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Water forecasts to quantify risks in the southern Murray–Darling Basin for informing water management decisions

Project RQ8a: Enhancing river operation outcomes using water forecasts and optimisation. Deliverable T2.8a.2

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Contents

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Executive summary

Project 8a of Theme 2 (T2.8a) of the Murray–Darling Basin Water and Environment Research Program (MD-WERP) aims to demonstrate the value of ensemble water forecasts for river operations decision-making in the Murray–Darling Basin (MDB). This report is the project's second deliverable. In this report, we describe the first of 2 case studies on how opportunities for ensemble water forecasting in the MDB can be realised.

For the case study, we focus on the upper Murray River from Hume Dam to Lake Mulwala. The system is managed by the Murray–Darling Basin Authority (MDBA) who are tasked with deciding the Hume Dam release, which combines with tributary inflows to meet the requirements of downstream users. The MDBA also manages Lake Mulwala as a buffer storage and seeks to maintain the level of the lake within a range (124.7-124.9 m).

To decide on the rate of release from Hume Dam requires some forecast of the system behaviour over the next 5 to 6 days. However, it is not trivial to generate the required forecasts. This is because of uncertainties in the system, namely uncertainties in the future Kiewa and Ovens inflows and future demands for water. The problem is further complicated by the different travel times of the Hume Dam release and Kiewa and Ovens tributary flows to Lake Mulwala, which make it challenging to accurately amalgamate forecasts of the Kiewa and Ovens inflows and demands for water with the Hume Dam release. In real-time river operations, these complicating factors can cause an over- or underestimation of the required Hume Dam release, which may result in the level of the Lake Mulwala weir pool either exceeding or falling below the desired operating range.

Thus, our goal for the case study is to create a quantitative risk model that can assist MDBA river operators with their real-time decision-making for the Hume Dam release. To meet the case study objectives, we obtain a hydrologic model to generate the required ensemble flow forecasts. Also, we develop multiple statistical models to forecast, from orders provided by state water agencies, downstream water demands and their uncertainties. Lastly, we develop a risk model integrating the flow and demand forecasts from the hydrologic and demand models to forecast, as a function of the Hume Dam release, the level of Lake Mulwala and with that, the risks of the lake level exceeding or falling below the desired range.

We obtain results for 2 forecast issue dates. The first represents a normal case where flows are within typical ranges. Plots of the results demonstrate the potential for our methods to inform real-time decisions relating to the Hume Dam release. The second issue date represents a nonstandard case where unregulated tributary inflows to Lake Mulwala are atypically high, which leads to a greatly increased risk of the Lake Mulwala level exceeding the desired range. The results show the limitation of our methods that presume (i) the Hume Dam release alone as a control variable to manage the lake level and associated risks and (ii) the Lake Mulwala release as constant over the forecast lead times. In reality however, where flows are extreme, an additional control variable, namely the release from Lake Mulwala at Yarrawonga Weir, is necessary to manage the system well.

1 Introduction

Project 8a of Theme 2 (T2.8a) of the Murray–Darling Basin Water and Environment Research Program (MD-WERP) aims to demonstrate the value of ensemble water forecasts for river operations decision-making in the Murray–Darling Basin (MDB). The project outcomes will provide new understanding on how ensemble water forecasts can assist with river operations, particularly with quantifying and managing risks.

This report is the project's second deliverable. In the first deliverable report (Robertson and Ng, 2021), (i) we summarised the available opportunities for ensemble water forecasting in the MDB to improve river operations and (ii) based on the opportunities, proposed 2 case studies, the first in the southern Basin and the second in the northern Basin, for demonstrating how some of the opportunities identified can be realised. In this second report, we describe the first case study in the southern Basin.

Several challenges impede the full incorporation of ensemble water forecasts to existing river operations decision-making in the southern MDB. Firstly, ensemble forecasts have only been available in the region for a relatively short time, which means that river operators have had limited opportunity to understand their characteristics and performance. Secondly, currently available forecasts — e.g. from the Bureau of Meteorology (BOM) 7-day Ensemble Streamflow Forecasting service — are only available for mostly unregulated tributaries, but not the regulated flow along the mainstem of the Murray that is of primary interest. Finally, current decision-making in the southern MDB largely relies on human judgement, which has limited capacity to quantitatively process ensemble forecasts.

Thus, for the case study, we aim to develop a risk model that is: (i) capable of quantitatively amalgamating real-time ensemble water forecasts of flows with upstream release decisions and with that, (ii) able to assess the likelihoods of achieving operational objectives (and conversely, the risks of failure) in the face of uncertain future flows as a function of operational decisions.

As Figure 1 below shows, we envisage the risk model as an additional tool to supplement human judgement for greater and more systematic use of ensemble forecasts in the southern Basin. We also envisage the risk model as paving the way for the adoption of more sophisticated tools, such as an optimisation model, that when combined with the risk model (and human judgement) have the potential to draw even greater benefit from ensemble forecasts.

In the following sections, we explain in detail the case study scope and objective and discuss our approach, methods, results, and intention for future work.

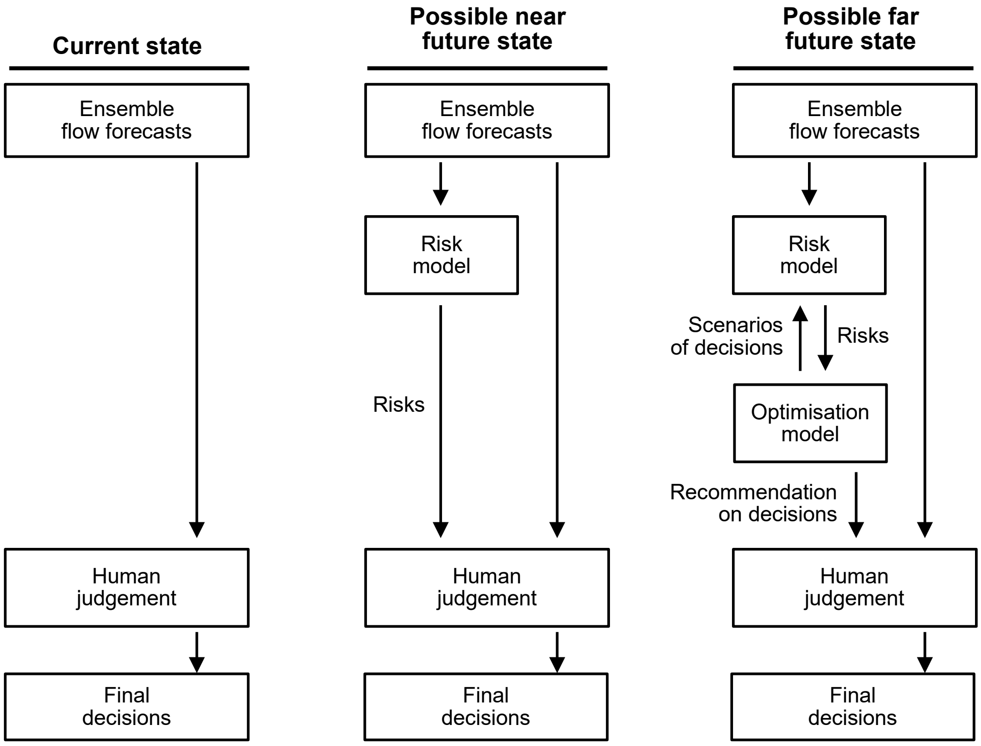

Figure 1. Potential of the risk model as an additional tool to supplement human judgement for greater and more systematic use of ensemble flow forecasts in river operations decision-making in the southern MDB, and to pave the way for the adoption of optimisation for even greater benefit from ensemble forecasts

2 Problem Motivation and Objectives

For the first case study of Project T2.8a in the southern MDB, we focus on the upper Murray River from Hume Dam to Lake Mulwala. The system is managed by the Murray–Darling Basin Authority (MDBA), who are tasked with deciding the Hume Dam release. Our goal for the case study is to create a risk model that can aid MDBA river operators in their real-time decision-making for the dam release.

To establish the motivation and objectives of the case study, we consulted with MDBA river operators. We developed a prototype risk model based on simple lag routing as a proof-of-concept to the MDBA on the use of hydrologic modelling to amalgamate ensemble flow forecasts with upstream decisions for assessing operational risks. The prototype model received, as input, the Hume Dam release and ensemble forecasts of tributary inflows to predict, as output, the risks of delivery shortfall and overbank flow. The results illustrated the trade-off between the different risks with respect to the Hume Dam release, which was useful for informing decisions on the release.

We formulated the case study motivation and objectives following feedback from the MDBA on the prototype risk model. When defining the motivation and objectives, we have endeavoured to reflect, as far as is feasible within the project timeframe, the major factors affecting the MDBA's real-life decision-making for the Hume Dam release, including their actual management objectives. We have also endeavoured to incorporate sources of uncertainty beyond tributary inflows, and for better accuracy, a calibrated hydrologic model of the system in place of the simple lag routing in the prototype. See Sections 2.1 and 2.2 below for the case study motivation and objectives respectively.

2.1 Problem motivation

As mentioned above, Hume Dam is managed by the MDBA, who releases water from the dam to meet orders from allocations. The release from the dam combines with tributary inflows from Kiewa and Ovens Rivers for delivery to (i) West Corurgan Private Irrigation District directly from the Murray near Corowa, (ii) Murray Valley Irrigation District via Yarrawonga Main Channel from Lake Mulwala, (iii) Murray Irrigation District via Mulwala Canal, also from Lake Mulwala and (iv) other users further downstream. See Figure 2 for a schematic of the system.

The MDBA also manages Lake Mulwala as a buffer storage for storing surplus water in times of excessive inflow for later use in times of inadequate inflow. The buffering capacity of the lake is essential in daily operation of the system as it allows for, to some degree, an over- or underestimation of the required Hume Dam release without significant consequences. However, the buffering capacity of the lake is limited as the MDBA desires — for recreational reasons, to reduce inundation impacts on adjacent properties and to ensure supply to irrigation districts is unconstrained— to maintain the level of the Lake Mulwala weir pool within a range (124.7-124.9 m) (A. Bishop, personal communication, 2022).

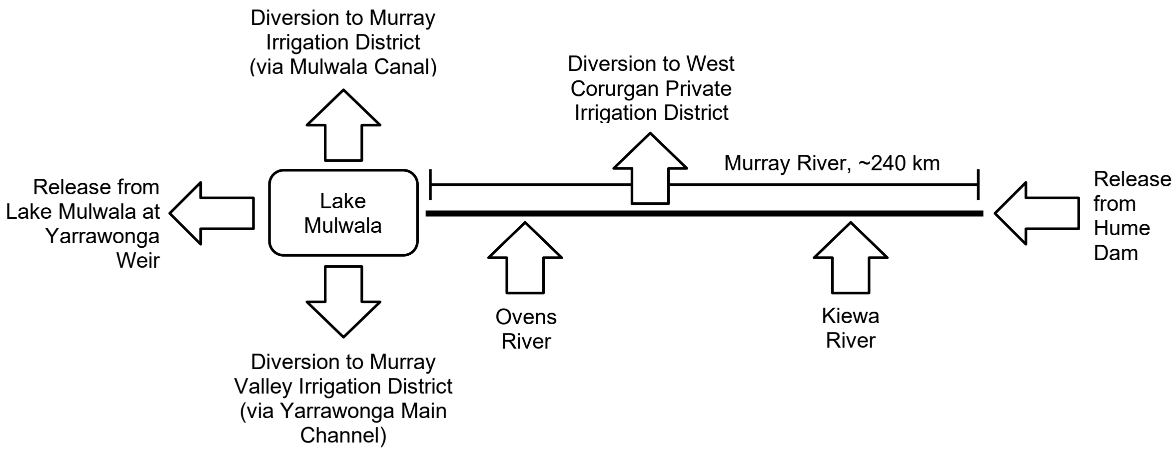

Figure 2. Schematic of the section of Murray River from Hume Dam to Lake Mulwala showing its (i) major tributaries, Kiewa and Ovens Rivers and (ii) major diversions to West Corurgan Private Irrigation District, Murray Valley Irrigation District (via Yarrawonga Main Channel) and Murray Irrigation District (via Mulwala Canal) and (iii) the release from Lake Mulwala at Yarrawonga Weir

To decide the rate of release from Hume Dam, the key variable for MDBA decision-making in the system, requires some forecast of the system behaviour over the next 5 to 6 days. However, it is not trivial to generate the required forecasts. This is because of uncertainties in the system, namely uncertainties in the future Kiewa and Ovens inflows. Both the Kiewa and Ovens are mostly unregulated and effectively free running streams and thus, their inflows can be highly variable depending on the climate. There are also uncertainties in the future demands for water. In the system, the above-mentioned irrigation districts provide orders to inform the MDBA of their demands in several days. Ideally, the demands equal the orders. However, in reality, they often differ, sometimes substantially, due to the unpredictability of weather and thus, unpredictability of irrigators’ water needs.

The problem is further complicated by the different travel times of the Hume Dam release and Kiewa and Ovens tributary flows to Lake Mulwala. The different travel times, ranging from one to 5 days, make it challenging to accurately amalgamate forecasts of the Kiewa and Ovens inflows and downstream demands for water with the Hume Dam release. The ability to amalgamate the various items is necessary for forecasting the inflow to Lake Mulwala and subsequently, volume and level of the lake as a function of the Hume Dam release, which is useful when deciding on the release. This ability is possible with a calibrated hydrologic model of the system of sufficient temporal and spatial resolutions. Though, as such a model is currently unavailable to MDBA river operators, their present capacity to realise the full potential of forecasts is limited. This is especially true in the case of ensemble forecasts, which are more accurate and reliable than deterministic ones but more complex and difficult to apply.

In real-time river operations, these complicating factors can cause an over- or underestimation of the required Hume Dam release, beyond what is acceptable as per the buffering capacity of Lake Mulwala. An overestimation can lead to potentially less efficient operations, while an underestimation can result in an inability to fully meet all demands. An over- or underestimation of the required release can also force the level of the Lake Mulwala weir pool to exceed or fall below the desired range (as given above). Of these risks, in day-to-day operations under typical conditions, it is the risks of the Lake Mulwala level exceeding or falling below the desired range that are of main concern (A. Bishop, personal communication, 2022).

2.2 Objectives

Given the problem motivation Section 2.1, our goal for the first case study of Project T2.8a in the southern MDB is to create a risk model that can aid MDBA river operators in their real-time decision-making for the Hume Dam release considering the risks of the level of Lake Mulwala exceeding or falling below the desired range. In light of this, our objectives for the case study are as follows:

1) To establish a hydrologic model, with ensemble flow forecasting ability, comprising sub-catchments of the section of Murray River from Hume Dam to Lake Mulwala and catchments of Kiewa and Ovens Rivers. The hydrologic model is (i) to generate retrospective ensemble forecasts of tributary inflows to the Murray, including inflows from Kiewa and Ovens Rivers, and (ii) to amalgamate the ensemble forecasts of the inflows with the Hume Dam release to produce ensemble forecasts of the mainstem flow along the Murray.
2) To develop statistical models to predict water extractions, given orders, to (i) West Corurgan Private Irrigation District, (ii) Murray Valley Irrigation District via Yarrawonga Main Channel and (iii) Murray Irrigation District via Mulwala Canal. The statistical models are to retrospectively forecast the water extractions and their uncertainties, which can be significant.
3) To integrate the outcomes from the first 2 objectives with a storage model of Lake Mulwala to create a risk model for forecasting, as a function of the Hume Dam release, the (i) risk of the Lake Mulwala level exceeding a higher threshold (124.9 m) and (ii) risk of it falling below a lower threshold (124.7 m). The risk model is to evaluate the consequences of different scenarios of the Hume Dam release, which is useful when deciding the dam release.
4) To generate results for selected forecast issue dates and various scenarios of the Hume Dam release to demonstrate our methods and their potential for real-time decision-making for the Hume Dam release.

3 Methods

In this section, we describe our methods to meet the case study objectives in Section 2.2. In Section 3.1, we describe a hydrologic-forecasting model for generating, retrospectively, the required ensemble flow forecasts. In Section 3.2, we describe our development of multiple water demand models to forecast actual demands for water from orders. In Section 3.3, we describe a storage model of Lake Mulwala and how outputs from the hydrologic-forecasting and demand models feed to it to yield predictions of the risks of the level of the lake exceeding or falling below the desired range. Finally, in Section 3.4, we describe scenarios of the Hume Dam release for generating results to demonstrate the potential of our methods for informing real-time decision-making for the dam release.

3.1 Hydrologic-Forecasting Model

To meet Objective 1 (Section 2.2), we adapt the hydrologic model from Ng et al. (2019) and Ng et al. (2022), who developed the model using the Short-term Water Information and Forecasting Tools (SWIFT2). SWIFT2 is a water forecasting platform developed by CSIRO (Perraud et al., 2015). It underlies the BOM 7-day Ensemble Streamflow Forecasting service and is thus, well-tested. The model is suited for generating retrospective ensemble streamflow forecasts at various locations throughout the case study system.

The hydrologic model comprises 87 nodes, 86 links and 86 subareas. It combines the 4-parameter GR4J rainfall-runoff model (Perrin et al., 2003), lag-and-route channel routing model and Error Reduction and Representation in Stages (ERRIS) model. ERRIS is an error model for reducing errors in streamflow forecasts (Li et al., 2017). For this present work, we omit ERRIS from the nodes along the Murray downstream of Hume Dam as ERRIS relies on observed data, which are unavailable for the scenarios of the Hume Dam release of interest.

We adopt the model parameters from Ng et al. (2019), who had estimated their values by calibrating the model to hourly flow observations at 21 sites, including the inlet to Lake Mulwala, and outlets of Ovens and Kiewa Rivers at Peechelba and Bandiana respectively. The authors had evaluated the parameters following a buffered leave-one-year-out cross-validation scheme, with a one-year buffer, over an 8-year period from 2008 to 2015. Thus, the parameters had been assessed on data independent from the model calibration and therefore, may be used here with confidence.

The hydrologic model runs on hourly time steps. Outputs from the model are the hourly streamflow at each node. Inputs to the model are the hourly potential evapotranspiration (PET) and rainfall over each sub-catchment. A third input to the model is the Hume Dam release, which we fix according to our purposes. Also entered to the model is the flow diversion to West Corurgan Private Irrigation District from the Murray near Corowa.

To generate retrospective 200-member ensemble flow forecasts with lead times to 6 days, we initially run the hydrologic model first in warmup mode for at least 4 years up to the forecast issue date. The long warmup period removes any effects of unavoidable arbitrary initial conditions at the start of the simulation. We run the model to the forecast issue date to estimate the model states at that time, which reflect levels of the system groundwater and soil moisture storages and flows in transit. With the initialised model states, we then run the model in forecast mode from the forecast issue date onwards to compute the desired forecasts. For subsequent forecast issue dates, the model states can be incrementally updated from a saved condition.

When in warmup up, we force the model with the historical Hume Dam release and historical PET and rainfall. We obtain the historical Hume Dam release from Water Data Online. We take the historical PET and rainfall from Ng et al. (2019) who derived the historical PET from gridded Australian Water Availability Project (AWAP) estimates (Raupach et al., 2012; Raupach et al., 2009) and the historical rainfall from BOM Australian Integrated Forecast System (AIFS) gauge observations. When in warmup mode, we also force the model with the historical diversion to West Corurgan Private Irrigation District, which we obtain from the MDBA (A. Bishop, personal communication, 2022).

When in forecast mode, we force the model with forecast PET and rainfall, which we take from Ng et al. (2022) who derived the forecast PET from climatology and the forecast rainfall from postprocessed BOM ACCESS-G (Australian Community Climate and Earth-System Simulator-Global) predictions (BOM, 2010). When in forecast mode, we also force the model with the future Hume Dam release, which we fix according to our purposes, and the forecast diversion to West Corurgan Private Irrigation District, which we compute from the demand models in Section 3.2 below.

The resulting flow forecasts are on hourly time steps. We convert them to daily time steps to be consistent with the demand models and Lake Mulwala risk model in Sections 3.2 and 3.3 below.

3.2 Water Demand Models

For Objective 2 (Section 2.2), we develop multiple statistical models to retrospectively forecast, from orders provided by state water agencies, the daily water extractions, and their uncertainties, to West Corurgan Private Irrigation District, Murray Valley Irrigation District (via Yarrawonga Main Channel) and Murray Irrigation District (via Mulwala Canal). For each district, we develop models for the months of September to April, each with its own set of parameters. We skip the late autumn and winter months of May to August as irrigation demands during these months are low if not zero.

To develop the models, we use a Bayesian Joint Probability (BJP) modelling approach (Robertson et al., 2013; Shrestha et al., 2015), originally developed for seasonal streamflow forecasting (Wang and Robertson, 2011). It is a highly flexible method appropriate for modelling a wide range of predictor-predictand relationships. Further, models developed using this approach have relatively few parameters, which reduces the problem of overfitting that is common in statistical modelling.

We conduct our analysis on real daily demand and order data from MDBA archives (A. Bishop, personal communication, 2022) for 2010-2016. As the BJP approach depends on the assumption of normality, we first transform the data using the Yeo-Johnson transformation (Yeo and Johnson, 2000) to normalise the data and homogenise their variances. To estimate the maximum likelihood values of the Yeo-Johnson transformation parameters, we use Shuffled Complex Evolution (Duan et al., 1994), a global optimisation algorithm. We obtain separate transformation parameters for the demand and order data.

For each irrigation district and each month of interest: (i) From the transformed data, we infer the parameters, and their uncertainties, of a multivariate normal distribution describing the joint distribution of the transformed demand and order data using Markov chain Monte Carlo sampling (Wang et al., 2019). (ii) We draw a sample of 200 sets of the parameters. (iii) For each set of the parameters, we condition the multivariate normal distribution on the transformed water orders, then sample from the resulting conditional distribution to produce a probabilistic forecast of the water demands. The sampled values are however, in transformed space. To convert them to untransformed space, we apply the inverse Yeo-Johnson transformation.

The raw forecasts are spatially uncorrelated. However, in reality, there is some correlation between the different irrigation districts. Thus, we apply the Schaake Shuffle (Clark et al., 2004) to instil in the forecasts realistic spatial characteristics.

3.2.1 Forecast verification

To validate the BJP models developed, we generate retrospective ensemble forecasts with lead times to 6 days for daily issue dates from every September to April from 2010 to 2016. We verify the forecasts according to 3 measures: (i) relative bias, (ii) the continuous ranked probability score (CRPS) and (iii) probability integral transform (PIT) uniform probability diagrams. The first 2 relate to the forecast accuracy, while the third to the forecast reliability, i.e., the statistical consistency between the forecast probabilities and observed frequencies. We verify the forecasts following a leave-one-month-out cross-validation scheme. This ensures that the forecasts are verified against data independent of the data used to calibrate the models and that performance scores are not over-estimated. It also means that the verification results are comparable to results obtainable under real-life operational conditions.

For a given set of ensemble forecasts, we calculate its relative bias as below:

$$B = 100\% \times (\overline{D_{\mathrm{F}}} - \overline{D_{\mathrm{O}}})/\overline{D_{\mathrm{O}}} \qquad (1)$$

B is the relative bias. $\overline{D_{\mathrm{F}}}$ is the mean of the forecast ensembles, and $\overline{D_{\mathrm{O}}}$ the mean of corresponding observations. The relative bias ranges from -∞ to +∞ and is ideally zero. A negative relative bias indicates an overall underestimation by the forecasts, while a positive relative bias indicates an overall overestimation.

The CRPS (Hersbach, 2000) is a well-known statistic to compare the cumulative distribution of an ensemble forecast with the corresponding observation. The CRPS is an attractive evaluation measure in ensemble forecasting as it reduces to the absolute error in the case of deterministic forecasts, which makes comparing between ensemble and deterministic forecasts straightforward. The CRPS has a negative orientation, i.e., the smaller its value, the more accurate a forecast; it tends to increase with the forecast bias and decrease with the forecast reliability. We compute the CRPS of an ensemble forecast as follows:

$$S_{\mathrm{F}} = \int_{-\infty}^{\infty} [F(y) - H(y - D_{\mathrm{o}})]^2 \, dy \qquad (2)$$

S_{F} is the CRPS of the forecast, $F(y)$ its cumulative distribution function and D_{o} its corresponding observation. H is the Heaviside step function whose value equals one for values of y greater than D_{o} and zero otherwise.

PIT uniform probability diagrams, or PIT diagrams for short, display the uniformity of PIT values, or lack thereof. PIT diagrams have the advantage of not requiring the subjective binning of data as required by PIT histograms (Diebold et al. 1998). We compute the PIT of an observation corresponding to an ensemble forecast as:

$$\pi = F(D_{\mathrm{o}}) \qquad (3)$$

where π is the PIT of the observation, D_{o} its value and $F(\ )$ the cumulative distribution function of the ensemble forecast. PIT values range between 0 and 1. Where a set of forecasts are perfectly reliable, the resulting PIT values are uniform such that when plotted against the uniform distribution in a PIT diagram, will align with the diagonal 1:1 line.

3.3 Lake Mulwala Risk Model

For Objective 3 (Section 2.2), we develop a water mass balance across Lake Mulwala to forecast, as a function of the Hume Dam release, the volume and level of the lake and with that, the risks of the lake level exceeding or falling below the desired range. The mass balance across Lake Mulwala, for a given forecast lead time t, is as below:

$$V_t = V_{t-1} + \Delta t\left(I_t - O_t - D_{\mathrm{M},t} - D_{\mathrm{Y},t}\right) \qquad (4)$$

Δt is the length of the forecast time step, which we set to 1 day. V_t is the volume of the lake at the end of t. I_t is the forecast inflow to the lake over t and is computed using the hydrologic-forecasting model from Section 3.1, that integrates the Hume dam release with previous days' and forecast tributary inflows. O_t is the expected release from the lake at Yarrawonga Weir over t and is predefined. $D_{\mathrm{M},t}$ and $D_{\mathrm{Y},t}$ are the forecast diversions from the lake to Mulwala Canal and Yarrawonga Main Channel respectively over t. To account for potential differences between the diversions and orders, that can be substantial, we compute $D_{\mathrm{M},t}$ and $D_{\mathrm{Y},t}$ using the demand models in Section 3.2.

Under normal conditions, O_t are mostly governed by downstream demands and are limited to 9000-9500 ML/day by the Barmah Choke, a narrow section of the Murray River downstream of Yarrawonga. Here, we assume O_t to be constant over the forecast horizon and to equal the real Lake Mulwala release on the forecast issue date as per MDBA records (A. Bishop, personal communication, 2022).

We assume forecast lead times to 6 days. Thus, equation (4) is true for all t from one to 6. At $t = 1$, V_{t-1} represents the volume of Lake Mulwala at the forecast issue date and time and is user-defined. We take its value from real data provided by the MDBA (A. Bishop, personal communication, 2022). For all subsequent t, we compute V_{t-1} from the previous day's mass balance.

Equation (4) is stochastic. I_t, $D_{\mathrm{M},t}$ and $D_{\mathrm{Y},t}$ comprise 200-member ensembles. Consequently, V_t also comprise 200-member ensembles. To derive V_t, for each forecast lead time t from one to 6, we compute equation (4) 200 times.

From V_t, we forecast the level of Lake Mulwala by interpolating from the capacity table below (Table 1) that has been provided by the MDBA (A. Bishop, personal communication, 2022). This yields, for each forecast lead time t, a 200-member ensemble of the forecast level. From the forecast level, we estimate the risks of it exceeding 124.9 m and of it falling below 124.7 m. These thresholds are as advised by the MDBA (A. Bishop, personal communication, 2022), who desires to maintain the lake level within a range for recreational reasons, to reduce inundation impacts on adjacent properties and to ensure supply to irrigation districts is unconstrained. We estimate these risks as follows:

$$R_{\mathrm{U},t} = \frac{1}{\mathrm{N}} \sum_{n=1}^{\mathrm{N}} X_{\mathrm{U},t,n} \tag{5}$$

$$R_{\mathrm{L},t} = \frac{1}{\mathrm{N}} \sum_{n=1}^{\mathrm{N}} X_{\mathrm{L},t,n} \tag{6}$$

where:

$$X_{\mathrm{U},t,n} = \begin{cases} 1, H_{t,n} > \mathrm{T_U} \\ 0, H_{t,n} \leq \mathrm{T_U} \end{cases} \tag{7}$$

$$X_{\mathrm{L},t,n} = \begin{cases} 1, H_{t,n} < \mathrm{T_L} \\ 0, H_{t,n} \geq \mathrm{T_L} \end{cases} \tag{8}$$

$\mathrm{T_U}$ equals 124.9 m and $\mathrm{T_L}$ 124.7 m; they represent the higher and lower thresholds, respectively, on the Lake Mulwala level. N is the size of the forecast ensembles of the lake level and equals 200. $R_{\mathrm{U},t}$ and $R_{\mathrm{L},t}$ are the risks of the lake level exceeding $\mathrm{T_U}$ and of it falling below $\mathrm{T_L}$ respectively. $H_{t,n}$ is the nth member of the forecast ensemble of the lake level at the end of forecast lead time t. $X_{\mathrm{U},t,n}$ and $X_{\mathrm{L},t,n}$ are binary indicator variables and are as defined by equations (7) and (8) respectively.

Table 1. Lake Mulwala storage capacity table relating the level of the lake with its volume as provided by the MDBA (A. Bishop, personal communication, 2022)

Level (m)	Volume (ML)		Level (m)	Volume (ML)		Level (m)	Volume (ML)
118.8	0		122.0	21800		123.6	63390
119.0	1000		122.1	22920		123.7	67120
119.2	2000		122.2	24550		123.8	70940
119.4	3100		122.3	26320		123.9	74840
119.6	4100		122.4	28260		124.0	78840
119.8	5200		122.5	30350		124.1	82920
120.0	6300		122.6	32600		124.2	87060
120.2	7300		122.7	35020		124.3	91260
120.4	8600		122.8	37620		124.4	95520
120.6	9700		122.9	40370		124.5	99840
120.8	11100		123.0	43260		124.6	104220
121.0	12400		123.1	46310		124.7	108670
121.2	14000		123.2	49500		124.8	113190
121.4	15600		123.3	52800		124.9	117790
121.6	17500		123.4	56220		125.0	122470
121.8	19600		123.5	59760		125.1	127240

3.4 Computational Scenarios

To meet Objective 4 (Section 2.2), using the models from above, we generate results to forecast the risks of the Lake Mulwala level exceeding or falling below the desired range (124.7-124.9 m) for 2 issue dates, 1 January 2012 and 6 December 2010. The 2012 issue date represents a normal case where flows are within typical ranges. The 2010 issue date represents an extreme case where flows are unusually high, and thus, the risk of the level of Lake Mulwala exceeding the desired range harder to manage. In both cases, we assume that all forecasts are issued at the start of the issue date and that all dates and times are in UTC+0.

For each forecast issue date, we obtain results for 39 scenarios of the Hume Dam release. This is to quantify the influence of the dam release on the abovementioned risks for informing real-time decision-making for the release, particularly its magnitude on lead day one of the forecast, i.e., the first 24 hours proceeding the forecast issue date and time. Thus, we differentiate the 39 Hume Dam release scenarios by lead day one's release. We also differentiate the scenarios by lead day two's release for more complete results.

To construct the Hume Dam release scenarios, for lead day one, we consider 13 levels of the dam release from $(Q_{\mathrm{P}} - 15\ \mathrm{m}^3/\mathrm{s})$ to $(Q_{\mathrm{P}} + 15\ \mathrm{m}^3/\mathrm{s})$ where Q_{P} is the actual release on the day immediately prior to the forecast issue date. Q_{P} is as per MDBA records (A. Bishop, personal communication, 2022). For lead day 2, we consider 3 levels of the release: $(Q_1 - 15\ \mathrm{m}^3/\mathrm{s})$, Q_1 and $(Q_1 + 15\ \mathrm{m}^3/\mathrm{s})$ where Q_1 is lead day one's release. For lead days 3 to 6, we assume the release to be the same as on lead day 2. In this manner, we obtain 39 scenarios of the Hume Dam release.

The -15 and $+15\ \mathrm{m}^3$/s bounds around Q_{P} and Q_1 when constructing the Hume Dam release scenarios are due to the '6-inch rule' (DELWP, 2015). The rule exists to reduce bank slumping. According to it, the maximum allowable fall in the water level at Doctors Point, ~13 km downstream of Hume Dam, is 6 inches a day. This equates to a maximum limit on any reduction in the Hume Dam release of ~15 m^3/s.

4 Results and Discussion

In this section, we discuss our results. In Section 4.1, we discuss the results from Section 3.2 to verify the retrospective BJP demand forecasts generated and with that, validate the demand models developed. In Section 4.2, we discuss the results from Section 3.4, which we generate by combining the hydrologic-forecasting model, demand models and risk model from Sections 3.1 to 3.3, to forecast the risks of the level of Lake Mulwala exceeding or falling below the desired range (124.7-124.9 m) as a function of the release from Hume Dam. The results demonstrate the potential of our methods for informing real-time decision-making for the dam release.

4.1 Water Demand Forecast Verification

Here, we discuss results to verify the retrospective BJP demand forecasts from Section 3.2, for the months of interest, September to April, and 3 irrigation districts modelled: West Corurgan Private Irrigation District, Murray Valley Irrigation District (Yarrawonga Main Channel) and Murray Irrigation District (Mulwala Canal). We verify the forecasts in terms of their relative biases, CRPSs and PIT diagrams, which measure their accuracy and reliability. The results provide a means of validating our methods. Also, as verification conditions are akin to real-time conditions, the results are useful as an indication of the performance of real-time forecasts that can be expected should we apply our methods operationally in real-time.

Figure 3 presents the relative biases of the retrospective BJP demand forecasts. We obtain the results by averaging across issue dates. For comparison, the figure also gives the relative biases of corresponding forecasts obtained by equating demands to orders. As the results show, the BJP forecasts have significantly smaller biases, whether negative or positive, than the forecasts from equating demands to orders and are thus, more accurate. In all cases, the relative biases of the BJP forecasts are between -5% and 5%. In some cases even, they are near zero, e.g., for January and February in the case of Murray Irrigation District (Mulwala Canal).

Figure 4 gives the mean CRPSs of the retrospective BJP demand forecasts, again, obtained by averaging across issue dates. The figure also gives the mean CRPSs of the forecasts from equating demands to orders, which essentially equates to their mean absolute errors as the forecasts are deterministic. From the figure, we observe the BJP forecasts to have smaller CRPSs than the forecasts from equating demands to orders. The BJP forecasts are therefore more accurate. This is true for all months and all 3 irrigation districts of concern.

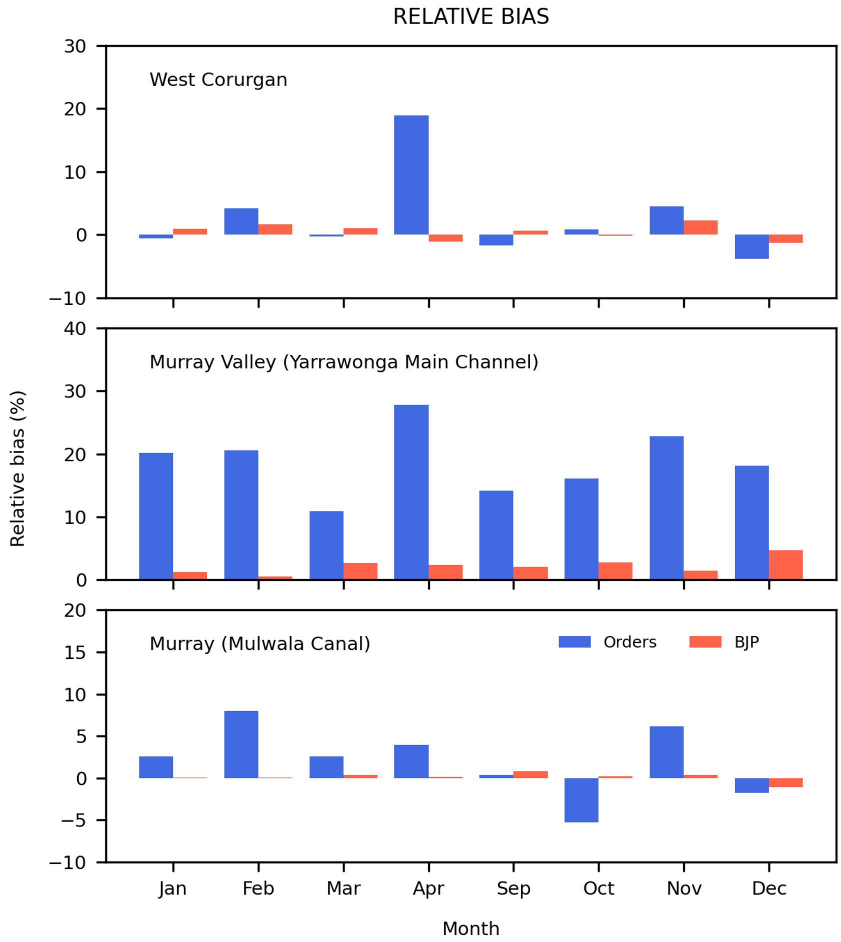

Figure 3. Relative biases of the retrospective BJP demand forecasts from Section 3.2 and corresponding forecasts from equating demands to orders, for the months of interest, September to April, and 3 irrigation districts modelled: West Corurgan Private Irrigation District, Murray Valley Irrigation District (Yarrawonga Main Channel) and Murray Irrigation District (Mulwala Canal)

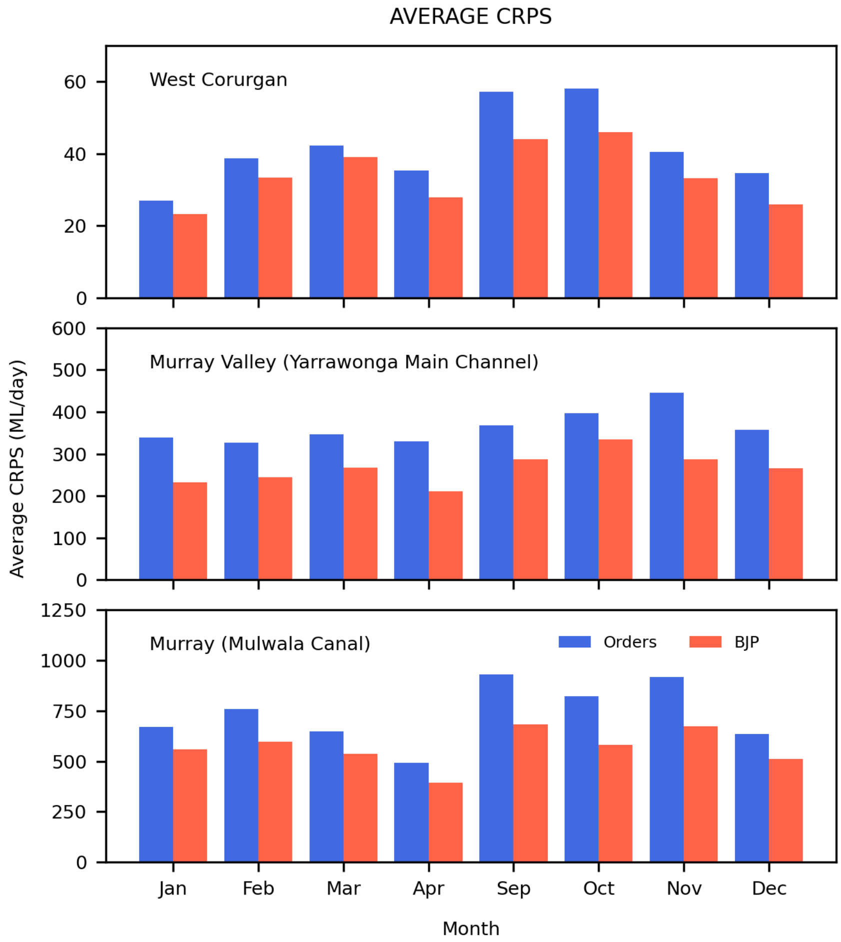

Figure 4. CRPSs of the retrospective BJP demand forecasts from Section 3.2 and corresponding forecasts from equating demands to orders, for the months of interest, September to April, and 3 irrigation districts modelled: West Corurgan Private Irrigation District, Murray Valley Irrigation District (Yarrawonga Main Channel) and Murray Irrigation District (Mulwala Canal)

Figure 5 shows the PIT reliability diagrams of the retrospective BJP demand forecasts from Section 3.2. We find the plots of the forecast PIT values, for all months and all 3 irrigation districts of concern, to closely match the diagonal 1:1 line. We can thus conclude that the forecasts are reliable, i.e., that their probabilities correspond well with observed frequencies. This means that the forecast probabilities can be trusted such that, for example, if it is predicted a high chance of a large demand, then it is likely that the demand will be large as predicted.

Figures 6-8 provide the 50, 80 and 95% confidence intervals and median of the retrospective BJP demand forecasts with respect to time. Figure 6 gives the confidence intervals and median of the forecast demand to West Corurgan Private Irrigation District, Figure 7 Murray Valley Irrigation District (Yarrawonga Main Channel) and Figure 8 Murray Irrigation District (Mulwala Canal). The figures also give the corresponding observed demands. We find from the figures that, for the most part, the observed demands to fall within the 90% confidence intervals and for a large part, to fall within the 50% confidence intervals. We also find the forecasts to track well the trends, i.e., rising and falling, of the observed demands.

However, in Figures 6-8, there are times where there is a systematic bias in the BJP forecasts, i.e., where the observed demands are persistently larger or smaller than their respective forecast medians. For example, in Figure 7 for Murray Valley Irrigation District (Yarrawonga Main Channel), in the third subplot, from January to February 2013, the observed demand is persistently larger than the forecast median and consistently trends toward the upper end of the BJP forecasts. This suggests the presence of temporal correlations that we have not accounted for in our methods, but which may be worth investigating in future work.

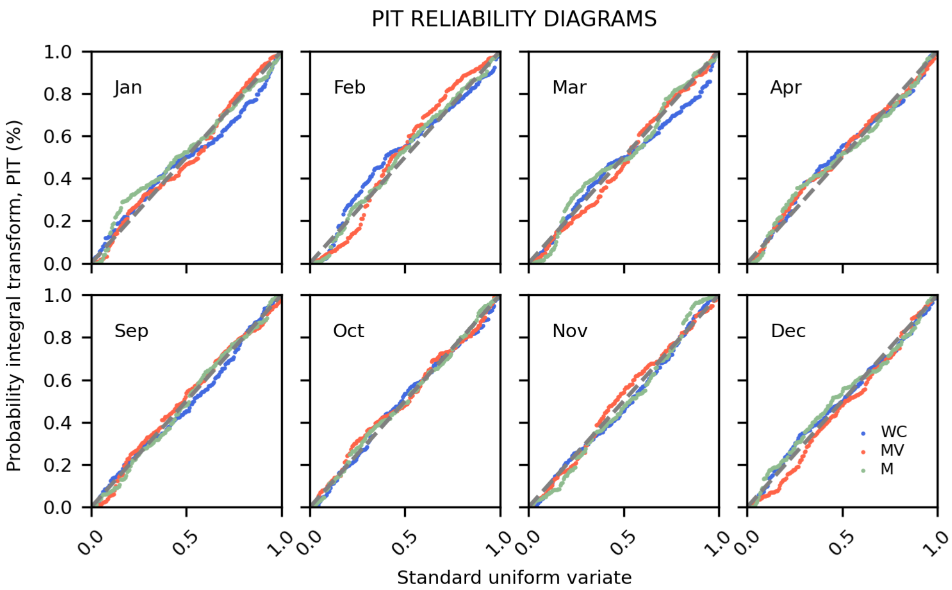

Figure 5. PIT diagrams of the retrospective BJP demand forecasts from Section 3.2 for the months of interest, September to April, and 3 irrigation districts modelled: West Corurgan Private Irrigation District (WC), Murray Valley Irrigation District (Yarrawonga Main Channel) (MV) and Murray Irrigation District (Mulwala Canal) (M)

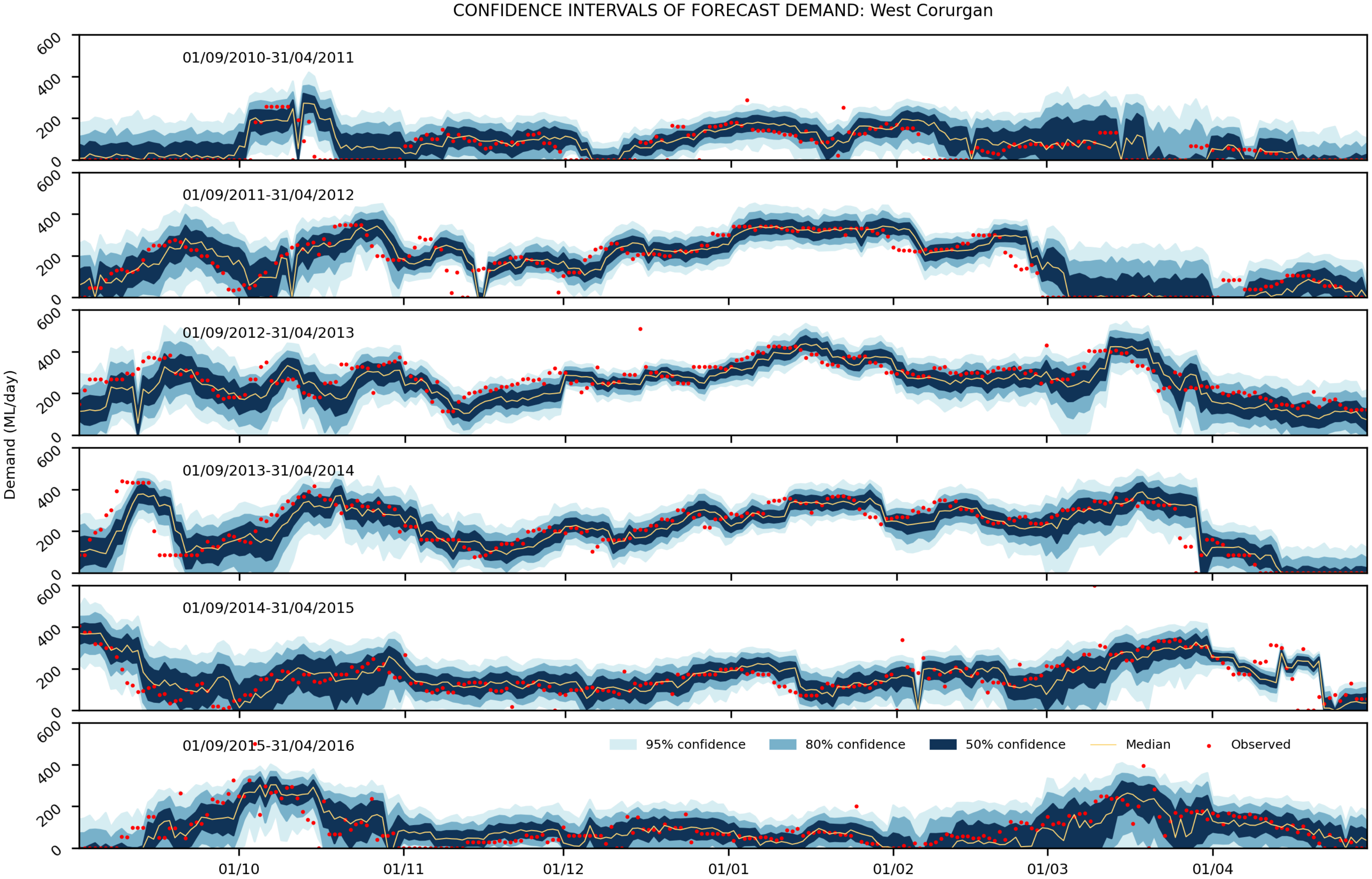

Figure 6. 50, 80 and 90% confidence intervals and median of the retrospective BJP demand forecasts from Section 3.2 for the case of West Corurgan Private Irrigation District and the corresponding observed demands; the results are with respect to time and for the months of interest

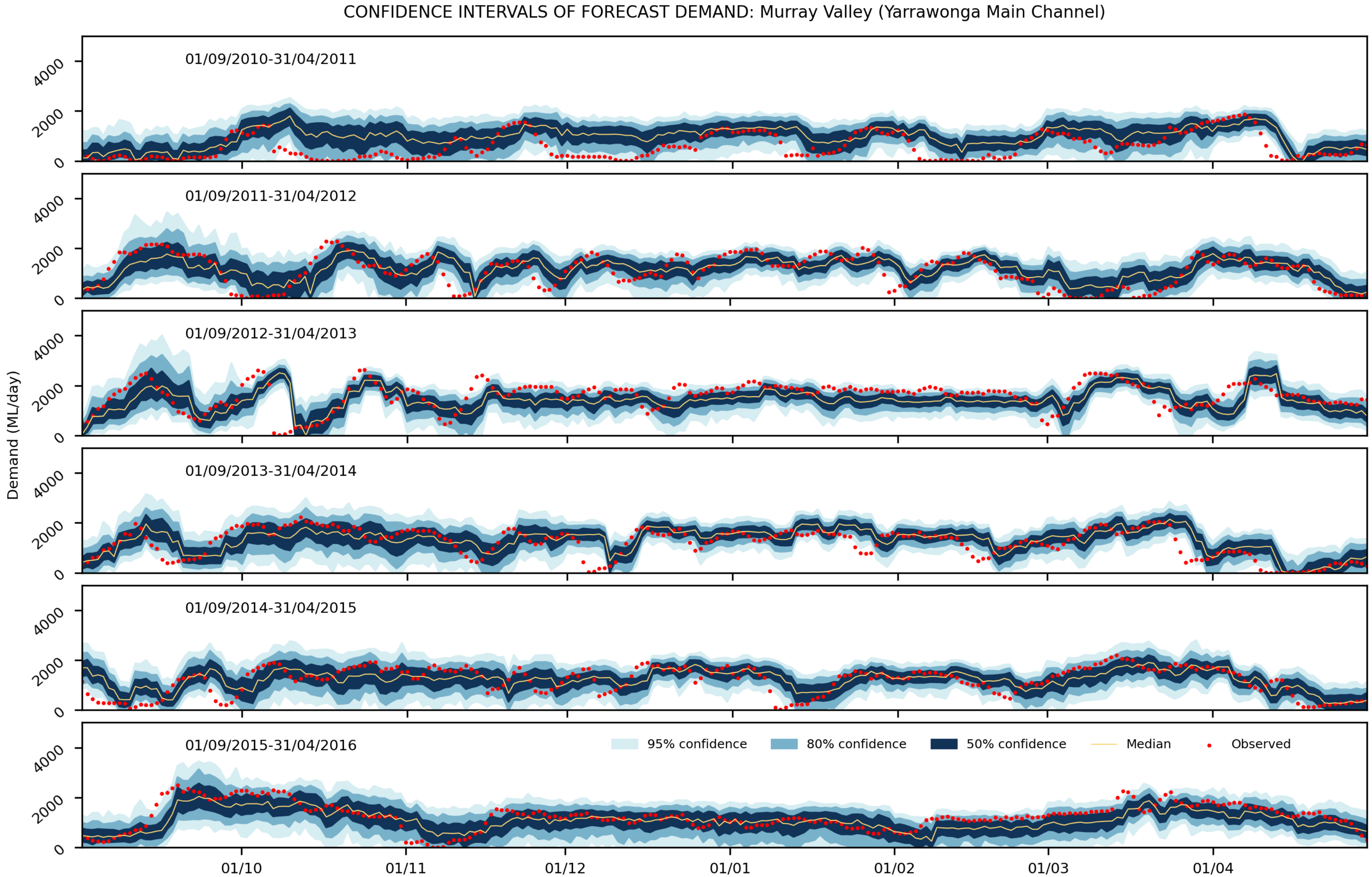

Figure 7. 50, 80 and 90% confidence intervals and median of the retrospective BJP demand forecasts from Section 3.2 for the case of Murray Valley Irrigation District (Yarrawonga Main Channel) and the corresponding observed demands; the results are with respect to time and for the months of interest

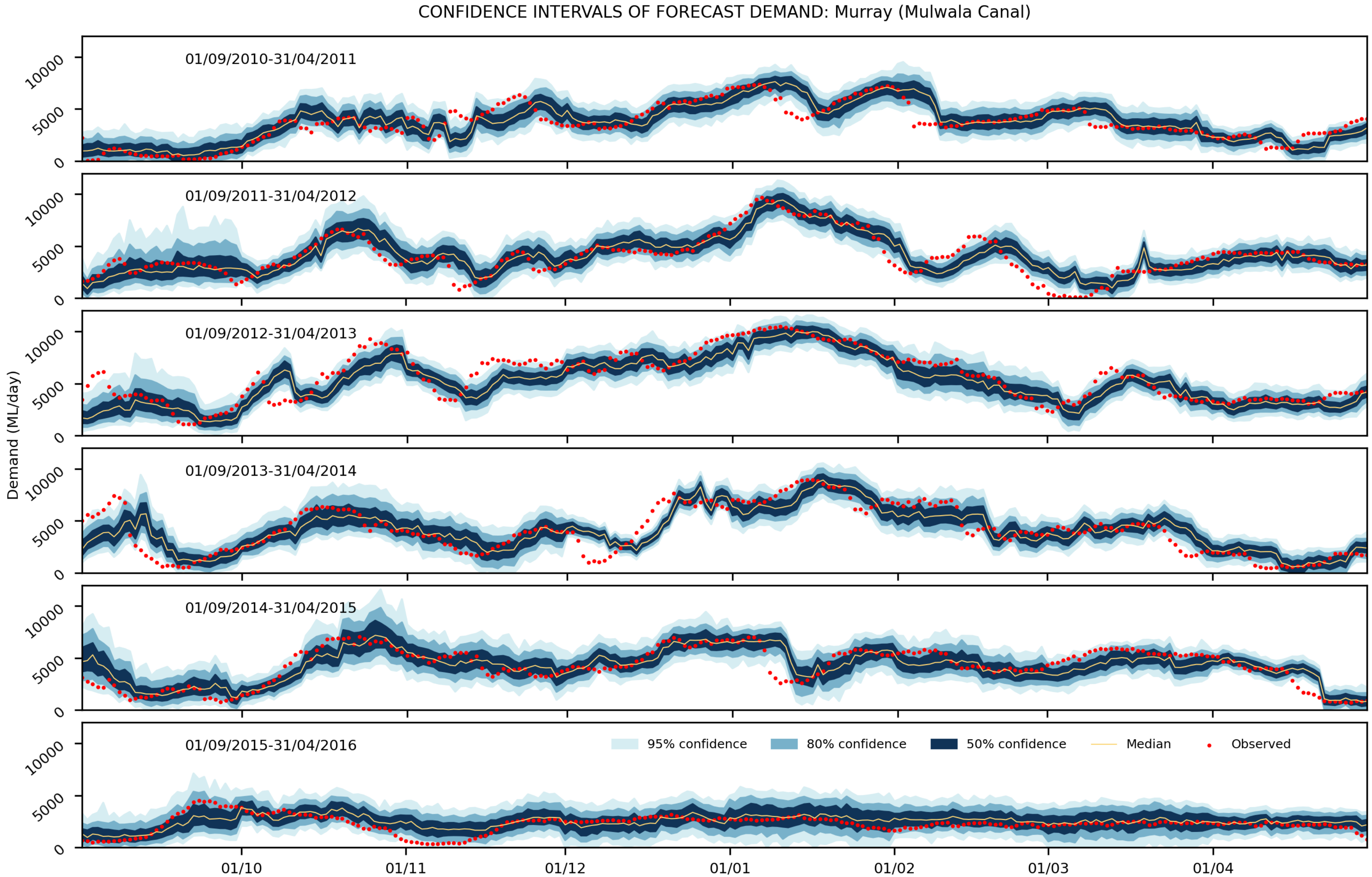

Figure 8. 50, 80 and 90% confidence intervals and median of the retrospective BJP demand forecasts from Section 3.2 for the case of Murray Irrigation District (Mulwala Canal) and the corresponding observed demands; the results are with respect to time and for the months of interest

4.2 Estimation of Operational Risks

In this section, we discuss our results from Section 3.4 giving the forecast risks of the level of Lake Mulwala exceeding or falling below the desired range (124.7-124.9 m) for multiple scenarios of the Hume Dam release. Section 4.2.1 gives the forecast risks for a normal case where flows are within typical ranges, while Section 4.2.2 gives the risks for an extreme case where flows are unusually high. The results demonstrate the potential and limitation of our methods for informing real-time decision-making for the Hume Dam release.

4.2.1 Normal case

Here, we present and discuss our results for a normal case where flows are non-extreme and within typical ranges. Figure 9 shows our forecasts of the risk consequences of a range of Hume Dam release scenarios for the forecast issue date 1 January 2012 and issue time 00:00:00 UTC+0. The forecasts are of the risks of the level of Lake Mulwala exceeding or falling below the desired range (124.7-124.9 m) given the Hume Dam release on lead day one, i.e., the release over the first 24 hours from the forecast issue date and time. The forecasts assume the release on lead days 2 to 6 to be the same as on lead day one and are of the risks at the end of lead day 5.

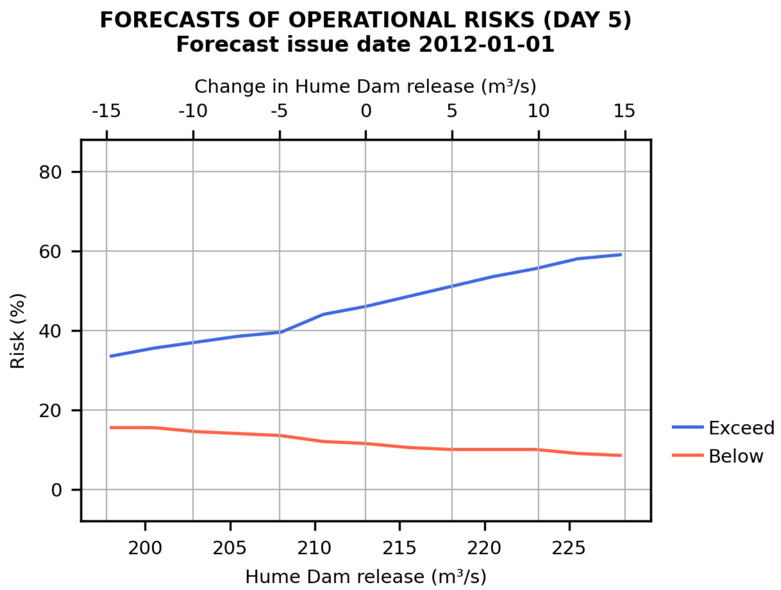

Figure 9. Forecasts of the risks, at the end of lead day 5 of the forecasts, of the level of Lake Mulwala exceeding or falling below the desired range; the forecasts are for the issue date 1 January 2012 and assume the Hume Dam release on lead day 2 and thereafter to be the same as on lead day one; the x-axes represent lead day one's release; the first x-axis (bottom) represents the release in terms of its absolute value; the second x-axis (top) represents the release in terms of its change from the previous day's release

Figure 9 gives a simplified easy-to-interpret view of our results. Figure 10 expands from Figure 9 to give a more comprehensive view of the results. In addition to the forecast risks at the end of lead day 5, Figure 10 gives too the risks at the end of lead days 3, 4 and 6. It also gives the risks for additional scenarios of the Hume Dam release: where the release on lead days 2 to 6 is greater than the release on lead day one by 15 m^3/s, and where it is lesser by 15 m^3/s.

We observe in Figure 10 that the forecast risks at the end of lead day 3 to be mostly insensitive to lead day one's Hume Dam release, regardless of lead day 2's release. They are thus uncontrollable by future adjustment of the Hume Dam release. This is as expected considering that the flow travel time from Hume Dam to Lake Mulwala is about 4 to 5 days depending on flow attenuation effects.

We also observe in Figure 10, the Hume Dam release on lead day one to start affecting the forecast risks from the end of lead day 4 and to be a particularly significant influence on the risks at the end of lead day 5. Similarly, we find the Hume Dam release on lead day 2 to start affecting, in a major way, the forecast risks from the end of lead day 5 and to be a particularly significant influence on the risks at the end of lead day 6. These findings are as expected given, again, the 4- to 5-day travel time from Hume Dam to Lake Mulwala.

Figure 10 is useful for informing decision-making for the Hume Dam release. It provides the risks that can be expected given a Hume Dam release scenario. For example, if we were to fix the release on lead day one to be the same as the previous day's release (~213 m^3/s) and on lead day 2 and thereafter to be greater than lead day's one release by 15 m^3/s (~228 m^3/s), it can be expected the risk, at the end lead day 5, of the level of Lake Mulwala exceeding the desired range to be ~50% and of it falling below the desired range to be ~10%.

From Figure 10, we can also infer the Hume Dam release strategy required for achieving a certain risk outcome. For instance, to minimise the risk at the end of lead day 5 of the level of Lake Mulwala exceeding the desired range while limiting the risk of it falling below the desired range to less than 20%, we find from the figure it best to set the Hume Dam release on lead day one to the previous day's release less 15 m^3/s (~198 m^3/s) and on lead day 2 and thereafter to less an additional 15 m^3/s (~183 m^3/s).

As a supplement to Figure 10, Figure 11 gives an alternative view of our results. The figure presents the results as time series showing the evolution of the forecast risks with lead time. The plots in the figure confirm our observation above from Figure 10 that the risks at the end of lead day 3 are relatively unaffected by both lead days one and 2's Hume Dam release and thus, effectively uncontrollable by adjusting the future release. The plots also confirm our observations that lead day one's Hume Dam release affects the forecast risks only from the end of lead day 4 and that lead day 2's release affect, in a major way, the risks only from the end of lead day 5.

Figure 12 gives further supplementary information. The figure gives our forecasts of the level of Lake Mulwala with respect to the forecast lead time. The plots in the figure are in terms of the forecast ensemble mean. Figure 12 may aid in better understanding the forecast risks in Figures 9-11 as it is more intuitive to visualise values of level than it is to visualise probabilities.

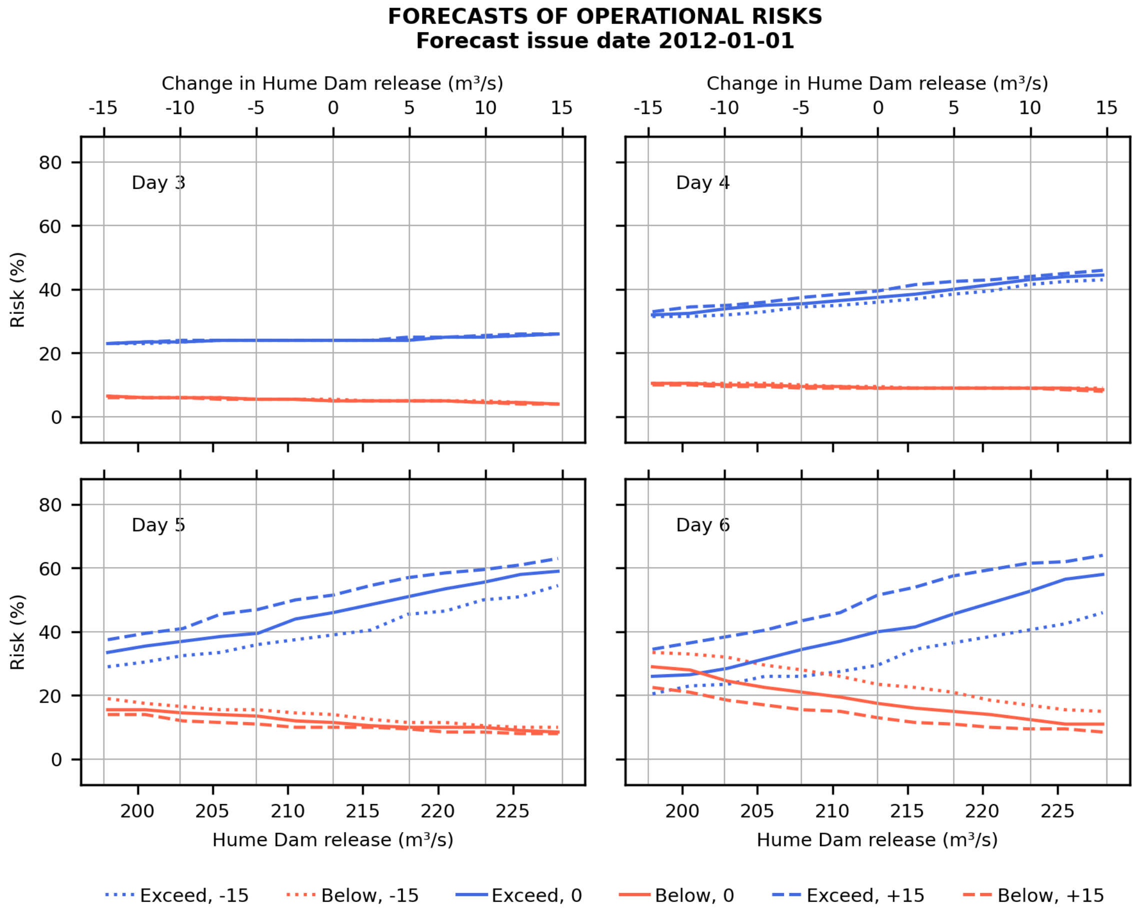

Figure 10. Forecasts of the risks, at the end of lead days 3 to 6 of the forecasts, of the level of Lake Mulwala exceeding or falling below the desired range; the forecasts are for the issue date 1 January 2012; the forecasts assume the Hume Dam release on lead day 2 and thereafter to be the same as (solid lines), less by 15 m^3/s than (dotted lines) or more by 15 m^3/s than (dashed lines) the release on lead day one; the x-axes represent lead day one's release; the first x-axis (bottom) represents the release in terms of its absolute value; the second x-axis (top) represents the release in terms of its change from the previous day's release

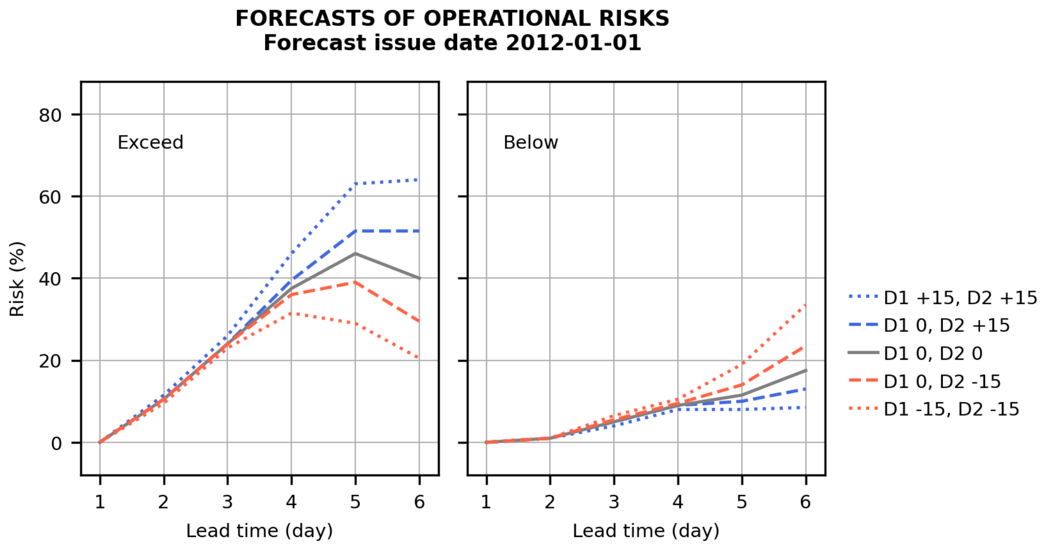

Figure 11. Forecasts of the risks of the level of Lake Mulwala exceeding or falling below the desired range, with respect to the forecast lead time; the forecasts are for the issue date 1 January 2012; the forecasts assume the Hume Dam release on lead day one (D1) to be the same, less by 15 m^3/s than or more by 15 m^3/s than the previous day's release, and the release on lead day 2 (D2) to be the same, less by 15 m^3/s than or more by 15 m^3/s than lead day one's release

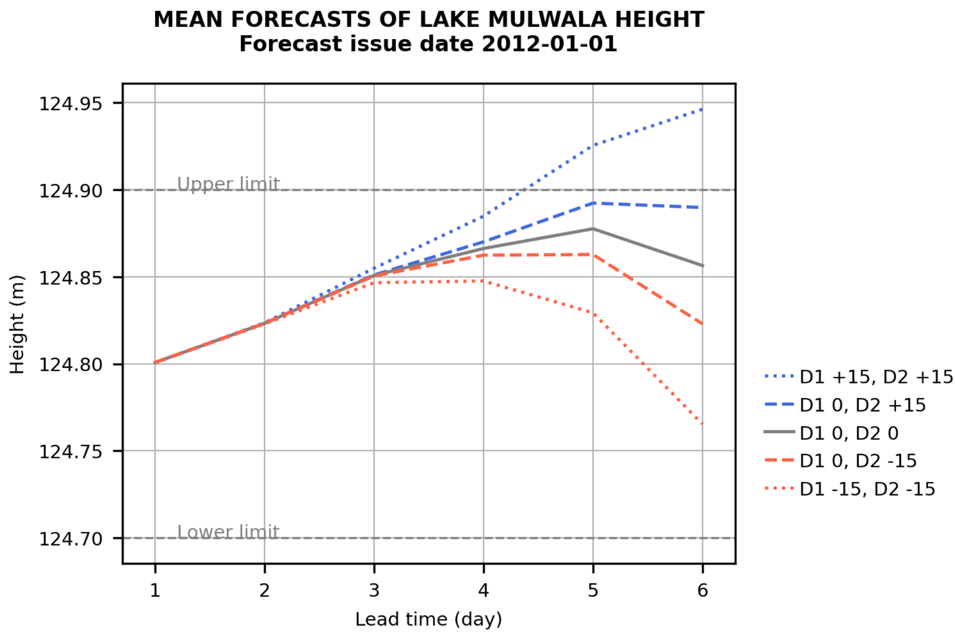

Figure 12. Mean forecasts of the level of Lake Mulwala with respect to the forecast lead time, for the issue date 1 January 2012 and in comparison with the upper and lower limits on the desired range of the lake level; the forecasts assume the Hume Dam release on lead day one (D1) to be the same, less by 15 m^3/s than or more by 15 m^3/s than the previous day's release, and the release on lead day 2 (D2) to be the same, less by 15 m^3/s than or more by 15 m^3/s than lead day one's release

4.2.2 Extreme case

Here, we discuss the results for an extreme case where flows are unusually high due to an upcoming storm event. The results illustrate the limitation of our current methods and assumptions.

Figure 13 shows our results for the forecast issue date and time 6 December 2010 00:00:00 UTC+0. The figure gives our forecasts of the risks, at the end of lead days 3 to 6, of the level of Lake Mulwala exceeding or falling below the desired range (124.7-124.9 m) for various scenarios of the Hume Dam release. As Figure 13 shows, it can be expected exceptionally high risks of the Lake Mulwala level exceeding the desired range. It can be expected the risks to range from ~70% at the end of lead day 3 to more or less 100% by the end of lead day 6. This is true in all scenarios of the Hume Dam release considered.

Figure 14 gives the forecast risks in terms of the forecast lead time. As in Figure 13, we find from Figure 14 that it can be expected exceptionally high risks of the level of Lake Mulwala exceeding the desired range regardless of the magnitude of the Hume Dam release. The large forecast risks are due to continued extreme high inflows, particularly from the Ovens, expected over the next several days. The high inflows translate to high forecast levels of the lake, as Figure 15 shows, and consequently, the large forecast risks.

Such large risks are undesirable. The results thus demonstrate the limitation of our methods that assume (i) the Hume Dam release alone as a control variable to manage the level of Lake Mulwala and associated operational risks, and (ii) the Lake Mulwala release as constant over the forecast lead times. The results demonstrate that where flows are extreme, an additional control variable is necessary, namely the release from Lake Mulwala at Yarrawonga Weir, to manage the system well. In times of high unregulated Kiewa and Ovens inflows, large releases from Lake Mulwala are necessary to maintain the level of the lake within the desired range. Such large releases are permitted during these times even if they were to exceed the capacity of the Barmah Choke.

However, to optimise the magnitude and timing of the Lake Mulwala release, in conjunction with the magnitude and timing of the Hume Dam release, for the best risk outcome can be challenging. How best to do so is beyond the scope of this report but is of future interest.

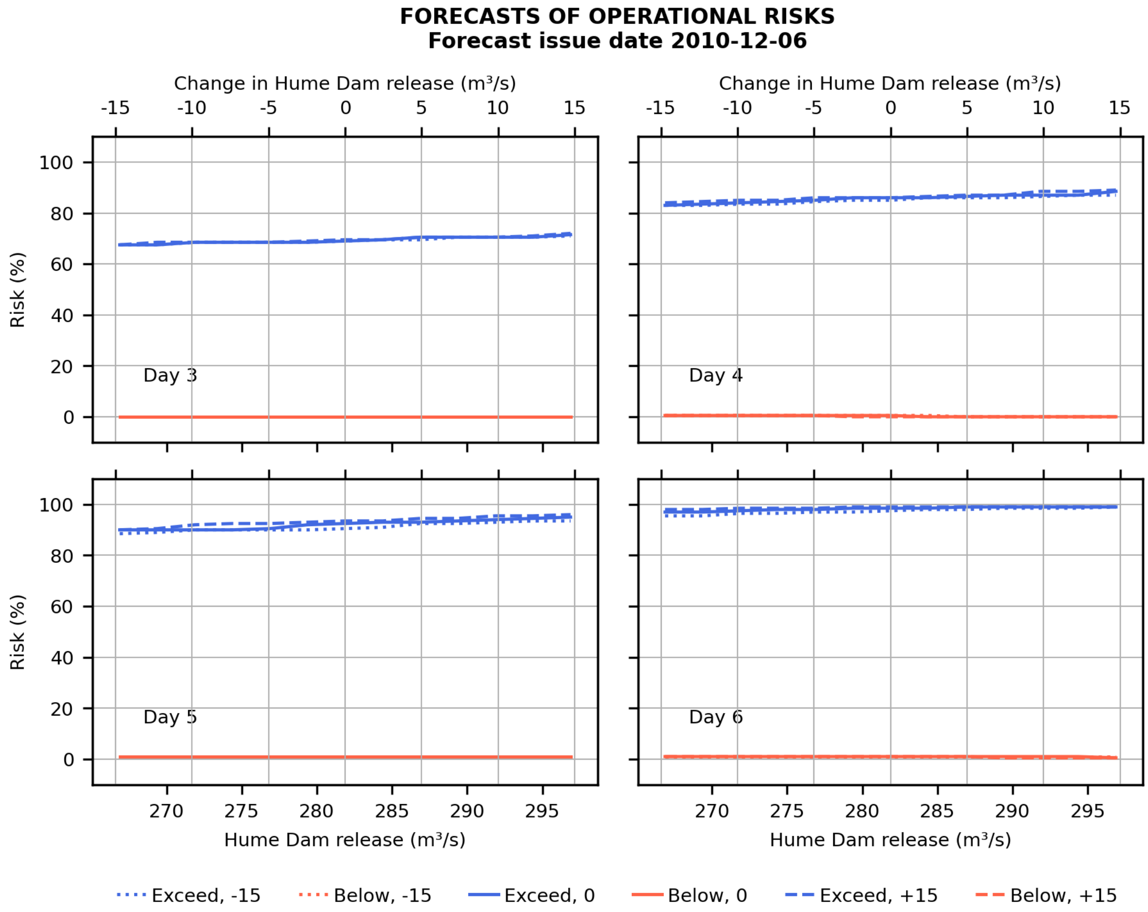

Figure 13. Forecasts of the risks, at the end of lead days 3 to 6 of the forecasts, of the level of Lake Mulwala exceeding or falling below the desired range; the forecasts are for the issue date 6 December 2010; the forecasts assume the Hume Dam release on lead day 2 and thereafter to be the same as (solid lines), less by 15 m^3/s than (dotted lines) or more by 15 m^3/s than (dashed lines) the release on lead day one; the x-axes represent lead day one's release; the first x-axis (bottom) represents the release in terms of its absolute value; the second x-axis (top) represents the release in terms of its change from the previous day's release

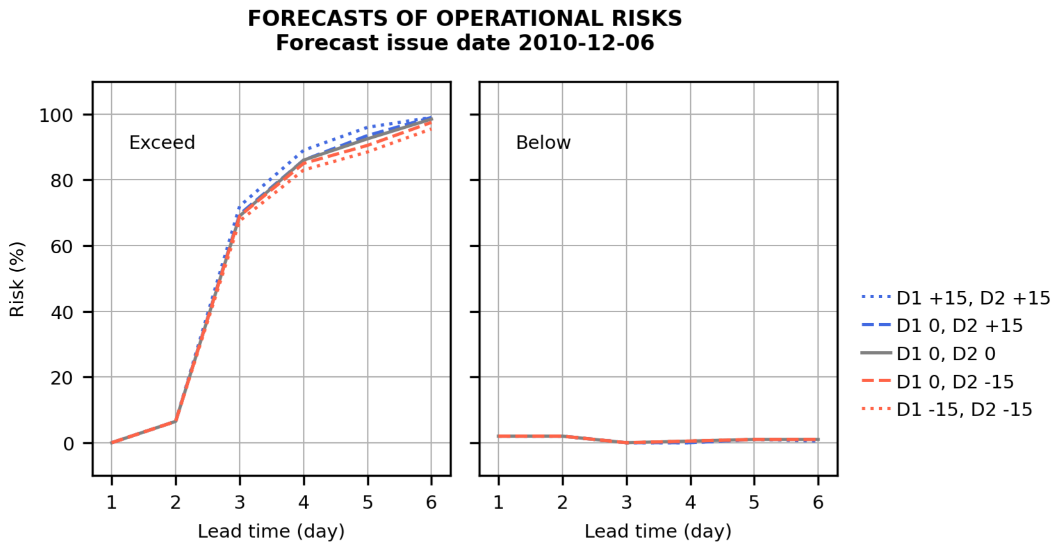

Figure 14. Forecasts of the risks of the level of Lake Mulwala exceeding or falling below the desired range, with respect to the forecast lead time; the forecasts are for the issue date 6 December 2010; the forecasts assume the Hume Dam release on lead day one (D1) to be the same, less by 15 m3/s than or more by 15 m3/s than the previous day's release, and the release on lead day 2 (D2) to be the same, less by 15 m3/s than or more by 15 m3/s than lead day one's release

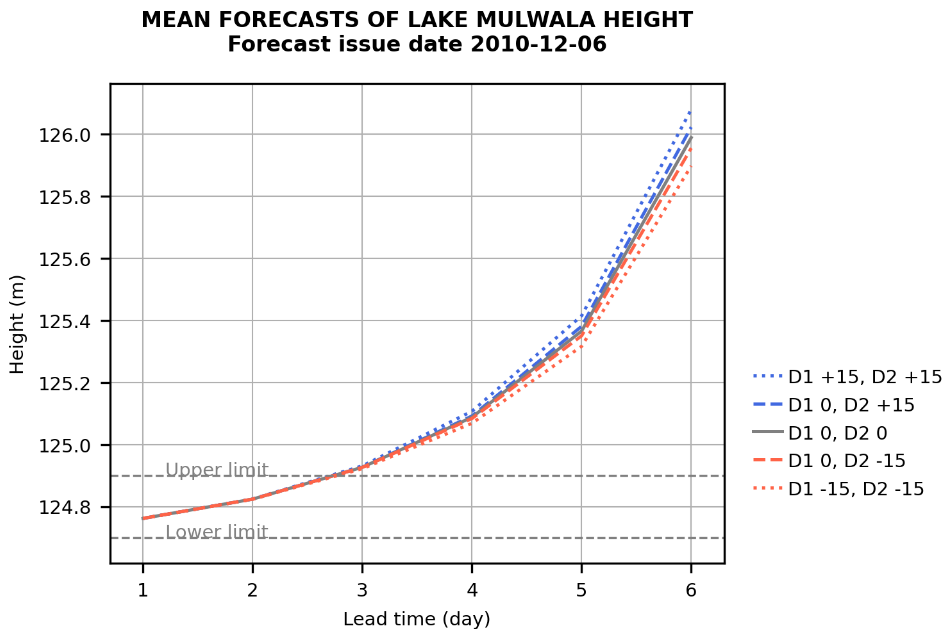

Figure 15. Mean forecasts of the level of Lake Mulwala with respect to the forecast lead time, for the issue date 6 December 2010 and in comparison with the upper and lower limits on the desired range of the lake level; the forecasts assume the Hume Dam release on lead day one (D1) to be the same, less by 15 m3/s than or more by 15 m3/s than the previous day's release, and the release on lead day 2 (D2) to be the same, less by 15 m3/s than or more by 15 m3/s than lead day one's release

5 Summary and Future Work

In this report, we describe our work for the first case study of Project T2.8a of MD-WERP on demonstrating how ensemble water forecasts can aid real-time decision-making in the southern MDB. For the case study, we focus on the upper Murray River from Hume Dam to Lake Mulwala. The system is managed by the MDBA, who are tasked with deciding the Hume Dam release, which combines with tributary inflows from Kiewa and Ovens Rivers, to deliver water to (i) West Corurgan Private Irrigation District, (ii) Murray Valley Irrigation District (via Yarrawonga Main Channel), (iii) Murray Irrigation District (via Mulwala Canal) and (iv) other users further downstream.

To meet the case study objectives, we adapt the SWIFT2 hydrologic model from Ng et al. (2019) and Ng et al. (2022) to generate the required ensemble flow forecasts. Also, we develop statistical models to forecast, from orders, the actual water demands, and their uncertainties, to West Corurgan Private Irrigation District, Murray Valley Irrigation District (Yarrawonga Main Channel) and Murray Irrigation District (Mulwala Canal). Lastly, we develop a risk model integrating the flow and demand forecasts from the hydrologic and demand models to forecast, as a function of the Hume Dam release, the level of Lake Mulwala and with that, the risks of the lake level exceeding or falling below the desired range.

We obtain results for 2 forecast issue dates, 1 January 2012 and 6 December 2010. The first issue date represents a typical case where flows are within ranges commonly observed. Plots of the results with respect to the Hume Dam release and forecast lead time demonstrate the potential of our methods for informing real-time decisions related to Hume Dam releases. The second issue date represents a nonstandard case where unregulated tributary inflows are atypically high, which leads to a greatly increased risk of the Lake Mulwala level exceeding the desired range. The results show the limitation of our methods that presume (i) the Hume Dam release alone as a control variable to manage the lake level and associated risks and (ii) the Lake Mulwala release as constant over the forecast lead times. In reality however, where flows are extreme, an additional control variable, namely the release from Lake Mulwala at Yarrawonga Weir, is necessary to manage the system well.

For future work, we intend on extending the methods introduced in this report to include the release from Lake Mulwala at Yarrawonga Weir as an additional control variable and thereby, expand their applicability to high flow periods. We will do so in continued consultation with MDBA river operators.

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