Units_Day"]
}

# Separate Date File into day/month/year
dates <- read.csv("Dates_2004_2016.csv",header = TRUE, sep = ",")
data_dates <- matrix(NA, dim(dates)[1], 6)
colnames(data_dates) <- c("Day", "Month", "Year", "Units/Day", "m3/Day", "Residential Costs (2016)")

for(i in 1:dim(data_dates)[1] ){
        data_dates[i,1] <- as.numeric( unlist( strsplit( as.character(dates[i,1]), split = "[/]" ) )[2] )
        data_dates[i,2] <- as.numeric( unlist( strsplit( as.character(dates[i,1]), split = "[/]" ) )[1] )
        data_dates[i,3] <- as.numeric( unlist( strsplit( as.character(dates[i,1]), split = "[/]" ) )[3] )
}

# reverse data set
raw_data <- apply( raw_data, 2, rev)

#Match dates
for(i in 1:dim(raw_data)[1] ){

# INDEX FOR THE PERIOD IN QUESTION
        m <-     as.numeric( unlist( strsplit( as.character(raw_data[i,"Date"]), split = "[/]" ) )[2] )
        y <- as.numeric( unlist( strsplit( as.character(raw_data[i,"Date"]), split = "[/]" ) )[1] ) + 2000
        d <- as.numeric( unlist( strsplit( as.character(raw_data[i,"Date"]), split = "[/]" ) )[3] )

        month <- m
        year <- which( data_dates[,"Year"] == y )
        day <- year[ which( data_dates[year,"Day"] == d ) ]
        index <- day[ which( data_dates[day,"Month"] == month ) ]

# INDEX FOR THE START OF THE NEXT PERIOD
if( i != dim(raw_data)[1] ){
        m1 <- as.numeric( unlist( strsplit( as.character(raw_data[i+1,"Date"]), split = "[/]" ) )[2] )
        y1 <- as.numeric( unlist( strsplit( as.character(raw_data[i+1,"Date"]), split = "[/]" ) )[1] ) + 2000
        d1 <- as.numeric( unlist( strsplit( as.character(raw_data[i+1,"Date"]), split = "[/]" ) )[3] )

        month1 <-        m1
        year1 <- which( data_dates[,3] == y1 )
        day1 <- year1[ which( data_dates[year1,"Day"] == d1 ) ]
        index1 <- day1[ which( data_dates[day1,"Month"] == month1 ) ]
}

        for(p in (index1+1):index ){
        ry <- which( data_dates[p, "Year"] == rates[,"Year"] )

                data_dates[p, "Units/Day"] <- as.numeric( raw_data[i, "Units/Day"] )
                data_dates[p, "m3/Day"] <- as.numeric( raw_data[i, "Units/Day"] ) * 2.83168466
                data_dates[p, "Residential Costs (2016)"] <- if( month == 6 | month == 7 | month == 8 | month == 9 ){
                        as.numeric( raw_data[i, "Units/Day"] ) *  rates[ry,"Summer"] }else{ as.numeric( raw_data[i,
"Units/Day"] ) * rates[ry,"Summer"]  }
```

```
        }}

# Remove Unused Dates (NA)
data_dates1 <- data_dates[complete.cases(data_dates),]

#MONTHLY DATA CALCS
daily_data <- data_dates1
colnames(daily_data) <- c("Day", "Month", "Year", "Units/Day", "m3/Day", "Residential Costs (2016)")

years <- c(2012:2016)
monthly_data <- matrix(NA, 1, 12*year_1)

# Calculate Monthly Consumption (only - costs are next)
colnames(monthly_data) <- names_y[2:length(names_y)]
rownames(monthly_data) <- acc[t]

for(y in 1:length(years) ){
for(m in 1:12 ){
        year_temp <- which( daily_data[,"Year"] == years[y])
        month_temp <- which( daily_data[,"Month"] == m)
        temp <- Reduce(intersect, list(year_temp, month_temp) )

        if( length(year_temp) == 0 ){ monthly_data[1, (m +((y-1)*12)) ] <- NA        }
        if( length(year_temp) != 0 ) { monthly_data[1,(m +((y-1)*12)) ] <- sum( daily_data[ temp, "m3/Day"] ) }
}}

all_monthly[t,1] <- as.character( t1[1,"Name"] )
all_monthly[t,2:dim(all_monthly)[2]] <- monthly_data
print(t)

} # end of ACCOUNT Loop

write.csv(all_monthly, file = " MONTHLY_CONSUMPTION_ALL.csv")
```

R Script 4 – Histogram and Summary

This script reads the table of annual consumption values output from R Script 2, and calculates summary statistics (table output) as well as a histogram.

```
setwd(SET_WORKING_DIRECTORY)
library(ggplot2)
raw <- read.csv("Annual_Consumption_All.csv",header = TRUE, sep = ",")
summary( raw[,"AVE_2012_2014"] )
qplot(raw[,"AVE_2012_2014"], geom="histogram", binwidth = 500, xlab = "Average Water Consumption 2012-2014", ylab =
"Frequency")
```

R Script 5 – Time Series Plots

This script reads the table of daily consumption values output from R Script 1, and plots a time series chart.

```
Setwd(SET_WORKING_DIRECTORY)
```

```
# SELECT ACCOUNT
acc <- 6004130

name_data <- read.csv(paste("DATA_FILE.csv", sep=""),header = TRUE, sep = ",", skip=0, nrows=1)
name <- colnames(name_data)[11]

#Water Rates (winter, summer)
rates <- read.csv("Water_Rates.csv",header = TRUE, sep = ",")

#RAW DATA CALCS
raw_data <- read.csv(paste("DATA_FILE.csv ", sep=""),header = TRUE, sep = ",", skip=1)
colnames(raw_data) <- c("Year", "Period", "Date", "Reading", "Consumption", "Measured In", "Consumption Billed", "Days",
"Units/Day", "Type", "Notes")

# Separate Date File into day/month/year
dates <- read.csv("Dates_Future.csv",header = TRUE, sep = ",") #1995-2017
data_dates <- matrix(NA, dim(dates)[1], 6)
colnames(data_dates) <- c("Day", "Month", "Year", "Units/Day", "m3/Day", "Residential Costs (2016)")

for( n in 1:dim(data_dates)[1] ){
		data_dates[n,1] <- as.numeric( unlist( strsplit( as.character(dates[n,1]), split = "[/]" ) )[2] )
		data_dates[n,2] <- as.numeric( unlist( strsplit( as.character(dates[n,1]), split = "[/]" ) )[1] )
		data_dates[n,3] <- as.numeric( unlist( strsplit( as.character(dates[n,1]), split = "[/]" ) )[3] )  }

#Match dates
months <- c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec")

for(q in 1:dim(raw_data)[1] ){
# INDEX FOR THE PERIOD IN QUESTION
		reading_date <- strsplit( as.character(raw_data[q,3]), split = "[-]" )
		month <- which( unlist(reading_date)[2] == months )

		year <- which( data_dates[,3] == as.numeric(unlist(reading_date)[3] ) +2000 )
		day <- year[ which( data_dates[year,"Day"] == as.numeric(unlist(reading_date)[1] ) ) ]
		index <- day[ which( data_dates[day,"Month"] == month ) ]

# INDEX FOR THE START OF THE NEXT PERIOD
if( q != dim(raw_data)[1] ){
		reading_date1 <- strsplit( as.character(raw_data[q+1,3]), split = "[-]" )
		month1 <-		which( unlist(reading_date1)[2] == months )

		year1 <- which( data_dates[,3] == as.numeric(unlist(reading_date1)[3] ) +2000 )
		day1 <- year1[ which( data_dates[year1,"Day"] == as.numeric(unlist(reading_date1)[1] ) ) ]
		index1 <- day1[ which( data_dates[day1,"Month"] == month1 ) ]
}
		for(p in (index1+1):index ){

 ry <- which( data_dates[p, "Year"] == rates[,"Year"] )
				data_dates[p, "Units/Day"] <- raw_data[i, "Units/Day"]
				data_dates[p, "m3/Day"] <- ( raw_data[i, "Units/Day"] ) * 2.83168466
				data_dates[p, "Residential Costs (2016)"] <- if( month == 6 | month == 7 | month == 8 | month == 9 ){
						( raw_data[i, "Units/Day"] ) *  rates[ry,"Summer"] }else{( raw_data[i, "Units/Day"] ) *
rates[ry,"Winter"]  }
		}}

# Remove Unused Dates (NA)
data_dates1 <- data_dates[complete.cases(data_dates),]

#DAILY DATA CALCS
daily_data <- data_dates1
colnames(daily_data) <- c("Day", "Month", "Year", "Units/Day", "m3/Day", "Residential Costs (2016)")
```

```
# Calculate Annual Consumption
years <- unique(daily_data[,"Year"])
annual_data <- matrix(NA, 2, length(years))
colnames(annual_data) <- years
rownames(annual_data) <- c("Water Consumption (m3)", "Water Costs ($)")

for(y in 1:length(years) ){
	annual_data[1,y] <- sum( daily_data[which( daily_data[,"Year"] == years[y] ), "m3/Day"] )
	annual_data[2,y] <- sum( daily_data[which( daily_data[,"Year"] == years[y] ), "Residential Costs (2016)"] )  }

# Calculate Monthly Consumption (only - costs are next)
months <- c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec")

years <- unique(daily_data[,"Year"])
monthly_data <- matrix(NA, length(years), 12)
colnames(monthly_data) <- months
rownames(monthly_data) <- years

for(y in 1:length(years) ){
for(m in 1:12 ){
	year_temp <- which( daily_data[,"Year"] == years[y] )
	monthly_data[y,m] <- sum( daily_data[ year_temp[ which( daily_data[year_temp, "Month"] == m ) ], "m3/Day"] )
}}

# Calculate Monthly Costs
years <- unique(daily_data[,"Year"])
monthly_costs <- matrix(NA, length(years), 12)
colnames(monthly_costs) <- months
rownames(monthly_costs) <- years

for(y in 1:length(years) ){
for(m in 1:12 ){
	year_temp <- which( daily_data[,"Year"] == years[y] )
	monthly_costs[y,m] <- sum( daily_data[ year_temp[ which( daily_data[year_temp, "Month"] == m ) ], "Residential
Costs (2016)"] )
}}

#include high-low limits in plot
high_low <- read.csv("High_Low_Limits.csv",header = TRUE, sep = ",")

### PLOT
jan1 <- which(data_dates1[,"Day"] == 1 & data_dates1[,"Month"] == 1)
years_1 <- unique(data_dates1[,"Year"] )
if( length(jan1) != length(years_1) ) { years_1 <- years_1[2:length(years_1)] }

pdf(paste("",name,"_",acc,"_Plot.pdf", sep="") )
par(mfrow=c(2,1))

library(plotrix)
plot((1:dim(data_dates1)[1]), data_dates1[,"m3/Day"], type = "l", xlab = "", ylab = "Water Consumption (m3/Day)",
		main = paste("",name," - ",acc,"", sep=""), lwd = 4, col = "#08306b", xaxt = 'n',
		cex.main = 0.7, cex.axis = 0.7, cex.lab = 0.7)
polygon( c((1:dim(data_dates1)[1]), (1:dim(data_dates1)[1])[length(1:dim(data_dates1)[1])]),
			c(data_dates1[,"m3/Day"], data_dates1[,"m3/Day"][1]), col = "#6baed6", border = NA)
axis(1, at = jan1, labels = years_1, cex.axis = 0.7)
abline( v = jan1, lwd = 0.5, col = "gray")
#abline( h = c(seq(0,max(data_dates1[,"m3/Day"]),100)), lwd = 0.5, col = "gray")

#include high limits in chart
#abline( h = 2.83168466 * high_low[ which( high_low[ ,"Account.Num"] == acc ), "Summer.High" ], col = "red")
```

```
#abline( h = 2.83168466 * high_low[ which( high_low[ ,"Account.Num"] == acc ), "Winter.High" ], col = "blue")

addtable2plot( -400 , ( max(data_dates1[,"m3/Day"])*-0.7), round(annual_data,0),bty="o", display.rownames=T, hlines=TRUE,
        vlines=TRUE,title="Annual Data", cex = 0.5, xpad = 0.7, ypad = 0.7)

dev.off()
```

R Script 6 – Normal Consumption Range Limits

This script reads the table of daily consumption values output from R Script 1, and calculates the high and low limits for the normal consumption range.

```
setwd(SET_WORKING_DIRECTORY)
raw <- read.csv("DATA_FILE.csv",header = TRUE, sep = ",")

# how many std. dev.
stdev_l <- 2

# For EACH ACCOUNT
accounts <- na.omit( unique( raw[, "Account_Num"] ) )
park_names <- unique( raw[, "Name"] )
high_low <- matrix(NA,length(accounts), 8)
colnames(high_low) <- c("Name", "Account Num", "Summer Ave", "Summer High", "Summer Low", "Winter Ave", "Winter
High", "Winter Low")

#Water Rates (winter, summer)
rates <- read.csv("Water_Rates.csv",header = TRUE, sep = ",")

for(a in 1:length(accounts)) {
a_data <- which( raw[, "Account_Num"] == accounts[a] )

# Separate Date File into day/month/year
dates <- read.csv("Dates_2004_2016.csv",header = TRUE, sep = ",")
data_dates <- matrix(NA, dim(dates)[1], 6)
colnames(data_dates) <- c("Day", "Month", "Year", "Units/Day", "m3/Day", "Residential Costs (2016)")

for(i in 1:dim(data_dates)[1] ){
        data_dates[i,1] <- as.numeric( unlist( strsplit( as.character(dates[i,1]), split = "[/]" ) )[2] )
        data_dates[i,2] <- as.numeric( unlist( strsplit( as.character(dates[i,1]), split = "[/]" ) )[1] )
        data_dates[i,3] <- as.numeric( unlist( strsplit( as.character(dates[i,1]), split = "[/]" ) )[3] )
}

#Match dates
months <- c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec")

for(i in 1:length(a_data) ){
# INDEX FOR THE PERIOD IN QUESTION
        reading_date <- strsplit( as.character(raw[a_data[i],"Date"]), split = "/" )
        month <- as.numeric( unlist(reading_date)[2])

        year <- which( data_dates[,"Year"] == as.numeric(unlist(reading_date)[1] )+2000 )
        day <- year[ which( data_dates[year,"Day"] == as.numeric(unlist(reading_date)[3] ) ) ]
        index <- day[ which( data_dates[day,"Month"] == month ) ]

# INDEX FOR THE START OF THE NEXT PERIOD
if( i != length(a_data) ){
        reading_date1 <- strsplit( as.character(raw[a_data[i]+1,"Date"]), split = "/" )
```

```
        month1 <-          as.numeric( unlist(reading_date1)[2] )

        year1 <- which( data_dates[,"Year"] == as.numeric(unlist(reading_date1)[1] )+2000 )
        day1 <- year1[ which( data_dates[year1,"Day"] == as.numeric(unlist(reading_date1)[3] ) ) ]
        index1 <- day1[ which( data_dates[day1,2] == month1 ) ]
        }

        for(p in (index1):index+1 ){
                data_dates[p, "Units/Day"] <- raw[a_data[i], "Consumption_Units_Day"]
                data_dates[p, "m3/Day"] <- ( raw[a_data[i], "Consumption_Units_Day"] ) * 2.83168466
        }}

# Remove Unused Dates (NA)
data_dates1 <- data_dates[complete.cases(data_dates),]

####Caluclate Summer/Winter Averages
summer_data <- which( data_dates1[ , "Month"] == 6 | data_dates1[ , "Month"] == 7 | data_dates1[ , "Month"] == 8  |
data_dates1[ , "Month"] == 9)
winter_data <- which( data_dates1[ , "Month"] == 1 | data_dates1[ , "Month"] == 2 | data_dates1[ , "Month"] == 3 | data_dates1[
, "Month"] == 4 | data_dates1[ , "Month"] == 5 | data_dates1[ , "Month"] == 10 | data_dates1[ , "Month"] == 11 | data_dates1[ ,
"Month"] == 12)

summer_ave <- mean( na.omit( data_dates1[summer_data, "Units/Day"] ))
winter_ave <- mean( na.omit( data_dates1[winter_data, "Units/Day"] ))

summer_sd <- sd( na.omit( data_dates1[summer_data, "Units/Day"] ))
winter_sd <- sd( na.omit( data_dates1[winter_data, "Units/Day"] ))

# CALCULATE LIMITS #################
high_low[a,1] <- as.character(park_names[a])
high_low[a,2] <- accounts[a]

        high_low[a,3] <- summer_ave
        high_low[a,4] <- summer_ave + ( summer_sd * stdev_l )

        if( is.na(summer_ave) == F) {
        high_low[a,5] <- if( ( summer_ave - (summer_sd * stdev_l) )  < 1 ) { 0 }
                                                        else{ ( summer_ave - (summer_sd * stdev_l) ) }
        }else { high_low[a,5] <- NA }

        high_low[a,6] <- winter_ave
        high_low[a,7] <- winter_ave + ( winter_sd * stdev_l)

        if( is.na(winter_ave) == F) {
        high_low[a,8] <- if( ( winter_ave - (winter_sd * stdev_l) )  < 1 ) { 0
                                                        }else{ ( winter_ave - (winter_sd * stdev_l) ) }
        } else { high_low[a,8] <- NA }
}
write.csv(high_low, file = "High_Low_Limits.csv")
```

R Script 7 – Normal Consumption Report and Charts

This script reads the table of normal consumption limits output from R Script 6 and a table of specific meter reading raw data output from the database to determine which meters’ consumption falls outside the normal range (output is a table of ‘flagged’ meters). The script also creates a time series plot of each flagged meter using the daily consumption values output from R Script 1.

```
setwd(SET_WORKING_DIRECTORY)
reading_period <- c(2016, 2)

summer_months <- c(6:9)
winter_months <- c(1:5, 10:12)
summer_after <- 5
summer_before <- 10

#Water Rates (winter, summer)
rates <- read.csv("Water_Rates.csv",header = TRUE, sep = ",")

con <- file(paste("DATA_FILE_",reading_period[1],"_",reading_period[2],".txt", sep=""), open="rt", raw=TRUE)
text <- readLines(con, skipNul = TRUE)
meter_names <- read.csv("Meter_Names.csv",header = TRUE, sep = ",")
separated <- strsplit(unlist(text), split = " ")
lines <- NULL

check.numeric <- function(N){ !length(grep("[^[:digit:]]", as.character(N)))  }

for(l in 1:length(separated)){
        if(length(separated[[l]]) == 0){next
        }else if(check.numeric(separated[[l]][which(separated[[l]] != "")[1]]) == TRUE && separated[[l]][which(separated[[l]]
!= "")[1]] > 5000000){
        lines <- append(lines, l)
        }else {next}        }

data <- matrix(NA, length(lines), 10)

for(l in 1:length(lines) ){
        location <- which(separated[[lines[l]]] != "")
        temp <- list()

        for( p in 1:length(location) ){  temp[[p]] <- separated[[lines[l]]][location[p]] }
        data[l,1:3] <- as.numeric(unlist(temp[1:3]))
        data[l,4:5] <- unlist(temp[4:5])
        data[l,6:9] <- as.numeric(unlist(temp[6:9]))
        data[l,10] <- if( typeof( as.character( meter_names$Tempest_Name[ which(meter_names$Tempest_Account ==
as.numeric(unlist(temp[1])) ) ] )        ) == "character"
                                && length( as.character( meter_names$Tempest_Name[
which(meter_names$Tempest_Account == as.numeric(unlist(temp[1])) ) ] ) ) == 0 ){ "Unknown"
                                }else{ as.character( meter_names$Tempest_Name[
which(meter_names$Tempest_Account == as.numeric(unlist(temp[1])) ) ] ) }}
        new_period <- NULL
        new_period <- rbind(new_period, data)
        closeAllConnections()

new_period_sorted <- new_period[order(new_period[,1]),]
colnames(new_period_sorted) <- c("Account_Num", "Seq", "Meter_Name", "Date", "Type", "Meter_Reading", "PP_Reading",
"Consumption_UNITS", "Std_Units", "Name")

# Determine Actual Month of Period
actual_month <- as.numeric( unlist( strsplit( new_period_sorted[1,"Date"], split = "/" ) )[2] )
        high_low <- read.csv("High_Low_Limits.csv",header = TRUE, sep = ",")
park_accounts <- high_low[,"Account.Num"]
park_names <- high_low[,"Name"]
parks_data <- matrix(NA, 0, 6)
```

```
colnames(parks_data) <- c("Name", "Account Num", "Date", "Consumption", "Days", "Cons Per Day" )
temp1 <- list()

# Determine Days in Period
cds <- read.csv("RAW_DATA_TEMPEST_ALL.csv",header = TRUE, sep = ",")
for( p in 1:length(park_accounts) ) {
if( length( which( as.numeric( new_period_sorted[, "Account_Num"] ) == park_accounts[p] ) ) != 0 ){
        index <- which( as.numeric( new_period_sorted[, "Account_Num"] ) == park_accounts[p] )
        for(g in 1:length(index)){
                name1 <- as.character( park_names[p] )
                account1 <- as.numeric(as.character( new_period_sorted[index[g], "Account_Num"] ))
                date1 <- as.character( new_period_sorted[index[g], "Date"] )
                cons1 <- as.numeric(as.character( new_period_sorted[index[g], "Consumption_UNITS"] ))

                temps <- which( cds[ ,"Account_Num"] == new_period_sorted[index[g], "Account_Num"] )

                dates <- strsplit( as.character( cds[temps,"Date"]), split = "/" )
                date11 <- strsplit( date1, split = "/" )
                d1 <- NULL
                for(d in 1:length(temps) ){
                        if( ( as.numeric(dates[[d]][1]) ) == as.numeric(date11[[1]][1]) ){ d1 <- append(d1,d) }
                        if( ( dates[[d]][2] ) == as.numeric(date11[[1]][2]) ){ d1 <- append(d1,d) }}
                ind <- d1[ which( duplicated(d1) ) ]

                days1 <- cds[ temps[ind], "Period_Days"]
                cons_day1 <- cons1 / days1

                temp1[[1]] <- name1
                temp1[[2]] <- account1
                temp1[[3]] <- date1
                temp1[[4]] <- cons1
                temp1[[5]] <- days1
                temp1[[6]] <- cons_day1

                if( length(unlist(temp1)) == 6 ){
                        parks_data <- rbind(parks_data, unlist(temp1))
                }                       }}}

###  DETERMINE IF PARK IS HIGH OR LOW   ##########################
high_parks <- matrix(NA, 0, 8)
colnames(high_parks) <- c("Name", "Account Num", "Date", "Consumption", "Days", "Cons Per Day", "Exceeded Limit",
"Backflow?" )
low_parks <- matrix(NA, 0, 8)
colnames(low_parks) <- c("Name", "Account Num", "Date", "Consumption", "Days", "Cons Per Day", "Exceeded Limit",
"Backflow?" )

for( i in 1:dim(parks_data)[1] ) {
        month_check <- as.numeric( unlist( strsplit( parks_data[i,"Date"] , split = "/") )[2] )
        temp_s_high <- high_low[ which( parks_data[i,"Account Num"] == high_low[, "Account.Num"] ), "Summer.High"]
        temp_s_low <- high_low[ which( parks_data[i,"Account Num"] == high_low[, "Account.Num"] ), "Summer.Low"]
        temp_w_high <- high_low[ which( parks_data[i,"Account Num"] == high_low[, "Account.Num"] ), "Winter.High"]
        temp_w_low <- high_low[ which( parks_data[i,"Account Num"] == high_low[, "Account.Num"] ), "Winter.Low"]
        limit_s <- NULL
        limit_w <- NULL

if( is.na( as.numeric(parks_data[i,"Cons Per Day"]) ) == F ){
        if(  as.numeric(parks_data[i,"Cons Per Day"]) >
                if( month_check > summer_after && month_check < summer_before ){ temp_s_high }else{temp_w_high} )
{
                limit_h <- parks_data[i,]
```

```
			limit_h <- append( limit_h, if( month_check > summer_after & month_check < summer_before){
temp_s_high }else{temp_w_high})
			high_parks <- rbind(high_parks, limit_h)}
		if(  as.numeric(parks_data[i,"Cons Per Day"]) <
			if( month_check > summer_after && month_check < summer_before){ temp_s_low }else{temp_w_low} ) {
			limit_l <- parks_data[i,]
			limit_l <- append( limit_l, if( month_check > summer_after & month_check < summer_before){ temp_s_low
}else{temp_w_low})
			low_parks <- rbind(low_parks, limit_l)
			}		}
}# End of Loop

################## HIGH PARK CHARTS
raw <- read.csv("DATA_FILE..csv",header = TRUE, sep = ",")

high_parks_a <- high_parks[,"Account Num"]
high_parks_n <- high_parks[,"Name"]
high_list <- list()
high_list_day <- list()
y2 <- list()
m2 <- list()
years1 <- list()
year_num <- list()

# For EACH ACCOUNT
accounts <- na.omit( unique( raw[, "Account_Num"] ) )
park_names <- unique( raw[, "Name"] )
#high_low <- matrix(NA,length(accounts), 8)
#colnames(high_low) <- c("Name", "Account Num", "Summer Ave", "Summer High", "Summer Low", "Winter Ave", "Winter
High", "Winter Low")

for(a in 1:length(high_parks_a) ){
a_data <- which( raw[, "Account_Num"] == high_parks_a[a] )

# Determine if the high parks are due to a backflow event
if( raw[a_data[length(a_data)], "Meter_Reading" ] < raw[a_data[length(a_data)-1], "Meter_Reading" ] ){
		high_parks[a,"Backflow?"] <- "Y"
}else{ high_parks[a,"Backflow?"] <- "N" }

# Separate Date File into day/month/year
dates <- read.csv("Dates_2004_2016.csv",header = TRUE, sep = ",")
data_dates <- matrix(NA, dim(dates)[1], 6)
colnames(data_dates) <- c("Day", "Month", "Year", "Units/Day", "m3/Day", "Residential Costs (2016)")

for(i in 1:dim(data_dates)[1] ){
		data_dates[i,1] <- as.numeric( unlist( strsplit( as.character(dates[i,1]), split = "[/]" ) )[2] )
		data_dates[i,2] <- as.numeric( unlist( strsplit( as.character(dates[i,1]), split = "[/]" ) )[1] )
		data_dates[i,3] <- as.numeric( unlist( strsplit( as.character(dates[i,1]), split = "[/]" ) )[3] ) }

#Match dates
months <- c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec")
for(i in 2:(length(a_data)-1) ){
# INDEX FOR THE PERIOD IN QUESTION
		reading_date <- strsplit( as.character(raw[a_data[i],"Date"]), split = "/" )
		month <- as.numeric( unlist(reading_date)[2])
		year <- which( data_dates[,3] == as.numeric(unlist(reading_date)[1] )+2000 )
		day <- year[ which( data_dates[year,"Day"] == as.numeric(unlist(reading_date)[3] ) ) ]
		index <- day[ which( data_dates[day,"Month"] == month ) ]

# INDEX FOR THE START OF THE NEXT PERIOD
if( i != length(a_data) ){
```

```
		reading_date1 <- strsplit( as.character(raw[a_data[i]+1,"Date"]), split = "/" )
		month1 <-		as.numeric( unlist(reading_date1)[2] )
		year1 <- which( data_dates[,3] == as.numeric(unlist(reading_date1)[1] )+2000 )
		day1 <- year1[ which( data_dates[year1,"Day"] == as.numeric(unlist(reading_date1)[3] ) ) ]
		index1 <- day1[ which( data_dates[day1,2] == month1 ) ] }

		for(p in (index1):(index + 1) ){
		ry <- which( data_dates[p, "Year"] == rates[,"Year"] )
			data_dates[p, "Units/Day"] <- raw[a_data[i]+1, "Consumption_Units_Day"]
			data_dates[p, "m3/Day"] <- ( raw[a_data[i]+1, "Consumption_Units_Day"] ) * 2.83168466
			data_dates[p, "Residential Costs (2016)"] <-
					if( month == 6 | month == 7 | month == 8 | month == 9 )
						{( raw[a_data[i]+1, "Consumption_Units_Day"] ) *  rates[ry,"Summer"] }
					else{( raw[a_data[i]+1, "Consumption_Units_Day"] ) * rates[ry,"Winter"] }
		}}

# Remove Unused Dates (NA)
data_dates1 <- data_dates[complete.cases(data_dates),]

#DAILY DATA CALCS
daily_data <- data_dates1
colnames(daily_data) <- c("Day", "Month", "Year", "Units/Day", "m3/Day", "Residential Costs (2016)")

# Calculate Annual Consumption
years <- unique(daily_data[,"Year"])
annual_data <- matrix(NA, 2, length(years))
colnames(annual_data) <- years
rownames(annual_data) <- c("Water Consumption (m3)", "Water Costs ($)")

for(y in 1:length(years) ){
		annual_data[1,y] <- sum( daily_data[which( daily_data[,"Year"] == years[y] ), "m3/Day"] )
		annual_data[2,y] <- sum( daily_data[which( daily_data[,"Year"] == years[y] ), "Residential Costs (2016)"] ) }

# Calculate Monthly Consumption
months <- c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec")
years <- unique(daily_data[,"Year"])
monthly_data <- matrix(NA, length(years), 12)
colnames(monthly_data) <- months
rownames(monthly_data) <- years

for(y in 1:length(years) ){
for(m in 1:12 ){
		year_temp <- which( daily_data[,"Year"] == years[y] )
		monthly_data[y,m] <- sum( daily_data[ year_temp[ which( daily_data[year_temp, "Month"] == m ) ], "m3/Day"] )  }}

# Calculate Monthly Costs
years <- unique(daily_data[,"Year"])
monthly_costs <- matrix(NA, length(years), 12)
colnames(monthly_costs) <- months
rownames(monthly_costs) <- years

for(y in 1:length(years) ){
for(m in 1:12 ){
		year_temp <- which( daily_data[,"Year"] == years[y] )
		monthly_costs[y,m] <- sum( daily_data[ year_temp[ which( daily_data[year_temp, "Month"] == m ) ], "Residential
Costs (2016)"] ) }}

high_list[[a]] <- monthly_data
high_list_day[[a]] <- daily_data[,"m3/Day"]

y2[[a]] <- which( daily_data[,"Year"] == reading_period[1] )
```

```
m2[[a]] <- y2[[a]][ which( daily_data[unlist(y2[[a]]),"Month"] == actual_month ) ][1]
years1[[a]] <- unique(daily_data[,"Year"])
temp1 <- NULL

for( y in 1:length(unlist(years1[[a]]))){ temp1[y] <- which( daily_data[,"Year"] == years1[[a]][y] ) [1] }
        year_num[[a]] <- temp1 }
write.csv(high_parks, file = paste("High_Low_Reports\\",reading_period[1],"_",reading_period[2],"_High_Parks_Report.csv",
sep="") )
write.csv(low_parks, file =   paste("High_Low_Reports\\",reading_period[1],"_",reading_period[2],"_Low_Parks_Report.csv",
sep="") )

# PLOTS - MONTHLY PLOTS /YEAR
pdf(paste("High_Low_Reports\\",reading_period[1],"_",reading_period[2],"_High_Month.pdf", sep="") )

par(mfrow=c(2,2))
for(c in 1:length(high_list) ){
all <- NULL
y1 <- which(rownames(high_list[[c]]) == reading_period[1])
m1 <- actual_month
ii <- m1 + ((y1) * 12) -12

for(l in 1:length(high_list[[c]][,1]) ){ all <- append(all, unlist(high_list[[c]][l,])) }
yrange <- range(all)
plot(1:length(all), all, type = "l", xlab = "Year", ylab = "Water Consumption (m3/month)", ylim = c( 0, yrange[2]), lwd = 2,
cex.main = 0.8, xaxt = 'n', main = paste("",high_parks_n[c]," - ",as.numeric(high_parks[c,2]),"", sep="") )
axis(1, at = c(seq(12,(length(years1[[c]]))*12, 12)), labels = ( years1[[c]][1:length(years1[[c]])] + 1) )
abline(v = ii, col = "blue")

if( actual_month == 6 | actual_month == 7 | actual_month == 8 | actual_month == 9){
        abline( h = 2.83168466 * as.numeric( high_low[ which( high_low[ ,3] == as.numeric(high_parks[c,"Account Num"]) ),
5 ] ), col = "red")
}else { abline( h = 2.83168466 * as.numeric( high_low[ which( high_low[ ,3] == as.numeric(high_parks[c,"Account Num"]) ), 8
] ), col = "red") }

if( high_parks[c, "Backflow?"] == "Y" ){ mtext("Backflow Event", side=3, cex=0.7) }
}
dev.off()

# DAILY PLOTS /YEAR
pdf(paste("High_Low_Reports\\",reading_period[1],"_",reading_period[2],"_High_Day.pdf", sep="") )
par(mfrow=c(2,2))
for(c in 1:length(high_list_day) ){
yrange <- range(high_list_day[[c]])
plot(1:length(high_list_day[[c]]), high_list_day[[c]], type = "l", xlab = "Year", cex.axis = 0.8, cex.main = 0.8,
                ylab = "Water Consumption (m3/day)", ylim = c( 0, yrange[2]), lwd = 0.001, xaxt = 'n',
                main = paste("",high_parks_n[c]," - ",as.numeric(high_parks[c,2]),"", sep="") )
axis(1, at = c(year_num[[c]][2:length(year_num[[c]])]), labels = years1[[c]][2:length(years1[[c]])] )
abline(v = (m2[[c]] + 15), col = "blue")

if( actual_month == 6 | actual_month == 7 | actual_month == 8 | actual_month == 9){
        abline( h = 2.83168466 * as.numeric( high_low[ which( high_low[ ,3] == as.numeric( high_parks[c,"Account Num"]) )
, 5 ] ), col = "red")
}else { abline( h = 2.83168466 * as.numeric( high_low[ which( high_low[ ,3] == as.numeric(high_parks[c,"Account Num"]) ), 8
] ), col = "red") }

if( high_parks[c, "Backflow?"] == "Y" ){
        mtext("Backflow Event", side=3, cex=0.7)
}}
dev.off()

####### LOW PARK CHARTS
```

```
raw <- read.csv("DATA_FILE.csv",header = TRUE, sep = ",")
low_parks_a <- low_parks[,"Account Num"]
low_parks_n <- low_parks[,"Name"]
low_list <- list()
low_list_day <- list()
y2 <- list()
m2 <- list()
years1 <- list()
year_num <- list()

# For EACH ACCOUNT
accounts <- na.omit( unique( raw[, "Account_Num"] ) )
park_names <- unique( raw[, "Name"] )
#high_low <- matrix(NA,length(accounts), 8)
#colnames(high_low) <- c("Name", "Account Num", "Summer Ave", "Summer High", "Summer Low", "Winter Ave", "Winter High", "Winter Low")

for(a in 1:length(low_parks_a) ){
a_data <- which( raw[, "Account_Num"] == low_parks_a[a] )

# Determine if the high parks are due to a backflow event
if( raw[a_data[length(a_data)], "Meter_Reading" ] < raw[a_data[length(a_data)-1], "Meter_Reading" ] ){
        low_parks[a,"Backflow?"] <- "Y"
}else{ low_parks[a,"Backflow?"] <- "N" }

# Separate Date File into day/month/year
dates <- read.csv("Dates_2004_2016.csv",header = TRUE, sep = ",")
data_dates <- matrix(NA, dim(dates)[1], 6)
colnames(data_dates) <- c("Day", "Month", "Year", "Units/Day", "m3/Day", "Residential Costs (2016)")

for(i in 1:dim(data_dates)[1] ){
        data_dates[i,1] <- as.numeric( unlist( strsplit( as.character(dates[i,1]), split = "[/]" ) )[2] )
        data_dates[i,2] <- as.numeric( unlist( strsplit( as.character(dates[i,1]), split = "[/]" ) )[1] )
        data_dates[i,3] <- as.numeric( unlist( strsplit( as.character(dates[i,1]), split = "[/]" ) )[3] ) }

months <- c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec")

for(i in 1:length(a_data) ){
# INDEX FOR THE PERIOD IN QUESTION
        reading_date <- strsplit( as.character(raw[a_data[i],"Date"]), split = "/" )
        month <- as.numeric( unlist(reading_date)[2])

        year <- which( data_dates[,3] == as.numeric(unlist(reading_date)[1] )+2000 )
        day <- year[ which( data_dates[year,"Day"] == as.numeric(unlist(reading_date)[3] ) ) ]
        index <- day[ which( data_dates[day,"Month"] == month ) ]

# INDEX FOR THE START OF THE NEXT PERIOD
if( i != length(a_data) ){
        reading_date1 <- strsplit( as.character(raw[a_data[i]+1,"Date"]), split = "/" )
        month1 <-               as.numeric( unlist(reading_date1)[2] )

        year1 <- which( data_dates[,3] == as.numeric(unlist(reading_date1)[1] )+2000 )
        day1 <- year1[ which( data_dates[year1,"Day"] == as.numeric(unlist(reading_date1)[3] ) ) ]
        index1 <- day1[ which( data_dates[day1,2] == month1 )
 }
        for(p in (index1):(index + 1) ){
        ry <- which( data_dates[p, "Year"] == rates[,"Year"] )
                data_dates[p, "Units/Day"] <- raw[a_data[i]+1, "Consumption_Units_Day"]
                data_dates[p, "m3/Day"] <- ( raw[a_data[i]+1, "Consumption_Units_Day"] ) * 2.83168466
                data_dates[p, "Residential Costs (2016)"] <-
                                if( month == 6 | month == 7 | month == 8 | month == 9 )
```

```
                                        {( raw[a_data[i]+1, "Consumption_Units_Day"] ) *  rates[ry,"Summer"] }
                                else{( raw[a_data[i]+1, "Consumption_Units_Day"] ) * rates[ry,"Winter"] }
        }}

# Remove Unused Dates (NA)
data_dates1 <- data_dates[complete.cases(data_dates),]

#DAILY DATA CALCS
daily_data <- data_dates1
colnames(daily_data) <- c("Day", "Month", "Year", "Units/Day", "m3/Day", "Residential Costs (2016)")

# Calculate Annual Consumption
years <- unique(daily_data[,"Year"])
annual_data <- matrix(NA, 2, length(years))
colnames(annual_data) <- years
rownames(annual_data) <- c("Water Consumption (m3)", "Water Costs ($)")

for(y in 1:length(years) ){
        annual_data[1,y] <- sum( daily_data[which( daily_data[,"Year"] == years[y] ), "m3/Day"] )
        annual_data[2,y] <- sum( daily_data[which( daily_data[,"Year"] == years[y] ), "Residential Costs (2016)"] ) }

# Calculate Monthly Consumption
months <- c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec")

years <- unique(daily_data[,"Year"])
monthly_data <- matrix(NA, length(years), 12)
colnames(monthly_data) <- months
rownames(monthly_data) <- years

for(y in 1:length(years) ){
for(m in 1:12 ){
        year_temp <- which( daily_data[,"Year"] == years[y] )
        monthly_data[y,m] <- sum( daily_data[ year_temp[ which( daily_data[year_temp, "Month"] == m ) ], "m3/Day"] ) }}

# Calculate Monthly Costs
years <- unique(daily_data[,"Year"])
monthly_costs <- matrix(NA, length(years), 12)
colnames(monthly_costs) <- months
rownames(monthly_costs) <- years

for(y in 1:length(years) ){
for(m in 1:12 ){
        year_temp <- which( daily_data[,"Year"] == years[y] )
        monthly_costs[y,m] <- sum( daily_data[ year_temp[ which( daily_data[year_temp, "Month"] == m ) ], "Residential
Costs (2016)"] ) }}

low_list[[a]] <- monthly_data
low_list_day[[a]] <- daily_data[,"m3/Day"]

y2[[a]] <- which( daily_data[,"Year"] == reading_period[1] )
m2[[a]] <- y2[[a]][ which( daily_data[unlist(y2[[a]]),"Month"] == actual_month ) ][1]

years1[[a]] <- unique(daily_data[,"Year"])
temp1 <- NULL

for( y in 1:length(unlist(years1[[a]]))){
        temp1[y] <- which( daily_data[,"Year"] == years1[[a]][y] ) [1] }
        year_num[[a]] <- temp1 }

# PLOTS - MONTHLY PLOTS /YEAR
pdf(paste("High_Low_Reports\\",reading_period[1],"_",reading_period[2],"_Low_Month.pdf", sep="") )
```

```
par(mfrow=c(2,2))

for(c in 1:length(low_list) ){
all <- NULL
y1 <- which(rownames(low_list[[c]]) == reading_period[1])
m1 <- actual_month
ii <- m1 + ((y1) * 12)-12

for(l in 1:length(low_list[[c]][,1]) ){ all <- append(all, unlist(low_list[[c]][l,])) }
yrange <- range(all)
plot(1:length(all), all, type = "l", xlab = "Year", ylab = "Monthly Water Consumption (m3)", ylim = c( 0, yrange[2]), lwd = 2,
cex.main = 0.8, xaxt = 'n',
                          main = paste("",low_parks_n[c]," - ",as.numeric(high_parks[c,2]),"", sep="") )
axis(1, at = c(seq(12,(length(years1[[c]]))*12, 12)), labels = (years1[[c]][1:length(years1[[c]])] + 1) )
abline(v = ii, col = "blue")

if( actual_month == 6 | actual_month == 7 | actual_month == 8 | actual_month == 9){
            abline( h = 2.83168466 * high_low[ which( high_low[ ,3] == as.numeric(low_parks[c,"Account Num"]) ), 6 ], col =
"red")
}else { abline( h = 2.83168466 * high_low[ which( high_low[ ,3] == as.numeric(low_parks[c,"Account Num"]) ), 9 ], col =
"red") }
}
dev.off()

# DAILY PLOTS /YEAR
pdf(paste("High_Low_Reports\\",reading_period[1],"_",reading_period[2],"_Low_Day.pdf", sep="") )
par(mfrow=c(2,2))
for(c in 1:length(low_list_day) ){
yrange <- range(low_list_day[[c]])
plot(1:length(low_list_day[[c]]), low_list_day[[c]], type = "l", xlab = "Year", cex.axis = 0.8,  cex.lab = 0.8, cex.main = 0.8,
                          ylab = "Water Consumption (m3/day)", ylim = c( 0, yrange[2]), lwd = 0.001, xaxt = 'n',
                          main = paste("",low_parks_n[c]," - ",as.numeric(high_parks[c,2]),"", sep="") )
axis(1, at = c(year_num[[c]][2:length(year_num[[c]])]), labels = years1[[c]][2:length(years1[[c]])], cex.axis = 0.8, cex.lab = 0.8  )
abline(v = (m2[[c]] + 15), col = "blue")

if( actual_month == 6 | actual_month == 7 | actual_month == 8 | actual_month == 9){
            abline( h = 2.83168466 * as.numeric( high_low[ which( high_low[ ,3] == as.numeric(low_parks[c,"Account Num"]) ),
6 ] ), col = "red")
}else { abline( h = 2.83168466 * as.numeric( high_low[ which( high_low[ ,3] == as.numeric(low_parks[c,"Account Num"]) ), 9 ]
), col = "red") }
}
dev.off()
```