IMPROVING UNDERSTANDING OF WATER DEMAND DRIVERS AND THE IMPLICATIONS FOR MEDIUM AND LONG-TERM FORECASTING

Russell Beatty [1]
1. Hydrology and Risk Consulting, Sydney, NSW, Australia

KEYWORDS
Water demand drivers forecasting

EXECUTIVE SUMMARY
Forecasts of future water demand have a central role in the planning of future water infrastructure. By improving our understanding of demand drivers we can have a direct impact on the accuracy of forecasts leading to more efficient outcomes for infrastructure investment. This paper provides an overview of a cross-sectional analysis of household water consumption for the Hunter Water area of operation. Similar results have been achieved in other Australian capital cities and New Zealand. The results suggest that the impact of real changes in household income could be included in some form in medium and long-term forecasts.

INTRODUCTION

Forecasts of future water demand have a central role in the planning of future water infrastructure. There are a wide range of factors influencing water demand. Some of those are well understood, and others less so (Figure 1). By improving our understanding of demand drivers we can have a direct impact on the accuracy of forecasts.

Accurate forecasts of demand have the potential to improve the efficiency of water supply investment in a number of ways. Firstly, more accurate forecasts of demand at the water distribution system level allow infrastructure to be sized more effectively, reducing the amount of unused capacity and the need for unplanned amplification. Secondly, understanding demand drivers allows more effective demand management programs to be planned and implemented. By utilising cost-effective demand management measures to achieve long-term reductions in demand, we reduce the reliance of ecologically and economically costly capital investment to meet demands.

This paper provides an overview of a relatively straightforward analysis approach that can be applied to customer database information that is commonly held by Australian water utilities. It demonstrates that the analysis can provide useful information that can improve the accuracy of demand forecasts in a variety of applications.

HIGHLIGHTS

- An innovative cross-sectional analysis of household water consumption has been undertaken using spatial data commonly held by water utilities
- The analysis is found to explain a significant proportion of variations in residential unattached dwelling water consumption across the supply area
- These findings have significant implications for medium and long-term demand forecasting

METHODOLOGY/ PROCESS

Water utilities have historically collected information on water consumption for the purpose of billing customers. Meters data is typically recorded on either a bi-annual or quarterly basis. The records held typically include the date of the previous reading, the date of the current reading, the two meter readings and the difference between the two, which equates to the property consumption. It is this consumption that is used to calculate the volumetric component of the customer’s water bill.

This customer database information has a number of applications in the development of forecasts of future demand. At the supply system level, changes in the number of accounts and consumption per account are utilised to plan for the future water needs of the community. Consumption records also have a role in the development of forecasts of future revenue. At the distribution system level, customer consumption data is regularly used as the starting point for the development of new infrastructure.

In the residential sector, the customer database provides a detailed sample of water consumption from a wide spectrum of customers both spatially and demographically. By coupling this information with census data, it is possible to generate a surprisingly accurate picture of the drivers of water demand.

In a cross-sectional analysis of water consumption, the analysis is examining why the water household in different areas of a water supply area vary from place to place. Consumption data is extracted on the basis of Census Collector Districts (CCD's). The Census information allows a number of key socioeconomic and demographic parameters to be estimated for each CCD. This includes household income, household size and the average age of the residents. The utilisation of cadastral data also allows the lot size of each customer to be used to generate an average lot size for each CCD. Soils data can also be extracted at the CCD level. The end result is a significant data set of potential water demand drivers that can be analysed for significance.

This analysis utilises a non-linear transformation of the independent variables to examine the relationship between demand drivers and responses (Beatty & Chapman, 2009). The regression equation takes the form:

$$C_i = \beta_0 + \beta_1 f_1(v_{1,i}) + \beta_2 f_2(v_{2,i}) + ... + \beta_n f_n(v_{n,i}) + \varepsilon_i$$

Where: C_i = the observed average household water consumption for CCD i;
β_0 to β_n are regression model coefficients
$f_n(v_{n,i}) = v_{n,i}$ if linear; or

$$f_n(v_{n,i}) = \tan^{-1}\left(\left(v_{n,i} - \frac{(v_{U,n} + v_{L,n})}{2}\right) \times \left(\frac{\pi}{v_{U,n} - v_{L,n}}\right)\right) \qquad \text{if non-linear}$$

Where: $v_{U,n}$ and $v_{L,n}$ are upper and lower shape constants for the transformation of variable n
$v_{1,t}$ to $v_{n,t}$ are independent variables for CCD_i
ε_i = model error term for CCD_i

An analyses of single dwelling water consumption were conducted for the Hunter Water areas of operation. The independent variables used in the analysis are shown in Table 1 below. The analysis used a stepwise regression approach for the selection of variables.

RESULTS/ OUTCOMES

The results for the regression model are provided in two tables below. These are:

- Table 2 – regression model results for the overall model; and
- Table 3 – model coefficients and t-statistics for the variables selected.

An example plots of the observed, fitted and model residuals are shown in Figure 2, It shows the significant amount of the variation in consumptions that can be explained by the fitted models. These results are consistent with previous analysis undertaken in other Australian cities and New Zealand (Montgomery Watson; Sinclair Knight Merz, 1995).

With respect to the potential drivers in demand, there are two determinants of the impact of a driver on water use. The first is the demand response identified in the regression modelling. The second and most important determinant is how rapidly a driver can change into the future. A demand driver with a large impact on demand in the regression model, may only have a small impact on future demand because changes in the magnitude of that driver are difficult to generate over time.

In the preparation of this paper, it was not possible to undertake a detailed demographic analysis. As an alternative, a number of scenarios for changes in demand drivers over a 50-year planning period we applied to the existing Hunter customer base.

Elasticities of water demand are defined as the response of water demand to changes in demand drivers. One of the most commonly discussed elasticities is the price elasticity of demand. In this report, we are focussing on the elasticities of demands of each of the drivers included in the analysis.
One expression commonly used for calculating elasticity is the equation (Weber, 1989):

$$\varepsilon = \frac{dq}{dp} \times \frac{p(i)}{q(i)}$$

Where: ε = elasticity of demand
p = demand driver
q = quantity of demand

Differentiating the equation, we can calculate the elasticity as:

$$\varepsilon = \frac{ln\left({}^{p_2}/{}_{p_1}\right)}{ln\left({}^{q_2}/{}_{q_1}\right)}$$

Where: p_1 and p_2 are the values of the drivers at times 1 and 2; and
q_1 and q_2 are the values of the quantity of demand at times 1 and 2

Over small ranges this equation can be simplified to:

$$\varepsilon = \frac{\left({}^{p_2}/{}_{p_1} - 1\right)}{\left({}^{q_2}/{}_{q_1} - 1\right)}$$

Or the % change in the driver divided by the percentage change in the quantity of demand.

Using the regression models, changes in each of the demand drivers were made and the impact across the customer base data set was predicted for different magnitudes of demand driver change. The elasticities were then calculated for each demand change.

The results show that demand is inelastic (that is elasticity is <1.0) for all the drivers examined. Interestingly, household size elasticities of demand are consistently around 0.4, which suggests that changes in household size do not bring a completely corresponding change in consumption. This is in agreement with end use measurement work undertaken in metropolitan Melbourne. Income elasticities are approximately 0.2 to 0.3 across the range examined. Interestingly, the results suggest an inelastic response (elasticity < 1.0) to household size, which is consistent with the results from end use monitoring studies in metropolitan Melbourne (Yarra Valley Water, 2004).

The potential impacts of changes in demand drivers were examined for the scenarios outlined in Table 4. The results of the analysis are shown in Figure 3. The results suggest that household income and household size are likely to have the most significant impact on future water consumption per household. Changes in the average lot size however, are unlikely to impact significantly on future water consumption. Some of the traditional thinking on water efficiency drivers, such as the assumption that reductions in lot sizes will have a significant impact on consumption, may not be supported by the results obtained here for both elasticities of demand or future demand scenarios. This income demand response may go some way to explaining the apparent persistence of household consumption seen in some jurisdictions in spite of improvements in the efficiency of water using fixtures and appliances (Beatty, Obrien, & Stewart, 2006).

While this analysis shows that there is potential for changes in household income to impact on water use levels, there is still uncertainty about:

- Which end uses of water in the residential sector are impacted;
- What the magnitude of this impact might be on medium and long-term forecasts; and
- How this information can be utilised in long-term forecasts.

CONCLUSION

Forecasts of future water demand have a central role in the planning of future water infrastructure. By improving our understanding of demand drivers, we can have a direct impact on the accuracy of forecasts. Water utilities have a large information base that can be called upon to generate insights into the underlying drivers of demand, with little processing. Using relatively straightforward analysis approaches and readily available census and GIS-based information, our understanding of the drivers of residential water demand can be significantly enhanced.

The analysis undertaken in the Hunter Water and other jurisdictions suggest that a clearer understanding of the factors influencing demand can be generated. Of the drivers investigated in these analyses, household income consistently shows the greatest potential to impact medium and long-term demands. The next steps would be to understand how this information could be integrated into future demand forecasts.

REFERENCES

Beatty, R., & Chapman, S. (2009). *Water Demand and Wastewater Flow Trend Tracking and Climate Correction Using a Short Baseline Calibration Methodology.* Newcastle: Hydrology and Water Reources Symposium.

Beatty, R., Obrien, S., & Stewart, B. (2006). The Future for Per Capita Water Demands and its Implication for Demand Management Programs. *Water*.

Montgomery Watson; Sinclair Knight Merz. (1995). Sydney Water Supply Strategy Phase II - Demand Study.

Weber. (1989). *Forecasting Demand and Measuring Price Elasticity.* Journal of the American Water Works Association.

Yarra Valley Water. (2004). Residential End Use Measurement Study.

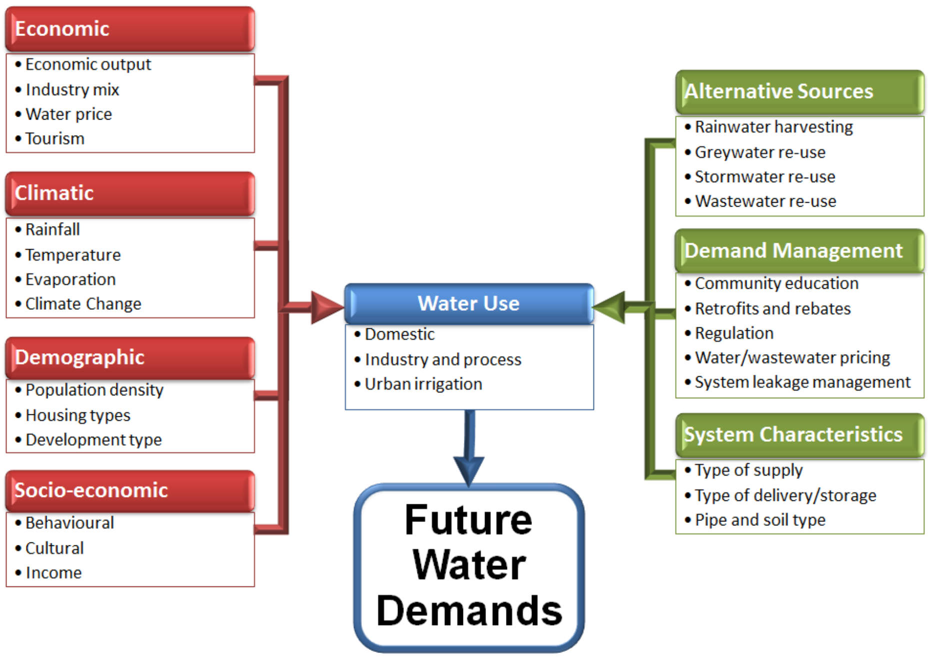

Figure 1: The Factors Influencing Water Use (adapted from Beatty, O'Brien and Stewart, 2006)

Table 1: Description of Explanatory or Independent Variables used in the Analysis

Variable	**Description**
Household Size	The number of persons per occupied private dwelling (Census).
Household Income	Household income for all housing types from Census data.
Soil Permeability Index	The weighted average of each of the dominant soil types
Average Lot Size	The average lot size per dwelling from customer database information.
Distance from Coastline	The distance of each CCD from the coastline. Used as a surrogate for the influence of different climatic zones.
Average Age of Residents	The average age of residents in the CCD from Census data.
Average Construction Date	The average of the year of construction from each property as recorded in the Hunter Water customer database. Used as a surrogate for the impact of newer water using fixtures and appliances and the impact of newer dwelling design on water use.

Table 2: Regression Analysis Results

Parameter	**Value**
R-squared	0.4971
Standard Error of Y Estimate:	21.60
F Statistic:	252.41
Degrees of Freedom	766

Table 3: Variable Statistical Significance

Variable	**Coefficient**	**T-statistic**
Intercept	208.74	75.40
Household size	10.34	7.82
Real average household income	14.17	10.26
Average lot size	27.24	10.66
Soil permeability index	Not statistically significant	Not statistically significant
Distance from Coastline	Not statistically significant	Not statistically significant
Average construction date	Not statistically significant	Not statistically significant
Average age of residents	Not statistically significant	Not statistically significant

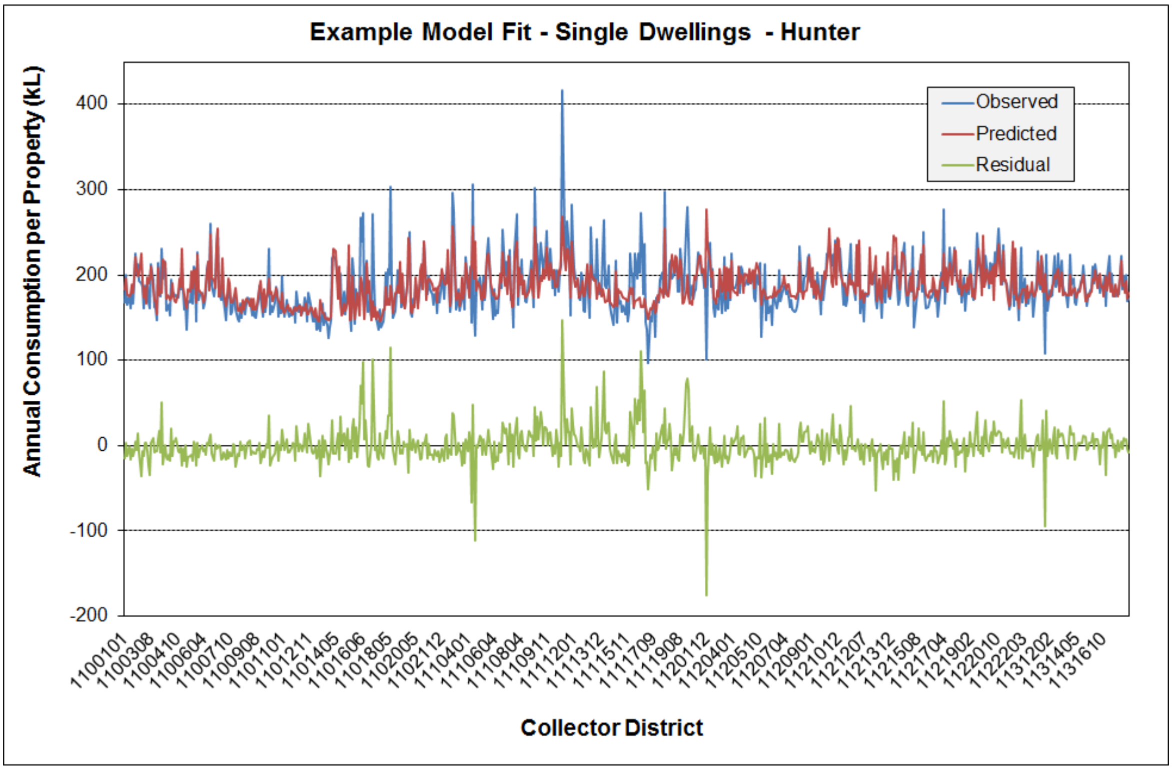

Figure 2: Example Regression Model Fit - Single Dwellings - Hunter

Table 4: Assumed Changes in Demand Drivers

Driver	**Discussion**	**Assumed Driver Range**
Household size	Falling household sizes have been a general trend for some time in throughout Australia. More recently, the picture in metropolitan Sydney has been relatively static, although the Hunter reason has seen the more consistent falls. In the future, a modest reduction is a reasonable assumption for scenario testing.	-8% to -2%
Real average household income	From 1996 to 2006 real household incomes grew at a rate of approximately 1.5% p.a. in both the Hunter and Sydney regions.	50% to 150%
Average lot size	To generate a feel for the problem, if we assured that over the next 50 years we have a 70% increase in population growth and this new population is in dwellings with lot sizes of +10% or -20% of current lot sizes, then the overall change in lot sizes will be between +4% and -8%.	-8% to +4%
Soil permeability index	The average soil permeability index across the CD's is 7.05. If 75% of new development occurs in the inland areas of the supply area with typical indices or between 7 and 8 (7.5 on average), then the result will be an increase in the average permeability index of approximately 2%.	+1% to +2%
Distance from Coastline	If 75% of future single dwelling development occurs at a distance 50% greater than the current average distance from the coastline, and there is a 100% increase in population, then there will be an approximately 20% increase in distance from the coastline.	+15% to +25%

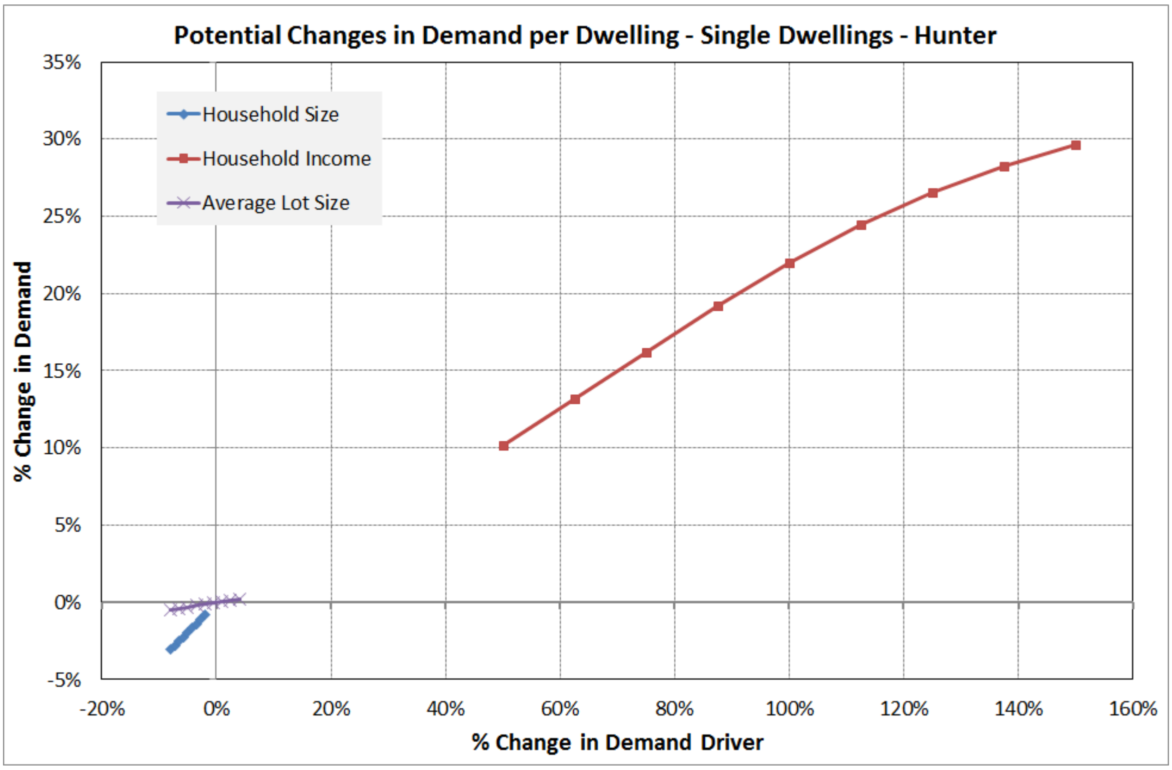

Figure 3: Predicted Changes in Demand per Dwelling - Residential Single Dwelling - Hunter