ICRC

independent competition and regulatory commission

FINAL REPORT

Review of water and sewerage services demand forecasting methods

Report 18 of 2021, December 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.

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Executive summary

We have reviewed the methods we use to forecast demand for water and sewerage services in the Australian Capital Territory (ACT). Our final decision is to largely maintain our previous forecasting approach and to make improvements to the data inputs used to forecast dam abstractions, develop future climate scenarios, and forecast connection numbers and billable fixtures. We will also update the datasets used in the model to include the latest available data. We have developed principles for when we would adjust the output of the model for major 'step change' events that would not otherwise be accounted for in our model.

We decided to do this review in our 2018 water and sewerage services price investigation to ensure our demand forecasting methods and data inputs remain fit for purpose. This will ensure we use appropriate demand forecasts in setting Icon Water's prices for water and sewerage services and assessing the prudency and efficiency of Icon Water's proposed expenditure during our next price investigation.

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

We released our draft report in September 2021 as the second step in the consultation process to give stakeholders an opportunity to comment on our draft decisions. We held a second stakeholder workshop in October 2021. We received a submission from Icon Water.

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

Water services demand components

Icon Water earns revenue from supplying 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 usage and water connection numbers to determine the prices that will allow Icon Water to recover its prudent and efficient costs.

Final decision

Our final decision is to maintain the top-down approach to forecasting 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 (which is a measure of water demand) 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. This type of model is a widely used statistical analysis technique that, put simply, uses time series data (past trends) to predict future trends in variables that determine the variable of interest, which in this case is 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 developing future climate scenarios to forecast dam abstractions.

Our final decision is to use a better data source to develop 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 for forecasting dam abstractions.

Our final decision is to forecast water customer numbers based on ACT population projections rather than past growth trends in connection numbers. We will use the ACT Government's population projections which are being updated to account for the effect of the COVID-19 pandemic. In the next price investigation, we will check to ensure that the ACT population projections that are used account for the impact of the COVID-19 pandemic. If ACT Government's updated population projections are not available, we will consider projections developed by the Australian Government's Centre for Population Studies that is an alternative data source.

We will continue to use data from 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 for major 'step change' events. We will consider them in the next price investigation, for example, if we need to estimate the impact of any changes to 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.

Our final decision is to use weekly data, rather than daily data, for variables used to forecast dam abstractions.

Other water demand components

We will retain our current methods for forecasting ACT water sales and billed water sales at Tier 1 and Tier 2.

Our final 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 prudent and efficient costs. We also need an estimate of sewage volumes to assess the sewage treatment costs faced by Icon Water.

Final decision

Our final 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.

1. Introduction

We have reviewed the methods used to forecast demand for water and sewerage services in the 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 was part of our broader strategy to make sure our modelling, forecasting methods and the data we use in determining regulated water and sewerage prices 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 supplying 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 reset principle to review demand forecasting methodologies that may be used in the 2023 water price investigation.

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 considered the issues raised in submissions in our draft report.

We released our draft report on 20 September 2021 as the second step in the consultation process to give stakeholders an opportunity to provide feedback on our draft decisions. We held a second stakeholder workshop on 6 October 2021. We received a submission from Icon Water which is available on our website.

This final report is the last step in the process for this review. It addresses stakeholder feedback on our draft report and presents our final decisions on the forecasting methods and the data inputs we will apply in the 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

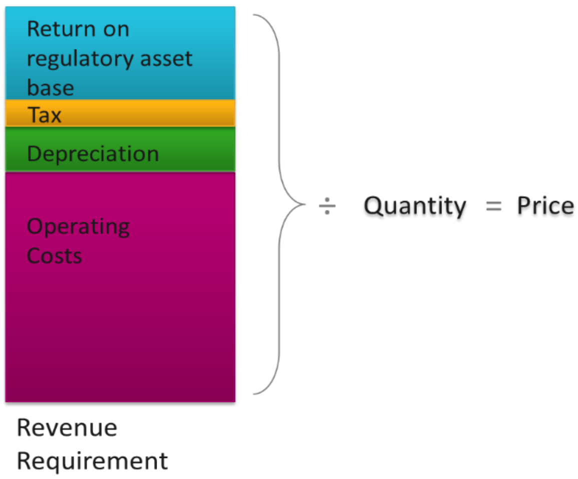
Demand forecasts are an important input for setting prices

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 to recover its prudent and efficient 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. We need forecasts of water connection numbers and water usage to determine prices that will allow Icon Water 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 be treated. We need an estimate of sewage volumes to assess 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 investigation. 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 demand forecasts are too low, the prices that we set will be too high. This means consumers' bills will be higher than what they should be for Icon Water to recover its costs. If 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 could 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 was 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 have determined 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 reviewed the current forecasting methods and data sources based on a set of assessment criteria (described in section 1.7). We considered the pros and cons of alternative forecasting approaches compared to the current approach. We identified appropriate forecasting methods and data sources based on the assessment criteria.

We have reviewed the methods for six components of water and sewerage services demand that we need to determine the maximum prices for water and sewerage services 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. We forecast the total number of additional billable fixtures 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. 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.

1.5. Technical advice on forecasting methods

We engaged the consultancy firm Marsden 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 us to maintain the current forecasting approach. The consultant's stage 1 report was published with our issues paper.

In stage 2, the consultant developed advice on how the current forecasting approach could be improved. We considered the advice in developing our draft decisions. The consultant's stage 2 report was published with our draft report.

In stage 3, the consultant made final refinements to the model to ensure it is statistically sound and produces reliable forecasts. We have considered its advice in developing this final report. The consultant's stage 3 report is in appendix 4.

1.6. Our approach to this review

1.6.1. Assessment criteria for the review

We used a set of criteria to assess our demand forecasting methods.

Having assessment criteria promotes 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).

We used the following assessment criteria in this review:

- **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**. 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 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 give 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.

1.6.2. 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). We considered Icon Water's specific comments on each criterion in our draft report.

On the criterion of transparency and replicability, Icon Water's view was 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. In our draft report, we considered that the data used in the model should be publicly available, widely accepted and sourced from a reputable organisation. We also considered that the model should use updated data that accounts for more recent observations.

Icon Water's view was 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 costs 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.

In our draft report, we accepted that the predictive ability of a model should be evaluated, on average, over the five-year regulatory period. However, we also considered the significant annual variability between forecast and actual water demand and investigated 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 showed 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 could not 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 final report).

On flexibility, Icon Water noted 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 (or major 'step change') to demand. In our draft report, we accepted there are different ways for a model to be flexible and the most appropriate way will depend on the specific circumstances.

Icon Water agreed that regulatory stability is an important element of the demand forecasting methodology. Icon Water's view was 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, in our draft report, we considered 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 was 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 can be understood by the general community because the relationship between weather and water demand can be intuitively understood. We accept that the overall forecasting approach should be intuitive. We also consider that the forecasting methods and tools should be simple and straightforward for stakeholders to understand and implement without requiring specialist skills.

1.7. 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. We released the draft report on 20 September 2021, which was the second step of our public engagement for this review. We held a second stakeholder workshop on 6 October 2021 and received one submission by the 25 October 2021 due date.

Releasing this final report is the final step for this review. We have considered stakeholder feedback on our draft report in preparing the final report.

Table 1.1 Review timeline

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	6 October 2021
Submissions on draft report close	25 October 2021
Final report	9 December 2021

1.8. Structure of the final report

The remainder of this final report is structured as follows:

- Chapter 2 gives an overview of our current forecasting methods and data.
- Chapter 3 gives an overview of our final decision on forecasting methods and data.
- Chapter 4 discusses our final decision on the methods and data used to forecast dam abstractions.
- Chapter 5 discusses our final 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 this review.
- Appendix 2 sets out technical details related to our final decision demand forecasting method for dam abstractions.

- Appendix 3 sets out technical details related to our final decision demand forecasting method for the other demand components.
- Appendix 4 is the consultant's stage 3 report.
- Appendix 5 gives an overview of the forecasting approaches used in other Australian jurisdictions.

2. Overview of our current forecasting approach

2.1. Forecasting water services demand

We apply a top-down approach to forecasting 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 forecast dam abstractions for each climate scenario and used the average of the forecasts 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.

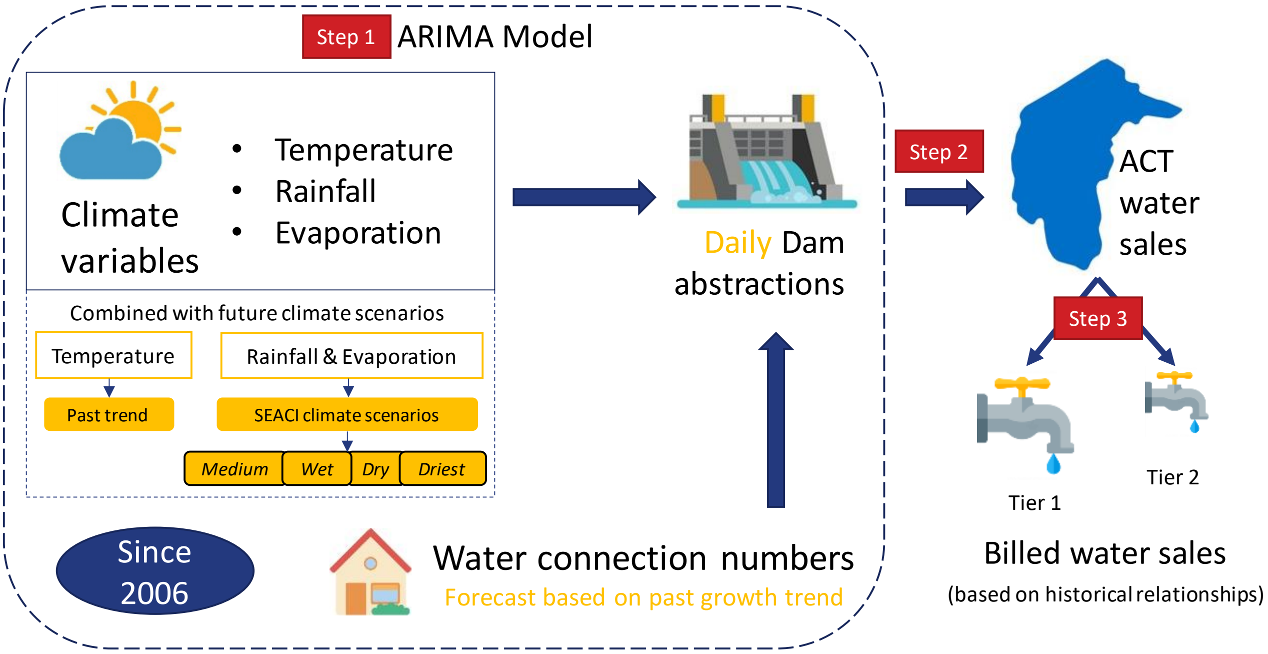
Step 2

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 first workshop held on 28 June 2021.

We considered stakeholders' comments in developing our draft decisions.

2.5. Overview of our draft report

Our draft decision was to largely maintain the current approach as we found that most of our current methods produce reliable forecasts.

We proposed some changes to ensure our methods and data remain fit for purpose and can better account for the impact of climate change and demographic changes. We considered:

- using a different data source to develop future climate scenarios. Our draft decision was to 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.
- using ACT Government's population projections to forecast connection numbers and billable fixtures. Our draft report noted that we will check to ensure that the ACT population projections we use in the next water and sewerage services price investigation account for the impact of the COVID-19 pandemic.
- using weekly data, instead of daily data, to forecast dam abstractions.

We developed principles to adjust the output of the model. We said that we will consider them in the next price investigation to review the impact of any changes to the SDL on water demand in the ACT, or any other major ‘step changes’ that will affect water demand and would not already be accounted for in our model.

Our draft decision was to retain the current method to forecast sewage volumes.

2.6. Overview of submissions to the draft report

We received a submission from Icon Water. Icon Water supported most of our draft decisions and commented on three specific matters: the use of weekly data, the way to include NARCLiM data in the model, and the statistical software used to implement the forecasting methods and data.

We also heard stakeholder views at the second workshop held on 6 October 2021.

We have considered stakeholders’ comments in developing our final decisions and have discussed them in more detail in chapters 3 to 5.

3. Overview of our final decisions

This chapter gives an overview of our final 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 have decided to confirm our draft decisions on the methods and data we will use to forecast water services demand components.

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 decided to confirm our draft decision to use a better 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. In this final report, we have considered Icon Water's comments and outlined how NARCLiM data should be applied to forecast dam abstractions.

We will continue to use water connection numbers to forecast dam abstractions. We have decided to confirm our draft decision to forecast water connection numbers based on ACT Government's 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 the 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.

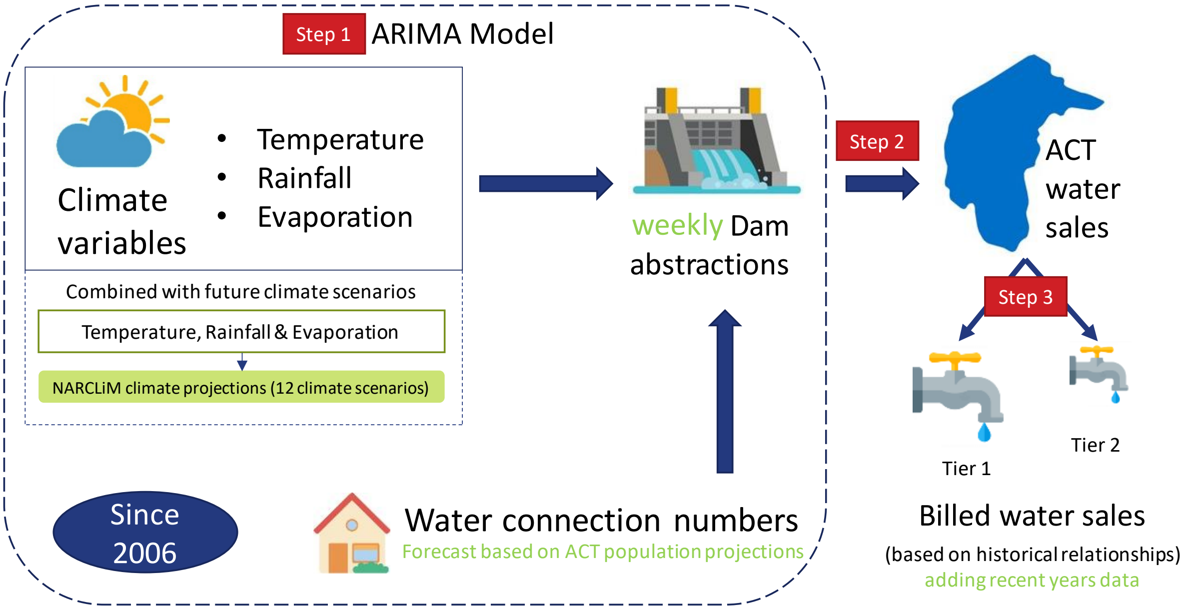
The current model does not account for the sustainable diversion limit (SDL) which limits the amount of water that can be taken from the rivers for towns, industries and farmers in the Murray-Darling basin. We have decided to confirm the principles we developed in our draft report to adjust the output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

The current model uses daily observations to forecast dam abstractions. We have decided to confirm our draft decision 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. In this final report, we have finalised the model specification based on the final refinements our consultant made to the model and considering Icon Water's comments to the draft report.

We will retain the current methods to forecast ACT water sales and billed water sales at Tier 1 and Tier 2. We have decided to confirm our draft decision 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 final decision approach to forecasting water services demand. The changes compared to our current approach are shown in green.

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



Source: our final decision

3.2. Forecasting sewerage services demand

We have decided to confirm our draft decision on the methods and data we will use to forecast sewerage services demand components.

Like the forecasts for water connection numbers, the forecasts for sewerage installations and billable fixtures will be based on ACT Government's 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 forecasting 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 final decisions on the method and data used to forecast dam abstractions. Section 4.1 is about the approach to forecasting 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 final decision

We have decided to confirm our 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 2021a and 2021b).

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

Details of the final 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.

Sydney Water and Hunter Water use demand forecasts not only in their regulatory pricing submissions but also for water conservation reporting. Their access to end users' water usage data allows them to model the economic level of water conservation and apply panel data regression and end use approaches to forecasting water demand.

Melbourne Water contracts the bulk of its supply through three large customers (the retail water businesses in Melbourne), which in turn distribute water to end users. As each of these customers does its own demand forecasting, Melbourne Water can make its demand forecasts based on the forecast 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.

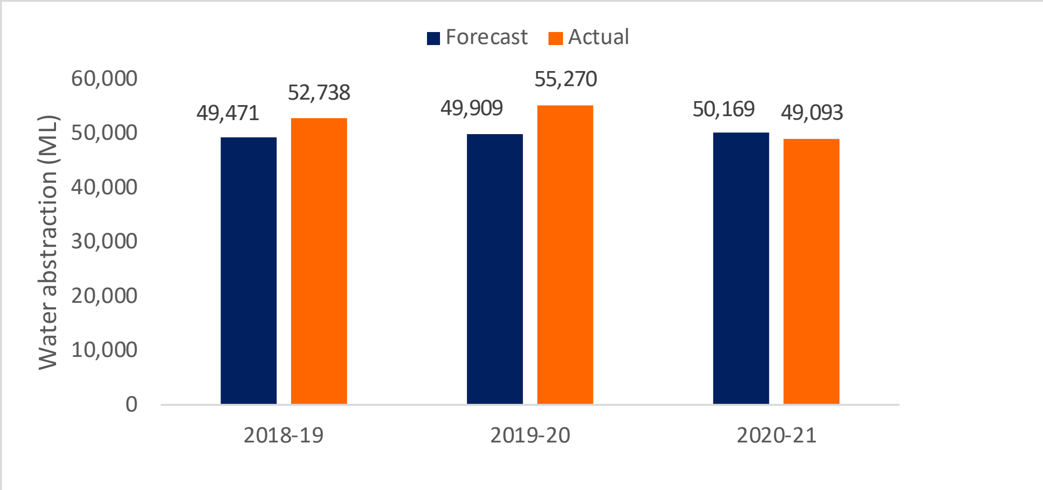
Criterion 2: Predictive ability

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 the model forecast. In the third year (2020-21), actual dam abstraction was 2% below the forecast because wetter than average conditions led to lower demand 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 that 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, such as 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 more 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, the 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 a 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 Icon Water to implement. The data on bulk water dam abstractions, rainfall, evaporation, temperature and customer numbers 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

In its stage 1 report, 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 considered identifying 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 out of the methods we considered (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 during rainy periods. Temperature data is used because water demand changes with temperature, with more demand during hot periods. The model uses evaporation data because of higher irrigation requirements for plants as they dry out during high evaporation periods. 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 final decision

We consider that the current model is fit for purpose and performing well. The changes we are making 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 decided to confirm our 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. In this final report, we have considered Icon Water's comments and outlined how NARCLiM data should be applied to forecast dam abstractions.

We will continue to use water customer numbers to forecast dam abstractions. We have decided to confirm our draft decision 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 observing past trends.

We will continue to use data from 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 decided to confirm the principles we developed in our draft report to adjust the output of the model for certain types of changes that affect water and sewerage services demand ('post-model adjustment principles'). We will consider them in the next price investigation, for example, to estimate the impact of any changes in the SDL on water demand.

The current model uses daily observations for climate and dam abstractions. We have decided to confirm our draft decision to use weekly data because we found this improves the model's predictive ability.

Climate variables

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

We will continue to use climate variables to forecast water demand because there is a direct relationship between water consumption and climate conditions measured 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 using climate change projections developed by reputed external agencies.

We have decided to confirm our draft decision 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 data set (Marsden Jacob Associates 2021b). Box 4.1 outlines the steps we will apply to develop future climate scenarios in the next price investigation.

Box 4.1 Steps 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.

We will apply the following process to develop future climate scenarios.

1. We will consider historical data on rainfall, evaporation and temperature that are available from 1965. These data will be split into successive time periods of equal length, which will depend on the forecast period. For example, if forecasts are produced for 6.5 years—from January 2022 to June 2028—to account for the investigation period and the regulatory period, the historical data would be split into 50 overlapping periods of 6.5 years each.

2. To develop future climate scenarios for temperature, rainfall and evaporation, we will use all 12 future climate change scenarios developed by NARCLiM. NARCLiM develops 12 separate regional climate projections for south-east Australia, including the ACT, that span a range of likely future changes in climate. For each NARCLiM scenario, the average impact on rainfall, temperature and evaporation by season will be calculated (this impact is called the 'adjustment factor'). Further detail on how adjustment factors are calculated is discussed below and in appendix 2.

3. For any given NARCLiM scenario, the relevant adjustment factor will be applied to the historical climate data for the time periods in step 1. This process will adjust rainfall, evaporation and temperature data for each time period to produce distinct sets of weather forecasts—one for each time period. Each distinct set of weather forecasts will be used with other explanatory variables to produce dam abstraction forecasts for that period. This forecasting process will be repeated for each time period established in step 1. The average of the forecasts across all the time periods will be taken to produce the demand forecast for a given NARCLiM scenario.

4. Step 3 will be repeated for all 12 NARCLiM scenarios. We will take the average of the forecasts for the 12 scenarios because it is not possible to accurately predict the actual climate conditions.

Our preferred climate change projections data source is NARCLiM

We compared the 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 2006 to 2099	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 the 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 the 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 provide broader geographic coverage.

Using NARCLiM will ensure consistency in developing future climate scenarios for all three climate variables—temperature, rainfall and evaporation. 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 that we use.

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 of our approach. In comparison, the SEACI data source was developed in 2012 and is now 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.

Stakeholders identified different data sources for developing future climate scenarios in their submission to the issues paper

Icon Water supported using the NARCLiM data set 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 considered 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 set, 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 final decision, we have made specific improvements to the model, such as 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 is more suited to our needs.

Professor White also said that the current 6% deadband is conservative and that it should be increased. Consideration of the 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.

Icon Water's response to the draft report

Icon Water commented on two issues relating to the application of NARCLiM data: calculation of adjustment factors and their application to develop future climate scenarios.

Calculation of adjustment factors

The SEACI data set produces an average projected change in climate variables. NARCLiM gives projections of weather variables; it does not give the projected 'change' in weather variables, which must be calculated.

The NARCLiM data set produces projections of weather variables for over 100 years (from 2006 to 2099) which have been developed based on a historical baseline data from 1951 to 2005. For the NARCLiM data set, the projected change (adjustment factor) can be calculated by calculating the difference between the projections and the historical baseline data.

In its submission to the draft report, Icon Water suggested using projections data for a 20-year period from January 2016 to December 2035, so the period is centred around the 2023–28 regulatory period. We consider this suggestion incorporates the principle in our draft report to align the projections period with the regulatory period. It is also an improvement over the suggestion Icon Water made in response to the issues paper to use projections data from 2020 to 2039, which would have included projections for a period further away from the regulatory period. Our consultant's view is also to include a longer projections period centred around the regulatory period for estimating the projected change. We have decided to accept this suggestion.

Icon Water observed that there is a mismatch between the periods of the NARCLiM historical climate data (1951 to 2005) and the historical data used in our demand model (1965 to 2021). Icon Water suggested using NARCLiM historical data from 1965, so the start years are aligned. Because NARCLiM historical data does not cover the period 2006 to 2021, Icon Water suggested adjusting the NARCLiM historical data to account for the difference in mean climate data between the observed 1965 to 2005 period and the 1965 to 2021 period. We consider the suggestion made by Icon Water will ensure the NARCLiM adjustment factors are calculated based on a like-for-like historical periods, and we have decided to accept it.

We will calculate NARCLiM adjustment factors by comparing average projections data from 2016 to 2035 against average historical mean-adjusted data from 1965 to 2021. Because the mean-adjusted NARCLiM data will already capture any pre-existing trends, the NARCLiM adjustment factors are in addition to any pre-existing trends.

Application of NARCLiM adjustment factors

For a given NARCLiM scenario, the relevant adjustment factor will be applied to the historical climate variables data as outlined in box 4.1.

Icon Water suggested removing the climate change trend from the historical climate data in the demand model before applying the NARCLiM adjustment factors. Icon Water's view is that if the historical data are not de-trended then the climate change trend will be double counted, first in the NARCliM adjustments and again in the actual historical data.

We do not agree with Icon Water's comment. As noted above, NARCLiM adjustment factors are in addition to any pre-existing trends that may be present in the historical data. Therefore, there is no need to de-trend the actual historical data used in the demand model. We note that in the last price investigation that used SEACI adjustment factors, no de-trending of the historical data was done in the demand model.

In its response to the draft report, Icon Water outlined a series of steps that will require producing 50 forecasts for each climate scenario—600 forecasts in total. The process involves averaging the outputs of the forecast model for a given climate scenario. Icon Water submits that those number of forecasts are required to preserve climate variability. We proposed in our draft report an alternative process which had the advantage of simplicity as it would have required producing 1 forecast for each NARCLiM scenario—12 forecasts in total. The alternative process was based on averaging the climate data for a given scenario.

Our consultant's analysis found the process outlined by Icon Water produced better results. Although it involves running about 50 forecasts for each climate scenario, it will capture the effect of the trends or cycles in weather conditions and the extreme weather events. On the contrary, averaging the climate input data over 50 periods, under the alternative process, will smooth out the most extreme variations in weather, which could distort the forecasts. Therefore, we have decided to accept the process Icon Water submitted in response to the draft report, which is also outlined in box 4.1.

The process outlined in box 4.1 requires averaging about 50 forecasts for a given climate scenario. We have decided to use a weighted average of those forecasts where higher weight is given to forecasts based on the most recent period of climate data. Because there would be pre-existing trends in the historical data, our consultant's analysis shows that giving higher weight to more recent data will capture that trend better, compared to taking a simple average across all data periods.

Sustainable diversion limit

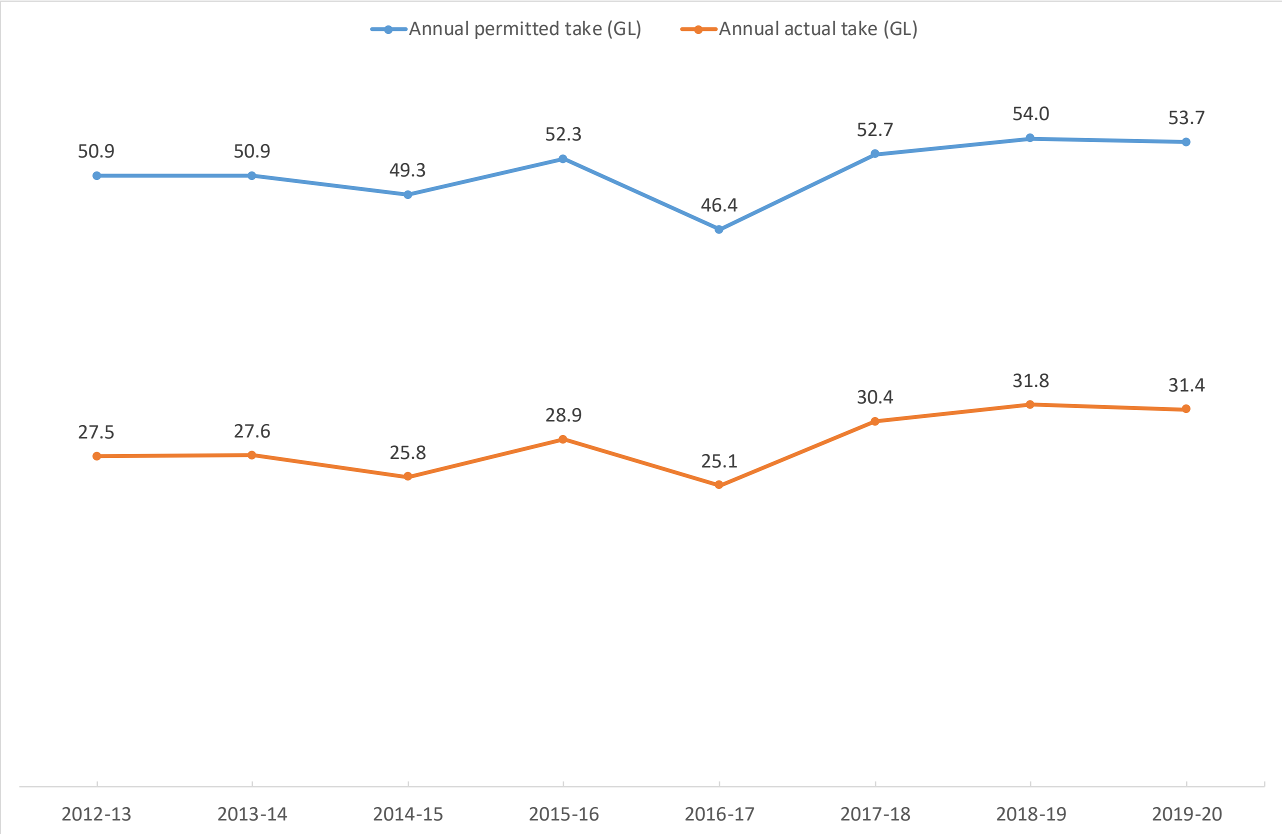
We have developed principles for adjusting the model output and will consider them in the next price investigation

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.

In our draft report, we developed principles for when we would adjust the output of the model (box 4.2). We have decided to confirm them and will consider them in the next price investigation, for example, to review the impact of any changes in the SDL on water demand.

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 how they are implemented, the specific details of the policy and how the policy will impact water demand. If details around the policy are uncertain, it can be difficult to incorporate its 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 consider the post-model adjustment principles to review the impact of any changes to the SDL

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 changes to the limits and the availability of new information such as actual water use figures. We have decided to confirm our draft decision that we will review the impact of any changes to the 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

In its response to our issues paper, 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 (Icon Water 2021a).

In its response to our draft report, Icon Water supported applying post-model adjustment such as potential changes to the SDL (Icon Water 2021b).

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 have decided to confirm our draft decision to continue to use data from 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 than it had before restrictions. A new relationship between water sales and climate variables developed in about July 2006 and has remained stable since then (ICRC 2015). Icon Water agreed with this conclusion in its 2018 submission (Icon Water 2018). Therefore, we use data from 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.
- Consumption trends showed that water restrictions had changed consumer habits when they were re-introduced and these behaviours have 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.

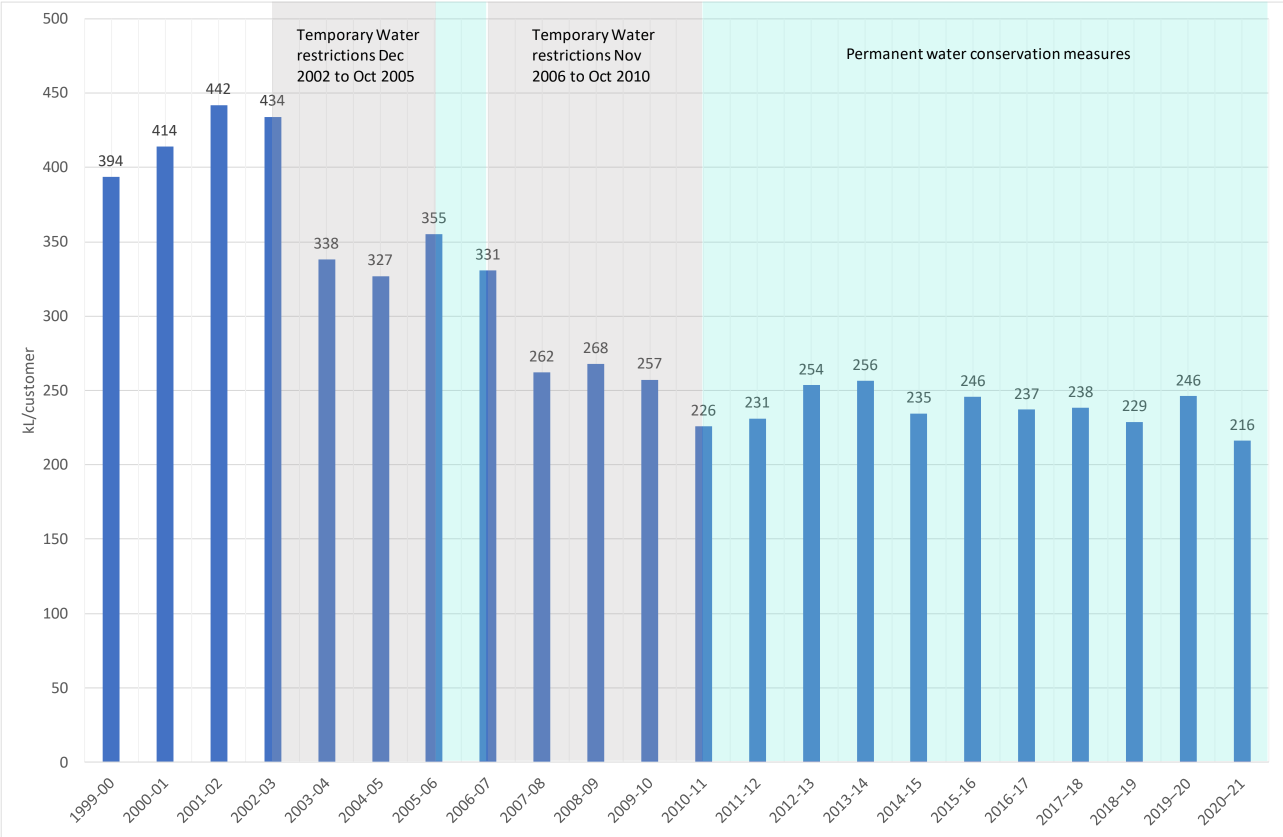
The first occurred after 2002-03 when temporary water restrictions were first introduced.

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

In its response to our issues paper, Icon Water submitted 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 2021a). 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.

In the existing forecasting model, future customer numbers are estimated based on past growth trends in customer numbers. We have decided to confirm our draft decision 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 observing past trends.

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). In the next price investigation, we will check to ensure that the ACT population projections that are used account for the impact of the COVID-19 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 estimates

The current approach of extrapolating past 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 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 this year.[2] We will monitor this development to ensure that the ACT population projections we use account for the impact of the pandemic. If ACT Government's updated population projections are not available for the next water price investigation, we will consider projections developed by the Australian Government's Centre for Population Studies that our consultant noted is an alternative data source.

Icon Water supports the current approach

In its response to our issues paper, Icon Water stated a preference for continuing to use water connection numbers in the ARIMA model as a proxy for population (Icon Water 2021a).

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.

In its response to our draft report, Icon Water supports using ACT population projections, rather than historical trends, to forecast future connection numbers (Icon Water 2021b).

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 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.

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

The ACT Government population projections[3] released in January 2019 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.

The ACT Government is seeking to update the ACT's population projections to account for the impact of the COVID-19 pandemic.

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 its 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.

In its response to our issues paper, Icon Water agreed 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 considered that the change in demand forecasts due to the 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 have decided to confirm our draft decision that that the current approach, where the model is updated to account for more recent data, is appropriate.

Variability of model outputs and data frequency

We will use weekly observations to forecast dam abstractions

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

We have decided to confirm our draft decision to use weekly data to forecast dam abstractions. In its stage 3 report, our consultant has confirmed the finding from its stage 2 report that using weekly data improved 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 forecasting 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.

Weekly data improves model performance

Our consultant's analysis in stage 3 report shows that a model based on weekly data performs better than daily data and monthly data.

[3] ACT Population Projection: 2018 to 2058

Our consultant compared the forecasting accuracy of the current daily data form of model with a form of model based on weekly and monthly observations. In its stage 3 report, the consultant used the optimal form of the weekly and monthly models that were selected after applying statistical tests and refinements. Like its stage 2 report, the consultant also considered additional variables to better capture extreme weather conditions, for example, number of days where daily temperature exceeded 30 degrees within the 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. Adding extra weather variables further improved the performance of the weekly data model.
- With monthly data, forecasting accuracy improved compared to daily data, and improved further when extra weather variables are added into the model. However, the weekly data model outperformed the monthly data model .

The data in Table 4.4 show that when using weekly data (in the augmented model), the difference between the annual forecast and actual volume was the lowest, at: 1.5% to 1.6% on average (lower difference means better performance). This contrasts with daily data where the average difference was the highest: 3.7% to 4.3% on average. The monthly data was in the middle with an average difference of 2.1% to 3.0%.

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%	1.59%	**1.51%**	2.38%	2.10%
RMSPE	4.27%	4.19%	1.64%	**1.59%**	2.96%	2.67%

Source: Marsden Jacob Associates (2021c)

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

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 10.91: it shows that for every additional day when daily temperature exceeded 30°C, dam abstractions increase on average by 11ML, 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 28.89: it means that for every additional day when daily temperature exceeded 35°C, dam abstractions increased on average by 29ML, 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 final model form, rainfall is included in linear form (amount of rainfall) and non-linear form (square root value of the amount of rainfall). In such cases, the effect of rainfall on dam abstractions is considered by looking at the coefficient estimates for the linear and non-linear forms as well as the amount of rainfall. The consultant's analysis shows that the relationship between dam abstractions and rainfall is like a U-shape: as rainfall increases, dam abstractions decrease but this decrease is less than proportionate.

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

Why weekly data performs better than daily data in forecasting over longer horizons

The demand forecasting model is used to produce forecasts over longer period (5 years). The model establishes the relationship between dam abstractions and climate by capturing the effect of the trends or cycles in weather conditions (like seasonal changes which will be evident over longer period) and the extreme weather events.

However, the nature of daily observations is that they give weight to factors that are irrelevant over a longer horizon. For example, they require considering the water consumption habits of customers on a day-to-day basis (such as using more water on the weekends than weekdays), which are not relevant to forecasting dam abstractions over a longer time span. They may also be affected by day-to-day variability in weather conditions, which may not represent trends or cycles in weather conditions. The information in daily data that is not relevant for longer term forecasting adds noise, which introduces statistical errors in estimating the relationship.

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

As noted above, the noise in daily observations introduces a degree of error in the forecasting process for models based on daily observations. These errors compound over time, meaning that the longer the forecast horizon, the greater the compounding error effect from daily observations.

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

To illustrate this point, we considered actual daily observations for temperature and dam abstractions for 3 years (2018-19 to 2020-21). For each day, we took an average of the observations for that day across the 3 years. The average of daily temperature and daily dam abstractions are shown on the left side in Figure 7. The average of weekly temperature and weekly dam abstractions are shown on the right side in Figure 7.

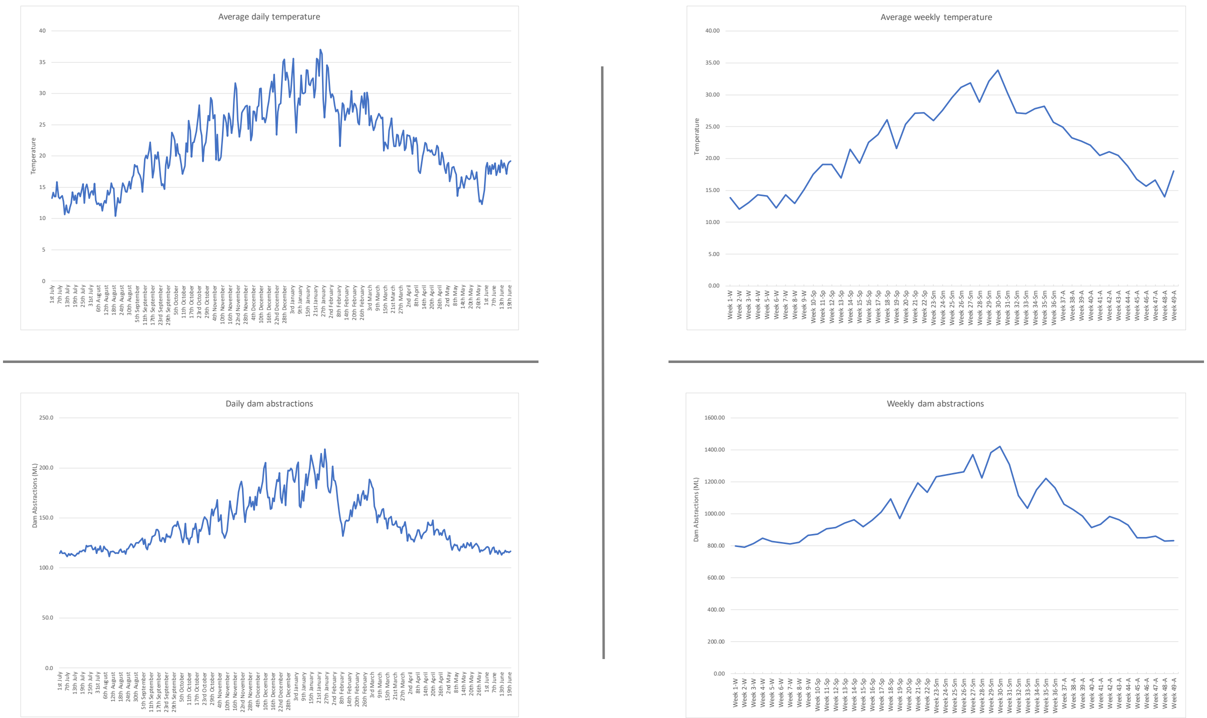
There are three points to note.

One, there is a seasonal trend in temperature and dam abstractions—average temperature rises from winter to spring to summer, then falls from summer to autumn. Dam abstractions show the same trend. This trend is more evident in the weekly data.

Two, daily data show the seasonal trend but there is also a lot of day-to-day variability in temperature, which is averaged out in the weekly data. The daily data model will give more weight to the day-to-day variability (the noise); therefore, it is less likely to identify the seasonal trend.

Three, the day of the week effect (weekends vs weekdays) is not evident from the figure but what is evident is the seasonal trend in water use. So, more important for longer term forecasting is the effect of trends or cycles in weather conditions on water demand and for that the weekly data model is more appropriate.

Figure 7. Comparison of daily and weekly observations



Source: our analysis based on data from Icon Water

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 means that 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, adding new variables may increase the complexity of the model.

Icon Water's view on data frequency

In its submission to our issues paper, Icon Water submitted that it was not aware of any evidence that using lower-frequency data would improve the predictive ability of the ARIMA model (Icon Water 2021a). It expressed concern that using monthly data would require significant effort to recalibrate the model to identify the best-fit model specification.

Our draft report noted that 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. In this final report, our consultant has done the model refinement and statistical testing to identify optimal form of the model.

In its submission to our draft report, Icon Water made several comments on using weekly data rather than daily data (Icon Water 2021b).

First, Icon Water considers that 'large data sets are better to capture the statistical relationship between water use and climate'.

We don't agree with Icon Water's argument. As shown by the illustration in Figure 7, although the daily data model has 7 times more observations than the weekly data model, there are statistical issues with using the daily data model. It gives more weight to the day-to-day variability in temperature and estimates more parameters (7 additional parameters for each day of the week). This can make it harder for daily data to capture the effect of trends or cycles in weather conditions on water demand. The weekly data model can better capture those patterns and cycles, which are relevant to forecasting dam abstractions over a longer horizon. Our consultant's stage 2 report provides theoretical arguments to show why daily observations may not be appropriate for forecasting over a longer time span (Marsden Jacob Associates 2021b).

Second, Icon Water argues that because of data aggregation the weekly data model will not capture the effect of intra-week variation in weather conditions on water demand. We accept that using weekly data will not capture intra-week variations in weather conditions but, as explained above, most intra-week variations create noise rather than improving the predictive ability of the model. However, there are some extreme intra-week weather events that we agree are important to capture because they can have a significant impact on overall water demand, not just the timing of water use across the week.

Our draft report proposed using additional explanatory variables to ensure the weekly data model captures the effect of intra-week extreme weather conditions on water demand. For example, including variables to capture the effect on water demand of the 'number of days where daily temperature exceeded 30°C or 35°C in a week' and the 'number of days without rain in a week'. We consider including these additional variables is a better way to account for the effect of extreme weather conditions in a week. They are better than capturing day of the week effect, which are not relevant to forecasting dam abstractions over longer horizon.

In our draft report, our consultant compared the forecasting performance of different models by using well-established measures of accuracy, such as the Root Mean Squared Percentage Error (RMSPE) and the

Mean Absolute Percent Error (MAPE). However, Icon Water questioned the validity of these measures for comparing models with different data frequency.

Since the models selected for comparison analyse data with different time frequency (daily, weekly and monthly), the consultant computed the above statistical measures based on the difference between the *yearly* forecast and the *yearly* actual values. This was done to ensure that the comparison among forecasting models with different time frequency is fair and objective. We consider this approach ensures these measures remain valid for comparing the performance of different models.

Our consultant has used data from July 2018 to June 2021 to evaluate different model forms and to finalise the optimal model specification. For this period, the consultant used actual weather variables to focus the analysis on model uncertainty rather than climate uncertainty. Icon Water has submitted that this period was unusual because there were 2 years of below-average rainfall and 1 year of above-average rainfall. We don't agree with Icon Water's argument because we consider the model specification that shows better predictive ability under varying climate conditions will be the best 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 made improvements to aspects of the forecasting model to better account for weather-related variability.

Our final decision on the form of the ARIMA Model

Table 4.5 summarises our final 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. The final statistical form of the model is in appendix 2.

Table 4.5 Summary of variables to be used under our final 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; separate variables for summer season and December month.
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.

Choice of statistical software

In the last investigation, the demand model was run using R, which is a free and open-source software. But it requires specialised programming skills which is a barrier to using and understanding R.

In the next price investigation, we will use Stata (a proprietary statistical software package) to run the demand model. Stata is widely used by statistical practitioners across government, industry and academia. Because it is simpler to use, Stata will be more accessible and transparent.

It is important to emphasise that the demand forecasts are determined by the methods and data inputs, and not by the choice of a statistical tool. For example, whether you use a calculator or an excel spreadsheet to do a given calculation, you will get the same result, but the time and effort required is different.

In its submission to our draft report, Icon Water said that using Stata will impose additional regulatory costs on both Icon Water and the Commission ($1200 per year for a 1-user licence). But this argument does not account for the indirect costs in the time required to use R compared to that required to use Stata. Because it is user-friendly and simpler to use, the time saved in using Stata will offset the cost of purchasing the Stata software.

Icon Water said that the demand methodologies should not be prescriptive of the software to be used. We consider it is open to stakeholders to use an alternative statistical software. We will publish a user manual on our website to make it easier for stakeholders that wish to use Stata to run the demand model. That manual will outline in simple English the steps to run the model, which has been difficult with R because the steps are coded in programming language. The manual will also make it easier for stakeholders that want to use different software to program the model into their own software.

5. Forecasting other demand components

This chapter discusses our final 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 final decisions

We have decided to confirm our 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 will 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

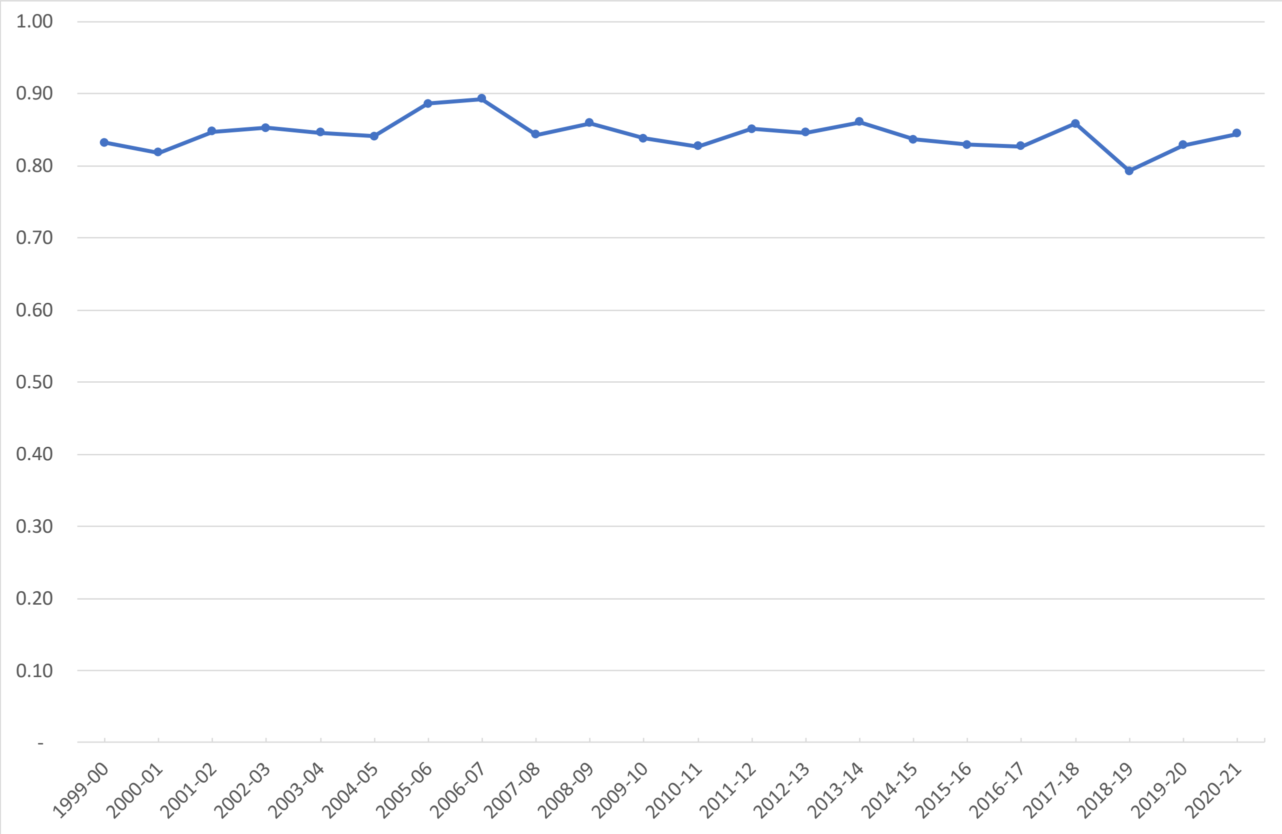
We have decided to confirm our draft decision to retain the current method to forecast total ACT water sales based on the historical shares of dam abstractions sold to ACT consumers. Box 5.1 outlines the current method.

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 8). The balance of water abstractions is accounted for by Queanbeyan consumption and water losses due to leaking pipes, theft, and metering errors.

Figure 8. Ratio of annual ACT water sales to annual dam abstractions

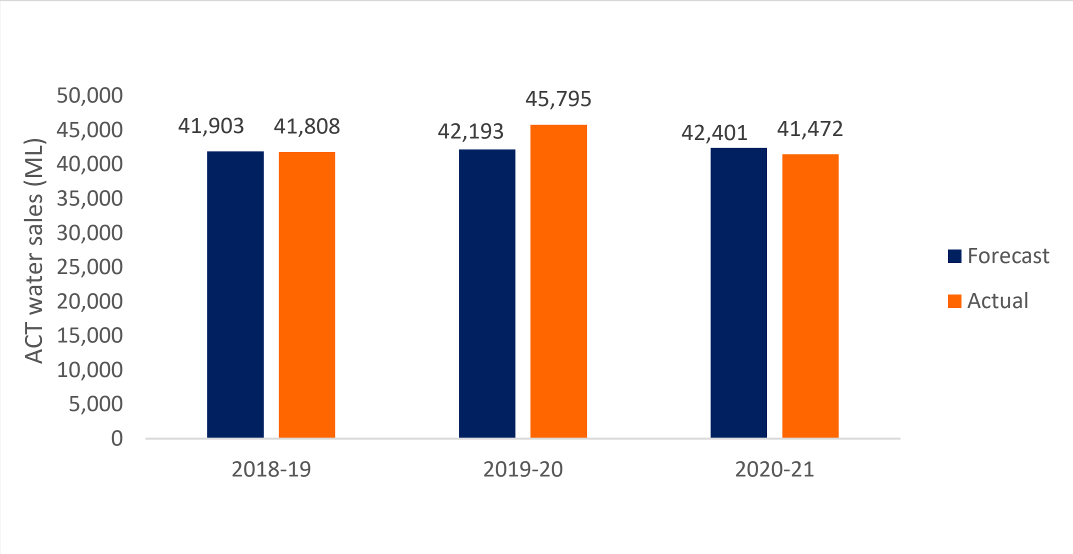


Source: our analysis based on Icon Water data

The current method produces reliable forecasts

In our draft report, 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 9 shows the forecast and actual ACT water sales for the first three years of the current regulatory period.

Figure 9. 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.

We have decided to confirm our draft decision to add more recent years' data to the existing dataset for the next water price investigation. 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

In its submission to our issues paper, Icon Water considered that the current method for estimating ACT water sales should be retained because it produces reliable forecasts (Icon Water 2021a). Icon Water supported our draft decision (Icon Water 2021b).

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.

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

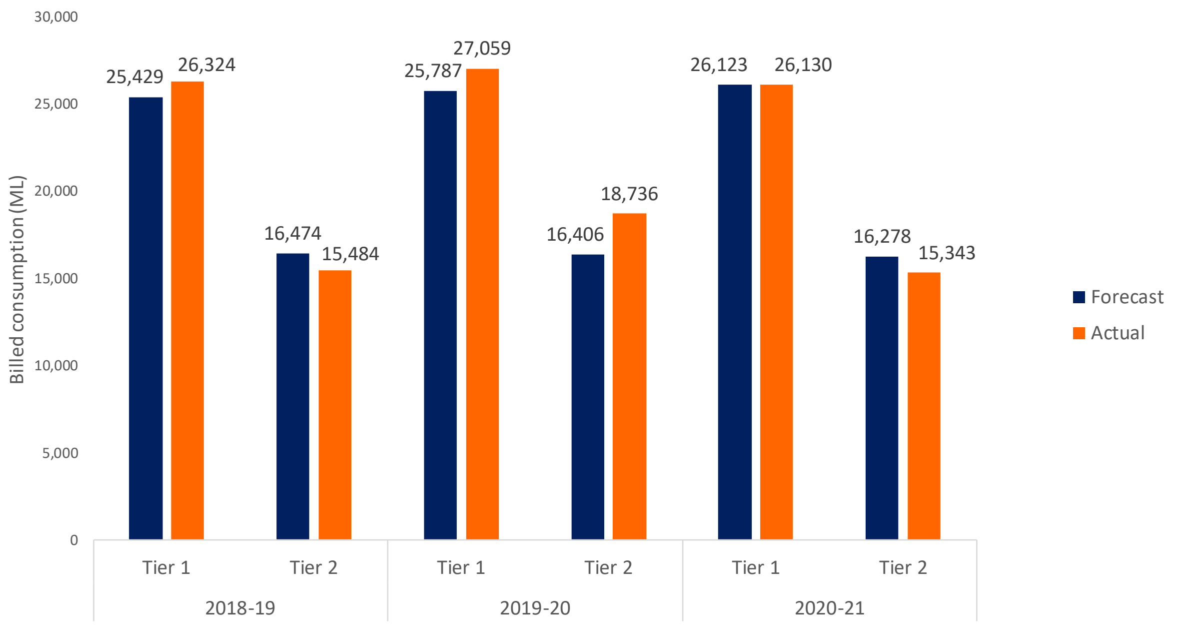
We have decided to confirm our draft decision to retain the current method to split ACT water sales into Tier 1 and Tier 2 by first separately forecasting Tier 1 sales, and then forecasting Tier 2 sales as the difference between total ACT water sales and the Tier 1 sales forecast. We will also retain 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.

In our draft report, we compared Tier 1 and Tier 2 sales forecasts in our 2018 water price investigation with the 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 10 shows the comparison between the forecast and actual Tier 1 and Tier 2 sales for the first three years of the regulatory period.

Figure 10. 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 have decided to confirm our draft decision to 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 that was available for this review.

Icon Water supports the current approach

In its submission to our issues paper, Icon Water supported the current method to split total ACT water sales into Tier 1 and Tier 2 categories. Icon Water suggested 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 2021a). Icon Water supported our draft decision (2021b).

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 the past growth trend to forecast connection numbers and billable fixtures

We have decided to confirm our draft decision to 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 this year.[5] We will monitor this development to ensure that the ACT population projections we use account for the impact of the pandemic. If ACT Government's updated population projections are not available for the next water price investigation, we will consider projections developed by the Australian Government's Centre for Population Studies that our consultant noted is an alternative data source. 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. We also found that the new method has a higher forecast accuracy compared to the current method (Table 5.1).

We therefore consider that forecasts based on ACT Government population projections will provide better data for forecasting connection numbers and billable fixtures.

We agree with Icon Water's suggested approach

In its submission to our issues paper, 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 2021a).

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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

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.

In our draft report, 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)

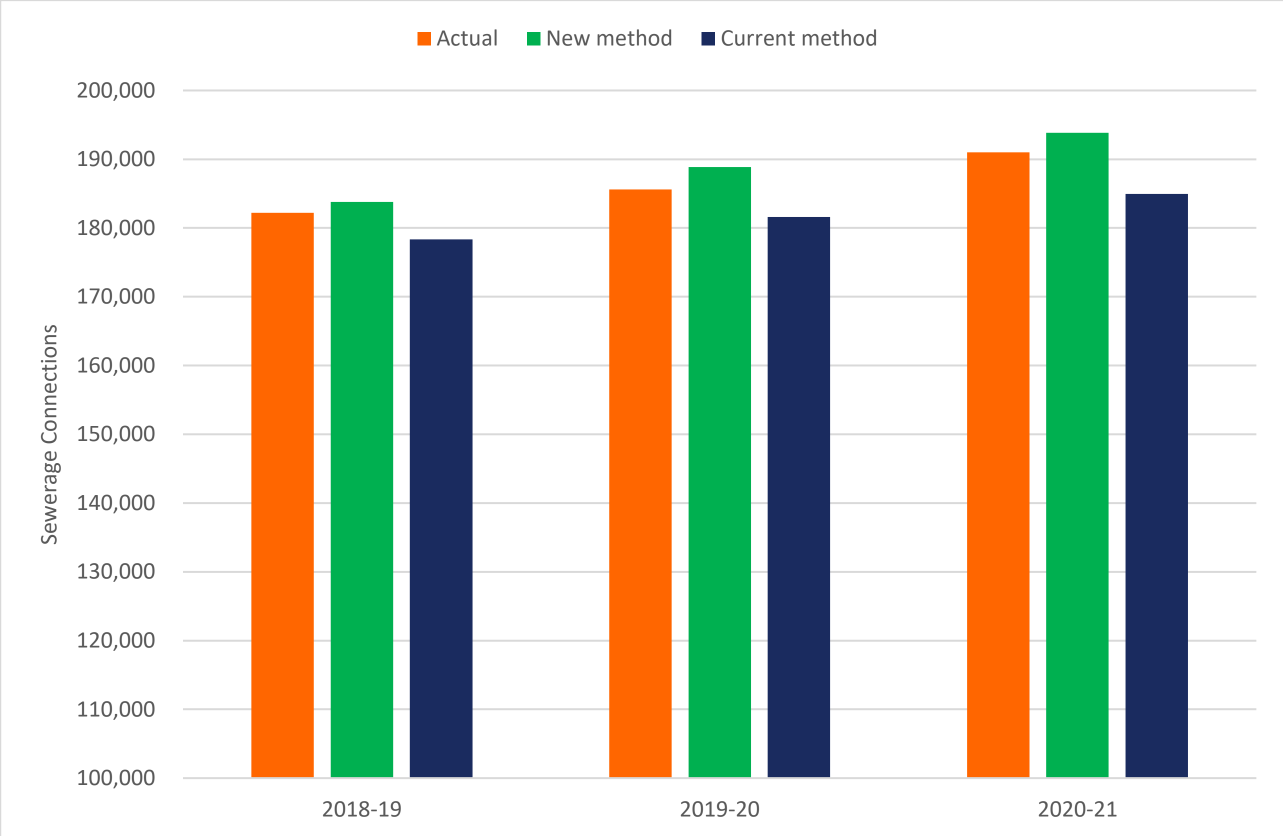
Notes: ‘minus -’ sign indicates the model underpredicts actual values and ‘plus +’ sign indicates the model overpredicts actual values.

Figures 11, 12 and 13 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 11. Water connection numbers: actual and forecast comparison

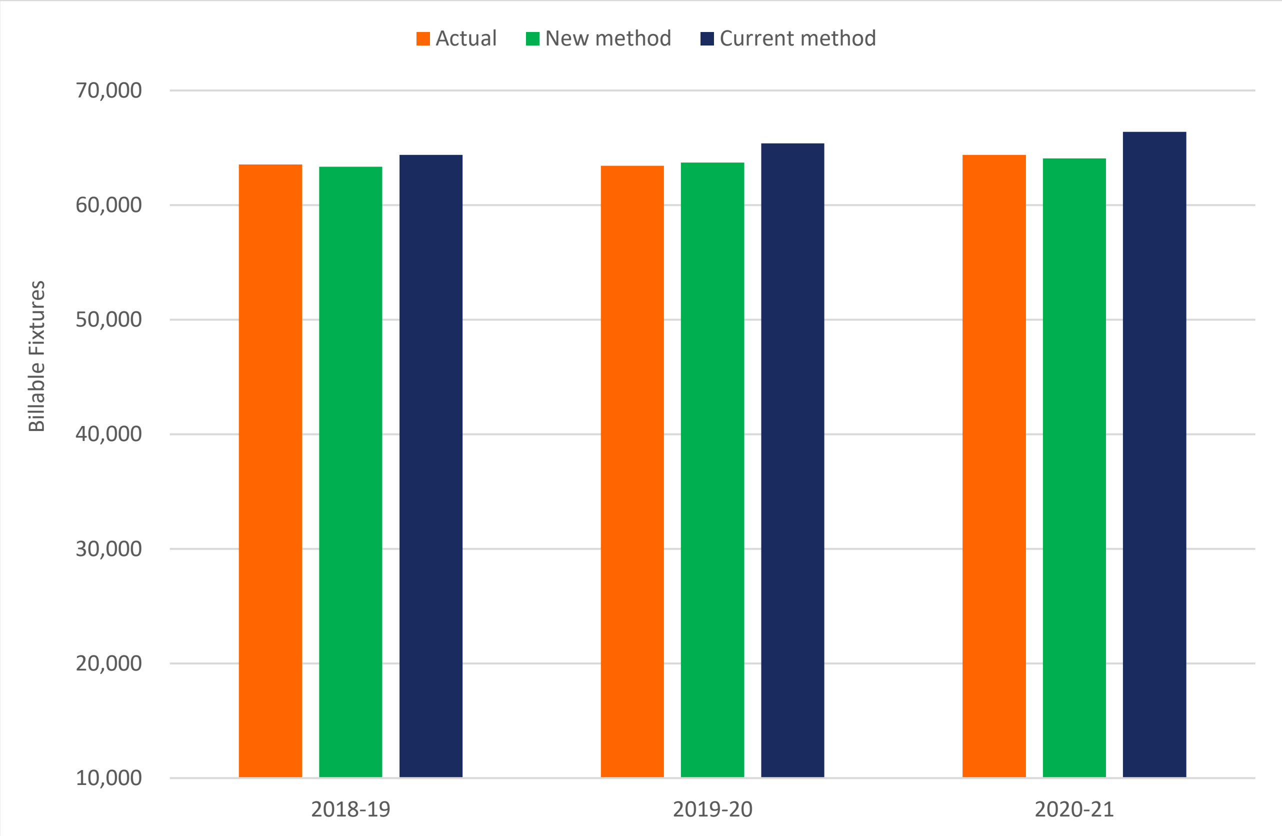
Source: our analysis based on data from Icon Water and ACT Government data (ACT Population Projections 2018 to 2058)

Figure 12. 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 13. 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

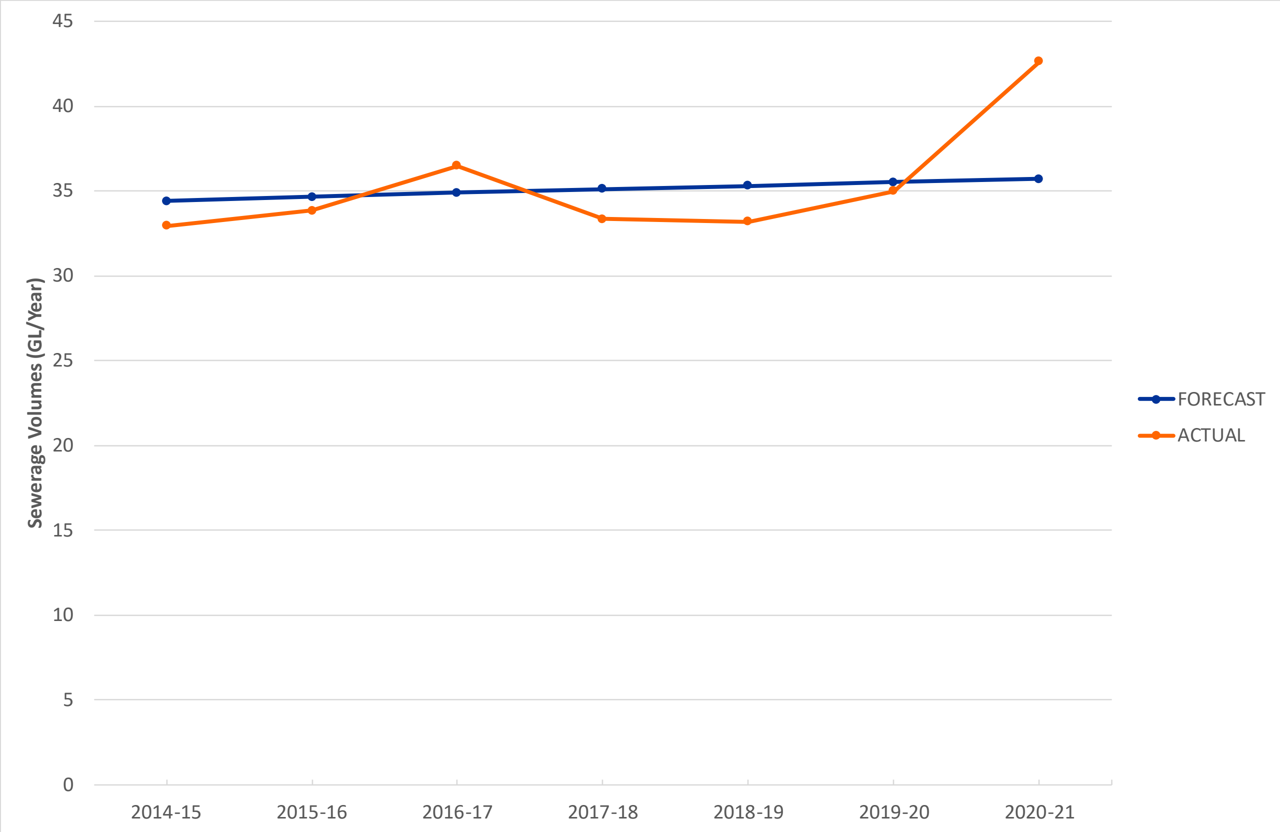
We will retain the current method to forecast sewage volumes

We have decided to confirm our draft decision 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 14). 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 14. Sewage volume: actuals and forecast comparison



Source: our analysis based on Icon Water data

Icon Water supports the current method

In its submission to our issues paper, Icon Water considered the current approach to forecast sewage volume is performing well and did not propose any changes (Icon Water 2021a).

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 scenarios 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 final decision form of forecasting model for dam abstractions

Form of the ARIMA model

Table A2.1 Final model specification

Variable	Description	Reasoning	Coefficient estimate
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.	0.78 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: 1.82 to 6.51 Squared: 0.04 These estimates show that dam abstractions increase in hot periods.
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)	Linear component: -3.79 to 11.15 Square root: -43.44 to -12.86 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: 31.03 to 46.38 These estimates show that total abstractions increase with higher levels of evaporation.

Variable	Description	Reasoning	Coefficient estimate
Customer numbers	Icon water customer connections at the end of a week	More customers will increase water demand, and will require more water abstractions	0.003 This estimate shows that increase in customers are related to more water abstractions.
Summer	Dummy variable for summer season (December to February)	To capture the effect of summer season on water demand.	16.98 (not statistically significant)
December	Dummy variable for December	Water demand in December is higher than other months in the ACT, likely due to high temperatures and summer holidays.	-15.62 (not statistically significant)
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.	10.91 to 28.89 This estimate shows extreme hot periods increase dam abstractions.
	• Number of days where rain exceeded 1mm	More days with high rainfall will result in less dam abstractions.	-14.89 This estimate shows that heavy rainfall period is related to lower dam abstractions.
	• Interaction effect between rainfall and evaporation	High levels of rainfall and low levels of evaporation is likely to be related to lower demand for water	-0.06 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 estimate shows a negative relationship with dam abstractions.
Sine function	These are included to account for seasonality (systematic, repetitive, periodic fluctuations in dam abstractions over the course of a week)		-21.27
Cosine function			-102.67

Variable	Description	Reasoning	Coefficient estimate
Moving average component	Forecast error of dam abstractions for the previous week (weeks)		-0.34 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 (2021c)

Estimated coefficients of the forecasting model

Variables	Coefficient	p-value	Sig.	Variables	Coefficient	p-value	Sig.
AR1	0.78	0.00	***	**Evap**	46.38	0.00	***
MA1	-0.34	0.00	***	**Evap1**	31.03	0.00	***
Intercept	77.40	0.38		**Temp_g30**	10.91	0.00	***
Temp0	6.51	0.00	***	**Temp_g35**	28.89	0.00	***
Temp3	2.30	0.02	**	**nudaysgeq1mm**	-14.88	0.00	***
Temp4	1.82	0.04	**	**Cumx**	-0.06	0.00	***
Temp_sq_lag2	0.043	0.025	**	**Summer**	16.98	0.12	
Rain0	-3.78	0.00	***	**December**	-15.62	0.17	
Rain1	11.15	0.00	***	**Cust**	0.003	0.00	***
Rain1sqrt	-43.44	0.00	***	**Sin**	-21.27	0.09	*
Rain2sqrt	-19.76	0.00	***	**Cosin**	-102.67	0.00	***
Rain3sqrt	-12.86	0.00	***				
BIC	6858.31			**AIC**	6751.88		

Note: '*', '**' and '***' indicate statistically significant coefficients using the 10%, 5% and 1% level of significance, respectively. Temp0 denotes the value of average maximum temperature at week t, Temp3 denotes the value of average maximum temperature at week t-3, and so one for the remaining variables.

Source: Marsden Jacob Associates (2021c)

Description of variables in the optimal weekly data model

- Dam release data for the previous week (this is the AR1 component)
- Forecast error of dam releases for the previous week (MA1)
- Average value of daily maximum temperatures (degrees Celsius) during week *t* (temp0, temp3, temp4, where temp0 denotes average maximum temperature for the latest week, temp3 denotes average maximum temperature for 3 weeks prior, and so on)
- Square root of daily maximum temperature for 2 weeks prior (Temp_sq_lag2)
- Average daily rainfall (mm) during a week (rain0, rain1, where rain0 denotes average daily rainfall for the latest week, and rain1 denotes average daily rainfall for 1 week prior)

- Square root of rainfall data (rain1sqrt, rain2sqrt, rain3sqrt, where rain1sqrt denotes the square root of average daily rainfall for 1 week prior and so on)
- Average daily evaporation during a week (evap0, evap1, where evap0 denotes average daily evaporation for the latest week, and evap1 denotes average daily evaporation for 1 week prior)
- Icon water customer connections at the end of a week (cust)
- number of days where daily temperature exceeded 30 °C during the previous week (*temp_g30*);
- number of days where daily temperature exceeded 35 °C during the previous week (*temp_g35*);
- number of days where rain exceeded 1 mm during the previous week (*nudaysgeq1mm*);
- binary variables that take the value of 1 if the first day of a week belongs to summer and December, respectively, and zero otherwise (Summer, December)
- The Fourier terms are computed based on the following formula:

$$F_t = \rho_1 sin\left(\frac{2\pi t}{52}\right) + \rho_2 cos\left(\frac{2\pi t}{52}\right),$$

When it comes to the Fourier terms, in the weekly model, the optimal choice of J is $J = 1$. Therefore, in the above equation $F_t(\boldsymbol{\rho}) = \rho_1 sin\left(\frac{2\pi t}{n}\right) + \rho_2 cos\left(\frac{2\pi t}{n}\right)$, where $\rho_1 \equiv \rho_{1,1}$ and $\rho_2 \equiv \rho_{2,1}$.

Climate scenarios and data used in the model

We will develop future climate scenarios and produce forecasts of dam abstractions as follows.

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

Second, historical data will be divided into a series of overlapping periods of equal length corresponding to the forecast period. For example, if forecasts are produced for 6.5 years—from January 2022 to June 2028—to account for the investigation period and the regulatory period, the historical data would be split into 50 overlapping periods of 6.5 years each.[6]

Third, for any given NARCLiM climate scenario (out of a total of 12), we compute the adjustment factors and apply those to all 50 overlapping periods, thus producing 50 distinct sets of weather forecasts for each scenario.

Fourth, out-of-sample predictions of total abstractions are obtained for each one of the 50 sets of weather forecasts, using dynamic forecasting based on the ARIMA model.

Fifth, we will average those out-of-sample predictions across all 50 sets of weather forecasts, to produce demand forecasts for the chosen NARCLiM scenario. We will use a weighted average by assigning the largest weight to the forecast based on the most recent period and the smallest weight to the earliest period. The weight for period 1 is 1/[n(n + 1)/2], period 2 is 2/[n(n + 1)/2] and so on to period 50 which has the weight of 50/[n(n + 1)/2], where ‘n’ is the number of overlapping periods.

6 Overlapping periods are determined by counting the number of successive periods of 6.5 years length from July 1965 to June 2021. So, first 6.5-year period is from 1 January 1966 to 30 June 1972, second 6.5-year period is from 1 January 1967 to 30 June 1973, and so on, to the last 6.5-year period which is from 1 January 2015 to 30 June 2021.

Sixth, this procedure (steps three to five) is repeated across all 12 NARCLiM climate scenarios, giving rise to 12 different 'forecast averages', one for each NARCLiM climate scenario.

Seventh, we will take the average of the forecasts for the 12 scenarios because it is not possible to accurately predict the actual climate conditions.

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):[7]

- 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.

Approach to developing adjustment factors

Each NARCLiM scenario gives the average monthly rainfall and temperature projections. On evaporation, NARCLiM does not provide data for evaporation, but for evapotranspiration. On the other hand, long-term historical evapotranspiration data for ACT are not available; rather, only data on evaporation are available. The existing adjustment approach enables using evapotranspiration-based adjustment factors to historical evaporation data to develop future climate scenarios for evaporation.

We will 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 evapotranspiration. We will use 1965 as the start date to align with the start date of the historical data available for use in the demand model. Because actual weather data in demand model are up to 2021, we will adjust NARCLiM historical data to account for the difference in mean climate data between the observed 1965 to 2005 period and the 1965 to 2021 period. Average monthly values will be created for this adjusted Narclim historical data for the period (1965 to 2021) and then grouped to determine seasonal averages for the period.
2. We will use monthly projections from 2016 to 2035 i.e. 20-year projections centred on the regulatory period. Using the same process as step 1, seasonal averages will be determined for this period.
3. Adjustment factors are calculated as the percentage change between the seasonal values for the 2016-2035 period and the 1965-2021 period for rainfall and evapotranspiration, while the adjustment factor for temperature is taken as the difference.

7 Climate Data Portal (nsw.gov.au)

Forecast of water installation numbers

We need forecasts of water installation numbers to forecast dam abstractions. We will use ACT Government's population projections to forecast water installation numbers, as discussed in section 5.4 of this report. If these are not updated to account for the impact of COVID-19, we will consider projections developed by the Australian Government's Centre for Population Studies.

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 positive correlation between customer numbers and water demand. Data for actual customer numbers is provided by Icon Water.

A Fourier seasonal term

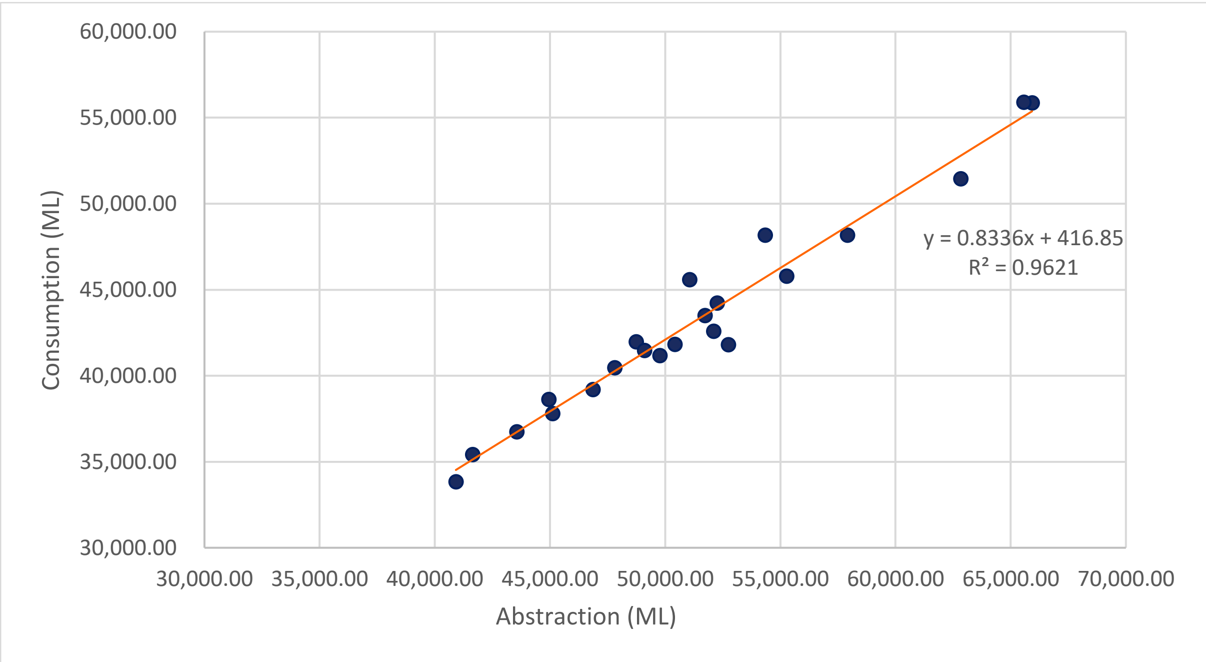
Adding a Fourier seasonal term to a forecasting model is a statistical technique used to incorporate annual regular and predictable changes in water demand to the forecasting model. Accuracy of forecasts can be improved by incorporating regular and predictable changes to the model. Data for a Fourier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

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

Total ACT water sales

Figure 15 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 15 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.

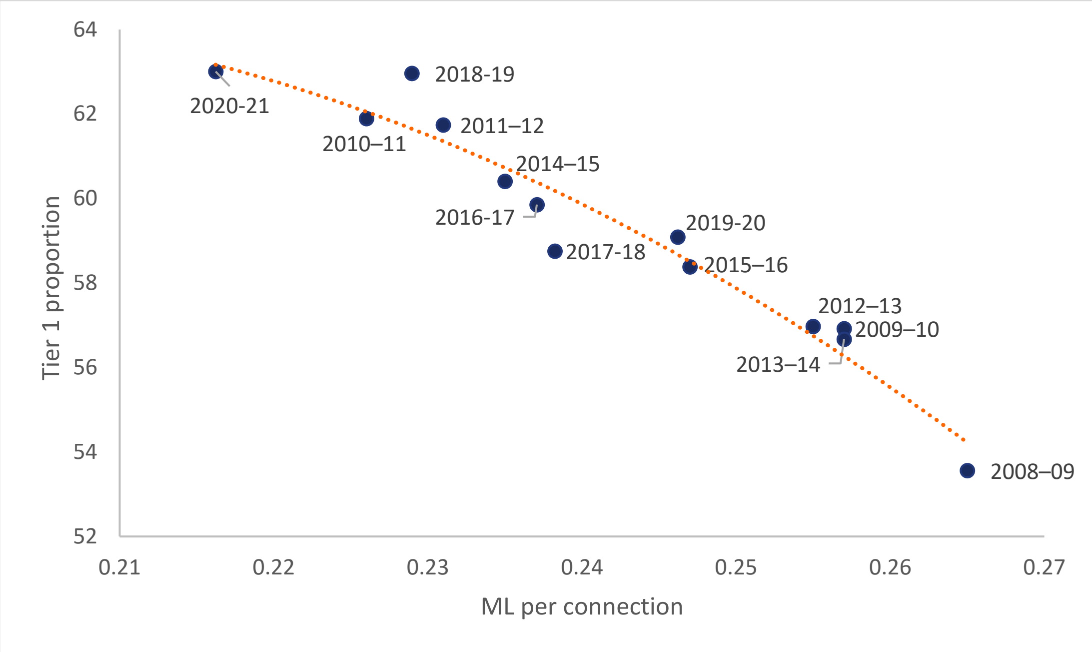
Table A3.1 Observed sales by Tier and connection numbers

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 16 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 equations 1 to 4 in the last investigation. Icon Water suggested that we assess the performance of a linear model as well (equation 5) (Icon Water 2021a).

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.

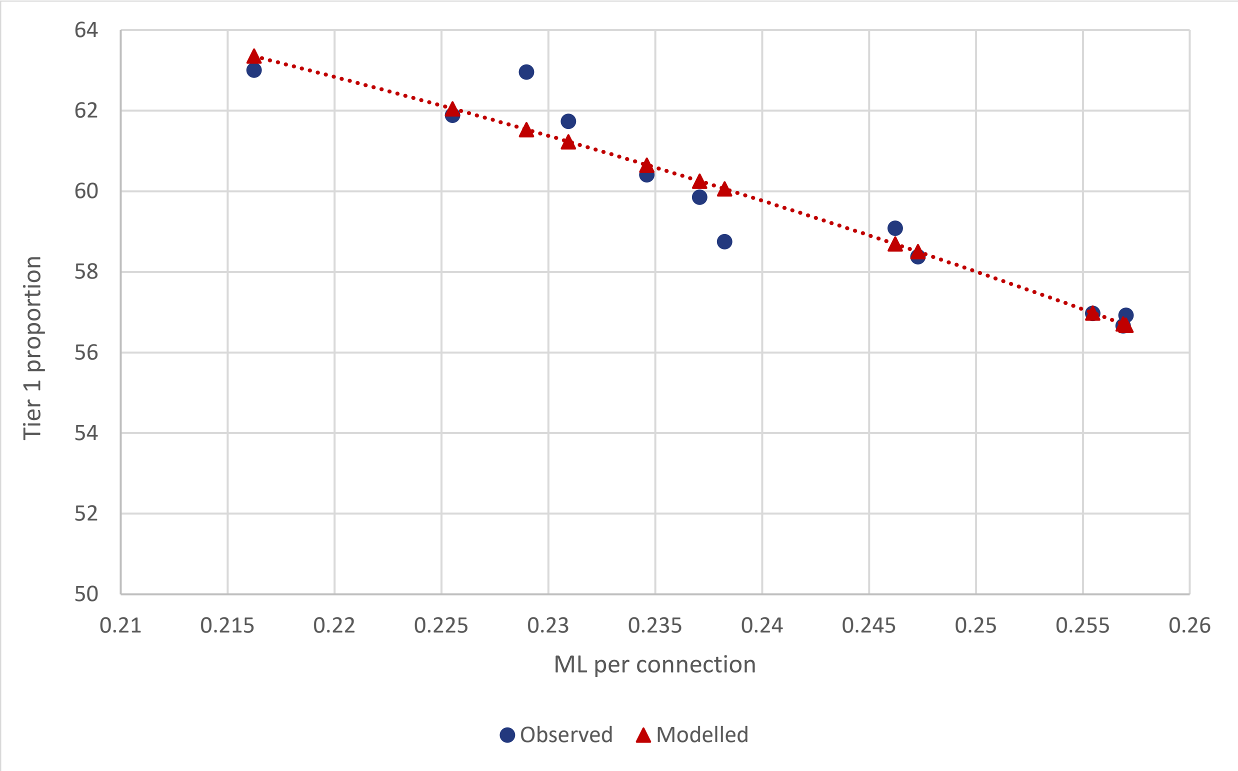
Table A3.3 Equation 4 parameter significance

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

Figure 17 Observed and modelled Tier 1 proportion



Source: our analysis based on data from Icon Water

Water connections, sewerage connections and billable fixtures

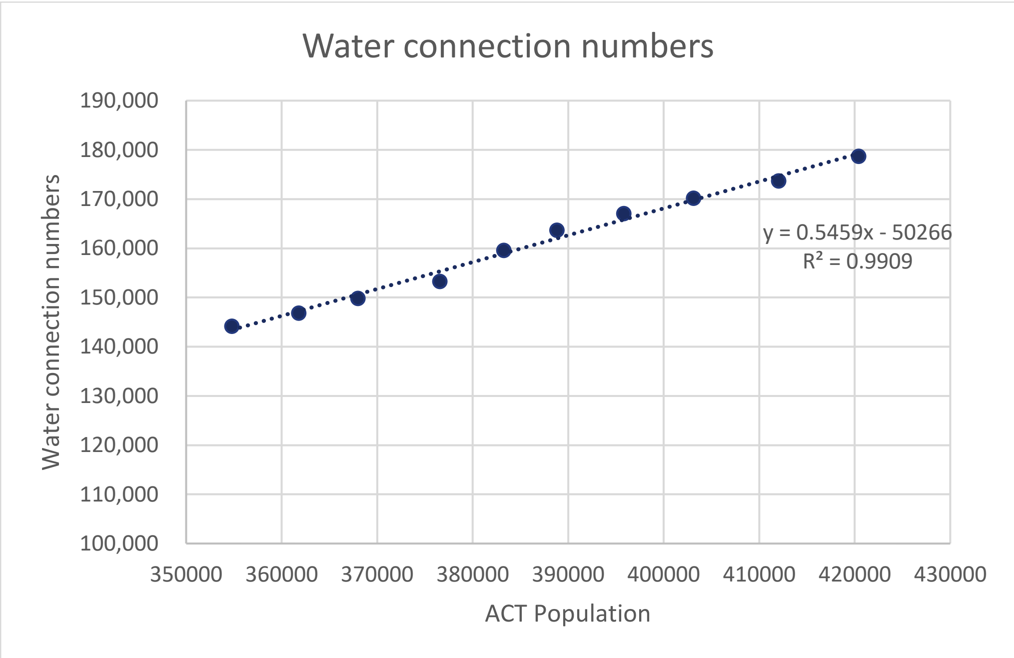
We will be changing the approach we use to forecast water and sewerage connection numbers and billable fixtures. We will be using the ACT Government population projections to forecast these variables. As noted in section 4.2 of this final report, the ACT Government's population projections are currently being updated to account for the effect of COVID-19, and the updated projections are expected to be published this year. We will monitor this development to ensure that the ACT population projections we use account for the impact of the pandemic. If ACT Government's updated population projections are not available for the next water price investigation, we will consider projections developed by the Australian Government's Centre for Population Studies that our consultant noted is an alternative data source.

We tested the approach using ACT Government's population data 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[8] and each of the three variables: water connection numbers, sewerage connection numbers and billable fixtures.

For this exercise, we modelled each relationship using a simple linear regression model. 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 had data. We then ran a simple linear regression model with population as the only explanatory variable. Figure 18 shows the result of the regression.

Figure 18 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)

For the next regulatory period, we will re-estimate this relationship using the latest data available to date and identify the linear regression model that best fits the data. Because there has been a recent decline in the rate of growth of ACT's population due to COVID-19, it is possible that another form of linear regression model may fit the data better (Marsden Jacob Associates 2021c).

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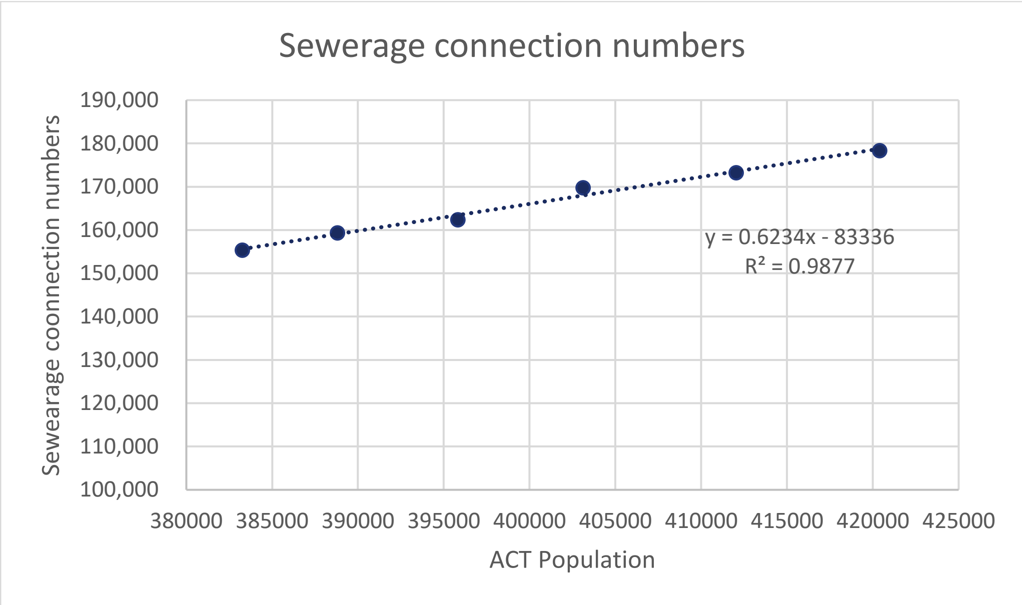
[8] Data source used for historical population data: [National, state and territory population, December 2020 | Australian Bureau of Statistics (abs.gov.au)]

To estimate the historical relationship between 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 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.

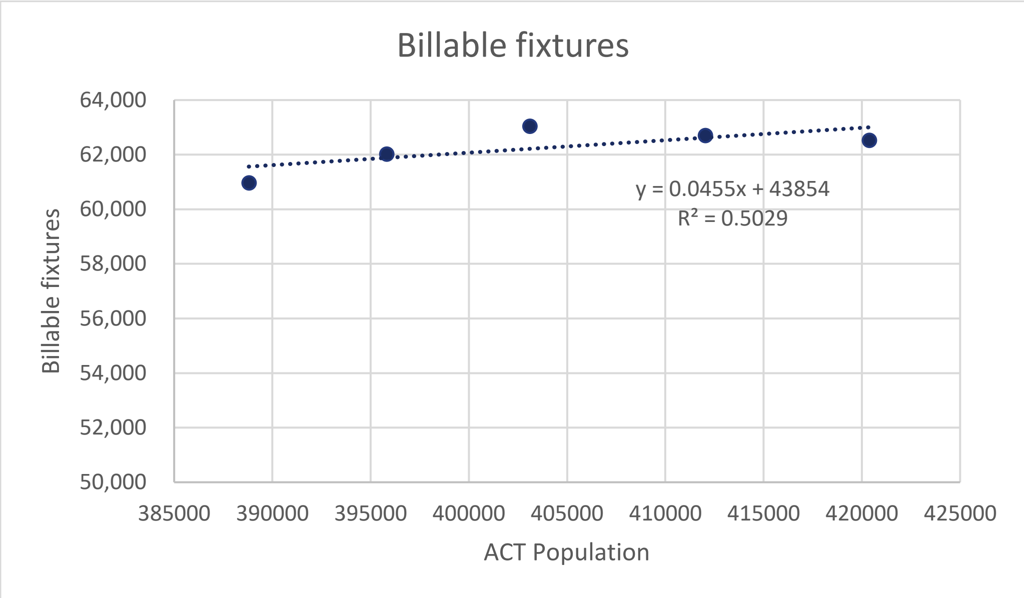
Figure 19 Relationship between ACT population and sewerage connection numbers (2012-13 to 2017-18)



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 20 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 20 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[9] 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)

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

Appendix 4 Consultant’s stage 3 report

[published separately with our final report]

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[10] 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)

[10] 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.

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 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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