MARSDEN JACOB ASSOCIATES

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Water demand forecasting methodology review – Stage 3

Final report

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A Marsden Jacob Report

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

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

Stage 1

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

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

Stage 2

In the second stage, the ICRC asked us to advise on how to best implement the forecasting approach that the ICRC chooses, following our Stage 1 advice. In this stage we recommended key changes in the proposed specification compared to the current approach: the lower time frequency of the data, and the inclusion of additional weather variables to improve forecasting accuracy. In addition, we made two further key recommendations on how to compute forecasts of water installations based on ACT population projections, and to use NARCLiM data to project future climate scenarios. Our advice is available on the ICRC website here.

Stage 3

This report is our final deliverable for Stage 3. The document outlines our process for undertaking optimal model selection, including the specification of the weather variables, their lags, as well as lags of the dependent variable and of the error term of the model, which are commonly used in ARIMA models. Moreover, the report provides the optimal model results and also outlines how to use the ARIMAX model to forecast dam abstractions, including:

- how to forecast explanatory variables for use as inputs in the forecasting model (e.g. how to develop future climate scenarios using NARCLiM data, how to forecast water installation numbers)
- provide the results of those forecast inputs
- describe the data used in the model
- how to develop annual dam abstraction forecasts.

Section 2.1 of this report outlines the final model specification and the final statistical form of the model. The variables for the optimal weekly form of the model are described in Table 1 along with data sources. Section 2.2 and Appendix 1 includes detailed results and estimated parameters for models with daily, weekly and monthly data, respectively. The estimation results for the weekly data model show good statistical properties compared to the existing daily data model: estimated coefficients have signs that are consistent with expectations; moreover, the new variables, which capture the effect of extreme weather conditions, improve the fit of the model. This is consistent with our findings from our stage 2 assessment.

Table 1: Variables used for optimal weekly data model

Variable	Description	Reasoning	Coefficient estimate	Data Source
Dam abstractions	Dam abstractions during a previous week	Dam abstractions are related over time. This is a function of the ARIMA model and is calculated using the model.	0.78 Data shows dam abstractions are positively related over time.	Provided by Icon Water
Temp	Average of daily maximum temperatures (degrees Celsius) during a week	Hot periods will result in more water abstractions to meet increasing water demand by customers	Linear component: 1.82 to 6.51 Squared: 0.04 These estimates show hot periods increase dam abstractions.	Bureau of Meteorology for the Canberra Airport station.
rain	Average daily rainfall (mm) during a week	Rainy periods will result in less water abstractions because part of customer's water demand will be met by rain (e.g. less water required for plants during rainy periods)	Linear component: -3.79 to 11.15 Square root: -43.44 to -12.86 These estimated parameters *combined* show a negative relationship between total abstractions and rainfall.	

Variable	Description	Reasoning	Coefficient estimate	Data Source
Evap	Average daily evaporation during a week	High evaporation rates will result in more water abstractions to meet higher irrigation requirements for plants/gardens as they dry.	Linear component: 31.03 to 46.38 These estimates combined show a positive relationship between total abstractions and evaporation	Bureau of Meteorology for the Burrinjuck Dam station
Customer	Icon water customer connections at the end of a week	More customers will increase water demand, and will require more water abstractions	0.003 This estimate shows that increase in customers are related to more water abstractions. The effect is statistically significant.	Provided by Icon Water
Cumx	This variable includes the cumulative sum (over the week) of rain * evaporation.	High levels of rainfall and low levels of evaporation is likely to be related to lower demand for water	-0.06 This variable has a negative relationship with dam abstractions and is highly significant.	Evaporation and rain data
Binary variables – Summer and December	Included as binary variables, which equal the value of 1 if time period t belongs to summer (December to February) and December, respectively, and zero otherwise.		-15.62 – December 16.98 – Summer These variables were not statistically significant.	Time periods
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 These estimates show extreme hot periods increase dam abstractions.	Bureau of Meteorology for the Canberra Airport station and Bureau of Meteorology for the Burrinjuck Dam station
	• Number of days in a week where rain is greater than 1 mm	More days with plenty of rain will result in less dam abstractions.	-14.89 This estimate shows that wet periods are related to lower dam abstractions.	

Variable	Description	Reasoning	Coefficient estimate	Data Source
sin	Sine and cosine functions.	These are included to account for seasonality (systematic, repetitive, periodic fluctuations in dam abstractions over the course of a week)	-21.27 The magnitude of this coefficient shows the amplitude of variation, i.e. the maximum horizontal distance from the wave's centre to the peak. That is, in the present case the sine varies between -19.76 and 19.76.	Self-defined
cosin			-102.67 See above, mutatis mutandis.	
Moving average component	Forecast error of dam abstractions for the previous week (weeks)	This is a function of the ARIMA model and is calculated using the model.	-0.34 This parameter enters the autocorrelation function of the dependent variable. In the absence of autoregressive components in the ARIMA specification, the value of -0.34 implies that the correlation between y and its lagged value equals $-0.34/(1+(-0.34)^2) \approx -0.30$.	Self-defined

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

Steps to ensure model and parameters are statistically sound

There were several steps we implemented to ensure the model and parameters are statistically sound, and to confirm the final model specification. We discuss these in section 2.1 of this report, with detailed results included in Appendix 1. These steps mainly deal with technical approaches that we used for determining best model fit.

Implementation of model changes

We have outlined steps for implementing model changes to produce dam abstraction forecasts in section **Error! Reference source not found.** of this report. This section details how the optimal ARIMAX model should be implemented including the steps for developing in- and out-of-sample forecasts, and how to forecast future weather conditions using the NARCLiM database, a multi-agency research project between the NSW and ACT governments and the Climate Change Research Centre at the University of NSW.

1. Introduction

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

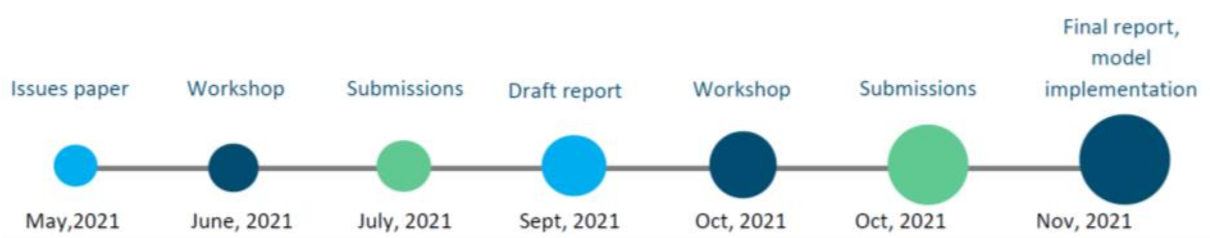
The ICRC decided in its 2018 determination for water and sewerage services prices for Icon Water to review its demand forecasting model before the next price investigation.

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

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

The ICRC review is being undertaken in consultation with key stakeholders. As part of this, ICRC released an issues paper in May 2021, held a workshop and sought submissions during June and July. ICRC has consulted with stakeholders through submissions and workshops following release of the draft report (Figure 1). The final model specification in this report will be used to produce forecasts for the next water and sewerage services price investigation to commence in July 2023.

Figure 1: ICRC review approach



1.1 Objectives

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

Stage 1

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

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

Stage 2

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

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

In this stage we recommended two key changes in the proposed specification compared to the current approach: the lower time frequency of the data, and the inclusion of additional weather variables to improve forecasting accuracy. In addition, we made two further key recommendations on how to compute forecasts of water installations based on ACT population projections, and the use of the NARCLiM dataset to project future climate scenarios. Our advice is available on the ICRC website here.

Stage 3

This report is our final deliverable for Stage 3. This report outlines our process for undertaking the final model specification and provides the optimal model results.

In this report we outline the final statistical form of the variables, that is, whether to use squared values, square root values, and how many 'lags' to use, which are commonly used in ARIMA models where it is assumed that the forecast value of a variable is dependent upon past observations of that variable.

Our report also outlines how to use the ARIMAX model to forecast dam abstractions, including:

- how to forecast explanatory variables for use as inputs in the forecasting model (e.g. how to develop future climate scenarios using NARCLiM data, how to forecast water installation numbers),
- provide the results of those forecast inputs
- describe the data used in the model
- how to develop annual forecasts using the optimal model based on weekly data.

2. Model specification

This chapter outlines our approach to model selection and the final model specification results. Building upon the current model specification[1], we specify the following ARIMAX model of general form:

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

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

$$+F_t(\boldsymbol{\rho}) + \textstyle\sum_{\tau=1}^{p} \alpha_\tau \, y_{t-\tau} + \varepsilon_t + \sum_{\tau=1}^{q} \theta_\tau \, \varepsilon_{t-\tau}, \;\; t = 1, \dots, T, \qquad (1)$$

where t is the time series index that denotes a week or a month, depending on the time frequency of the data, y_t denotes the observation of the dependent variable at time period t, i.e. the weekly/monthly bulk volume of dam water abstractions; $temp_{t-\tau}$ ($rain_{t-\tau}$) [$evap_{t-\tau}$] denotes the average value of daily maximum-temperature (rainfall) [evaporation] at time period $t-\tau$; $summer_t$ and $december_t$ denote binary variables that take the value of 1 if time period t belongs to summer (December to February) and December, respectively, and zero otherwise;[2] $customer_t$ denotes the number of customers at time period t; $\varepsilon_{t-\tau}$ is the unobserved error term of the model, which is assumed to be white noise with mean zero.

In addition, $\boldsymbol{w}_t = (w_{1t}, w_{2t}, \dots, w_{Kt})$ denotes a $K_w \times 1$ vector of additional weather variables, with $K_w = 10$, which is defined as follows:

- $w_{1t} \equiv$ number of days where daily temperature exceeded 30 °C during the previous week/month (*temp_g30*);
- $w_{2t} \equiv$ number of days where daily temperature exceeded 35 °C during the previous week/month (*temp_g35*);
- $w_{3t} \equiv$ number of days where daily temperature exceeded 40 °C during the previous week/month (*temp_g40*);
- $w_{4t} \equiv$ number of consecutive days where daily temperature exceeded 30 °C during the previous week/month (*temp_g30cons*);
- $w_{5t} \equiv$ number of consecutive days where daily temperature exceeded 35 °C during the previous

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[1] Icon Water, 2018-23 Price Proposal Attachment 4 - Demand Forecasts

[2] To be more specific, we have used the first day of each time period t in order to classify whether an observation belongs to summer and\or December.

week/month (*temp_g35cons*);

- w_{6t} ≡ number of consecutive days where daily temperature exceeded 40 °C during the previous week/month (*temp_g40cons*);
- w_{7t} ≡ number of days without rain during the previous week/month (*nudaysnorain*);
- w_{8t} ≡ number of consecutive days without rain during the previous week/month (*nuconsdaysnorain*);
- w_{9t} ≡ number of days where rain exceeded 1 mm during the previous week/month (*nudaysgeq1mm*);
- w_{10t} ≡ number of days where rain exceeded 2 mm during the previous week/month (*nudaysgeq1mm*).

Finally, the Fourier terms are computed based on the following formula:

$$F_t(\boldsymbol{\rho}) = \sum_{j=1}^{J} \left[\rho_{1,j} sin\left(\frac{2\pi jt}{n}\right) + \rho_{2,j} cos\left(\frac{2\pi jt}{n}\right)\right], \tag{2}$$

where $\boldsymbol{\rho} = \left(\rho_{1,1}, \dots, \rho_{1,J}, \rho_{2,1}, \dots \rho_{2,J}\right)'$ and $n \in \{52,12\}$, depending on whether the time frequency of the data is weekly or monthly, respectively.

Table 2 provides a description of the model variables that were considered for the Box-Jenkins process, along with the data sources.

Table 2: Description of the model variables and data sources

Variable	Description	Reasoning	Data Source
y_t, Dam abstractions	Dam abstractions during a previous week/month	Dam abstractions are related over time. This is a function of the ARIMA model and is calculated using the model.	Provided by Icon Water
temp	Average of daily maximum temperatures (degrees Celsius) during a week/month	Hot periods will result in more water abstractions to meet increasing water demand by customers	Bureau of Meteorology for the Canberra Airport station.
rain	Average daily rainfall (mm) during a week/month	Rainy periods will result in less water abstractions because part of customer's water demand will be met by rain (e.g. less water required for plants during rainy periods)	
evap	Average daily evaporation during a week/month	High evaporation rates will result in more water abstractions to meet higher irrigation requirements for plants/gardens as they dry.	Bureau of Meteorology for the Burrinjuck Dam station

Variable	Description	Reasoning	Data Source
cumx	Cumulative interaction effect between rain*evap	High levels of evaporation and low levels of rainfall is likely to be related to higher demand for water	
customer	Icon water customer connections at the end of a week/month	More customers will increase water demand, and will require more water abstractions	Provided by Icon Water
w_t, **Additional weather variables to capture the effect of extreme weather conditions on dam abstractions**	• Number of days where daily temperature exceeded 30 °C, 35 °C or 40 °C in a week/month	More days with extreme high temperature will result in more dam abstractions.	Bureau of Meteorology for the Canberra Airport station and Bureau of Meteorology for the Burrinjuck Dam station
	• Number of days without rain in a week/month	More days without rain will result in more dam abstractions.	
	• Number of days where rain exceeded 1 and 2mm in a week/month	More days with high rainfall will result in less dam abstractions.	
sin	Sine and cosine functions.	These are included to account for seasonality (systematic, repetitive, periodic fluctuations in dam abstractions over the course of a week)[3]	Self-defined
cosin			
Moving average component	Forecast error of dam abstractions for the previous week/month (weeks/months)	This is a function of the ARIMA model and is calculated using the model.	Self-defined

2.1 Model selection

Our approach to model selection is based on the Box-Jenkins methodology.

Specifically, to begin with, we tested for a unit root in $y_t \equiv releases_t$, using a Dickey-Fuller test. Since the null hypothesis of a unit root was soundly rejected using the 1% level of significance, there was no need to apply differencing in the series y_t to make it stationary. In other words, since the

[3] An alternative way of modelling seasonality involves specifying seasonal versions of ARIMA models using seasonal differencing of some order. However, this approach is mainly designed for relatively short seasonal periods, e.g. 4 for quarterly data. In contrast, weekly data have a seasonal period of 52. As argued by Hyndman and Athanasopoulos (2021) (Section 15.5, Forecasting: principles and practice, 3rd edition, OTexts: Melbourne, Australia. OTexts.com/fpp3. Accessed on November 29, 2021), seasonal differencing of such high order does not make a lot of sense and a harmonic regression approach is preferrable.

order of integration for y_t is zero, our starting point is an ARMAX(p,q) specification, which is equivalent to an ARIMAX(p,0,q) process.

Subsequently, we proceeded using three steps, which are summarised below.

1. Identification of lag order of weather variables. The optimal lag order of the weather variables was determined using "best-subset selection", based on a well-established model information criterion, in particular the Bayesian Information Criterion (BIC).[4]

2. Estimation and Selection of ARMAX(p,q). This step involved estimation of several ARMAX models with different values of p and q. The optimal order of the AR and MA components was determined using BIC.

3. Diagnostic Checking. This step involved checking whether the optimal model is adequate by examining the signs and stability of the coefficients, as well as performing tests for normality, unit roots and serial correlation on the residuals.

The approach to model selection for determining the optimal model has been applied on data with weekly and monthly frequency. For the last price investigation, Icon Water had applied the Box-Jenkins methodology to identify the optimal form of the daily data model which is the existing form of the ARIMA model. We used the existing daily data model to compare the forecasting performance of the models with different data frequency, which is discussed in section 2.2.

A detailed explanation of each step in the model selection process is provided in the sections below.

2.1.1 Identification of lag order of the weather variables

In more compact form, the general form of the model above can be written as follows:

$$y_t = \boldsymbol{x}_{1t}'\boldsymbol{\beta}_1 + \boldsymbol{x}_{2t}'\boldsymbol{\beta}_2 + \sum_{\tau=1}^{p_0} \alpha_\tau \, y_{t-\tau} + \varepsilon_t + \sum_{\tau=1}^{p_4} \theta_\tau \, \varepsilon_{t-\tau}, \qquad (3)$$

where $\boldsymbol{x}_{1t}$ denotes a $K_1 \times 1$ vector that contains all weather variables and their lagged values, including $\boldsymbol{w}_t$, while $\boldsymbol{x}_{2t}$ denotes a $K_2 \times 1$ vector that contains all remaining covariates, i.e. $summer_t$, $december_t$, $customer_t$, a constant, and $F_t(\boldsymbol{\rho})$, the Fourier terms.

Model specification requires one to determine the optimal order of the lags of the right-hand side variables. This specification problem is far from trivial because the model is nonlinear and there exists a large number of possible combinations of (i) weather variables, (ii) their associated lagged values, and (iii) lags of y_t and ε_t, i.e. the values of p and q (the order of the AR and MA components, respectively). This renders the task of optimal model selection difficult.

For this reason, we put forward a two-stage procedure that can be described as follows.

[4] An alternative would be to use Akaike Information Criterion (AIC). We prefer BIC because there already exists a large number of potential explanatory variables (and their associated lags), and thereby the AIC can give rise to a largely overparameterized model. We would like to point out that we have also compared the forecasting accuracy of the optimal weekly\monthly models, selected using BIC and AIC. For both weekly and monthly data, the optimal model selected based on BIC outperformed the optimal model selected based on AIC.

In the first stage, we regress y_t on all right-hand side exogenous variables, leaving the AR and MA components to be absorbed by the error term. In other words, we specify the following general Distributed Lag (DL) model

$$y_t = \boldsymbol{x}'_{1t}\boldsymbol{\beta}_1 + \boldsymbol{x}'_{2t}\boldsymbol{\beta}_2 + u_t, \tag{4}$$

where

$$u_t = \sum_{\tau=1}^{p_0} \alpha_\tau \, y_{t-\tau} + \varepsilon_t + \sum_{\tau=1}^{p_4} \theta_\tau \, \varepsilon_{t-\tau}$$

denotes the resulting composite error component.

Since the weather variables are "strictly exogenous" with respect to the purely idiosyncratic error component, i.e. $E(\varepsilon_t|\boldsymbol{x}_{11}, \dots, \boldsymbol{x}_{1T}, \boldsymbol{x}_{21}, \dots, \boldsymbol{x}_{2T}) = 0$ for $t = 1, \dots, T$, we also have $E(u_t|\boldsymbol{x}_{11}, \dots, \boldsymbol{x}_{1T}, \boldsymbol{x}_{21}, \dots, \boldsymbol{x}_{2T}) = 0$. Therefore, the least-squares estimates of $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ are unbiased and consistent. "Strict exogeneity" means that weather conditions do not get feedback from dam releases. That is, changes in the level of dam releases do not cause (say) a given day to be hot, rainy or humid (but the reverse can be true). This assumption is natural.

Subsequently, the optimal lag order of the weather variables is determined based on a procedure known as "best-subset selection", which is common in machine learning literature. To describe this, let $K_{max}(= K_1 + K_2)$ denote the maximum possible number of explanatory variables and their lags used in the DL model above, and let K be the number of regressors used in estimation. Best-subset selection involves finding the value of K together with the associated combination of regressors corresponding to the smallest BIC (Bayesian Information Criterion) value.

To be more specific, the general DL model is estimated using $K \in \{1, 2, 3, \dots, K_{max}\}$ regressors. For each value of K, all possible combinations of regressors (of size K) are considered. The best combination corresponds to the one minimising the residual sum of squares. Once the optimal combination of regressors is determined for each value of K, the optimal value of K, denoted as K^*, is the one that minimises BIC. For further details and variations on variable selection processes and alternative information criteria please refer to Hyndman and Athanasopoulos (2021)[5].

When it comes to the Fourier terms, in both weekly and monthly models, 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 $\rho_2 \equiv \rho_{2,1}$.

It is worth mentioning that this is by no means the only strategy available to identify the lag order of the model in terms of the weather variables. Specifically, an alternative strategy for determining the dynamic specification of the weather variables is called "pre-whitening". This process involves three steps, which need to be undertaken for *each* explanatory variable of the model. In the first step, an ARIMA(p_x, d_x, q_x) model is fitted and the residuals are stored. Since the values of p, d and q are selected optimally using model information criteria (e.g. BIC or AIC), these residuals are

[5] Hyndman and Athanasopoulos, Forecasting: Principles and Practice, Monash University, 2021. Hyndman and Athanasopoulos, 2021, Forecasting: principles and practice, 3rd edition, OTexts: Melbourne, Australia. OTexts.com/fpp3. Accessed on November 29, 2021,

approximately white-noise. In the second step, the dependent variable, y_t, is filtered based on the estimated ARMA coefficients obtained in step 1. In the third and final step, the cross-correlation function (CCF) between the filtered values of y_t and the residuals from step 1, are plotted in order to identify possible lags of the explanatory variable. This procedure is repeated for all explanatory variables.

Some remarks are worth emphasising. Firstly, "pre-whitening" is primarily a visual tool that might facilitate preliminary identification of a *set* of possible dynamics of the model, depending on the complexity of the problem. As it is the case with all visual procedures, such a tool involves a certain degree of subjectivity. This can compromise transparency and replicability. Ultimately, the optimal specification is therefore determined using model information criteria and subsequent diagnostic tests on the residuals of the optimal model.

Secondly, "pre-whitening" might work satisfactorily as a preliminary identification tool in simple problems involving few explanatory variables. However, in more complex problems, pre-whitening can dramatically distort the structure of variability and dependability among time series. That is, the properties of the original time series may no longer carry over to those of the respective pre-whitened time series.

For these reasons, we have not used "pre-whitening" in the model specification process.

2.1.2 Estimation and Selection of ARMAX(p,q)

In the second stage, holding K^* fixed and retaining the corresponding regressors as part of the model, we estimate a set of ARMAX(p,q) models for different values of p and q. Similarly, to the DL model, the optimal values of p and q are determined based on BIC.

To illustrate, let $\boldsymbol{x}_{1t}^*$ and $\boldsymbol{x}_{2t}^*$ denote the optimal right-hand side variables, as determined in step 2.1.1, and $\boldsymbol{\beta}_1^*, \boldsymbol{\beta}_2^*$ denote the corresponding coefficients. In the second step, we determine the optimal values of p and q based on the following model:

$$y_t = (\boldsymbol{x}_{1t}^*)'\boldsymbol{\beta}_1^* + (\boldsymbol{x}_{2t}^*)'\boldsymbol{\beta}_2^* + \sum_{\tau=1}^{p_0} \alpha_\tau\, y_{t-\tau} + \varepsilon_t + \sum_{\tau=1}^{p_4} \theta_\tau\, \varepsilon_{t-\tau},$$

Thus, letting $\boldsymbol{\alpha}^*$ and $\boldsymbol{\theta}^*$ denote the vectors of parameters corresponding to the optimal values of p and q, $\boldsymbol{\delta}^* \equiv \left(\boldsymbol{\beta}_1^{*'}, \boldsymbol{\beta}_2^{*'}, \boldsymbol{\alpha}^{*'}, \boldsymbol{\theta}^{*'}\right)'$ is estimated from the optimal model above.

The aforementioned two-stage procedure has several advantages. Firstly, it is transparent and easily replicable because it relies solely on BIC minimisation, rather than on any visual tools. Secondly, it simplifies the complex task of dynamic specification in cases where there exists a large number of explanatory variables and a large choice of potential lags of these variables. Notably, the least-squares estimates of the first-stage coefficients are consistent since the right-hand side variables of the DL model are strictly exogenous. Therefore, the model selection approach is statistically sound.

2.1.3 Diagnostic checking

Finally, the optimal model is validated using a range of diagnostic checks, comprising of (i) an examination of the signs and statistical significance of the coefficients, (ii) tests for unit roots and serial correlation on the residuals, and (iii) stability of the AR and MA coefficients.

2.2 Model results

2.2.1 Forecasting accuracy of different specifications

The training period used for the weekly and monthly models is July 1, 2006 – June 30, 2018, that is, it spans twelve years of data. The validation period is July 1, 2018 – June 30, 2021, spanning three years of data. Since our emphasis lies in comparing the forecasting accuracy of the various models, it is worth mentioning that we have computed in-sample forecasts for abstractions based on actual weather conditions during the period 2018-2021. In contrast, in 2017 Icon Water produced forecasts based on predicted weather conditions. This implies that the forecasting accuracy of all models presented here (including that of the daily model) would be higher than that reported by Icon Water, even if the benchmark model was identical.

When testing forecasting accuracy of the model ex-post, we recommend isolating model uncertainty from uncertainty in predicting weather conditions. By producing forecasts of total abstractions based on actual weather conditions, the error in predicting weather is zero, and therefore any discrepancies between forecast and actual values of total abstractions can be attributed to model uncertainty.

To determine the preferred time frequency of dam abstraction data, we have compared the forecasting accuracy of approaches using daily, weekly and monthly dam abstractions. To this end, we have used two different measures of forecasting accuracy, namely the Mean Absolute Percentage Error (MAPE) and the Root Mean Squared Percentage Error (RMSPE). These two measures are defined as follows:

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

and

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

where F_t denotes the *yearly sum* of the daily\weekly\monthly forecasts; A_t denotes the yearly sum of the daily actual abstractions, and $n = 3$ because the validation period consists of three years.[6]

MAPE is based on the percentage of absolute forecast errors, and therefore it is relatively easy to

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[6] The benchmark ARIMAX model using daily observations has the same representation as that reported in Icon Water's 2018-23 price proposal to the ICRC. See Icon Water, 2018-23 Price Proposal Attachment 4 - Demand Forecasts, Table 2-4.

understand. For example, if the MAPE equals 3, then, on average, the annual forecast is off by 3%.

Since our objective lies in comparing the forecasting accuracy of models with different time frequency, it is worth emphasising that both MAPE and RMSPE are computed based on the *yearly* sum of daily/weekly/monthly forecasts, whereas A_t remains the same across models with different time frequency, subject to minor rounding errors for weekly data.[7] This ensures that forecasting accuracy across models with different time frequency is comparable.

In our stage 2 report, we compared the forecasting performance of different models by using RMSPE and MAPE. In its response to ICRC's draft report, Icon Water questioned the validity of these measures for comparing models with different data frequency.

Since the models that were selected for comparison analyse data with different time frequency (daily, weekly and monthly), we 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. Therefore, we consider these measures remain valid for comparing the performance of different models.

In particular, both forecasting accuracy measures make use of the term:

$$\frac{F_t - A_t}{A_t},$$

where F_t denotes the *yearly* forecast of dam abstractions, obtained by summing the forecast daily/weekly/monthly observations over year t, where t spans three financial years, 2018/19, 2019/20, 2020/21. Similarly, A_t denotes the *yearly* actual daily dam abstractions.

Note that the same value of A_t is used to compute forecasting errors, regardless of the time frequency of the data. That is, whether a model is based on daily observations or weekly\monthly ones, the value of A_t remains the same, subject to rounding errors. The only variable that changes is F_t, as expected.

Table 3 compares the impact on the MAPE and RMSPE for each data frequency when:

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

In what follows, "Benchmark" refers to the model without extra weather variables (i.e. without the vector $\boldsymbol{w}_t$), whereas "Augmented" refers to the model that includes the additional $\boldsymbol{w}_t$.

[7] We note that, unlike daily- and monthly-frequency data, with weekly data it is commonly the case that one week crosses over two financial years. As an example, consider the week starting on June 26 2010 and ending on July 2 2010. Then 5/7 of that week belongs to the financial year 2009-10 and 2/7 belongs to the next financial year. To account for that, when computing the actual data on releases (A_t), the first five days of that week, should be attributed to 2009-2010 and the last two days should be attributed to 2010-11. When it comes to predicted values, F_t, we recommend that 5/7 of the value of total releases predicted that week should be attributed to 2009-10 and 2/7 should be attributed to 2010-11.

Table 3: 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%

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

The results can be summarized as follows:

- The optimal model based on weekly data outperforms the models based on daily and monthly data by a large margin. Moreover, there is some further improvement in the weekly model due to the use of additional weather variables.
- With monthly data, forecasting accuracy improves compared to daily data, more so when extra weather variables are added into the model. However, the model based on weekly data outperforms the model with monthly data.

The results indicate that using weekly data and adding extra variables, the annual forecast is off by 1.5% roughly, on average. This contrasts with daily and monthly data, where the annual forecast is, on average, off by 3.7% and 2.1%, respectively.

This is consistent with our findings from our stage 2 assessment where we noted that the model using weekly data performs better. Intuitively, one reason behind the higher forecasting accuracy observed with lower frequency data is that we make use of dynamic forecasting. Dynamic forecasting uses the forecast (as opposed to the actual) value of the lagged dependent variable to obtain the forecasts. Therefore, the forecast errors tend to compound over time. This means that with daily data, abstractions are predicted over hundreds of days ahead, resulting in less accurate forecasts.

On the other hand, there is a limit as to how low the time frequency of the data may go, since the lower the time frequency, the smaller the sample size available for estimation, which can affect the accuracy of the forecasts. The modelling exercise shows that weekly data performs comparatively better than monthly data.

On this basis, the following model results are based on using weekly observations of dam abstractions.

2.2.2 ARIMA: optimal model results, with training period July 1, 2006 – June 30, 2018

The following provides a description of the explanatory variables included in the optimal model. The results for the optimal model using weekly observations are reported below:

- 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 week 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 time period t belongs to summer and December, respectively, and zero otherwise (Summer, December)
- The Fourier terms are computed based on the following formula:

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

where ρ_1 and ρ_2 have been defined earlier. The results show that the optimal model is an ARMAX model of order (1,1), i.e. both autoregressive AR and MA components are of order 1.[8]

Overall, the estimated coefficients have the expected sign and most of them are statistically significant at the 5% level, except for the seasonal variables, namely Summer and December.

The lack of statistical significance for the coefficient of December indicates that the conditional expected value of releases in December is no different from the rest of the summer (January and February). The coefficient of Summer is only marginally insignificant at the 10% level. Therefore, we consider it is safer to retain both variables into the model for the out-of-sample forecasts.

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[8] As discussed earlier, we found that the series y_t is stationary, and therefore the ARIMAX(p,d,q) model reduces to an ARMAX(p,q) model.

Table 4: Co-efficient estimates for the final model specification using weekly observations

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.

Further detailed model results and diagnostic checking are included in Appendix 1.

2.3 Model implementation and developing dam abstraction forecasts

To implement the model to generate out-of-sample forecasts of total dam abstractions, we need to obtain forecasts of water installation numbers and weather conditions for the next regulatory period. This section outlines our recommended approach to obtaining these key inputs and generating out-of-sample forecasts of total dam abstractions.

2.3.1 Customer projections

When it comes to forecasts of water installations, it is important that these forecasts take into account the impact of Covid-19 and the resulting border closures on future customer growth for Icon Water. In particular, ignoring the impact of Covid-19 may lead to significantly higher forecasts of water installations than actual ones. For example, we note that ACT's annual population forecasts during the period 2021-22 to 2030-31, updated by the Australian Government's Centre for Population to account for Covid-19, are on average 2.3% lower than the previous forecasts made without taking into account the effect of Covid-19, as shown in Table 5.

Table 5 Population projections ACT under pre and post COVID scenarios

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

For this reason, we have computed forecasts of water installations using the following two-step procedure. In the first step, we used linear regression analysis to model the relationship between bi-annual historical data of Icon Water's water installations and ACT's population during the period December 2006 to June 2021. In particular, the following polynomial of 3rd order was fitted:

$$cust_t = \beta_0 + \sum_{k=1}^{3} \beta_k \, (pop_t)^k + \varepsilon_t, \;\; t = 1, \dots, T(=30).$$

The results are as follows:

$$\widehat{cust}_t = \frac{-283136.4}{(88267.7)} + \frac{2.652}{(0.639)} pop_t + \frac{-6.180 \times 10^{-6}}{(1.560 \times 10^{-6})} pop_t^2 + \frac{5.930 \times 10^{-12}}{(1.300 \times 10^{-12})} pop_t^3$$

$$R^2 = 0.9957$$

The 3rd order polynomial fits the data better compared to a regression where pop_t is the only covariate. This is because there has been a recent decline in the rate of growth of ACT's population due to Covid-19 and the resulting border closures.

In the second stage, we imputed future water installations using the Covid-19-updated population forecasts for ACT, as listed in the above table. As an example, the value of water installations for 2024 is obtained as follows:

$$\widehat{cust}_{2024} = -283136.4 + 2.652 \, \widehat{pop}_{2024} + -6.180 \times 10^{-6} \, (\widehat{pop}_{2024})^2 + 5.930 \times 10^{-12} \, (\widehat{pop}_{2024})^3$$

where $\widehat{pop}_{2024}$ denotes the 2024 population forecast for ACT produced by the Australian Government's Centre for Population.

We understand the ICRC is considering using the ACT Government's population projections which accounts for future development activities in the ACT and is being updated to account for the effect of Covid-19. If these updated ACT Government population projections are not available for the next price investigation, we recommend using population forecasts for the ACT produced by the Australian Government's Centre for Population.

2.3.2 Weather data

To generate forecast weather conditions, we have relied on the NARCLiM database, a multi-agency research project between the NSW and ACT governments and the Climate Change Research Centre at the University of NSW.

The NARCLiM project has produced a suite of twelve regional climate projections for south-east Australia, including Canberra, spanning the range of likely future changes in climate. NARCLiM is explicitly designed to sample a large range of possible future climates, and provides daily and monthly forecasts of weather conditions that go as far as 2030 in their so-called "Near Future" setup and as far as 2079 in their "Far Future" set up.

NARCLiM contains two types of simulated historical weather data: "raw" data and "bias-corrected" data. The latter account for differences between the data produced by the GCM\RCM models and the actual observed data. In other words, the "bias-correction procedure" is used to correct simulated data for a period in which observations are available, the so-called "control period". Since for future projections, observations are not available, one cannot "correct" relative to true values but can adjust the values based on the correction established for the control period. Therefore, it is common to use the term "bias-adjustment" to distinguish between the procedure used for future periods with the bias-correction used for the control period.

In our model, we already use observed weather data in the calibration period (as opposed e.g. to using NARCLiM simulated weather data) and thereby it makes sense to continue with "bias-adjusted" NARCLiM data, which take into account pre-existing trends.

We have calculated NARCLiM adjustment factors by comparing average climate projections data from 2016 to 2035 against average historical bias-adjusted data from 1965 to 2021. The 20-year period spanning 2016 to 2035 has been selected. We consider that using projections over a long-time span (20 years) centred around regulatory period is reasonable and sound.[9]

Because the bias-adjusted NARCLiM data already capture any pre-existing trends, the NARCLiM adjustment factors will be in addition to any pre-existing trends. Therefore, we do not consider any de-trending of historical data is required, as suggested by Icon Water.

Instead of using adjustment factors, an alternative approach would be to rely on direct future climate projections produced by NARCLiM. However, the problem lies in that NARCLiM does not provide data for evaporation, which are used in the demand model, but only for evapotranspiration. On the other hand, long-term historical evapotranspiration data for ACT are not available; rather, only data on

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[9] Icon Water, Submission on ICRC's Review of water and sewerage services demand forecasting methodology draft report, October 2021, p.9.

evaporation are available. The existing adjustment approach enables using evapotranspiration-based adjustment factors to historical evaporation data in order to develop future climate scenario for evaporation. We also note that we are not able to incorporate direct NARCLiM climate projections for the forecast period, as there are 12 different scenarios, and it is difficult to know which scenario or scenarios will occur. An adjustment factor approach abstracts from this issue as it is focuses on the comparison between average climate conditions over a long term in the future (20 years) and over last 50 years.

Approach to out-of-sample forecasting of total releases

Our approach has been to take historical data from July 1965 to the latest date of actual data are divided into ‘x’ overlapping periods of equal length of ‘y’ years, where y is the length of the forecast period. For example, if actual data are available to 7 November 2021 and the forecasts are produced from 8 November 2021 to 30 June 2028 i.e. for 6 years and 8 months, historical data are split into 50 overlapping periods of equal length of 6 years and 8 months.

Subsequently, 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 adjusted weather patterns, for each scenario.

As noted above, NARCLiM adjustment factors are in addition to any pre-existing trends that may be present in the historical data since the data are bias-adjusted. Therefore, there is no need to detrend 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.

Next, out-of-sample forecasts of total abstractions are obtained for each one of the 50 sets of weather patterns, using dynamic forecasting based on the optimal ARMAX model.

Finally, we compute a weighted average of those out-of-sample forecasts across all 50 sets of weather patterns. Taking a simple average would imply giving same weight to the forecasts based on NARCLiM-adjusted weather conditions in the 1960s and 1970s, and to the forecasts based on NARCLiM-adjusted weather conditions in the 2000s and 2010s. However, there would be pre-existing trends in the historical data. More recent data will better reflect that trend rather than the data that is further in the past. So, out-of-sample forecasts based on more recent weather conditions are likely to be more reflective of the future abstractions than predictions based on the distant past weather conditions.

Icon Water had noted this issue of accounting for climate trends in historical data, but the alternative of de-trending is not appropriate, as discussed above. Therefore, herewith we propose a simple and transparent method that assigns more importance (i.e. a larger weight) to forecasts that are conditional on more recent weather patterns, and less importance (smaller weight) to those conditional on earlier weather patterns. To achieve that, we multiply the forecast values of releases corresponding to weather pattern $\tau = 1, \dots, n(= 50)$, by $\tau/[n(n+1)/2]$, where $\tau = 1$ corresponds to the weather pattern observed for the earliest period of length 6 years and 8 months, $\tau = 2$ corresponds to the weather pattern observed for the second earliest period of length 6 years and 8 months, and so on. The benefits of using a weighted average are illustrated in Appendix 1. The charts show that the weighted average approach better captures some of the upwards peaks of actual releases compared with the simple average.

This procedure is repeated across all 12 NARCLiM climate scenarios. That is, in total we produce 600 forecasts, which we average in batches of 50, giving rise to 12 different ‘forecast averages’, one for each NARCLiM climate scenario.

We also considered adopting a simpler approach which applied an adjustment factor to the average of the 50-year historical dataset for each scenario, thus only producing 12 forecasts in total. However, this resulted in overwhelmingly smoothing out the extreme variations in weather, which can potentially result in material under-forecasting.

Computing NARCLiM Climate Adjustment Factors

The following outlines how we have computed the NARCLiM adjustment factors and developed climate (temperature, rainfall and evaporation) forecasts. Steps 1a-1c outline how we computed season-specific correction factors:

1a. We compute average monthly climate observations by averaging across daily values within each of the 12 months, during the period 1965 – 2005. We take an average of the monthly averages across three-month periods, corresponding to each of the four seasons of the year, i.e. summer, autumn, winter and spring.

1b. We repeat step 1a, this time by averaging across daily climate values during the period 1965 – 2021.

1c. The difference between the season-specific climate values obtained in steps 1a and 1b is used as a season-specific correction factor that accounts for the fact that the NARCLiM baseline climate data end in 2005 rather than 2021 and therefore these do not account for any climate change developments during the past 16 years (i.e. 2006 to 2021).

2. We compute monthly-specific means of climate, by averaging monthly climate historical data produced by NARCLiM (bias-adjusted) across a period of 50 years, i.e. during 1965 – 2005. Subsequently, we take an average of the monthly averages over three-month periods, corresponding to each of the four seasons of the year, i.e. summer, autumn, winter and spring.

Subsequently, we add the correction factor obtained in steps 1a – 1c onto the season-specific values obtained in step 2.

3. For each of the 12 future climate scenarios available by NARCLiM, we compute monthly-specific means of predicted climate, by averaging monthly climate projections produced by NARCLiM across a period of 20 years; namely during 2016 – 2035.

Subsequently, we take an average of the monthly averages over three-month periods, corresponding to each of the four seasons of the year, i.e. summer, autumn, winter and spring.

4. The difference in the season-specific values obtained in step 3 and step 2 is the NARCLiM seasonal adjustments factors.

5. To obtain the climate forecasts we adjust each one of the 50 climate scenarios using the NARCLiM seasonal adjustment factors computed in step 4.

Data adjustments for weekly data model

As noted throughout our report, we have made some adjustments to account for the weekly data in the model. These adjustments include:

- Unlike with daily and monthly data, with weekly data it is common that one week will cross over two financial years. As an example, consider a week starting on June 26 2010 and ending on July 2 2010. Then 5/7 of that week belongs to the financial year 2009-10 and 2/7 belongs to the next financial year. To account for that, when it comes to the actual data on releases, the first five days of that week, should be attributed to 2009-2010 and the last two days should be attributed to 2010-11. When it comes to predicted values, we have attributed 5/7 of the value of total releases predicted that week to 2009-10 and 2/7 to 2010-11.
- To account for weeks being partially in Summer and December, in the model we have used the first day of each time period t in order to classify whether an observation belongs to summer and/or December.

Appendix 1. Detailed model results

A1.1. Unit root test on y_t for the weekly time series

The output below shows results on the Dickey-Fuller unit root test on the dependent variable, y_t. The null hypothesis is that the y_t series has a unit root, i.e. it exhibits a stochastic trend. The results show that the null hypothesis is rejected at the 1% level of significance. At the same time, the coefficient of the deterministic trend is statistically insignificant. This confirms that no differencing of y_t is required and thus an ARMA model is sufficient.

```
Dickey-Fuller test for unit root                   Number of obs   =       626

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -6.952            -3.960            -3.410            -3.120
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

------------------------------------------------------------------------------
D.releases  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------+-----------------------------------------------------------------
    releases |
         L1. |  -.1443491   .0207622    -6.95   0.000    -.1851214   -.1035767
      _trend |   .0243724    .023748     1.03   0.305    -.0222635    .0710084
       _cons |   122.2256   19.32751     6.32   0.000     84.27067    160.1806
------------------------------------------------------------------------------
```

A1.2. Stata model final results for the optimal weekly model

```
ARIMA regression

Sample:  5 - 627                                Number of obs     =        623
                                                Wald chi2(22)     =    5498.70
Log likelihood = -3351.938                      Prob > chi2       =     0.0000

------------------------------------------------------------------------------
             |                 OPG
    releases |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
releases     |
        temp |    6.50867     1.51816     4.29   0.000     3.533132    9.484209
   temp_lag3 |    2.29675    .9757859     2.35   0.019     .3842451    4.209255
   temp_lag4 |   1.822711    .9133514     2.00   0.046     .0325754    3.612847
temp_sq_lag2 |   .0434932    .0194666     2.23   0.025     .0053394     .081647
        rain |  -3.789757    .8868176    -4.27   0.000    -5.527887   -2.051626
   rain_lag1 |   11.15212    2.132769     5.23   0.000      6.97197    15.33227
rain_sqrt_lag1 | -43.44157  7.037278    -6.17   0.000    -57.23438   -29.64875
rain_sqrt_lag2 | -19.75853   2.94018    -6.72   0.000    -25.52117   -13.99588
rain_sqrt_lag3 |  -12.8602   3.22286    -3.99   0.000    -19.17689   -6.543513
        evap |   46.38282    3.433152    13.51   0.000     39.65397    53.11168
   evap_lag1 |   31.03152    3.410243     9.10   0.000     24.34757    37.71547
    temp_g30 |    10.9107    2.365901     4.61   0.000     6.273622    15.54778
    temp_g35 |   28.89207    3.306967     8.74   0.000     22.41053     35.3736
 nudaygeq1mm |  -14.88511    2.788365    -5.34   0.000    -20.35021   -9.420017
        cumx |  -.0561724    .0052858   -10.63   0.000    -.0665323   -.0458124
      summer |    16.9807     10.9494     1.55   0.121    -4.479728    38.44112
    december |  -15.61618    11.40352    -1.37   0.171    -37.96667    6.734304
        cust |   .0025903    .0005224     4.96   0.000     .0015665    .0036141
         sin |  -21.26738    12.54978    -1.69   0.090    -45.86451    3.329738
       cosin |  -102.6682    22.67398    -4.53   0.000    -147.1084   -58.22803
       _cons |   77.40742    87.97572     0.88   0.379    -95.02183    249.8367
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L1. |   .7828671    .0331385    23.62   0.000     .7179169    .8478174
             |
          ma |
         L1. |  -.3393397    .0583852    -5.81   0.000    -.4537725   -.2249069
-------------+----------------------------------------------------------------
      /sigma |   52.51114    1.095994    47.91   0.000     50.36303    54.65925
------------------------------------------------------------------------------

Akaike's information criterion and Bayesian information criterion

-----------------------------------------------------------------------------
       Model |        Obs  ll(null)  ll(model)      df         AIC        BIC
-------------+---------------------------------------------------------------
           . |        623         .  -3351.938      24    6751.876   6858.305
-----------------------------------------------------------------------------
```

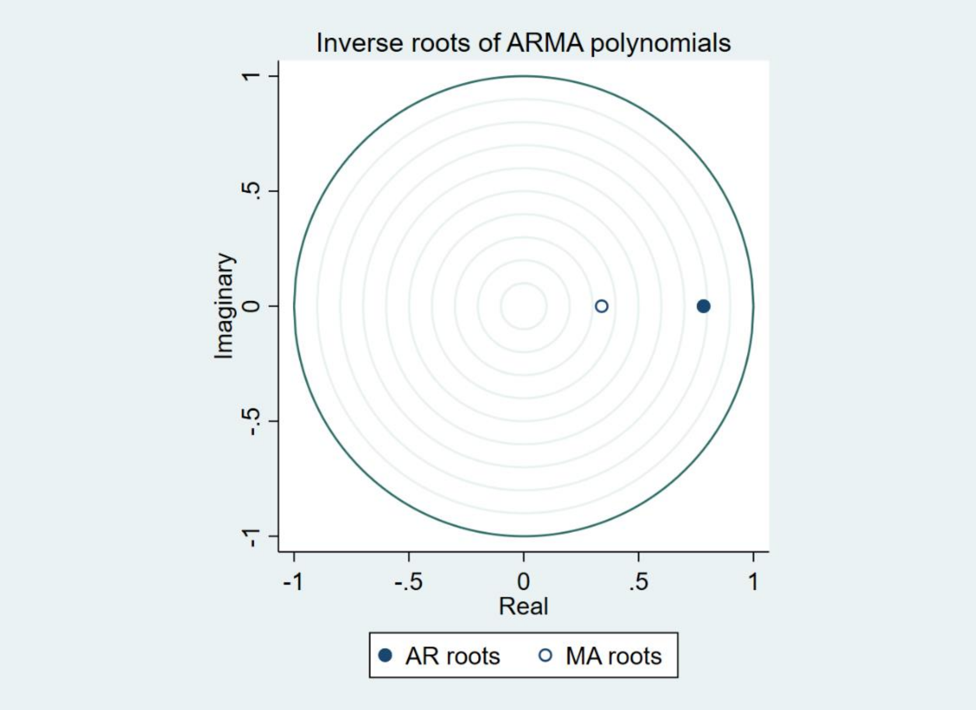
A1.3. Results for the Ljung-Box test for white noise of the ARMA residuals of the optimal weekly model

The output below report results on the Ljung-Box test for white nose of the ARMA residuals. The null hypothesis is that the residuals are white noise, i.e. serially uncorrelated. The null hypothesis is not rejected at the 1% level of significance. This indicates that the model is well-specified.

```
Portmanteau test for white noise
───────────────────────────────────────
 Portmanteau (Q) statistic =    35.7130
 Prob > chi2(40)           =     0.6636
```

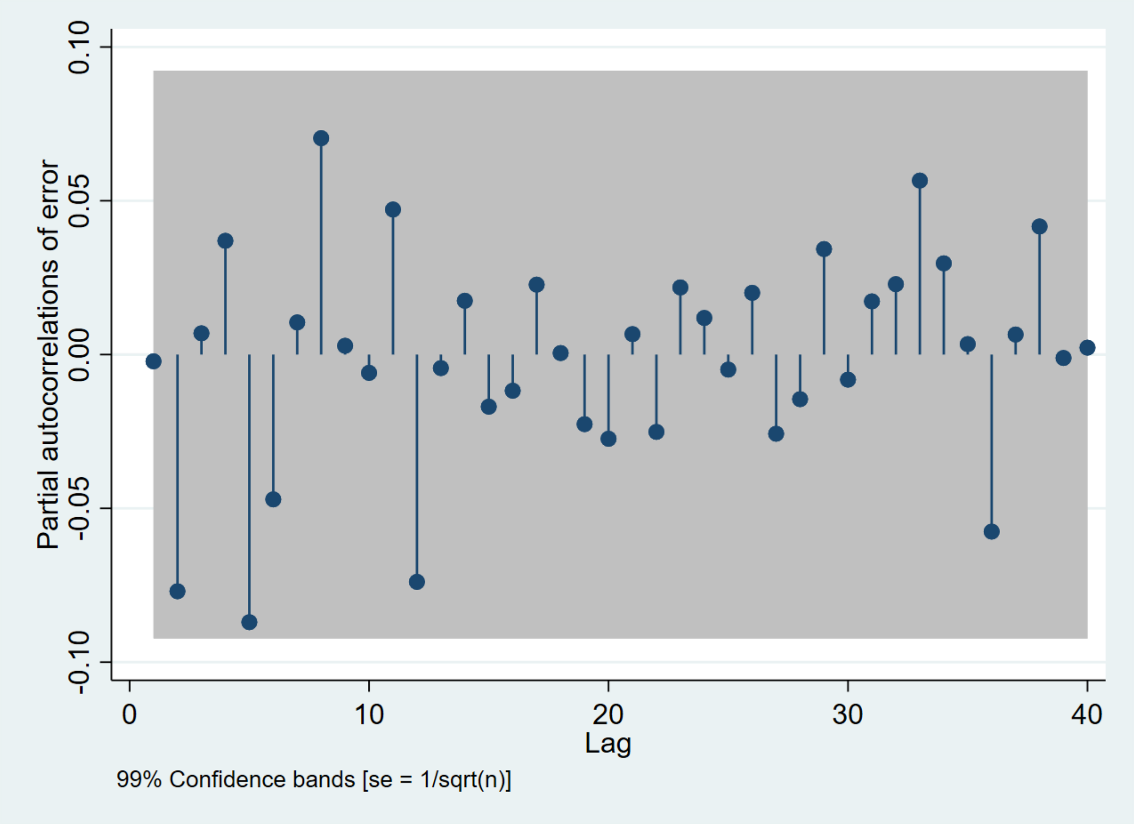
A1.4. Stability condition after estimating the parameters of an ARMA model using the optimal weekly model

The diagram below show that the inverse of the root of the AR polynomial lies inside the unit circle. Therefore, the process is stationary, invertible and has an infinite-order MA representation. Moreover, since the inverse of the MA root lies inside the unit circle, the estimated ARMA is invertible.

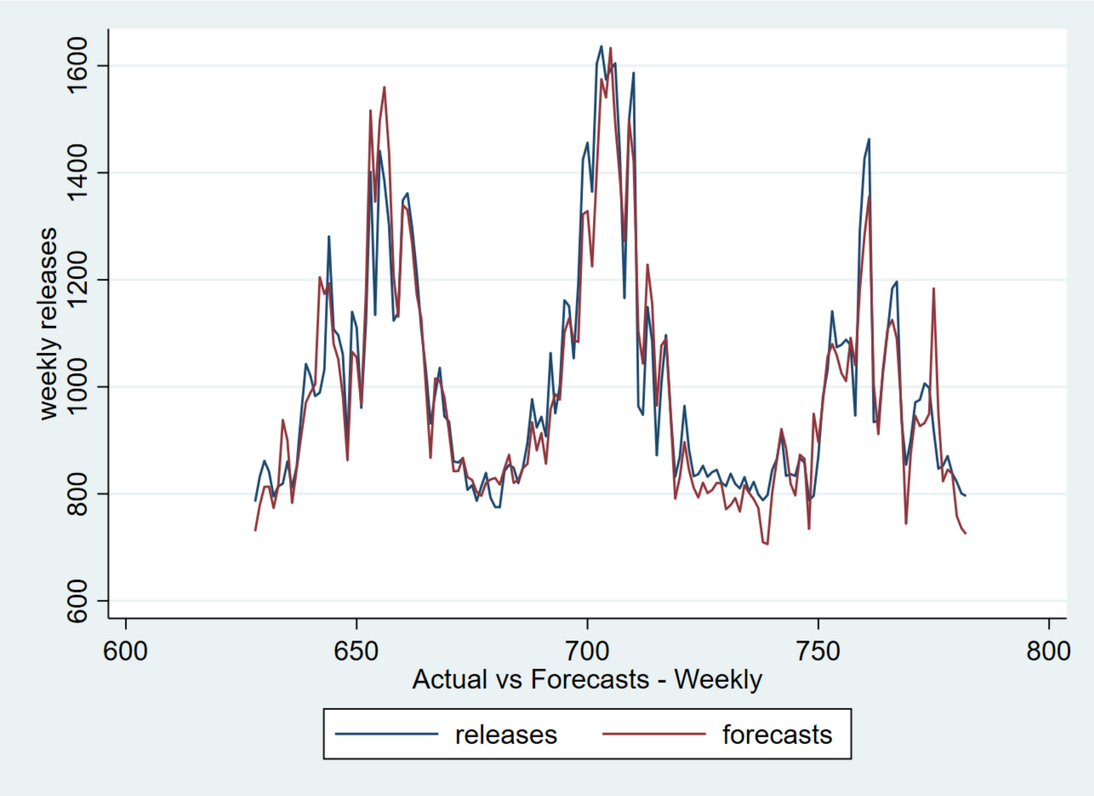


A1.5. Partial Autocorrelation Function (PAC) plot on the residuals of the optimal weekly model

The following figure shows the plot of the partial autocorrelation function for the optimal ARMA residuals. The ACF function provides information about the degree of autocorrelation in the residuals. In a well-specified model, the residuals should be white noise. All partial autocorrelations lie within the 99% confidence interval which indicates no presence of serial correlation in the errors.



A1.6. In-sample forecasts for the optimal weekly model during July 2018 to June 2021



A1.7. Stata model final results for the weekly "benchmark" model

```
ARIMA regression

Sample: 5 thru 627                              Number of obs     =        623
                                                Wald chi2(19)     =    5308.30
Log likelihood = -3401.209                      Prob > chi2       =     0.0000
```

releases	Coefficient	OPG std. err.	z	P>|z|	[95% conf.	interval]
releases						
temp	12.98256	1.08666	11.95	0.000	10.85275	15.11237
temp_lag3	1.844614	1.007932	1.83	0.067	-.1308973	3.820125
temp_lag4	1.465535	.9963961	1.47	0.141	-.4873651	3.418436
temp_sq_lag2	.0647735	.0207201	3.13	0.002	.0241628	.1053842
rain	-6.627188	.7462497	-8.88	0.000	-8.089811	-5.164566
rain_lag1	9.694658	2.300161	4.21	0.000	5.186424	14.20289
rain_sqrt_lag1	-33.98765	7.544195	-4.51	0.000	-48.774	-19.2013
rain_sqrt_lag2	-17.19505	3.137562	-5.48	0.000	-23.34456	-11.04554
rain_sqrt_lag3	-10.91119	3.476292	-3.14	0.002	-17.72459	-4.097778
evap	58.47382	3.353479	17.44	0.000	51.90112	65.04652
evap_lag1	34.68955	3.900997	8.89	0.000	27.04373	42.33536
cumx	-.0620667	.0056215	-11.04	0.000	-.0730846	-.0510488
summer	34.29999	12.19688	2.81	0.005	10.39455	58.20544
december	-26.9099	12.35946	-2.18	0.029	-51.134	-2.685791
cust	.0025418	.0005462	4.65	0.000	.0014713	.0036122
sin	-30.18435	13.29059	-2.27	0.023	-56.23343	-4.135258
cos	-179.8311	22.97179	-7.83	0.000	-224.855	-134.8072
_cons	-107.1437	88.55245	-1.21	0.226	-280.7034	66.41587
ARMA						
ar						
L1.	.7718127	.0367736	20.99	0.000	.6997377	.8438877
ma						
L1.	-.337904	.0598295	-5.65	0.000	-.4551677	-.2206402
/sigma	56.83547	1.161484	48.93	0.000	54.559	59.11194

Note: The test of the variance against zero is one sided, and the two-sided confidence interval is truncated at zero.

A1.8. Stata model final results for the monthly "benchmark" model

```
ARIMA regression

Sample: 4 thru 144                              Number of obs     =        141
                                                Wald chi2(18)     =    1181.23
Log likelihood = -975.3926                      Prob > chi2       =     0.0000
```

releases	Coefficient	OPG std. err.	z	P>|z|	[95% conf.	interval]
releases						
temp	125.3794	25.06568	5.00	0.000	76.25158	174.5073
temp_lag3	398.8317	1056.678	0.38	0.706	-1672.22	2469.883
temp_sq_lag3	-4.639308	8.456302	-0.55	0.583	-21.21335	11.93474
temp_sqrt_lag2	283.3024	172.0361	1.65	0.100	-53.88215	620.4869
temp_sqrt_lag3	-1855.413	6341.811	-0.29	0.770	-14285.13	10574.31
evap	299.6096	76.354	3.92	0.000	149.9585	449.2607
evap_lag1	889.9162	843.6173	1.05	0.291	-763.5434	2543.376
evap_sq_lag1	-52.1682	40.00107	-1.30	0.192	-130.5689	26.23246
evap_sqrt_lag1	-1694.999	2051.057	-0.83	0.409	-5714.997	2324.999
rain_sqrt_lag1	-165.8066	77.34188	-2.14	0.032	-317.3939	-14.21926
cumx	-.0360546	.0070121	-5.14	0.000	-.049798	-.0223112
summer	-19.36943	146.9886	-0.13	0.895	-307.4618	268.723
december	238.6634	130.1335	1.83	0.067	-16.39359	493.7203
cust	.0100964	.0028176	3.58	0.000	.0045739	.0156188
sin	-589.4599	269.7376	-2.19	0.029	-1118.136	-60.78382
cosin	-820.163	269.4376	-3.04	0.002	-1348.251	-292.0749
_cons	814.2352	11338.88	0.07	0.943	-21409.56	23038.03
ARMA						
ar						
L1.	.5137539	.4326061	1.19	0.235	-.3341385	1.361646
ma						
L1.	-.3444493	.4794543	-0.72	0.472	-1.284162	.5952637
/sigma	244.3114	15.31207	15.96	0.000	214.3003	274.3225

```
Note: The test of the variance against zero is one sided, and the two-sided
      confidence interval is truncated at zero.
```

A1.9. Stata model final results for the monthly "augmented" model

```
ARIMA regression

Sample: 4 thru 144                              Number of obs     =        141
                                                Wald chi2(20)     =    1489.06
Log likelihood = -962.5973                      Prob > chi2       =     0.0000
```

releases	Coefficient	OPG std. err.	z	P>|z|	[95% conf.	interval]
releases						
temp	90.30256	25.14893	3.59	0.000	41.01156	139.5936
temp_lag3	1507.289	1069.343	1.41	0.159	-588.5848	3603.162
temp_sq_lag3	-12.84544	8.290071	-1.55	0.121	-29.09368	3.402798
temp_sqrt_lag2	303.4289	142.2349	2.13	0.033	24.65357	582.2042
temp_sqrt_lag3	-8605.923	6520.25	-1.32	0.187	-21385.38	4173.532
evap	203.646	75.21334	2.71	0.007	56.23055	351.0614
evap_lag1	1409.659	870.5343	1.62	0.105	-296.5573	3115.875
evap_sq_lag1	-71.99616	42.51765	-1.69	0.090	-155.3292	11.33689
evap_sqrt_lag1	-2913.708	2084.202	-1.40	0.162	-6998.669	1171.253
rain_sqrt_lag1	-182.2828	66.5167	-2.74	0.006	-312.6531	-51.91244
temp_g35	60.09848	16.38072	3.67	0.000	27.99285	92.20411
nudaynorain	24.48947	9.868906	2.48	0.013	5.146766	43.83217
cumx	-.0266499	.0076214	-3.50	0.000	-.0415876	-.0117122
summer	-140.2582	143.1579	-0.98	0.327	-420.8425	140.3261
december	358.5707	130.6573	2.74	0.006	102.4872	614.6543
cust	.0102896	.0030999	3.32	0.001	.004214	.0163652
sin	-594.369	268.964	-2.21	0.027	-1121.529	-67.20928
cosin	-432.2852	236.975	-1.82	0.068	-896.7476	32.17721
_cons	13086.91	11857.76	1.10	0.270	-10153.87	36327.69
ARMA						
ar						
L1.	.6596953	.2563044	2.57	0.010	.1573479	1.162043
ma						
L1.	-.4581987	.3161696	-1.45	0.147	-1.07788	.1614823
/sigma	223.0883	13.99832	15.94	0.000	195.6521	250.5245

Note: The test of the variance against zero is one sided, and the two-sided confidence interval is truncated at zero.

A1.10. Stata model results for the daily "benchmark" model

```
ARIMA regression

Sample: 12 thru 3927, but with a gap            Number of obs     =      3915
                                                Wald chi2(44)     = 105672.15
Log likelihood = -13710.76                      Prob > chi2       =    0.0000

------------------------------------------------------------------------------
             |                 OPG
    releases | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
releases     |
        temp |
         --. |  -.6356576   .1954649    -3.25   0.001    -1.018762   -.2525534
         L1. |  -7.073349    1.70067    -4.16   0.000     -10.4066   -3.740097
        L12. |  -.4674113   .1858433    -2.52   0.012    -.8316574   -.1031652
             |
     temp_sq |
         --. |   .0250529   .0036714     6.82   0.000     .0178571    .0322488
         L1. |   .1072585   .0123181     8.71   0.000     .0831155    .1314016
         L5. |   .0056551   .0008761     6.46   0.000     .0039381    .0073722
        L12. |   .0132019   .0034946     3.78   0.000     .0063527    .0200512
             |
   temp_sqrt |
         L1. |   32.17863   10.74127     3.00   0.003     11.12614    53.23113
             |
        rain |
         --. |   .5008775   .0513329     9.76   0.000     .4002668    .6014882
         L1. |   .5246239    .055226     9.50   0.000     .4163829    .6328649
             |
   rain_sqrt |
         --. |  -3.479885    .244133   -14.25   0.000    -3.958377   -3.001393
         L1. |  -3.968403    .272036   -14.59   0.000    -4.501584   -3.435222
         L3. |  -.4800134   .1323951    -3.63   0.000     -.739503   -.2205239
         L6. |    .261719   .1310995     2.00   0.046     .0047687    .5186692
         L7. |  -.5026938   .1210821    -4.15   0.000    -.7400104   -.2653772
         L8. |  -.3806779   .1166198    -3.26   0.001    -.6092485   -.1521072
             |
        evap |
         --. |   1.169129    .259716     4.50   0.000     .6600945    1.678163
         L1. |   1.048587   .2712357     3.87   0.000     .5169746    1.580199
         L2. |    1.16591   .0995899    11.71   0.000     .9707176    1.361103
         L3. |   .8802369    .101016     8.71   0.000     .6822492    1.078225
         L4. |    .451609   .1066219     4.24   0.000      .242634     .660584
             |
     evap_sq |
         --. |   .0964083   .0257314     3.75   0.000     .0459757    .1468409
         L1. |   .0644446   .0252853     2.55   0.011     .0148863    .1140028
         L5. |    .048726   .0092481     5.27   0.000        .0306     .066852
             |
        cumx |   -.016222   .0010552   -15.37   0.000    -.0182902   -.0141538
     cumtemp |  -.0783389   .0220299    -3.56   0.000    -.1215168    -.035161
     cumrain |   .1388312   .0284157     4.89   0.000     .0831375    .1945249
         sun |   6.282126   .9298528     6.76   0.000     4.459648    8.104604
         mon |   12.34532   1.073846    11.50   0.000     10.24062    14.45002
         tue |   6.771112   1.159786     5.84   0.000     4.497973    9.044251
         wed |   5.634283   1.272024     4.43   0.000     3.141161    8.127405
         thu |   4.698764   1.232361     3.81   0.000      2.28338    7.114148
         fri |   4.848397   1.020322     4.75   0.000     2.848603    6.848192
         dec |   4.144669   1.228465     3.37   0.001     1.736921    6.552417
      summer |  -2.428318   1.450305    -1.67   0.094    -5.270863     .414228
        cust |   .0002968     .00015     1.98   0.048     2.74e-06    .0005909
         sin |   2.758761   2.197255     1.26   0.209    -1.547779    7.065301
       cosin |   4.315682   2.620058     1.65   0.100    -.8195375    9.450901
       _cons |   26.91358   30.13102     0.89   0.372    -32.14213    85.96929
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L1. |   1.280842   .0313267    40.89   0.000     1.219443    1.342241
         L2. |  -.3257398   .0254033   -12.82   0.000    -.3755295   -.2759502
             |
          ma |
         L1. |  -.7473589   .0278566   -26.83   0.000    -.8019569   -.6927609
-------------+----------------------------------------------------------------
ARMA7        |
          ar |
         L1. |   .9152356   .0321983    28.43   0.000     .8521282     .978343
         L2. |   -.031127    .019132    -1.63   0.104     -.068625    .0063711
             |
          ma |
         L1. |  -.7207276   .0282599   -25.50   0.000    -.7761159   -.6653392
-------------+----------------------------------------------------------------
      /sigma |   8.026927   .0627181   127.98   0.000     7.904002    8.149852
------------------------------------------------------------------------------
Note: The test of the variance against zero is one sided, and the two-sided
      confidence interval is truncated at zero.
```

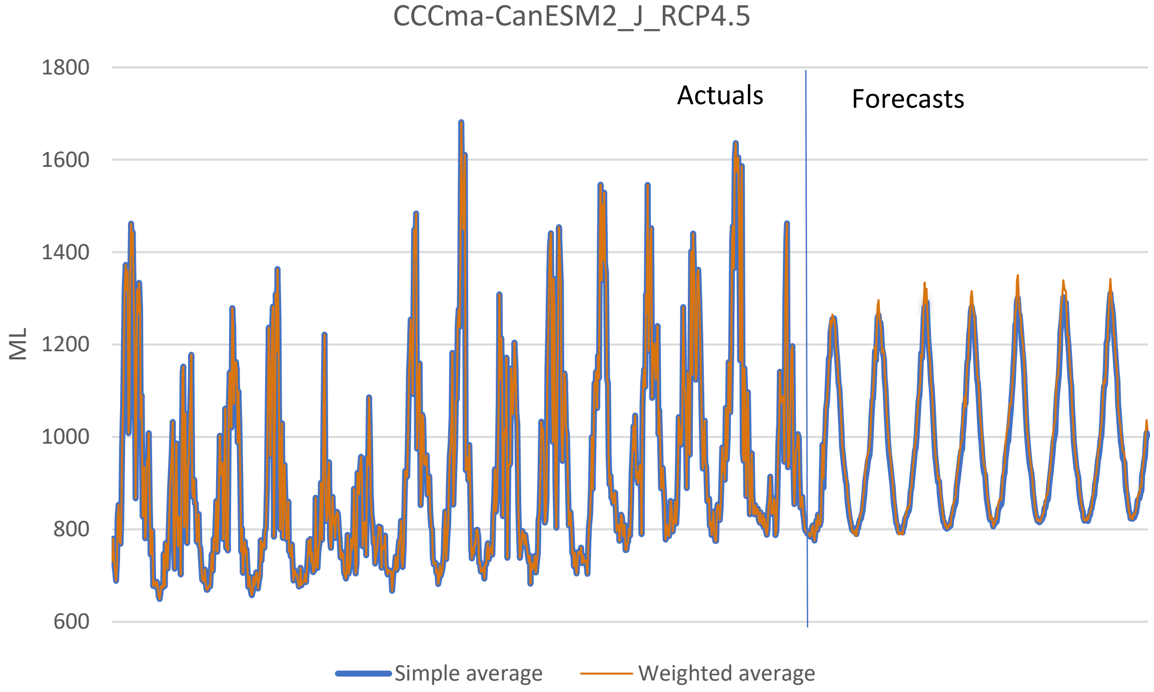
A1.11. Stata model results for the daily “augmented” model

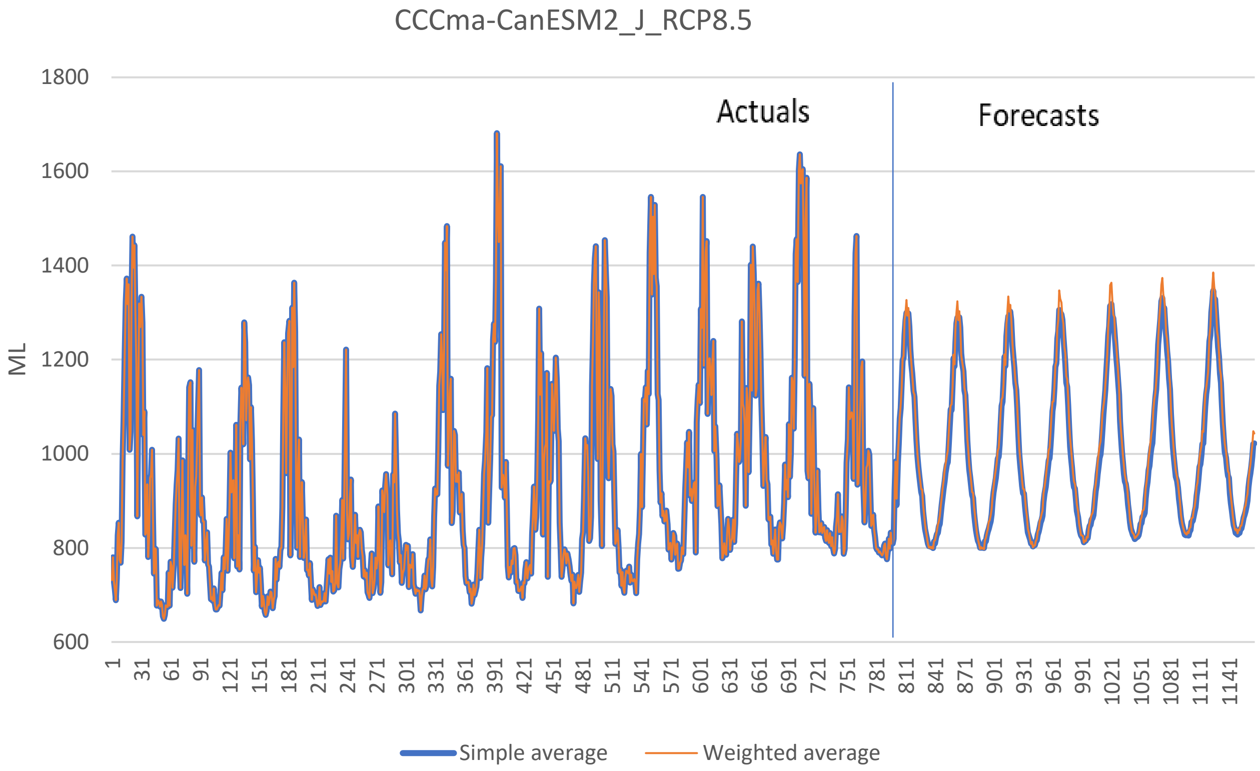
```
ARIMA regression

Sample: 12 thru 3927, but with a gap            Number of obs     =      3915
                                                Wald chi2(47)     = 112326.52
Log likelihood = -13700.56                      Prob > chi2       =    0.0000

------------------------------------------------------------------------------
             |                 OPG
    releases | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
releases     |
        temp |
         --. |  -.6514732   .1938243    -3.36   0.001    -1.031362   -.2715845
         L1. |  -7.981397   2.028009    -3.94   0.000    -11.95622   -4.006572
        L12. |  -.4773042   .1857446    -2.57   0.010    -.8413569   -.1132514
             |
     temp_sq |
         --. |   .0253145   .0036361     6.96   0.000     .0181879    .0324411
         L1. |   .1157031   .0156874     7.38   0.000     .0849562    .1464499
         L5. |   .0057544   .0008746     6.58   0.000     .0040402    .0074686
        L12. |   .0133237   .0034923     3.82   0.000     .0064789    .0201684
             |
   temp_sqrt |
         L1. |   36.94334   12.37749     2.98   0.003      12.6839    61.20278
             |
        rain |
         --. |   .4054549   .0569256     7.12   0.000     .2938828    .5170271
         L1. |   .4713036   .0575249     8.19   0.000     .3585568    .5840504
             |
   rain_sqrt |
         --. |  -2.976194   .2744773   -10.84   0.000     -3.51416   -2.438229
         L1. |  -3.672695   .2841228   -12.93   0.000    -4.229565   -3.115824
         L3. |  -.4226095   .1324597    -3.19   0.001    -.6822257   -.1629934
         L6. |   .3292219   .1321639     2.49   0.013     .0701854    .5882584
         L7. |  -.5825195   .1222904    -4.76   0.000    -.8222043   -.3428348
         L8. |  -.4536439   .1178368    -3.85   0.000    -.6845998   -.2226879
             |
        evap |
         --. |    1.10556    .260575     4.24   0.000     .5948428    1.616278
         L1. |   .9407146   .2718417     3.46   0.001     .4079146    1.473515
         L2. |   1.095693   .1005909    10.89   0.000     .8985384    1.292848
         L3. |   .8172341   .1023415     7.99   0.000     .6166484     1.01782
         L4. |   .3933971   .1086623     3.62   0.000     .1804228    .6063713
             |
     evap_sq |
         --. |   .1014326    .025865     3.92   0.000     .0507381    .1521272
         L1. |   .0715488   .0253517     2.82   0.005     .0218604    .1212373
         L5. |   .0449269   .0092634     4.85   0.000     .0267711    .0630828
             |
        cumx |  -.0163333   .0010595   -15.42   0.000    -.0184099   -.0142567
     cumtemp |  -.0871426    .021917    -3.98   0.000    -.1300991    -.044186
     cumrain |   .1859015   .0303734     6.12   0.000     .1263708    .2454322
         sun |   6.292645   .9364672     6.72   0.000     4.457203    8.128087
         mon |   12.34155   1.078199    11.45   0.000     10.22832    14.45479
         tue |    6.74024    1.16149     5.80   0.000      4.46376    9.016719
         wed |   5.620608   1.272798     4.42   0.000      3.12597    8.115247
         thu |   4.706281   1.231608     3.82   0.000     2.292374    7.120188
         fri |    4.84134   1.024178     4.73   0.000     2.833988    6.848691
         dec |   4.151659   1.222934     3.39   0.001     1.754752    6.548566
      summer |  -2.424963   1.444769    -1.68   0.093    -5.256658    .4067321
        cust |   .0003023   .0001502     2.01   0.044     7.94e-06    .0005966
         sin |   2.948544    2.19214     1.35   0.179    -1.347973     7.24506
       cosin |   5.911891    2.63163     2.25   0.025     .7539904    11.06979
    temp_g35 |  -.4244705   .8223144    -0.52   0.606    -2.036177    1.187236
    temp_g40 |  -2.863611   1.574092    -1.82   0.069    -5.948775    .2215525
 nudaygeq1mm |  -1.273972   .3087555    -4.13   0.000    -1.879122   -.6688228
       _cons |    23.0336   31.62038     0.73   0.466    -38.94121    85.00841
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L1. |   1.284877   .0304951    42.13   0.000     1.225107    1.344646
         L2. |  -.3283189   .0247627   -13.26   0.000     -.376853   -.2797849
             |
          ma |
         L1. |  -.7551262   .0270915   -27.87   0.000    -.8082245   -.7020279
-------------+----------------------------------------------------------------
ARMA7        |
          ar |
         L1. |   .9186684   .0323196    28.42   0.000     .8553232    .9820136
         L2. |  -.0338743   .0191715    -1.77   0.077    -.0714498    .0037013
             |
          ma |
         L1. |  -.7224889      .0284   -25.44   0.000    -.7781519   -.6668259
-------------+----------------------------------------------------------------
      /sigma |   8.006017   .0623198   128.47   0.000     7.883872    8.128161
------------------------------------------------------------------------------
Note: The test of the variance against zero is one sided, and the two-sided
      confidence interval is truncated at zero.
```

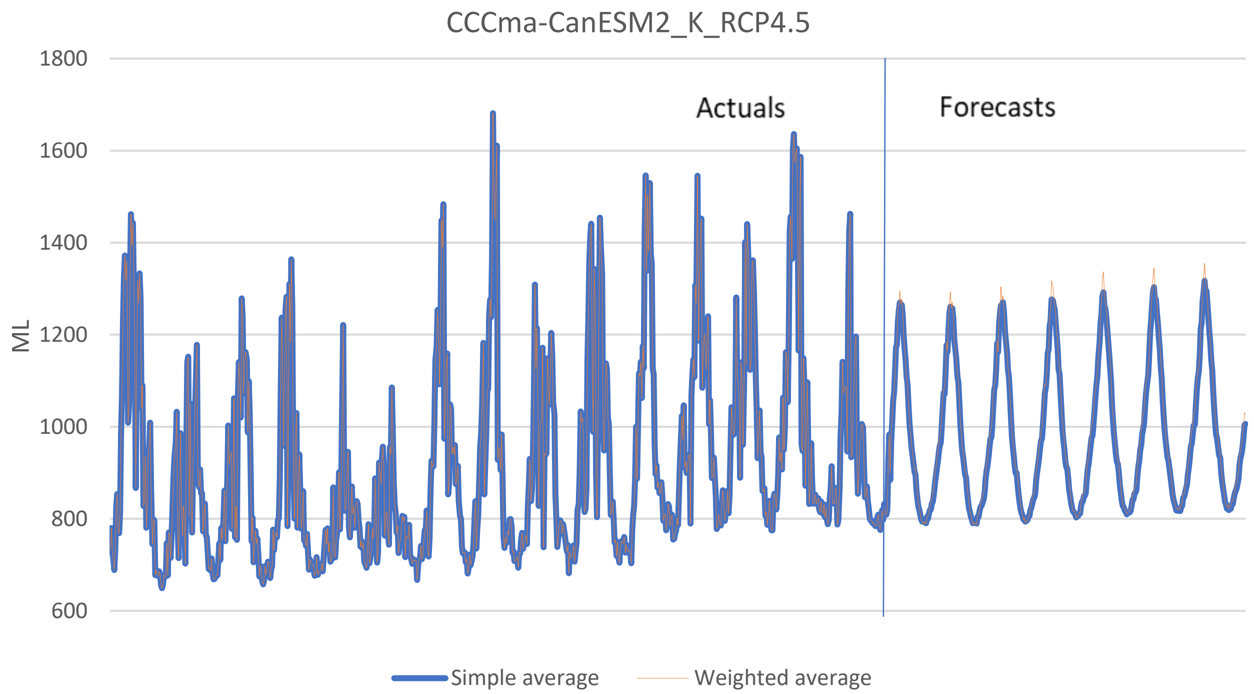
A1.12. Weekly dam abstraction forecasts – comparison of simple average vs weighted approach to climate data

The charts below compare weekly dam abstraction forecasts under a simple average approach compared with the weighted average approach for a sample of the NARCLiM climate scenarios

Figure 2: Weekly dam abstraction forecasts from July 2006 to June 2028 – comparison of simple average vs weighted average for a sample of NARCLiM climate scenarios




CCCma-CanESM2_J_RCP8.5
1800
1600
1400
1200
1000
800
600
ML
Actuals
Forecasts
1
31
61
91
121
151
181
211
241
271
301
331
361
391
421
451
481
511
541
571
601
631
661
691
721
751
781
811
841
871
901
931
961
991
1021
1051
1081
1111
1141
Simple average
Weighted average


CCCma-CanESM2_K_RCP4.5
1800
1600
1400
1200
1000
800
600
ML
Actuals
Forecasts
Simple average
Weighted average

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