ICRC
independent competition and regulatory commission

DRAFT REPORT

Review of water and sewerage services demand forecasting methods

Report 16 of 2021, September 2021

The Independent Competition and Regulatory Commission is a Territory Authority established under the *Independent Competition and Regulatory Commission Act 1997* (the ICRC Act). We are constituted under the ICRC Act by one or more standing commissioners and any associated commissioners appointed for particular purposes. Commissioners are statutory appointments. Joe Dimasi is the current Senior Commissioner who constitutes the Commission and takes direct responsibility for delivery of the outcomes of the Commission.

We have responsibility for a broad range of regulatory and utility administrative matters. We are responsible under the ICRC Act for regulating and advising government about pricing and other matters for monopoly, near-monopoly and ministerially declared regulated industries, and providing advice on competitive neutrality complaints and government-regulated activities. We also have responsibility for arbitrating infrastructure access disputes under the ICRC Act

We are responsible for managing the utility licence framework in the ACT, established under the *Utilities Act 2000* (Utilities Act). We are responsible for the licensing determination process, monitoring licensees' compliance with their legislative and licence obligations and determination of utility industry codes.

Our objectives are set out in section 7 and 19L of the ICRC Act and section 3 of the Utilities Act. In discharging our objectives and functions, we provide independent robust analysis and advice.

Correspondence or other inquiries may be directed to the Commission at the following address:

Independent Competition and Regulatory Commission
PO Box 161
Civic Square ACT 2608

We may be contacted at the above address, or by telephone on (02) 6205 0799. Our website is at www.icrc.act.gov.au and our email address is icrc@act.gov.au.

How to make a submission

This draft report provides an opportunity for stakeholders to provide feedback and evidence to inform the development of the final report. It will also ensure that relevant information and views are made public and we can consider them in making our final decision.

Submissions on the draft report close on **Monday 18 October 2021**.

Submissions may be mailed to us at:

Independent Competition and Regulatory Commission
PO Box 161
Civic Square ACT 2608

Alternatively, submissions may be emailed to us at icrc@act.gov.au. We encourage stakeholders to make submissions in either Microsoft Word format or PDF (OCR readable text format – that is, they should be direct conversions from the word-processing program, rather than scanned copies in which the text cannot be searched).

For submissions received from individuals, all personal details (for example, home and email addresses, and telephone and fax numbers) will be removed for privacy reasons before the submissions are published on the website.

We are guided by the principles of openness, transparency, consistency and accountability. Public consultation is a crucial element of our processes. Our preference is that all submissions are treated as public and are published on our website unless the author of the submission indicates clearly that all or part of the submission is confidential and not to be made available publicly. Where confidential material is claimed, we prefer that it is provided as a separate document and clearly marked 'In Confidence'. We will assess the author's claim and discuss appropriate steps to ensure that confidential material is protected while maintaining the principles of openness, transparency, consistency, and accountability. For more information on how to make a submission that contains confidential information and how we treat confidential submissions, please refer our submissions guide at www.icrc.act.gov.au/submissions.

We can be contacted at the above address, by telephone on (02) 6205 0799 or through our website at www.icrc.act.gov.au.

Table of Contents

List of Figures

List of Tables

List of Boxes

Executive summary

We are reviewing the methods used to forecast demand for water and sewerage services in the Australian Capital Territory (ACT). We decided to do this review in our 2018 water and sewerage services price investigation.

This review is part of our broader strategy to ensure our demand forecasting methods and data inputs remain fit for purpose. This will ensure we use appropriate demand forecasts to set Icon Water's prices for water and sewerage services and assess the prudency and efficiency of Icon Water's proposed expenditure during our price investigations.

We released an issues paper on 28 May 2021 as the first step in the consultation process for this review. We held a stakeholder workshop on 28 June 2021. We received submissions from Icon Water and Professor Ian White. We have considered feedback and information provided in the submissions in making this draft decision.

This report is the second step in our consultation process for this review. It presents our draft decisions on the methods and data we will use to forecast demand for water and sewerage services in the next water and sewerage services price investigation.

We welcome stakeholder feedback on our draft report, which will inform our final report.

Water services demand components

Icon Water earns revenue from water services through a two-tier usage charge that depends on the amount of water used, and a supply charge (per day). We need forecasts of water sales and water connection numbers to determine the prices that will allow Icon Water to earn enough revenue to recover its costs.

Draft decisions

Our draft decision is to maintain the top-down approach to forecast water sales in the ACT. The starting point is to forecast the volume of water abstractions from Icon Water's dams, which will be used to estimate water sales in the ACT.

Forecasting dam abstractions

We will retain the current method, which is a multivariate Autoregressive Integrated Moving Average (ARIMA) model, to forecast dam abstractions.

We will continue using climate variables (temperature, rainfall and evaporation) as drivers of water demand, noting that these climate variables also affect water supply. We will retain the current approach of using future climate scenarios to forecast dam abstractions. We have made a draft decision to use a different data source for future climate scenarios. For the next regulatory period, we will use the NSW and ACT Regional Climate Modelling (NARCLiM) climate change projections.

We will continue to use water customer numbers in forecasting dam abstractions. Our draft decision is to forecast water customer numbers based on ACT population projections rather than past growth trends in connection numbers. We will review our position to ensure that the ACT population projections we use to forecast Icon Water's customer numbers account for the impact of the Covid-19 pandemic.

We will continue to use data from July 2006 to account for the change in consumer behaviour that occurred during the millennium drought.

We have developed principles for when we would adjust the output of the model. We may apply these principles in the next price investigation, for example, to incorporate any changes to the sustainable diversion limit, which limits the amount of water that can be taken from the rivers for towns, industries and farmers in the Murray-Darling basin.

Our draft decision is to use weekly data, rather than daily data, to forecast dam abstractions. This position is subject to further refinement of the model and stakeholder feedback on this draft report.

Other water demand components

We will retain the current methods we use to forecast ACT water sales and billed water sales at Tier 1 and Tier 2. Our draft decision is to add more recent years' data to the existing dataset to forecast billed water sales and the Tier 1 and Tier 2 split.

Sewerage services demand components

Icon Water earns revenue from sewerage services through a fixed supply charge for residential customers and non-residential customers. There is an additional fixed charge that applies to non-residential customers with more than two flushable fixtures. We need forecasts of sewerage installations and flushable fixtures to determine prices that will allow Icon Water to recover its costs. We also need an estimate of sewage volumes to understand the sewage treatment costs faced by Icon Water.

Draft decisions

Our draft decision is to forecast sewerage installations and billable fixtures based on ACT population projections rather than past growth trends in installation numbers and billable fixtures.

We will retain the current method to forecast sewage volumes.

Next Steps

We will hold a second stakeholder workshop in early October. This will provide an opportunity for stakeholders to ask questions and give feedback on our draft decisions.

We plan to release the final report in November 2021, which will set out the methods and data we will use in the next price investigation to set prices from 1 July 2023.

1. Introduction

We are reviewing the methods used to forecast demand for water and sewerage services in the Australian Capital Territory (ACT). Good demand forecasts are important because they help us to set prices that allow Icon Water to recover only prudent and efficient costs. Good demand forecasts help Icon Water plan its operations and investment program to meet demand. They also help us estimate the cost of providing services, including assessing the prudency and efficiency of Icon Water's proposed expenditure during our price investigations.

We review our regulatory models and forecasting methods regularly to confirm that they remain appropriate and to ensure they reflect relevant developments in the regulated industry, technology, and consumer preferences and behaviours. We consider modelling and forecasting approaches adopted by other regulators to ensure our methods are based on good regulatory practice. We also check for new and improved data sources to make sure we use the best available information and data in our models and forecasts. This review is part of our broader strategy to make sure our modelling, forecasting methods and the data we use remain fit for purpose.

1.1 Background to the review

We are the ACT's independent economic regulator. We regulate prices, access to infrastructure services and other matters in relation to regulated industries in the ACT. We also have functions under the *Utilities Act 2000* (Utilities Act) for licensing electricity, natural gas, water and sewerage utility services, and making industry codes.

Icon Water is the monopoly provider of water and sewerage services in the ACT. We set the maximum prices Icon Water can charge for the supply of water and sewerage services, and the guaranteed service levels for water and sewerage services in the Consumer Protection Code (ICRC 2020a), made under the Utilities Act.

We undertake price investigations under Part 3 of the ICRC Act, and issue price directions under Part 4 of the ICRC Act. The *Price Direction: Regulated Water and Sewerage Services 2018–23* (2018 Price Direction) sets out our methodology for setting the maximum prices that Icon Water can charge for water and sewerage services from 1 July 2018 to 30 June 2023.

We decided to review our demand forecasting methods in our 2018 water and sewerage services price investigation. In the 2018 Price Direction, we established a review of forecasting methodologies for forecast demand that may be used in the 2023 water price investigation, as a reset principle.

We saw value in checking that our methods remain fit for purpose, and we are using the best available data, or if there is scope to improve our forecasting methods or data sources. During our 2018 price investigation, we found the medium-term demand forecasts were highly sensitive to minor updates to the data used in the models. We also noted that future changes in the climate, water policies and population growth in the ACT could potentially cause historical trends to become less accurate for use in our forecasting model. We concluded it was important to check our methods and data inputs.

We released an issues paper on 28 May 2021 as the first step in the consultation process for this review. We held a stakeholder workshop on 28 June 2021. We received submissions from Icon Water and Professor Ian White. The submissions are available on our website. We have considered issues raised in submissions in the relevant chapters of this report.

The publication of this draft report is the second step in our consultation process for this review. Stakeholder submissions on the draft report will inform our development of the final report scheduled for release in November 2021.

We have made a draft decision to improve aspects of our forecasting methods and the data we use. If we make a final decision to change aspects of our forecasting methods and data sources, we will apply those improvements in our next price investigation to set regulated water and sewerage services prices for the regulatory period beginning on 1 July 2023.

1.2 Importance of demand forecasts

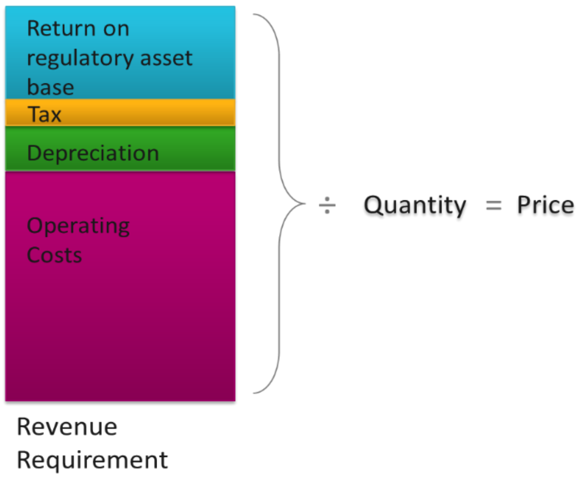
Demand forecasts are an important input for setting prices

We use demand forecasts to set maximum prices for water and sewerage services so Icon Water can recover its costs of providing those services.

We use a 'building block' methodology to determine the prudent and efficient costs that Icon Water can recover from its customers in a regulatory period. Under the building block model, the revenue that Icon Water can earn for a regulatory period is the sum of the operating expenditure, a contribution to the cost of capital investments made over time, and allowances for forecast tax paid by the business.

This total allowed revenue is then divided by the forecast demand for each service, which includes estimates of future water usage and expected number of water and sewerage service connections, to derive a price for each service (illustrated in Figure 1). That is, Icon Water's costs are spread over the demand to set the prices.

Figure 1. Simplified building block methodology



We need forecasts for water and sewerage services demand to set prices for individual services

We need forecasts of demand for water and sewerage services to help estimate the unit cost of providing these services (for example, the cost per kL of water). We also use demand forecasts to calculate prices that will allow Icon Water to earn enough revenue given its costs:

- Icon Water earns revenue from water services through a supply charge (per day) and a two-tier usage charge that depends on the amount of water used by a customer. Therefore, we need forecasts of water connection numbers and water usage to determine prices that will allow Icon Water to earn enough revenue to recover its costs.

- Icon Water earns revenue from sewerage services through fixed supply charges. There is a fixed supply charge for residential customers and non-residential customers. There is also an additional fixed charge that applies to non-residential customers with more than two flushable fixtures. We need forecasts of sewerage installations and flushable fixtures to determine prices that will allow Icon Water to recover its costs.
- The cost of sewerage services depends on the volume of sewage that will need to be treated. Therefore, we need an estimate of sewage volumes to understand the sewage treatment costs faced by Icon Water.

Good demand forecasts ensure only prudent and efficient costs are included in setting prices

Demand forecasts help us to assess the prudency and efficiency of Icon Water's proposed expenditure during our price investigations. Icon Water's cost of providing the services is influenced by demand. For example, Icon Water's infrastructure needs to be large enough to meet projected demand but not too large so that unnecessary costs are incurred. Good demand forecasts can help us assess whether Icon Water's capital investment program and forecast operating costs are prudent and efficient. This helps us ensure that consumers pay for only those costs that are necessary to meet their demand for services.

Good demand forecasts also help Icon Water plan its operations to meet demand. For example, they improve Icon Water's information base for its investment decisions. This helps Icon Water ensure that it incurs only those costs needed to meet demand for water and sewerage services, that is, prudent and efficient costs.

Good demand forecasts ensure consumers pay reasonable prices and Icon Water recovers its costs

Most of Icon Water's costs are fixed. We use demand forecasts to allocate these fixed costs across the water and sewerage services that are supplied to consumers. We then add the costs that are directly related to providing services (known as variable costs). Together these costs are recovered through prices.

If demand forecasts in a regulatory period are significantly different from actual demand, prices will not reflect Icon Water's assessed costs. If the demand forecasts are too low, the prices that we set will be too high. This means the consumers' bills will be higher than what they should be for Icon Water to recover its costs. If the demand forecasts are too high, the prices that we set will be too low and Icon Water will not recover its prudent and efficient costs. This could affect Icon Water's financial sustainability and its ability to keep providing water and sewerage services.

Our objective is to choose the methods that give forecasts that are likely to be closer to actual demand, so the effects of inaccurate demand forecasts on consumers and Icon Water are minimised.

We have a mechanism in place to share water demand forecasting risk between Icon Water and customers

Although our objective is to improve forecasting accuracy, predicting future water demand by its nature gives rise to the risk that actual demand may differ from forecast demand. That means the actual revenue earned by Icon Water from water sales will be higher or lower than the allowable revenue. We call this water demand risk. We have a mechanism in place to manage this demand risk (box 1.1).

Box 1.1 The ‘deadband’ mechanism to share water demand risk

Our mechanism to manage water demand risk allows an adjustment at the end of the regulatory period if we find that Icon Water’s actual revenue from ACT water sales over the regulatory period is materially different from the allowable revenue. We use a materiality threshold (known as the ‘deadband’) of 6%. That means if in a regulatory period Icon Water over-recovers or under-recovers its allowed revenue from water usage charges by more than 6%, we will make an adjustment to Icon Water’s allowable revenue in the following regulatory period.

Our end of period adjustment means Icon Water can recover material under recoveries from customers and must return material over recoveries to customers during the following regulatory period. Under this approach, Icon Water bears the water demand risk up to the level of the 6% and consumers bear the risk beyond 6%. The deadband essentially shares the risk of water usage being lower or higher than forecast between Icon Water and its customers.

The ‘deadband’ was introduced during the 2008-13 regulatory period to address the risks posed by setting prices in advance of knowing actual demand. It gives Icon Water an incentive to better understand the factors driving water usage to manage the risk of lower water consumption, while limiting Icon Water’s exposure to demand risk to 6%.

We reviewed the deadband mechanism during our review of incentive mechanisms in relation to water and sewerage services and found that it results in an appropriate allocation of water demand risk between Icon Water and its customers (ICRC 2020b).

Therefore, in this review we are not considering the deadband mechanism. Rather, our focus in this review is to identify ways to improve the forecast accuracy of our model to reduce the demand risk.

1.3 Scope of the review

In this review, we will determine the water and sewerage services forecasting methods and data to be used in the next water price investigation, which is likely to start in late 2021.

We intend to review the current forecasting methods and data sources based on a set of assessment criteria (described in section 1.7). We will consider the pros and cons of alternative forecasting approaches compared to the current approach. We will identify appropriate forecasting methods and data sources based on the assessment criteria.

We intend to review the methods for six components of water and sewerage services demand that we need to determine the maximum water and sewerage prices in the ACT. The components are:

1.3.1 Water services demand components

1. **Total water abstractions from dams**

   Forecast volume of dam abstractions in each year is used to estimate the billed water sales in the ACT (discussed below) and to estimate the annual Water Abstraction Charge paid by Icon Water to the ACT Government.

2. **Billed water sales at Tier 1 and Tier 2**

   Icon Water sells water at two price tiers. Tier 1 rate applies to water usage up to 50kL per quarter and Tier 2 rate applies to water usage above that amount. Water sales are forecast for these two tiers separately.

3. **Total number of water service connections**

   Total number of water service connections in each year are forecast to estimate Icon Water's revenue from water supply charges in each year.

1.3.2 Sewerage services demand components

4. **Total number of sewerage services connections**

   Total number of sewerage service connections in each year are forecast to estimate Icon Water's revenue from sewerage supply charges in each year.

5. **The number of additional billable fixtures**

   A flushable fixture is either a toilet, urinal or other fixture with a flushing cistern or flush valve. Non-residential customers with more than two flushable fixtures pay a separate fee for each additional fixture. Total number of additional billable fixtures is forecast to estimate Icon Water's revenue from supply charges for these fixtures.

6. **Sewage volumes**

   Forecasts of sewage volumes are required to estimate sewage treatment costs, which are then used to set Icon Water's sewerage prices.

1.4 Purpose of the draft report

There are two reasons for this draft report. The first is to inform stakeholders of our draft decisions on the methods and data we will use to forecast demand for water and sewerage services. The second is to allow stakeholders an opportunity to provide feedback on our draft decisions, which will inform our final report.

1.5 Our role and objectives

Under the ICRC Act, we have the following objectives as set out in sections 7 and 19L of the ICRC Act (box 1.2).

Box 1.2 Sections 7 and 19L: Commission objectives

Section 7:

(a) to promote effective competition in the interests of consumers;

(b) to facilitate an appropriate balance between efficiency and environmental and social considerations;

(c) to ensure non-discriminatory access to monopoly and near-monopoly infrastructure.

Section 19L:

To promote the efficient investment in, and efficient operation and use of regulated services for the long-term interests of consumers in relation to the price, quality, safety, reliability and security of the service.

When making a price direction, in addition to the terms of reference and legislative objectives, we need to consider the provisions set out in section 20(2) of the ICRC Act (box 1.3).

Box 1.3 Section 20(2): Commission's considerations

(a) the protection of consumers from abuses of monopoly power in terms of prices, pricing policies (including policies relating to the level or structure of prices for services) and standard of regulated services; and

(b) standards of quality, reliability and safety of the regulated services; and

(c) the need for greater efficiency in the provision of regulated services to reduce costs to consumers and taxpayers; and

(d) an appropriate rate of return on any investment in the regulated industry; and

(e) the cost of providing the regulated services; and

(f) the principles of ecologically sustainable development mentioned in subsection (5);

(g) the social impacts of the decision; and

(h) considerations of demand management and least cost planning; and

(i) the borrowing, capital and cash flow requirements of people providing regulated services and the need to renew or increase relevant assets in the regulated industry; and

(j) the effect on general price inflation over the medium term; and

(k) any arrangements that a person providing regulated services has entered into for the exercise of its functions by some other person.

1.6 Technical advice on forecasting methods

We have engaged the consultancy firm Marsden and Jacob Associates to provide expert technical advice for this review.

In stage 1, the consultant compared alternative forecasting approaches to the current approach and advised that we maintain the current forecasting approach. The consultant's stage 1 report was published with our issues paper.

In stage 2, the consultant has developed advice on how the current forecasting approach could be improved. We have considered its advice in developing this draft report. The consultant's stage 2 report is in appendix 4.

1.7 Our approach to this review

1.7.1 Assessment criteria for the review

We are proposing to use a set of criteria to assess our demand forecasting methods.

Having assessment criteria will promote consistency in decision making when assessing different models. In developing the assessment criteria, we considered the pricing principles in our final report on regulated water and sewerage services prices for 2018-23 (ICRC 2018). These pricing principles are reproduced in appendix 1 for ease of reference. We developed these pricing principles during our tariff structure review 2016-17 (ICRC 2017a).

The assessment criteria that we are proposing to use in this review are:

- **Economic logic, transparency and replicability**. This means that the model should be based on well-established theory, assumptions used in the model should be clearly documented and can be tested, modelling should be based on well-established statistical methods, and stakeholders should reasonably understand the processes involved and be able to replicate the results.
- **Predictive ability**. This is to review how accurate the model is in predicting actual outcomes.
- **Flexibility**. The model's ability to accommodate changing circumstances such as change in climate and water policies.
- **Regulatory stability**. The forecasting methodology needs to be relatively stable over time to give stakeholders certainty. The methods should only be updated where there is sufficient evidence that the change would increase the accuracy of the predictions.
- **Simplicity**. The methods should be simple for consumers to understand and straightforward for the utility service provider to implement.

We consider that these criteria will address our legislative objectives and the matters that we are required to consider under section 20(2) of the ICRC Act. The allowable revenue we determine based on the forecast demand, must promote efficient investment in, and the efficient operation and use of, regulated services for the long-term interests of consumers.

These criteria promote confidence in our forecasting methods among the regulated business, consumers, investors, and other stakeholders.

The criteria ensure that the methods are simple, and stakeholders can replicate the models. Improved predictive ability will provide Icon Water confidence that it can earn sufficient revenue to recover its costs, and it will encourage Icon Water to make prudent and efficient investment decisions. Regulatory stability will promote efficient investment in, and use of, the relevant services because it gives investors the confidence to make investments in long-lived water assets.

1.7.2 Icon Water's view on the assessment criteria

In the issues paper, we sought stakeholder comments on our assessment criteria for this review. Icon Water submitted that it supports the assessment criteria (Icon Water 2021).

On the criterion of transparency and replicability, Icon Water's view is that the model should use reliable and publicly available data to forecast water demand. For example, Icon Water said that wherever possible proprietary data, subscription data, or other third-party data should not be used because there is a risk that those data could be discontinued or modified. We agree that the data used in the model should be publicly available, widely accepted and sourced from a reputable organisation. We also consider that the model should use updated data that accounts for more recent observations.

Icon Water's view is that predictive ability should be assessed based on how accurate the forecast is, on average, over the regulatory period rather than in every year of the regulatory period. Icon Water reasoned that was because demand forecasts are used to set prices for it to recover its efficient revenue over a five-year regulatory period. Icon Water says it is not feasible for a model to accurately predict changing weather conditions from year to year.

We accept that the predictive ability of a model should be evaluated, on average, over the five-year regulatory period. However, we also consider that if there is significant annual variability between forecast and actual water demand, we should investigate if aspects of the forecasting model could be improved to reduce the variability. For example, a comparison of forecast and actual dam abstractions data for the first three years of the regulatory period shows that the difference in:

- 2018-19 was +6% (actual abstractions were greater than forecast)
- 2019-20 was +10% (actual abstractions were greater than forecast)
- 2020-21 was -2% (actual abstractions were less than forecast)

Although, on average, over the three years the actual abstractions were 5% greater than forecast, the significant annual variability in the first two years due to drier than average weather conditions cannot be overlooked. We have identified aspects of the forecasting model that can be improved to better account for weather-related variability (see section 4.2 of this draft report).

On flexibility, Icon Water notes that there are different ways in which a model can accommodate changing circumstances. Some changes can be accommodated within the model itself. However, some events may require alternative treatments, for example, a post-model adjustment that involves modifying the output of the model to account for an expected future shock to demand. We accept there are different ways for a model to be flexible and the most appropriate way will depend on the specific circumstances.

Icon Water agrees that regulatory stability is an important element of the demand forecasting methodology. Icon Water's view is that methodological changes should only be made where there is strong evidence that the benefits will outweigh the costs and risks. Since this review is about demand forecasting methods, we consider that the methods should only be updated where there is sufficient evidence that the change would increase the accuracy of the predictions. We used this test in the 2018 water and sewerage services price investigation, and accepted Icon Water's proposed forecasting model, rather than retaining the Industry Panel model. We did that because the evidence indicated that Icon Water's proposed model increased forecast accuracy.

On the criterion of simplicity, Icon Water's view is that the high-level approach to the forecasting method should be intuitive for the community to understand the main drivers of water demand. For example, the model used to forecast dam abstractions is capable of being understood by the general community because the relationship between weather and water demand can be intuitively understood.

1.8 Timeline

We released the issues paper on 28 May 2021, which was the first step of our consultation. We held a stakeholder workshop on 28 June 2021 and received two submissions by the 9 July 2021 due date.

Releasing this draft report is the second step of our public engagement for this review. We will hold a second workshop in early October to allow stakeholders to ask questions and provide feedback on the changes we propose to make to the demand forecasting methods and data sources. The closing date for submissions on the draft report is Monday 18 October 2021.

Releasing the final report is the final step of our public engagement for this review. We will consider stakeholder feedback on our draft report in preparing the final report.

Table 1.1 Key dates for the review

Task	Date
Release of issues paper	**28 May 2021**
Workshop I	**28 June 2021**
Submissions on issues paper close	**9 July 2021**
Draft report	20 September 2021
Workshop II	early October 2021
Submissions on draft report close	18 October 2021
Final report	November 2021

1.9 Structure of the draft report

The remainder of this draft report is structured as follows:

- Chapter 2 gives an overview of our current forecasting methods and data.
- Chapter 3 gives an overview of our draft decision forecasting methods and data.
- Chapter 4 discusses our draft decision on the methods and data used to forecast dam abstractions.
- Chapter 5 discusses our draft decision on the methods and data used to forecast other demand components: billed water sales at Tier 1 and Tier 2 prices, total number of water service connections, total number of sewerage service connections, number of additional billable fixtures, and sewage volume.
- Appendix 1 sets out the pricing principles we considered when developing the assessment criteria for the review.
- Appendix 2 sets out technical details related to our draft decision demand forecasting method for dam abstractions.
- Appendix 3 sets out technical details related to our draft decision demand forecasting method for the other demand components.

- Appendix 4 is the consultant's stage 2 report.
- Appendix 5 gives an overview of the forecasting approaches used in other Australian jurisdictions.

2. Overview of our current forecasting methods and data

2.1 Forecasting water services demand

We apply a top-down approach to forecast water sales in the ACT. There are three steps, which are described below and presented in Figure 2.

Step 1

The first step is to forecast the volume of water abstractions from Icon Water's dams. We start with dam abstractions because they are a good indicator of billed water sales and data are available on a daily frequency. Dam abstractions are also used to assess Icon Water's operating and capital costs, and to estimate the water abstraction charge.

The dam abstractions model uses climate related data on rainfall, temperature and evaporation, which are available on a daily frequency. We use climate variables because we consider that there is a direct relationship between water consumption and climate variables. For example, there will be low demand for water on rainy days, and high demand for water on hot days and when evaporation rate is high. The changing water demand due to weather conditions will have an impact on water abstractions from Icon Water's dams.

We need information on what future climate conditions will look like. In our 2018 water and sewerage services price investigation, we used four separate climate scenarios (driest, dry, medium and wet) developed by the South Eastern Australian Climate Initiative (SEACI). We used these scenarios to develop future climate scenarios for rainfall and evaporation. However, the future scenario for temperature was developed based on the historical trend. We used the average of dam abstractions forecasts from the different climate scenarios because it is not possible to accurately predict the actual climate conditions.

A stable relationship between water demand and climate variables will ensure reliable forecasts. For example, we know that water demand is high during summer months. But changes in consumer behaviour can affect the relationship between water sales and climate variables. Such behavioural changes can include the use of more water efficient appliances, installation of more water efficient garden watering systems, and water recycling systems.

During the millennium drought, many consumers changed their behaviour in response to water restrictions that were in place in the ACT from 2002 to 2010. We found that water demand in the period during, and after, water restrictions increased less in response to warmer and drier weather compared to in the period before restrictions. A new relationship between water sales and climate variables developed in 2006 which has remained stable since then. Therefore, we use data from 2006 to forecast dam abstractions.

The forecast model also uses data on water connection numbers, because water demand increases when there are more consumers. Future water connection numbers are estimated based on the past growth trend in the connection numbers.

The model we currently use to forecast dam abstractions is a multivariate Autoregressive Integrated Moving Average (ARIMA) model. ARIMA models are used for forecasting variables that are measured over time, like dam abstractions.

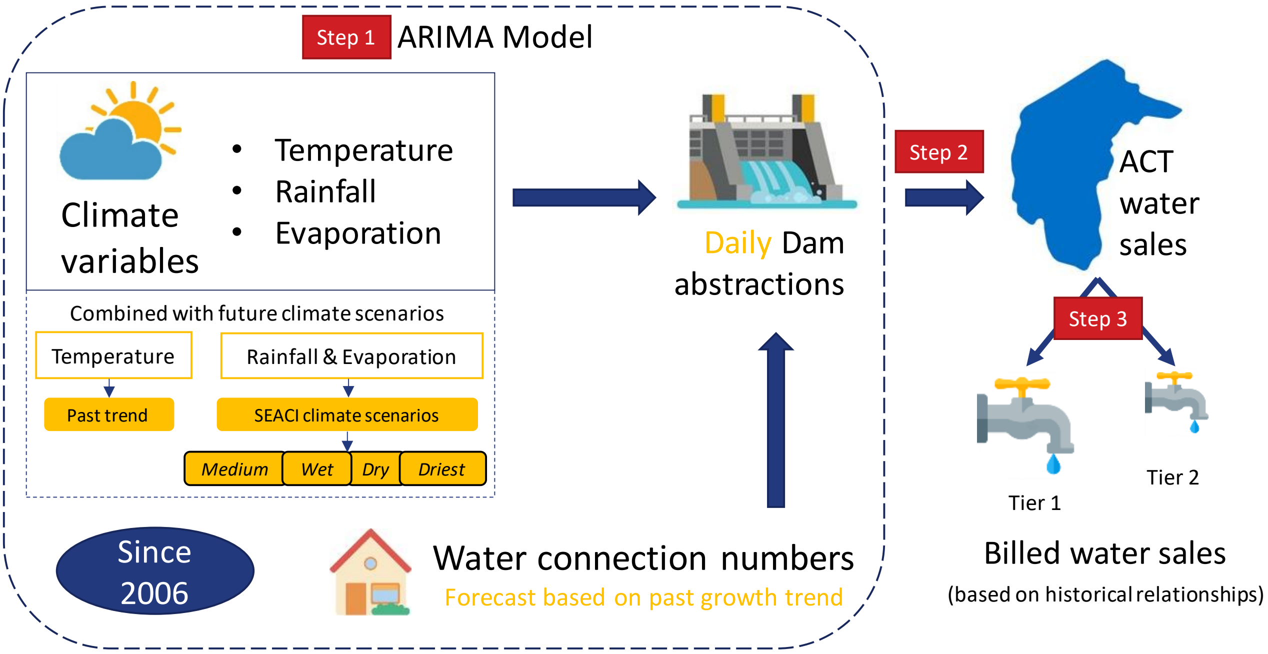
Step 2

In step 2, we forecast the share of dam abstractions that will be sold to ACT consumers. Icon Water sells some of its dam abstractions to Queanbeyan city council and part of dam abstractions includes water leakages, water lost due to theft, and unaccounted water due to metering errors. We look at the historical shares of dam abstractions sold to ACT consumers to forecast the future share.

Step 3

Icon Water sells water at two price tiers. So, in step 3, total ACT water sales is split into Tier 1 and Tier 2. The split is based on the historical relationship between the average amount of water consumed by each customer and the proportion of Tier 1 sales.

Figure 2. Simplified representation of the current approach for forecasting water services demand



Source: Our analysis based on Icon Water (2021)

2.2 Forecasting sewerage services demand

Like the forecast for water connection numbers, the forecasts for sewerage installations and billable fixtures are made based on the past growth trend.

Sewage volumes are forecast based on a range of factors including average sewage volume per resident, population growth, groundwater flow into the sewerage system, and climate conditions.

2.3 Matters raised in the issues paper

Our issues paper sought feedback from stakeholders on whether improvements could be made to the forecasting methods and data used to forecast the components of water and sewerage services demand.

We identified specific issues for stakeholder comments relating to issues like how to incorporate future changes in the climate, water policies, population growth and consumer behaviour. For example, we sought stakeholders’ feedback on:

- other more suitable data sources to account for climate change
- if, and how, the sustainable diversion limit should be incorporated into the model. It limits the amount of water that can be taken from the rivers for towns, industries, and farmers in the Murray-Darling basin
- whether to use ACT population projections to forecast connection numbers
- how to incorporate changes in consumer behaviour and what sort of data to use
- any changes in the forecasting methods needed to improve the stability of the forecasts
- whether we should change the frequency of data used in the model (from daily data to monthly data) to improve the model's ability to account for climate change
- whether the model used to forecast dam abstractions remains appropriate
- whether the methods and data used to forecast other demand components—billed water sales at Tier 1 and Tier 2 prices, total number of water service connections, total number of sewerage service connections, number of additional billable fixtures, and sewage volume—remain appropriate.

2.4 Overview of submissions to the issues paper

We received submissions from Icon Water and Professor Ian White. Icon Water commented on a range of issues and Professor White commented on the specific issue of climate change data.

We also heard stakeholder views at the workshop held on 28 June 2021.

We have considered stakeholders' comments in developing our draft decisions, which are discussed in chapters 3 to 5 of this report.

3. Overview of our draft decisions

This chapter gives an overview of our draft decisions on forecasting methods and data sources. Further details are given in chapters 4 and 5 and in the appendices.

3.1 Forecasting water services demand

We will maintain the top-down approach to forecast water sales in the ACT. The starting point will be to forecast the volume of water abstractions from Icon Water's dams, which will be used to estimate water sales in the ACT.

We will retain the current dam abstractions forecasting method (ARIMA model). We consider that the model meets our assessment criteria. It uses information on climate and customer numbers to provide reliable forecasts. The model is replicable and transparent and provides regulatory stability.

We will continue using climate variables (temperature, rainfall and evaporation) as drivers of water demand. We will retain the current approach of using future climate scenarios to forecast dam abstractions. We have made a draft decision to use a different data source for future climate scenarios. For the next regulatory period, we will use the NSW and ACT Regional Climate Modelling (NARCLiM) climate change projections, which are now widely accepted and provide a single, up-to-date source for localised climate change projections.

We will continue to use water connection numbers to forecast dam abstractions. Our draft decision is to forecast water connection numbers based on ACT population projections rather than past growth trends in connection numbers. This approach allows the model to account for demographic changes that could not be captured by looking at a past trend.

We will continue to use data from July 2006 to account for the change in consumer behaviour that occurred during the millennium drought. The evidence shows that water consumption behaviour in the ACT has remained stable since then.

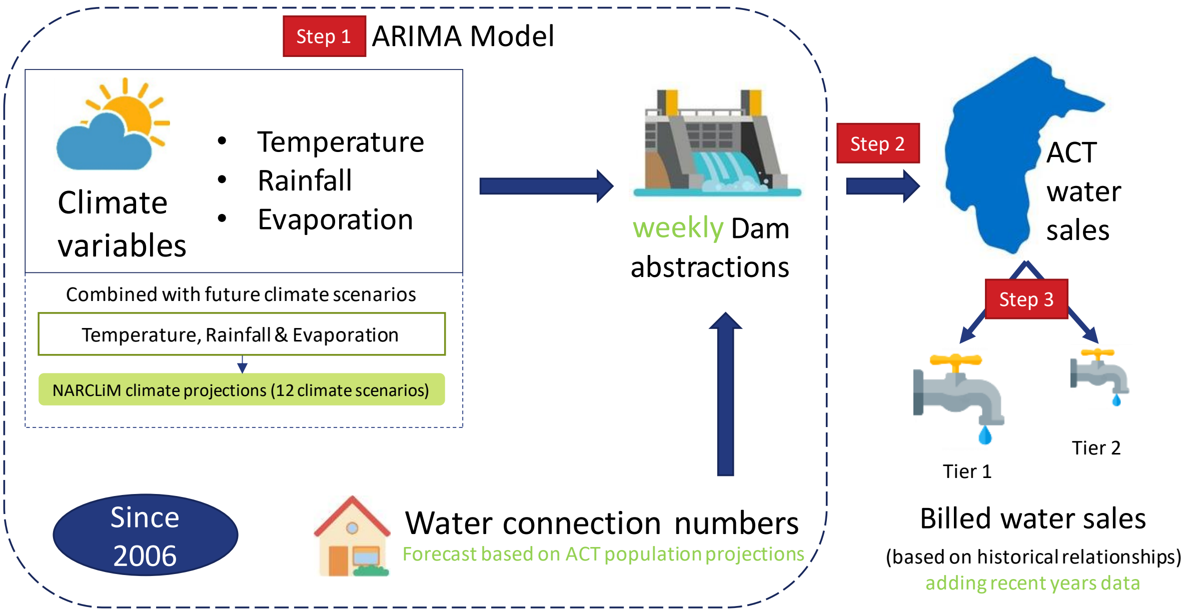
The current model does not account for the sustainable diversion limit (SDL) which limits the amount of water that can be taken from the rivers for towns, industries and farmers in the Murray-Darling basin. We have developed principles to adjust the output of the model for certain types of changes that affect water and sewerage services demand and may apply them in the next price investigation to consider any changes to the SDL.

The current model uses daily observations to forecast dam abstractions. Our draft decision is to use weekly data to forecast dam abstractions. We found that the form of model based on weekly data improves the predictive performance of the model. This position is subject to further refinement of the model specification and stakeholder feedback.

We will retain the current methods to forecast ACT water sales and billed water sales at Tier 1 and Tier 2. Our draft decision is to add more recent years' data to the existing dataset to forecast billed water sales and the Tier 1 and Tier 2 split.

Figure 3 is a simplified representation of the draft decision approach to forecast water services demand. The changes compared to our current approach are shown in green.

Figure 3. Simplified representation of the draft decision approach for forecasting water services demand



Source: our draft decision

3.2 Forecasting sewerage services demand

Like the forecasts for water connection numbers, the forecasts for sewerage installations and billable fixtures will be based on ACT population projections rather than past growth trends in installation numbers and billable fixtures.

We will retain the current method to forecast sewage volumes. The current approach produces reliable forecasts and will provide regulatory stability.

4. Forecasting dam abstractions

We apply a top-down approach to forecast water sales in the ACT. The starting point is to forecast the volume of water abstractions from Icon Water's dams, which is used to estimate water sales in the ACT.

This chapter discusses our draft decisions on the method and data used to forecast dam abstractions. Section 4.1 is about the approach to forecast dam abstractions. Section 4.2 is about the functional form of the model and data used to forecast dam abstractions.

4.1 Dam abstractions forecasting approach

Summary of the draft decision

We will retain the current method, which is a multivariate Autoregressive Integrated Moving Average (ARIMA) model, to forecast dam abstractions.

We consider that the ARIMA model meets our assessment criteria. It uses information on climate and customer numbers to provide reliable forecasts. The model is replicable and transparent and provides regulatory stability. Our consultant compared alternative forecasting approaches to the ARIMA approach and advised that the ARIMA approach is appropriate and fit for purpose (Marsden Jacobs Associates 2021a). Icon Water submitted that the ARIMA model remains appropriate (Icon Water 2021).

Our draft decision is therefore to retain the ARIMA model. We have identified several components of the ARIMA model that can be improved, and these are discussed in section 4.2.

Details of this draft decision

The ARIMA model satisfies our assessment criteria

Our assessment of the ARIMA model against the assessment criteria is as follows:

Criterion 1: Economic logic, transparency and replicability

We forecast dam abstractions because it serves multiple purpose. Dam abstractions are a good indicator of water sales in the ACT. They are also needed to assess Icon Water's operating and capital costs, and to estimate the water abstraction charge.

We use the ARIMA approach because it is used for forecasting variables that are measured over time, like dam abstractions. It is an approach that looks at the relationships between dam abstractions and the factors that influence dam abstractions such as climate and customer numbers over time and makes a forecast assuming these relationships will hold in the future. The ARIMA approach allows adjusting these relationships if we believe historical data will not be a useful predictor on its own.

The ARIMA model is a transparent and replicable method. It is based on well-established statistical processes and is a widely used forecasting approach. The assumptions used in the ARIMA model are clearly documented and modelling can be done using well-established procedures.

We assessed forecasting models used in other jurisdictions and found that there is no single well-accepted forecasting model. Different forecasting methods are used in other jurisdictions. For example, Sydney Water uses a panel data approach, Hunter Water and Melbourne Water use end-use modelling, and SA

Water uses a simple regression model. Although the forecasting methods are different across jurisdictions, the main drivers of water demand used in these jurisdictions—climate variables, population and water conservation measures—are common.

Utilities in other jurisdictions appear to use the demand forecasting methodology most suited to the type of data they have access to and the purpose of demand forecasts.

In the case of Sydney Water and Hunter Water, which use panel data regression and end use approaches respectively, demand forecasts are used in their regulatory submissions for setting prices as well as for water conservation reporting.

Melbourne Water contracts the bulk of its supply through three large customers, which in turn distribute water to the end user. As each of these customers does their own demand forecasting, Melbourne Water can make its demand forecasts based on the usage of its three largest customers.

SA Water uses an econometric model based on the historical water usage it has access to, and forecasts demand based on relationships observed between water demand and its drivers after the millennium drought.

Appendix 5 summarises forecasting methods used in the other jurisdictions.

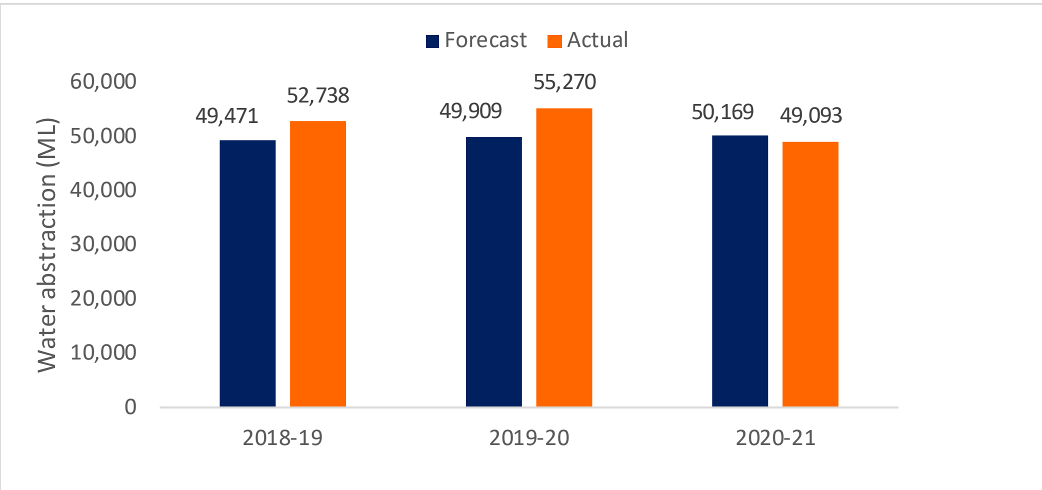
Criterion 2: Predictive ability

The evidence available to us indicates that the ARIMA model provides reliable forecasts. We compared dam abstraction forecasts made in our 2018 water price investigation with actual volumes for the first three years of the current regulatory period. We found the model has reasonable predictive ability because the average difference over that three-year period is less than 5%.

Although overall the model is performing well, there is significant annual variability in the forecasts. Figure 4 compares the forecast and actual annual dam abstractions. In the first two years, actual dam abstractions were 6% to 10% more than forecast because drier than average conditions resulted in higher demand than forecast by the model. In the third year (2020-21), actual dam abstraction was 2% below the forecast because wetter than average conditions have meant demand is less than forecast.

The annual variability between forecast and actual dam abstractions is largely driven by climate related factors. Therefore, we have investigated how to better account for climate variability to improve the model's performance. Section 4.2 provides details on this investigation and outlines our draft decision on the changes we consider can improve the model's performance.

Figure 4. Water abstractions from Icon Water's dams: actual and forecast comparison



Source: our analysis based on data from Icon Water

Criterion 3: Flexibility

Flexibility refers to the model's ability to accommodate changing circumstances such as changes in climate and water policies. The current ARIMA model has flexibility to respond to certain changes in circumstances. It accounts for short-term fluctuations in weather conditions and the seasonal impact on water demand. It also accounts for step changes in water demand, for example, it accounts for the sustained step-change in water use in the ACT that we noted had occurred following the millennium drought (ICRC 2015). This step change reflected changes in consumer behaviour in response to the water restrictions that were imposed during the millennium drought, where consumers installed drought tolerant gardens and water efficient appliances to conserve water and lower their water bills.

We consider that the model is flexible and that its performance can be improved by making modifications to account for the impact of climate changes on water demand, such as by considering up to date climate data sources. The post model adjustments that can be applied to the ARIMA model also provide flexibility. These modifications are discussed in section 4.2.

Criterion 4: Regulatory stability

We consider that the forecasting methodology needs to be relatively stable over time to give stakeholders certainty. We also consider that the methods should only be updated where there is sufficient evidence that the change would increase the accuracy of the predictions.

Retaining the ARIMA model will provide regulatory stability because we currently use the ARIMA model to forecast water demand and stakeholders are familiar with the modelling approach. Our consultant assessed alternative models and advised us that on balance ARIMA model is preferred. The evidence available to us indicates that the ARIMA model provides reliable forecasts. It can also be modified to improve its performance. The other modelling approaches that the consultant reviewed are more complex to implement, due to the requirement to observe water demand of set group of consumers over time and then develop estimation methods to generalise the observed data.

Criterion 5: Simplicity

Our view is that the ARIMA model is objective, transparent and relatively straightforward for the utility service provider to implement. The data on bulk water dam abstractions, rainfall and temperature that are required to implement the model are readily available. The method can be implemented using well-established methodologies using standard statistical software. The model is based on the relationship between weather and water demand, which can be intuitively understood.

ARIMA model is preferred over other approaches

Our consultant compared the performance of the ARIMA approach and 3 other approaches against our assessment criteria. The alternative approaches that were considered are:

- **Panel data:** A data set based on surveying the same panel of people over time and observing how their responses change.
- **End use modelling:** Water usage is estimated by observing water demand of different customer groups such as residential houses, residential units and non-residential customers, and aggregating their usage to produce demand forecasts.
- **Historical average:** Demand is forecast using a base level of historic usage adjusted for estimates of customer and population growth.

The ARIMA model that we use for dam abstractions performed better against the assessment criteria than the other approaches that were considered.

Our view is that ARIMA approach is transparent and reproducible and is suitable for producing medium to long-term forecasts.

The consultant advised that the ARIMA approach is simpler to implement compared to the panel data approach. Our view is that although the ARIMA approach may not be as flexible as the panel data approach, the ARIMA model that we use is flexible enough to accommodate changing circumstances as noted above. For this reason, we consider it appropriate to identify ways to improve the performance of the existing ARIMA approach, which are discussed in section 4.2.

Table 4.1 gives a summary traffic light assessment of the consultant's assessment of different forecasting approaches. Further details on the consultant's advice can be found in its stage 1 report that was published with our issues paper.

Table 4.1 Demand forecasting approaches: traffic light assessment

Assessment Criteria	ARIMA	Panel data modelling	End-use modelling	Historical average approach
Transparency and reproducibility				
Predictive ability				
Flexibility				
Simplicity				
Regulatory stability				

Meets the assessment criteria

Partially meets the assessment criteria

Does not meet the assessment criteria

Icon Water supports retaining the ARIMA approach

Icon Water supports the continued use of the ARIMA model for forecasting demand, stating that the ARIMA model performs well against the assessment criteria (Icon Water 2021).

Icon Water considers that the ARIMA model performs well because water demand is highly dependent on weather and climate, and notes that the existing model is designed to account for the historical relationship between weather and water demand as well as future climate change scenarios.

Background on the ARIMA approach

We first proposed using the ARIMA model in 2015 because we found the ARIMA model produced the most reliable forecasts (ICRC 2015). In our 2018 water and sewerage services price investigation, we adopted Icon Water's proposed ARIMA model, which was a variant of the model we had proposed in 2015. We found that Icon Water's ARIMA model provided greater forecast accuracy than the model used by the Industry Panel (ICRC 2018). The industry panel used an end use modelling approach to separately forecast annual water sales for four specified customer segments based on a set of weather and water restrictions variables for the regulatory period (Icon Water 2017).

The current form of the ARIMA model uses climate related data such as rainfall, temperature and evaporation, as well as water connection numbers. Rainfall data is used because water demand changes with the amount of rainfall, with less demand for water on rainy days and during rainy periods. Temperature data is used because water demand changes with temperature, with more demand on hot days and during hot periods. The model uses evaporation data which is likely due to higher irrigation requirements for plants as they dry when evaporation is higher. Water connection numbers are included because water demand increases when there are more consumers (ICRC 2017b).

4.2 Functional form of ARIMA model and data used to forecast dam abstractions

Summary of the draft decision

We consider that the current model is fit for purpose and performing well. The changes we are proposing will future proof the model to adapt to a more dynamic and uncertain environment, especially where climate change is concerned.

We will continue using climate variables (temperature, rainfall and evaporation) as drivers of water demand. We will retain the current approach of using future climate scenarios to forecast dam abstractions. We have made a draft decision to use a different data source for informing these future climate scenarios. For the next regulatory period, we will use the NSW and ACT Regional Climate Modelling (NARCLiM) climate change projections, which are now widely accepted and provide a single, up-to-date source for localised climate change projections.

We will continue to use water customer numbers to forecast dam abstractions. We have accepted Icon Water's suggestion to change the method used to forecast water customer numbers. The method will be based on ACT population projections rather than past growth trends in connection numbers. This approach allows the ARIMA model to account for demographic changes that could not be captured by looking at a past trend.

We will continue to use data from July 2006 to account for the change in consumer behaviour that occurred during the millennium drought. The evidence shows that water consumption behaviour in the ACT has remained stable since then.

The current ARIMA model does not account for the sustainable diversion limit (SDL) which limits the amount of water that can be taken from the rivers for towns, industries and farmers in the Murray-Darling basin. We have developed principles to adjust the output of the model ('post-model adjustment principles') and may apply them in the next price investigation if necessary to account for the impact of any changes in the SDL on water demand.

The current model uses daily observations for climate and dam abstractions. Our draft decision is to use weekly data because we found this improves the model's predictive ability. This position is subject to further refinement of the model specification.

Climate variables

We will continue using climate variables as drivers of water demand but use a new data source to develop future climate scenarios

Our draft decision is to continue to use climate variables because there is a direct relationship between water consumption and climate conditions given by rainfall, evaporation and temperature.

Developing an understanding of what future climate conditions will look like is important to forecast dam abstractions. We will retain the current approach to develop future climate scenarios by adjusting historical climate data by climate change projections developed by reputed external agencies. Box 4.1 outlines the current approach.

Our draft decision is to use NARCLiM climate change projections. NARCLiM is a NSW Government led partnership that provides high resolution climate change projections across NSW. The partnership began in 2011 and now includes the NSW, ACT and South Australian Governments and the Climate Change Research Centre at the University of NSW.

NARCLiM will replace the climate change projections data that, for the current regulatory period, were sourced from the South Eastern Australian Climate Initiative (SEACI). Our consultant's advice is also to use the NARCLiM database (Marsden Jacob Associates 2021b).

Box 4.1 Current approach to develop future climate scenarios

To forecast dam abstractions, we need to understand what the conditions for rainfall, evaporation and temperature over the forecast period would be. However, climate variables are difficult to predict, especially over a 5-to-6-year period, as is required by the ARIMA model.

In our 2018 water and sewerage services price investigation, future climate scenarios were developed using the following process.

1. We considered historical daily rainfall, evaporation and temperature dating back to 1965. These data were split into successive time periods of 6.5 years each, which was chosen because during the 2018 investigation dam abstractions were forecast for 6.5 years to June 2023.

2. The average data for those time periods was calculated to establish the reference climate scenario for rainfall, evaporation and temperature, which included average daily data for temperature, rainfall and evaporation for 6.5 years.

3. To develop future climate scenarios for rainfall and evaporation, we used four future climate change scenarios (dry, driest, wet and medium) developed by SEACI. Each SEACI scenario gives the average impact on rainfall and evaporation by season for an increase in global warming by one degree Celsius. This impact is expressed in percentage terms and is called 'adjustment factor'. For each climate change scenario, the relevant adjustment factors were applied to the rainfall and evaporation data in the reference climate scenario. This process gave adjusted daily rainfall and evaporation data, which represented the expected rainfall and evaporation conditions for the forecast period.

4. To develop future climate scenario for temperature, the trend in daily maximum temperature was estimated using daily data from June 1965 to March 2017. We assumed this trend will continue over the 6.5 year period. The maximum daily temperature in the reference climate scenario was adjusted to reflect this trend which represented the expected temperature conditions for the forecast period.

Our preferred climate change projections data source is NARCLiM

We compared NARCLiM data source against two other climate change projections data sources: SEACI (which was used in the last price investigation) and the Australian Community Climate and Earth System Simulator—Seasonal (ACCESS-S), which was suggested by Professor Ian White in his submission to our Issues Paper (Table 4.2).

Table 4.2 Comparison of climate change projections data sources

	NARCLiM	SEACI	ACCESS-S
Acceptance	Icon Water, Sydney Water, IPART, ACT Government, NSW Government, SA Government	Murray-Darling Basin Authority	Bureau of Meteorology (BoM), CSIRO
Updates	Projections developed in 2014 and updated in 2020 to reflect the release of new global climate change projections	Projections developed in 2012	Projections are continuously developed (the model is dynamic)
Geographic coverage	ACT specific at 10km resolution	South-Eastern Australia	Australia wide, but available at 60km resolution
Climate variables coverage	Temperature, rainfall, evaporation	Rainfall, evaporation	Rainfall, temperature
Projections future period	Projections available from 2020 to 2100	Not specified. Projections developed for 1 and 2 degrees of global warming.	Seasonal outlook

Source: our analysis based on information from NARCLiM: https://climatechange.environment.nsw.gov.au/climate-projections-for-NSW/About-NARCliM; ACCESS-S: http://www.bom.gov.au/climate/ahead/about/model/access.shtml; SEACI: http://www.seaci.org/research/futureProjections.html

We found that NARCLiM data source is widely used, including for regulated price setting. For example, Sydney Water used it in its demand forecasts for the 2020–24 regulatory period, which was accepted by Independent Pricing and Regulatory Tribunal (IPART). Icon Water uses it for network planning; the ACT Government uses it in its climate adaptation planning; and the NSW Government uses it to inform strategic planning initiatives relating to infrastructure, transport emergency risk assessment and regional water strategies.

NARCLiM provides highly localised ACT specific data at a 10km resolution, which is relevant for forecasting ACT specific water demand whereas SEACI and ACCESS-S have a broader geographic coverage.

Using NARCLiM will ensure consistency in developing future climate scenarios for all three climate variables—temperature, rainfall and evaporation—that we use. This is because NARCLiM will be a single source to adjust all three climate variables. SEACI and ACCESS-S only provide projections for two of the three variables.

NARCLiM projections are updated periodically as new global climate change projections are released. For example, NARCLiM projections were first developed in 2014 and updated in 2020 to incorporate more recent global climate models released by the Intergovernmental Panel on Climate Change. This periodic updating will ensure that NARCLiM data set will remain relevant for years to come, promoting stability within our approach. In comparison, the SEACI data source was developed in 2012 and is currently 10 years old. The ACCESS-S data source is updated continuously, but it provides short-term projections which are not useful for a 5-year regulatory period.

More information on NARCLiM climate change projections is given in appendix 2.

Stakeholders identified different data sources for developing future climate scenarios

Icon Water supports using the NARCLiM data source because it reflects recent climate modelling and said that it meets the assessment criteria of transparency and replicability because the information is publicly available (Icon Water 2021).

Professor Ian White submitted that warming seas around the globe have created more volatile weather events, such as the intense storms and flooding experienced by Sydney in early 2021. He considered that our current approach does not account for increasing climate volatility. Professor White considers that ACCESS-S is the most reliable data source for seasonal projections (Professor Ian White 2021).

We agree with Professor White that there is scope to improve our current model to better account for climate volatility. In adopting the NARCLiM data source, which was updated in 2020 to incorporate more recent global climate models released by the Intergovernmental Panel on Climate Change, we expect that the model will be able to account for increasing climate volatility. In this draft decision, we have identified specific improvements to the model: use of low frequency data (weekly instead of daily) to better capture variability in weather conditions. These are discussed later in this section.

We note Professor White's comment about ACCESS-S being the most reliable data source for seasonal climate events. However, as discussed above, we consider that NARCLiM data source is more suited to our needs.

Professor White also said that the current 6% deadband is conservative and that it should be increased. The consideration of deadband is outside the scope of this review. We reviewed the deadband mechanism during our review of incentive mechanisms in relation to water and sewerage services and found that it results in an appropriate allocation of water demand risk between Icon Water and its customers (ICRC 2020b). In that review, we said that we will consider the deadband threshold during the next water and sewerage services price investigation.

Sustainable diversion limit

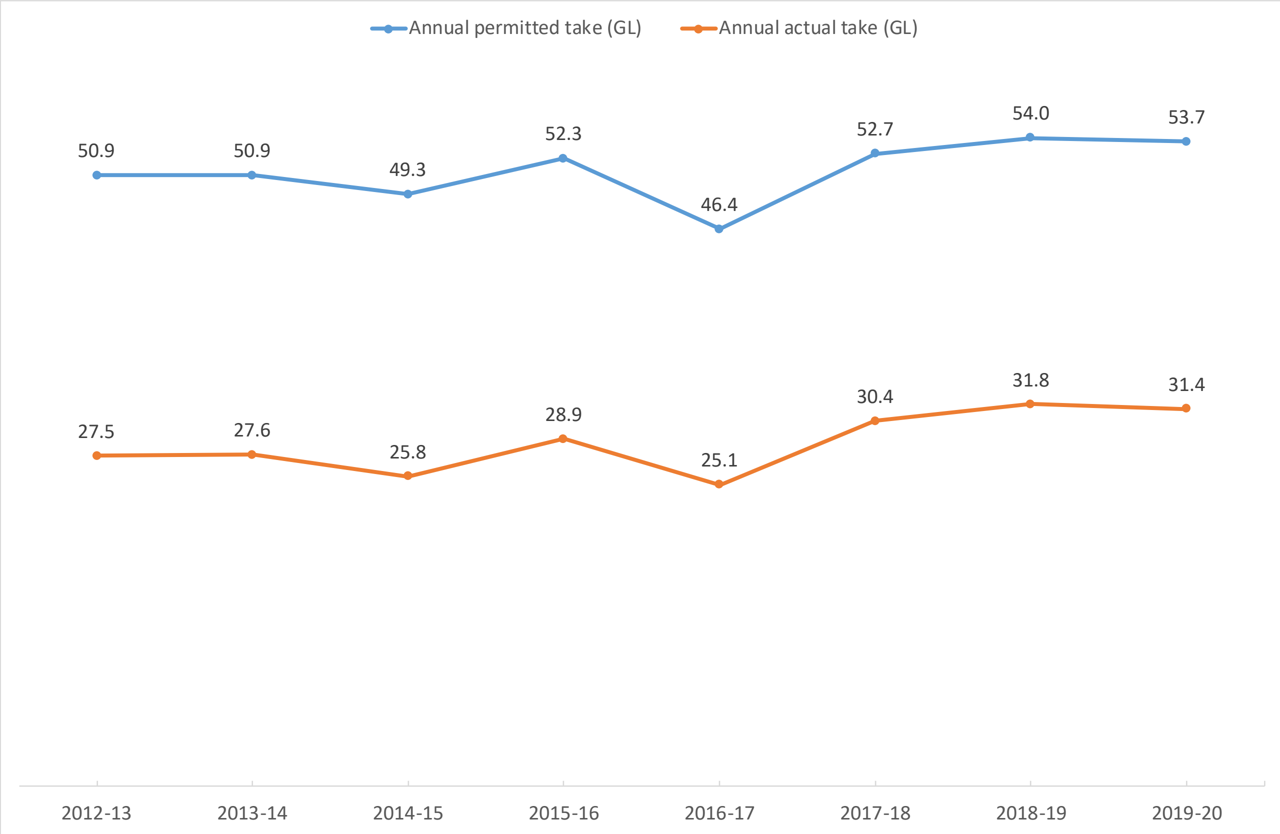
We have developed principles for adjusting the model output and may apply them in the next price investigation

The current ARIMA model does not account for the sustainable diversion limit (SDL) which limits the amount of water that can be taken from the rivers for towns, industries and farmers in the Murray-Darling basin.

The evidence shows that the SDL is unlikely to have any immediate impact on water demand in the ACT. SDLs came into effect on 1 July 2019 and represent the maximum long-term annual average quantities of water that can be taken on a sustainable basis from Basin water resources. The ACT's annual actual take has been about half of the annual permitted take (Figure 5). This evidence shows that potential reductions in the SDL are unlikely to have medium term impacts on dam abstractions in the ACT.

We have developed principles to adjust the output of the model and may apply them in the next price investigation to account for the impact of any changes to the SDL on water demand. Box 4.2 sets out the principles.

Figure 5. ACT annual permitted take and actual take (GL)



Source: our analysis based on data from https://www.mdba.gov.au/sites/default/files/pubs/appendix-2-surface-water-sustainable-diversion-limit-accounts-7-years.pdf; https://www.mdba.gov.au/sites/default/files/pubs/murray-darling-basin-sustainable-diversion-limit-compliance-outcomes-2019-20-report.pdf

Annual permitted take limits change in a manner that it is difficult to forecast within the model

The SDL and annual permitted take change from year to year as they are based on climate, water trade, usage patterns and development of infrastructure, making it difficult to forecast future limits and their impact on dam abstractions.

Under the SDL framework, credits and debits can be accumulated. A credit is recorded for a given year if actual take was less than the permitted take. A debit is recorded if actual take was more than the permitted take. Each year the credits/debits are added to those from the previous year and so can build up over time. The ACT's balance at the end of the first year of SDL was +22.3GL.[1] The accumulation of credits/debits can make it challenging to forecast future limits and their impact on dam abstractions.

[1] https://www.mdba.gov.au/sites/default/files/pubs/murray-darling-basin-sustainable-diversion-limit-compliance-outcomes-2019-20-report.pdf

An appropriate approach is to adjust the model output to account for the impact of SDL changes

Policy impacts can have several uncertainties associated with them such as implementation, specific details of the policy and its impact on water demand. If these details are uncertain, it can be difficult to incorporate the impact into the forecast method.

The post-model adjustment process typically involves adjusting the output of the model to account for the impact of a policy change on forecast demand. The process provides flexibility in capturing the impact of a policy change and is transparent.

We will apply post-model adjustment principles to consider the impact of SDL on water demand

Currently, the SDL is unlikely to have medium term impacts on water demand in the ACT. Whether SDLs will be a future constraint will depend on the changes to the limits and the availability of new information such as actual water use figures. We will consider a model adjustment process to consider the impact of SDL as per our post-model adjustment principles, outlined in box 4.2.

Box 4.2 Post-model adjustment principles

Post-model adjustments are used to adjust the output of the model to account for future impacts of events. These adjustments should adhere to a set of principles:

- The event is outside the control of the regulated business (such as government policy change).
- The event is specific and its impact on water demand is direct and certain (such as water restrictions, forcing demand for water to decrease).
- There is a reasonable and transparent way to measure the impact and adjust the model to account for the event (for example, adjusting gas demand forecasts based on the switching rate of customers from gas to electricity).

The Australian Energy Regulator (AER) recently used a post-model adjustment approach to account for future impacts of climate change policy on gas demand. The determination for EvoEnergy used a model adjustment to consider factors that were not present within historical data, in this case, a reduction in gas consumption arising from the ACT Government's Climate Change Strategy 2020–25, which aims for net zero emissions by 2045 (AER 2021).

The implementation of this policy is a specific event that was outside of EvoEnergy's control and has a clear impact on gas demand as consumers are encouraged to switch from gas to electricity. To estimate the impact of the policy, the AER considered data from the incremental impact of the ACT Energy Efficiency Improvement Scheme (EEIS), which provides incentives for gas customers to switch to electricity. The AER found the switching rate caused by the EEIS was a reasonable basis for forecasting customer responses to the policy in future (AER 2021).

Icon Water supports the use of post-model adjustments to account for future changes to the SDL

Icon Water submitted that it is challenging to model the impact of future policy changes and that the SDL will not have any immediate impacts over the foreseeable future. Icon Water suggested using post-model adjustments to account for any changes to the SDL in the future.

Background information on SDL

The ACT is in the Murrumbidgee River catchment, which feeds into the Murray–Darling River system. In 2019, federal and state Murray-Darling Basin water ministers established an annual limit called the SDL as a major change in water management policy. SDLs limit how much water, on average, can be used in the Murray-Darlin Basin by towns and communities, farmers, and industries, to keep the rivers and environment healthy.

The ACT has obligations under the Murray–Darling Basin Agreement and Murray–Darling Basin Plan to comply with the SDL (EPSDD 2019). The SDL introduced a new water accounting and compliance framework in the Murray–Darling Basin, replacing the previous 'Cap on Surface Water Diversions' compliance framework.

The Murray-Darling Basin Authority assesses and monitors Basin state compliance with SDLs. The Basin Plan requires Basin state governments to manage the use of water within SDLs. Complying with SDLs is based on the concepts of permitted take and actual take.

- Permitted take is an annualised expression of the SDL. It is the volume of water that is expected to be extracted during a water year under the SDL.
- Actual take is how much water was extracted in a given water year.

Although the SDL framework began in July 2019, Basin states have been trialling the SDL framework since 2012.

The SDL puts a limit on the amount of water abstractions from Icon Water's dams. As our current model forecasts dam abstractions, the limit given by the SDL could constrain the output of the model.

Changes in consumer behaviour

We will retain the current approach to account for changes in consumer behaviour

We will continue to use data from July 2006 to account for the change in consumer behaviour that occurred during the millennium drought. The evidence shows that water consumption behaviour in the ACT has remained stable since then.

During the millennium drought, many consumers changed their behaviour in response to water restrictions that were in place in the ACT from 2002 to 2010 (box 4.3). We found that water demand in the period during and after water restrictions increased less in response to warmer and drier weather compared to in the period before restrictions. A new relationship between water sales and climate variables developed in about July 2006 which has remained stable since then (ICRC 2015). Icon Water agreed with this conclusion in its 2018 submission (Icon Water 2018). Therefore, we use data since July 2006 to forecast dam abstractions.

Box 4.3 Changes in water consumption behaviour during the Millennium Drought

- Different stages of water restrictions and water conservation measures have been in place in the ACT since December 2002 (Table 4.3).
- The ACT was initially subject to temporary water restrictions from December 2002 to October 2005. This was followed by 1 year of permanent water conservation measures from November 2005 to October 2006. Temporary water restrictions were re-introduced in November 2006 and were in place till October 2010. Since November 2010, the ACT has been subject to permanent water conservation measures.
- During the millennium drought, many consumers changed their behaviour in response to water restrictions and higher water prices. Such behavioural changes included the use of more water efficient appliances, installation of more water efficient garden watering systems, and greywater diversion to other domestic uses (such as by transferring rinse water from washing machines to gardens).
- In our 2015 report, we found that consumption behaviour changed during the second period of water restrictions and a new and stable relationship had developed between water sales and climate variables from about July 2006.
- The evidence showed that the first round of water restrictions had changed consumer habits which remained stable even after restrictions were lifted.

Table 4.3 Water restrictions and water conservation measures in the ACT

Restriction level	Start date	End date
First period of temporary water restrictions (December 2002 to October 2005)		
• Stage 1 (low level restrictions)	Dec-02	Apr-03
• Stage 2 (moderate level restrictions)	Apr-03	Sep-03
• Stage 3 (high level restrictions)	Oct-03	Feb-04
• Stage 2 (moderate level restrictions)	Mar-04	Aug-04
• Stage 3 (high level restrictions)	Sep-04	Feb-05
• Stage 2 (moderate level restrictions)	Mar-05	Oct-05
Permanent water conservation measures	Nov-05	Oct-06
Second period of temporary water restrictions (November 2006 to October 2010)		
• Stage 2 (moderate level restrictions)	Nov-06	Dec-06
• Stage 3 (high level restrictions)	Dec-06	Aug-10
• Stage 2 (moderate level restrictions)	Sep-10	Oct-10
Permanent water conservation measures	Nov-10	Current

Source: Icon Water's website (https://www.iconwater.com.au/water-education/water-and-sewerage-system/dams/water-storage-levels.aspx)

Notes: The ACT has a 4 stage scheme of water restrictions which is put in place when water supplies are scarce and reductions in water use is required. Stage 1 is the low level restrictions. Stage 4 is the highest level of water restrictions, which was not imposed during the millennium drought. Permanent water conservation measures are like stage 1 restrictions.

Water consumption behaviour has remained stable even after water restrictions were lifted

A visual inspection of Figure 6 shows two step-changes in water consumption since 1999-2000.

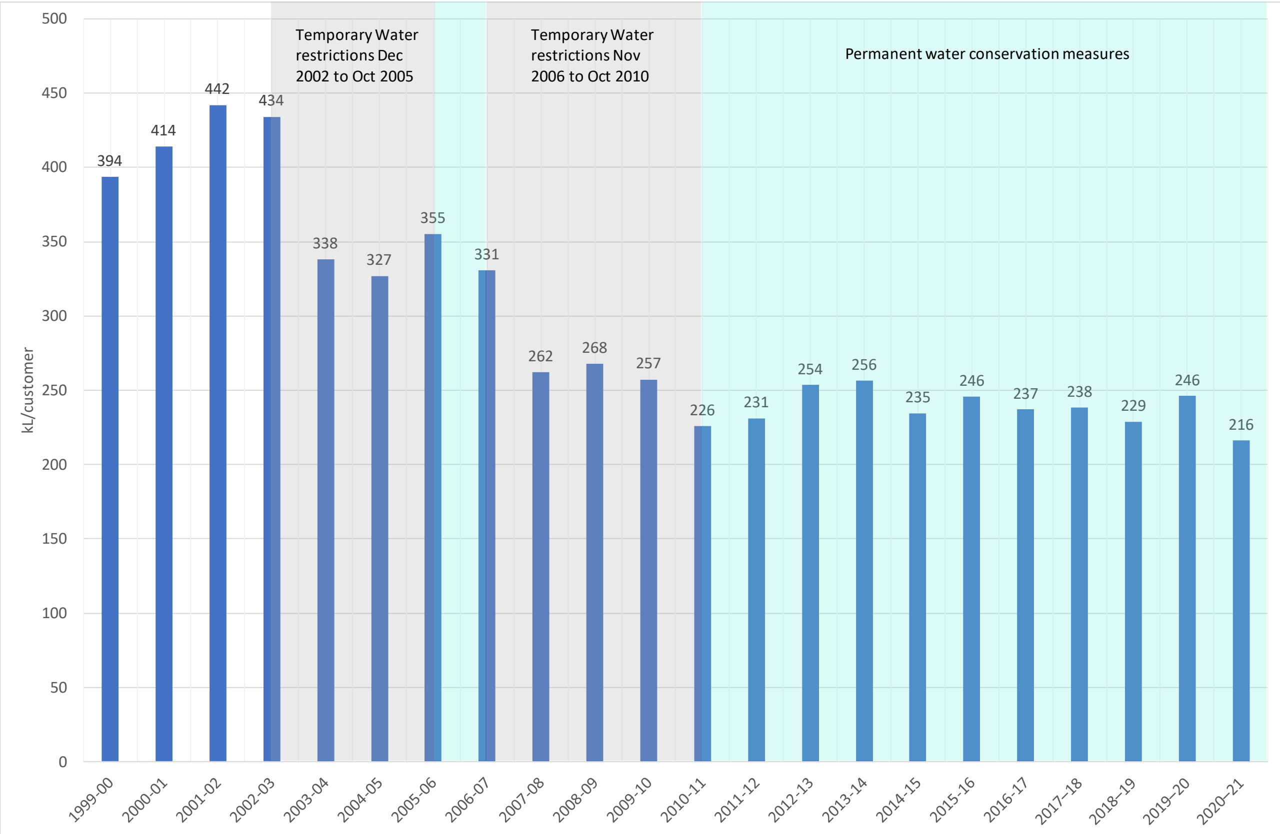
The first occurred after 2002-03 when temporary water restrictions were first introduced.

The second occurred after 2006-07 when temporary water restrictions were re-introduced. Per capita water consumption has remained stable since then.

The new relationship between water sales and climate variables that developed in about July 2006 is observed in the stable per capita water consumption from 2007-08. The delayed response is expected because people adapt slowly to restrictions, due to habit formation and because it takes time to install water efficient systems and replace appliances.

Therefore, we will continue to use data since 2006 in the ARIMA model.

Figure 6. Annual water consumption per customer (kL/customer)



Source: our analysis based on Icon Water data

Icon Water supports the current approach

Icon Water's view is that the most appropriate way to account for changes in consumer behaviour is to adopt an updated data period that reflects the change that has occurred (Icon Water 2021). In support of that view, Icon Water referred to our position in the 2018 investigation to use data from 2006 to account for a sustained step-change in water use in the ACT following the millennium drought.

Demographic changes

We will use ACT population projections rather than the past growth trend to forecast customer numbers

We will continue to use water customer numbers to forecast dam abstractions because water demand increases when there are more consumers.

Currently future customer numbers are estimated based on the past growth trend in customer numbers. Our draft decision is to change the method used to forecast customer numbers. The method will be based on the ACT Government population projections to provide a forward-looking forecast of customer numbers. This approach allows the ARIMA model to account for demographic changes that could not be captured by looking at a past trend.

It is now acknowledged that the Covid-19 pandemic has affected the drivers of ACT's population growth, and the ACT's population growth is expected to be lower than what was expected before the pandemic (ACT Government 2021). We will review our position to ensure that the ACT population projections we use to forecast Icon Water's customer numbers account for the impact of the pandemic.

Further details of the new method to forecast customer numbers are given in section 5.4 and appendix 3.

Population projections provide forward looking forecasts

The current approach of extrapolating previous trends in Icon Water's customer numbers may not account for changing demographic trends, such as increasing population density as more people in the ACT live in apartments rather than detached homes.

The ACT Government's population projections account for population growth including from migration and uses assumptions based on the ACT Government's long-term land release program and expected development activity, which can influence the number of future water customers and hence water demand.

We note the ACT Government's population projections are being updated to account for the effect of Covid-19, and the updated projections are expected to be published in the second half of 2021.[2] We will monitor this development to ensure that the ACT population projections we use account for the impact of the pandemic.

Icon Water supports the current approach

Icon Water has stated a preference for continuing to use water connection numbers in the ARIMA model as a proxy for population (Icon Water 2021).

Icon Water observed a strong historical relationship between the number of water connections and the ACT population. It noted that connection numbers can be highly influenced by factors such as government and private property development, and that future growth in connections may be different from the past growth rate. It suggested using the ACT Government population projections to forecast water connection numbers.

Background on demographic changes

Demographic changes can reflect changes in population growth and may also relate to changes in average age and family structure. These changes may result in changes in the mix of housing types (for example, the proportion of freestanding houses and apartments) that will have direct effects on water demand. A family living in a detached house with a backyard is likely to consume more water than the same sized family living

2 https://www.treasury.act.gov.au/snapshot/demography/act

in an apartment. An increase in the average age of the ACT community, coupled with a move to downsizing, could lead to a greater share of apartments or townhouses with small outdoor areas, which tend to use less water for outdoor uses.

The ACT Government population projections[3] are based on the Australian Bureau of Statistics *Population by Age and Sex, Regions of Australia* (2017) and assumptions about fertility, mortality and migration. The projections also use assumptions based on the ACT Government's long-term land release program and expected development activity.

Stability of model outputs

In our 2018-23 water price investigation, we found the demand forecasts changed significantly when Icon Water added 11 months of data from April 2017 to February 2018 for their revised pricing proposal. The forecast water abstractions increased by 1.3 % to 1.5 % in each year over the 2018-23 regulatory period. This indicates that the demand forecasts produced by the current ARIMA model are sensitive to minor updates to the data used in the model.

Icon Water agrees that more recent data are given greater weight in the ARIMA model. However, it noted that the cumulative increase was 1.4% over the 5-year regulatory period. Icon Water considers that the change in demand forecasts due to addition of more recent data is a function of the ARIMA model. It noted that when additional data is added to a forecasting model, it should be expected that the forecasts will change because the dynamic nature of the model ensures that the model satisfies the 'flexibility' criterion and does not remain static over time. Icon Water suggests retaining the current approach.

We agree with Icon Water's submission and consider the current method to update the model to account for more recent data is appropriate.

Variability of model outputs and data frequency

We will use weekly data, subject to further refinement of the model

The current model uses daily observations for climate and dam abstractions.

Our draft decision is to use weekly data to forecast dam abstractions. Our consultant has found that using weekly data improves the predictive performance of the model compared to daily or monthly observations.

We consider that using weekly data is intuitively sound because daily data are influenced by factors that are not relevant to forecast dam abstractions over longer horizons, for example, water consumption habits of customers on a day-to-day basis (such as using more water on the weekends than weekdays). Such day-to-day differences are not relevant to forecasting dam abstractions over a 5-year regulatory period.

Our draft decision is subject to further refinement of the model specification, which will depend on our final position on the draft decisions set out in this report.

Weekly data improves model performance

Our consultant's analysis shows that weekly data performs better than daily or monthly data.

Our consultant compared the forecasting accuracy of the current daily data model with a model based on weekly and monthly observations. It also considered additional variables to better capture extreme weather conditions, for example, number of days where daily temperature exceeded 30 degrees within the

[3] ACT Population Projection: 2018 to 2058

previous week (month) and number of days where daily rainfall exceeded 1 mm within the previous week (month).

The consultant assessed forecasting accuracy by estimating well known measures of Root Mean Square Percentage Error (RMSPE) and the Mean Absolute Percent Error (MAPE). RMSPE and MAPE measure the average difference (squared or absolute, respectively) between the yearly forecast and actual values. In the 2018 investigation, Icon Water used these measures to compare the performance of its form of ARIMA model against the form we identified in our 2015 report.

The consultant found that (Table 4.4):

- Forecasting accuracy improved significantly with weekly data relative to daily data, as both MAPE and RMSPE values are more than halved. There is little effect from adding extra weather variables.
- With monthly data, forecasting accuracy improved compared to daily data, and improved further when extra weather variables are added into the model.

The data in Table 4.4 show that when using weekly data (in the benchmark model), the difference between the annual forecast and actual volume was the lowest: 1.6% to 1.9% on average (lower difference means better performance). This contrasts with daily data where the average difference was the highest: 3.8% to 4.3% on average. The monthly data was in the middle with an average difference of 2.1% to 2.9%.

Table 4.4 Forecasting accuracy using daily, weekly and monthly data

	Daily data		Weekly data		Monthly data	
	Benchmark	Augmented	Benchmark	Augmented	Benchmark	Augmented
MAPE	**3.80%**	3.71%	**1.61%**	1.63%	3.14%	**2.06%**
RMSPE	**4.27%**	4.19%	**1.86%**	1.87%	4.01%	**2.87%**

Source: Marsden Jacob Associates (2021b)

Note: Benchmark – without additional weather variables, Augmented – with additional weather variables

Why weekly and monthly data perform better than daily data in forecasting over longer horizons

The nature of daily observations is that they can be affected by fluctuations that are irrelevant over a longer horizon. For example, they may be affected by outlier events on the day, such as an extreme hot day, which may not represent normal weather conditions. Daily observations are also heavily influenced by intra-week variation. For example, models based on daily data require taking into account the impact of the day of the week on total abstractions such as weekends vs weekdays, which are not relevant to forecasting dam abstractions over longer horizon. The information in daily data that is not relevant for longer term forecasting is called ‘noise’.

The noise in daily observations may make it harder to identify trends or cycles in weather conditions that are relevant to forecasting dam abstractions over longer horizon.

The noise in daily observations introduces a degree of error in the forecasting process for models based on daily observations. These errors will compound over time. So, the longer the forecast horizon, the greater will be the compounding error effect from daily observations. Our forecast horizon is 5 years, which is the length of the regulatory period.

In comparison, intra-week seasonal variations and outlier events are averaged out with weekly and monthly data, thus avoiding forecasting errors caused by noise in the data. Also, low frequency data (weekly or monthly) are better suited to show trends and cycles in weather conditions.

Why weekly data performs better than monthly data

A potential limitation with using monthly observations is that there are fewer observations to estimate the relationship between dam abstractions and their drivers such as climate and customer numbers: 12 monthly observations compared to 52 weekly observations in a year. There is some degree of information loss with monthly data relative to weekly data. Information loss will affect the forecasting accuracy of models that use monthly data.

This information loss would make weekly data perform better than monthly data, as shown in Table 4.4.

The information loss may be overcome by adding explanatory variables that capture new information. The consultant's analysis shows that the performance of monthly data improved when new explanatory variables designed to capture extreme weather events were added. However, this may increase the complexity of the model.

Icon Water's view on data frequency

Icon Water submitted that it was not aware of any evidence that using low-frequency data would improve the predictive ability of the ARIMA model. It expressed concern that using monthly data would require significant effort to recalibrate the model to identify the best-fit model specification.

We consider the process of recalibrating the model to identify the best-fit model specification is a normal process. We did that in 2015 when we proposed using the ARIMA model. Icon Water also did that process in 2018 when it proposed using its form of ARIMA model, compared to our form of the ARIMA model.

Background on forecast variability

We consider that if there is significant annual variability between forecast and actual water demand, we should investigate whether aspects of the forecasting model could be improved to reduce the variability.

For example, a comparison of forecast and actual dam abstractions data for the first three years of the regulatory period (Figure 4) shows that the difference in:

- 2018-19 was +6% (actual abstractions were greater than forecast)
- 2019-20 was +10% (actual abstractions were greater than forecast)
- 2020-21 was -2% (actual abstractions were less than forecast)

Although, on average, over the three years the actual abstractions were 5% greater than forecast, the significant annual variability in the first two years due to drier than average weather conditions cannot be overlooked. As discussed in this section of the report, we have identified aspects of the forecasting model that can be improved to better account for weather-related variability.

Our draft decision on the form of the ARIMA Model

Table 4.5 summarises our draft decision on the drivers of water demand we will use, the reason for selecting them, and the data sources we will use to estimate them.

Table 4.5 Summary of variables to be used under our draft decision on the form of the model

Drivers of water demand	Reasoning	Data source
Maximum temperature (degrees Celsius)	Temperature data is used because water demand changes with temperature, with more demand during hot periods	Canberra Airport weather station data reported by the Bureau of Meteorology (BoM); NARCLiM climate change projections data
Rainfall (mm)	Rainfall data is used because water demand changes with the amount of rainfall, with less demand for water during rainy periods.	Rainfall data at Canberra Airport reported by BoM; NARCLiM climate change projections data
Evaporation rate (mm)	High evaporation rates are related to higher irrigation requirements for plants/gardens as they dry.	Evaporation data for Burrinjuck Dam reported by BoM; NARCLiM climate change projections data
Water customer numbers	An increase in customers will increase demand for water.	Icon Water (historical customers data); Australian Bureau of Statistics (historical population data); ACT Government population projections data
Dam abstractions (ML)	Represents historical dam abstractions and allows us to identify a relationship between dam abstractions over time.	Icon Water (historical data); this is a function of the ARIMA model and is calculated using the model.
Seasonality	To capture the effect of different volumes of water use in different seasons such as high water use in summer months and low water use in winter months.	Calculated using a mathematical formula to capture annual seasonal pattern.
Unforeseeable events	Accounts for the impact of unforeseeable and unobserved events on water demand (such as bushfires).	This is a function of the ARIMA model and is calculated using the model.

Our consultant's analysis shows that the weekly data model has better statistical properties than the daily data model.

For example, the estimated effect of the additional variables included in the weekly data model to capture the effect of extreme weather conditions on dam abstractions is as expected. The estimated coefficient for the variable 'number of days where maximum daily temperature exceeded 30 °C' within the previous week is 9.88: it shows that for every additional day when daily temperature exceeded 30 °C, dam abstractions increase on average by 10ML, keeping all other variables constant.

The weekly data model also shows that the impact on dam abstractions is more than proportionate when the temperature threshold is increased to 35 °C. The estimated coefficient for the variable 'number of days where maximum daily temperature exceeded 35 °C' is 24.34: it means that for every additional day when daily temperature exceeded 35 °C, dam abstractions increased on average by 24ML, keeping all other variables constant.

In contrast, the daily data model shows an unexpected result for extreme hot days. The estimated coefficient for the variables that are designed to consider the effect on water demand of days when temperature exceeded 35 °C or 40 °C has a negative sign (-2.86 to -0.42): this would mean days when the temperature exceeded 35 °C or 40 °C are associated with lower dam abstractions, keeping all other variables constant. This counterintuitive result is caused by the noise (very high volatility) in daily observations.

Our consultant's analysis also shows that the estimated coefficients for the weekly model have signs that are consistent with expectations. For example, in the model, evaporation is included in linear form (amount of evaporation) and non-linear form (squared value and square root value of the amount of evaporation). In such cases, the effect of evaporation on dam abstractions is considered by looking at the coefficient estimates for the linear and non-linear forms as well as the amount of evaporation. The consultant's analysis shows that the relationship between dam abstractions and evaporation is like a U-shape: as evaporation increases, dam abstractions increase but this increase is less than proportionate.

The detailed estimation results are presented in the appendix 2 and in the consultant's report in appendix 4.

Our next steps to finalise the model specification

After we have finalised our decisions set out in this draft report, taking into account information and views provided by stakeholders, our consultant will make final refinements to the model to ensure it is statistically sound and reliable.

Based on our consultant's advice, we will finalise the model to ensure it best fits the data. The final model specification will establish the final statistical form of the drivers of water demand listed in Table 4.5: whether to use squared values, square root values and how many 'lags' to use, which is commonly used in ARIMA models where it is assumed that the forecast value of a variable is dependent upon past observations of that variable (for example, using past dam abstractions to forecast future dam abstractions).

5. Forecasting other demand components

This chapter discusses our draft decision on the methods and data used to forecast the other water and sewerage services demand components, which are:

- total ACT water sales
- billed water sales at Tier 1 and Tier 2
- total number of water service connections, total number of sewerage service connections, number of billable fixtures
- sewage volume.

5.1 Summary of the draft decisions

We will retain the current method to forecast ACT water sales and billed water sales at Tier 1 and Tier 2. The current approach produces reliable forecasts and will provide regulatory stability. The only change we will make is to add more recent years' data to the existing dataset to forecast billed water sales and the Tier 1 and Tier 2 split.

We have accepted Icon Water's suggestion to change the method to forecast water and sewerage services connection numbers and number of billable fixtures. The method will be based on ACT population projections rather than past growth trends in connection numbers and billable fixtures. We consider ACT population projections are a better indicator of the future connection numbers and billable fixtures. There is a stable relationship between ACT population numbers and these demand components, so using population forecasts will capture future demographic changes and provide a better indicator to forecast connection numbers and billable fixtures.

We will retain the current method to forecast sewage volumes. The current approach produces reliable forecasts and will provide regulatory stability.

5.2 Total ACT water sales

We will retain the current method to forecast total ACT water sales

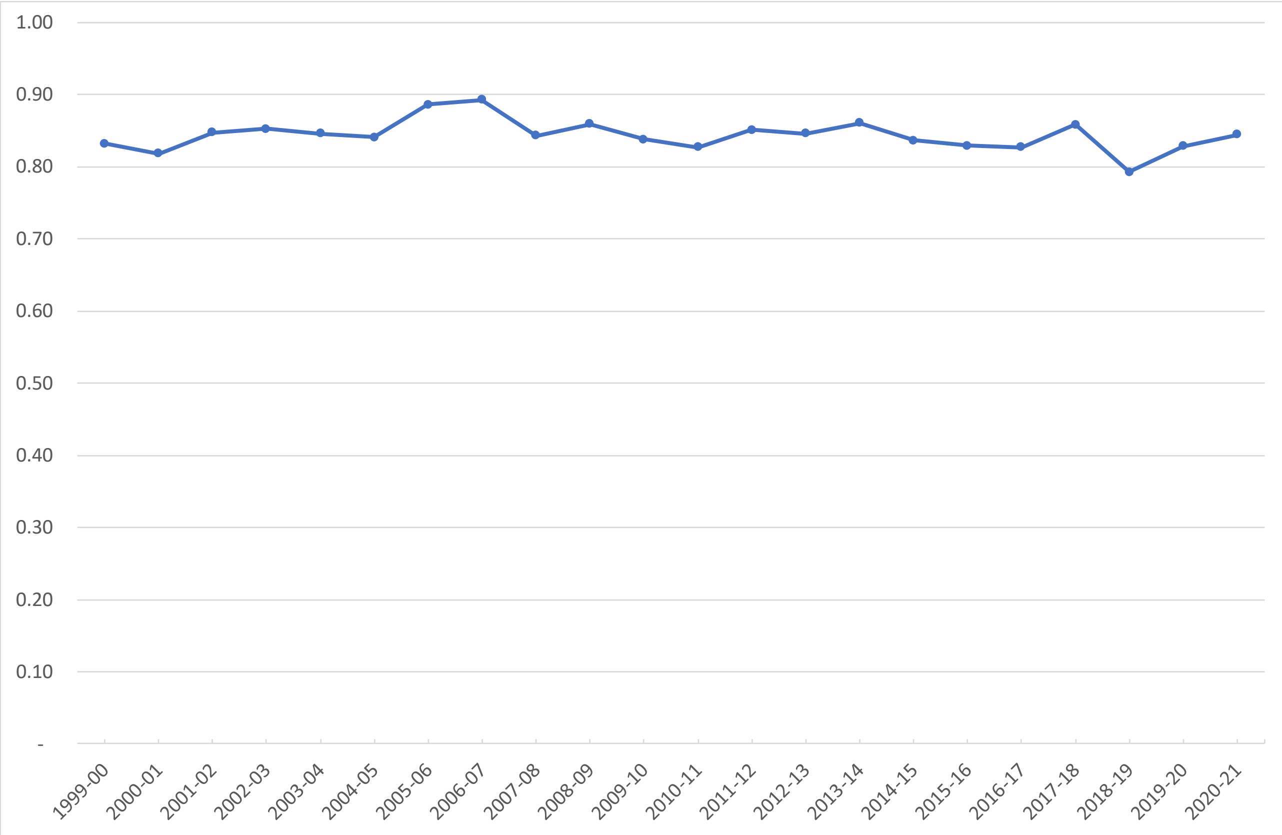
We will retain our current method to forecast total ACT water sales based on the historical shares of dam abstractions sold to ACT consumers. Box 5.1 outlines the current method.

We consider it appropriate to retain the current method because there is a stable relationship between ACT water sales and dam abstractions, and the method produces reliable forecasts. Therefore, the current method meets our assessment criteria of predictive ability and regulatory stability.

There is a stable relationship between ACT water sales and dam abstractions

On average, ACT water sales accounts for about 80% to 90% of the volume of water abstractions from Icon Water's dams, and this ratio has been stable for over two decades (Figure 7). The balance of water abstractions is accounted for by Queanbeyan consumption and water losses due to leaking pipes, theft, and metering errors.

Figure 7. Ratio of annual ACT water sales to annual dam abstractions

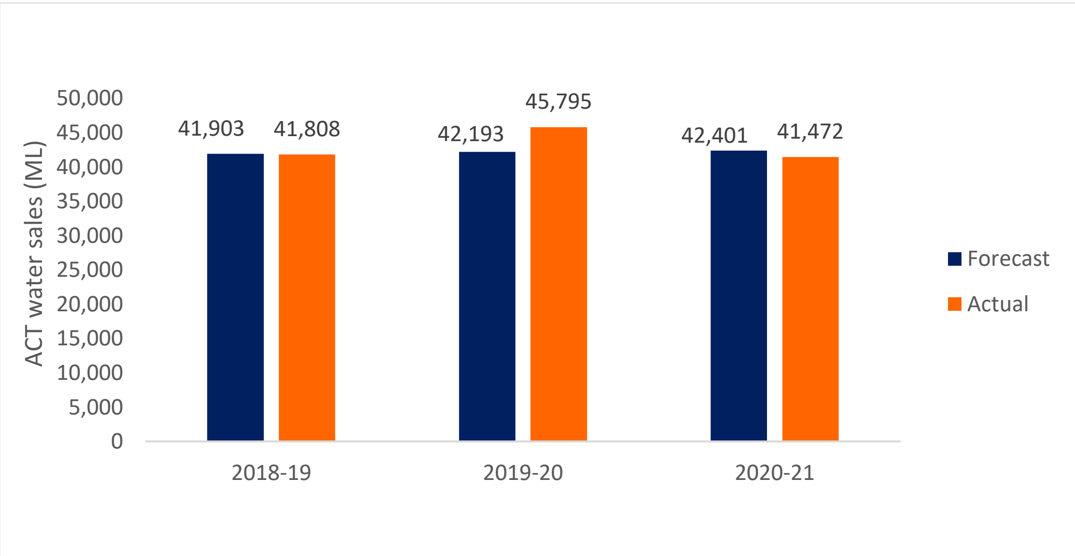


Source: our analysis based on Icon Water data

The current method produces reliable forecasts

We compared forecast ACT water sales made in our 2018 water price investigation with actual ACT water sales for the first three years of the current regulatory period. We found that the forecasts are reasonably accurate because the average difference over the period is 2%. Figure 8 shows the forecast and actual ACT water sales for the first three years of the current regulatory period.

Figure 8. Total ACT water sales: actual and forecast comparison



Source: our analysis based on data from Icon Water

We will add more recent years' data to the existing dataset to forecast ACT water sales

In our 2018 water and sewerage service price investigation, the ACT water sales forecast was based on the historical relationship between ACT water sales and dam abstractions from 1999-2000 to 2015-16.

For the next water price investigation, we will add more recent years' data to the existing dataset. This will ensure the relationship between ACT water sales and dam abstractions is estimated based on a longer dataset that includes the latest available data.

Icon Water supports using the current method

Icon Water considers that the current method for estimating ACT water sales should be retained because it produces reliable forecasts (Icon Water 2021).

Box 5.1 Steps used to forecast ACT water sales from dam abstractions

1. The historical relationship between annual ACT water sales and annual dam abstractions is estimated using a linear regression model and historical data.

2. Daily dam abstractions forecast from the ARIMA model are aggregated to calculate forecast annual dam abstractions for each year of the regulatory period.

3. The relationship estimated in step 1 is applied to the annual dam abstractions forecast obtained in step 2, to estimate the forecast annual volume of ACT water sales for each year of the regulatory period.

5.3 Billed water sales at Tier 1 and Tier 2

We will retain the current method to forecast billed water sales at Tier 1 and Tier 2

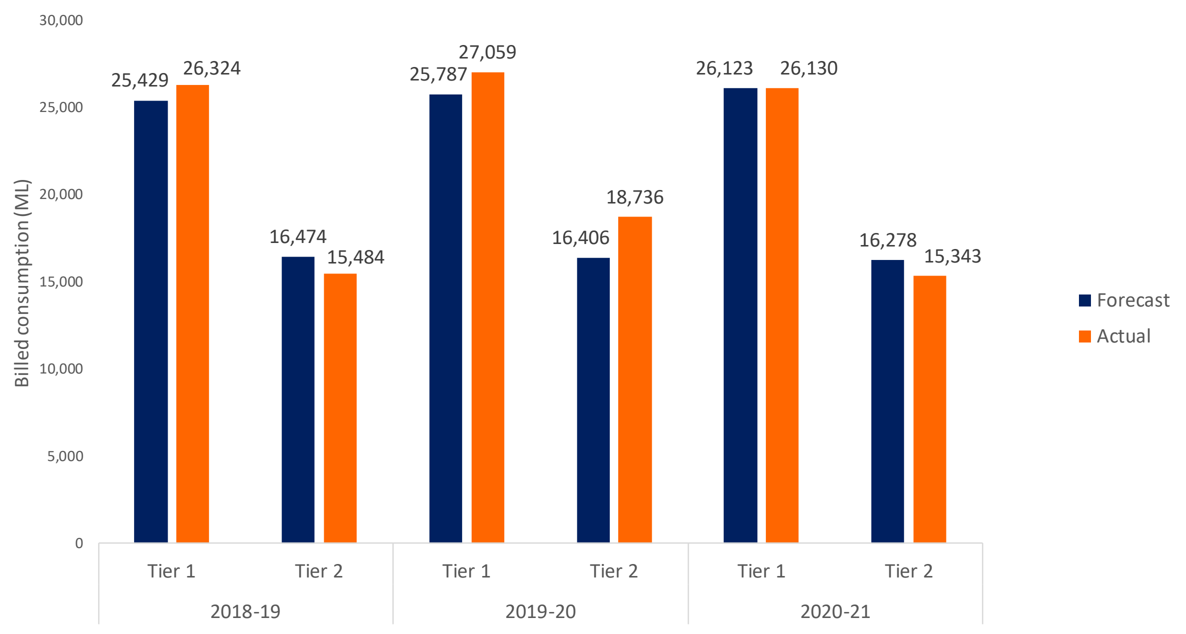
We will retain the current method to split ACT water sales into Tier 1 and Tier 2 by first separately forecasting Tier 1 sales, and then forecasting Tier 2 sales as the difference between total ACT water sales and the Tier 1 sales forecast. We will also retain the current method to forecast Tier 1 sales based on the historical relationship between the average amount of water consumed by each customer per year and the proportion of water sales falling into the Tier 1 category. Box 5.2 outlines the current approach.

We consider it appropriate to separately forecast Tier 1 sales, because they account for a greater proportion of total ACT water sales (on average 60% in the current regulatory period).

We consider it appropriate to retain the current methods because they produce reliable forecasts and will provide regulatory stability.

We compared Tier 1 and Tier 2 sales forecasts in our 2018 water price investigation with actual volume of water sales for the first three years of the regulatory period. We found that the forecasts are reasonably accurate because the average difference over the period is less than 3%. Figure 9 shows the comparison between the forecast and actual Tier 1 and Tier 2 sales for the first three years of the regulatory period.

Figure 9. Billed consumption (Tier 1 and Tier 2 sales): actual and forecast comparison



Source: our analysis based on data from Icon Water

We will add more recent years' data to the existing dataset to forecast Tier 1 water sales

The current method to forecast Tier 1 sales uses a small sample of seven annual observations. We will add more recent years' data to the existing dataset to forecast Tier 1 sales for the next regulatory period.

In our 2018 water and sewerage service price investigation, the Tier 1 sales forecast was based on the historical relationship between the average amount of water consumed per connection and the proportion of total sales falling into the Tier 1 category. That relationship was defined based on annual data from 2009-10 to 2015-16.

For the next water price investigation, we will add more recent years' data to the existing dataset and update the relationship to ensure it is based on the expanded dataset and provides the most accurate forecast. Appendix 3 gives further details on the different forms of the relationship we modelled to identify the best form using the latest available data to date.

Icon Water supports the current approach

Icon Water supports the current method to split total ACT water sales into Tier 1 and Tier 2 categories.

Icon Water suggests adding more recent years' data to the existing dataset to estimate the relationship between average water consumption per installation and observed proportion of Tier 1 sales (Icon Water 2021).

Box 5.2 Steps used to forecast Tier 1 and 2 water sales

The Tier 1 price applies to water consumption up to 50 kL per quarter per water connection and the Tier 2 price applies to consumption above that.

1. The historical relationship between the proportion of Tier 1 sales and the average water consumption per customer is estimated based on historical annual data.

2. Forecast average water consumption per customer is calculated by dividing the forecast total ACT water sales by the forecast water connection numbers for each year of the regulatory period.

3. The relationship estimated in step 1 is applied to the forecast average water consumption per customer in step 2 to forecast the proportion of Tier 1 sales for each year of the regulatory period.

4. The forecast proportion of Tier 1 sales in step 3 is applied to the forecast total ACT water sales to get forecast Tier 1 sales for each year of the regulatory period.

5. The Tier 2 sales forecast is calculated as the difference between the total ACT water sales forecast and the Tier 1 sales forecast in step 4.

5.4 Water and sewerage services connection numbers and billable fixtures

We will use ACT population projections rather than past growth trend to forecast connection numbers and billable fixtures

We will change the method to forecast water and sewerage service connection numbers and number of billable fixtures. The new method will be based on ACT population projections. It will replace the current method that was based on the Industry Panel's approach to use past growth trends in connection numbers and billable fixtures.[4] As outlined in section 4.2, the ACT Government's population projections are currently being updated to account for the effect of Covid-19, and the updated projections are expected to be published in the second half of 2021.[5] We will monitor this development to ensure that the ACT population projections we use account for the impact of the pandemic. Box 5.3 outlines the new method to forecast connection numbers and billable fixtures.

We consider that the past growth trend may not be a good indicator of the future trend because of demographic changes and future property development in the ACT that will influence the future number of water and sewerage connections and billable fixtures.

We found there is a stable and strong relationship between connection numbers and billable fixtures, and ACT population. The ACT Government population projections[6] are based on the Australian Bureau of Statistics *Population by Age and Sex, Regions of Australia* (2017) and uses assumptions based on the ACT Government's long-term land release program and expected development activity.

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[4] In the 2018 water and sewerage services price investigation, forecasts of water and sewerage installations and billable fixtures were made based on the observed annual growth rates for those services over the 2013-14 to 2017-18 period. The observed annual growth rates of water installations, sewerage installations, and billable fixtures were 1.84 %, 1.83 %, and 1.55 %, respectively. These annual growth rates were applied to 2017-18 actual values to obtain forecasts for the regulatory period.

[5] https://www.treasury.act.gov.au/snapshot/demography/act

[6] ACT Population Projection: 2018 to 2058

We also found that the new method has a higher forecast accuracy compared to the current method.

We therefore consider that forecasts based on ACT Government population projections will provide a better indicator to forecast connection numbers and billable fixtures.

We agree with Icon Water's suggested approach

Icon Water observed a strong historical relationship between the number of connections and billable fixtures and the ACT population. It noted that connection numbers can be highly influenced by factors such as government and private property development, and that future growth in connections may be different from the past growth rate. So, it suggested using the ACT Government population projections to forecast connection numbers and billable fixtures (Icon Water 2021).

The new method to forecast water and sewerage services connection numbers and billable fixtures

We need forecasts of water and sewerage services installations to set the supply charges for water and sewerage services. Forecasts of billable (flushable) fixtures are required to set the separate fixtures charge for non-residential customers with more than two flushable fixtures.

Box 5.3 Steps of the new method to forecast connection numbers and billable fixtures

1. The historical relationship between ACT population and each demand component of water service connection numbers, sewerage service connection numbers, and billable fixtures will be estimated separately using a linear regression model and historical data.

2. The relationship estimated in step 1 will be applied to ACT Government population projections to forecast water service connection numbers, sewerage service connection numbers and billable fixtures for the 2023-28 regulatory period.

We applied the new method to forecast connection numbers and billable fixtures for the current regulatory period. We went back to 2018 and used the data that was available then on connection numbers, billable fixtures, and ACT population to estimate separately the historical relationship between ACT population and each of the three demand components. We then applied the estimated relationship to the annual ACT population projections from 2018-19 to 2020-21 to obtain the forecasts for the first three years of the current regulatory period. Further details are in appendix 3.

We compared the forecast performance of the new method and the current method against the actual data. We found that for each of the three demand components, forecasts using the new method are more accurate than the forecasts based on the current method. The average difference based on the new method is less than 2% over the period. In comparison, the average difference for forecasts based on the current method is more than 2% over the period. Table 5.1 compares the percentage difference between actual and forecasts using the current method and the new method over the period from 2018-19 to 2020-21.

Table 5.1 Connection numbers and billable fixtures: current method and new method

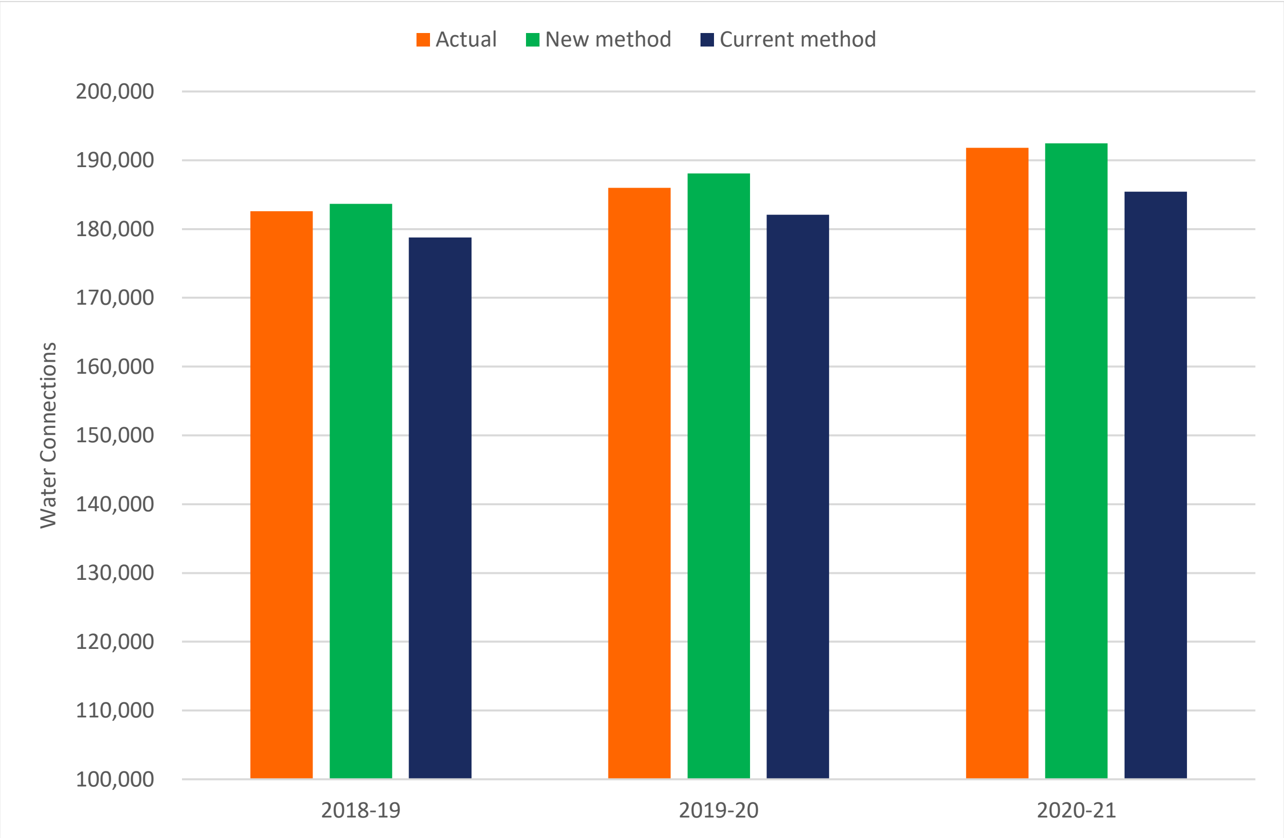
Demand components	Current method (average % difference from actual values)	New method (average % difference from actual values)
Water connection numbers	-2.51%	0.68%
Sewerage connection numbers	-2.49%	1.38%
Billable fixtures	2.50%	-0.11%

Source: our analysis based on Icon Water data and ACT Government data (ACT Population Projections 2018 to 2058)

Notes: 'minus -' sign indicates the model underpredicts actual values and 'plus +' sign indicates the model overpredicts actual values.

Figures 10, 11 and 12 present the forecasts for the two methods: new method and current method, and the actual values for the first three years of the regulatory period, from 2018-19 to 2020-21.

Figure 10. Water connection numbers: actual and forecast comparison

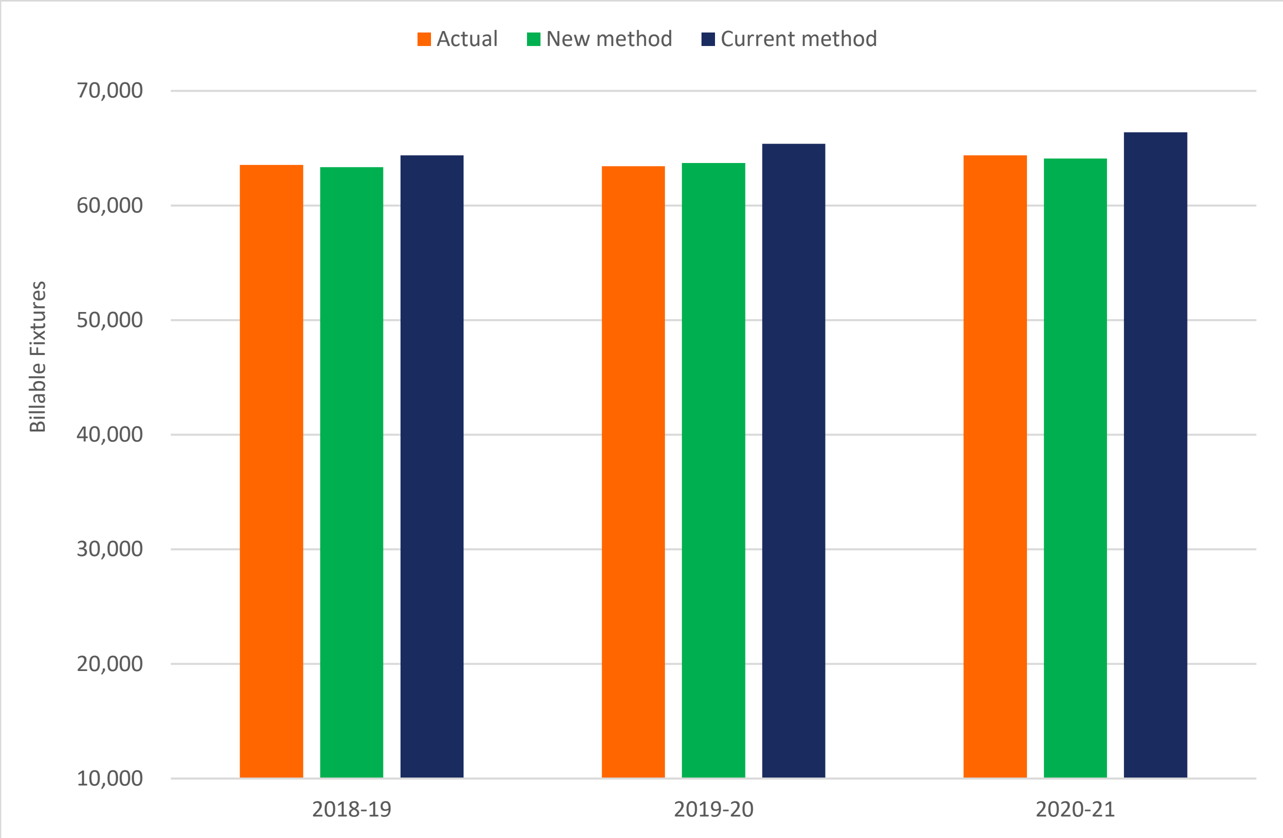


Source: our analysis based on data from Icon Water and ACT Government data (ACT Population Projections 2018 to 2058)

Figure 11. Sewerage connection numbers: actuals and forecast comparison

Source: our analysis based on data from Icon Water and ACT Government data (ACT Population Projections 2018 to 2058)

Figure 12. Billable fixtures: actuals and forecast comparison



Source: our analysis based on data from Icon Water and ACT Government data (ACT Population Projections 2018 to 2058)

5.5 Sewage volume

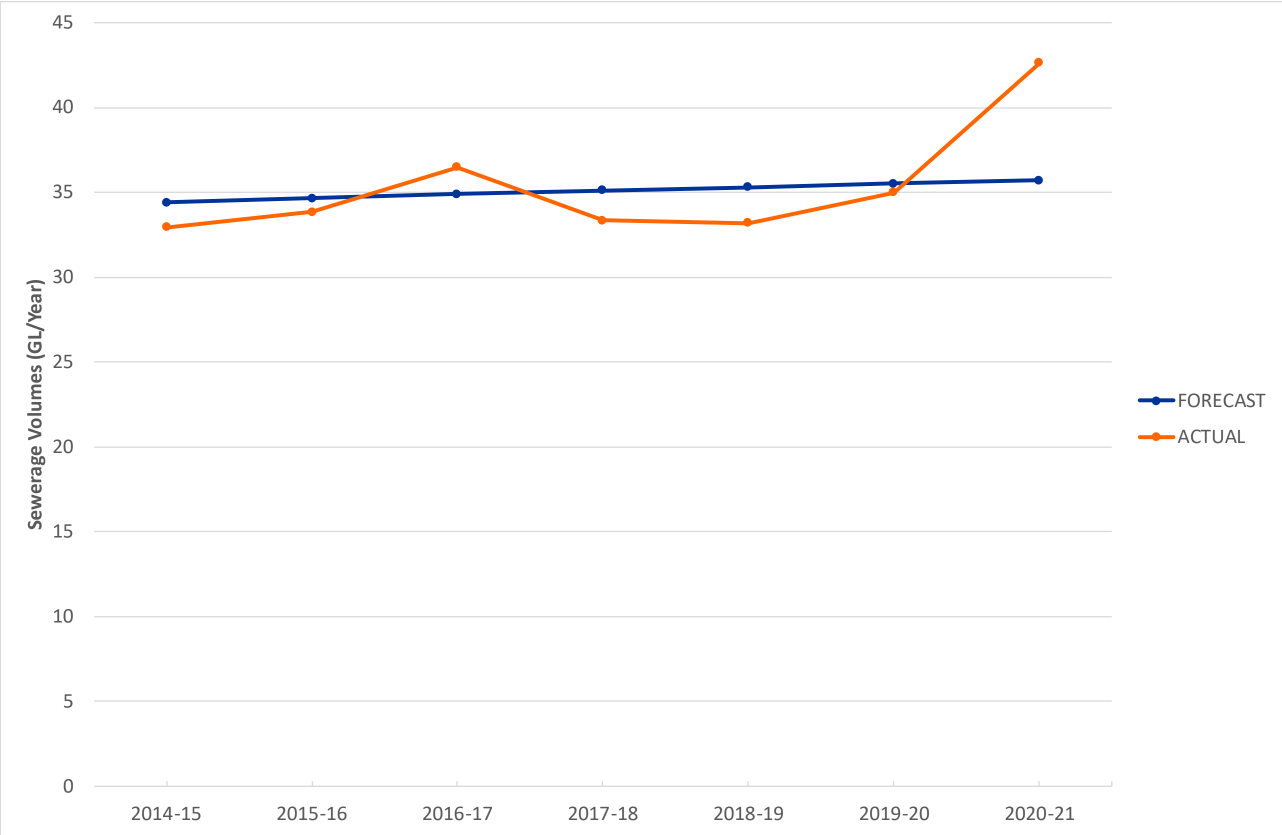
We will retain the current method to forecast sewage volumes

We consider it appropriate to retain the current method because it accounts for factors that are most likely to affect sewage volumes, like average sewage volume per resident, population growth, groundwater flow into the sewerage system, and climate conditions. Box 5.4 outlines the current method.

The current method produces reliable forecasts and meets our assessment criteria of predictive ability and regulatory stability.

Icon Water developed the method to forecast sewage volumes in 2014. We compared forecast and actual sewage volumes for 7 years from 2014-15 to 2020-21. We found that the forecasts are reasonably accurate because the average difference over the period is less than 1%, and in 6 years the forecast sewage volume was close to the actual sewage volume (Figure 13). The year 2020-21 was an exception because above average rainfall resulted in greater than forecast sewage flow into the Lower Molonglo Water Quality Control Centre.

Figure 13. Sewage volume: actuals and forecast comparison



Source: our analysis based on Icon Water data

Icon Water supports the current method

Icon Water considers the current approach to forecast sewage volume is performing well and did not propose any changes (Icon Water 2021).

Box 5.4 Method to forecast sewage volumes

Icon Water uses historical average sewage flow into the Lower Molonglo Water Quality Control Centre from 1998 to 2013, and estimates the long-term trend in sewage volume for four scenarios that are based on assumptions about:

- average annual sewage volume per resident which depends on water conservation practices
- population projections
- long term weather scenarios (dry, average or wet)
- seasonal impact
- rates of groundwater or surface storm water flow into the sewerage system

The average of the four scenario is used to forecast sewage volumes.

Appendix 1 Our pricing principles

Table A1.1 Regulatory objectives and pricing principles for water and sewerage services tariffs

Category	Aspect	Detail
Objective	**Overarching interpretation**	To promote efficient investment in, and efficient operation and use of, regulated services for the long-term interests of consumers in relation to the price, quality, safety, reliability and security of the service. The various aspects of economic efficiency are given emphasis but with the ultimate objective being the long-term interests of consumers. 'Economic efficiency' when properly defined encompasses environmental objectives. Consumer interests must take account of equity and other social impacts, as required by the ICRC Act. Economic efficiency considerations related to pricing are a starting point but need to be balanced with environmental and social considerations.
Pricing principle	**1. Economic efficiency in use**	Regulated prices should promote the economically efficient use of Icon Water's water and sewerage services infrastructure and should also encourage economically efficient use of the water resource itself. This includes having regard to uneconomic bypass where water supply is sourced from a higher cost alternative.
	2. Economic efficiency for investment and operation	Regulated prices and supporting regulatory arrangements should facilitate the efficient recovery of the prudent and efficient costs of investment and operation. The finance recovery aspect of this principle is often described as ensuring revenue adequacy or financial viability. Costs also need to be efficient, which is primarily dealt with by auditing and incentive-sharing mechanisms.
	3. Environmental considerations	Regulated prices and complementary mechanisms should ensure that environmental objectives are effectively accounted for.
	4. Community impact – gradual adjustment	Any change to prices or other regulatory arrangements that will have substantial consumer impacts should be phased in over a transition period to allow reasonable time for consumers to adjust to the change.
	5. Community impact – fair outcomes for low-income households	Adverse impacts on households with low incomes need to be limited or moderated by phasing and other compensating mechanisms or limits on changes to regulated prices or other regulatory arrangements.
	6. Regulatory governance – simplicity	Regulated prices and their form should be simple for consumers to understand and straightforward for the utility to implement.
	7. Regulatory governance – transparency	Regulated prices should be set using a transparent methodology and be subject to public consultation and scrutiny.

Appendix 2 Technical details of the draft decision form of forecasting model for dam abstractions

Form of the ARIMA model

Table A2.1 Regulatory objectives and pricing principles for water and sewerage services tariffs

Variable	Description	Reasoning	Coefficient estimate from modelling exercise
Dam abstractions	Dam abstractions during a previous week	Dam abstractions are related over time. This is a function of the ARIMA model and is calculated using the model.	0.68 Data shows dam abstractions are positively related over time.
Temperature	Average of daily maximum temperatures (degrees Celsius) during a week	Hot periods will result in more water abstractions to meet increasing water demand by customers	Linear component: 3.70 to 7.73 Squared: 0.05 These estimates show that dam abstractions increase in hot periods, and the squared component show that the increase in abstractions is more than proportionately to the increase in temperature.
Rainfall	Average daily rainfall (mm) during a week	Rainy periods will result in less water abstractions because part of customer's water demand will be met by rain (e.g. less water required for plants during rainy periods)	Non-linear components • Squared: 0.38 • Square root: -25.30 to -13.32 These estimates together show a negative relationship between total abstractions and rainfall.
Evaporation	Average daily evaporation during a week	High evaporation rates will result in more water abstractions to meet higher irrigation requirements for plants/gardens as they dry.	Linear component: 25.10 to 101.40 Squared: -6.40 Square root: -202.92 These estimates together show that total abstractions increase with higher levels of evaporation, and the non-linear components show that abstractions increase less than proportionately.

Variable	Description	Reasoning	Coefficient estimate from modelling exercise
Customer numbers	Icon water customer connections at the end of a week	More customers will increase water demand, and will require more water abstractions	0.002 This estimate shows that increase in customers are related to more water abstractions, but the effect is not material.
Additional weather variables to capture the effect of extreme weather conditions on dam abstractions	• Number of days where daily temperature exceeded 30 °C or 35 °C in a week	More days with extreme high temperature will result in more dam abstractions.	9.88 to 24.35 This estimate shows extreme hot periods increase dam abstractions.
	• Number of days without rain in a week	More days without rain will result in more dam abstractions.	3.17 This estimate shows that dry period is related to higher dam abstractions.
	• Interaction effect between rainfall and evaporation	High levels of evaporation and low levels of rainfall is likely to be related to higher demand for water	-0.05 The interaction term implies that impact of a change in rainfall on total abstractions also depends on the level of evaporation (and vice versa). The estimated magnitude of this term implies that the interaction effect is rather small empirically.
Sine function	These are included to account for seasonality (systematic, repetitive, periodic fluctuations in dam abstractions over the course of a week)		-19.76
Cosine function			-122.63
Moving average component	Forecast error of dam abstractions for the previous week (weeks)		-0.18 This is a function of the ARIMA model and is calculated using the model. This parameter enters the autocorrelation function of the dependent variable.

Source: Marsden Jacob Associates (2021b)

Climate scenarios and data used in the model

Reference climate scenario

We will develop future climate scenarios based on a reference climate scenario. We will develop the reference climate scenario as follows.

First, we will use historical climate data from 1965 onwards, because Burrinjuck Dam evaporation data are available from 1965.

Second, for this draft decision we assume historical data are available till December 2021. The time period between July 1965 and December 2021 will be divided into 50 overlapping 6.5-year time periods.[7] We have chosen 6.5 years as the length of each period because if we do the forecast in early 2022 which is around 1.5 years before the start of the five-year regulatory period of July 2023.

Third, we will develop reference climate scenario using the average data for the 50 time periods. That means our reference climate scenario has daily data for the maximum temperature, rainfall and evaporation for a 6.5-year time period.

Proposed approach to future climate scenarios using NARCLiM

NARCLiM projections include the latest set of global climate models (GCMs) provided by the Intergovernmental Panel on Climate Change. Each GCM (there are 3) consists of 2 separate Regional Climate Models (RCMs), which in turn provides projections based on two emissions scenarios, referred to as Representation Concentration Pathways (RCPs):[8]

- RCP4.5 – A scenario which assumes some mitigation of greenhouse gas emissions is achieved
- RCP8.5 – A scenario which assumes very limited mitigation of greenhouse gas emissions is achieved

NARCLiM provides data on 12 different climate scenarios, made up of the different combinations of GCMs (3), RCMs (2) and RCPs (2).

NARCLiM provides projections by observing trends in historical data from 1951 to 2005.

In our demand forecasting model, we will use the rainfall, evaporation and temperature variables to develop our future climate scenarios.

Approach to developing adjustment factors

Each NARCLiM scenario gives the average monthly rainfall, temperature and evaporation projections from 2020 to 2100.

We propose to use the following steps to determine the adjustment factors:

1. Monthly historical data from 1951 to 2005 is provided by the NARCLiM data source for temperature, rainfall and evaporation. Average monthly values are created for this 55-year period and then grouped to determine seasonal averages for the period.
2. We will use monthly projections from 2022 to 2028 to coincide with the forecast period. Using the same process as step 1, seasonal averages are determined for the period.
3. Adjustment factors are calculated as the percentage change between the seasonal values for the 2022-2028 period and the 1951-2005 period for rainfall and evaporation, while the adjustment factor for temperature is taken as the difference.

We will finalise the above steps in our final report.

Forecast of water installation numbers

We need forecasts of water installation numbers to forecast dam abstractions. We will use ACT population projections to forecast water installation numbers, as discussed in section 5.4 of this report.

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[7] Overlapping periods are determined by subtracting the overlap period from the number of years of data observations. For example, there are 57 yearly observations between 1965 and 2022, subtracting the 5.5-year overlap period from this gives 51.5 overlapping periods, which we have rounded down to 51 periods.

[8] Climate Data Portal (nsw.gov.au)

Data used in the model

Dam abstractions

This is the variable we forecast using the model. Icon Water abstractions water from its dams to meet demand from ACT and Queanbeyan customers. This data is sourced from Icon Water.

Maximum temperature

Temperature data will be sourced from the Bureau of Meteorology, which reports weather data for Canberra based on the weather conditions at Canberra Airport weather station. Temperature data is used in the model because water demand changes with temperature, with hot days having more demand.

Rainfall

Rainfall data at Canberra Airport will be sourced from the Bureau of Meteorology. Rainfall data is used because water demand changes with the amount of rainfall, with rainy days having less demand for water.

Evaporation

Evaporation data for Burrinjuck Dam, measured in millimetres, will be sources from the Bureau of Meteorology. The Bureau of Meteorology measures evaporation as the amount of water which evaporates from a specific standardized open space. The model uses data for Burrinjuck Dam because historical data for Canberra Airport weather station (like for other climate variables) is not available for a longer time period.

December dummy variable

The model has a dummy variable for December to capture the effect of that month on water demand. Water demand in December is higher than other months in the ACT, likely due to high temperatures and summer holidays.

Summer dummy variables

The model has a dummy variable for summer season (December to February) to capture the effect of hot summer season on water demand.

Water customer numbers

The model has the number of Icon Water's water customers, as measured by the number of water connections. Water customer numbers have been included because there is a strong positive correlation between customer numbers and water demand. Data for actual customer numbers is provided by Icon Water.

A Fourier seasonal term

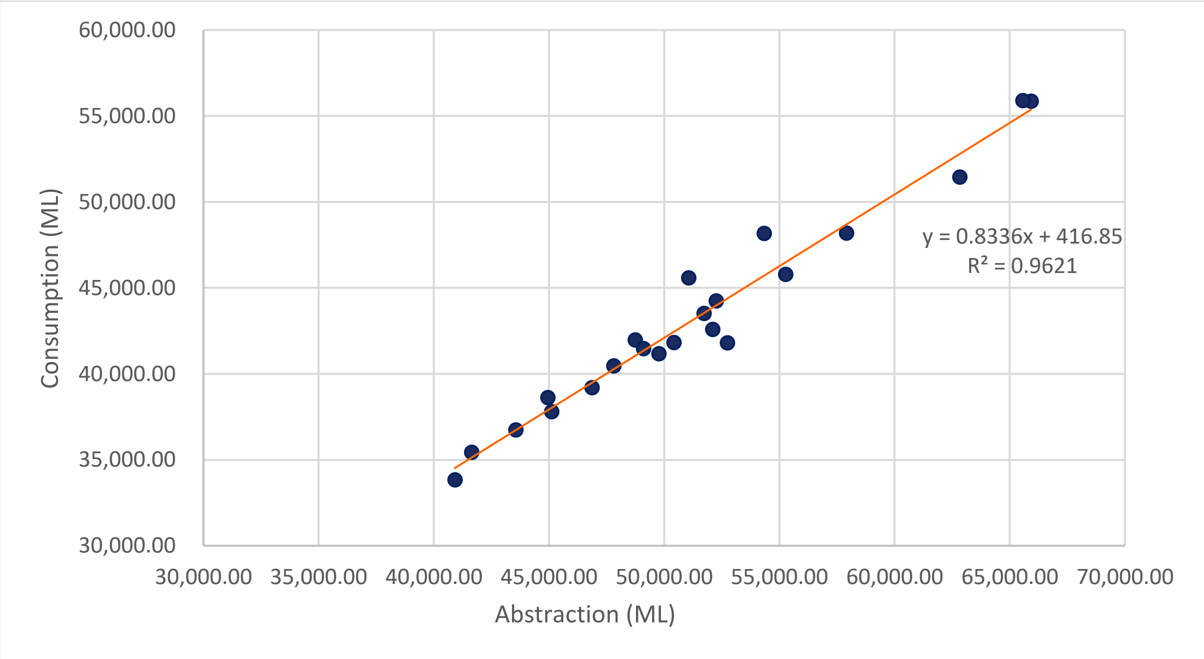
Adding a Fourier seasonal term to a forecasting model is a statistical technique used to incorporate annual regular and predictable changes in water demand to the forecasting model. Accuracy of forecasts can be improved by incorporating regular and predictable changes to the model. Data for a Fourier term is created using a mathematical formula.

Appendix 3 Technical details of the draft decision forecasting model for other demand components

Total ACT water sales

Figure 14 shows the relationship between annual dam abstractions and billed consumption from 1999-2000 to 2020-21. As seen in the figure, there is a strong relationship between the two variables.

Figure 14 Annual dam abstractions and billed consumption, 1999-2000 to 2020-21



Source: our analysis based on data from Icon Water

Billed water sales at Tier 1 and Tier 2

Tier 1 proportion

To estimate the proportion of total water sales that is expected to fall into the Tier 1 category, we estimate an equation that best fits the relationship between the average amount of water consumed per connection and proportion of total sales falling into the Tier 1 category.

We have re-estimated different forms of the relationship using the latest available data to date and identified that our current equation still provides the best fit. Table A3.1 shows the relationship between the average amount of water consumed per connection and observed Tier 1 proportion from 2008-09 to 2020-21.

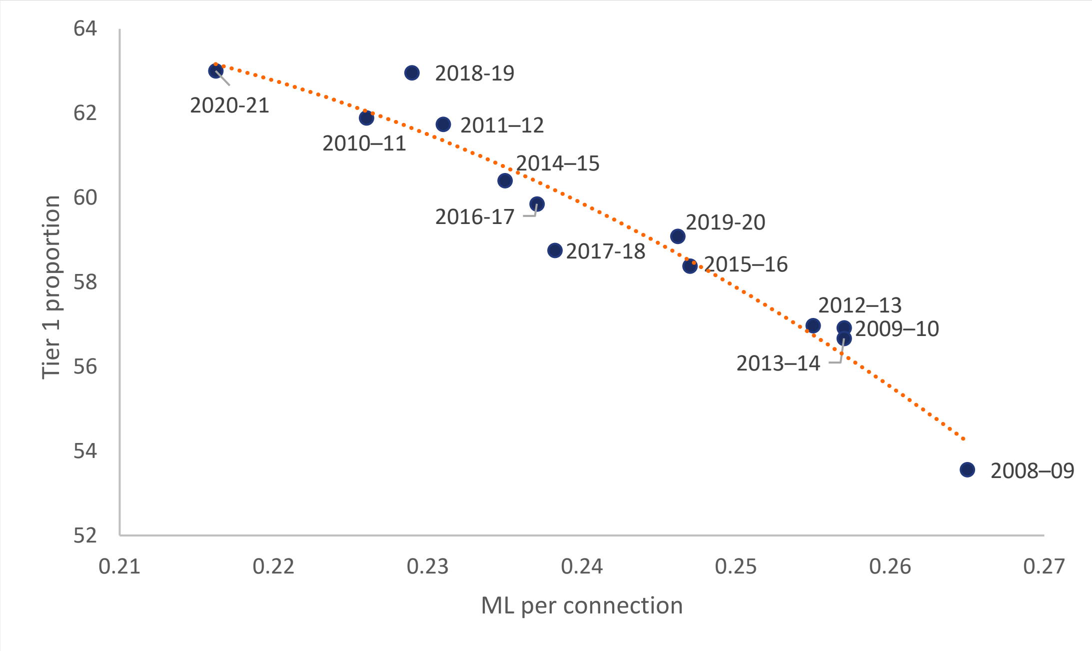
Table A3.1 Observed sales by Tier and connection numbers

Year	Total ACT sales (ML)	Tier 1 sales (ML)	Tier 2 sales (ML)	Connections (#)	ML/ connection/ year	Observed Tier 1 proportion
2008–09	38,179	20,448	17,731	144,165	0.265	53.56
2009–10	37,744	21,485	16,259	146,853	0.257	56.92
2010–11	33,780	20,906	12,874	149,794	0.226	61.89
2011–12	35,393	21,851	13,541	153,256	0.231	61.74
2012–13	40,428	23,032	17,396	158,258	0.255	56.97
2013–14	41,928	23,759	18,169	163,223	0.257	56.67
2014–15	39,152	23,652	15,500	166,886	0.235	60.41
2015–16	41,786	24,393	17,393	168,981	0.247	58.38
2016-17	41,182	24,650	16,532	173,715	0.237	59.86
2017-18	42,581	25,019	17,562	178,728	0.238	58.76
2018-19	41,808	26,324	15,484	182,599	0.229	62.96
2019-20	45,795	27,059	18,736	185,997	0.246	59.09
2020-21	41,472	26,130	15,343	191,803	0.216	63.00

Source: our analysis based on data from Icon Water

Figure 15 shows the observed relationship between the Tier 1 proportion and average customer consumption. A visual examination of the data suggests an exponential relationship.

Figure 15 Observed Tier 1 proportion and ML per connection, 2008-09 to 2020-21



Source: our analysis based on data from Icon Water

Box A3.1 Equations tested to identify the best equation to forecast Tier 1 water sales

We re-estimated several equations using the nonlinear least squares, linear model and polynomial functions and identified the best equation based on following criteria.

- best fit between observed and modelled values
- statistical significance of the estimated coefficients
- ability of the equation to forecast sensible values

We considered these forms of equations (equations 1 to 4) in the last investigation, so we are following the same approach. In its submission, Icon Water suggested that we assess the performance of a linear model as well (equation 5).

equation 1: $y = e^{a+bx}$

equation 2: $y = a.e^{bx}$

equation 3: $y = ax^2 + bx + c$

equation 4: $y = c + a.e^{bx}$

equation 5: $y = a + bx$

where:

y is Tier 1 proportion of total ACT water sales

x is the average annual ACT water consumption per customer

a b and c are the coefficients determined by the regression results of the historical relationship between y and x

The form of equation we currently use is equation 4. We found in our 2018-23 investigation that the 2008-09 data point biased the parameter values estimation (ICRC 2018). This was because 2008-09 was the last year of the Millennium Drought and in that year per capita water consumption was very low. As a result, this data point was removed. Therefore, we use annual data from 2009-10 to 2020-21 to test each equation.

Table A3.2 shows the performance of each of the equations against the observed values. Equation 4 still provides the best fit.

Table A3.2 Observed and modelled Tier 1 proportions and residuals

		Equations, modelled proportion					Equations, residuals				
Year	**Observed**	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
2009–10	56.92	56.84	56.84	56.70	56.68	56.80	**0.08**	**0.08**	0.22	0.24	0.13
2010–11	61.89	62.06	62.06	62.05	62.05	62.06	0.18	0.18	**0.16**	**0.16**	0.18
2011–12	61.74	61.13	61.13	61.21	61.23	61.16	0.61	0.61	0.52	**0.51**	0.58
2012–13	56.97	57.09	57.09	56.99	56.98	57.06	0.12	0.12	0.02	**0.01**	0.09
2013–14	56.67	56.86	56.86	56.72	56.71	56.82	0.20	0.20	0.06	**0.04**	0.15
2014–15	60.41	60.51	60.51	60.63	60.65	60.54	0.10	**0.10**	0.22	0.24	0.13
2015–16	58.38	58.41	58.41	58.48	58.51	58.42	0.03	**0.03**	0.10	0.13	0.05
2016-17	59.86	60.10	60.10	60.23	60.26	60.13	0.24	**0.24**	0.37	0.40	0.28
2017-18	58.76	59.90	59.90	60.03	60.06	59.94	1.14	**1.14**	1.28	1.31	1.18
2018-19	62.96	61.47	61.47	61.52	61.53	61.49	1.50	1.50	1.44	**1.43**	1.48
2019-20	59.09	58.58	58.58	58.67	58.70	58.60	0.51	0.51	0.42	**0.39**	0.48
2020-21	63.00	63.69	63.69	63.40	63.35	63.62	0.69	0.69	0.40	**0.35**	0.61
						Total	**5.382**	**5.382**	**5.218**	**5.217**	**5.337**

Source: our analysis based on data from Icon Water; Data in bold font indicates the smallest residual for each year

Equation 4 produces the least total residual among all the equations. The data in bold font also shows that equation 4 produces the least residual in 7 of the 12 years compared to the other equations. Equation 3 produces a similar fit to equation 4 in terms of total residual however, none of the parameter estimates for equation 3 are statistically significant. Table A3.3 shows the parameter estimates for equation 4. One of the parameter estimates is significant at the 95 percent level.

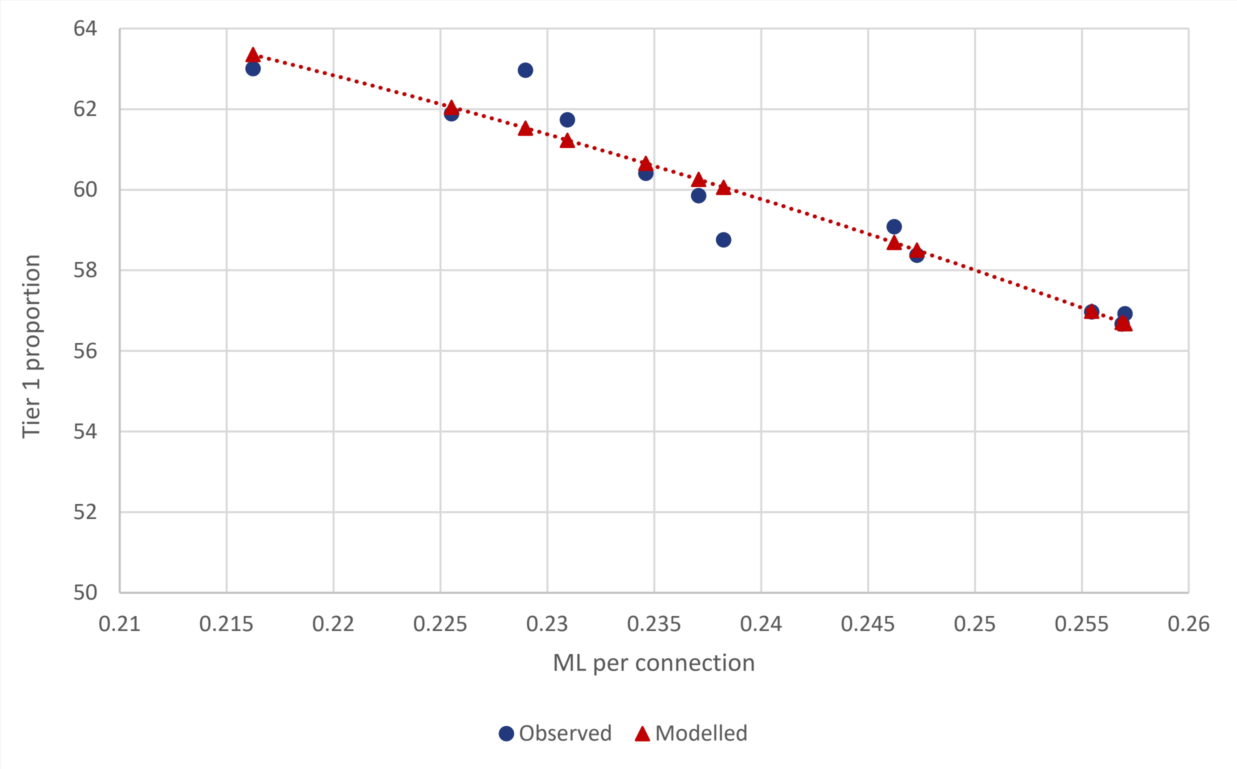
Table A3.3 Equation 4 parameter significance

	Coefficient	Standard error	t-value	p-value	Significance
a	-2.048480	11.7908	-0.17373	0.865919	
b	9.137684	16.456	0.55528	0.592237	
c	78.12876	32.980	2.36896	0.041981	**

Source: our analysis based on data from Icon Water

Figure 16 shows the modelled Tier 1 proportion over the 2009-10 to 2020-21 period, in comparison to the observed values.

Figure 16 Observed and modelled Tier 1 proportion



Source: our analysis based on data from Icon Water

Water connections, sewerage connections and billable fixtures

We will be changing the approach we use to forecast water and sewerage connection numbers and billable fixtures. We will be using the ACT Government population projections to forecast these variables. As noted in section 4.2 of this draft report, the ACT Government's population projections are currently being updated to account for the effect of Covid-19, and the updated projections are expected to be published in the second half of 2021. We will monitor this development to ensure that the ACT population projections we use account for the impact of the pandemic

We tested this approach for the current regulatory period and obtained forecasts from 2018-19 to 2020-21 and then compared them to the actual values for the same period.

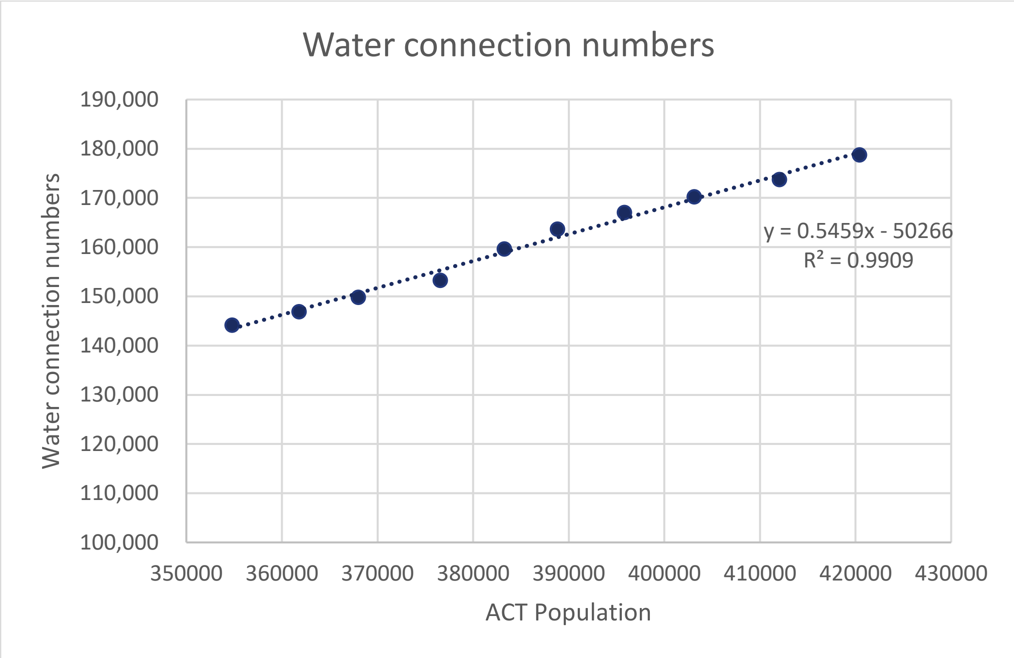
We first estimated the historical relationship between ACT population[9] and each of the three variables: water connection numbers, sewerage connection numbers and billable fixtures.

We modelled each relationship using a linear regression model.

[9] Data source used for historical population data: National, state and territory population, December 2020 | Australian Bureau of Statistics (abs.gov.au)

To estimate the historical relationship between water connection numbers and ACT Population, we used annual ACT Population data and water connection numbers from 2008-09 to 2017-18. Year 2008-09 was used because this is the oldest date for which we have data. We then ran a linear regression model. Figure 17 shows the result of the regression. For the next regulatory period, we will re-estimate this relationship using the latest data available to date.

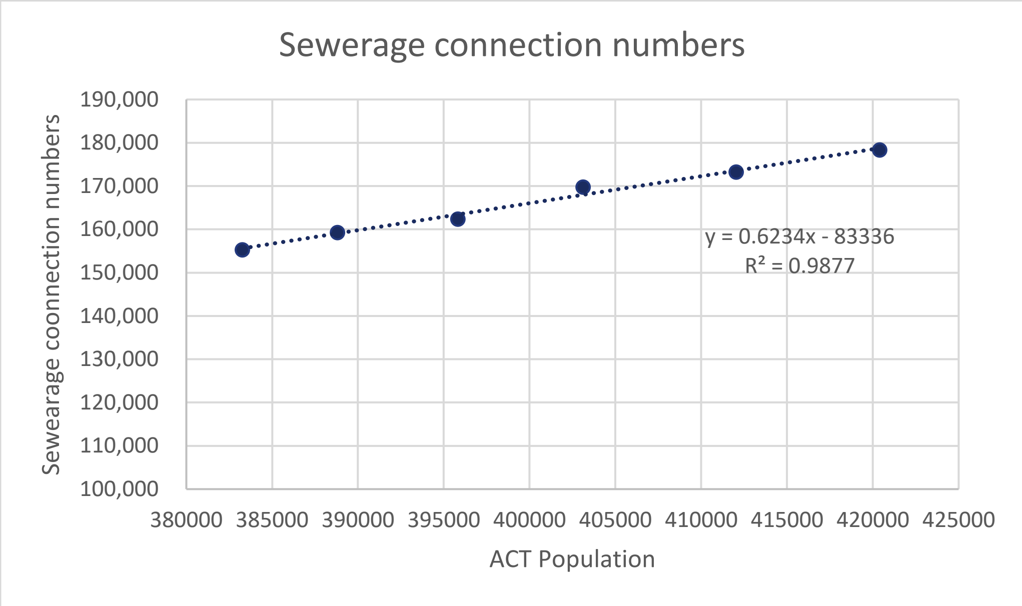
Figure 17 Relationship between ACT population and water connection numbers (2008-09 to 2017-18)



Source: our analysis based on data from Icon Water and ABS ACT Population data (ABS National, state and territory population)

To estimate the historical relationship between sewerage connection numbers and ACT Population, we used annual ACT Population data and sewerage connection numbers from 2012-13 to 2017-18. Year 2012-13 was used because this is the oldest date for which we had data. We then ran a linear regression model. Figure 18 shows the result of the regression. For the next regulatory period, we will re-estimate this relationship using the latest data available to date.

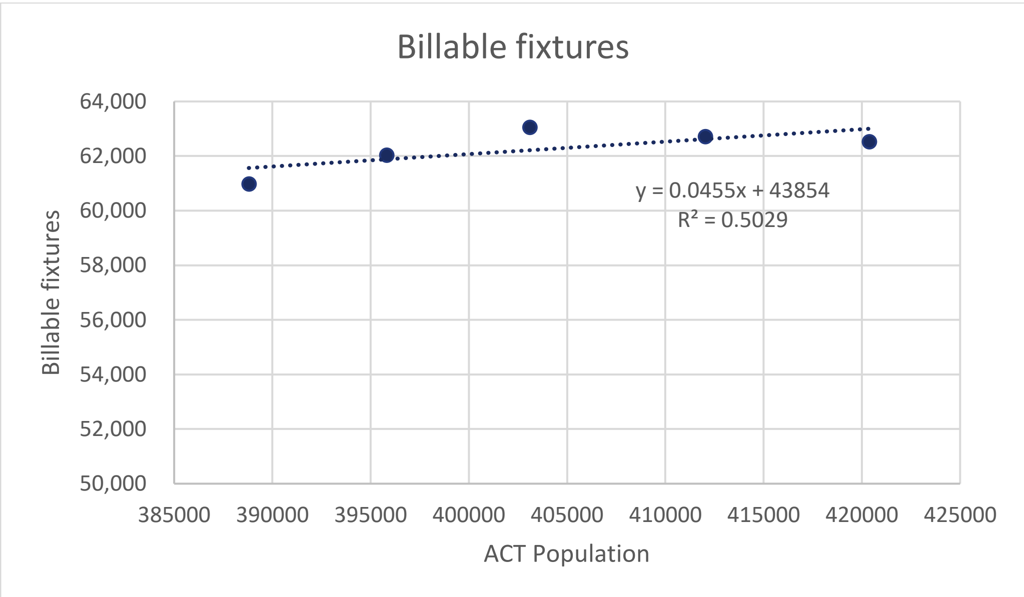
Figure 18 Relationship between ACT population and sewerage connection numbers (2012-13 to 2017-18)



Source: our analysis based on data from Icon Water and ABS ACT Population data (ABS National, state and territory population)

To estimate the historical relationship between billable fixtures and ACT Population, we used annual ACT Population data and sewerage connection numbers from 2012-13 to 2017-18. Year 2012-13 was used because this is the oldest date for which we had data. We then ran a linear regression model. Figure 19 shows the result of the regression. For the next regulatory period, we will re-estimate this relationship using the latest data available to date.

Figure 19 Relationship between ACT population and billable fixtures (2012-13 to 2017-18)



Source: our analysis based on data from Icon Water and ABS ACT Population data (ABS National, state and territory population)

We applied each of these regressions to ACT Government population projections[10] data from 2018-19 to 2020-21 to forecast water connections, sewerage connection and billable fixtures for the same period.

We compared these forecasts to actual values of connection numbers and billable fixtures from 2018-19 to 2020-21 to assess forecast accuracy. Table A3.4 shows this comparison.

Table A3.4 Connection numbers and billable fixtures: forecast and actuals

Year	Water connections numbers		Sewerage connection numbers		Billable fixtures	
	Forecast	**Actual**	**Forecast**	**Actual**	**Forecast**	**Actual**
2018-19	183,657	182,599	183,797	182,221	63,351	63,554
2019-20	188,093	185,997	188,862	185,586	63,721	63,440
2020-21	192,469	191,803	193,859	191,013	64,086	64,367

Source: our analysis based on data from Icon Water and ACT Government data (ACT Population Projections 2018 to 2058)

[10] Data source for ACT Populations Projections: ACT Population Projection: 2018 to 2058

Appendix 4 Consultant's stage 2 report

economics
public policy
markets
strategy

MARSDEN JACOB ASSOCIATES

Water demand forecasting methodology review – Stage 2

Draft report

15 September 2021

A Marsden Jacob Report

Prepared or Independent Competition and Regulatory Commission
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Tables

Figures

Executive summary

Marsden Jacob Associates has been engaged to review Icon Water's demand forecasting methodology in preparation for the Independent Competition and Regulatory Commission's 2023 price review.

Our advice to the ICRC covers two stages, with objectives set out below.

Stage 1

In Stage 1, the ICRC asked us to advise on whether the current Auto-Regressive Integrated Moving Average (ARIMA) approach to forecasting water demand is appropriate and fit for purpose, considering other approaches that could be used. The ICRC also asked us to advise on whether there would be significant benefits from moving to an alternative forecasting approach.

Our Stage 1 advice supported the use of the ARIMA model and is available on the ICRC website here.

Stage 2

In the second stage, the ICRC asked us to advise on how to best implement the forecasting approach that the ICRC chooses, following our Stage 1 advice. ICRC has asked our advice the address matters including:

- the general model specification, including dependent and explanatory variables and functional form
- how to ensure the model can appropriately account for changes in climate and demographics (e.g., population projections)
- any steps needed to ensure the model and parameters are statistically sound (e.g. parameters are stationary and structural breaks in time series are dealt with appropriately)
- how recommended changes should be made/implemented, including advising on the data sources and any adjustments that would be needed (e.g. adjustments to make data stationary).

This report

This report is our final deliverable for Stage 2. Our Stage 2 report outlines the updated water demand forecasting model specification and recommended approach to updating the ARIMA model for the next regulatory period.

The model specification and recommended approach for updating the ARIMA model set out in this report will be implemented in Stage 3 of the ICRC model review. We note that model implementation, testing and refinement during Stage 3 may result in the final demand model specification and parameters values being different from those included in this report. Material in this section should be read with this in mind. Initial estimates in this report have been provided at the request of the ICRC, and to give stakeholders an understanding of the order of magnitude of the coefficients for model parameters estimated to date, where data has been available.

Recommended changes to model specification

We have recommended two key changes in the proposed specification compared to the current approach: the lower time frequency of the data, and the additional weather variables proposed:

- **Time frequency of the data to weekly from daily**. We discuss the logic for this recommended change in section 3.1 of this report. Our modelling exercise in Section 4.3 shows that forecasting accuracy improves significantly with weekly data relative to daily data model. Our modelling exercise also shows that weekly data performs comparatively better than monthly data. Therefore, at this stage, our recommended specification is the weekly data model.
- **Include additional weather variables**. We discuss the logic for this recommended change to model specification in section 3.2 of this report. Our modelling exercise in Section 4.2 shows that additional weather variables improve the forecasting accuracy of the model using monthly data, but may have little effect in a weekly model. However, we note that the model implementation, testing and refinement during Stage 3 may result in the parameter values, and so the effect of the additional variables, being different from those included in this report. Therefore, at this stage, our recommendation is to retain these additional weather variables till final refinement and testing are done to identify the final model specification that best fits the data.

The variables for the recommended weekly form of the model are described in **Error! Reference source not found.**.

Table 5: Stage 2 modelling exercise: variables used for weekly data model

Variable	Description	Reasoning	Coefficient estimate from modelling exercise	Data Source
Dam abstractions	Dam abstractions during a previous week	Dam abstractions are related over time. This is a function of the ARIMA model and is calculated using the model.	0.68 Data shows dam abstractions are positively related over time.	Provided by Icon Water
Temp	Average of daily maximum temperatures (degrees Celsius) during a week	Hot periods will result in more water abstractions to meet increasing water demand by customers	Linear component: 3.70 to 7.73 Squared: 0.05 These estimates show hot periods increase dam abstractions.	Bureau of Meteorology for the Canberra Airport station.

Variable	Description	Reasoning	Coefficient estimate from modelling exercise	Data Source
rain	Average daily rainfall (mm) during a week	Rainy periods will result in less water abstractions because part of customer's water demand will be met by rain (e.g. less water required for plants during rainy periods)	Squared: 0.38 Square root: -25.30 to -13.32 These estimates combined show a negative relationship between total abstractions and rainfall.	
Evap	Average daily evaporation during a week	High evaporation rates will result in more water abstractions to meet higher irrigation requirements for plants/gardens as they dry.	Linear component: 25.10 to 101.40 Squared: -6.40 Square root: -202.92 These estimates combined show a positive relationship between total abstractions and evaporation	Bureau of Meteorology for the Burrinjuck Dam station
customer	Icon water customer connections at the end of a week	More customers will increase water demand, and will require more water abstractions	0.002 This estimate shows that increase in customers are related to more water abstractions, but the effect is not material.	Provided by Icon Water
Additional weather variables to capture the effect of extreme weather conditions on dam abstractions	• Number of days where daily temperature exceeded 30 °C or 35 °C in a week	More days with extreme high temperature will result in more dam abstractions.	9.88 to 24.35 This estimate shows extreme hot periods increase dam abstractions.	Bureau of Meteorology for the Canberra Airport station and Bureau of Meteorology for the Burrinjuck Dam station
	• Number of days without rain in a week	More days without rain will result in more dam abstractions.	3.17 This estimate shows that dry period is related to higher dam abstractions.	

Variable	Description	Reasoning	Coefficient estimate from modelling exercise	Data Source
	• Interaction effect between rain*evap	High levels of evaporation and low levels of rainfall is likely to be related to higher demand for water	-0.05 The interaction term implies that impact of a change in rainfall on total abstractions also depends on the level of evaporation (and vice versa). The estimated magnitude of this term implies that the interaction effect is rather small empirically.	
sin	Sine and cosine functions.	These are included to account for seasonality (systematic, repetitive, periodic fluctuations in dam abstractions over the course of a week)	-19.76 The magnitude of this coefficient shows the amplitude of variation, i.e. the maximum horizontal distance from the wave's centre to the peak. That is, in the present case the sine varies between -19.76 and 19.76.	Self-defined
cosin			-122.63 See above, mutatis mutandis.	
Moving average component	Forecast error of dam abstractions for the previous week (weeks)	This is a function of the ARIMA model and is calculated using the model.	-0.18 This parameter enters the autocorrelation function of the dependent variable. In the absence of autoregressive components in the ARIMA specification, the value of -0.18 implies that the correlation between y and its lagged value equals $-0.18/(1+(-0.18)^2) \approx -0.17$.	Self-defined

Note: coefficient estimate range is based on point estimates for different forms of a variable (squared, square root, lag, no lag) and are considered for estimates that are statistically significant with a p-value of at most 0.05

In stage 3, the final model specification will establish the final statistical form of the variables listed in Table 1, that is, whether to use squared values, square root values, and how many 'lags' to use, which are commonly used in ARIMA models where it is assumed that the forecast value of a variable is dependent upon past observations of that variable.

Section 4.4 reports point estimates of the parameters for the selected model corresponding to the weekly observations and Appendix A1.2 includes detailed results and estimated parameters from the modelled exercise for models with daily, weekly and monthly data, respectively. The estimation results for weekly and monthly data models show good properties compared to the existing daily data model: estimated coefficients have signs that are consistent with expectations; moreover, the new variables, which capture the effect of extreme weather conditions, improve the fit of the model.

As discussed in more detail in sections 3.1, 3.4, and 3.7 of this report, the recommended weekly data model specification better accounts for future changes in climate, demographics (e.g. population projections):

- **Lower frequency data potentially avoid a clash between modelling climate change adaptation and predictive ability over longer horizons**, in that there is a plausible range of values for the autoregressive parameter that is consistent with both.
- **Computing forecasts of water installations based on ACT population projections produced by the Australian Government's Centre for Population** has the advantage that these projections are up-to-date and include the impact of Covid-19 and resulting border closures on future population growth. In contrast, population (or water installation) projections based on past data, prior to 2020-21, do not consider the effect of Covid-19, and therefore they are likely to be highly inaccurate. We understand the ICRC is considering using the ACT Government's population projections which accounts for future development activities in ACT and is being updated to account for the effect of Covid-19.[11]

Steps to ensure model and parameters are statistically sound

There are several steps that will be implemented in Stage 3 to ensure the model and parameters are statistically sound, and to confirm the final model specification. We discuss these in section 3.2 of this report. These steps mainly deal with technical approaches that will be used for determining best model fit.

Implementation of model changes

We outline recommended steps for implementing model changes in section 2.3 of this report. This section details how the ARIMAX model should be implemented including the approach for developing in- and out-of-sample forecasts, testing of the time-step for the final model specification, and how to forecast future weather conditions. We recommend that future weather conditions are based on the NARCLiM database, a multi-agency research project between the NSW and ACT governments and the Climate Change Research Centre at the University of NSW.

[11] https://www.treasury.act.gov.au/snapshot/demography/act

1. Introduction

Marsden Jacob Associates has been engaged to review Icon Water's demand forecasting methodology in preparation for the Independent Competition and Regulatory Commission's 2023 price review.

The ICRC decided in its 2018 determination for water and sewerage services prices for Icon Water to review its demand forecasting model before the next price investigation.

The ICRC 2018 regulatory determination noted that the Auto-Regressive Integrated Moving Average (ARIMA) model for demand forecasting did not fully account for climate, demographic changes and projections. ICRC identified these issues as potential weaknesses in the forecasting model.

The ICRC determination also noted that the medium-term demand forecasts were highly sensitive to minor updates to the data used in the model. The ICRC has noted that this may reflect the weighting of recent observations and absence of leading indicators in the model. This has also been identified as a potential weakness in the forecasting model.

The ICRC review is being undertaken in consultation with key stakeholders. As part of this, ICRC released an issues paper in May 2021, held a workshop and sought submissions during June and July. ICRC will consult with stakeholders through submissions and workshops following release of the draft report (Figure 20). The final model specification from the next stage of this review will be used to produce forecasts for the next water and sewerage services price investigation to commence in July 2023.

Figure 20: ICRC review approach

1.1 Objectives

The ICRC engaged Marsden Jacob as technical advisors on the demand forecasting review. Our support to ICRC covers two stages, with objectives set out below.

Stage 1

In Stage 1, the ICRC asked us to advise on whether current ARIMA approach to forecasting water demand is appropriate and fit for purpose, considering other approaches that could be used. ICRC also asked us to advise on whether there would be significant benefits from moving to an alternative forecasting approach.

Our Stage 1 advice supported the use of the ARIMA model and is available on the ICRC website here.

Stage 2

In the second stage, the ICRC has asked we advise on how to best implement the forecasting approach that the ICRC chooses, following our Stage 1 advice. The ICRC has asked that our advice addresses matters including:

- the general model specification, including dependent and explanatory variables and functional form
- how to ensure the model can appropriately account for changes in climate and demographics (e.g. population projections)
- any steps needed to ensure the model and parameters are statistically sound (e.g. parameters are stationary and structural breaks in time series are dealt with appropriately)
- how recommended changes should be made/implemented, including advising on the data sources and any adjustments that would be needed (e.g. adjustments to make data stationary).

ICRC has asked we provide reasons for our advice based on research and evidence. We understand our Stage 2 advice will be released with ICRC's draft report.

Stage 3.

There will be a Stage 3 to this work, which is outside the scope of the current report. Stage 3 will involve further refinements to the forecasting model described in this Stage 2 report, using the implementation approach discussed in Chapter 2.

Model implementation, testing and refinement during Stage 3 may result in the final demand model specification and parameters values being different from those included in this report. This is a normal part of model development. Stage 3 model estimation will include estimating some variables that are not included in the Stage 2 model in Chapter 2 due to data not being available at the time of writing this report.

1.2 Approach and report structure

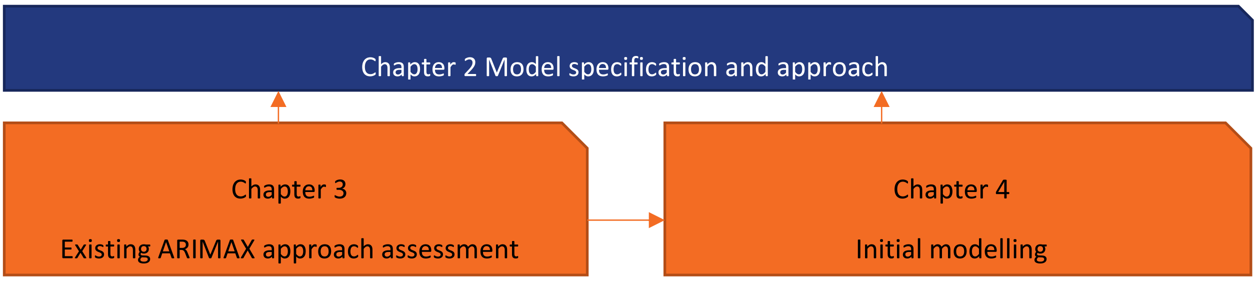
The report structure is summarised in Figure 2 and reflects our Stage 2 approach.

Chapter 2 in this report outlines our recommended approach together with general model specification, based on our work presented in Chapters 3 and 4. We have presented the model specification first, as this helps frame understanding for Chapters 3 and 4.

Our recommended model specification and approach in Chapter 2 are informed by our completing:

- **a review of the existing ARIMAX approach and assessment** to identify key issues and recommendations to improve the existing ARIMA methodology. This work is summarised in Chapter 3
- **initial modelling that allowed us to test model specification and whether different model specifications** may deliver material improvements to the forecasting accuracy of the demand model. The outcome of this work is summarised in Chapter 4.

Figure 21: Report structure



2. Model specification and approach to updating ARIMA.

Based on our recommendations in Chapters 3-4, this Chapter outlines the model specification and recommended approach to updating the ARIMA for the next regulatory period.

As discussed in Chapter 1, the model specification and recommended approach for updating the ARIMA model set out in this Chapter will be implemented in Stage 3. As we discussed in section 1.1, model implementation, testing and refinement during Stage 3 may result in the final demand model specification and parameters values being different from those included in this report. Material in this section should be read with this in mind. Initial estimates in this chapter have been provided to give stakeholders understanding of the order of magnitude of coefficients for model parameters estimated to date, where data has been available.

2.1 Updating model specification

The general model specification takes the following form:

$$y_t = \sum_{k\in\{1,2,4\}} \sum_{\tau=0}^{p_1} \beta_{k,\tau} (temp_{t-\tau})^{k/2} + \sum_{k\in\{1,2,4\}} \sum_{\tau=0}^{p_2} \gamma_{k,\tau} (rain_{t-\tau})^{k/2} + \sum_{k\in\{1,2,4\}} \sum_{\tau=0}^{p_3} \delta_{k,\tau} (evap_{t-\tau})^{k/2}$$

$$+(\lambda evap_t \times rain_{t)} + \mu_1 summer_t + \mu_2 december_t + \xi\ customer_t + \boldsymbol{\phi}'\boldsymbol{X}_t$$

$$+\rho_1 \sin_t + \rho_2 \cosin_t + \sum_{\tau=1}^{p_0} \alpha_\tau\, y_{t-\tau} + \varepsilon_t + \sum_{\tau=1}^{p_4} \theta_\tau\, \varepsilon_{t-\tau}, t = 1, \dots, T,$$

where y_t denotes the observation of the dependent variable at time period t (say, the weekly bulk volume of dam water abstractions), τ is forecast error, $y_{t-\tau}$ denotes the value of the dependent variable at time period $t-\tau$ and $\varepsilon_{t-\tau}$ is the unobserved error term of the model, which is assumed to be white noise with mean zero. In addition, $\boldsymbol{X}_t$ denotes a vector of additional weather variables, as described in section 3.2.

Parameters $\beta_{k,\tau}$, λ, μ_1, μ_2, ρ_1, ρ_2 and $\boldsymbol{\phi}$ are estimated by the model. The unknown autoregressive parameter of the model α presents a measure of persistence. $\{p_h\}_{h=0}^{4}$ will be estimated using the Box-Jenkins procedure discussed in section 2.2. The same holds true when it comes to estimating the remaining parameters of the model.

There are two key changes in the proposed specification compared to the current approach: the lower time frequency of the data, and the additional weather variables proposed:

- **Time frequency of the data changes to weekly from daily**. We discuss the logic for this recommended change in section 3.1. Our modelling exercise in Section 4.3 using shows that that forecasting accuracy improves significantly with weekly data relative to daily data. Our modelling exercise also shows that weekly data performs comparatively better than monthly data. Therefore, at this stage, our recommended specification is the weekly data model.

- **Include additional weather variables**. We discuss the logic for this recommended change to model specification in section 3.2. Our modelling exercise in Section 4.2 shows that additional weather variables improve the forecasting accuracy of the model using monthly data, but may have little effect in a weekly model. However, at this stage, our recommendation is to retain these additional weather variables until final refinement and testing are done to identify the final model specification that best fits the data.

The variables for the weekly form of the model are described in **Error! Reference source not found.** along with data sources. Section 4.4 reports point estimates of the parameters for the selected model corresponding to the weekly observations and Appendix A1.2 includes detailed results and estimated parameters for the updated model with daily, weekly and monthly data, respectively.

Table 6: Updated model variables for the weekly form of the model and data source

Variable	Description	Reasoning	Data Source
y_t, **Dam abstractions**	Dam abstractions during a previous week	Dam abstractions are related over time. This is a function of the ARIMA model and is calculated using the model.	Provided by Icon Water
temp	Average of daily maximum temperatures (degrees Celsius) during a week	Hot periods will result in more water abstractions to meet increasing water demand by customers	Bureau of Meteorology for the Canberra Airport station.
rain	Average daily rainfall (mm) during a week	Rainy periods will result in less water abstractions because part of customer's water demand will be met by rain (e.g. less water required for plants during rainy periods)	
evap	Average daily evaporation during a week	High evaporation rates will result in more water abstractions to meet higher irrigation requirements for plants/gardens as they dry.	Bureau of Meteorology for the Burrinjuck Dam station
customer	Icon water customer connections at the end of a week	More customers will increase water demand, and will require more water abstractions	Provided by Icon Water
X_t, **Additional weather variables to capture the effect of extreme weather conditions on dam abstractions**	• Number of days where daily temperature exceeded 30 °C or 35 °C in a week	More days with extreme high temperature will result in more dam abstractions.	Bureau of Meteorology for the Canberra Airport station and Bureau of Meteorology for the Burrinjuck Dam station
	• Number of days without rain in a week	More days without rain will result in more dam abstractions.	
	• Interaction effect between rain*evap	High levels of evaporation and low levels of rainfall is likely to be related to higher demand for water	

Variable	Description	Reasoning	Data Source
sin **cosin**	Sine and cosine functions.	These are included to account for seasonality (systematic, repetitive, periodic fluctuations in dam abstractions over the course of a week)	Self-defined
Moving average component	Forecast error of dam abstractions for the previous week (weeks)	This is a function of the ARIMA model and is calculated using the model.	Self-defined

In addition to the above explanatory variables, it is worth considering additional weather variables related to evaporation, soil moisture index and humidity. Both variables are available in the NARCLiM database, to be discussed below.

As discussed in more detail in sections 3.1, 3.4, and 3.7 the updated model specification better accounts for future changes in climate, demographics (e.g. population projections):

- Lower frequency data potentially avoid a clash between modelling climate change adaptation and predictive ability over longer horizons, in that there is a plausible range of values for the autoregressive parameter that is consistent with both.
- Computing forecasts of water installations based on ACT population projections produced by the Australian Government's Centre for Population has the advantage that these projections are up-to-date and include the impact of Covid-19 and resulting border closures on future population growth. In contrast, population (or water installation) projections based on past data, prior to 2020-21, do not consider the effect of Covid-19, and therefore they are likely to be highly inaccurate. We understand the ICRC is considering using the ACT Government's population projections which accounts for future development activities in ACT and is being updated to account for the effect of Covid-19.

2.2 Steps to ensure model and parameters are statistically sound

There are a number of steps that will be implemented in Stage 3 to ensure the model and parameters are statistically sound, and to confirm the final model specification.

Model selection

Model selection to determine the best-fit will be implemented in Stage 3 using the standard Box-Jenkins procedure. The Box-Jenkins procedure involves:

1. Identification. This step involves determining the order of the model required (p, d, and q) to capture the salient dynamic features of the data. This step mainly relies on the use of graphical procedures (plotting the series, the ACF (autocorrelation function) and PACF (partial ACF), etc).

2. Estimation and Selection. This step involves estimation of the parameters of the different models (using step 1) and proceeds to a first selection of models using information criteria, such as AIC and BIC. Model selection will also be informed at this stage by examining the accuracy of aggregate (annual) in-sample forecasts obtained during the validation period. In-sample forecast accuracy will be assessed using the MAPE and the RMSPE.

3. Diagnostic Checking. This step involves determining whether the model(s) specified and estimated are adequate using residual diagnostics. In particular, the fitted models will be checked by considering plots, as well as the autocorrelations of the residual series (the series of residual, or error, values). If necessary, these steps may be applied iteratively until step 3 does not produce any improvement in the model.

Finally, aggregate (annual) out-of-sample forecasts will be produced for each financial year of the next regulatory period.

2.3 Implementation of model changes

To update the ARIMAX model with the recommended changes, we recommend using actual data corresponding to the period July 2006 to June 2021. The training sample could be the period July 2006 - June 2018. The validation period will correspond to the period July 2018 -June 2021. Subsequently, out-of-sample forecasts of total abstractions will be obtained for each year during the next regulatory period.

For the training and validation periods, the data sources will be mostly consistent with those used by the existing approach of Icon Water. As shown in **Error! Reference source not found.** the dependent variable will be actual dam abstractions, made available to us by Icon Water. Data on temperature\rain-related variables are publicly available by the Bureau of Meteorology for the Canberra Airport station. Data on evaporation are publicly from the same source for the Burrinjuck Dam station. Data on customer numbers are made available to us by Icon Water.

Initial ARIMAX models should be estimated using weekly and monthly observations, using the model selection steps discussed in section 2.3.

To implement out-of-sample forecasts of total abstractions, we need forecasts of weather conditions during the next few years. Previously, South Eastern Australian Climate Initiative (SEACI) data was used for conditioning past climate data with future climate projections. For this model update we recommend mostly relying on the NARCLiM database, a multi-agency research project between the NSW and ACT governments and the Climate Change Research Centre at the University of NSW.

The NARCliM project has produced a suite of twelve regional climate projections for south-east Australia, including Canberra, spanning the range of likely future changes in climate. NARCliM is explicitly designed to sample a large range of possible future climates, and provides daily forecasts of weather conditions that go as far as 2030 in their so-called "Near Future" setup. Weekly and monthly weather variables will be constructed from daily NARCliM forecasts.

Out-of-sample predictions of total abstractions will be obtained using dynamic forecasting. This step will produce a "mean forecast" by averaging weather variables across the 12 different regional climate projections, produced by NARCLiM for the near future (up to 2028). To check the sensitivity of the forecasts to alternative future weather scenarios, additional weather forecasts will be used based on different quantiles of the distribution of the climate projections.   Additional forecasts should be produced based on each of the twelve individual climate projections, which will then be summarised using mean, median and different quantiles.

3. Assessment on the current ARIMA approach

The Auto-Regressive Integrated Moving Average model, or ARIMA for short, is a popular statistical model used to analyse and forecast time series data. In this section we outline our assessment of the current ARIMA methodology.

An Auto-Regressive Integrated Moving Average model combines an autoregressive (AR) model with a moving average (MA) model. An AR model uses past values of the forecast variables as predictors. A MA model uses past values of forecasted errors.

The main objective in ARIMA is to model autocorrelations in the data, i.e. the dependence of the observations over time. When the series are non-stationary (or "integrated") such that the autocorrelations of the data depend on the time at which the series is observed, ARIMA differences the data to allow the series to become stationary. Typically, specification of ARIMA models relies on the so-called Box-Jenkins method, which is a systematic process for identifying, fitting, and checking time series models.

For high-frequency data, such as with daily observations, ARIMA also allows modelling seasonal variation, by augmenting the model with additional seasonal terms. When the seasonal patterns are non-stationary, ARIMA can make use of seasonal differencing to allow the series to become seasonally stationary.

ARIMA can also incorporate exogenous control variables. In regression analysis, the standard notation used for such variables is given by "x". Hence, ARIMA models with exogenous regressors are commonly known as ARIMAX models.

ARIMAX models have been used to analyse and forecast daily observations of ACT bulk water volumes, obtained from dam abstractions. The daily abstractions data are aggregated into monthly totals comparable in coverage to the monthly billed consumption data. Subsequently, the regression estimate of the ratio of historical billed consumption to abstractions is applied to the annual abstractions to calculate a forecast of Icon Water annual billed sales. The annual billed sales forecast is split into Tier 1 and Tier 2 consumption, based on the historical relationship between water consumption per installation and the observed proportion of total sales falling into the Tier 1 category.

Compared to other commercial applications of ARIMA to support demand forecasting for regulated utilities we have reviewed, and based on our review of Icon Water's documentation, the quality of implementation of the method is high, and the various steps undertaken have been documented well. We discuss these issues in more detail in our Stage 1 advice available on the ICRC website here.

In the next section we identify some key issues and identify recommendations to further improve the existing ARIMA methodology. These recommendations reflect and extend on observations made in our Stage 1 review.

3.1 Time frequency (Short-term versus long-term forecasts using daily data)

3.1.1 Key issues

The existing ARIMA methodology makes use of daily observations on total volumes of water from dam abstractions. This approach is well suited for producing *short-term* forecasts of dam abstractions, such as one day, two days or one week ahead.

However, daily data are not best suited for producing forecasts over longer horizons, such as one month ahead, or multiple years ahead. There are three main reasons why daily data are not best suited for producing forecasts over longer horizons:

- **the prediction interval is likely to be much wider for longer horizons than it is for shorter ones.** A common feature of prediction intervals is that they typically increase in length as the forecast horizon increases, particularly so for dynamic forecasting. Dynamic forecasting uses the forecast (as opposed to the actual) value of the lagged dependent variable to obtain the forecasts of abstractions. Therefore, any forecast errors tend to compound over time. With daily data, one needs to forecast ahead several (hundreds of) time periods and so any error in forecasting the lagged dependent variable can feed into the distant future.
- **daily observations are heavily influenced by intra-week (seasonal) variation.** Thus, models based on daily data estimate parameters that may not be relevant for (or even distort) forecasts over long-term horizons. For example, models based on daily data require taking into account the impact of the day of the week on total abstractions (e.g. whether it is a weekday or a weekend). Such intra-week seasonality will not be important when forecasting abstractions over long time horizons. Essentially, the existing approach using daily observations requires estimation of day-specific parameters, which are not relevant for longer term forecasting.
- **daily data give rise to a clash between modelling climate change adaptation and forecasting ability over longer horizons.** Human behaviour is intrinsically dynamic. For example, because of the force of habit and technical constraints (such as the need to install water saving devices), households may not change their water consumption patterns instantaneously, only over time. Imperfect knowledge and uncertainty may also contribute to persistence, or a delayed response to shocks by decision makers.[12]

In dynamic regression models, the costs of instantaneous adjustment are often characterised by the magnitude of the autoregressive parameters.

To illustrate, consider a simple Auto-Regressive Distributed Lag (ARDL) model of order 1 in the autoregressive component and 0 in the distributed lag (i.e. an ARDL(1,0) model):

$$y_t = \alpha y_{t-1} + \beta x_t + \varepsilon_t; \qquad t = t, \dots, T, \tag{1}$$

where y_t denotes (say) the bulk volume of daily dam water release at time period t, y_{t-1} denotes the value of the total volume of dam water release during the previous day, x_t denotes (say) temperature at time period t, and ε_t is the unobserved error term of the model, which is assumed to be white noise with mean zero, such that $E[\varepsilon_t | y_{t-1,} x_t] = 0$. Finally, α and β denote the unknown parameters of the model. The autoregressive component of the model above accounts for the fact that consumers may take time to adjust fully to long-lasting (or permanent) changes in climate, such as temperature. The more time it takes to adjust to climate change, the more "persistent" the variable of interest (total abstractions) is.

Suppose that temperature goes up by one unit and, on average, it stays to that level thereafter due to climate change. The short-term (or immediate) effect of the change in temperature on water consumption

[12] See e.g. Bun and Sarafidis (2015), 'Dynamic Panel Data Models'. In B. Baltagi (eds.) *Oxford Handbook of Panel Data*, Oxford University Press, Ch. 3, pp. 76-110.

is given by β. The long-term (or total) effect over time is given by $\beta/(1-\alpha)$. The speed of adjustment towards the total effect is given by $(1-\alpha)$.

The smaller (larger) the value of α is, the higher (lower) the speed of adjustment. For instance, when for $\alpha = 0.95$, it takes 45 time periods (i.e. 45 days, when daily data are used) for 90% of the long-term effect to be realised. This means that the dependent variable of the model (total abstractions) is highly persistent. On other hand, when $\alpha = 0.5$, it takes 4 time periods (4 days) for 90% of the long-term effect to be realised.[13] That is, a value of α equal to 0.5 implies that consumers adapt almost completely to a permanent unit change in climatic conditions within 4 days. Such a rate of adaptation is unrealistic. Therefore, when it comes to modelling climate change adaptation, high values of α would be more plausible.

Unfortunately, as shown in Section A1.1, with high values of α, it becomes more difficult to forecast accurately future values of y_t. In particular, the accuracy of the forecasts can diminish considerably once one deviates sufficiently from one- or two-day ahead forecasts.

The above discussion illustrates a tension in the use of daily data to (i) forecast long-term water consumption and (ii) model climate change adaptation. On the one hand, the use of daily data for modelling long-term adaptation to climate change promises the most hope when the value of the autoregressive parameter (denoted by α) is high (and hence, the speed of adjustment is low). On the other hand, it is precisely in these contexts, where the magnitude of α is close to unity, that the predicted value of water consumption in the medium to long-term will be associated with a large forecast error. In other words, while high values of α offer the most hope to capture the dynamics of climate change adaptation using daily data, these are the values most likely associated with larger forecast errors.

3.1.2 Our recommendation

We recommend making use of lower time frequency data in the ARIMA model. Weekly, monthly or quarterly time series may be useful in providing additional information relative to the use of daily data alone. We illustrate how this approach can improve the forecasting accuracy of the model in section 4.

The use of lower frequency data can alleviate many of these issues. For example, intra-week seasonal variation will average out with weekly or monthly data, thus avoiding estimating parameters that are irrelevant for forecasting over long horizons.

Moreover, forecasting analysis based on lower frequency data can avoid a clash between climate change adaptation and predictive ability over longer horizons, in that there is a plausible range of values for the autoregressive parameter that is consistent with both.

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[13] To illustrate, suppose that $\beta = 3$ and $\alpha = 0.5$. The long-term impact of a unit increase in x equals $\beta/(1-\alpha) = 3/(1-0.5) = 6$, or 6 units of total water volume per day. The speed of adjustment equals $1 - 0.5 = 0.5$. A unit increase in temperature is expected to increase water consumption by 3 units the first day (or 0.5 of the total effect, which equals 6). During the second day, water consumption will increase by another 1.5 units ($(6-3) \times 0.5$). During the third day, water consumption will increase by another 0.75 units ($(6-4.5) \times 0.5$), and so on. Note that it takes 4 time periods for 90% of the total effect to be realised.

3.2 Ability to model extreme weather scenarios

3.2.1 Key issues

Some of the explanatory variables used in the current ARIMA model, which aim to capture the effect of weather, can be invariant to different weather scenarios. For example, the "sum of daily temperature data in the previous seven days (CumTemp)" would take the same value if (a) maximum daily temperature equals 25 °C for the past seven days, or (b) maximum daily temperature equals 19 °C for five out of the past seven days, and 40 °C for the remaining two days. These two different weather patterns may have different impact on water consumption.

To the extent that this holds true in practice, similar forecasts can be produced across different weather conditions. In this case, the model might not be sufficiently "responsive" to different weather scenarios.

To illustrate, consider Table 3 below, which reports out-of-sample forecast values of yearly total water demand, across 4 different weather scenarios.

The difference in the amount of *summer* rainfall between the driest and the wet scenarios is roughly equal to 14.5 percentage points.[14] Despite such a large difference in the amount of rainfall across these two scenarios, the forecast value of total demand for (say) 2018-19 under the wet scenario is only 0.5% smaller than the forecast value under the driest scenario.

Table 7: Forecast value of yearly total demand

	Medium	Dry	Driest	Wet	Average
2018-19	49,426	49,483	49,611	49,361	49,470
2019-20	49,865	49,922	50,050	49,800	49,909
2020-21	42,607	42,662	42,776	42,542	42,647

3.2.2 Our recommendation

There is room for improvement when it comes to the model's ability to account for extreme weather conditions. Improving the ability to account for weather is very important because weather is a key driver of water demand. We recommend creating additional explanatory variables to effectively capture the impact of extreme weather, including the following:

- Number of days where daily temperature exceeded 30, 35 or 40 °C within a time interval to be determined.
- Number of consecutive days where daily temperature exceeded 30, 35 and 40 °C within a time interval to be determined.
- Number of days without rain within a time interval to be determined.
- Number of consecutive days without rain within a time interval to be determined.
- Number of days where rainfall exceeded 1 mm or 2 mm, within a time interval to be determined.

[14] See Table A2.3 (row 3) in ICRC's Issues Paper entitled "Review of water and sewerage services demand forecasting methodology".

- Number of days where rainfall was less than or equal to 1 mm or 2 mm, within a time interval to be determined.

Many of these variables have been applied successfully in forecasting water demand elsewhere; see e.g. Barker et al (2020) for a recent study in the Australian context.[15]

In addition to the above explanatory variables, it is worth considering additional weather variables related to evaporation, in particular, soil moisture content and humidity. Both variables are available in the NARCLiM database, which will be discussed below.

3.3 Future climatic scenarios

3.3.1 Key issues

Currently, future climatic scenarios are incorporated into the model in two different ways. When it comes to temperature, future trends are estimated using simple regression analysis of daily temperature on a *linear* trend. On the other hand, for rainfall and evaporation, 4 different scenarios are employed based on data from the South Eastern Australian Climate Initiative (SEACI 2012); namely a medium scenario, a wet scenario, a dry and a driest one.

Our view is that this strategy may not the most suitable approach for future climatic scenarios for several reasons:

- **it is not clear that the trend in temperature is linear.** In fact, preliminary analysis using data for Burrinjuck Dam NSW (Station Number 73007), indicates that the trend is highly nonlinear.
- **the trend estimate appears to be highly sensitive** to the estimation period (i.e. sample) used in the regression.
- **temperature is highly correlated with rainfall and evaporation.** High levels of evaporation and low levels of rainfall may be accompanied by high levels of temperature. However, the current climate analysis does not allow for that. For instance, the driest scenario over the summer involves 6% less rain, 4% higher evaporation, yet temperature does not adjust accordingly. This can distort the effectiveness of the model to capture different climatic scenarios.

3.3.2 Our recommendation

We recommend the construction of future climatic scenarios using a single database, such as NSW and ACT Regional Climate Modelling (NARCLiM).

The NARCLiM database provides a more up-to-date source of climate change data and would account for changes in key weather conditions, such as temperature and rainfall. We note that this approach is supported by Icon Water, as outlined in its submission to the ICRC's demand forecasting issues paper[16]. We will consider this database as well in Stage 3.

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[15] Barker, A., Pitman, A., Evans, J., Spaninks, F., Uthayakumaran, L. (2020). Drivers of future water demand in Sydney, Australia: examining the contribution from population and climate change. Journal of Water and Climate Change 12(2), 1168-1183.

[16] Icon Water, Response to Demand forecasting Issues Paper, 9 July 2021.

3.4 Population projections

3.4.1 Key issues

Under the current approach, forecasts of water installations are computed based on historical growth rates of the same variable. This implies that these forecasts do not consider the impact of Covid-19 and the resulting border closures on future customer growth for Icon Water.

Ignoring the impact of Covid-19 may lead to significantly higher forecasts of water installations than actual ones. For example, we note that ACT's annual population forecasts during the period 2021-22 to 2030-31, updated by the Australian Government's Centre for Population to account for Covid-19, are on average 2.3% lower than the previous forecasts made without taking into account the effect of Covid-19, as shown in Table 8.

Table 8 Population projections ACT under pre and post COVID scenarios

Year	Post-Covid 19 scenario	Pre-Covid 19 scenario	Percentage difference
2021-22	431,400	436,000	-1.10%
2022-23	432,800	440,900	-1.80%
2023-24	435,800	445,700	-2.20%
2024-25	439,900	450,500	-2.40%
2025-26	444,000	455,200	-2.50%
2026-27	448,000	459,800	-2.60%
2027-28	452,000	464,200	-2.60%
2028-29	455,900	468,500	-2.70%
2029-30	459,700	472,700	-2.80%
2030-31	463,400	476,700	-2.80%

3.4.2 Our recommendation

To account for the impact of Covid-19, we recommend adopting the following two-step procedure. In the first step, historical data of Icon Water's water installations are regressed on ACT's population. This allows one identifying the relationship between the two variables. In the second stage, future water installations are imputed based on the aforementioned regression model using as predictor the Covid-19-updated population forecasts for ACT. We understand the ICRC is considering using the ACT Government's population projections which accounts for future development activities in ACT and is being updated to account for the effect of Covid-19.[17] If these updated ACT Government population projections are not available at the time of stage 3 finalisation, we recommend using population forecasts for ACT produced by the Australian Government's Centre for Population. An important consideration is to ensure that the ACT population forecasts account for the impact of Covid-19.

[17] https://www.treasury.act.gov.au/snapshot/demography/act

3.5 Forecasting accuracy

3.5.1 Key issues

The out-of-sample forecasting performance of the model needs to be assessed using well-established measures of accuracy, such as the Root Mean Squared Error (RMSE), the Root Mean Squared Percentage Error (RMSPE) and the Mean Absolute Per cent Error (MAPE). RMSE/RMSPE and MAPE will be computed based on the average value of the (squared or absolute, respectively) difference between the *yearly* forecast and actual values.

Currently, out-of-sample forecasting performance has been accessed in terms of the Mean Per cent Error (hereafter, MPE). This denotes the average value of the difference (neither squared, nor absolute) between the yearly forecast and the actual value. There are three years available for validation, namely 2018-19 to 2020-21.

The MPE is a useful measure for checking forecasting *bias*. That is, in the present context it may help to examine the extent to which yearly forecast errors roughly balance out over the relevant period of time, which is currently set to three years.

On the other hand, the MPE is less useful as a measure of forecasting accuracy. This is mainly because the MPE can fail to distinguish between really good models and really bad ones.

To illustrate, consider two competing forecasting models, A and B. Suppose that forecasting performance is assessed over two years. In year 1, Model A overpredicts actual demand by 100%, whereas in year 2 Model A underpredicts demand by 99%. On the other hand, Model B overpredicts actual demand by 1% in year 1 and it is spot on in its prediction in year 2 (i.e., the forecasting error is zero). As it turns out, for both Model A and Model B, the value of MPE equals 1%. That is, according to this measure, both A and B perform equally well. That is, of course, not true.

In addition, since MPE is computed over a small number of years, the average forecast error can be sensitive to one or two forecast errors (outliers), which can be due to e.g. extreme weather conditions. If such outliers in yearly forecasts are overlooked and not studied carefully, the performance of the model may remain sensitive. From a statistical point of view, MPE is a random variable with unknown finite sample properties. It may take a single large forecast error to substantially distort the predictions.

3.5.2 Our recommendation

Our recommendation is that effort should be made to improve forecasts on an annual basis, not just over the regulatory period. The reporting of accuracy performance should be reported using established accuracy measures, such as the RMSE and the MAPE. Improving on the yearly forecasts and complementing the MPE measure with more appropriate accuracy measures will increase transparency, and may lead to a better forecasting model over each five-year regulatory period. We have used these accuracy measures in our analysis in section 4.

3.6 Model uncertainty vs uncertainty in predicting weather conditions.

3.6.1 Key issues

When it comes to the accuracy of out-of-sample forecasts, the performance of the model largely depends on two factors: the accuracy of predicting weather conditions; and the accuracy of the model in terms of predicting total abstractions conditional on weather being known. The former reflects uncertainty due to the inherent difficulty of predicting future weather, and the latter reflects model uncertainty.

While the former might be unavoidable, since weather is difficult to predict, the latter needs to be carefully studied. Ideally, when weather conditions are predicted correctly, no matter what these conditions are, the forecast values should be close to actual ones, despite any peaks or troughs observed on actual weather.

It appears that the bulk of forecast errors in the current model is attributed to "unusual weather conditions". For this reason, we consider it is important that the forecasting analysis makes a distinction between uncertainty that is due to predicting future weather conditions, and model uncertainty.

3.6.2 Our recommendation

Efforts should be made to distinguish between model uncertainty and uncertainty due to unpredictability of weather conditions. Specifically, when testing forecasting accuracy of the model ex-post, we recommend isolating model uncertainty by producing forecasts of total abstractions based on predicted weather conditions, and also forecasts in terms of actual weather conditions. In the latter case, the error in predicting weather is zero, and therefore any discrepancies between forecast and actual values of total abstractions can be attributed to model uncertainty.

To measure out-of-sample forecast accuracy, it is useful to produce two values of MAPE, one based on actual weather conditions and one based on predicted weather conditions. The magnitude of the former reflects model uncertainty. The magnitude of the difference between the two values of MAPE reflects the impact of weather uncertainty. Note that ex ante, the latter is the only feasible option.

3.7 Estimation and lag order selection

3.7.1 Key issues

Under the existing approach, identification of the number of lags to be used in terms of weather variables is undertaken outside the ARIMA model, based on some form of pre-whitening. This can undermine simplicity, as well as estimation efficiency.

3.7.2 Our recommendation

We recommend that identification and model selection for the ARIMA model is undertaken based on the Box-Jenkins procedure.

This may increase estimation efficiency and improve the transparency of the preferred specification. For this reason, it is advised not to use pre-whitening of the observations (pre-whitening removes autocorrelation and trends from the cross-correlation function).

3.8 Policy adjustments

It is desirable to be able to accommodate in the forecasting model future policy changes, such as sustainable diversion limits. To the extent that there are data available, such policy changes should be incorporated within the model prior to producing the forecasts. Otherwise, post-model adjustments may be the only feasible method within the ARIMA approach. Alternatively, consumer-specific billed water data may be useful in identifying the impact of policy changes.

3.9 Terminology

We recommend referring to the model as "ARIMAX", since the model uses exogenous variables.

4. Modelling exercise

We have completed a targeted modelling exercise to support our analysis on forecasting accuracy, and our recommendations on time frequency and additional weather variables.

This section outlines the findings from this modelling exercise. Our modelling has focussed on whether two key recommendations deliver improvements to model forecasting accuracy:

- Use lower time frequency data in the ARIMA model, such as weekly and monthly time series to provide additional information relative to the use of daily data alone and improve forecasting accuracy
- Create additional explanatory variables to effectively capture the impact of extreme weather.

4.1 Approach

We have used actual data over the period July 2006 to June 2021. The period July 2006 – June 2018 is the estimation (or "training") period, which is used to estimate the parameters of the ARIMA model. The forecasting accuracy of the model is then tested based on the "validation" period, July 2018 – June 2021.

The underlying approach and data sources are consistent with those used by Icon Water:

- Actual dam abstractions – Icon Water data
- Daily rainfall – Canberra airport weather station
- Daily temperature – Canberra airport station
- Daily evaporation – Burrinjuck Dam weather station
- Daily Customer numbers – Icon Water data.

We have reproduced Icon Water's demand model based on daily data, and then examined the forecasting accuracy of the model:

- with additional variables for rainfall and temperature
- using weekly data
- using monthly data.

To compare like with like and ensure consistency, we have adopted the following strategy. Firstly, using the daily data, we summed the actual daily abstractions observed during the validation period, over each one of the three financial years used for validation; namely, 2018-19, 2019-20, 2020-21. At the same time, we summed the forecast daily abstractions over each one of the three financial years. We then computed the Mean Absolute Percentage Error (MAPE), defined as follows:

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{F_t - A_t}{A_t}\right|$$

where F_t denotes the *yearly sum* of the daily forecasts; A_t denotes the yearly sum of the daily actual abstractions, and $n = 3$ because the validation period consists of 3 financial years. Because the MAPE is a percentage of absolute forecast errors, it is easier to understand than many other measures of forecasting accuracy, such as the Root Mean Squared Error (RMSE). For example, if the MAPE equals 3, then, on average, the annual forecast is off by 3%.

We have also used an alternative measure, the Root Mean Squared Percentage Error (RMSPE). This is similar to the well-known RMSE, except it is expressed in percentage terms. The RMSPE is defined as follows:

$$RMSPE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left[100 \times \left(\frac{F_t - A_t}{A_t}\right)\right]^2}.$$

Since our emphasis lies in comparing the forecasting accuracy of the various models, we have computed forecasts for abstractions based on actual weather conditions during the period 2018-2021. This means that the forecasting accuracy of all models presented here will be higher than that reported by Icon Water, even if the benchmark model is identical to theirs.

Subsequently, we have followed the same procedure for weekly and monthly data. In particular, we have used the period July 2006 – June 2018 to estimate the ARIMAX model using weekly (monthly) observations. We have obtained weekly (monthly) forecasts for the period July 2018 – June 2021. Finally, we summed the actual weekly (monthly) abstractions and the forecast weekly (monthly) abstractions over each one of the three financial years used for calibration; namely, 2018-19, 2019-20, 2020-21. We computed the MAPE and RMPSE again for these models.

The benchmark ARIMAX model using daily observations has the same representation as that reported in Icon Water's 2018-23 price proposal to the ICRC[18].

4.2 Explanatory variables for weather conditions

In our assessment of the current ARIMA model in Chapter 3 we noted that some of the explanatory variables used, which aim to capture the effect of weather, are invariant to different weather scenarios. We have therefore recommended creating additional explanatory variables to effectively capture the impact of extreme weather, including:

- Number of days where daily temperature exceeded 30, 35 or 40 °C within the previous week (month)
- Number of *consecutive* days where daily temperature exceeded 30, 35 and 40 °C within the previous week (month)
- Number of days without rain within the previous week within the previous week (month)
- Number of *consecutive* days without rain within the previous week.
- Number of days where rainfall exceeded 1 mm or 2 mm, within the previous week (month)
- Number of days where rainfall was less than or equal to 1 mm or 2 mm, within the previous week (month).
- To simplify things, we have used least-squares regression to select which of these explanatory variables are statistically significant. The following were found to be statistically significant:

[18] Icon Water, 2018-23 Price Proposal Attachment 4 - Demand Forecasts, Table 2-4.

- Number of days with daily temperature exceed 30 degrees
- Number of days with daily temperature exceed 35 degrees
- Number of days with daily rainfall greater or equal to 1 mm.

In Stage 3, we will use the Box-Jenkins procedure for rigorous model selection. This means that the results in this assessment with additional explanatory variables may not be optimal, but they can be considered as a "worst case outcome". We expect that with the application of the Box-Jenkins procedure is going to result in lowering MAPE further than what is reported below.

4.3 ARIMAX model with lower frequency data

The new models using lower frequency data have the following representation:

$$y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \sum_{\tau=0}^{2} \beta_{1,\tau}\, temp_{t-\tau} + \sum_{\tau=0}^{2} \beta_{2,\tau}\,(temp_{t-\tau})^2 + \sum_{\tau=0}^{2} \beta_{3,\tau}\sqrt{temp_{t-\tau}}$$

$$+\textstyle\sum_{\tau=0}^{2} \gamma_{1,\tau}\, rain_{t-\tau} + \sum_{\tau=0}^{2} \gamma_{2,\tau}\,(rain_{t-\tau})^2 + \sum_{\tau=0}^{2} \gamma_{3,\tau}\sqrt{rain_{t-\tau}}$$

$$+\textstyle\sum_{\tau=0}^{2} \delta_{1,\tau}\, evap_{t-\tau} + \sum_{\tau=0}^{2} \delta_{2,\tau}\,(evap_{t-\tau})^2 + \sum_{\tau=0}^{2} \delta_{3,\tau}\sqrt{evap_{t-\tau}}$$

$$+\lambda evap_t \times rain_t + \mu_1 summer_t + \mu_2 december_t + \xi customer_t$$

$$+\rho_1 \sin_t + \rho_2 \mathrm{cosin}_t + \varepsilon_t + \theta\varepsilon_{t-1}, t = 1, \ldots, T,$$

where t is a time index that denotes a single week or a month, depending on the time frequency. Thus, we have estimated an ARIMAX(2,0,1) model without a seasonal component. Moreover, to simplify things, we have used selected the preferred model using least-squares combined with a procedure known as "best-subset selection", common in the machine learning literature. In stage 3 model development, we will perform model selection using the Box-Jenkins procedure. Finally, we note that we have also augmented this model using the additional weather variables identified in section 3.2. Appendix A1.2 provides a list of the explanatory variables we used for this modelling exercise for the daily, weekly and monthly data models.

4.4 Results

In what follows, we report point estimates of the parameters for the selected model corresponding to the weekly observations. Detailed results for the three model specifications are located in the appendix A1.2.

$$y_t = 7.73\, temp_t + 3.70\, temp_{t-1} + 0.05\,(temp_{t-2})^2$$

$$+0.39\,(rain_{t-1})^2 + 0.10\,(rain_{t-2})^2 - 25.30\,(rain_t)^{1/2} - 20.27\,(rain_{t-1})^{1/2} - 13.23\,(rain_{t-2})^{1/2}$$

$$+98.56\, evap_t + 25.10\, evap_{t-1} + 101.40\, evap_{t-2} - 6.40\,(evap_{t-2})^2 - 202.92\,(evap_t)^{1/2} - 141.60\,(evap_{t-2})^{1/2}$$

$$+9.88\, tempg30_t + 24.35\, tempg35_t + 3.17\, noconsdaynorain_t - 0.05 cumx_t + 0.003\, customer_t$$

$$-19.77 \sin_t - 122.63\, \mathrm{cosin}_t + 233.69 + 0.67 y_{t-1} + 0.06 y_{t-2} + \hat{\varepsilon}_t - 0.18\hat{\varepsilon}_{t-1}.$$

As outlined above, to compare the forecasting accuracy of the current and recommended approaches, we have computed the impact on the MAPE and RMSPE when:

- including additional weather variables using daily data

- using weekly and monthly data compared with using daily data, with and without the additional weather variables.

Table 9: Forecasting accuracy using daily, weekly and monthly data

	Daily data		Weekly data		Monthly data	
	Benchmark	Augmented	Benchmark	Augmented	Benchmark	Augmented
MAPE	3.80%	3.71%	1.61%	1.63%	3.14%	2.06%
RMSPE	4.27%	4.19%	1.86%	1.87%	4.01%	2.87%

Note: Benchmark – without additional weather variables, Augmented – with additional weather variables

The results can be summarized as follows:

- **With daily data, there is only minor improvement in forecasting accuracy** when adding extra weather variables
- **The forecasting accuracy improves significantly with weekly data relative to the daily data model, as both MAPE and RMSPE values are more than halved**. On the other hand, there is little effect of adding extra weather variables. But we note that temperature-based additional variables are statistically significant and have coefficient signs which are consistent with expectations (Appendix A1.2).
- **With monthly data, forecasting accuracy improves compared to daily data, more so when extra weather variables are added into the model**.

Thus, the results in Table 5 imply that using daily data (and actual weather variables), the annual forecast is off by 3.7% roughly, on average. This contrasts with weekly (monthly) data, where the annual forecast is off only by 1.7% (2.1%), on average.

Intuitively, one reason behind the higher forecasting accuracy observed with lower frequency data is that we make use of dynamic forecasting. Dynamic forecasting uses the forecast (as opposed to the actual) value of the lagged dependent variable to obtain the forecasts. Therefore, the forecast errors tend to compound over time.[19] This means that with daily data, abstractions are predicted over hundreds of days ahead, resulting in less accurate forecasts.

On the other hand, there is a limit as to how low the time frequency of the data may go, since the lower the time frequency, the smaller the sample size available for estimation, which can affect the accuracy of the forecasts. In this modelling exercise, weekly data performs comparatively better than monthly data. Therefore, at this stage, our recommended specification is the weekly data model.

The following three graphs depict the actual vs forecast values of abstractions using daily, weekly and monthly data, and include the additional weather variables from July 2018 to June 2021.

[19] In contrast, static forecasting uses the actual value of the lagged dependent variable when it is available. For out-of-sample true forecasting, dynamic forecasting is the only feasible approach, hence it makes more sense to use.

Figure 22: Actual vs forecast volumes using daily data, July 2018 – June 2021

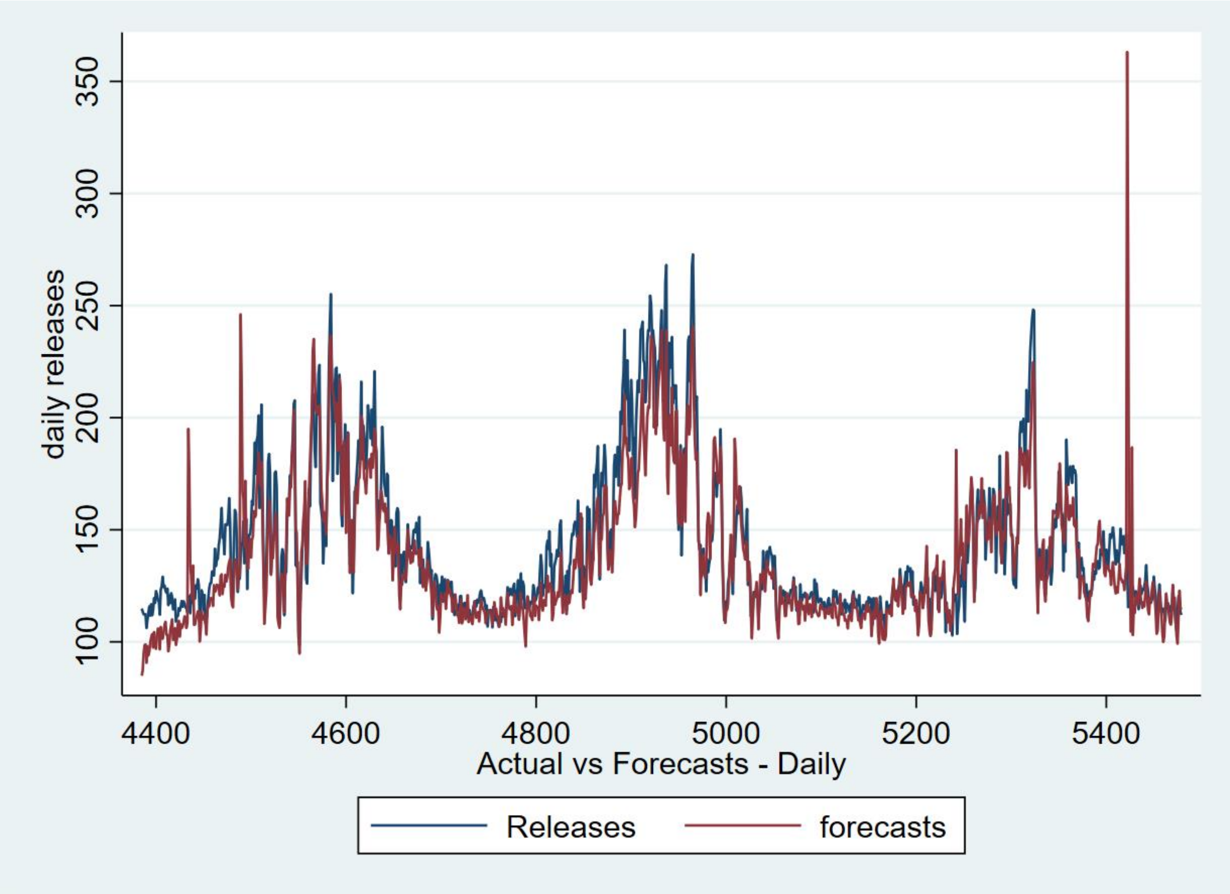


Figure 23: Actual vs forecast volumes using weekly data, July 2018 – June 2021

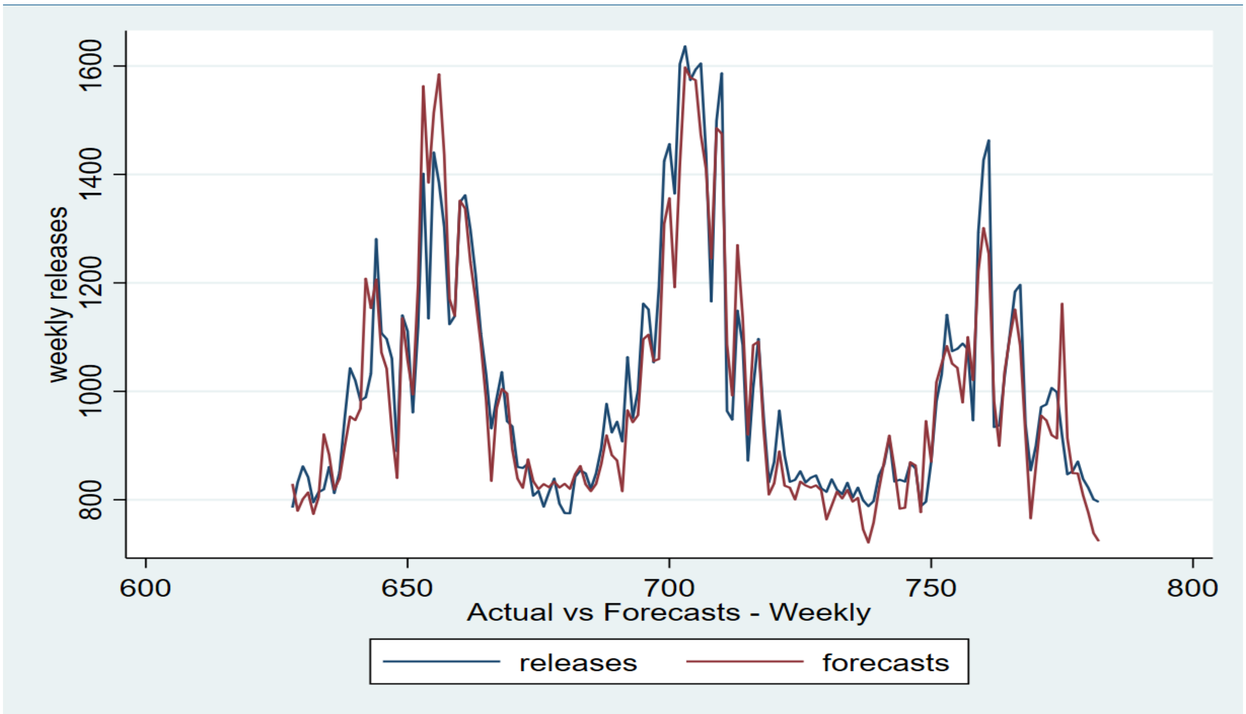
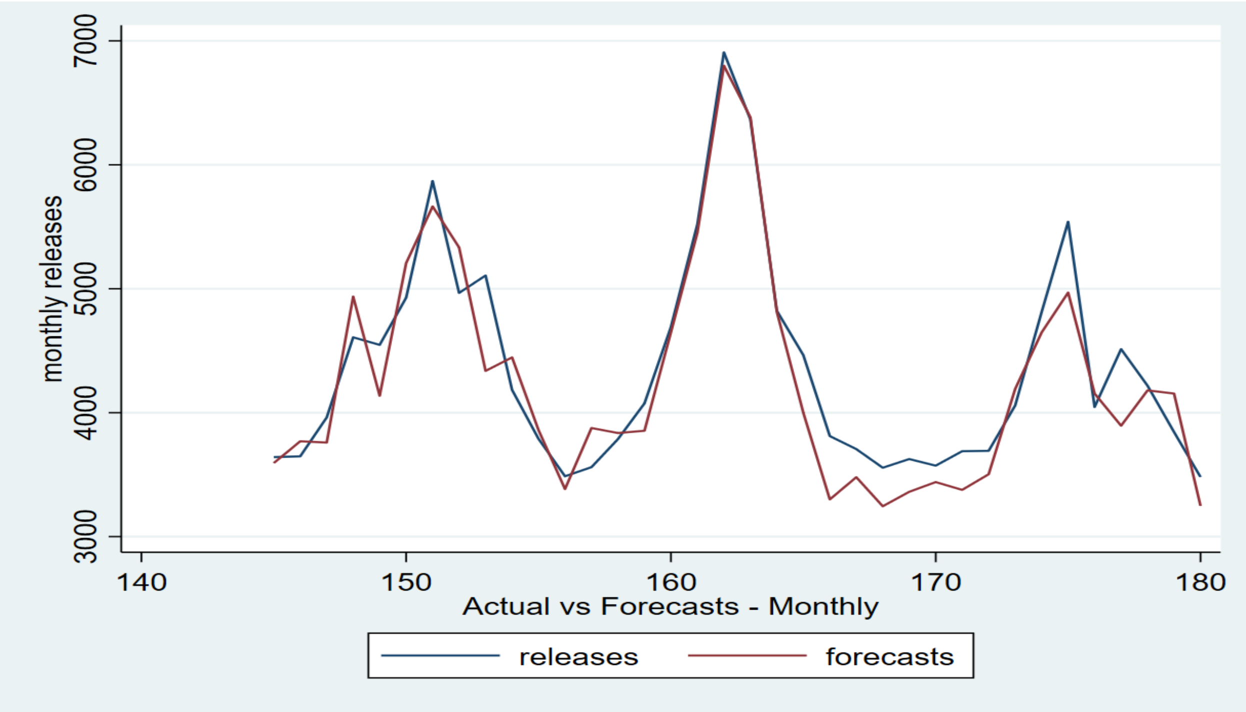


Figure 24: Actual vs forecast volumes using monthly data, July 2018 – June 2021



Appendix 1. ARIMA model assessment – detailed analysis

A1.1. Short-term versus long-term forecast using daily data

Consider the following first order autoregressive, AR(1), model:

$$y_t = \alpha y_{t-1} + \varepsilon_t; \qquad t = t, \dots, T, \tag{1}$$

where y_t denotes the observation of the dependent variable at time period t (say, the daily bulk volume of dam water release), y_{t-1} denotes the value of the dependent variable at time period $t-1$ and ε_t is the unobserved error term of the model, which is assumed to be white noise with mean zero, such that i.e. $E[\varepsilon_t|y_{t-1}, y_{t-2}, \dots, y_0] = 0$ for all $t \geq 1$. Finally, α denotes the unknown autoregressive parameter of the model and presents a measure of persistence. The larger the value of α is, the more persistent the series becomes, i.e. the "more permanent" a shock into the system at time period t (ε_t) is likely to be in the future.

At time T (the last observation of the sample), the "best linear unbiased predictor" of y for period $T+1$ (one-step ahead forecast) is given by

$$\hat{y}_T^{(T+1)} = E[y_{T+1}|y_T, y_{T-1}, \dots, y_0] = E[(\alpha y_T + \varepsilon_{T+1})|y_T, y_{T-1}, \dots, y_0] = \alpha y_T. \tag{2}$$

Similarly, at time T, the "best linear unbiased predictor" of y for period $T+2$ (two-step ahead forecast) is given by

$$\hat{y}_T^{(T+2)} = E[y_{T+2}|y_T, y_{T-1}, \dots, y_0] = E[(\alpha y_{T+1} + \varepsilon_{T+2})|y_T, y_{T-1}, \dots, y_0] \\ = \alpha E[y_{T+1}|y_T, y_{T-1}, \dots, y_0] + E[\varepsilon_{T+2}|y_T, y_{T-1}, \dots, y_0] \\ = \alpha^2 y_T. \tag{3}$$

In general, at time T, the "best linear unbiased predictor" of y for time period $T+\tau$ (i.e., the τ-step ahead forecast) is given by

$$\hat{y}_T^{(T+\tau)} = \alpha^\tau y_T;\ \tau \geq 1. \tag{4}$$

Let $e_T^{(T+\tau)} \equiv y_{T+\tau} - \hat{y}_T^{(T+\tau)}$ denote the forecast error for the τ-step ahead prediction, $\tau \geq 1$. That is, the forecast error is the difference between the actual and predicted value of y at period $T+\tau$, where the prediction is made at period T. The variance of the forecast error one-step ahead equals:

$$var\left(e_T^{(T+1)}\right) = var\left(y_{T+\tau} - \hat{y}_T^{(T+\tau)}\right) = var(\alpha y_T + \varepsilon_{T+1} - \alpha y_T) = \sigma_\varepsilon^2, \tag{5}$$

where $\sigma_\varepsilon^2 = var(\varepsilon_{T+1})$.

Similarly, it can be shown that the variance of the forecast error τ steps ahead is given by

$$var\left(e_T^{(T+\tau)}\right) = \sigma_\varepsilon^2\left(1 + \alpha^2 + \alpha^4 + \dots + \alpha^{2(\tau-1)}\right) = \sigma_\varepsilon^2 \frac{1-\alpha^{2\tau}}{1-\alpha}, \tag{6}$$

since the term in the middle involves a sum of a geometric progression with finitely many sums.

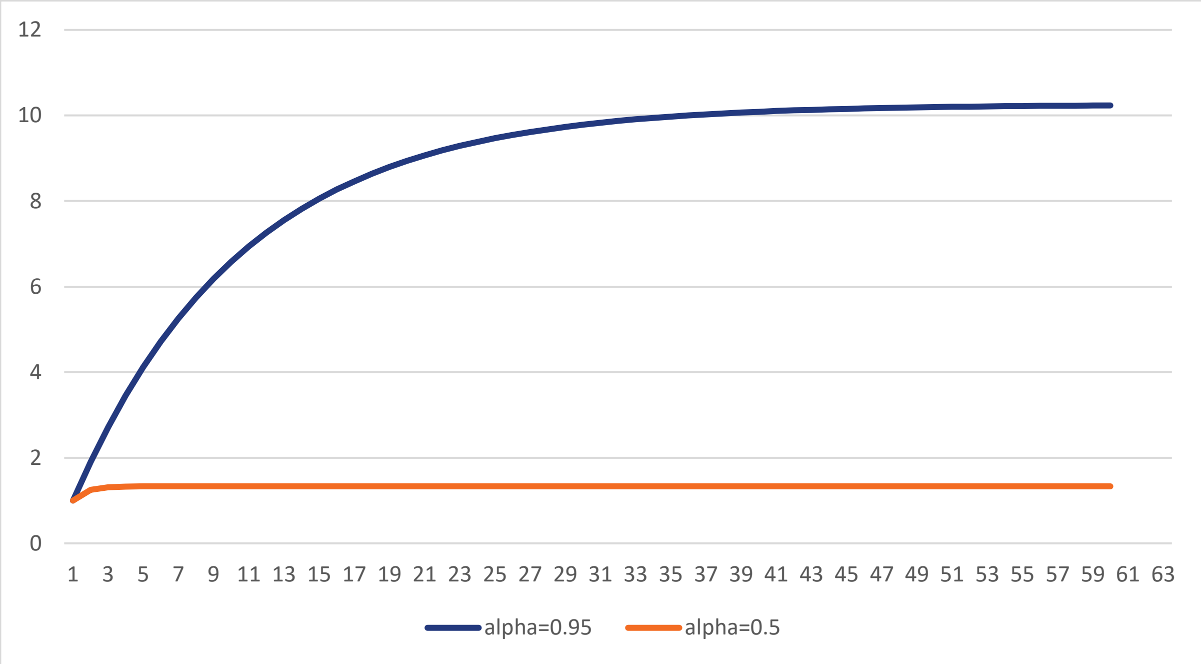
Notice that $var\left(e_T^{(T+1)}\right) < var\left(e_T^{(T+2)}\right) < \dots < var\left(e_T^{(T+\tau)}\right)$. As τ gets larger (i.e. as the forecasting horizon gets longer), the variance of the forecast error increases. Provided that the AR process is stationary, i.e. $|\alpha| < 1$, the forecast variance will approach a fixed limit. How large the difference between this limit and the value of (say) $var\left(e_T^{(T+1)}\right)$ is, depends on the magnitude of α. Moreover, the magnitude of α directly determines the speed of adjustment towards this limit. The larger the value of α is in absolute terms, the larger the variance of the forecast error will become as τ gets larger, relative to the variance of the one-step ahead forecast error.

The above analysis implies that when α is large, the accuracy of the forecast can diminish considerably once one deviates sufficiently from one- or two-day ahead forecasts. In other words, for relatively longer forecasting horizons, the prediction interval of the forecast value is likely to be very wide.

For example, for $\alpha = 0.95$ and $\sigma_\varepsilon^2 = 1$, the variance of the one-day and two-day ahead forecast equals 1 and (roughly) 1.9, respectively. On the other hand, the variance of the forecast error one week and one month ahead equals (roughly) 5.2 and 9.8, respectively. That is, the variance of the forecast error one week ahead (one month ahead) is already about 5 (10) times larger than that one day ahead.

This is illustrated in the following diagram, which depicts the variance of the forecast error as the forecasting horizon increases, for $\sigma_\varepsilon^2 = 1$ and two values of α, namely $\alpha \in \{0.5, 0.95\}$.

Figure 25: Variable of forecast error as the forecasting horizon increases



Although the actual model used is far more complicated than the AR(1) model considered in the analysis above, the conclusions remain relevant. In particular, the results presented in Table 2-6 of Attachment 4 of the 2018-2023 Water and Sewerage Price Proposal by Icon Water, report that the sum of the autoregressive coefficients equals 0.95. Thus, the prediction interval of the forecast value of total water consumption is likely to be fairly wide over forecasting horizons that are as long as one month ahead. Notably, small changes in the specification, or adding a small number of new observations in the model, can lead to substantially different forecasts.

It is worth noting that this point is acknowledged by Icon Water in its 2018-2023 Water and Sewerage Price Proposal[20], where it is stated that "(the) ICRC ARIMA models are designed primarily for short-term forecasting…". Yet, little can be done to rectify the problem when using daily data.

[20] See e.g. page 16 in Attachment 4 of Icon Water's 2018-23 Water and Sewerage Price Proposal.

A1.2. Detailed results of the modelling exercise done in stage 2 review

Table 10: Form of variables used in daily, weekly and monthly data models

Variable	Daily data	Weekly data	Monthly data
Temperature (degrees Celsius)	Maximum temperature during a day with/without lags, squared and square root forms	Average of daily maximum temperatures during a week with/without lags, squared and square root forms	Average of daily maximum temperatures during a month with/without lags, squared and square root forms
Rain (mm)	Daily rainfall with/without lags, squared and square root forms	Average daily rainfall during a week with/without lags, squared and square root forms	Average daily rainfall during a month with/without lags, squared and square root forms
Evaporation (mm)	Daily evaporation with/without lags, squared and square root forms	Average daily evaporation during a week with/without lags, squared and square root forms	Average daily evaporation during a month with/without lags, squared and square root forms
Customer numbers	Icon water customer connections at the end of each day	Icon water customer connections at the end of a week	Icon water customer connections at the end of a month
Additional weather variables to capture the effect of extreme weather conditions	Variable taking the value of 1 if temperature exceeded 35 °C and 40 °C, 0 otherwise	Number of days where daily temperature exceeded 30 °C and 35 °C in a week	Number of days where daily temperature exceeded 40 °C in a month
	Variable taking the value of 1 if rainfall exceeded 1mm	Number of days without rain in a week	Number of days without rain in a month
	Interaction effect between sum of daily rain*sum of daily evaporation in previous seven days	Interaction effect between average rain*average evaporation in a week	Dropped
Sin and cosine functions	To account for seasonality (systematic, repetitive, periodic fluctuations in dam abstractions) over the course of a day, week or month		
Past dam abstractions	Dam abstractions for the previous day (days)	Dam abstractions for the previous week (weeks)	Dam abstractions for the previous month (months)
Moving average component	Forecast error of dam abstractions for the previous day (days)	Forecast error of dam abstractions for the previous week (weeks)	Forecast error of dam abstractions for the previous month (months)

Table 11: Coefficient estimates for current ICRC ARIMA model and models used in the modelling exercise with daily, weekly and monthly observations

Variables	Current ICRC ARIMA model	Model with daily data	Model with weekly data	Model with monthly data
Dam abstractions	-0.33 to 1.28	-0.33 to 1.28	0.68	0.33

Variables	Current ICRC ARIMA model	Model with daily data	Model with weekly data	Model with monthly data
Temperature				
linear	-7.08 to -0.46	-7.98 to -0.48	3.70 to 7.72	-
square	0.01 to 0.11	0.01 to 0.11	0.05	2.37
square root	32.17	36.94	-	367.70
Rain				
linear	0.50 to 0.52	0.40 to 0.47	-	-
square	-	-	0.39	-
square root	-3.96 to 0.26	-3.67 to 0.33	-25.30 to -13.23	-226.75 to -163.86
Evaporation				
linear	0.45 to 1.16	0.40 to 1.11	25.10 to 101.40	308.15 to 1421.35
square	0.05 to 0.10	0.04 to 0.10	-6.40	-80.77
square root	-	-	-202.92	-
Customer numbers	0.00	0.00	0.00	0.01
• Number of days where daily temperature exceeded 'x' °C in time t	Not considered	-2.86 to -0.42 (not significant)	9.88 to 24.35	147.58
• Number of days without rain in time t.			3.17 (not significant)	19.89
• Day when rain exceeded 1mm		-1.27		
• Interaction effect between rain*evap	-0.02	-0.02	-0.05	-
• Summer season	-2.53 (not significant)	-2.42 (not significant)	Not considered	
• December month	4.16	4.15		
• Sum of daily temperature	-0.08	-0.09		
• Sum of daily rainfall	0.14	0.18		
• weekdays	4.72 to 12.35	4.71 to 12.34		
• weekends	6.28	6.29		
Sin	-1.87 (not significant)	2.95 (not significant)	-19.77 (not significant)	-660.97
Cosin	-5.21	5.91	-122.63	-541.74
Moving average component	-0.75 to -0.72	-0.75 to -0.72	-0.18	0.20

Note: coefficient estimate range is based on point estimates for different forms of a variable (squared, square root, lag, no lag) and are considered for estimates that are statistically significant with a p-value of at most 0.05. To note the sign of the coefficient need not necessarily be equal to what is expected when it comes to the sign of the coefficient for the linear component.

A1.3. Stata model estimate outcome: weekly observations

ARIMA regression

Sample: 3 - 627	Number of obs	=	625
	Wald chi2(24)	=	4655.95
Log likelihood = -3353.694	Prob > chi2	=	0.0000

releases	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf.	Interval]
releases						
temp						
--.	7.726546	1.538939	5.02	0.000	4.710281	10.74281
L1.	3.702127	1.135641	3.26	0.001	1.476312	5.927942
temp_sq						
L2.	.0524901	.0209145	2.51	0.012	.0114984	.0934818
rain_sq						
L1.	.3876719	.0597516	6.49	0.000	.2705608	.5047829
L2.	.1027969	.0996851	1.03	0.302	-.0925824	.2981761
rain_sqrt						
--.	-25.29694	3.418958	-7.40	0.000	-31.99797	-18.59591
L1.	-20.27051	4.335796	-4.68	0.000	-28.76852	-11.77251
L2.	-13.23156	3.807896	-3.47	0.001	-20.6949	-5.768219
evap						
--.	98.55549	15.0718	6.54	0.000	69.01531	128.0957
L1.	25.10312	4.039422	6.21	0.000	17.18599	33.02024
L2.	101.3963	55.82864	1.82	0.069	-8.025825	210.8184
evap_sq						
L2.	-6.397347	2.342534	-2.73	0.006	-10.98863	-1.806064
evap_sqrt						
--.	-202.9191	60.86373	-3.33	0.001	-322.2098	-83.62837
L2.	-141.5946	142.8705	-0.99	0.322	-421.6156	138.4265
temp_g30	9.877715	2.360426	4.18	0.000	5.251365	14.50406
temp_g35	24.34584	3.267082	7.45	0.000	17.94247	30.7492
nuconsdaynorain	3.174417	1.708605	1.86	0.063	-.1743882	6.523222
cumx	-.0481238	.0053879	-8.93	0.000	-.0586839	-.0375636
cust	.0024974	.0005109	4.89	0.000	.0014959	.0034988
sin	-19.76763	11.11826	-1.78	0.075	-41.55902	2.023766
cosin	-122.632	23.17523	-5.29	0.000	-168.0546	-77.20935
_cons	233.6858	133.8629	1.75	0.081	-28.68067	496.0523
ARMA						
ar						
L1.	.6775693	.2184787	3.10	0.002	.249359	1.10578
L2.	.0557353	.1414643	0.39	0.694	-.2215296	.3330002
ma						
L1.	-.1824606	.2156544	-0.85	0.398	-.6051355	.2402142
/sigma	51.75817	1.184266	43.70	0.000	49.43705	54.07929

A1.4. Stata model estimate outcome: monthly observations

```
ARIMA regression

Sample:   3 - 144                               Number of obs     =        142
                                                Wald chi2(16)     =    1534.28
Log likelihood = -969.7328                      Prob > chi2       =     0.0000

------------------------------------------------------------------------------
             |                 OPG
    releases |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
releases     |
     temp_sq |   2.374535   .5126225     4.63   0.000     1.369814    3.379257
             |
   temp_sqrt |
         L2. |   367.7015   138.1873     2.66   0.008     96.85929    638.5437
             |
   rain_sqrt |
         --. |  -226.7549   73.06642    -3.10   0.002    -369.9625   -83.54736
         L1. |  -163.8554   62.09934    -2.64   0.008    -285.5679   -42.14297
             |
        evap |
         --. |   308.1469   133.3383     2.31   0.021     46.80873    569.4851
         L1. |   1421.346   596.2708     2.38   0.017     252.6766    2590.015
             |
     evap_sq |
         L1. |  -80.77556   30.11163    -2.68   0.007    -139.7933   -21.75785
             |
   evap_sqrt |
         --. |   -443.218   514.0348    -0.86   0.389    -1450.708    564.2716
         L1. |  -2686.401   1391.062    -1.93   0.053    -5412.833    40.03124
             |
        cust |   .0098856   .0029167     3.39   0.001      .004169    .0156022
         sin |  -660.9652   205.6648    -3.21   0.001    -1064.061   -257.8697
       cosin |  -541.7447   179.0812    -3.03   0.002    -892.7374   -190.7519
    temp_g40 |    147.576    54.8585     2.69   0.007     40.05537    255.0967
 nudaynorain |   19.88708   9.872218     2.01   0.044     .5378912    39.23627
       _cons |   484.2859   1395.543     0.35   0.729    -2250.927    3219.499
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L2. |   .3274589   .0768848     4.26   0.000     .1767675    .4781502
             |
          ma |
         L1. |   .2035456   .0937991     2.17   0.030     .0197027    .3873884
-------------+----------------------------------------------------------------
      /sigma |   223.4729   12.11046    18.45   0.000     199.7368    247.2089
------------------------------------------------------------------------------
```

A1.5. Stata model estimate outcome: daily observations

```
ARIMA regression

Sample:  12 - 3927, but with a gap              Number of obs     =       3915
                                                Wald chi2(47)     =  112326.51
Log likelihood = -13700.56                      Prob > chi2       =     0.0000

------------------------------------------------------------------------------
             |                 OPG
    releases |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
releases     |
        temp |
         --. |  -.6514732   .1938243    -3.36   0.001    -1.031362   -.2715845
         L1. |  -7.981397   2.028009    -3.94   0.000    -11.95622   -4.006572
        L12. |  -.4773042   .1857446    -2.57   0.010    -.8413569   -.1132514
             |
     temp_sq |
         --. |   .0253145   .0036361     6.96   0.000     .0181879    .0324411
         L1. |   .1157031   .0156874     7.38   0.000     .0849562    .1464499
         L5. |   .0057544   .0008746     6.58   0.000     .0040402    .0074686
        L12. |   .0133237   .0034923     3.82   0.000     .0064789    .0201684
             |
   temp_sqrt |
         L1. |   36.94334   12.37749     2.98   0.003      12.6839    61.20278
             |
        rain |
         --. |   .4054549   .0569256     7.12   0.000     .2938828    .5170271
         L1. |   .4713036   .0575249     8.19   0.000     .3585568    .5840504
             |
   rain_sqrt |
         --. |  -2.976194   .2744773   -10.84   0.000     -3.51416   -2.438229
         L1. |  -3.672695   .2841228   -12.93   0.000    -4.229565   -3.115824
         L3. |  -.4226095   .1324597    -3.19   0.001    -.6822257   -.1629934
         L6. |   .3292219   .1321639     2.49   0.013     .0701854    .5882585
         L7. |  -.5825196   .1222904    -4.76   0.000    -.8222043   -.3428348
         L8. |  -.4536439   .1178368    -3.85   0.000    -.6845998   -.2226879
             |
        evap |
         --. |    1.10556    .260575     4.24   0.000     .5948428    1.616278
         L1. |   .9407145   .2718417     3.46   0.001     .4079145    1.473515
         L2. |   1.095693   .1005909    10.89   0.000     .8985384    1.292848
         L3. |   .8172342   .1023415     7.99   0.000     .6166484     1.01782
         L4. |   .3933971   .1086623     3.62   0.000     .1804229    .6063714
             |
     evap_sq |
         --. |   .1014326    .025865     3.92   0.000     .0507381    .1521272
         L1. |   .0715488   .0253517     2.82   0.005     .0218604    .1212373
         L5. |   .0449269   .0092634     4.85   0.000     .0267711    .0630828
             |
        cumx |  -.0163333   .0010595   -15.42   0.000    -.0184099   -.0142567
     cumtemp |  -.0871425    .021917    -3.98   0.000    -.1300991    -.044186
     cumrain |   .1859015   .0303734     6.12   0.000     .1263708    .2454323
         sun |   6.292645   .9364672     6.72   0.000     4.457203    8.128087
         mon |   12.34155   1.078199    11.45   0.000     10.22832    14.45478
         tue |    6.74024    1.16149     5.80   0.000      4.46376    9.016719
         wed |   5.620609   1.272798     4.42   0.000      3.12597    8.115247
         thu |   4.706281   1.231608     3.82   0.000     2.292374    7.120188
         fri |    4.84134   1.024178     4.73   0.000     2.833988    6.848691
         dec |   4.151659   1.222934     3.39   0.001     1.754752    6.548566
      summer |  -2.424963   1.444769    -1.68   0.093    -5.256658    .4067319
        cust |   .0003023   .0001502     2.01   0.044     7.94e-06    .0005966
         sin |   2.948543    2.19214     1.35   0.179    -1.347972    7.245059
       cosin |   5.911889    2.63163     2.25   0.025     .7539894    11.06979
    temp_g35 |  -.4244704   .8223144    -0.52   0.606    -2.036177    1.187236
    temp_g40 |  -2.863612   1.574092    -1.82   0.069    -5.948776     .221552
 nudaygeq1mm |  -1.273972   .3087555    -4.13   0.000    -1.879122   -.6688228
       _cons |    23.0336   31.62038     0.73   0.466     -38.9412     85.0084
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L1. |   1.284877   .0304951    42.13   0.000     1.225107    1.344646
         L2. |   -.328319   .0247627   -13.26   0.000     -.376853   -.2797849
             |
          ma |
         L1. |  -.7551262   .0270915   -27.87   0.000    -.8082245   -.7020279
-------------+----------------------------------------------------------------
ARMA7        |
          ar |
         L1. |   .9186684   .0323196    28.42   0.000     .8553232    .9820136
         L2. |  -.0338743   .0191715    -1.77   0.077    -.0714498    .0037013
             |
          ma |
         L1. |  -.7224889      .0284   -25.44   0.000    -.7781519   -.6668259
-------------+----------------------------------------------------------------
      /sigma |   8.006017   .0623198   128.47   0.000     7.883872    8.128161
------------------------------------------------------------------------------
```

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Appendix 5 Other Australian jurisdictions' approaches to forecasting water demand

This appendix summarises the demand forecasting models used by water utilities in other jurisdictions. In developing this summary, we considered the reasoning behind the adopted approaches in these jurisdictions.

Each of the utilities reviewed here use the demand forecasting methodology that was most suited to the type of data they were readily able to access and how the demand forecasts were used.

In the case of Sydney Water and Hunter Water, which uses panel data regression and end use approaches respectively, demand forecasts are not only used as part of their regulatory determination for setting prices, but they are also used for water conservation reporting, which is required under IPART's ELWC methodology. This explains their need for a flexible approach that considers additional factors than may be adequately provided under an ARIMA approach.

Melbourne Water contracts the bulk of its supply through three large customers, which in turn distribute water to the end user. As each of these customers does their own demand forecasting, Melbourne Water is able to make its demand forecasts based on the usage of its three largest customers.

SA Water uses an econometric model based on the historical water usage it has access to, and forecasts demand based on relationships observed between water demand and its drivers after the millennium drought.

SA Water

SA Water is regulated by the Essential Services Commission of Australia (ESCOSA), which uses a cost-based (building block) approach to determine a revenue cap for drinking water and sewerage services.

SA Water's demand forecasting model was introduced in its 2013 Regulatory Business Proposal. SA Water developed the model to account for the increasingly volatile water demand (in the aftermath of the millennium drought) and considering that a growing share of SA Water's revenue is derived from water sales led (SA Water 2013).

For the 2020-24 regulatory period, SA Water used an econometric regression model based on the relationship between annual bulk water usage, and climate (rainfall, evaporation and temperature) and population. Due to the seasonal pattern of water demand, SA Water's water demand model also incorporates separate regression models for summer and winter (Acil Allen 2019).

SA Water uses the model for water planning and calculation of revenue and pricing for regulatory purposes. SA Water has access to water usage and other data extending back to the late 1992. However, in calibrating its demand model it chose not to use data collected before December 2010 when water restrictions were lifted and replaced with permanent water wise measures. Through a process of trial and error, the 'best' regression model is identified and used for forecasting from 2017-18 to 2023-24 (Acil Allen 2019).

Forecasts of bulk water usage per capita are produced for low, medium, average and high scenarios of climate. These climate scenarios are developed based on the climate patterns observed in the historical data. Monthly bulk water usage values are calculated by multiplying the per capita forecast by projected population figures using a 0.60 % annual growth rate. The monthly forecasts are then aggregated for annual forecasts. Applying the non-revenue water proportion of 13.50% then provides the split of water demand into billed water and non-revenue water demands (Acil Allen 2019).

SA Water developed the demand forecasting model considering the following principles set out by ESCOSA that demand forecasts should:

- be free from statistical bias
- recognise and reflect key drivers of demand
- be based on sound assumptions using the best available information
- be consistent with other available forecasts and methodologies
- be based upon the most recently available data
- reflect the particular situation and the nature of the market for services
- be based upon sound and robust accounts of current market conditions and future prospects (SA Water 2013).

SA Water's demand model applies a post-model adjustment to account for improvements to water efficiency. In arriving at its estimate of water efficiency, SA Water considered:

- the uptake of more water efficient products of toilets, washing machines and showerheads from its household appliance efficiency models for South Australia
- the changing household densities and housing types in South Australia (Acil Allen 2019).

SA Water's analysis concluded that an efficiency per capita rate of 0.2 % per annum should be applied to the forecasts of the regression model (Acil Allen 2019).

We note the similarities in the demand drivers used by SA Water and those used in the ACT. The above information suggests that SA Water adopted an econometric modelling approach due to its flexibility to accommodate different climate scenarios and the availability of required data, given that SA Water intended to capture changes in consumer demand arising from drought related response measures.

Melbourne Water

Melbourne Water is regulated by the Essential Services Commission of Victoria (ESC), which implements a price cap form of price control. Melbourne Water uses an end use approach to determine observed water usage, using information provided by its three major customers: City West Water, South East Water and Yarra Valley Water (ESC 2021).

Melbourne Water forecasts bulk water demand based on forecasts provided by these retail water businesses (which use integrated-supply demand planning models to forecast demand). The inputs for the model are taken from periodic end use studies (ESC 2021). Key features of this modelling approach are:

- total demand estimate is a function of separate residential, non-residential water and non-revenue water forecasts
- efficiencies of appliance-based end uses and other parameters such as showering frequency and duration can be incorporated
- various calibration variables can be used such as residential water demand for outdoor water use, non-residential water demand and non-revenue water
- most recently completed end use studies are used.

Non-residential forecasts rely on bottom-up aggregation of historical demands and projections using observed trends or relationships. Non-revenue water forecasts rely on observed trends or relationships to factors and are adjusted for any future non-revenue water management activities.

Melbourne Water uses these end use data observations in conjunction with population projections and climate data to develop its demand forecasts. As the bulk of Melbourne Water's demand is contracted through these three large customers, it makes sense for Melbourne Water to adopt an end use approach due to the relative ease it has in obtaining this data.

Sydney Water

Sydney Water is regulated by Independent Pricing and Regulatory Tribunal (IPART), which uses a building block approach to determine the notional revenue requirement for Sydney Water paired with demand forecasts to apply a price cap. Sydney Water uses a panel data regression approach to forecast water demand. Panel data regressions use repeated observations for the same customers over time to forecast demand.

Sydney Water uses a three-part approach for water demand forecasting:

1. It uses historical information to determine what factors influence water consumption. To do this, Sydney Water divides its customer base into 34 segments based on factors such as dwelling or business type, lot size and whether the property was built under the Building Sustainability Index[21] system.
2. Sydney water then estimates an econometric panel data model for each segment based on historical customer usage. The parameters of this model capture the impact of the factors that influence water consumption within each group, such as price elasticity, weather, and seasonality on water demand.
3. Sydney Water then forecasts water demand by feeding in the forecast growth in customer numbers in each customer segment, climate projections, and estimates of system water losses and price elasticity to the econometric model (IPART 2020).

Sydney Water's model forecast water demand based on average climate conditions because the model is not able to accurately predict climate conditions over the regulatory period (IPART 2020).

Sydney Water's approach appears necessary for it to carry out its water conservation obligations under IPART's Economic Level of Water Conservation methodology (ELWC). Under the ELWC, Sydney Water is required to submit (for IPART's approval) reports outlining their approach to, and principles for, their methodology for determining their economic level of water conservation (Sydney Water 2019). This includes addressing the following elements of water conservation:

- Water leakage
- Water recycling
- Water efficiency (including demand management)

The ELWC methodology enables Sydney Water to adopt an approach to demand forecasting that allows them flexibility to forecast the data requirements specified above. We also note that dam abstraction data would be held by Water NSW and may not be something that Sydney Water has ready access to, whereas they do have ready access to end use customers.

Hunter Water

Hunter Water uses a supply demand planning model called the Integrated Supply-Demand Planning (iSDP) model to forecast water demand. Hunter Water's iSDP model forecasts the water demand for average climate conditions. Unanticipated climate events such as drought or above average rainfall are not

[21] The Building Sustainability Index is a sustainability planning system in the NSW. Its requirements apply to all residential dwelling types in NSW and meeting its requirements is a part of the development application process.

considered in Hunter Water's model. Therefore, these events can significantly affect the accuracy of forecasts.

The model uses demographic factors such as population growth, number of dwellings/connections and household size to forecast demand. Hunter Water updates demographic and connection numbers annually as part of its planning process.

The model forecasts water demand for residential customers and non-residential customers separately.

For residential customers, it forecasts demand based on expected water uses for various activities such as residential toilets, showers, taps, washing machines and gardens. The iSDP model has separate model modules to calculate demand for each activity. These modules forecast demand based on detailed information on installed equipment and the frequency of use. Hunter Water has access to annual sales data for individual appliances which it uses as an input to the model. In some cases, Hunter Water estimates the sales using data on appliance ownership in each year in combination with assumptions about the duration of time that appliances remain in service prior to being replaced.

For non-residential customers, it uses a trend analysis to forecast the demand. Hunter Water uses economic trends, changes in recycled water demand and water conservation measures as inputs to the model.

The model calculates non-revenue water using Water Services Association of Australia national reporting methodology.

Like Sydney Water, Hunter Water is subject to IPART's ELWC methodology and therefore requires a more flexible approach than ARIMA to facilitate the forecasting of variables required to meet requirements (Hunter Water 2020).

ACT – Icon Water

In 2015, we released a technical paper outlining the ARIMA approach to forecast water demand. We considered that the approach then used—Cardno's approach to forecast water usage per customer based on annual observations for water users separated into four subgroups—was insufficient (ICRC 2015b). We found that Cardno's approach:

- restricted data availability, as it relied on 13 annual observations
- did not consider the effect of the millennium drought on changing water consumption behaviour of consumers.

We considered that Cardno's approach overstated demand for water given that it did not account for the step-change in demand from the millennium drought and that this created a risk that Icon Water would not be able to recover its efficient costs due to the lower prices that would have eventuated from overstated forecast demand.

In comparison, we found in 2015 that data on water abstractions from Icon Water's dams was readily available. We found there was a stable and direct relationship between dam abstractions and ACT water sales and considered dam abstractions was a good indicator of water demand by ACT consumers. We also required dam abstractions forecast to assess Icon Water's operating and capital costs and the water abstraction charge. We found ARIMA approach was better suited to model dam abstractions, because data are available at a high frequency for a long time period (ICRC 2015).

Abbreviations and acronyms

ABS	Australian Bureau of Statistics
ACCESS-S	Australian Community Climate and Earth System Simulator -Seasonal
ACT	Australian Capital Territory
AER	Australian Energy Regulator
AIC	Akaike Information Criteria
ARIMA	Autoregressive Integrated Moving Average
BoM	Bureau of Meteorology
EEIS	Energy Efficiency Improvement Scheme
ELWC	Economic Level of Water Conservation
ENSO	El Nino-Southern Oscillation
ESC	Essential Services Commission of Victoria
ESCOSA	Essential Services Commission of South Australia
GCM	Global climate model
GL	Gigalitre
ICRC	Independent Competition and Regulatory Commission
IOD	Indian Ocean Dipole
IPART	Independent Pricing and Regulatory Tribunal
iSDP	Integrated Supply-Demand Planning
kL	kilolitres
MAPE	Mean Absolute Percent Error
MDBA	Murray-Darling Basin Authority
ML	Megalitres
NARCLiM	NSW and ACT Regional Climate Modelling
NSW	New South Wales
RCM	Regional Climate Model

RCP	Representation Concentration Pathways
RMSPE	Root Mean Square Percentage Error
SA	South Australia
SDL	Sustainable diversion limit
SEACI	South Eastern Australian Climate Initiative

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