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Modelling Water Use in Regional Queensland

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1 Introduction

Capital expenditure is the key cost driver for water and sewerage service providers. For example, economic modelling of the water business in Mackay shows that 80% to 90% of the cost of the provision of water supply services to the community is driven by the cost of the capital installed to deliver the services. Similar findings have been raised in QWRAP investigations across the state. Effective utilisation of assets is a key strategy in driving down the cost of providing services into the future.

Uncertainty surrounding future water use often introduces risk in asset decision making resulting in conservative decisions surrounding the construction of trunk water infrastructure. By improving the understanding of current and future water demand, it is predicted that the following changes can be made to the management of Water Infrastructure:

- reduced operational and capital costs through optimised decision making
- reduced capital costs through a reduction in conservatism in design
- reduced emergency construction of additional trunk water infrastructure through improved forward planning of trunk infrastructure

The major contributing factor leading to the uncertainty surrounding future water use is variation in water demand from the community. This variability creates uncertainty in the following three areas:

- operational decisions associated with running the bulk water supply treatment and distribution assets
- short run decisions to manage infrastructure capacity such as water restrictions and temporary supplies
- addressing long run infrastructure decisions through the construction of new capital or accessing new water sources

Mackay Regional Council in Partnership with the Queensland Water Directorate has investigated the ability to predict future water use based on modelling underlying drivers of water demand in response to changing weather conditions. This modelling was initiated for the Nebo Rd Water Treatment Plant in Mackay and expanded across the following water supply areas in Queensland.

- Cairns Regional Council
- Fraser Coast Regional Council
- Longreach Regional Council
- Rockhampton Regional Council
- Toowoomba Regional Council
- Townsville Regional Council

This report investigates:

- the application of the Model built to predict water use in Mackay across other water utilities in Queensland

- the potential implications of the Model in understanding variability in water use across water supply schemes

2 The Value of Understanding Future Water Use

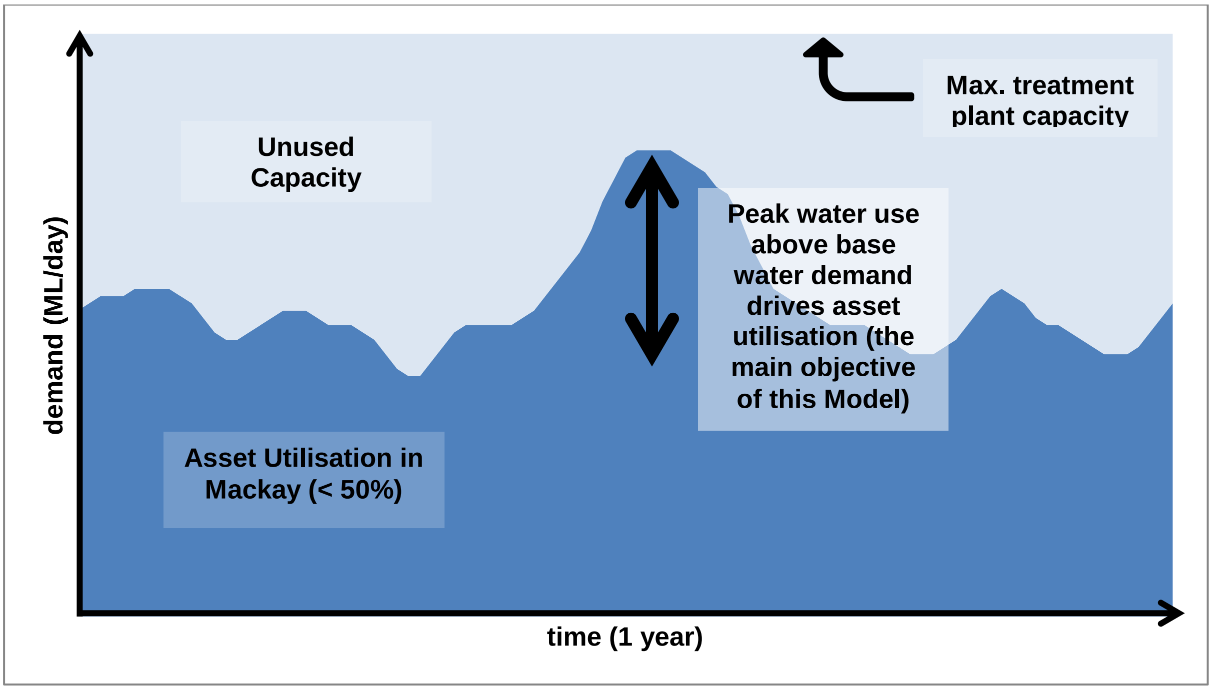

Figure 1. Asset utilisation in Mackay

2.1 Operational

Better understanding of water demand will assist in operational and tactical decision making in a number of ways. At present it is difficult to discern whether fluctuations in demand result from weather or if are caused by other factors (e.g. leaks, major events, and restriction levels, one-off changes in industrial use). These impacts overlap and are cumulative making it difficult to attribute changes in demand. For example, large leaks in trunk mains have been found in some cases to be concealed by fluctuations in outdoor demand. Better understanding of the timing and magnitude of each of the impacts and the ability to separate them from underlying climatic drivers could improve decision making in managing water sources, storages and treatment plants.

2.2 Short Run Capital Decision Making

Short-run decision-making deals with balancing temporary high and low periods of demand with appropriate levels of supply and stored water. However, in many communities capacity for production and storage means that there are significant constraints on such decisions. In some cases, water restrictions may be required to manage the peak daily water use for a short period. However, the effect of demand management actions such as the implementation of water restrictions is often difficult to determine particularly when masked by the background effects of climate-driven demand variation. The ability to predict and filter out variation caused by weather would provide greater opportunities for using short-run decision making to alleviate demand and supply imbalance and avoid expensive capital investment solely to manage rare or temporary issues.

2.3 Long Run Capital Decision Making

Long-run capital investment is driven by peak demand. The highest projected demand determines the necessary size of in-ground infrastructure and the capacity of treatment plants and many water supplies. Demand modelling has the potential to improve the ability to predict not only the peak demand (under different climate scenarios) but also the impact of demand management and other water security controls (e.g. alternative sources, storage options). This improved understanding coupled with stringent risk analysis could allow for more appropriate timing, sizing, and scoping of infrastructure solutions, saving significant investment over time.

2.4 Water Prediction Model Concept

The Water Prediction Model is based on observations that water use in a community throughout any given year includes a significant proportion of outdoor water use. Further, outdoor water use is known to be influenced by rainfall [1] [3] and temperature [7]. The Model is based primarily on rainfall and either evapotranspiration (ETo) or temperature:

- The amount of rainfall in the community. Rainfall reduces outdoor water use immediately and has and ongoing impact (which can last for several months after the rain has fallen and depends on soil moisture retention (and thus types).
- The level of evapotranspiration (ETo) in the community. Evapotranspiration is a measurement that reflects how local climatic factors combine to increase both evaporation and transpiration (by plants) both of which tend to dry soils. Preliminary work showed that increasing ETo was a better predictor of increased domestic water use than temperature.
  The Model uses daily rainfall and either daily temperature or daily ETo measurements from the Bureau of Meteorology to predict daily water use.
- Temperature. Increasing temperature is known to drive increased water use.

As well as these daily climate variables, for each community a ‘base load demand’ (or average indoor water use) was estimated from the underlying data based on available data and assumptions of the levels of the following factors (see appendix D):

  - residential connections
  - commercial connections
  - customer water leaks
  - non-revenue water
  - growth in the community

Regression analysis was used to generate two empirical relationships:

1. the relationship between rainfall and water use
2. the relationship between ETo (or temperature) and water use

These competing relationships were combined in the Water Prediction Model to predict the variation in water use compared to the base load demand.

3 Water Prediction Model

The Water Prediction Model was established in the Amazon Web Services environment. The Model consists of the following four components:

- Model Inputs

- Model Calibration
- Model Generator
- Model Visualisation

The Model has been set up to predict a single days water use based on the previous day's value, recent rainfall, ETo and the base load demand for each community.

3.1 Model Inputs

The Model uses daily rainfall and either ETo or temperature for each water supply scheme. The meteorological data is sourced from the Bureau of Meteorology (BOM) using the closest weather station to the water supply scheme. These records are imported into a database and organised by the source weather station. Once the source weather station has been identified and established the mode inputs are automatically imported using Amazon Web Services.

The BOM provides rainfall back to the late 1800s while ETo is available from January 2009 at the earliest. The Model calibration and comparison against actual water use is therefore not possible before January 2009. The BOM do not calculate ETo for all water supply schemes. Further, there are regularly periods where the ETo data is not available from the BOM. In these cases, temperature is used to approximate ETo.

Initial investigations showed that the accuracy of the Model was increased when ETo was used as an input rather than temperature. However, while the majority of BOM meteorological stations measure temperature daily, only a limited number also measure ETo. For this reason, an analysis was undertaken of the accuracy of the Model's predictions using temperature versus those using ETo (see Section 4.4).

The Model uses historic actual water use for the scheme for comparison and calibration. For the Mackay water schemes, the historic actual water use is automatically imported from Monitor Pro and spreadsheets. For Water Supply Schemes outside of Mackay the water actual historic water use is manually loaded.

3.2 Model Calibration

The Model is calibrated for each water supply scheme. There are two sets of Calibration Settings:

1. Baseload Demand. The baseload demand is calculated from existing information (from SWIM) and standard assumptions (see appendix D) about different water uses. It roughly correlates to the minimum annual water demand.
2. Water Use Driver Correlation Factors. Two Water Use Correlation Factors were used for each model run to represent how the outdoor water use in a community responds to changes in rainfall and to either ETo or Temperature. The Water Use correlation factors are generated by calibrating the Model against a community's water use in the first 6 to 12 months of data. Once established the Water Use Driver Correlation Factors remain constant in the Model.

The full list of Calibration Settings is included in appendix C, and each region's values are listed in appendix D.

3.3 Model Generator

The Model Generator is a C# .NET application that takes the meteorology data and Calibration Settings, and uses them to generate new daily predictions for each region. Once generated, the daily predictions are cached in a database for further analysis and reporting.

3.4 Model Visualisation

The Model features a basic intranet portal for data visualisation and reporting, allowing water use to be plotted for a given organisation, region, and date range.

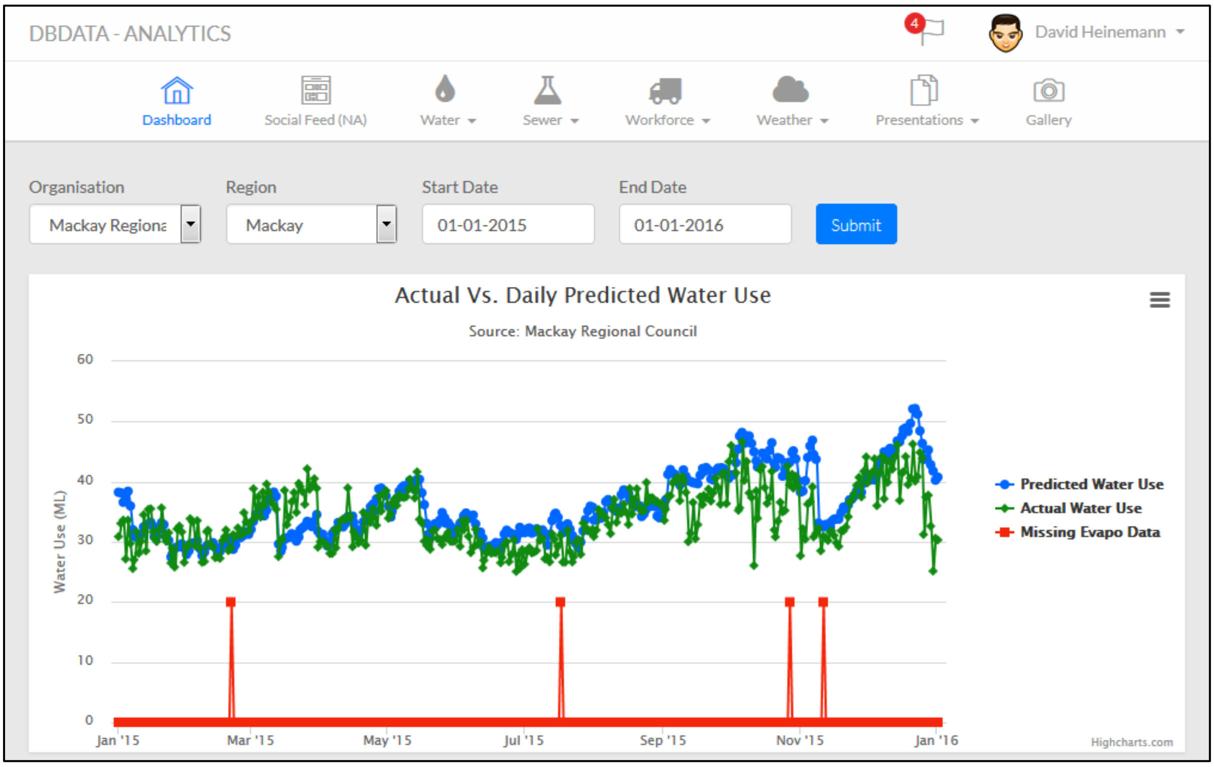

Figure 2. The Water Prediction Model portal

This portal is not yet available externally and its charts do not translate well to paper. As a result, the charts in this report are created using Microsoft Excel.

3.5 Model Limitations and Opportunities

The Model has a number of limitations and assumptions that affect its accuracy. A summary of these and how they are managed in the Model are as follows.

3.5.1 Reservoirs

Almost all water supply schemes have reservoirs that provide a buffer between the water produced and the water consumed in a water supply scheme. The Model predicts demand on the downstream side of a reservoir. The Model is calibrated on water production on the upstream side of a reservoir.

To minimise the impact on the reservoir the Model outputs have been produced as a 3-day rolling average.

3.5.2 Daily Variations in Base Water Demand

All other things being equal water schemes have variations in the baseload water demand based on the day of the week. It is anticipated that these variations are impacted by factors such as:

- base water restrictions
- industrial demand variations due to factors such as work days and non-work days
- behavioural variations due to factors such as work days and non-work days and restriction regimes

Initial analysis showed these variations to have a range of between 0 and 2% impact on baseload demand. The variations have been managed in the Model by a calibrated "day of the week" factor.

3.5.3 Seasonal Variations in Base Water Demand

To varying extent, water supply schemes are impacted by seasonal variations in the water use by industry. The extent of seasonal variations is relatively limited and although this has been identified, the Model does not yet deal with these variations.

3.5.4 Impact of Events Based Drivers

There are events that occur that result in the amount of water use being used in a scheme being driven by a factor other than the prevailing weather conditions. These events may include factors such as:

- water restrictions
- changes in the way that water is supplied
    - shutdown to allow work on the assets
    - restriction in water production to accommodate dirty water events in the WTP source water
- structural shifts in underlying demand
- major water leaks

The Model does not predict the impacts of these events. However, it is anticipated that the Model will be able to identify some occasions when these events have occurred.

4 Findings

The Water Prediction Model has been established for the following water Supply schemes:

- Mackay Regional Council
- Cairns Freshwater Creek
- Hervey Bay Burgowan (Fraser Coast)
- Maryborough Teddington (Fraser Coast)
- Longreach Town
- Rockhampton Glenmore
- Toowoomba Mt Kynoch
- Townsville Douglas

A comparison of the prediction of water use compared to actual water use for the past 5 years for each scheme is detailed in appendix A.

Modelled predictions using ETo/temperature and rainfall reasonably approximate actual water use in each region. However, the Model produces better predictions for some regions than others.

4.1 Model Weaknesses

After testing and analysis, two key weaknesses were identified in the Model. First, the relationship between water use, Rainfall, and ETo are not always reflected accurately during summer. Second, the Model assumes that rainfall is uniform across the entire region, but in reality, it is not.

4.1.1 Relationship between Water Use, Rainfall, and ETo

During the summer months, the relationship between water use, rainfall, and ETo are not always reflected accurately. Summer brings frequent rainfall, which decreases water use. Although the actual water use rapidly increases after rainfall stops, the predicted water use may increase slowly, or not at all. This leads to the predicted water use plateauing as demonstrated in Figure 3, which can take months to recover.

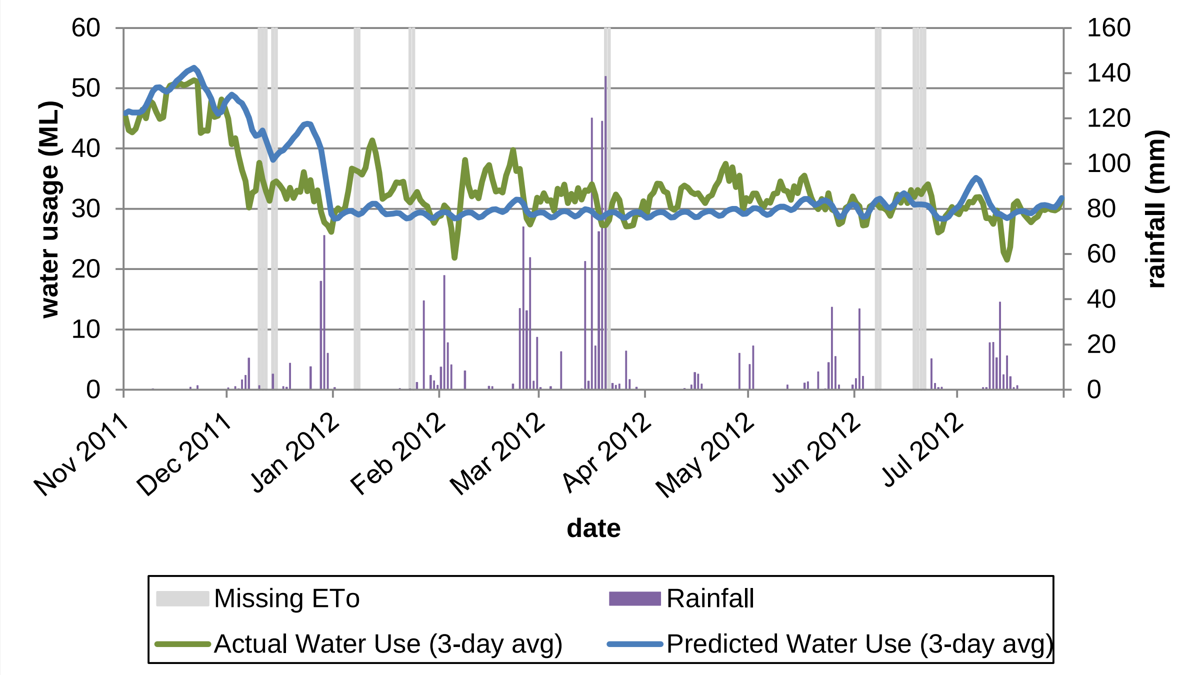

Figure 3. Predicted water use plateauing during the summer of 2012 in Mackay

The cause of this problem is not yet clear, however, it does not seem noticeable in winter. It could be associated with the ETo Rate used in each region. Perhaps each season should use a different ETo Rate instead of using one throughout the whole year or other factors such as soil moisture and humidity could be investigated as additional drivers during different seasons.

4.1.2 Regional rainfall variation

Rainfall rarely covers the whole region, so while it rains at the BOM station, other areas may be dry. For example, analysis of Mackay's sewer system and rain gauges show variation in rainfall across the area. However, the Model assumes that rainfall is distributed evenly across the region. This means that variation in rainfall will reduce the accuracy of predicted water use.

The extent of this effect is currently unknown, but potential solutions are proposed in section 4.6.2.

4.2 Model Strengths

The Model has a number of strengths. It is effective at compensating for small gaps in the BOM's ETo data, and is resilient enough that standard assumptions about base load allow effective prediction of water use across a range of communities using only rainfall and ETo as daily input variables.

4.2.1 Compensating for Gaps in ETo Data

The BOM's ETo data suffers from availability problems due to the way it is calculated. The BOM uses the Penman-Monteith equation, which calculates ETo from several inputs including wind speed and solar radiation [4]. If any of those inputs are unavailable, the ETo is unavailable too. Although missing ETo is uncommon in most regions, it causes problems for the Model, which requires ETo to function.

To compensate for missing ETo, the Model uses substitution. Sequences of up to five missing (null) ETo records are substituted with the mean of the nearest records on either side. This should be accurate enough for predicting water use. Using the mean would be questionable for larger gaps, so these are substituted with a value of zero. This causes the predicted water use to plummet, clearly indicating an error. Although this is not ideal, there would be greater risk of interpolating ETo because of its natural variability. For this reason, extended periods without ETo readings are clearly marked on the Model’s outputs. More work will be necessary to handle larger gaps, and some options are proposed in section 4.6.

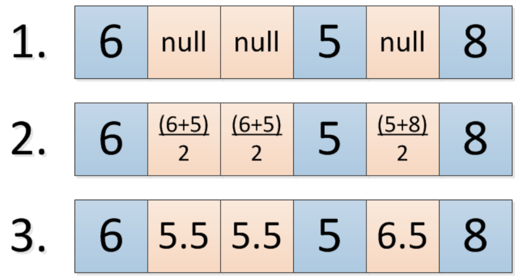

Figure 4. Filling in missing ETo data

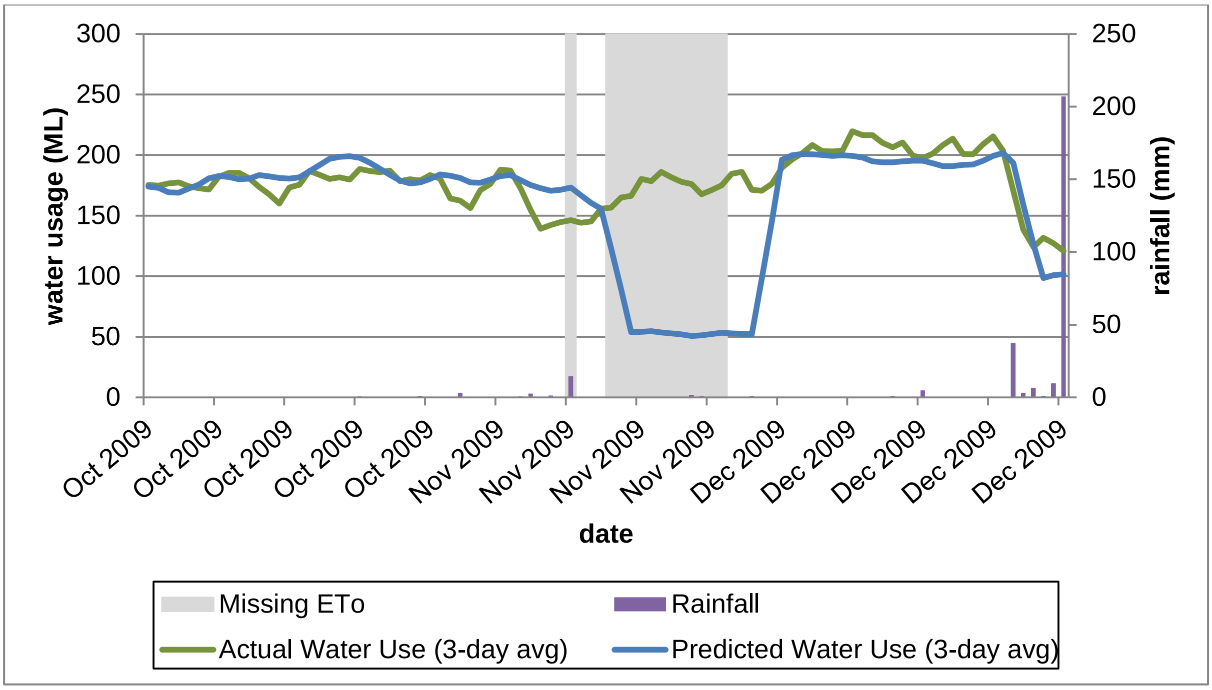

Figure 5. Effects of small and large ETo gaps on Townsville’s predicted water use

4.2.2 Tolerance and Resilience

Real values to calculate the Calibration Settings could not be obtained due to time and resource constraints. As a result, some of these Settings were entered as assumptions in some communities, often using Mackay’s values as the default.

Despite these limitations, the Model predictions closely mirror actual water use in most regions, showing its tolerance for these assumptions. Lists of the Calibration Settings and their values are included appendix C and appendix D.

4.3 Applicability to Regions and Climate Zones

Graphing in appendix A and appendix B demonstrates that the Model predictions closely mirror actual water use for most regions and climate zones. Appendix A compares the actual and predicted water use, while appendix B plots the difference between the two. It is clear that reasonably accurate predictions can be produced despite the assumptions made and despite not accounting for population change (i.e. growth rates) in regions other than Mackay. It is likely that improved predictions could be obtained if this additional data was available.

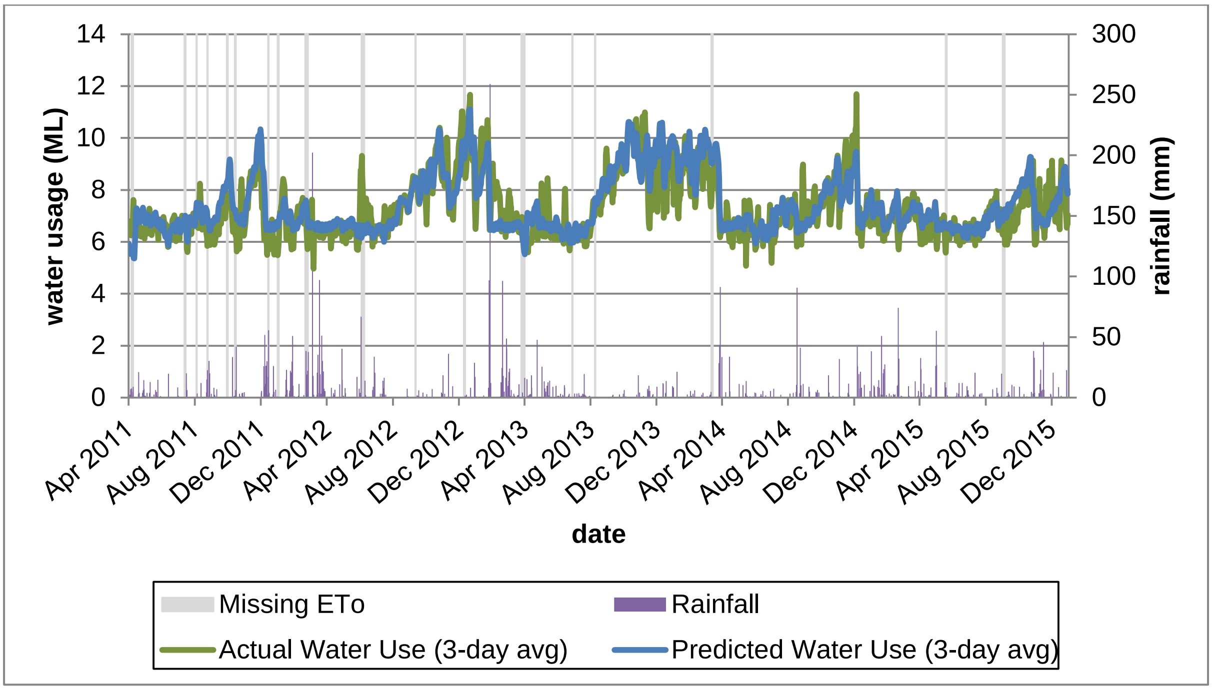

Figure 6. Predicted versus actual water use in Maryborough

However, there is room for improvement. For example, Rockhampton's predicted water use follows the same general patterns as the actual water use, but it does not reflect the frequent drops, nor the extremely low water use in the summer of 2010-2011. The predicted water use also drifts away from the actual water use in some regions. However, this could be resolved in the future using growth rate data, which has shown to account for some annual variation in Mackay.

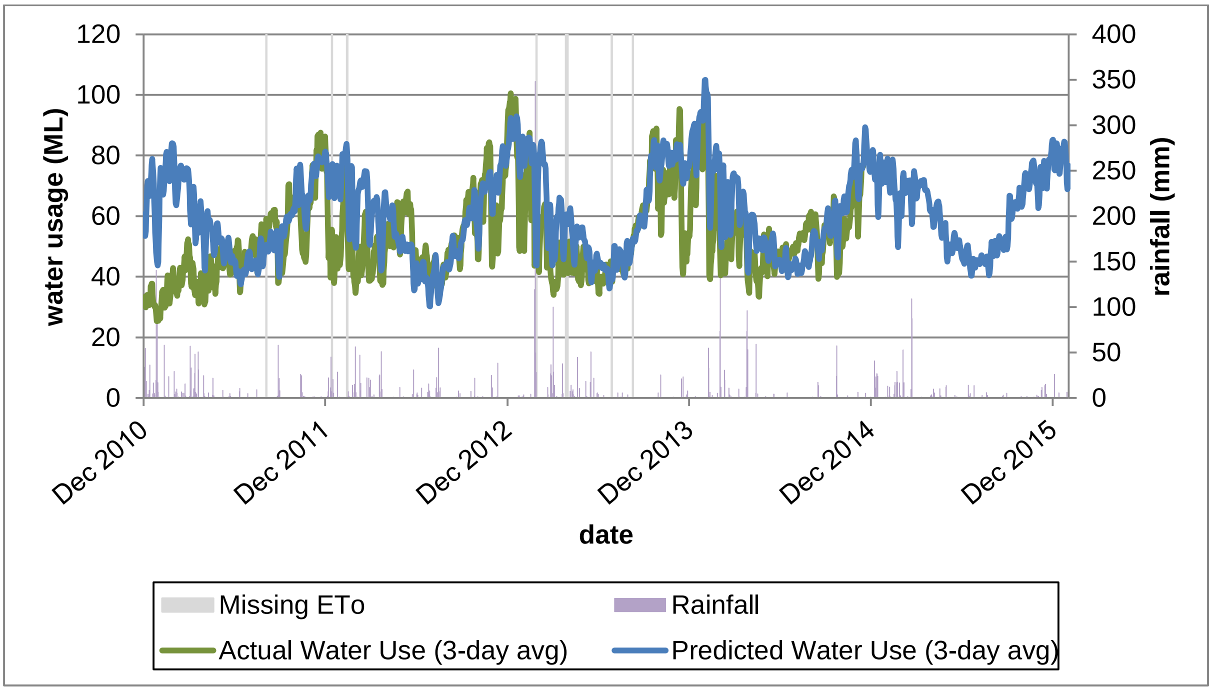

Figure 7. Predicted versus actual water use in Rockhampton

4.3.1 R^2 Results

The correlation between each region's Predicted and Actual Water Use can be assessed by performing a linear regression, then finding the coefficient of determination, or R^2 (pronounced 'r squared'). The resulting R^2 for each region is listed in Table 1.

Hervey Bay, Mackay, Maryborough, and Townsville all scored over 65%, which indicates that the majority of the Actual Water Use could be explained by the Predicted Water Use inputs, such as ETo, Rainfall, and Residential Connections.

However, there is still much room for improvement. Longreach, Rockhampton, and Toowoomba scored under 45%, which suggests that there are other major factors not accounted for. These may be included among the default settings outlined in appendix C and appendix D, or they could be other factors not yet considered.

Region	R^2 [%]
Hervey Bay	69.64
Mackay	69.11
Maryborough	67.80
Townsville	62.04
Cairns[1]	56.88
Toowoomba	44.81
Rockhampton	39.39
Longreach	35.84

Table 1. R^2 result for each region

4.3.2 Individual Analysis

As each region has varying climates and circumstances, it is difficult to speculate why some regions are more readily modelled than others are. What is clear is that reasonable predictions can be made of overall water demand using solely environmental variables (rainfall and ETo). This means that beyond local differences in base load and indoor water use, much of the variability in demand can be explained by outdoor water use. While it is well known that outdoor water use forms a large proportion of urban demand, the level to which it determines both variability and peak demand was greater than expected.

The mechanism for this effect is assumed to be related to irrigation driven by consumer perceptions of hot and dry conditions (low rainfall and high ETo) and the impact this has on the areas they irrigate. There may be a component driven by the physiological response of plants to high ETo in the absence of rain or the relationship may be a cultural response to ensure outdoor areas are not limited by water. Either way, this has important implications for how demand management programs, operational decisions, and short and long-run decision making should be approached.

Demand management addressing indoor water use will reduce the baseline and to a lesser extent, the maximum demand in any community, but will have little impact on variability. Periods of high water use driven primarily by urban irrigation will remain the key drivers of peak demand. This effect is exacerbated by the cumulative effect of climate-driven demand, as high water use will be common, or universal in hotter periods building on the well-understood diurnal oscillations in base-load.

Understanding how outdoor water use drives demand in different communities could also reveal better locally-relevant options for managing demand or planning infrastructure. Each of modelled communities (see appendix A and appendix B) are examined briefly below with respect to what these initial predictions might mean in each.

4.3.2.1 Cairns

The Model predicted variability and maximum use well in Cairns, but was not effective in describing the lowest periods of water use (i.e. during heavy summer rain). The predicted values were mostly within 5 ML of actual water use (appendix B) but this difference increased to ± 10 ML in some of the

[1] To calculate Cairns' R^2 accurately, predictions prior to 17th November 2010 were excluded from the linear regression. The BOM did not record ETo prior to that date, which reduces the accuracy of those records.

summer periods. The Model could be recalibrated to allow for very low demand during these periods, but clearly shows that outdoor water use is driving variability and peak demand in Cairns. There is no clear evidence of events affecting Cairns water use, but it would be interesting to investigate the impact of peak tourist periods and, at a smaller scale, the impact of cruise ships. Cairns also had one of the lowest ETo rates (appendix D) indicating that the outdoor water use is less responsive to changes in ETo than in most other communities. Together these factors could mean that demand management may be useful in reducing peaks in water use but may not have strong impact on small timescale variability.

4.3.2.2 Hervey Bay

The Model predicted water use in Hervey Bay well (usually within ± 3 ML – see appendix B) though there was a gradual decrease in the overall matching of predictions suggesting that all water use had decreased over the period examined. In Mackay, this sort of change was shown to result from general population changes or large shifts in commercial water use. The overall ‘Growth’ of a community can be used by the Model but was not used in this study due to a lack of data. Even at the start of the prediction period, the Model often underestimated peak water use and the Model’s accuracy was lowest during summer particularly during extended rain in 2012, 2013 and to a lesser extent in 2014. These periods are likely also impacted by the heavy tourism influx to Hervey Bay in summer

4.3.2.3 Longreach

After an initial calibration period, the Model is good at predicting actual water use in Longreach from around February 2010, although it tends to underestimate some of the highest spikes in the variable water use in the town. Major discrepancies occur between September 2010 and March 2011, reflecting inaccurate data on actual water use (which falls to an impossible 0 ML/d on four separate occasions). At these times, the Model likely provides a better approximation of real water use than does the available data.

Between February and May in 2012 and 2013, there are two anomalies where actual water use remains relatively steady (except after rainfall) while predicted use is much lower. Both incidents follow a particularly heavy rainfall event after which water use immediately returns to a higher than predicted volume. Potential causes for this anomaly could include inaccurate rainfall data, a large leak, or a large additional use of the supply (e.g. flushing, road construction).

Between September 2013 and March 2014, the Model overestimates the water use, which follows a pattern that is dissimilar to other parts of the period under investigation. It would be interesting to see whether local events (like water restrictions or educational programs) were effective during this summer period.

4.3.2.4 Mackay

The Model is very accurate for Mackay, which is the only town for which a growth factor (based on population change) is used in the Model runs. This allows for gross size-related changes in water use from year to year. The predictions are generally within 5 ML of actual use with some large under-predictions (e.g. around December 2009 and January 2013). These are most likely caused by missing ETo data (appendix D). The Model is particularly good at predicting peak water use, but is less accurate during heavy rainfall between December and May each year where it tends to underestimate variability in use.

4.3.2.5 Maryborough

Model predictions were generally within 1 ML of actual use in Maryborough with exceptions generally related to underestimation of spikes in water use. This is particularly obvious during summer periods where multiple peaks result in the Model repeatedly under-predicting use.

Repeated exceptions of over-prediction occur only during November 2013 to May 2014. It would be interesting to see whether local events (such as restrictions or community awareness campaigns) were active during this summer, resulting in lower than expected consumption. A large spike in actual water use in June 2012 provides a good example of a likely local event causing unusually high consumption unrelated to weather and should be investigated further.

This preliminary investigation suggests that water use in Maryborough is fairly stable and predictable, and unlike many communities, consumption is not increasing gradually over the time period investigated. This could mean that long run capital investment can be planned more conservatively than in other areas. In contrast, the multiple unexpected (short term) spikes in water use (which are seemingly unrelated to climate) could indicate that temporary storage could provide a buffer to operational demand and the need to rapidly produce water during high use.

4.3.2.6 Rockhampton

The Model predictions approximate water use in Rockhampton from June 2011 (see appendix C) following the initial calibration period but repeatedly over-estimate use during summer periods (appendix D). In many cases, the over-prediction occurs immediately following rain indicating that outdoor watering in Rockhampton is slower to return to pre-rain levels than is predicted by the Model. Rockhampton also has the highest ETo factor (i.e. predicted response in outdoor water use based on local water loss – see appendix D) which will exacerbate this over-prediction making the Model overly sensitive following rainfall. More local data and further calibration is necessary to allow the Model to predict the variable water use in Rockhampton.

Despite its inaccuracy in predicting all of the variability, the Model provides a reasonable estimation of the overall peak periods of demand. This could be useful in determining the maximum and minimum water use during a year based on climate factors (or climate predictions). This is illustrated in appendix C where the Model’s predictions are provided for the 2015 period despite there being no data available on actual water use during this period.

4.3.2.7 Toowoomba

Water use in Toowoomba is more consistent over daily and yearly timeframes than the other communities in this study, perhaps reflecting the town’s history of drought, careful water management, and possibly more stable ETo. The Model accurately predicts the overall trend in water use, but does not reflect the daily variability well. It tends to underestimate use throughout the period studied, possibly because it also has the lowest ETo Rate (appendix D). Unlike other communities, water use in Toowoomba appears to be relatively unaffected by rain (even after large events) and overall and peak use has remained stable throughout the period studied. The consistency of water use in Toowoomba suggests that short and long-run decision making on water infrastructure should be simplified as production and storage capacities can be relatively easily predicted.

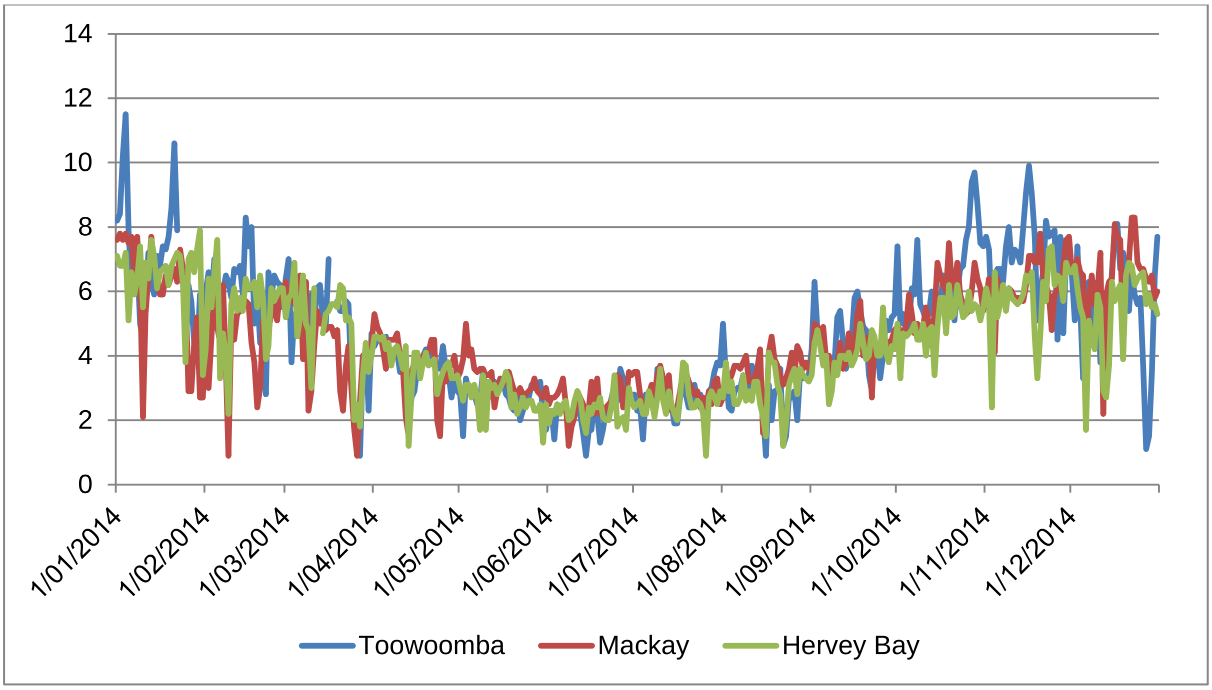

Figure 8. Comparison of ETo in Toowoomba, Mackay, and Hervey Bay during 2014

4.3.2.8 Townsville

Despite under-predicting during times of heavy rainfall, the Model predicts actual water use in Townsville fairly accurately with one exception. Commencing in February 2013 and repeated in November 2013, there is a clear step-change increase in water use (of 10-20 ML/d) greater than what is predicted based on previous consumption. If this offset is overlooked, the variability and extremes of use are well represented by the modelled data until September 2015 when water use appears to drop uncharacteristically for the start of a dry summer period.

A temporary increase in water use in April 2012 following a period of high rainfall could be indicative of a local event. Water use rises rapidly, and then remains at a constant level for around a month, a pattern that can potentially indicate a leak or large ongoing extraction (e.g. from industry or construction). Additionally, in June 2012 there was an unusual drop in water use to 10% of normal values for around one week.

It would be interesting to determine if there has been a driver(s) for these discrepancies, such as increased water use, unmetered consumption, or even a small change in the recording or reporting methodology. The high annual variability and continuous overall growth in water use in Townsville indicate that the supply system requires a broad capacity, and that this need is likely increasing.

4.4 Effectiveness of Estimating ETo from Temperature

To make the Model more relevant for areas where no local ETo data exists, the option of calibrating predictions using temperature was tested to compare accuracy.

A simple relationship was expressed using the equation

$$f = \frac{T}{E}$$

where E = evapotranspiration [mm]
T = maximum temperature [ºC]

It is known that the relationship between ETo and temperature is more complex than represented here. A literature review shows that the most promising relationship is described using Hargreaves' equation, which uses average temperature, solar radiation and two constants [6]. This and other solutions to the missing ETo data are explored further in section 0.

To test the efficacy of the estimated ETo, the Maryborough and Rockhampton predictions were regenerated using it instead of the BOM's ETo. The models predictions for Maryborough were some of the most accurate when compared with actual water use using the BOM's ETo, as shown in Figure 9.

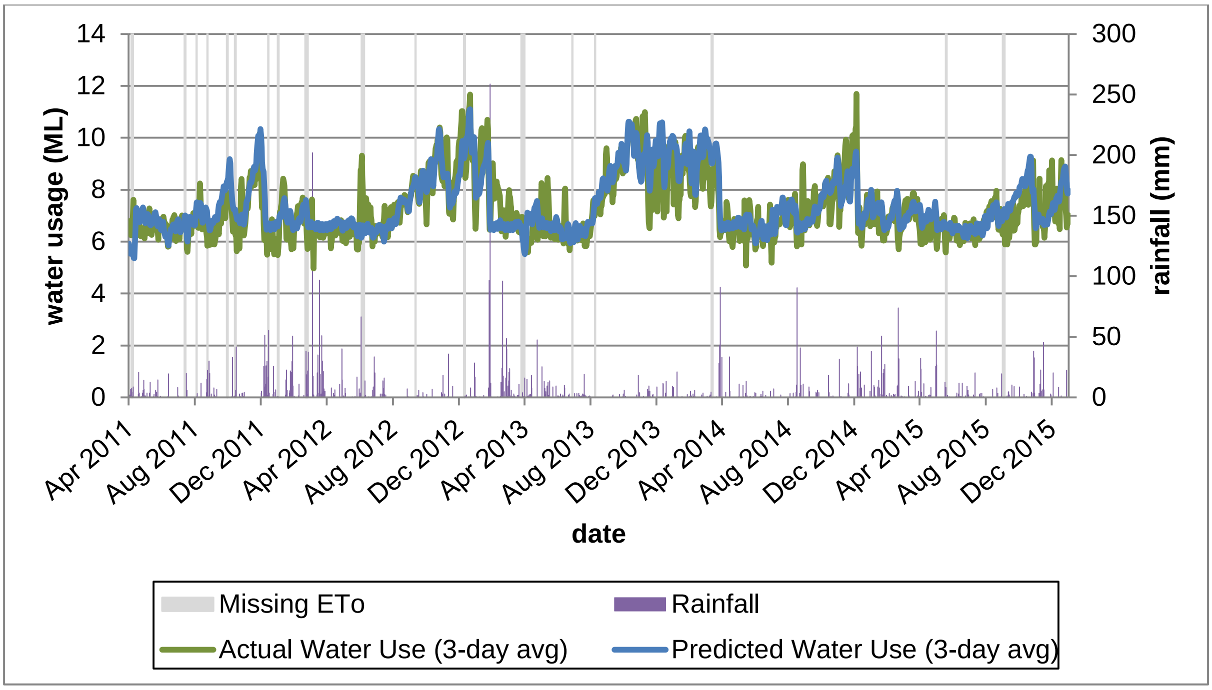

Figure 9. Maryborough's predicted water use, using the BOM's ETo

Figure 10 shows that using Temperature in the Model instead of ETo reduced the prediction accuracy.

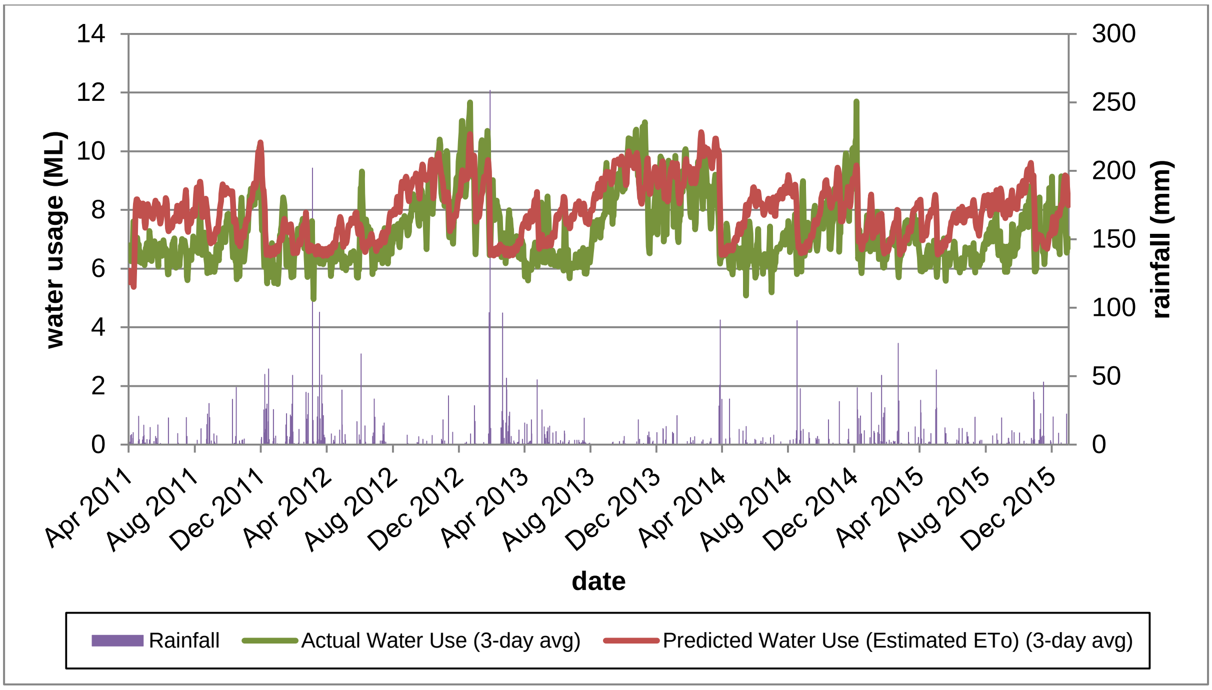

Figure 10. Maryborough's predicted water use, using temperature to estimate ETo

As a contrasting example, producing accurate predictions for Rockhampton was already a challenge due to the way its water use drops frequently in summer. Figure 11 shows that although it is not a perfect match, the predicted water use successfully follows the overall trend.

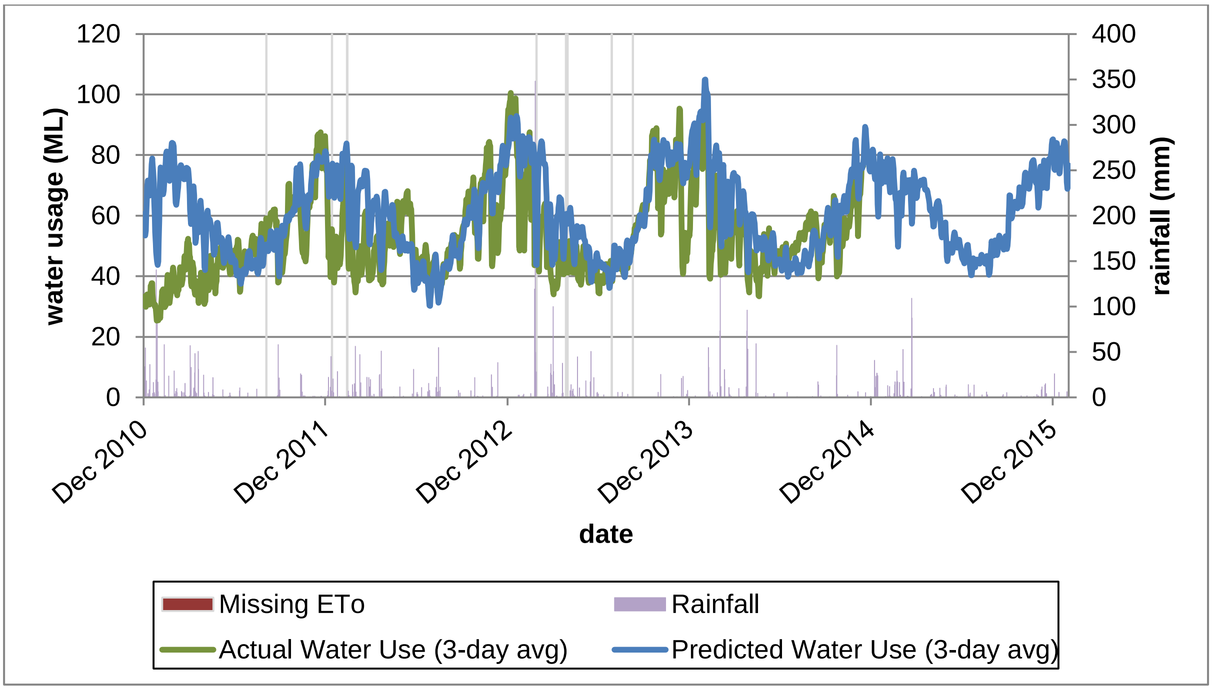

Figure 11. Rockhampton's predicted water use, using the BOM's ETo

Using temperature to estimate ETo makes the predictions much worse. As shown in Figure 12, the predicted water use is much higher than normal in winter, and is somewhat lower than normal in summer and the variation does not match actual water demand.

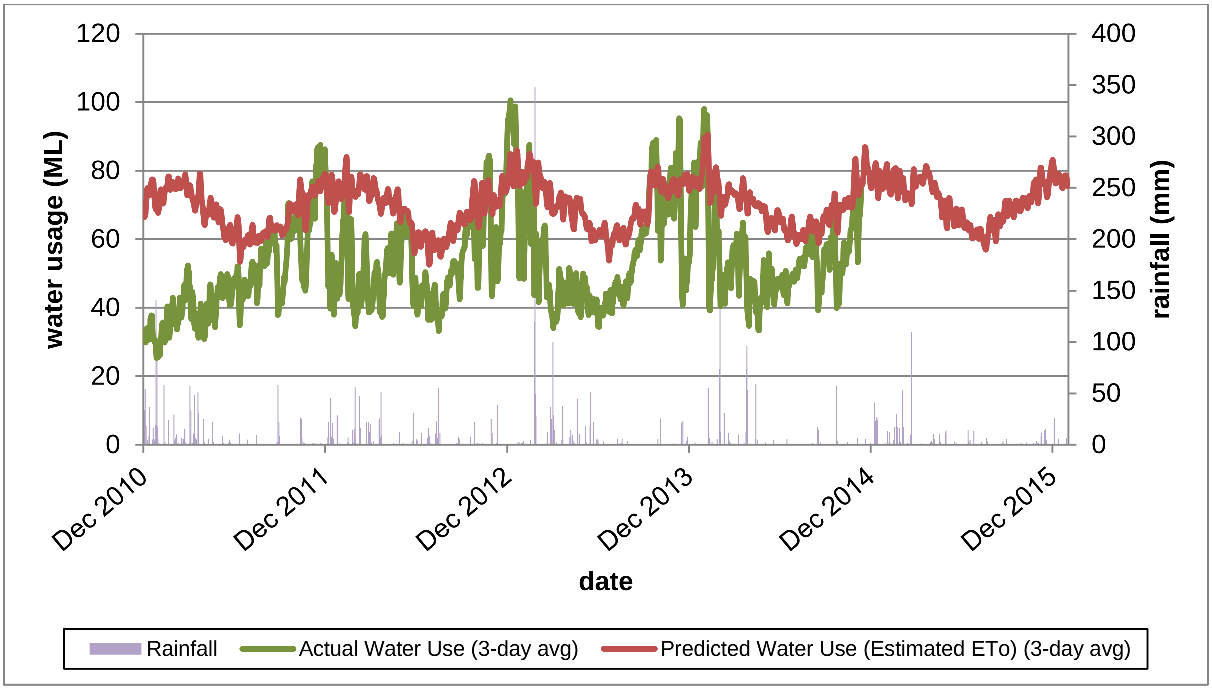

Figure 12. Rockhampton's predicted water use, using estimated ETo

The cause of these problems becomes apparent when the estimated ETo is graphed against the BOM's ETo in Figure 13. Using Temperature to estimate ETo provides a poor match for actual ETo and poorly reflects the variation obvious from day to day. As a result, using Temperature instead of ETo is not recommended for predicting water use.

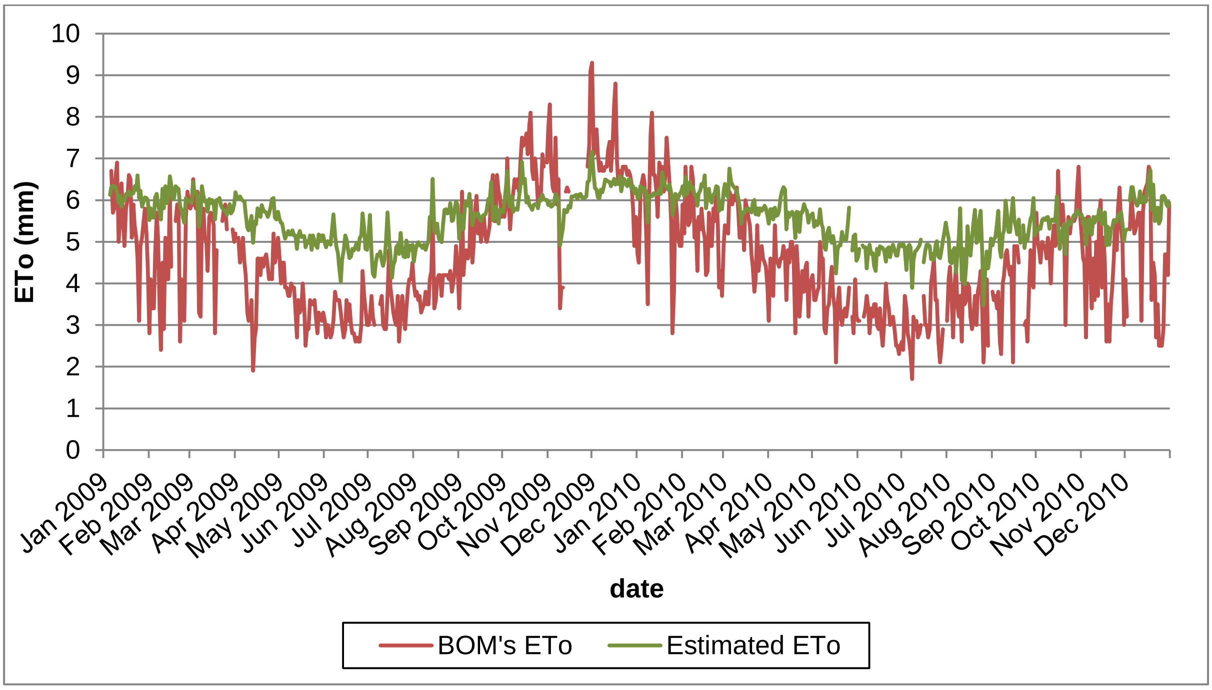

Figure 13. BOM's ETo versus estimated ETo in Mackay

4.5 Impact of Events upon the Model

Water use is impacted by many day-to-day factors such as rainfall and ETo, but major events such as cyclones are also expected to play a part. This section analyses the impact of such events on the actual and predicted water use.

4.5.1 Tropical Cyclone Yasi (2011)

On 3rd February 2011, category 5 tropical cyclone Yasi crossed the Queensland coast just 138 km south of Cairns [2]. Unfortunately, its impact on Cairns cannot be analysed as the event occurred during a gap in Cairns' supplied data. Therefore, Townsville and Mackay will be analysed instead.

4.5.1.1 Townsville

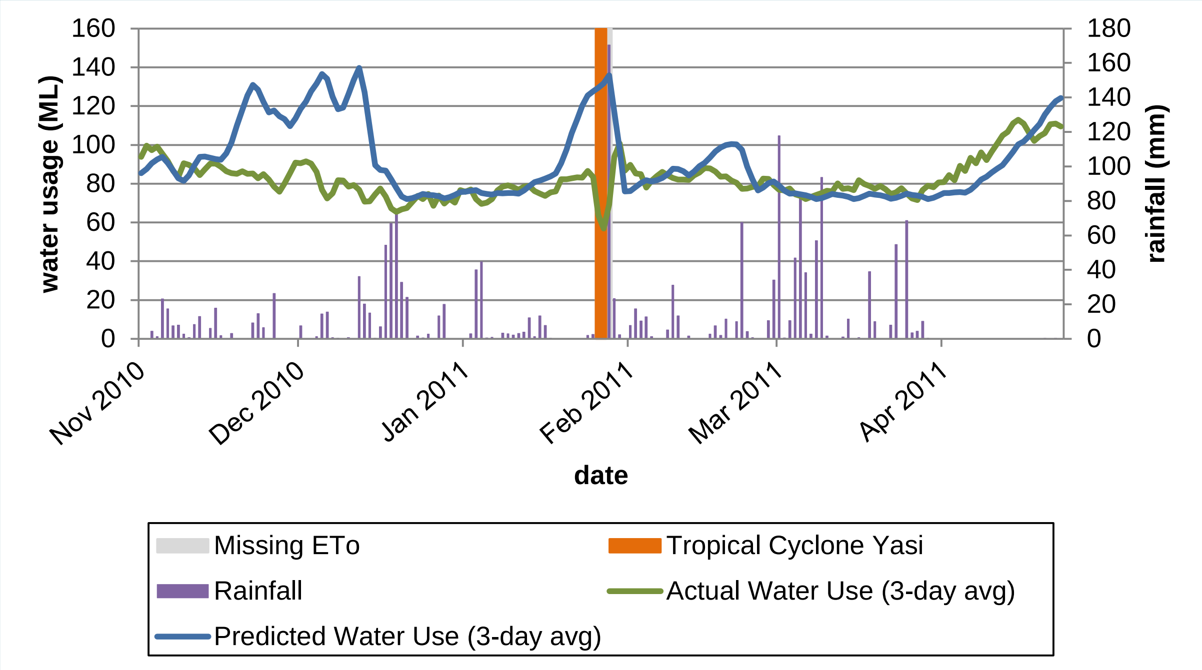

Figure 14. Townsville predicted versus actual water during tropical cyclone Yasi

During tropical cyclone Yasi, the actual water use clearly dropped as low as 57 ML. It might be speculated that heavy rainfall was the primary cause, and not the cyclone itself. However, this appears unlikely. Similar rainfall events during this summer did not substantially reduce the water use. The only substantial change to water use occurred during the cyclone.

On the other hand, the predicted water use showed a sharp increase due to the dry period prior to the cyclone.

4.5.1.2 Mackay

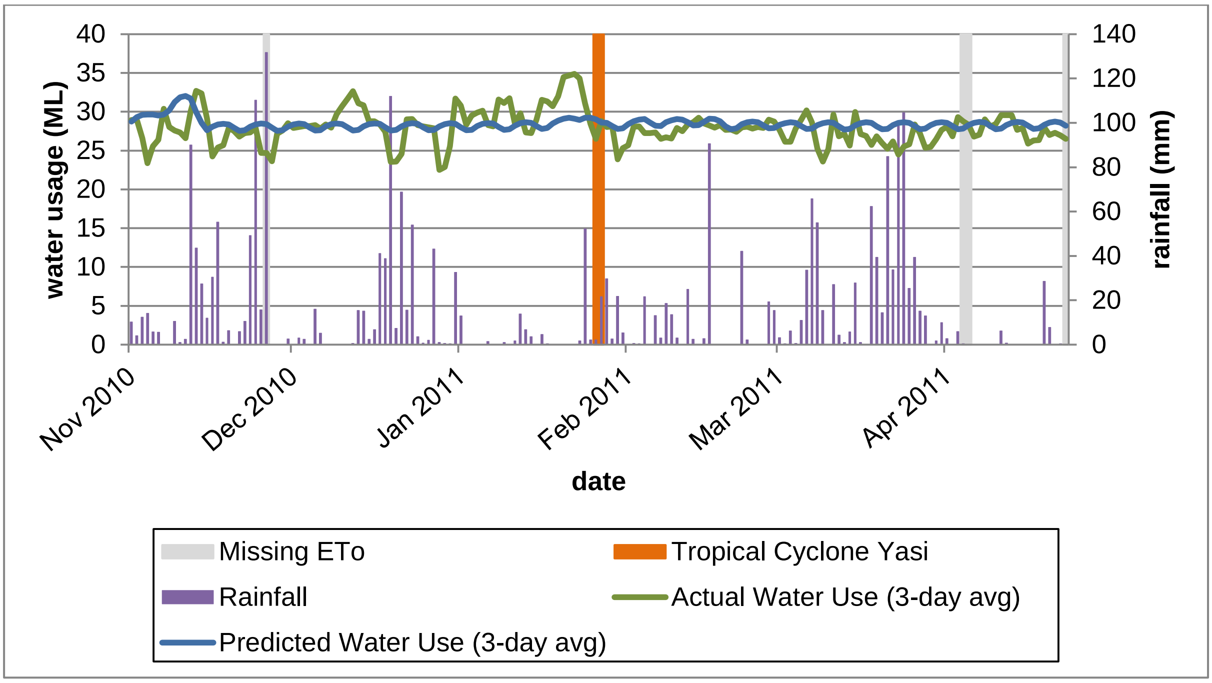

Figure 15. Mackay predicted versus actual water use during tropical cyclone Yasi

Despite an early warning for people in low-lying and waterfront areas to relocate [2], Mackay was removed from the warning zone just before the cyclone's crossing and felt little impact [5]. As a result, there was very little change in actual water use. Because the change is so small, it is difficult to determine whether the change was caused by the cyclone or other factors. There was little rainfall at the time, so it is unclear whether how much it contributed.

No change was observed in the predicted water use. It plateaued in the previous month and did not decrease further with either the cyclone or rainfall.

4.5.2 Tropical Cyclone Oswald (2013)

On 17th January 2013, Tropical Cyclone Oswald developed in the Gulf of Carpentaria. It travelled down Queensland's east coast before dissipating after the 26th [8].

4.5.2.1 Cairns

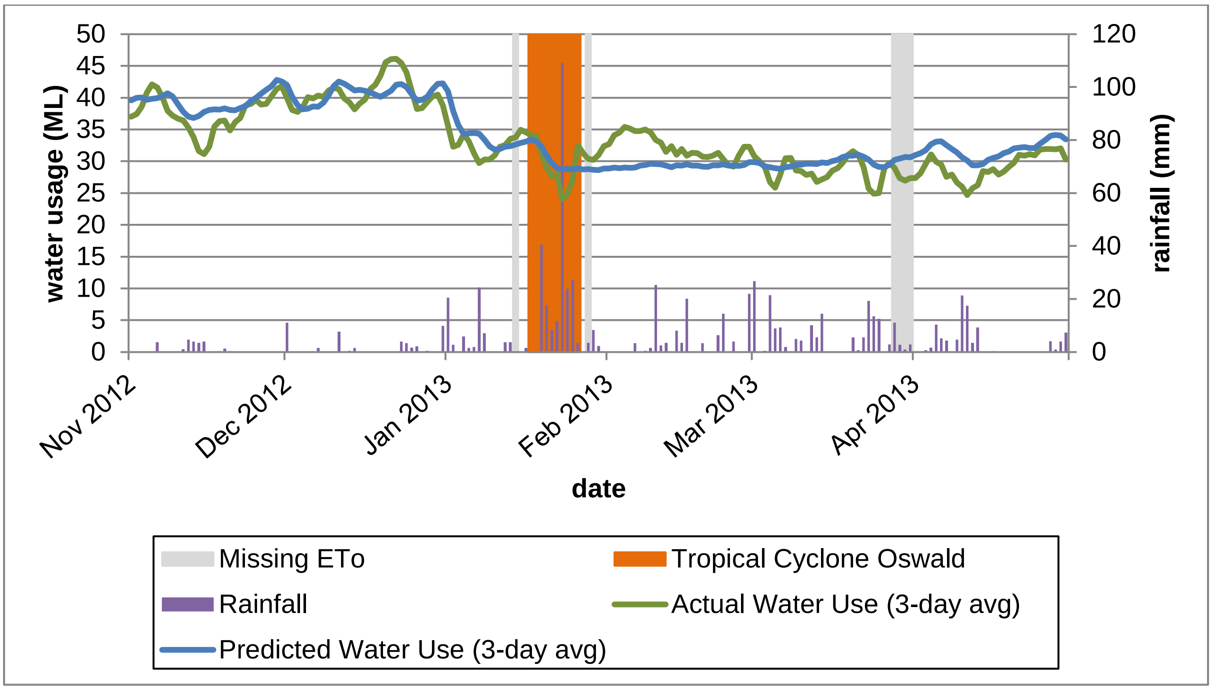

Figure 16. Cairns predicted versus actual water use during tropical cyclone Oswald

Cairns' water use dropped substantially during tropical cyclone Oswald, reaching its lowest point as rainfall exceeded 100 mm. Unlike the effects of Yasi on Townsville and Mackay, this time the predicted water use also decreased. Since the predicted water use takes rainfall into account and not cyclones, this would suggest that rainfall was the key factor in Cairns' reduced water use.

After the cyclone moved on, the predicted water use did not recover due to frequent rainfall over the next several months.

4.5.2.2 Rockhampton

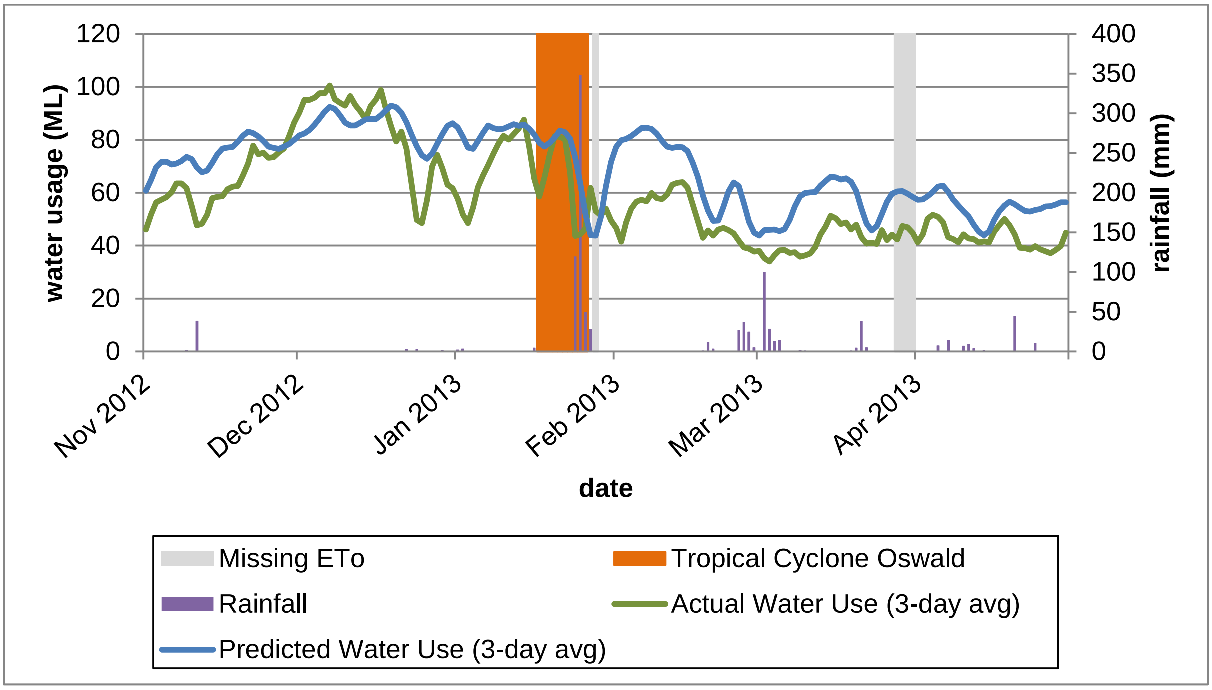

Figure 17. Rockhampton predicted versus actual water use during tropical cyclone Oswald

As in Cairns, both the actual and predicted water use decreased towards the end of the cyclone. Since the predicted water use does not account for cyclones, this would again suggest that rainfall was the key factor in reduced water use. The actual water use recovered somewhat after the cyclone. However, the Model predicted it would be higher, given the small amount of rainfall in the following two weeks.

4.6 Potential Improvements to the Model

It is likely that the predictions could better reflect actual water use if more data were available about local variation in indoor water use, population, industry change over time, and if other local variations could be tested. Two additional options have been identified to expand the Model and improve its overall accuracy: increasing tolerance for missing ETo data, and addressing regional rainfall variation by dividing each region into a collection of sub-regions.

4.6.1 Improving ETo Accuracy

Since the Model relies heavily on ETo, it is important to find a consistent source of this data. As discussed in section 4.2.1, gaps in the BOM's data are uncommon, but problematic. These gaps are resolved by substitution of an interpolated average, but a better solution would be ideal. Calculating ETo entirely from temperature was investigated as a potential solution in section 4.4, however, it was found to be unreliable and is not recommended. Two other options are proposed for further investigation.

The first option to use ETo from the nearest BOM station. Figure 18 shows that BOM stations with regular ETo monitoring are numerous, and most towns ought to have at least one neighbour in the same climate zone with ETo. If a region's primary BOM station is missing ETo, it could be substituted with the ETo from a nearby station.

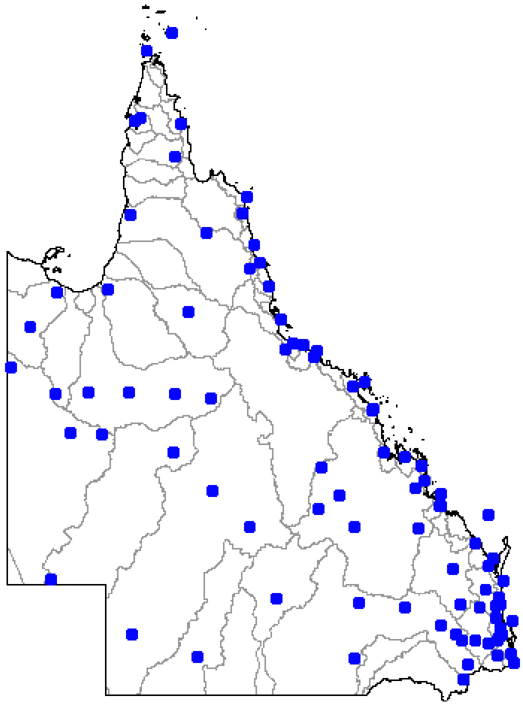

Figure 18. Map of Queensland BOM stations with ETo data. Reproduced by permission from the Bureau of Meteorology 2016, http://www.bom.gov.au/watl/eto/.

For example, the Cairns Aero and Cairns Racecourse stations are about 8 km apart, but graphing in Figure 19 shows a close relationship between their ETo readings. The Cairns Racecourse station may be a good substitute when ETo is unavailable from Cairns Aero. Further research will be required to determine whether this applies to other stations separated by greater distances.

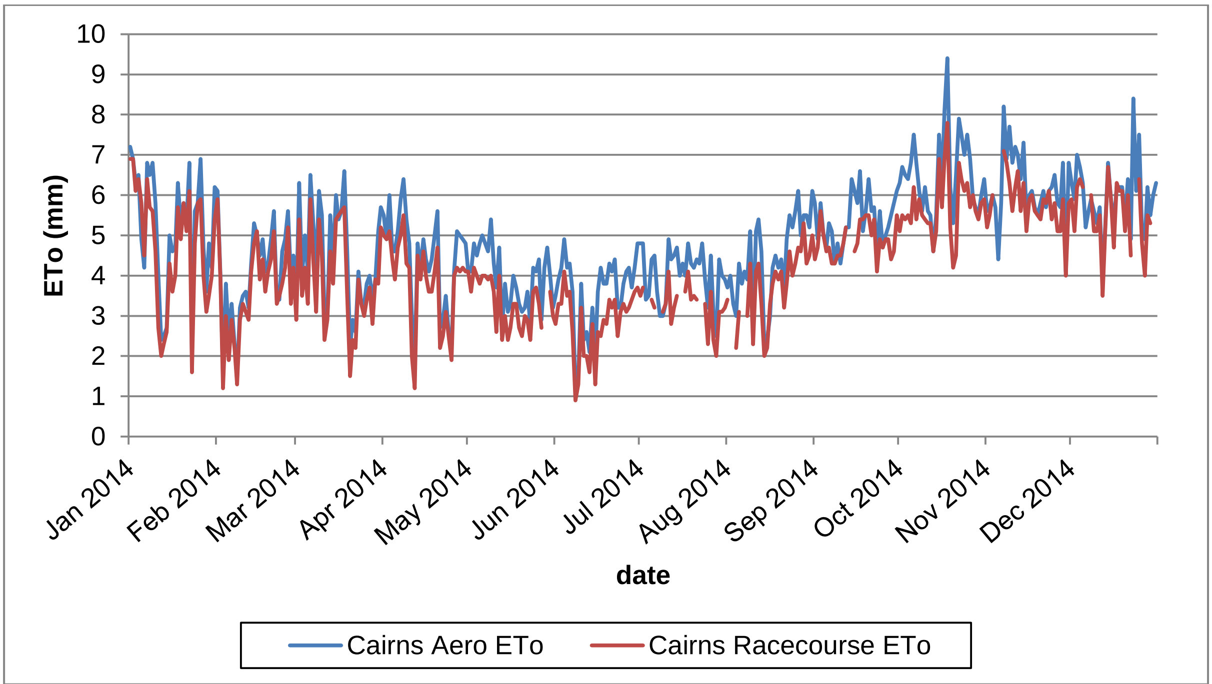

Figure 19. BOM's ETo at the Cairns Aero station versus Cairns Racecourse

A second option is to use Hargreaves' equation as an alternative to the BOM's Penman-Monteith equation. Hargreaves' equation is much simpler and produces a reasonable ETo estimate using just solar radiation and temperature [6]:

$$\text{ETo} = 0.0135 \cdot RS(T + 17.8)$$

where RS = solar radiation [mm]
T = average temperature [ºC]

Hargreaves' equation would allow ETo to be calculated when the BOM's is unavailable, provided solar radiation and average temperature can still be obtained. Graphing the Hargreaves and BOM ETo together in Figure 20 shows that they are very similar.

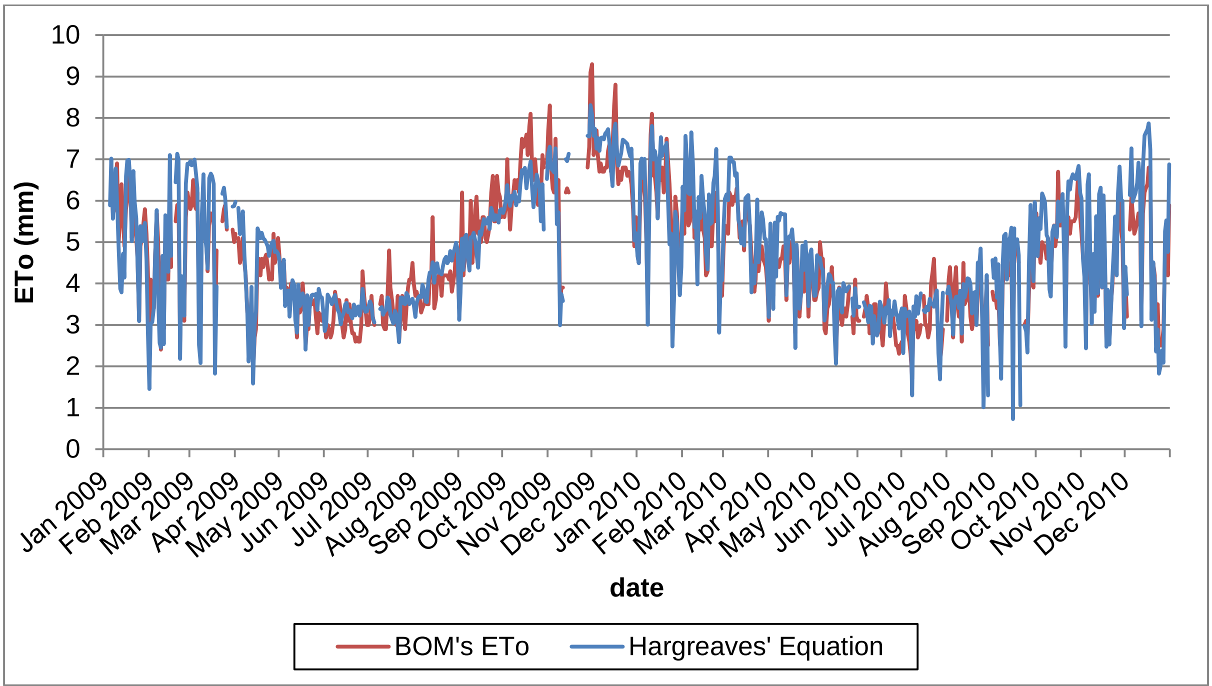

Figure 20. BOM's ETo versus Hargreaves' Equation in Mackay

These two options could be also combined to create a tiered approach where each region has its own user-definable hierarchy of stations and actions. For example:

	Station	Action
1.	A	Use the BOM's ETo
2.	A	Use Hargreaves' equation
3.	B	Use the BOM's ETo
4.	B	Use Hargreaves' equation
5.	C	Etc.

This will ensure that the most reliable stations and methods are used first, falling back to others depending on data availability.

4.6.2 Addressing Regional Rainfall Variation

As identified in section 4.1, the Model assumes rainfall is spread evenly throughout a region, however, testing in Mackay shows that it varies.

One way to address this is to divide each region into sub-regions and provide them with their own rain gauge and Calibration Settings. The total predicted water use for a region would then be equal to the sum of its sub-regions. Accuracy could be further improved by installing a pyranometer and thermometer in each sub-region to measure solar radiation and temperature. This way, local ETo could be calculated with Hargreaves' equation instead of relying on BOM stations dozens of kilometres away.

References

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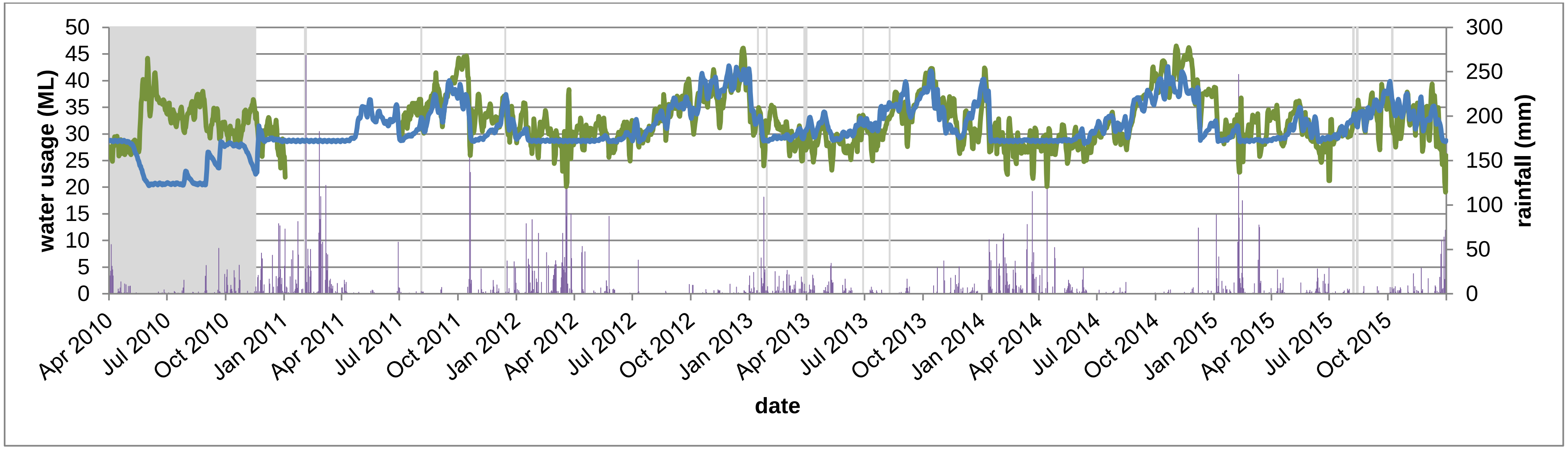
8. NASA. 2013. “February 2, 2013 – Tropical Cyclone Oswald (11P) over Australia”. Accessed 30 June 2016. http://modis.gsfc.nasa.gov/gallery/individual.php?db_date=2013-02-02.

Appendix A: Results of ETo-based Model

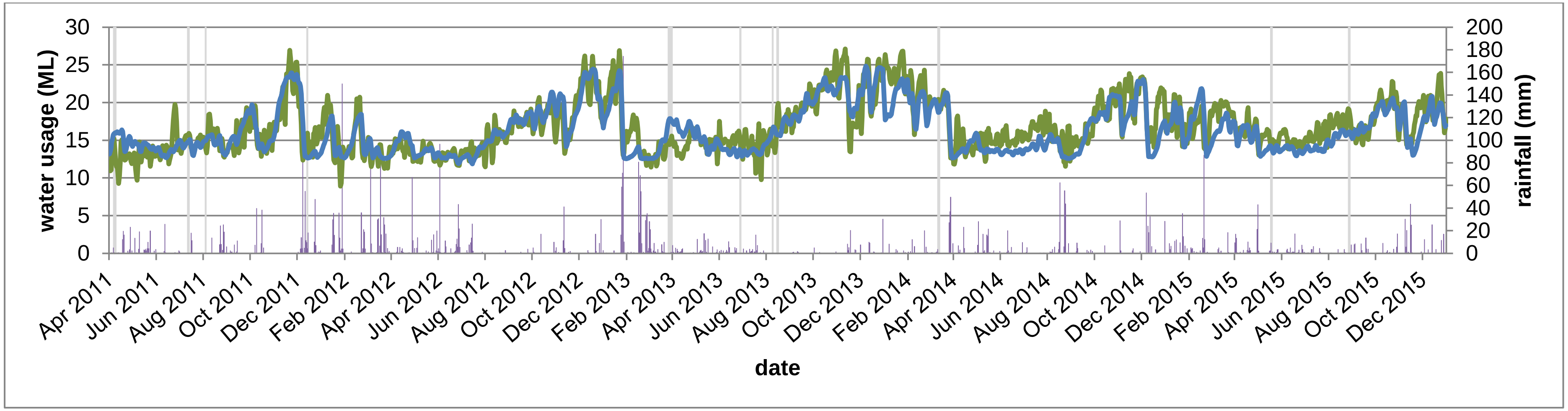
This appendix shows the results of the ETo-based Model. For the purpose of comparison, an initial three-month calibration period is omitted and all graphs use the following legend:

- Actual Water Use [ML] (3-day avg.)
- Predicted Water Use [ML] (3-day avg.)
- ETo Unavailable
- Rainfall [mm]

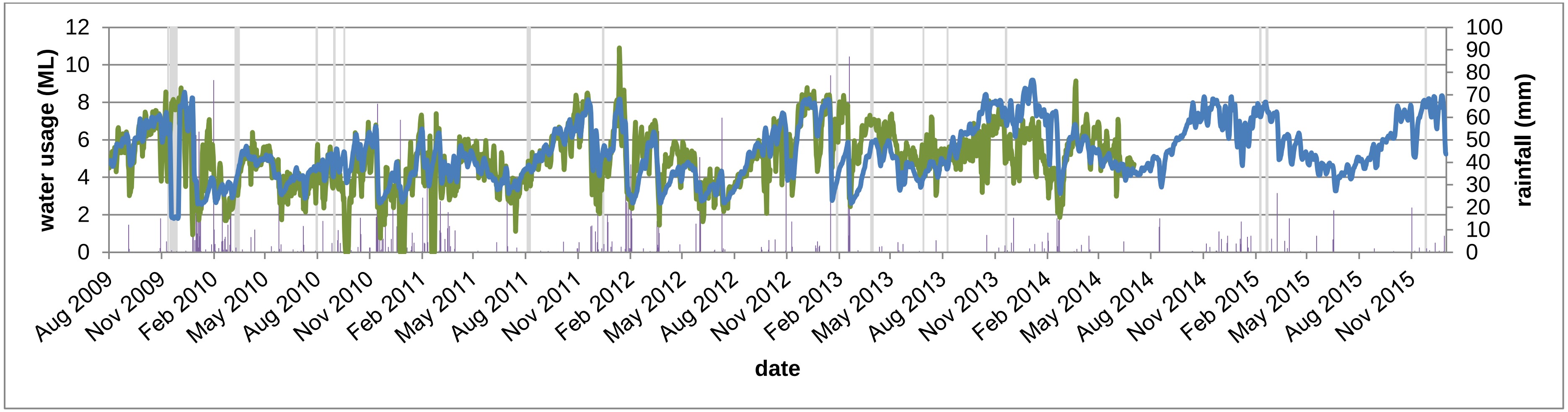
Cairns



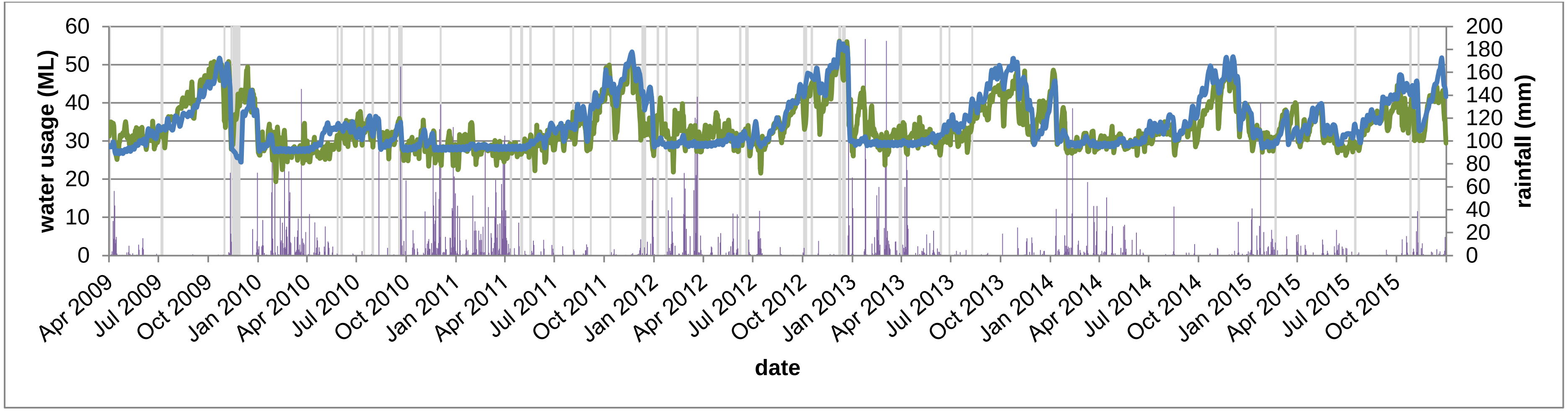
Hervey Bay



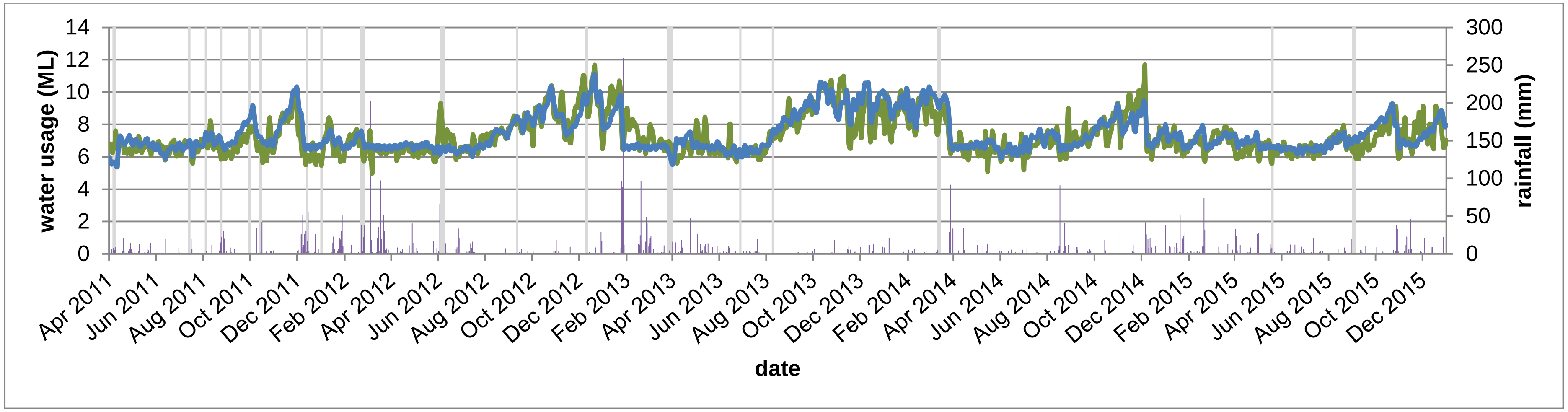
Longreach



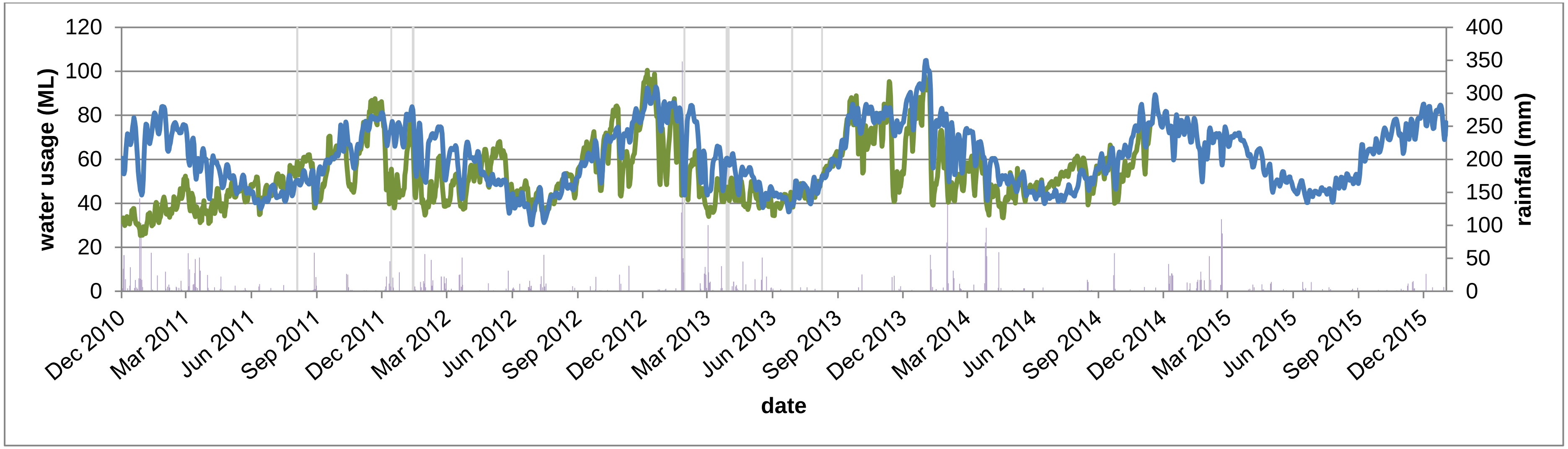
Mackay



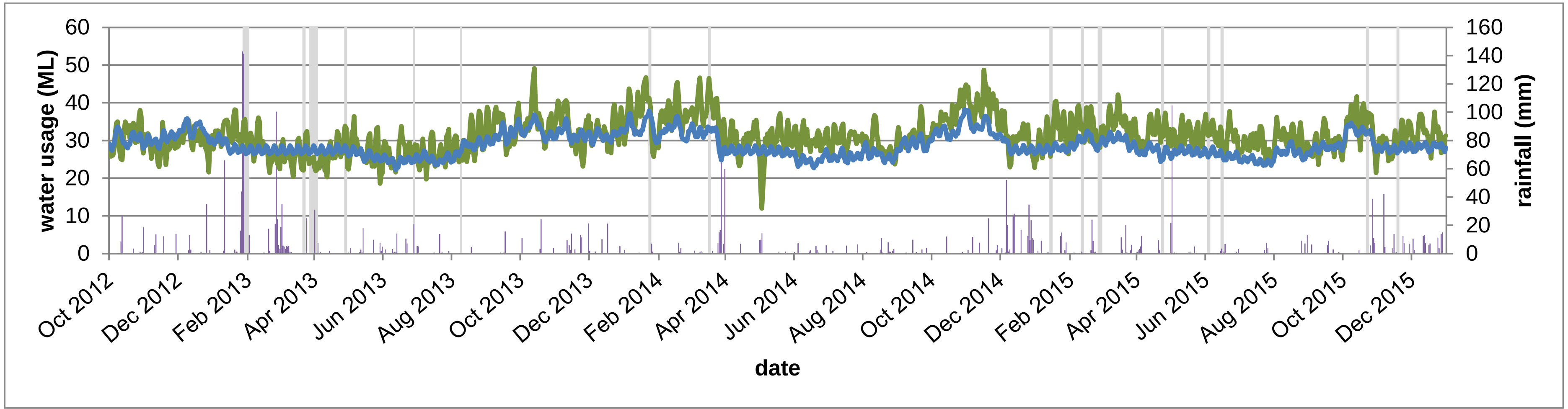
Maryborough



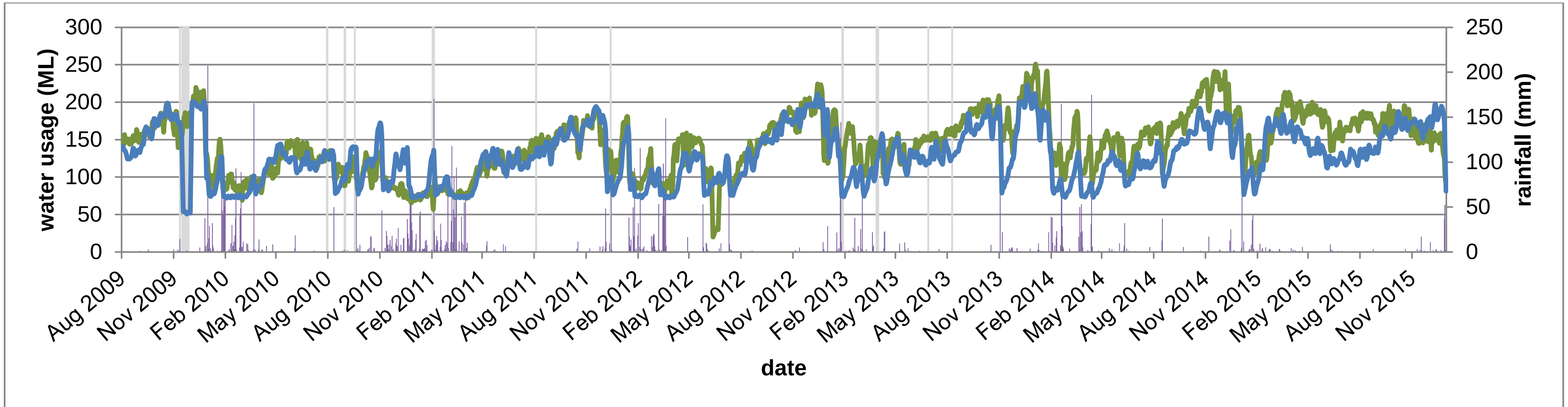
Rockhampton



Toowoomba



Townsville

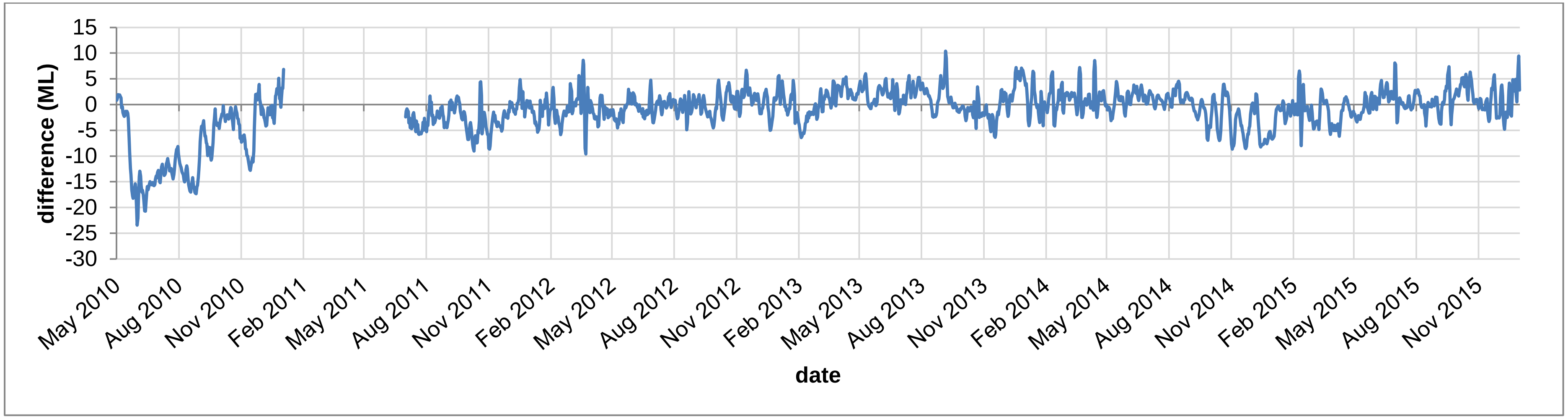


Appendix B: Difference between Predicted and Actual Water Use

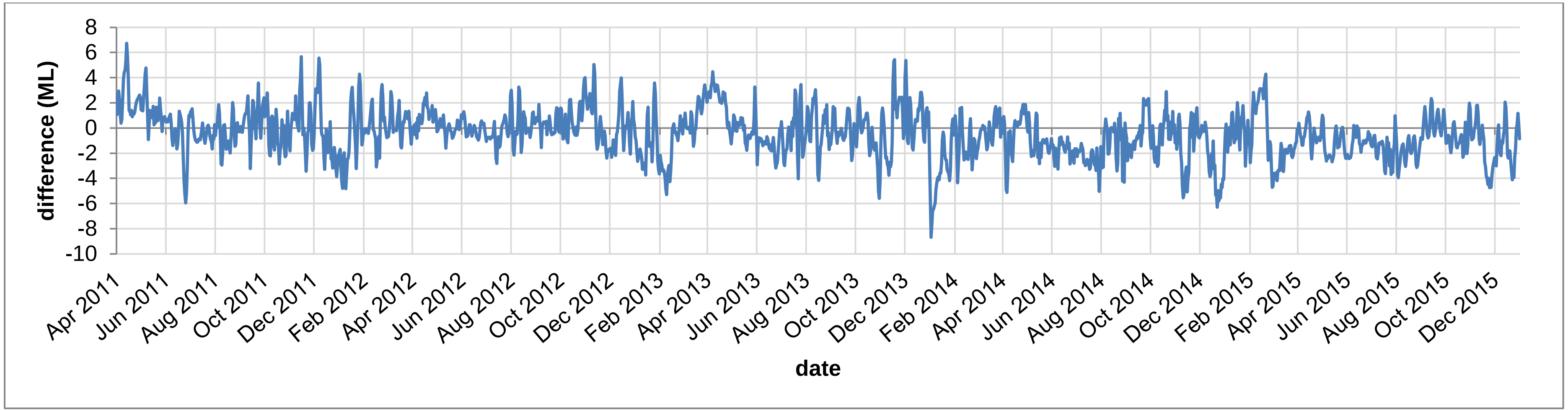
This appendix uses the data from appendix A to show the difference between each region's predicted and actual water use over time. This gives a visualisation of the Model's accuracy for each region. For the purpose of comparison, the difference is calculated from the three-day average of the predicted and actual water use. An initial three-month calibration period is omitted and all graphs use the following legend:

Difference [ML]

Cairns[2]

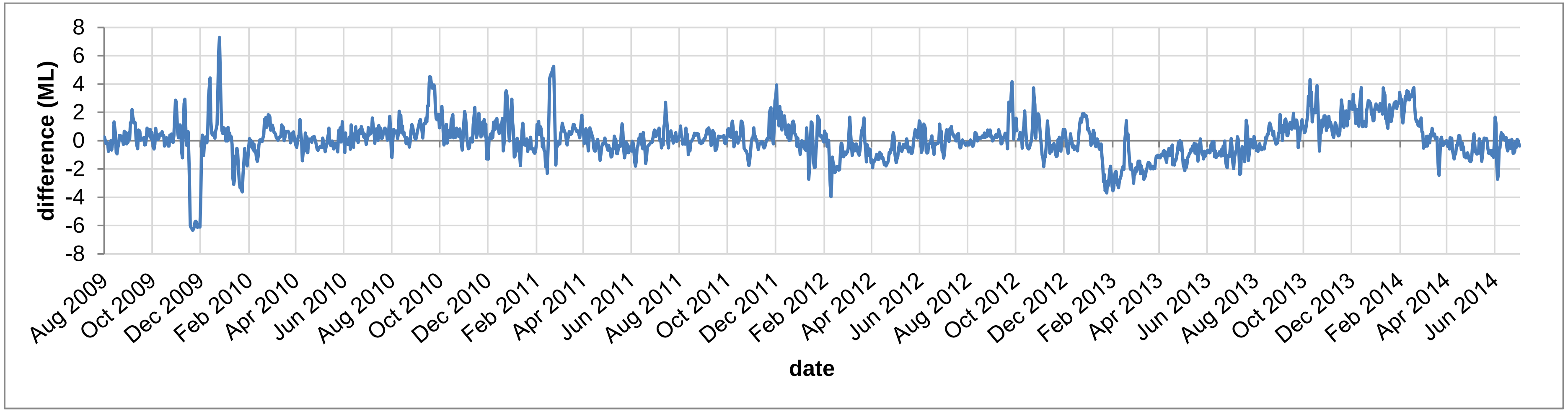


Hervey Bay

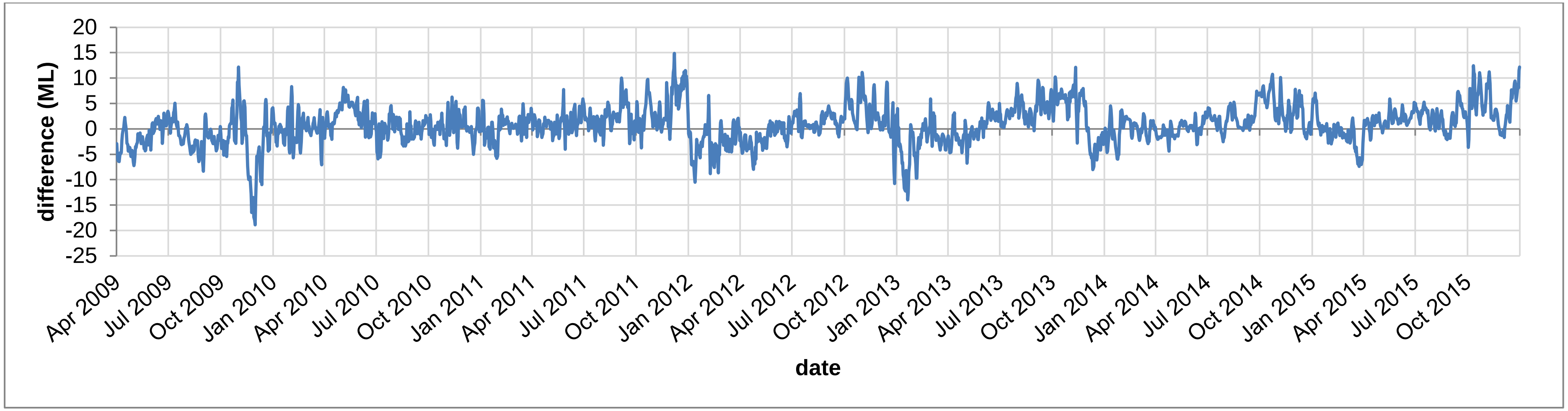


[2] Note that the BOM recorded no ETo for Cairns until 17th November 2010, which reduces accuracy of predictions until that date.

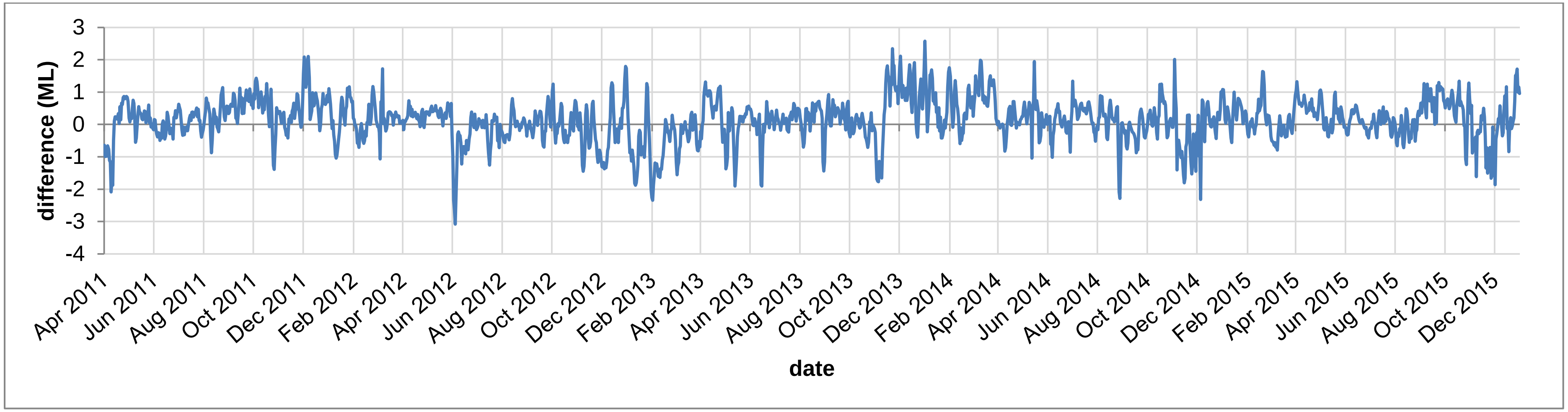
Longreach



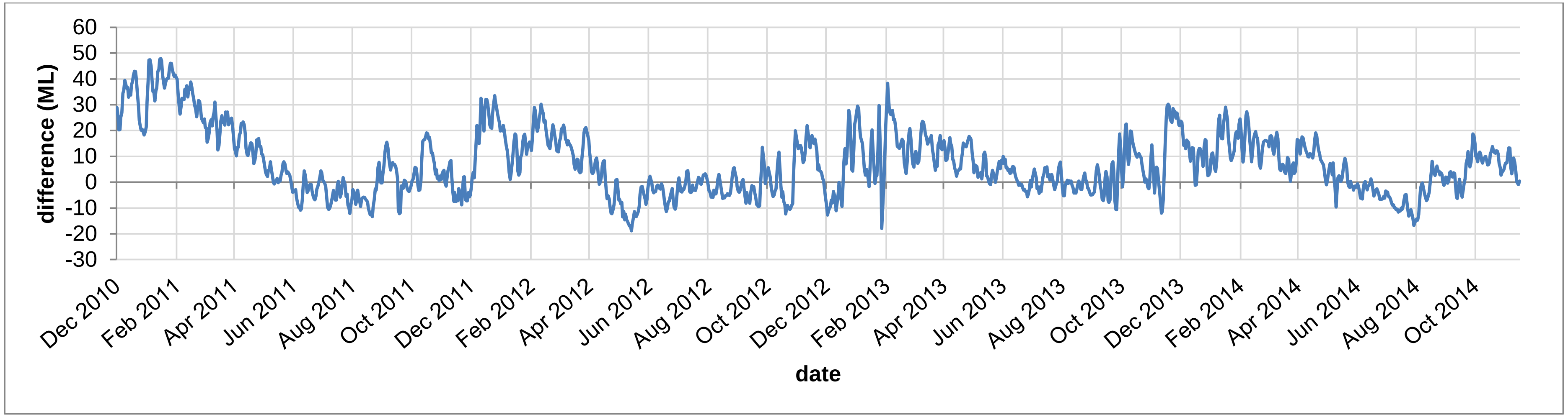
Mackay



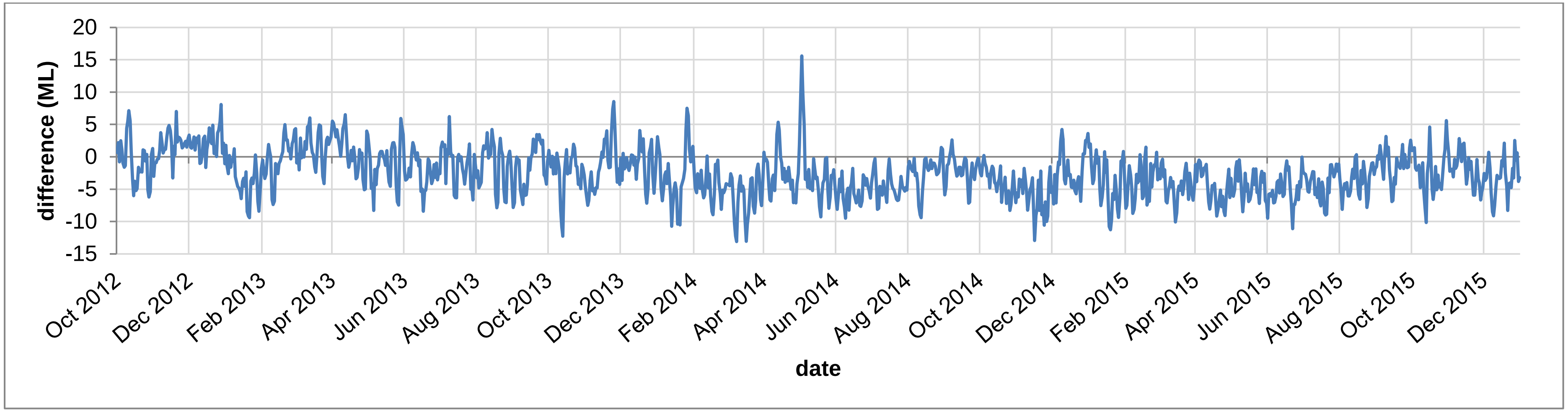
Maryborough



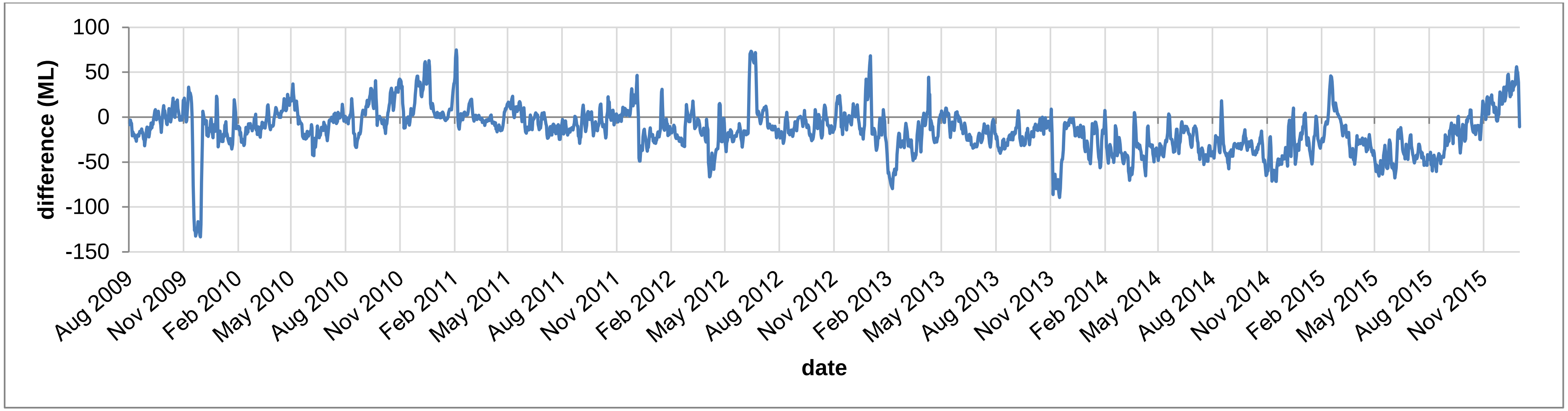
Rockhampton



Toowoomba



Townsville[3]



[3] Note that the BOM recorded no ETo for Townsville between 16th November 2009 and 27th November 2009, which reduces accuracy of predictions in that period.

Appendix C: Description of Calibration Settings

This appendix describes the Calibration Settings used by the Model. An asterisk (*) indicates that this setting is using Mackay's value as the default because real data could not be obtained. A full list of default Settings and their values is included in appendix D. All other Calibration Settings vary from region to region.

average indoor water use: The estimated amount of water used by the average residential property, per day.

base load: The estimated daily water use across all residential and commercial properties before accounting for other factors, given by

$$\frac{APR}{1{,}000{,}000} + C$$

where A = **average indoor water use** [L]
P = **people per household**
R = **residential connections**
C = **commercial water use** [ML]

capture efficiency[*]: The percentage of rainwater captured from the average roof into a tank.

commercial connections: The number of commercial connections at **starting date**.

commercial under-registration[*]: The estimated percentage of water consumed in commercial properties that is not registered due to problems with water meter accuracy.

commercial water use: The estimated amount of water used by commercial properties at the **starting date**.

day of week factor: The percentage of the average daily water use that is used on average on each day of the week (e.g. Monday), given by

$$F = \frac{D}{A}$$

where D = average water use on the weekday in question
A = average daily water use on any weekday

ETo rate: The rate at which outdoor water use scales with ETo.

ETo station number: The ID number of the nearest BOM station with ETo data. This may be the same as the **rainfall station number** if that station also measures ETo.

growth rate: The rate at which the **residential connections**, **commercial connections**, and **commercial water use** increase or decrease in a given financial year. Apart from Mackay, the growth rates for each region are assumed to be 0% (no growth) because real data could not be obtained for each region.

houses with rainwater tanks[*]: The estimated number of houses that have rainwater tanks.

internal rainwater use[*]: The volume of rainwater that the average household uses indoors.

people per household*: The average number of people per household.

persons per connection*: The estimated number of people per residential connection.

rainfall factor: The rate at which outdoor water use returns to normal after a rainfall event.

rainfall station number: The ID number of the nearest BOM station with rainfall data.

real losses*: The estimated percentage of water lost due to infrastructure problems such as leaks.

residential connections: The number of residential connections that existed at the **starting date**.

residential under-registration*: The estimated percentage of water consumed in residential properties that is not registered due to problems with water meter accuracy.

roof area*: The area of the average roof, used for calculating amount of rain water captured into tanks.

starting date: The date to start generating predictions from. Must be no earlier than 1st January 2009, as the BOM's ETo measurements do not go back any further.

unauthorised consumption*: The estimated percentage of water consumed illegally, for example, through illegal connections or by bypassing water meters.

unmetered, unbilled, authorised consumption*: The estimated percentage of water consumption which is not measured or billed.

Appendix D: Values used in Calibration Settings

This appendix records the values used for each Calibration Setting and region.

Variable Settings

These Calibration Settings vary from region to region.

	Starting Date	Residential Connections	Commercial Connections	Avg. Indoor Water Use [L]	Commercial Water Use [ML]	Base Load (Calculated) [ML]	ETo Rate	Rainfall Factor
Cairns	2010-01-01	63098	4019	85.000	5.30	19.08	0.100	0.0200
Hervey Bay	2011-01-01	24017	1591	100.000	3.00	9.08	0.160	0.0300
Longreach	2009-05-01	1275	325	95.155	2.00	2.31	0.210	0.0250
Mackay	2009-01-01	29043	2445	185.000	8.45	22.04	0.151	0.0165
Maryborough	2011-01-01	9324	1385	100.000	3.00	5.36	0.110	0.0200
Rockhampton	2010-09-01	25926	2595	185.000	8.45	20.58	0.350	0.0165
Toowoomba	2012-07-01	48095	3375	130.000	4.00	19.82	0.080	0.0100
Townsville	2009-05-01	67895	3877	240.000	20.00	61.23	0.250	0.0300

Default Settings

These Calibration Settings are using Mackay's values as the default.

General Settings

Persons Per Connection	Unmetered Unbilled Authorised Consumption [%]	Unauthorised Consumption [%]	Residential Under-registration [%]	Commercial Under-registration [%]	Real Losses [L]
2.53	0.5	0.1	3.5	3.5	143

Rainwater Tanks

Roof Area[m^2]	Capture Efficiency [%]	Internal Rainwater Use [L]	Tank Size [L]	Houses with Rainwater Tanks	People per Household
150	85	72	5000	3000	2.5

Growth Rates

Due to time and resource constraints, accurate growth rates could not be obtained for each region. Therefore, all growth rates are assumed to be 0% (no growth) except for Mackay.

	Growth Rate [%]							
	2008-2009	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016
Mackay	2.55	2.00	2.00	3.00	0.00	-1.50	-2.00	-3.00

BOM Stations

In most regions, the closest BOM station provides both rainfall and ETo data. In the case of Mackay and Rockhampton, the ETo must be fetched separately.

	Rainfall Station	ETo Station
Cairns	031011 Cairns Aero	
Hervey Bay	040405 Hervey Bay Airport	
Longreach	036031 Longreach Aero	
Mackay	033303 Mackay Alert	033045 Mackay Aero
Maryborough	040126 Maryborough	
Rockhampton	039264 Rockhampton	039083 Rockhampton Aero
Toowoomba	041529 Toowoomba Airport	
Townsville	032040 Townsville Aero	

Appendix E: Comparison of ETo Sources

The below graph compares three potential sources for ETo:

- the BOM's ETo data
- an approximation derived from the BOM's maximum temperature (see section 4.4)
- Hargreaves' equation, which uses the BOM's temperature and solar radiation data (see section 0)