Review of water and sewerage services demand forecasting methodology

Icon Water submission to ICRC Issues Paper

9 July 2021

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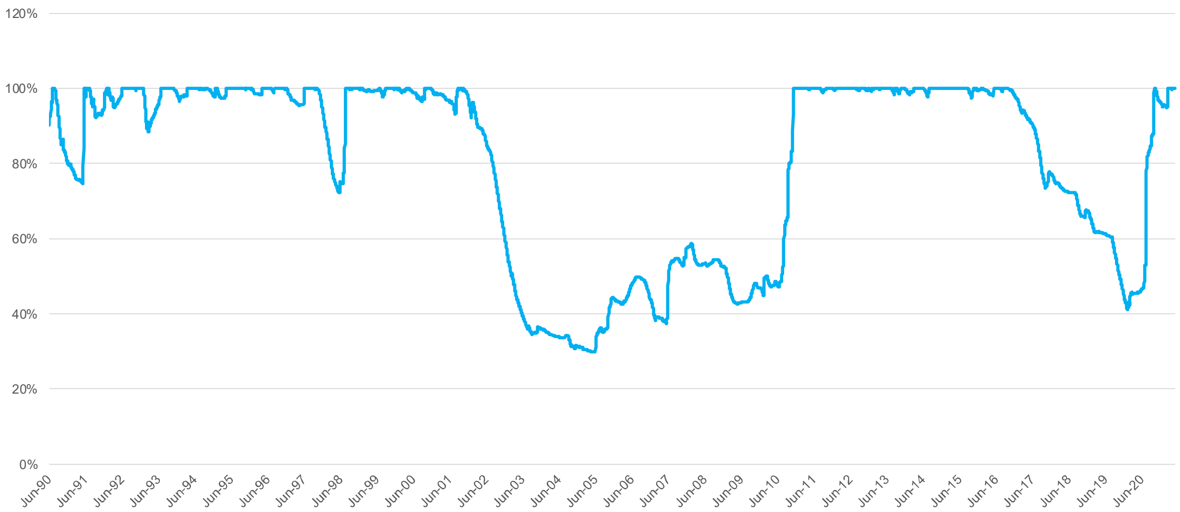
1 Executive summary

The Independent Competition and Regulatory Commission (the Commission) is reviewing demand forecasting methodologies for regulated water and sewerage services in the Australian Capital Territory (ACT). The review is a reset principle under the 2018–23 Price Direction,[1] and will set the approach for forecasting demand in the 2023–28 regulatory period. In May 2021, the Commission published an Issues Paper and invited responses from stakeholders to provide feedback and evidence to inform the draft report. Icon Water commends the Commission for taking the initiative to conduct the review and appreciates the opportunity to respond to the Issues Paper.

As the Commission has acknowledged, forecasting demand is an integral part of the price-setting process and critical to ensuring that the ACT community only pays for the prudent and efficient costs of water and sewerage services. Icon Water shares the Commission's objective of ensuring the demand forecasts are as accurate as possible to achieve the best outcome for the ACT community. For the model to demonstrate good predictive ability, it is important to consider whether the demand forecasting methods still represent the best available evidence and forecasting approaches.

Icon Water understands that forecasting demand is complex. Over the current regulatory period, Icon Water's dam levels have decreased to as low as 45 per cent before recently recovering to 100 per cent (Chart 1). This variability is primarily driven by weather events entirely outside of Icon Water's control. Icon Water considers that the demand model has performed well despite climatic variability during the current regulatory period. Between July 2018 and June 2021, the demand forecast has been within approximately 5 per cent of actual water usage.

Chart 1: ACT dam storage levels 1990 to 2021



Source: Icon Water data, updated June 2021

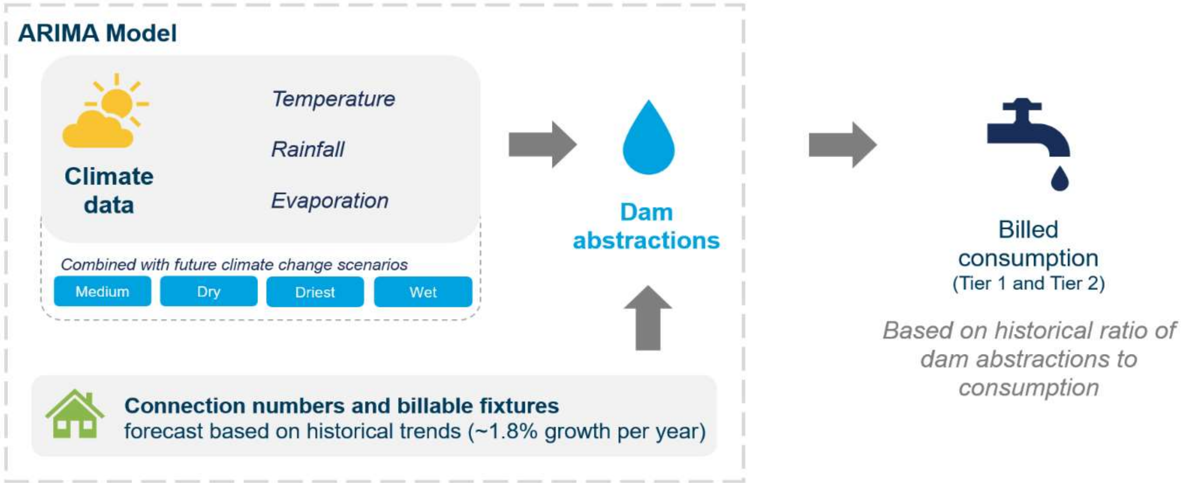
Icon Water supports the continued use of the Commission's Autoregressive Integrated Moving Average (ARIMA) model. The Commission developed the ARIMA model in 2015, following a series of technical papers that found a strong and stable relationship between water sales and climate variables.[2] The ARIMA model is designed to forecast dam abstractions and billed consumption over a five-year

[1] Independent Competition and Regulatory Commission, *Price Direction Regulated water and sewerage services 1 July 2018 to 30 June 2023*, 1 May 2018.

[2] Independent Competition and Regulatory Commission, *Water demand forecast: Final technical paper,* April 2015.

regulatory period. The model is largely based on the observed historical relationship between weather and water demand, but also accounts for future climate change scenarios over the forecast period (Figure 1).

Figure 1: Simplified representation of the ARIMA model



The ARIMA model performs well because water demand is highly dependent on the weather and climate. In dry years, consumers use more water, and in years with higher rainfall, they use less water. The Commission correctly identifies that it is challenging to forecast changing weather conditions from year to year and even more challenging to predict extreme climate events. Icon Water supports the use of risk-management tools such as the demand 'deadband' to account for significant and difficult-to-predict changes in demand, and to manage risk effectively.

As identified by the Commission, simplicity and stability of demand forecasts can be just as important as predictive ability. Icon Water acknowledges the risks of attempting to account for a large number of social, climatic, economic and demographic variables within a demand forecasting model. Doing so can result in complex demand models, that are difficult for stakeholders to understand and costly to implement. Notably, many drivers of water demand change gradually over time, and it may not be necessary to account for such changes in a five-year forecast.

While there are alternative modelling approaches available, it is essential to consider whether the benefits outweigh the costs and risks of moving away from the current approach. Icon Water considers that the ARIMA model performs well, and there is no evidence that alternative models would produce better outcomes for the ACT community.

This submission sets out Icon Water's responses to the questions raised in the Commission's Issues Paper. Section 2 of the submission provides our views on the Commission's proposed assessment criteria. Sections 3 to 8 are organised around the major themes in the Commission's Issues Paper, including how to treat water policy changes, climate change, demographics, and consumer behaviour within the demand model. Section 9 addresses water and sewerage demand components, including billed sales, connection numbers, and sewage volumes.

2 Assessment criteria

Question 1: *Do stakeholders have any comments on the assessment criteria proposed by us?*

Question 2: *Do you consider the ARIMA model remains appropriate, considering the assessment criterion in chapter 1, any other factors you think are relevant, and the available evidence? If you consider an alternative model would be better, please describe the model and explain why it would be better than the ARIMA model.*

The Commission's Issues Paper proposes five assessment criteria to assess the demand forecasting methods. These are:

1) Economic logic, transparency and replicability
2) Predictive ability
3) Flexibility
4) Regulatory stability
5) Simplicity

Icon Water generally supports these criteria and considers that they align with the principles Icon Water proposed for the demand forecast in its 2018–23 Water and Sewerage Price Proposal.[3]

Icon Water also supports the continued use of the Commission's ARIMA model. We agree with the conclusions of the Commission's consultant, Marsden Jacobs, that the ARIMA model generally performs well against the assessment criteria. While there are alternative modelling approaches, such as panel models, it is essential to consider whether the benefits would outweigh the costs and risks of changing the demand forecasting methodology.

If it is necessary to change the methodology, it is preferable first to consider adapting the ARIMA model before considering alternatives. Doing so will promote greater regulatory stability and stakeholder confidence in the methodologies, while avoiding the costs and risks of a fundamental shift in the modelling approach.

This section sets out Icon Water's comments against each of the Commission's criteria and provides Icon Water's assessment of the current forecasting methodology against each criterion.

2.1 Economic logic, transparency and replicability

1. 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.

Icon Water agrees that the demand forecasts should be based on sound economic theory, transparency and replicability. We consider that the model should have a robust statistical basis and should be developed using an objective model selection process that considers observed historical relationships and the ACT context.

The model should be transparent and replicable so that informed stakeholders can understand the mechanics of the model, scrutinise the results, and identify any potential errors or areas for

[3] Icon Water, *2018–23 Water and Sewerage Price Proposal,* Attachment 4: Demand forecasts, 30 June 2017.

improvement. Transparency is vital for achieving community confidence and support in the demand forecasting methods.

Icon Water considers that, wherever possible, the demand models should be developed using freely available and widely used software. A high degree of accessibility reduces the barriers for stakeholders to use and scrutinise the model. For example, R is an open-source statistical language extensively documented and used across industry and academia, with an extensive library of packages available to extend its functionality. Similarly, spreadsheet software, such as Microsoft Excel, is ubiquitous in economic and business modelling.

Transparency and replicability also require adopting best-practice modelling techniques, including well-structured code, clear annotations, error checking, dependency tracking, and version control. This also mitigates the risk of creating a 'black-box' model which is difficult to test and verify.

Reliable and robust data

An extension of this criterion is the continued use of reliable and robust data. The data series should have a long history with a strong expectation that the data will continue to be collected into the future. Wherever possible, the data should be freely available and accessible. For instance, the current ARIMA model uses dam releases and climate data as the principal basis for the forecast. The extended data series ensures consistency between the estimates used for determining operating expenditure, capital expenditure, and those used for revenue recovery purposes. Dam abstraction data and climate data are also expected to continue to be available for the foreseeable future. Climate data is publicly available from the Australian Bureau of Meteorology, a highly reliable and reputable data source.

Using other data, such as surveys or certain types of data published by third parties, may not provide a long historical time series. There is also a risk that the data could be discontinued or subject to methodological changes that may make it difficult to update the demand forecasts.

2.1.1 How the ARIMA model performs against the criterion of economic logic, transparency, and replicability

Icon Water considers that the ARIMA model satisfies this criterion.

The ARIMA methodology is widely accepted, widely used, and based on sound statistical methods. The model was developed using the widely-regarded standard Box-Jenkins approach (see Box 1) and included numerous statistical tests for model fit and parameterisation, such as the Akaike Information Criterion. [4]

Box 1: Box-Jenkins Approach: Model selection process steps[5]

The development of the ARIMA model was based on the Box-Jenkins approach (Box and Jenkins 1970), as described in the Commission's technical papers on water demand forecasting. The Box-Jenkins approach to modelling ARIMA processes was described in a seminal book by statisticians George Box and Gwilym Jenkins in 1970.

The model selection process adopted by Icon Water in the 2018–23 pricing review:

1) Data analysis

[4] The Akaike Information Criterion (AIC) is a statistical measure for model selection. All else being equal, the model with the lower AIC value is to be preferred as the better model. This statistic rewards goodness of fit and includes a penalty for increasing parameter numbers.

[5] Icon Water, *2018–23 Water and Sewerage Price Proposal,* Attachment 4: Demand forecasts, 30 June 2017, p. 14.

a) select the desired dependent variable and determine the relevant explanatory variables to be tested in the model identification stage

b) plot the data to look for patterns, such as seasonality or trends in the data over time

c) assess consistency in the relationship between the dependent and explanatory variables over time to inform the choice of model estimation period.

2) Model identification

a) check for stationarity and evidence of cointegration between variables (when dealing with multivariate models), then differencing the data if necessary

b) identify the potential model structure by comparing the empirical autocorrelation patterns with theoretical ones using the auto-correlation function (ACF) and partial auto-correlation function (PACF)

c) run multiple alternative model specifications and select the preferred specification with reference to the Akaike Information Criterion and the significance of the equation coefficients.

3) **Parameter estimation** – this step involves estimating the values of the parameters of the preferred model specification over the selected estimation period.

4) **Diagnostic checking** – the fourth stage involves examining the assumptions of the model by testing the model residuals for stationarity through visual inspection and statistical methods.

5) **Accuracy assessment** – assess forecast accuracy using a range of measures such as the root mean square error (RMSE). The RMSE is a standard measure of the difference between the values forecast by a model and the observed values.

6) **Assessment against principles** – performance against the set of forecast approach principles set out in Icon Water's 2018–23 Pricing Submission.

7) **Forecasting** – equipped with the preferred model that has been identified, estimated and checked, the final step is to use it to compute forecasts.

As part of the 2018–23 Price Investigation, the Commission agreed that the ARIMA model was methodologically sound, noting that:[6]

> *'Icon Water's submission presented the underlying theory, model selection process and test statistics associated with the ARIMA model. It provided evidence that the model is appropriately established, implemented and provides reliable results and that Icon Water's proposed ARIMA model delivers greater forecast accuracy for the 2013–18 period than the Cardno model or the Commission's 2013 ARIMA model.'*

The ARIMA model is also generally transparent and replicable. The model is written primarily in R, a free and open-source statistical programming language used widely in industry and academic settings. It mainly relies on the R 'forecast' package, which is extensively described in Hyndman, R. J. and G. Athanasopoulos (2012).[7]

Moreover, the model is publicly available on the Icon Water and the Commission websites,[8] allowing stakeholders to replicate the results, examine and scrutinise the code. The transparency of the model

[6] Independent Competition and Regulatory Commission, *Draft Report Regulated water and sewerage services prices 2018–23*, p 126.

[7] R Hyndman and G Athanasopoulos, *Forecasting: principles and practice: Online textbook on forecasting*, Monash University, Australia. (https://www.otexts.org/fpp/9/1).

[8] The demand model is available on the Icon Water website (http://ourprices.iconwater.com.au/attachments/) and on the ICRC's website (https://www.icrc.act.gov.au/water-and-sewerage/regulated-water-and-sewerage-services-prices-201823).

is enhanced because it does not rely on any confidential and sensitive data and requires relatively few data inputs. The model primarily relies on historical climate data, publicly available from the Australian Bureau of Meteorology.

The ARIMA model also includes basic annotations and instructions on how to use it. However, Icon Water considers that there is scope to further improve the transparency and replicability of the model by simplifying the code, making the model more user-friendly, and improving the code annotation. This is further addressed under the 'Simplicity' criterion (Section 2.5).

Icon Water notes that alternative models, such as a panel or end-use model, may not meet the criteria of transparency and replicability. Alternative models often require significantly more data and assumptions compared to ARIMA models. In some cases, the data may rely on surveys, unit-record data or third-party data, which can have mixed levels of reliability. Panel models, which use unit-record data, would require significant time and effort to clean and analyse the data and adjust for different customer billing cycles. The Commission also noted this in its 2016 technical paper on the price elasticity of water demand in the ACT, which explained the significant effort and complexity involved in cleaning and transforming Icon Water's unit record data to be amenable to panel data analysis.[9] Furthermore, some unit-record data may be confidential in nature, diminishing the transparency and replicability of results.

2.2 Predictive ability

2. Predictive ability. This is to review how accurate the model is in predicting actual outcomes.

Predictive ability is a central consideration for demand forecasts and essential to ensuring Icon Water's prices are set on an efficient and cost-reflective basis.

We note, however, that predictive ability does not necessarily require the demand model to predict outcomes in all circumstances accurately. Instead, predictive power should be evaluated using the forecast time-horizon and how the forecast is used. In the present context, water and sewerage demand forecasts are used to set Icon Water's prices to recover its efficient revenue over a five-year regulatory period. Therefore, we should not expect the model to be accurate every year of the regulatory period, nor is it necessary that the model is exact beyond five years. When evaluating predictive ability, we should instead examine how accurate the forecast is, on average, over a five-year regulatory period.[10] A similar observation was made by the Commission in its response to the Industry Panel's 2014 review of water and sewerage pricing:[11]

> *"The purpose of the water sales forecasting undertaken during a review of water and sewerage services is to determine what price of water would allow Icon Water to achieve the level of revenue that the review has determined is required to allow it to meet its prudent and efficient costs, including providing a return to its shareholders. The level of water sales in a future year cannot be known with certainty, being subject to influence by a range of factors, most importantly, variations in climate. Since predicting the weather is notoriously difficult, the Commission contents itself with identifying the price that will on average, across those varying circumstances, allow Icon Water to receive required revenue.*

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[9] Independent Competition and Regulatory Commission (ICRC), *Technical paper 1: Price elasticity of water demand in the ACT*, 2016, p 21.

[10] Where data for a full regulatory period are not yet available, we should use the longest period for which data are available, or conduct out-of-sample testing.

[11] Independent Competition and Regulatory Commission, *Regulated water and sewerage services The Industry Panel process: Outcomes and prospects*, May 2015, p. 27.

The objective of water sales forecasting in the context of a review is then, not to forecast what sales will actually be in a particular year, but to estimate what water sales would be on average over the period for which prices are being set. Where it has been established that a statistical model captures the relationship between water sales and the factors determining it, the usual method of ascertaining the average level of water sales is to run the model across a range of scenarios that represent the likely range of variation of the determining factors and average the forecasts so obtained."

The Commission correctly observes that it is not feasible for a model to predict changing weather conditions from year to year accurately. Similarly, the model cannot predict extreme climate events or other shocks to demand such as significant social, environmental or economic events. These events elude traditional forecasting approaches by their very nature. Therefore a risk-based treatment, such as the deadband,[12] is more appropriate.

Risk management tools such as the deadband play an important role because Icon Water is largely not in a position to manage demand risk. This is because demand is predominantly influenced by factors outside of Icon Water's control. In particular:

- the number of new connections is determined by the government and private property development;
- water demand is primarily driven by climate conditions, which are challenging to predict;
- government water conservation and efficiency policies can result in revenue shortfalls that Icon Water is unable to avoid; and
- Icon Water is unable to adjust its prices within the regulatory period in response to changing demand.

While demand variability is largely outside of Icon Water's control, the deadband recognises that some degree of demand fluctuation is a normal business risk. However, more extreme changes in demand, such as from significant climate events, are a risk that is more appropriately shared with the whole community.

Icon Water considers that the demand deadband remains a suitable risk management tool, however it may be necessary to reconsider the threshold value for the deadband if there is a change in the risk environment (such as prolonged drought conditions). Icon Water noted this in its submission to the Commission's Review of incentive mechanisms.[13]

It is also important to define suitable metrics for measuring predictive ability. For example, the Commission's consultant Marsden Jacobs suggests the Mean Square Error (MSE) and the Mean Absolute Percent Error (MAPE) as possible measures. As discussed above, predictive ability is measured over a five-year regulatory period. It is less important that the model is highly accurate on annual or monthly timescales. Similarly, the model should be regarded as having a good predictive ability even if the forecast errors are positive in some years and negative in others, but where these errors mostly cancel out over a five-year period. Therefore, MAPE may be a better measure than MSE in some circumstances.

When evaluating predictive ability, it is important to assess the forecasts over a suitably long period, as close to a five-year regulatory period as possible. If this is not possible, we may also use dynamic out-

[12] The demand deadband is a mechanism that limits Icon Water's risk of water demand volatility to ±6% of the approved demand forecast. If actual water demand is up to 6% higher (or lower) than the forecast, Icon Water's revenue will fall (or rise) with no consequences for customer bills. However, any incremental revenue that Icon Water gains (or loses) in excess of the 6% threshold must be returned to (or recovered from) consumers in the subsequent regulatory period.

[13] Icon Water, *Water and sewerage service price regulation: incentive schemes Icon Water submission to ICRC Issues Paper*, 28 February 2020.

of-sample tests. The dynamic forecast test requires withholding a portion of the sample data (the test data) from the estimation and using the rest of the data (the training data) for estimating the model. As Hyndman (2014) states:[14]

> *"It is important to evaluate forecast accuracy using genuine forecasts. That is, it is invalid to look at how well a model fits the historical data; the accuracy of forecasts can only be determined by considering how well a model performs on new data that were not used when estimating the model."*

2.2.1 How the ARIMA model performs against the criterion of predicitive ability

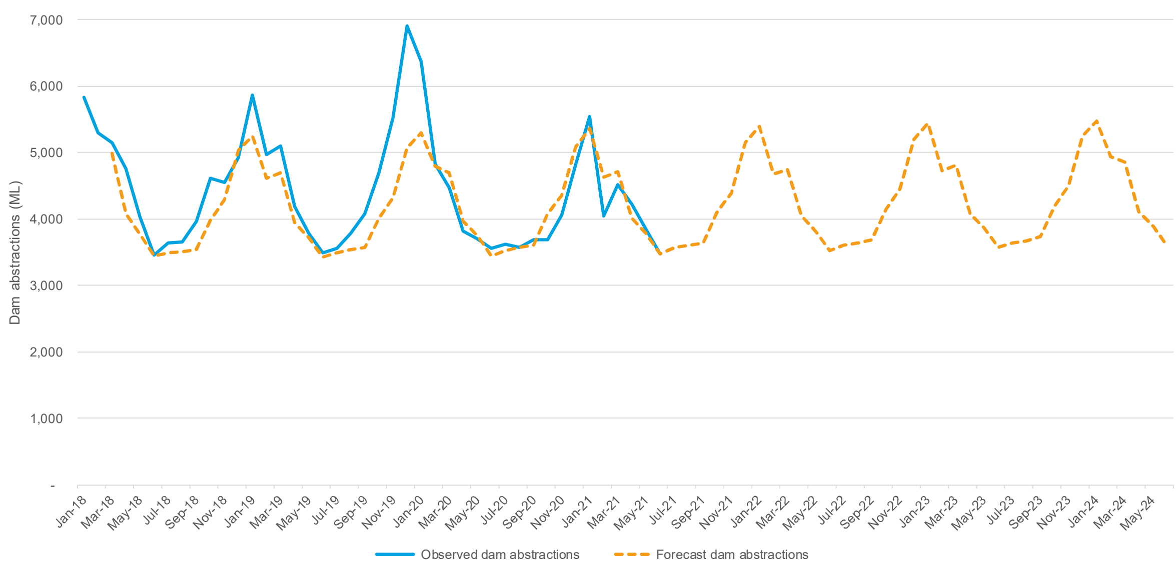
Icon Water agrees with the Commission's finding that the ARIMA model provides reliable forecasts. For the current regulatory period so far (between 2018–19 and 2020–21), actual dam abstractions were within approximately 5% of the forecast. Chart 2 shows monthly data for forecast and actual dam abstractions for the current regulatory period.

The higher than forecast dam abstractions resulted from the prolonged dry weather conditions experienced in 2018–19 and 2019–20. More recently, the ACT has experienced periods of above-average rainfall, which has contributed to actual dam abstractions being lower than forecast during 2020–21.

As discussed above, predictive ability should be evaluated by reference to a five-year regulatory period. It is not necessary, nor is it practical, for the ARIMA model to produce highly accurate demand forecasts on shorter-time scales highly influenced by weather variability.

Notwithstanding the unusually dry weather conditions experienced in 2018–19 and 2019–20, Icon Water considers that the ARIMA model has performed very well and has demonstrated strong predictive power.

Chart 2: Comparison of monthly forecast and actual dam abstractions for the current regulatory period



Source: Icon Water analysis of dam abstraction data and the Commission's final demand forecast for 2018–23

[14] R Hyndman and G Athanasopoulos, *Forecasting: principles and practice: Online textbook on forecasting*, Monash University, Australia. (https://www.otexts.org/fpp/9/1).

The Marsden Jacobs report on the forecasting methodology notes that the ARIMA model only has a moderate level of predictive ability compared to alternative models.[15] However, we note that the Marsden Jacobs report does not provide any evidence that alternative models would produce more accurate forecasts compared to the ARIMA model in the ACT.

The findings appear to be based on how the ARIMA model does not account for structural changes in different population segments, nor does it explicitly model changes in demographics and consumer behaviour. However, given that these changes typically occur gradually over time, Icon Water considers that they can be captured in the time-trend component of the ARIMA model. Furthermore, it is unnecessary for the demand model to produce forecasts for different customer segments since Icon Water's tariffs do not depend on customer type. In contrast to some other water utilities, such as Hunter Water, Icon Water applies the same water tariff structure across all residential and commercial customers. Therefore, a panel or end-use model is not needed to account for differences across customer groups.

We also note it is a common misconception that adding more explanatory variables to a model will necessarily improve its predictive ability. In fact, doing so can lead to over-fitting, where the regression coefficients start to represent the 'noise' of the model rather than genuine statistical relationships.[16]

2.3 Flexibility

3. Flexibility. The model's ability to accommodate changing circumstances such as change in climate and water policies.

Icon Water agrees that demand forecasts should adjust to reflect evolving circumstances and policy. However, the way in which flexibility is achieved will depend on the nature of the changing circumstances.

Most changes in the underlying drivers of demand occur gradually over time. This includes climate change, demographic shifts, and evolving consumer preferences. Demand models that include a time-trend component can be sufficiently flexible to accommodate slow-moving changes, without needing to explicitly model the specific changes taking place.

However, some changing circumstances can occur suddenly, and will not be reflected in historical time trends. This can include changes to water policy, and significant economic or social change. Such events are difficult to anticipate within a demand model and may require alternative treatments. For example, this could include making post-model adjustments. This involves modifying the output of an econometric model (e.g. making a percentage adjustment) to account for an expected future shock to demand. This approach was recently approved by the Australian Energy Regulator (AER) for Evoenergy's gas forecast, which included post-model adjustments to account for future impacts of climate change policy on ACT gas demand.[17] Post-model adjustments have the advantage of providing significant flexibility to assess the full context of a specific demand shock, without needing to explicitly model the shock within the underlying model. It also contributes to maintaining the simplicity of the forecast model, while transparently describing the adjustment being made to its output.

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[15] Independent Competition and Regulatory Commission, *Review of water and sewerage services demand forecasting methodology*, May 2021, p, 37.

[16] The AIC, which the ICRC and Icon Water have applied in the ARIMA model selection process, includes a penalty for increasing parameter numbers.

[17] Australian Energy Regulator, 2021, Final Decision Evoenergy Access Arrangement 2021 to 2026 Overview, p. 23, accessed from https://www.aer.gov.au/system/files/AER%20-%20Final%20decision%20-%20Evoenergy%20access%20arrangement%202021-26%20-%20Overview%20-%20April%202021.pdf

Other changing circumstances, such as major weather events, are very difficult to predict and are preferably managed through risk-sharing mechanisms such as the demand deadband.

2.3.1 How the ARIMA model performs against the criterion of flexibility

Icon Water considers that the ARIMA methodology satisfies the flexibility criterion.

By using dam releases as the primary basis for the forecast, the model implicitly captures gradual changes in underlying water usage patterns through the historical time-trend. This includes gradual changes in climate, demographics and consumer behaviour. Similarly, water prices typically change slowly over time, and there is significant evidence that water demand is price-inelastic.[18] Therefore, Icon Water does not consider that these effects need to be explicitly modelled in the ARIMA model, particularly over a relatively short five-year forecast window.

The ARIMA model uses a very long climate data series (rain and temperature from 1939 and evaporation from 1965) to establish long-term climate trends and the reference climate scenario. The ARIMA model is also flexible in its ability to account for future climate change. The current model also accounts for several future climate scenarios, based on data from the South Eastern Australian Climate Initiative program. It is also relatively straightforward to update the climate change scenarios to account for new climate-science data, to ensure the projections remain current (see Section 4).

More significant and sudden step-changes in consumption can be treated outside of the ARIMA model. Post-model adjustments are one way to account for future events that are not yet reflected in historical trends. This involves making an ex-post adjustment to the output of a forecasting model to reflect the impacts of a future shock to demand. The advantage of post-model adjustments is that they provide flexibility to account for specifics of the demand shock without requiring complex modifications to the underlying econometric model.

Flexibility in the ARIMA model can also be achieved by adjusting the period of sample data used for estimating the model. For instance, there was a sustained step-change in water use in the ACT following the millennium drought which reflected a greater community awareness of the importance of water conservation. The Commission identified this structural break between water consumption and climate data in its first technical paper on water demand forecast.[19] As a result, data prior to the structural break (before 2006), was excluded from the model estimation period for the 2018–23 water demand forecast. There are several well-established statistical tests that can be used to detect structural breaks in time series data, and these can be useful for identifying any future step-changes in water consumption. The statistical tests are explained in detail in section 2.3.3 of Icon Water's 2017 submission to the 2018–23 price review.

2.4 Regulatory stability

4. 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.

Icon Water agrees that regulatory stability is an important element of the demand forecasting methodology. In this context, regulatory stability refers to the methodologies being employed and not necessarily the forecast outputs which should reflect changes to the forecast variables over time (see Section 5). Regulatory stability helps promote stakeholder confidence in the forecasts, provides greater

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[18] Independent Competition and Regulatory Commission, *Tariff Structure Review 2016–17 Regulated water and sewerage services*, March 2017.

[19] Independent Competition and Regulatory Commission, *Technical paper: Water demand Forecasting Regulated water and sewerage services Biennial recalibration 2015*, January 2015, pp. 15-21.

price-certainty, and enables Icon Water to undertake long-term planning in the best interests of its customers.

Icon Water believes there are several factors that can contribute to regulatory stability, including:

1) Employing forecasting methods that are proven to be effective and reliable, as well as widely used and accepted;
2) Using data sources that are easily accessible, consistent over time, and expected to remain supported for the foreseeable future. For example, climate data from the Australian Bureau of Meteorology;
3) Wherever possible, minimising the use of proprietary data, subscription data, or other third-party data which could be discontinued, modified, or costly to reproduce (e.g. survey data);
4) Where it is necessary to make changes, preferentially seeking to incorporate the changes in the existing methodology, rather than moving to alternative methodologies; and
5) Only making changes where there is strong evidence that the benefits will outweigh the costs and risks, having regard to the proposed assessment criteria.

2.4.1 How the ARIMA model performs against the criterion of regulatory stability

The ARIMA model satisfies the regulatory stability criterion by default, as it is the current model being used. Icon Water considers that there is currently no alternative methodology that would satisfy this criterion. This is because there is no evidence that moving to an alternative model would increase the accuracy of the forecasts, while there are significant risks and complexities associated with changing the approach.

The ARIMA model also uses climate and dam abstraction data that are easily available, consistent over time, and expected to remain available for the foreseeable future.

2.5 Simplicity

5. Simplicity. The methods should be simple for consumers to understand and straightforward for the utility service provider to implement.

Icon Water generally supports the criterion of simplicity, which can help to promote greater confidence in the demand forecasts, and reduce regulatory and implementation costs.

The way simplicity is achieved will depend on the audience, and it is important that this criterion is satisfied for both experts and non-experts in demand forecasting.

While it is not necessary for a typical consumer to understand the details of the forecasting methodology, the high-level approach and major components should be intuitive. This helps to promote greater confidence in the forecasts, as well as educating the community about the main drivers and trends for water use in the ACT. To achieve this, the forecasting models should be supported by clear, plain-English documentation.

Many members of the community have an interest in monitoring water use and water conservation in the ACT. Icon Water maintains a 'water education' section on its website, which includes regularly updated statistics about dam storage levels and daily water consumption.[20]

Simplicity is also an important feature for forecasting practitioners and informed members of the community who may wish to scrutinise or replicate the demand forecasts. Wherever possible, the model and underlying data should be publicly available and clearly annotated to allow the results to be

[20] See https://www.iconwater.com.au/Water-education/

replicated. The models should also be based on freely available and widely supported software tools and packages.

Finally, simplicity is also an important feature for regulators and regulated businesses, allowing the models to be easily updated, tested and refined. Simplicity can be greatly enhanced by exercising care and statistical rigour in selecting model parameters. Each explanatory variable that is added to the model increases its complexity, the risk of errors, and the costs of implementation. New variables should only be added where there is a strong and proven statistical basis for doing so.

2.5.1 How the ARIMA model performs against the criterion of simplicity

Icon Water considers that the ARIMA model satisfies the simplicity criterion.

The core principles behind the ARIMA model are capable of being understood by the general community. This is because the model uses only dam abstractions and climate data as the principal basis for forecasting, and the relationship between weather and water demand can be intuitively understood.

For similar reasons, the ARIMA model is also simple to implement. It has a relatively small data requirement, and much of the data is publicly available from reputable and reliable sources (e.g. the Bureau of Meteorology and Icon Water). Once established, there is no ongoing cost in updating the ARIMA model, as it does not require third-party data subscriptions, surveys, or software licenses.

Other types of models, such as panel models, are less likely to meet the simplicity criteria. Panel models typically require making assumptions on the relationship between demand and customer segment or household specific factors. They are also based on unit-record data which can be confidential in nature. This results in a more complex model than ARIMA and creates the risk of a 'black box' model which cannot be readily understood by most consumers nor verified by independent experts.

Icon Water also believes that ARIMA satisfies the simplicity criterion for more informed stakeholders and forecasting practitioners. The model is supported by technical documentation, and interested stakeholders can find a significant body of readily accessible academic literature explaining ARIMA models and how they can be implemented in R. For instance, Hyndman and Athanasopoulos's online textbook provides a valuable open-access resource which describes how ARIMA models can be implemented in R.[21]

Nonetheless, Icon Water considers there is scope to improve the simplicity of the Commission's ARIMA model. Currently, the model is contained within an Excel workbook and separate R model. The model requires running four separate climate scenarios, then manually importing the results of each scenario into the Excel workbook. Some components of water demand are estimated in the Excel workbook (e.g. the Tier 1 and Tier 2 volume split), while other are estimated in R (e.g. the relationship between dam abstractions and billed consumption). The R model currently spans around 600 lines, some of which serve secondary purposes (such as generating charts) and are not strictly necessary for forecasting. While the R code contains basic comments explaining the key features, the code can be challenging to follow for those unfamiliar with R, and some variables follow a complex naming structure that may not be self-explanatory or intuitive to readers.

Icon Water suggests improvements are possible to help make the model more clear, concise and user-friendly. This would not only make the model easier to understand and implement, but it can reduce the scope for errors and promote greater confidence in the results.

Icon Water suggests that the Commission consider making the following changes to the demand model to improve its simplicity:

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[21] R Hyndman and G Athanasopoulos, *Forecasting: principles and practice: Online textbook on forecasting*, Monash University, Australia. (https://www.otexts.org/fpp/9/1).

- ensuring the R code is concise and follows good practice for code style and readability – for example, renaming variables to be more descriptive and removing or separating code that is not strictly necessary for the forecasts;
- improving the annotation of the R code so that users can clearly understand each step of the calculations being performed;
- specifying package versions and dependencies to reduce the risk of errors or incorrect results if users update a package to a different version;
- improving the integration between the R model and Excel workbook, and minimising the number of manual steps that the user must perform. For example, this could include automating the modelling of climate scenarios, and bringing some calculations from the Excel workbook into the R code; and
- ensuring consistency in climate scenario adjustments – for example, applying a single adjustment to account for climate change impacts rather than two separate adjustments (see Section 4) which explains the temperature adjustment as a within-model adjustment and the South Eastern Australian Climate Initiative (SEACI) adjustments to rainfall and evaporation data as post-model adjustments).

These improvements can make the model more accessible and the code easier to read, understand, share and verify.

3 Incorporating policy changes

> ***Question 3:*** *How should future policy changes like sustainable development limits be incorporated in our forecasting model? Are any changes needed to improve how we incorporate such policy changes in our forecasting?*

In the Issues Paper, the Commission notes that the ARIMA model does not explicitly account for government policy changes and suggests whether the model can be improved to reflect changes, such as sustainable diversion limits.

The impacts of future policy changes are typically not reflected in historical data, and therefore they can be challenging to model within a classical statistical framework. For example, ARIMA models and other econometric models infer future outcomes based on observed historical relationships. Policy changes are particularly challenging to forecast if the policy details are not announced at the time of forecasting. Uncertainties associated with government policy impacts may include the timing, implementation, specific details of the policy, community response, and the broader ACT context.

When the details of a policy are relatively specific (for example, if the government legislates a future water conservation target), the impacts can be modelled using a post-model adjustment. The Commission could make post-model adjustments to ARIMA model outputs for some or all years of the forecast period.

Adjustments could be applied to dam abstractions, connection numbers, and Tier 1 and Tier 2 billed consumption.

Post-model adjustments have the benefit of being highly transparent and precise. Using post-model adjustments does not require adding new explanatory variables or modifying the underlying statistical models. The efficacy of post model adjustments can be validated by crosschecking forecast demand against any targets or outcomes set by government policy. When making post-model adjustments, consideration should be given to avoid double counting any already captured changes in historical trends.

Post-model adjustments were recently approved by the AER for Evoenergy's gas network in response to the ACT Government's commitment to phase out fossil fuel gas by 2045.[22]

Where future policies and initiatives are unknown or highly uncertain, it is more appropriate to adopt a risk-management approach rather than making highly uncertain forecasts. Risk management tools include the demand 'deadband' and regulatory pass-through mechanisms. The 2018–23 Price Direction allows for cost-pass throughs for 'service standard events' and 'regulatory obligations events'. These events cover certain situations where legislative or administrative changes result in (positive or negative) costs to Icon Water over $2 million. If an approved pass-through event is triggered, Icon Water can pass on customers' associated costs or cost savings.

3.1 Sustainable Diversion Limit

The ACT's Water Strategy 2014–44 finds that a mixture of policy responses will be required to meet additional future water demand, including continued efficiency and demand reduction measures, accessing water markets and water trading.[23]

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[22] This was the regulatory outcome in response to the ACT Government's commitment under the Parliamentary Agreement of the 10th Legislative Assembly (Australian Energy Regulator, *Final Decision Evoenergy Access Arrangement 2021 to 2026 Overview*, April 2021, pp. 22-24).

[23] ACT Government Environment and Planning, *ACT Water Strategy 2014-44 Striking the Balance*, August 2014.

The Murray-Darling Basin Authority's water recovery targets involve recovering a portion of surface water and groundwater entitlements.[24] States and territories in the Murray-Darling Basin have an annual sustainable diversion limit (SDL) on the volume of water diverted from the river system for consumptive use. The SDLs restrict the amount of water, on average, that can be taken from the rivers for towns, industries, and farmers in the Murray-Darling basin and is based on climate, trade, usage patterns, and development of infrastructure.[25]

In the Issues Paper, the Commission notes that the:[26]

> *"Federal and state Murray-Darling Basin water ministers have committed to introduce sustainable diversion limits by 2024 as a major change in water management policy."*

The Basin Plan specifies that the reduction amount for the Australian Capital Territory is 4.9GL per year.[27] The ACT is yet to achieve their shared reduction amount (SRA).

The SDL applies to the ACT, and the ACT Government manages water access entitlements and licences to ensure that Icon Water and other users remain within limits. The SDL varies annually based on water availability.[28] Currently, the ACT is well within the SDL as recent net diversions from river systems are only around half of the SDL. Therefore, Icon Water considers that SDL changes will not have immediate impacts and will be manageable over the foreseeable future. However, a transfer of entitlements or significant increases in water demand will bring forward when the SDL is reached in the ACT. Changes in government policy can be appropriately incorporated into future demand forecasts using post-model adjustments.

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[24] Murray-Darling Basin Authority, *Progress on water recovery*, accessed 30/06/2021 from https://www.mdba.gov.au/progress-water-recovery

[25] Murray-Darling Basin Authority, *Sustainable diversion limits*, accessed 28 June 2021 from https://www.mdba.gov.au/basin-plan-roll-out/sustainable-diversion-limits

[26] Independent Competition and Regulatory Commission, *Review of water and sewerage services demand forecasting methodology*, May 2021, p. 13.

[27] Basin Plan 2012, Chapter 6, Part 2, Division 2, 6.05(3)(f).

[28] The long-term average SDL is currently 53.44GL per year for the ACT. However, the previous long-term cap was 40.5GL per year for the ACT (Murray-Darling basin Authority, *Transition Period Water Take Report 2018–19*, December 2020, p. 39).

4 Climate change

The Commission's Issues Paper observes that climate has a direct effect on water demand, and therefore weather variables are significant in producing good demand forecasts. We agree that climate is a crucial determinant of water demand in the ACT.

The current ARIMA model applies two adjustments to account for climate change impacts.[29] The first is applying a temperature trend factor to the forecast climate variables in the model.[30] An examination of the annual average maximum daily temperature at Canberra Airport over the period since 1939–40 shows a declining trend in temperature from the start of this period until 1955–56, followed by an increasing trend after that. A temperature trend factor is applied to the forecast climate scenarios to account for the rising trend in maximum temperature.

The second is an adjustment to the forecast rain and evaporation climate variable, which uses four climate scenarios based on those developed by SEACI. The climate scenarios represent a range of potential climate outcomes, with above or below average temperature, rainfall and evaporation. The final dam abstraction forecast is derived as the average of the estimates for each climate scenario.

Icon Water considers that it is essential to maintain the most up to date and reliable climate data available in the water demand forecast model. Icon Water agrees with the Commission that it would be prudent to update the SEACI climate scenarios to reflect more recent climate change modelling.

> ***Question 4:*** *Is our demand forecasting model flexible enough to incorporate potentially larger changes in climate and resulting weather and rainfall patterns?*

Short-term variability in climatic conditions is inherently difficult to predict. It can reasonably be expected that there will be some years where more or less water is sold relative to the forecast due to normal fluctuations in weather patterns. Significantly, short-term climate variability will not necessarily undermine the effectiveness of the demand forecasts because the objective of the forecasts is to set prices over five years. In many instances, short-term variability in climate and water demand will balance out over a regulatory period.

The risk of short-term variability is somewhat mitigated using climate change scenarios in the ARIMA model, which attempt to capture the best available evidence regarding changing weather and rainfall patterns. The ARIMA model also uses climate data from 1965 to establish a reference climate scenario and long-term trends in temperature, climate patterns, and seasonal variation. However, it is difficult to incorporate extreme climate events because they are difficult to predict.

Icon Water acknowledges that it is possible for more extreme and prolonged climatic events to occur,[31] which can cause demand over the regulatory period to be significantly different to the forecast. We consider that a risk-management approach, such as the deadband, is appropriate for recognising the possibility of significant weather variations. Under the deadband, Icon Water fully bears the risk of water demand varying within ± 6% of the forecast. The risk of more considerable variations in demand is shared with the community. As discussed in Icon Water's submission to the Commission's review of

[29] See section 2.9.1 of Attachment 4: Demand Forecasts, 2017 Icon Water Submission to the 2018-23 Price Review.

[30] The forecast climate variables are obtained by averaging 45 separate climate scenarios derived from observed climate over a succession of 6.5-year intervals over the period since 1 July 1965 (the start of the Burrinjuck evaporation data series).

[31] This could include wetter years invoked by either La Niña or a negative Indian Ocean Dipole phase and drier years brought about by El Niño or a positive Indian Ocean Dipole phase. Details on the El Niño Southern Oscillation can be found on the Bureau of Meteorology's website: http://www.bom.gov.au/climate/enso/#tabs=Pacific-Ocean

incentive mechanisms,[32] it may be appropriate to change the deadband threshold value if the water demand risk environment significantly changes. For example, during the Millennium Drought, the deadband was reduced to 3%, recognising that dry conditions and weather conservation measures increased the likelihood of not meeting the demand forecast.

Question 5: *Do stakeholders have any suggestions on other more suitable climate change data sources we could use in the model?*

The Commission's ARIMA model uses climate data based on the SEACI developed in 2012. The demand model has four different climatic scenarios, including driest, dry, medium and wet.

For network planning and water security assessments, Icon Water has recently moved to use data from the NSW and ACT Regional Climate Modelling (NARCliM) project to model the potential impacts of climate change.[33] This aligns with the ACT's climate adaptation planning, which is also based on NARCliM data.[34] NARCLiM data has also been used by the NSW Government to inform government strategic planning initiatives relating to infrastructure, transport, and emergency risk assessment.[35]

Icon Water considers that NARCLiM is a more up-to-date and robust source of climate change data and recommends that the Commission consider adopting NARCLiM data in the ARIMA model.

Two iterations of NARCliM data have been released to date:

- NARCliM 1.0, released in 2014, based on the CMIP3 ensemble of global climate models; and
- NARCliM 1.5, released in 2020, based on the CMIP5 ensemble of global climate models.

While both datasets are available for use, Icon Water relies on the NARCliM 1.5 data because it is based on more recent climate science. NARCliM 1.5 contains 12 different model outputs, based on varying key assumptions:

- three different global climate models (GCMs)
- two different regional climate models (RCMs) used to downscale the GCM output to a local scale
- two different carbon emissions scenarios.

The 12 different models provide 12 alternative projections of future climate at a local scale across south-eastern Australia. Further information on the NARCliM project is available on their website,[36] including frequently asked questions and a *Technical Methods Report*.

For each of the 12 models, Icon Water has obtained a time series of rainfall, evaporation and temperature at the closest grid location to Canberra Airport. This data covers:

- the 1951–2005 climate reference period; and
- the 2020–2039 future period.

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[32] Icon Water, *Water and sewerage service price regulation: incentive schemes Icon Water submission to ICRC Issues Paper*, 28 February 2020.

[33] NARCliM data, released in 2020, were not available at the time of the 2018–23 price investigation. Icon Water has commenced using NARCliM data from from 2021.

[34] ACT Government, *2019–20 Minister's annual report under the climate change and greenhouse gas reduction Act 2010*, 2020.

[35] NSW Government, *About NARCliM*, accessed June 2021 from https://climatechange.environment.nsw.gov.au/Climate-projections-for-NSW/About-NARCliM

[36] https://climatedata-beta.environment.nsw.gov.au/

The climate change impacts are then calculated for each model by comparing the average values in each season. This generates degree increases in temperature and percentage changes in rainfall and evaporation. All changes are relative to the 1950–2005 period. Preliminary results, which could be incorporated into the ARIMA model, are presented in Appendix 1.

Icon Water considers that using NARCliM 1.5 may be more suitable for climatic adjustments because the data is updated to reflect recent climate modelling, and it meets the Commission's assessment criteria of transparency and replicability because the information is publicly available. Using NARCiM 1.5 would also harmonise the application of climate projections across water demand forecasting, Icon Water's network planning, and ACT Government climate adaptation initiatives.

5 Stability of model outputs

The Commission's Issues Paper indicates that the ARIMA model is sensitive to data updates. When the Commission used additional data, demand forecasts for the 2018–23 price investigation varied between the draft and final decisions.

Icon Water agrees with the Commission that more recent data are given greater weight in the ARIMA model. This is a function of the moving average (MA) element of the ARIMA model and the constraints imposed on the MA parameters to make the MA model invertible[37] (and therefore identifiable[38]). A moving average model uses past errors rather than using past values of the forecast variable in an autoregression (AR) model. Following Hyndman and Athanasopoulos,[39] we can write any invertible MA(q) process as an AR(∞) process (of infinite order). For example, consider the MA(1) process, $y_t = \varepsilon_t + \theta_1 \varepsilon_{t-1}$. In its AR(∞) representation, the most recent error can be written as a linear function of current and past observations:

$$\varepsilon_t = \sum_{j=0}^{\infty} (-\theta)^j \, y_{t-j}$$

When |θ| >1, the weights increase as lags increase, so the more distant the observations, the greater their influence on the current error. When |θ| =1, the weights are constant in size, so distant observations have the same influence as recent ones. Hyndman and Athanasopoulos state that as neither of these situations makes much sense, we require |θ| <1, so the most recent observations have a higher weight than observations from the more distant past. Thus, the process is invertible when |θ| <1.

Moreover, when additional data is added to a forecasting model, it should be expected that the forecasts will change, and this is not necessarily due to the absence of leading indicators. The dynamic nature of the model ensures that the model satisfies the 'flexibility' criterion and does not remain static over time.

Question 6: *Do stakeholders have any suggestions on whether changes are needed to improve the stability of our demand forecasting model?*

Icon Water's view is that the ARIMA model is flexible and robust. When additional data observations are used in the ARIMA model, forecast dam abstractions are also updated. Icon Water considers it would be of concern if the demand forecast model were invariant to new data observations.

The Commission's issues paper states that:[40]

> *"The forecast water releases increased by 1.3 per cent to 1.5 per cent in each year over the 2018-23 regulatory period, a cumulative increase of 10 per cent by the end of the 5-year regulatory period."*

Icon Water agrees that annual dam abstractions increased by 1.3 to 1.5 per cent between the Commission's Draft Report and Final Report, which reflected a more sustained trend of dry conditions

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[37] For a more detailed treatment of invertibility, see Granger, C.W. and Anderson, A (1978), On the invertibility of time series models, Stochastic Processes and their Applications, Volume 8, Issue 1, November 1978, Pages 87-92 (https://www.sciencedirect.com/science/article/pii/0304414978900698).

[38] Identifiability is an important property of a statistical model, determining whether the model parameters may be recovered from the observed data and is required in order for precise inference to be possible.

[39] R Hyndman and G Athanasopoulos, *Forecasting: principles and practice: Online textbook on forecasting*, Monash University, Australia. (https://otexts.com/fpp2/MA.html).

[40] Independent Competition and Regulatory Commission, *Review of water and sewerage services demand forecasting methodology*, May 2021, p, 14; Independent Competition and Regulatory Commission, *Final report Regulated water and sewerage services prices 2018–23*, May 2018, p. 146.

in the updated data. However, as shown in Table 1, the cumulative increase was 1.4 per cent over the five-year regulatory period, rather than 10 per cent as suggested by the Commission.

Table 1 Dam abstraction forecasts for the 2018-23 regulatory period (ML)

Year	Commission Draft Report	Commission Final Report	% change
2018-19	48,844	49,471	1.3%
2019-20	49,178	49,909	1.5%
2020-21	49,498	50,169	1.4%
2021-22	49,966	50,670	1.4%
2022-23	50,415	51,196	1.5%
Total	**247,901**	**251,415**	**1.4%**

Source: Independent Competition and Regulatory Commission

Icon Water also notes that the change in the demand forecast may be partially explained by the relatively short historical data series used for the 2018–23 demand forecast. The forecast relied on billed consumption data from 2006. An additional 11 months of observations resulted in a proportional increase in the sample data of around 9 per cent.[41] Icon Water expects that the model's sensitivity will diminish over time as more historical observations are added.

The Commission suggested that the sensitivity of model output reduces the reliability of the model. However, Icon Water proposes that this reflects the model's flexibility rather than a representation of weakness where the model's stability needs to be addressed. Icon Water suggests that the demand model should be flexible, and the methodology should encapsulate regulatory stability.

[41] The Draft Report used data from July 2006 to March 2017 (129 months) and the Final Report used data from July 2006 to February 2018 (140 months of data). That is, an additional 11 months of data was added to the ARIMA model when it was updated in early 2018 by the ICRC.

6 Data frequency

The ARIMA model currently uses high-frequency data (daily observations) for climate and dam release data. The Commission and Marsden Jacobs Associates agreed that we should consider data frequency used in the model.

Marsden Jacobs Associates suggest that changing the frequency of the data from daily to monthly or quarterly could improve the model's ability to account for climate change, which generally occurs slowly over time.[42] They suggest that medium to long-term forecasts should be done using low-frequency data because behavioural responses to exogenous shocks are slow due to habit formation and technological constraints.[43] However, Marsden Jacobs Associates did not present evidence to show how climate change adjustments based on low-frequency data, compared to high-frequency data, would improve the predictive ability of the Commission's ARIMA model. Following the 'regulatory stability' principle, changes should only be made where there is strong evidence that they would improve model accuracy.

Icon Water notes that other demand models previously considered by the Commission relied on averages of monthly climate data, which lost the relationship between water sales and climate variables. This is one of the reasons the Commission adopted the ARIMA model instead of the Breusch-Ward or the Cardno model, which did not perform well against observed dam abstractions.[44]

Moreover, there are significant challenges involved with moving from daily to monthly or quarterly data. It would not simply be a matter of averaging the climate variables, but instead, the model would need to be recalibrated with the complete application of the Box-Jenkins selection process (see Box 1 in Section 2.1.1). The adjustments for temperature trend and the matrix of forecast vectors (which applies the first set of climate scenarios) will also require adjusting, as will the monthly billed data calculation process since it currently relies on daily dam release data.

Overall, Icon Water is not aware of any evidence that using low-frequency data would improve the predictive ability of the ARIMA model and is concerned about the risks and complexities associated with changing the current approach. In particular, using monthly data would require significant effort to recalibrate the model, and it is possible that its predictive ability will be diminished through a less precise relationship between climate variables and water sales. Therefore, Icon Water favours retaining the current method of using daily observations for climate and dam abstractions.

[42] Independent Competition and Regulatory Commission, *Review of water and sewerage services demand forecasting methodology*, May 2021, p, 43.

[43] Independent Competition and Regulatory Commission, *Review of water and sewerage services demand forecasting methodology*, May 2021, p, 43.

[44] Icon Water, *2018–23 Water and Sewerage Price Proposal,* Attachment 4: Demand forecasts, 30 June 2017, pp. 3-8.

7 Demographic considerations

***Question 7:** Is the past trend in customer numbers likely to still be an appropriate indicator of future demographic changes? Do stakeholders have any suggestions on other data sources that may be more suitable to represent forecast demographic changes in the ACT?*

***Question 8:** Is the forecasting model flexible enough to account for step changes in the trend of demographic changes? If not, how could we improve our forecasting approach to account for potential demographic changes?*

Icon Water's demand forecasts include projections of connection numbers and billable fixtures necessary to forecast the number of fixed charges for water and sewerage services. Water connection numbers are also used as an explanatory variable in the ARIMA model to forecast water demand. Water connection numbers are also used as an explanatory variable in the ARIMA model to forecast water demand. During the 2018–23 price review, water installations had a reasonably high parameter significance level and improved the Akaike Information Criterion (AIC) in the ARIMA model.[45] However, the population was not found to be statistically significant.

Based on these findings, Icon Water supports the continued use of connection numbers in the ARIMA model as a proxy for population and does not consider there is enough evidence to replace it with a population variable at this time. Icon Water remains open to considering population growth in future recalibrations of the ARIMA model if there is strong evidence that the parameter is statistically significant and reliable population forecasts are available.

In its Issues Paper, the Commission notes that demographic changes can influence water demand. Demographic changes include changes to population age, family structure, and housing mix (for example, changes in the proportion of freestanding houses).

Icon Water notes that demographic changes typically occur gradually over time and are unlikely to be significant changes over the timescale of a five-year regulatory period. To the extent that demographic changes occur gradually, they would be implicitly reflected in the ARIMA model through the historical time-trends of dam abstractions and connection numbers.

Directly modelling demographic changes can be challenging, involve making many assumptions, and require significantly more data (such as in an end-use model). Explicitly modelling demographic variables could reduce the transparency of the demand forecast mode and increase its complexity. Marsden Jacobs and Associates also describes the challenges of explicitly modelling slow-moving demographic changes since time series analysis requires sufficient variation in variables over time.[46] There was no evidence to show that directly modelling demographic variables would improve the predictive ability of the demand model over a five-year forecast horizon, and therefore Icon Water does not consider any changes are necessary. Avoiding modifications that do not improve the model's predictive ability helps achieve the Commission's assessment criterion of regulatory stability.

More significant and sudden step-changes in demographics with a material impact on demand can be incorporated using post-model adjustments. Post-model adjustments can be used where the changes are not captured in historical data, but the future impacts on water demand can be reasonably deduced. For example, post-model adjustments can be deployed where a new large customer is expected to connect to the network during the regulatory period.

[45] Icon Water, *2018–23 Water and Sewerage Price Proposal,* Attachment 4: Demand forecasts, 30 June 2017, s2.4.3.

[46] Marsden Jacobs and Associates, *Water demand forecasting methodology review – Stage 1*, 19 May 2021, p 44.

8 Consumer behaviour

Question 9: *How could we improve the way we incorporate changes on consumer behaviour into our demand forecasting model? What sort of data could we use to measure behavioural changes in the use of water?*

Water consumption patterns evolve as technology, the climate, and consumer preferences change. Changing preferences and behaviours can be reflected in a number of ways, including greater uptake of water-efficient appliances, improved irrigation systems and drought-hardy gardens, or changes in commercial practices.

The Commission's issues paper seeks to examine whether modifications are necessary to the ARIMA model to account for changes in consumer behaviour that could have a medium to long-term impact on water consumption patterns. The Commission is also investigating whether the model should account for structural changes across different consumer segments.

Icon Water considers that similar to demographics, consumer behaviour evolves gradually over time. Gradual changes in water consumption patterns are reflected in historical trends, which inform statistical models, including ARIMA. For example, appliance upgrades occur typically every five to ten years. The Australian Tax Office determines that the effective life for washing machines and dishwashers is eight years, and for gardening water installations, the effective life is five years.[47]

Another consideration is that Icon Water has a single regulated water tariff structure that is applied uniformly across all customers. The current water tariff structure comprises a fixed supply charge and two tiers of usage charges which are based on consumption. The prices are calculated based on aggregated water demand. Therefore, it is not necessary to separately model water consumption patterns for specific customer segments, such as commercial or residential customers.

Further, there are significant challenges associated with explicitly modelling changing consumer behaviour. This may require analysing unit-record customer data, undertaking surveys, or obtaining third party data. Such approaches can make the demand model more complex, costly to maintain and reduce the transparency and replicability of the results. Marsden Jacobs Associates also described this problem, noting that End-Use models have a lower degree of transparency, replicability, predictive ability, simplicity, and regulatory stability relative to the ARIMA model.[48]

Considering these factors, an ARIMA approach that captures historical trends remains an appropriate forecasting methodology over a five-year forecast horizon.

Nonetheless, there may be a significant and sustained step-change in water usage patterns that is not reflected in historical observations from time to time. For example, there was a structural break in the time series of dam abstractions following the Millennium Drought. The structural break in the ARIMA model was treated by excluding data before 2006 for the 2018–23 demand forecast estimation period.

Structural breaks in time series data are common and often ignored by modellers.[49] While the academic literature provides some advice on forecasting with a structural break, for example, Pesaran and

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[47] Australian Taxation Office, *Taxation Ruling TR 2020/3,* 24 June 2020.

[48] Independent Competition and Regulatory Commission, *Review of water and sewerage services demand forecasting methodology*, May 2021, p, 37.

[49] See, for example, Rapach, D.E., Strauss, J.K. and Wohar, M.E. (2008), "Chapter 10 Forecasting Stock Return Volatility in the Presence of Structural Breaks", Rapach, D.E. and Wohar, M.E. (Ed.) Forecasting in the Presence of Structural Breaks and Model Uncertainty (Frontiers of Economics and Globalization, Vol. 3), Emerald Group Publishing Limited, Bingley, pp. 381-416. https://doi.org/10.1016/S1574-8715(07)00210-2 (https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.1084.4743&rep=rep1&type=pdf).

Timmerman (2007),[50] the simplest approach is to estimate the model using post-break data. This is the approach adopted by the Commission in its 2015 demand modelling paper, where it stated:

> *"The Commission considers that the analysis in the previous chapters provides strong support for the thesis that a new relationship between water sales and climate variables established itself in about July 2006 and has remained stable ever since. Starting from that point, we now have data series spanning some eight and a half years. Importantly, these now include years presenting a variety of climate experience."*[51]

Following in the Commission's footsteps, Icon Water considers that using post-break data remains an appropriate way to deal with structural breaks in the data.

[50] M. Hashem Pesarana and Allan Timmermann (2007), Journal of Econometrics, Volume 137, Issue 1, March 2007, Pages 134-161 show that in a regression with a single break, the optimal window for estimation includes all of the observations after the break, and some of the observations before the break.

[51] ICRC, 2015. Technical paper: Water demand forecasting, Regulated water and sewerage services: Biennial recalibration 2015, Report 1 of 2015, January 2015, page 35.

9 Other demand forecasting components

***Question 10:** Are our current methods for forecasting billed water sales at Tier 1 and Tier 2, total number of water consumers, total number of sewerage service consumers and the number of additional billable fixtures still appropriate? If not, do you have suggestions to improve the methods used to forecast these variables?*

In addition to forecasting dam abstractions using the ARIMA model, it is also necessary to forecast other components of water and sewerage demand, including:

- billed water sales;
- the Tier 1 and Tier 2 split of billed water sales;
- number of water and sewerage connections;
- the number of billable fixtures; and
- sewage volumes.

These forecasts are used to set Icon Water's regulated water and sewerage prices and assess the prudency and efficiency of Icon Water's proposed expenditure.

Icon Water generally supports the current methods used to forecast these demand components and considers the forecasts reliable because the forecasts have strong predictive ability. The Commission's issues paper similarly concludes that the estimates have been reasonably accurate.[52]

The sections below describe the forecasting methodologies and Icon Water's considerations regarding their suitability for the next regulatory period.

9.1 Billed water sales

The volume of water abstracted from the dams is higher than the volume of billed consumption in the ACT. This is because it is necessary to account for non-revenue water[53] and bulk water sales to Queanbeyan-Palerang Regional Council. ACT billed water sales account for about 85 per cent of total dam abstractions.

The Commission estimates billed water sales by first aggregating daily releases to monthly volumes, then uses a linear regression to estimate the historical relationship between monthly dam abstractions and billed consumption.

Icon Water considers that this methodology produces reliable forecasts with a good predictive ability. For the regulatory period to date,[54] actual billed consumption was 5.6% higher than the Commission's forecast for the 2018–23 period. This is similar to the ARIMA model forecast error of 5.3% for dam releases over the same period (see Section 2.2.1), and largely influenced by dry weather conditions during 2019–20. A similar forecast error suggests that the method for estimating billed water sales from dam abstractions is sound and should be retained.

9.2 The Tier 1 and Tier 2 split of billed water sales

Icon Water's regulated water tariff has two tiers that apply to different levels of water use. The Tier 1 price is payable on the first 50kL of water used by a customer per quarter. The Tier 2 price, which is

[52] Independent Competition and Regulatory Commission, *Review of water and sewerage services demand forecasting methodology*, May 2021, p. 19.

[53] Non-revenue water includes water losses (metering errors, leakages, and unauthorised consumption) and unbilled authorised water consumption.

[54] At the time of writing, billed consumption data are available up to March 2021.

higher, applies to water used over 50kL per quarter.[55] Therefore, for revenue recovery purposes, it is necessary to apportion aggregate billed water sales into Tier 1 and Tier 2 sales for each year of the regulatory period.

The Commission's current approach to estimating the Tier 1 and Tier 2 split involves estimating an equation that best fits the relationship between the average amount of water consumed per installation annually and the observed proportion of total sales falling into the Tier 1 category. For the 2018–23 period, the relationship was estimated based on actual observations between 2008–09 and 2015–16. For this data, the best fit was given by an exponential equation:[56]

$$y = 92.40684 - 9.41389e^{5.18345x}$$

Where y is the tier proportion of total ACT water sales, measured as a proportion of 100 units; and x is the average ACT installation consumption per annum in megalitres (ML).

Icon Water generally supports the methodology of forecasting Tier 1 based on the historical relationship. However, the functional form of the relationship between average water consumption per installation and observed Tier 1 sales will need to be re-estimated based on the latest available data ahead of the 2023–28 regulatory period. Recalibrating the equation is particularly important given that the current relationship is estimated using a reasonably small sample of eight historical observations. Therefore, the results may be sensitive to new data. It is necessary to assess whether an exponential equation still produces the best fit or if alternatives (such as a linear model) are preferred.

As part of this process, consideration should also be given to whether any outlier data points should be excluded from the estimation. For example, in its draft decision for the 2018–23 price review, the Commission excluded the 2008–09 data point as an outlier, noting it was influenced by the Millennium Drought and exhibited unusually low consumption per capita.[57]

9.3 Connection numbers and billable fixtures

Icon Water's forecast of connection numbers and billable fixtures for 2018–23 period was based on the observed historical growth rate over 2013–14 to 2017–18. This resulted in a forecast growth rate of 1.84 per cent for water installations, 1.83 per cent for sewerage installation, and 1.55 per cent for billable fixtures. In its Issues Paper, the Commission observes that the forecasts are within 2 per cent of actual values, and that the forecasting method has shown a high degree of accuracy during the regulatory period to date.

Icon Water agrees with the Commission's finding, however, notes that the forecast growth rates are based on a relatively small sample of historical data between 2013–14 and 2017–18. Given that connection numbers are highly influenced by factors such as government and private property development, it is important to consider whether there is evidence that future growth in connections will be different from the past.

Icon Water has also observed that the forecast growth rates correspond to forecasts of population growth over the same period. Table 2 shows the ACT Government's population growth forecasts for the 2018–23 period. The average annual growth rate over the period is 1.81 per cent.

[55] In practice, due to differences in the timing of meter reads, the Tier 1 price is billed for consumption up to 0.548kL on average per day of the billing cycle, and the Tier 2 price applies to consumption thereafter.

[56] Independent Competition and Regulatory Commission, *Final demand model 2018–23*, May 2018.

[57] Independent Competition and Regulatory Commission*, Draft report: Regulated water and sewerage services prices 2018–23*, December 2017, p 181.

Table 2: ACT Government population projections

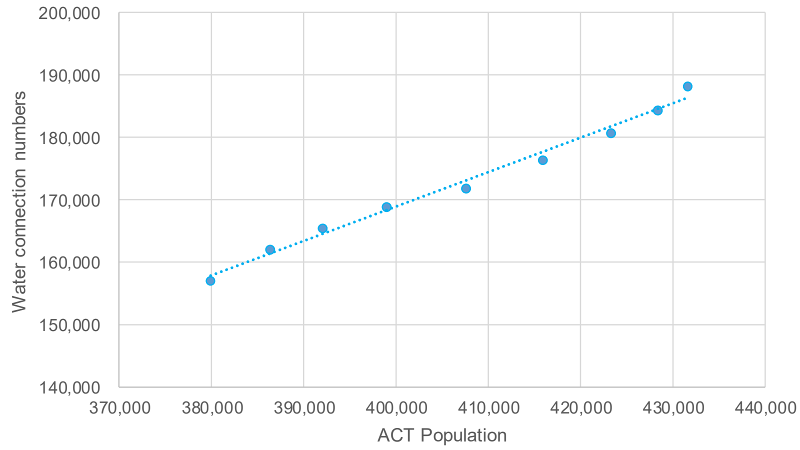
Year (as of June)	Projected ACT Population	Annual growth rate
2019	428,509	1.95%
2020	436,635	1.90%
2021	444,651	1.84%
2022	452,590	1.79%
2023	460,440	1.73%
	Average	**1.81%**

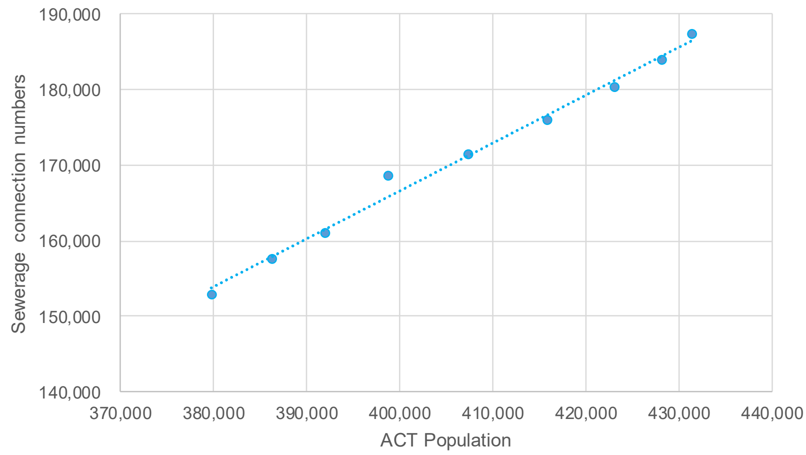
Source: ACT Government, ACT Population Projections 2018 to 2058, January 2019.

The ACT Government's population projections are based on the Australian Bureau of Statistics (ABS) *Population by Age and Sex, Regions of Australia* (2017)[58] and assumptions on fertility, mortality, and migration. The projections also use assumptions based on the ACT Government's long-term land release program and expected development activity.

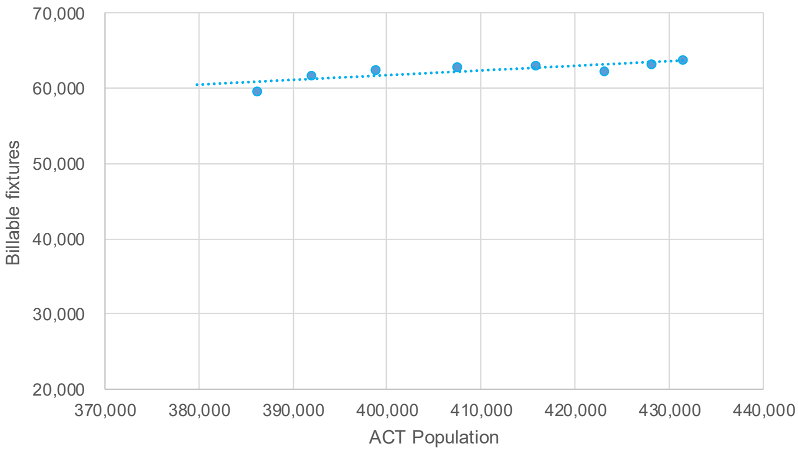
Icon Water notes that the number of connections and billable fixtures is correlated to the ACT population, as shown in the Chart 3 below.

Chart 3: Relationship between ACT population and connection numbers / billable fixtures (2012–13 to 2020–21)





58 Australian Bureau of Statistics, *Regional Population by Age and Sex, Australia*, Cat No 3235, September 2018.



Source: Icon Water analysis of ACT Government data (ACT Population Projections 2018 to 2058, January 2019).

Icon Water recommends that the Commission consider forecasting the number of connections and billable fixtures by estimating the historical relationship between each variable and the ACT population. The relationship can be applied to ACT Government population projections for the 2023–28 regulatory period.

9.4 Sewage volumes

Forecasts of sewage volumes are not included in the ARIMA model, but they are required for the purpose of forecasting sewage treatment costs, which are used to set Icon Water's sewerage prices.

Icon Water uses a predictive model to forecast future sewage flows (inflow) into the Lower Molonglo Water Quality Control Centre (LMWQCC). To estimate the long-term trend, Icon Water considers a range of possible scenarios based on variables such as change in average flow per equivalent population (linked to water conservation practices), population growth estimates and rates of inflow and infiltration into the sewerage system. However, short-term factors in any particular year, such as weather or seasonal impacts, mean that the outcome in any year may vary.

Overall, Icon Water considers that the current approach is performing well and does not propose any changes at this time.

Appendix 1 Climate change adjustments

The current ARIMA model uses climate data based on the South Eastern Australian Climate Initiative (SEACI) from 2012. The climate scenarios used in ARIMA include 'driest', 'dry', 'medium', and 'wet'. The climate adjustments used for rainfall and temperature variables in the ARIMA model are presented below in Table A.1.

The NSW and ACT Regional Climate Modelling (NARCliM) project has recently modelled the potential impacts of climate change. This reflects more updated climate change science from 2020. The NARCliM project considered 12 different climate scenarios for southeast Australia to provide robust projections that span the range of likely future changes in climate. Icon Water uses NARCliM scenarios for its network planning and water security assessments, and also aligns with ACT's climate adaptation planning. Icon Water also considers that it is important for the ARIMA model to use to most up-to-date climate change data available for the ACT.

Icon Water has undertaken preliminary analysis of how NARCliM data could be incorporated into the ARIMA model. The suggested climatic adjustments based on Icon Water's analysis are presented in Table A.2.

Icon Water analysis is preliminary and based on raw data for the ACT region, including:

- temperature data obtained from the Bureau of Meteorology's ACORN-SAT database where available, otherwise Canberra Airport observations, otherwise SILO infilled data;
- rainfall data from Canberra Airport observations where available, otherwise SILO infilled data; and
- evaporation data based on a synthetic series available from SILO at Canberra Airport.

The climate factors could change depending upon the reference period used in the analysis. In this analysis, the 1951-2005 period is used as the climate reference and 2020-2039 as the future period.

Each of the columns in Table represents likely NARCliM climate scenarios.

Icon Water would welcome further engagement with the Commission on possible climate scenarios and potential adjustment factors to be used in the next regulatory period. We also note that, where adjustments in the ARIMA model are updated, the Commission's model will need to be recalibrated using the Box-Jenkins approach, including the model selection process (outlined in Box 1 in Section 2.1.1).

Table A.1: South Eastern Australian Climate Initiative (SEACI) Scenarios

	Scenario	Wet	Medium	Dry	Driest
Rain	**summer**	8.50%	-1.53%	-4.60%	-6.07%
	autumn	5.78%	5.90%	-3.93%	-6.56%
	winter	1.99%	-8.17%	-8.24%	-18.41%
	spring	-2.50%	-7.81%	-15.35%	-26.83%
Evaporation	**summer**	2.56%	2.81%	2.81%	4.15%
	autumn	3.27%	4.15%	4.15%	7.39%
	winter	5.23%	1.83%	1.83%	4.70%
	spring	3.48%	2.30%	2.30%	0.78%

Table A.2: Potential NARCliM Adjustment Factors

Scenarios	GCM	CCCma-CanESM2				CSIRO-BOM-ACCESS1-0				CSIRO-BOM-ACCESS1-3			
	RCM	J		K		J		K		J		K	
	Emissions	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5
Rainfall adjustment	**summer**	26.1%	18.3%	12.5%	12.2%	4.1%	17.5%	0.1%	18.4%	19.5%	16.8%	31.7%	-3.6%
	autumn	17.7%	13.9%	18.4%	-10.7%	15.9%	-1.7%	-17.3%	-18.8%	-2.4%	-0.1%	12.0%	1.8%
	winter	-4.6%	-13.7%	-4.7%	-13.3%	-6.7%	-1.8%	-15.5%	-13.5%	-13.3%	-3.4%	-9.3%	-17.0%
	spring	-7.4%	-10.4%	-10.6%	-18.8%	-3.9%	15.8%	-10.1%	-16.8%	-1.8%	-26.8%	3.7%	-25.8%
Evaporation adjustment	**summer**	1.5%	2.7%	1.1%	3.1%	2.0%	1.0%	2.9%	1.1%	0.8%	1.5%	0.8%	2.3%
	autumn	2.3%	5.0%	2.2%	4.6%	2.3%	2.6%	3.8%	3.9%	0.7%	1.7%	0.0%	1.7%
	winter	2.4%	3.6%	2.3%	3.2%	2.6%	2.2%	4.2%	3.4%	3.3%	3.3%	4.4%	4.2%
	spring	3.3%	4.1%	3.2%	5.2%	2.0%	2.7%	2.4%	4.0%	3.0%	1.8%	3.5%	2.6%

**These are preliminary results based on Icon Water analysis of NARCliM data. The reference period for climate data is the period of 1951-2005.*