UNCOVERING THE INFLUENCE OF CLIMATE ON WATER DEMAND

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ABSTRACT

How much influence does climate have on water demands? Are water restrictions successful at reducing peak demands during dry summers? This paper will discuss answers to these questions through presentation of climate correction modelling results from New Zealand water suppliers.

It is well known that demand per capita varies significantly across the country and this will be due to a wide range of drivers such as household income, property size, industrial demand, and weather influences. The influence of climate is a significant factor in New Zealand's municipal water demands, particularly in areas with high garden watering. Hotter and drier summers than normal usually result in higher peak day demands which are often managed through water restrictions.

This paper will present findings from statistical regression analysis of municipal water demands and climate influences using the Water Demand Trends Tracking and Climate Correction Tool. This Excel-based statistical model calibrates demand with climate parameters (e.g. soil moisture index, rainfall and maximum temperature) to identify the influence of climate on demand. The model also calculates the climate-corrected demand which is the demand that would have occurred under normal climate conditions. The tool enables the user to plot and compare predicted demand with actual demand to see if the latter was different. The tool identifies the underlying demand trend without the influence of climate and can assist with analysing the impact of water restrictions and other demand management measures.

Climate corrected demand analysis enables water suppliers to more accurately forecast baseline water demands and have a better understanding of the underlying demand trends and potential demand drivers. These methods will also assist water suppliers to prepare water demand forecasts that meet the recommendations set out by the Office of the Auditor General 2010 report: "Planning to meet the forecast demand for drinking water".

KEYWORDS

Water demand management, climate impact, water demand forecasting

1 INTRODUCTION

Recent dry summers and increasing pressures on our fresh water sources have brought water supply and demand issues to the forefront in New Zealand. Over-allocation of water source catchments has raised awareness that fresh water may not be as limitless and plentiful as previously perceived.

As water suppliers increase demand management programmes and introduce water restrictions to curb peak day demand, there is a need to understand and potentially quantify the impact of these initiatives on water demands.

A wide range of drivers have the potential to impact water demands, as shown in Figure 1. Improved understanding of the factors influencing demand allows more accurate demand forecasts and appreciation of the historic and future trends in water use.

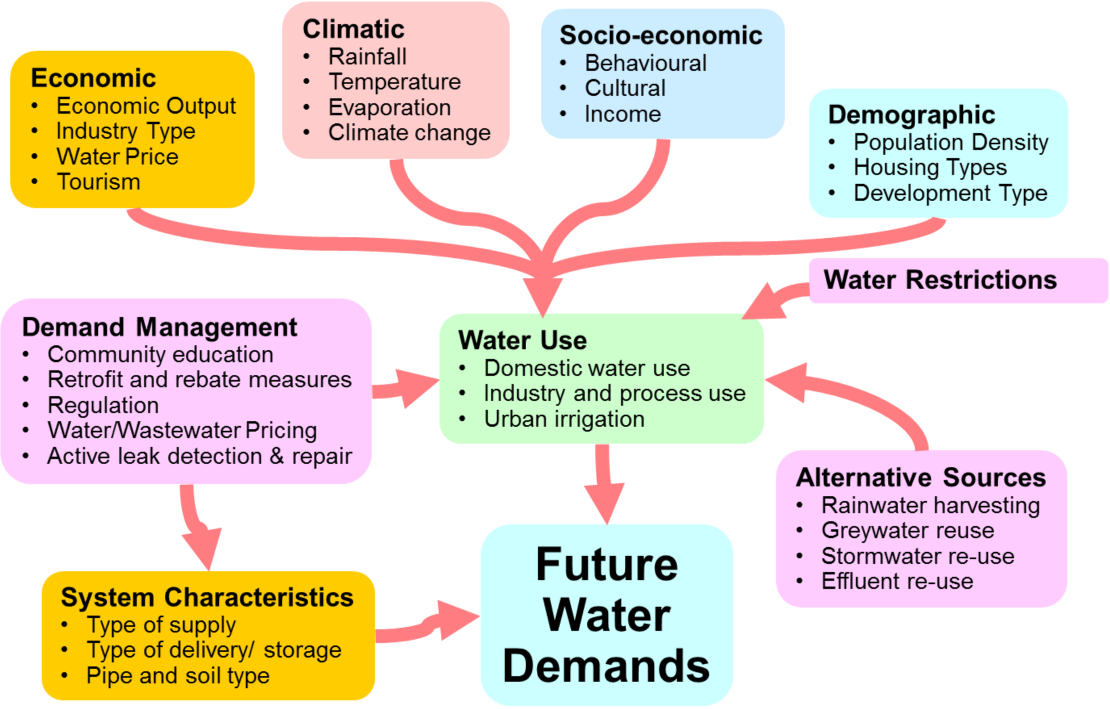

Figure 1: Water demand drivers

Climate influences can have a significant impact on water demands, particularly in New Zealand cities with high garden watering and seasonal outdoor use.

MWH have developed an in-house software Water Demand Trend Tracking and Climate Correction package called WaterTrac which is used to monitor trends in bulk water production. There are two versions of WaterTrac, a daily model and a monthly model. This software is designed to provide water utilities with information about climate influences on water demands and underlying trends in water demands after climate correction.

The purpose of the WaterTrac model is to provide information that will enable water suppliers to answer questions like:

1. “I have to prepare forecasts of future water demand but I have been told that the last few years were cool with higher than average rainfall. What correction to the historical records do I need to make?”

2. “We have had pay for use pricing in place for a number of years now, but demands seem to be trending up again. Is this a “rebound” effect or have the last few years just been hot and dry?”

3. “Last year we ran a community education campaign. What impact on water production did it have?”

4. “I am trying to determine the safe yield of my existing headworks using computer simulation. What equation can I use to predict demands?”

WaterTrac is operated in the MS Excel spreadsheet environment for data input and output, but is hard-coded in Visual Basic and does not need to rely on MS Excel for the complex calculations required.

2 MODELLING BACKGROUND

2.1 REGRESSION ANALYSIS

WaterTrac uses a non-linear multi-variable regression analysis approach to explain the day to day climate influences on water demands. The non-linear regression analysis approach is unique as many other water demand regression analysis models assume a linear regression analysis.

The advantages of using a non-linear transformation are illustrated in Figure 2 below, which shows typical linear and non-linear responses to four common climate variables. If we take the example of rainfall, while it has a significant impact on soil moisture and hence demand, it has a very minor impact in its own right. Typically, small amounts of rainfall have an immediate damping effect on demand, with additional rainfall having little or no effect. Hence the use of rainfall in its linear (untransformed) form will result in an under-prediction of rainfall impacts at low levels of rainfall, and an over-prediction of impacts at high rainfall levels.

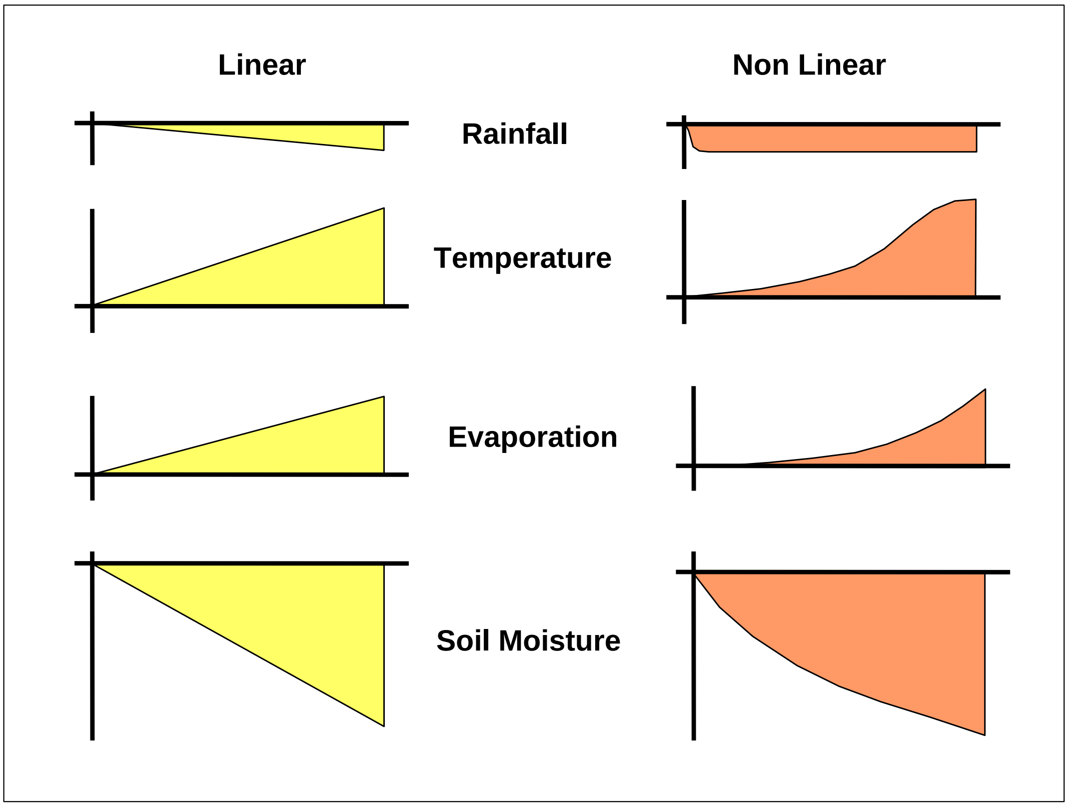

Figure 2: Typical Linear and Non-Linear Demand Responses

Model outputs include:

- Regression calibration statistics.
- The long-term hindcast of calibrated model demands and flows through the full climate record.
- Climate corrected demands (including upper and lower 95% confidence intervals in the daily model).
- Historical peak to climate corrected average demands.

Once the climate influence has been established the influence of other demand drivers can be assessed, such as:

- water restrictions
- demand management programs
- water pricing changes.

2.2 DATA REQUIRED

The following raw input data is required to run WaterTrac:

1. Daily readings of maximum temperature, rainfall and potential evapotranspiration (24-hour Penman potential evapotranspiration) from NIWA. The full historical record for the closest weather station.

2. Daily or monthly bulk water production data corrected for reservoir fluctuations. At least three years of data required.

3. Annual estimates of the population served by the water supply.

2.3 THE CLIMATE CORRECTION PROCESS

The process of climate correction in the WaterTrac model can be summarised as follows:

1. The soil moisture index parameters are derived from the input climate data (antecedent rainfall and evaporation). It is included as one of four climate independent variables.

2. A regression model is progressively calibrated using the four climate variables and recognised statistical techniques. The calibration is undertaken over a period of relatively 'normal' water consumption (e.g. free of enforced water restrictions) with a good range of climatic conditions.

3. A 'hindcast' is created which uses the calibrated model to predict water production over the climate record. This provides long term modelled demand responses to climate drivers. It also allows verification of the long term stability of the model.

4. Consideration of the long term average and predicted average for the trend tracking period are used to create a climate corrected trend of water production. The 365 day/12 month rolling average trends for observed per capita production versus climate corrected water per capita production are plotted.

The WaterTrac model adopts a simple soil moisture store model as a climate variable in the regression analysis. The soil moisture index is used to model the antecedent soil moisture effects on demand or flow. This particular soil moisture store model has been found to generate high correlations with water demand or flow in many separate applications. The soil moisture index equation is discussed in detail in Section 2.4.

The soil moisture index model allows the observed evaporation data to be raised to some power. The exponent can be entered by the user or the software can be used to search for the optimal value as part of the soil moisture index calibration exercise (the latter is the default in the model). Empirical experience in a number of studies has found that an evaporation power greater than 2.0 will give optimal results for water demand modelling.

The calibration period for the regression model sets the baseline for the comparative trend tracking. Although any time period can be selected for the baseline, there are a couple of guidelines:

- The calibration period should cover at least one full year and as long a period of relatively stable demand regime as possible. It should always span a multiple of full years so that there is no bias towards any season (where a full year starts on one date and ends on the preceding date a year later as per the current calibration period described above).

- The calibration period should ideally incorporate a full range of climate conditions including a hotter, drier than average summer period as well as a cooler and wetter winter period. This is to reduce the likelihood of the model extrapolating when predicting responses with more extreme climate periods.

2.4 SOIL MOISTURE INDEX

The model is unique in that it offers a simple soil moisture store model as a climate variable in the regression analysis. The soil moisture index is used to model the antecedent soil moisture effects on demand or flow. This particular soil moisture store model has been found to generate high correlations with water demand or flow in many separate applications.

The soil moisture index is calculated using the following equation:

$$S_t = SMI_{t-1} + M_R \times R_t - M_E \times E_t^P \times \frac{SMI_{t-1}}{100} - B \times \frac{SMI_{t-1}}{100}$$

$$SMI_t = 0 \text{ if } \mathrm{S_t} < 0$$

$$SMI_t = 100 \text{ if } \mathrm{S_t} > 100$$

$$SMI_t = \mathrm{S_t} \quad otherwise$$

Where SMI_t = Soil moisture index at time t

R_t = Rainfall at time t

E_t = Evaporation at time t

M_R = Rainfall multiplier

M_E = Evaporation multiplier

P = Evaporation power

B = Base flow coefficient

The base flow coefficient is used when modelling wastewater flows where the soil moisture index approximates a groundwater index. When modelling water demands, the base flow coefficient is set to zero.

3 EXAMPLE MODEL CALIBRATION

For the example water supplier, the monthly WaterTrac model was developed using four years of water demand data. Several calibration periods were tested over the four years of available data. A two year calibration period from 1 January 2014 to 31 December 2015 provided the best statistical model.

Four independent variables were tested during the calibration phase. Evaporation was tested in the initial regression analysis but resulted in a negative variable coefficient and low T statistic (absolute value). We would typically expect a positive rather than a negative variable response for evaporation, i.e. as evaporation increases, demands would also be expected to increase. We excluded evaporation from the regression analysis in the calibrated model.

The T-test statistic is used to determine the significance of individual variables. As a rule of thumb, in the regression analysis of daily water demand, a T statistic of absolute value greater than 2.0 suggests that the variable is significant in the regression and should be included in the regression model. The absolute value of the T statistic for evaporation was close to -2 meaning that evaporation was not statistically significant. A 2.0 value for the T statistic equates to a 95% confidence interval that includes the value. The model user could confirm actual values for the T statistic through reference to T-test statistical tables.

The calibration correlation is typical for this type of model and produced an R^2 statistic of 0.77 for the monthly model, which is to say, that 77% of the variations in daily per capita water production during the calibration period could be explained by the fitted model with the selected climate variables. The modelled variable responses for the three selected climate variables in the monthly model are shown in Figure 3.

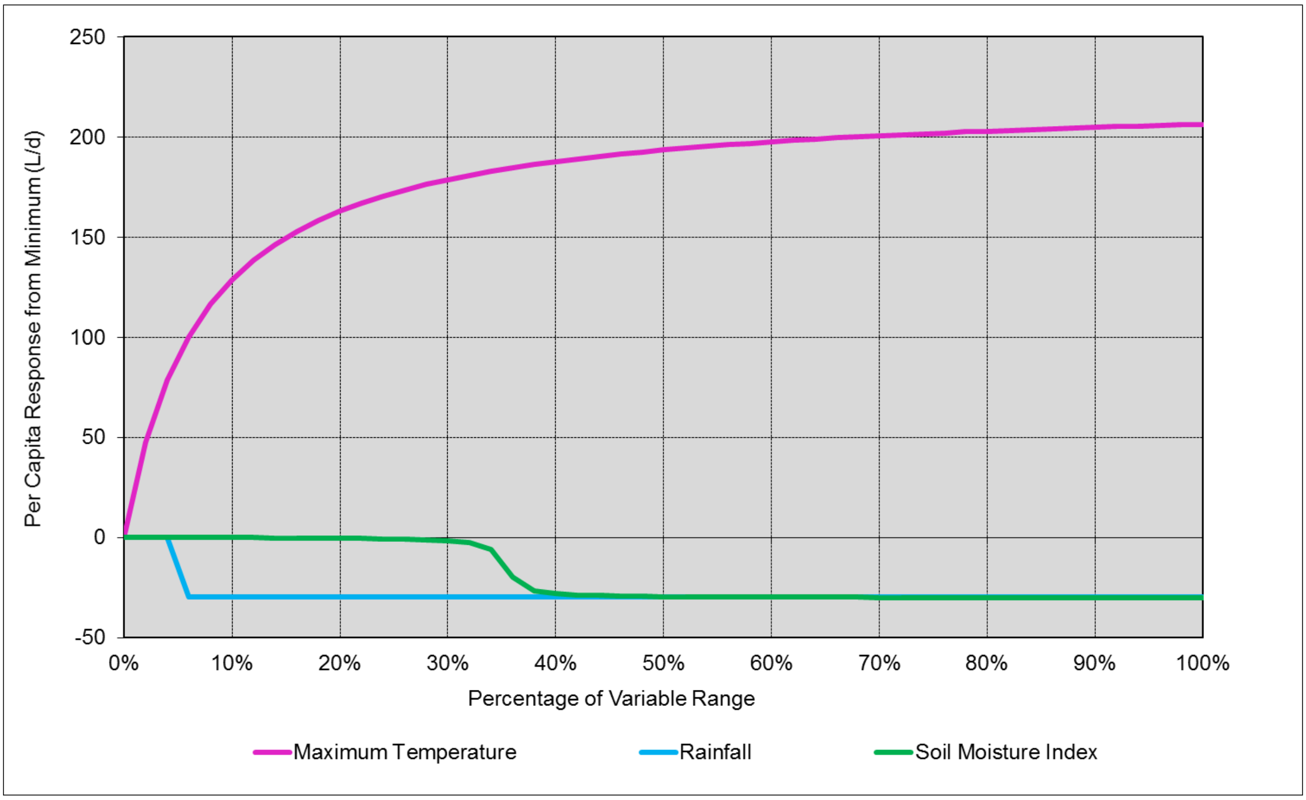

Figure 3: Modelled Variable Responses for the Three Climate Variables (Monthly Model)

The vertical axis on the plot represents the per capita response in L/capita/day for each of the three explanatory climate variables. The x-axis shows the corresponding percentage of the range for each of the climate variables. The plot shows that the climate variables produced the expected response patterns for the sample monthly model. Maximum temperature shows a positive response with water demands (e.g. as maximum temperature increases, water demands increase and the highest range of maximum temperature corresponds to a maximum response of approximately 200 L/capita/day).

Rainfall and soil moisture index show a negative response with water demands (e.g. as rainfall increases, water demands decrease).

4 EXAMPLE MODEL RESULTS

Climate corrected production results are shown in Figure 4. Observed data is the raw non-climate corrected monthly water demand per capita. Predicted data is the regression model’s predicted demand per capita. The residual is the difference between observed and predicted values and indicates the ability of the model to predict demands during the calibration period. Periods of high historic water restrictions are also shown on the graph. Alert Level 3 is a total ban on domestic sprinklers – only hand held hosing permitted. Alert Level 3 also includes restrictions on outdoor water use for commercial/non-residential properties.

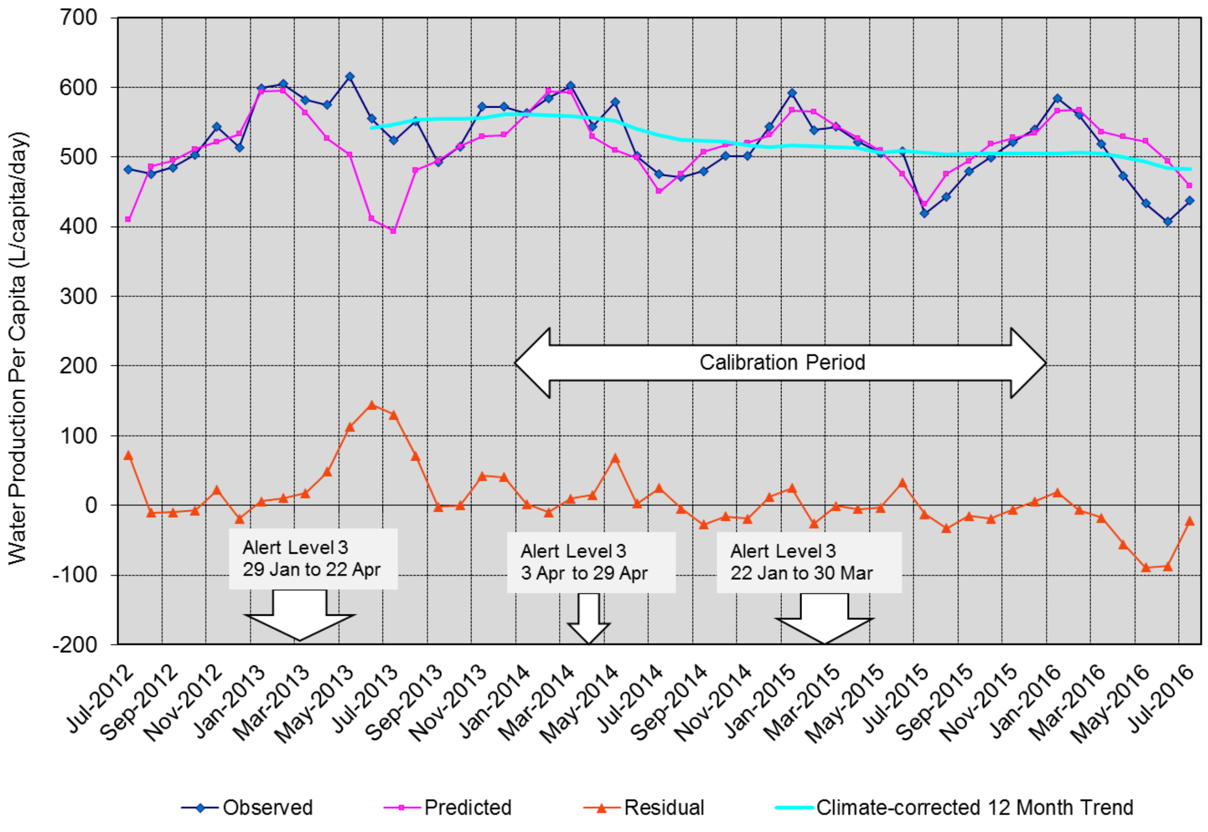

Figure 3: Monthly Regression Analysis of Per Capita Demands

The graph in Figure 4 also shows the 12 month rolling average climate correction trend for the historical records. This trend line shows that the climate corrected 12-month average demand has varied from a high of 560 L/capita/day to a low of 480 L/capita/day in July 2016 (the end of the data period). The highest value of 560 L/capita/day occurred from December 2013 to January 2014 during Alert Level 1 restrictions.

The 12 month rolling average climate correction trend has been steadily decreasing since the peak in early summer 2013/14, indicating that customers have been reducing their water demands, most likely due to the water supplier's active water demand management education programme.

5 CONCLUSIONS

In conclusion, the WaterTrac model can be used to:

1. Correct historical demand records for the influence of climate.
2. Identify whether changes in demand patterns are due to external influences such as demand management efforts or to climate variation from normal conditions.
3. Predict climate driven demands from climate forecasts.