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Using ensemble streamflow forecasts to inform seasonal outlooks of water allocation in the Murray Darling Basin

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Abstract

Water is a limited and highly valuable resource. In many parts of the world, water agencies allocate water according to agreed entitlement systems. The allocations are largely based on water already available in storages and rivers. Water agencies may also issue seasonal water allocation outlooks by anticipating future inflows to the storages and rivers. These outlooks are meant to assist water entitlement holders to plan for their crop planting, irrigation, and participation in water markets. Currently, these outlooks are generally based on historical inflow observations (climatology) and are often determined for a small selection of possible climatic scenarios (e.g., extreme dry, dry, average, and wet). These outlooks have large uncertainties which require the users to manage high risks themselves, leading to inefficient water use. In this study, we investigate the use of ensemble seasonal inflow forecasts to improve the production of seasonal water allocation outlooks through a case study - the Goulburn system in central Victoria, Australia. This is a complex system with active water trade both within the region and outside with the larger connected southern Murray-Darling Basin. In this case study, we integrate Australian Bureau of Meteorology's seasonal streamflow forecasts with Goulburn-Murray Water's water allocation to produce fully probabilistic water allocation outlooks. We evaluate the outlooks for three irrigation seasons from 2017 to 2020. We compare these outlooks with those produced from using inflows based on climatology only, an approach akin to the current practice of Goulburn-Murray Water. Using seasonal streamflow forecasts resulted in outlooks up to 60% (average 20%) closer to actual determinations, with uncertainty reduced by up to 65% (average 19%) Improvements were most obvious for short lead times, and later in the irrigation season. This is a clear demonstration of how integration of streamflow forecasts can improve end user products, which can lead to more efficient water use and water market participation.

Keywords

Seasonal allocation outlook, seasonal streamflow forecast, inflow forecast, forecast uncertainty, forecast application.

Practical applications

This paper demonstrates how skilful forecasts of streamflow can be used to produce meaningful products for end users. Specifically, improvements are made to outlooks of water that will be made available to irrigators in dry years. The new outlooks are up to 60% closer, with up to 65% less uncertainty. These improved outlooks allow entitlement holders to more confidently plan for the irrigation season, leading in turn to more efficient water use. The method presented here should provide benefits for any water management systems where skilful streamflow forecasts are available. Beyond its use for high reliability water share outlooks, it could easily be adapted for other water manager applications such as outlooks of low reliability water shares in very dry years, or risk of spill (insufficient storage capacity) in wet years.

Introduction

Water is a critical natural resource and all communities in the world rely on it. Demand for water often exceeds availability, driven by both increases in demand (such as from population growth) or reduction in supply (such as from droughts). In developed water systems such as the Murray Darling Basin (MDB), Australia, water managers can avoid overuse by employing a system of entitlements to set levels of priority for different water uses, such as between urban and irrigation uses. For the same water use, the entitlement system may also allocate water to individual users. In the MDB, an entitlement is a right to take a certain volume of water per year, these are typically associated with a certain supply priority or reliability (MDBA, 2020). When available water is insufficient to meet full entitlements, the water manager can restrict access, starting with the lowest priority use (Young, 2014). This helps manage risks, ensuring that the higher priority uses are met first and that downstream uses are considered prior to upstream extraction.

The proportion of an entitlement that is made available for a given year is referred to as an allocation, while the allocation at any given time is referred to as a seasonal allocation, or seasonal determination (MDBA, 2020). Determinations balance supply and demand by easing restrictions on consumption in response to realized system inflows (MDBA, 2020). They are based on current system conditions (i.e., the volume of water currently in storage), and may include a very conservative (e.g., 99% probability of exceedance) future inflow estimate. They are almost certain to increase as the season progresses with inflows exceeding the very conservative estimate. Entitlement holders would therefore expect higher determinations by the end of the season and may plan their activities around that assumption (DELWP, 2022). For example, consider the holder of a 1 GL entitlement during a dry year. At the start of the irrigation season, with little water in storages, the water authority may issue a seasonal determination of 5%, meaning the entitlement holder can access 50 ML of water.

Through the irrigation season, as water enters the system, the seasonal determination is adjusted upwards, until at the end of the season it reaches 50%, meaning the entitlement holder can access 500 ML of water. The uncertainty in allocation introduces various risks into their operations. For example, if an irrigator overcommits at the start of the season, they may have to purchase water at an inflated price later in the season, or to lose a crop, wasting the water, fertilizer, seed, and fuel already used on it. Conversely, if the irrigator reduces the crop area in expectation of a dry season which doesn't eventuate, they will have unnecessarily reduced their yield and income.

Water managers across MDB typically provide further information to entitlement holders in the form of allocation outlooks (NVRM, 2022). These are estimates of future seasonal allocations based on more realistic predictions of future inflows. These outlooks can improve the efficiency of water and other resource use. Allocation outlooks are vitally important to water entitlement holders, for example, allowing irrigators of annual crops to make more informed decisions on their production area for the season, and environmental water holders to plan flow events to inundate areas of interest (Kaune et al., 2020). They can also inform interactions of water users with the water market, buying or selling their allocation, or storing it (carryover) for the following season.

Currently, allocation outlooks are generally produced based on inflow estimates from historical observations of the system, combined with current storage volume information. To provide a range of possible outcomes, scenario cases (e.g., dry, average, or wet) may be developed corresponding to probabilities of exceedance in the historical record (e.g., NVRM, 2022). Unfortunately, these allocation outlooks tend to have large uncertainties, limiting their usefulness. The use of improved inflow assumptions informed by seasonal streamflow forecasts has the potential to both improve the accuracy of outlooks and reduce the uncertainty (Kaune et al., 2020).

Seasonal inflow forecasts have been used for various applications, such as to support reservoir operations (Alemu et al., 2011; Anghileri et al., 2016; Boucher et al., 2012), and inform the development of early flood warning systems (Winsemius et al., 2014). However, their use for informing seasonal water allocation outlooks has received little attention. A recent theoretical application of ensemble inflow forecasts to improve water supply (Lu et al., 2017) illustrates their potential to improve accuracy. Their use to improve allocation outlooks is also supported (Kaune et al., 2020); however, work to date has not made use of an operational allocation algorithm, nor has it compared outlooks using seasonal forecasts with outlooks using current operational methods, instead comparing them to actual determinations (assuming an extreme dry scenario). These works support the use of seasonal inflow forecasts but have not developed tools that can be directly implemented by water agencies with real allocation rules.

Here we evaluate allocation outlooks informed by seasonal streamflow forecasts and provide detailed methods to allow uptake in other systems. The method produces an ensemble forecast-based outlook, which can be summarized as a probabilistic distribution of allocation for entitlement holders. We demonstrate the application of the new method in a developed system, using an operational allocation algorithm with real allocation rules, producing outputs in a comparable format to existing outlooks. We then evaluate the outputs, demonstrating improved accuracy and reduced uncertainty, which will lead to greater confidence in using the allocation outlooks for decision-making by end users.

Materials and methods

Here we present the methods in three parts. First, broad description of current methods for producing allocation determinations and outlooks are provided, followed by how to incorporate streamflow forecasts, and prepare a probabilistic proxy for the current method

for use in evaluations. Second, details of our study area are provided. And third, the evaluation methods used are introduced.

Producing allocation determinations and outlooks

Allocation determinations are produced using a water allocation algorithm which is developed according to operating rules for the water resources system (see Figure 1). It combines static components, such as reservoir volumes and channel flow capacities, and dynamic components such as initial storage volume, water in transit, trade balances, and expected losses. Allocation determinations must have very conservative assumptions about future inflows to ensure water is not over-allocated in dry years.

The same water allocation algorithm can be used to produce allocation outlooks to inform entitlement holders of their likely total seasonal allocation. The key distinction from its use in preparation of allocation determinations is the inclusion of more realistic future inflows.

Incorporating ensemble inflow forecasts

Future flow estimates could be better informed using existing skilful forecasts of seasonal streamflows. These forecasts are based on some understanding about catchment and climate conditions and are therefore expected to produce more accurate and less uncertain allocation outlooks. An overview of the process is presented in Figure 2. Streamflow forecasts for all relevant sites are combined with climatology beyond the forecast horizon using a Schaake Shuffle (see Figure 5 for an example). Climatology here is defined as the

171 probability distribution of inflows derived from a period of, say 30 or more years of historical
172 record, with no direct consideration of current catchment and climate factors, and therefore
173 unchanging across years. Each member of the resulting ensembles is run through the
174 allocation determination algorithm to produce a forecast informed ensemble allocation
175 outlook.

176 Inflow forecasts may be derived via several approaches, which may vary in the
177 specific catchment and climate conditions used. A dynamical approach for example may
178 make use of rainfall forecasts from global circulation models as inputs to a hydrological
179 model (Bennett et al., 2016). Alternatively, statistical approaches have been developed by
180 training models directly on a set of predictors such as antecedent catchment conditions and
181 derived climate indices (Troin et al., 2021). Antecedent catchment conditions can impact
182 future inflows, with a wet catchment more responsive to rainfall, and soil and groundwater
183 storage contributing to inflows over several months (Chiew et al., 1998). Antecedent climate
184 conditions, such as derived climate indices (e.g., El Niño/La Niña and Southern Oscillation
185 Index) are also shown to correlate well to inflows across the globe (Hamlet and Lettenmaier,
186 1999; Troin et al., 2021; Zaerpour et al., 2021).

187

188 *Ensemble inflow climatology*

189 The current deterministic approach to producing allocation outlooks is not directly
190 comparable to the probabilistic ensemble approach presented above. The scenarios used are
191 based on exceedance probabilities from the historical record, so it is mostly akin to a
192 climatology-based approach. Climatology approaches consider flows across a long period to
193 be random samples from a single distribution. A deterministic climatology would therefore
194 be the mean or median, while an ensemble climatology also includes uncertainty.

195 Climatological streamflows can be considered a special case of forecasts where no predictor
196 information is used. Using climatological streamflows alone in the production of allocation
197 outlooks produces and ensemble allocation roughly equivalent to current practice, but
198 statistically comparable to the forecast informed approach presented above.

199

200 ***Case study***

201 To demonstrate the application of the methods for producing water allocation
202 outlooks, we consider the Goulburn system in the Murray Darling Basin (MDB), in Australia.
203 The MDB is large ($>10^6$ km^2), extending over four states, and supporting about 40% of the
204 country's agricultural production. Since 2007, it has been managed by the Murray Darling
205 Basin Authority (MDBA), which has overseen the further development of an extensive water
206 trade market. The basin is impacted by alternating droughts and floods, and water availability
207 is heavily reliant on rainfall along its mountainous eastern and southern boundary. The
208 Goulburn catchment is located in the south and while it covers only 2% of the MDB area, it
209 contributes 11% of total flows. Inflows to the Goulburn system are regulated at two locations
210 (Lake Eildon and Goulburn Weir), which provide the water resources for fulfilling water
211 holders' entitlements. The system is managed by Goulburn-Murray Water (GMW) along with
212 neighbouring systems across northern Victoria. The system supplies several large irrigation
213 areas and is linked to neighbouring systems (Campaspe and Loddon) via channels and
214 pipelines (see Figure 3) forming the Goulburn Murray Irrigation District, with trade also
215 possible to the Lower Murray and the Lower Darling under certain circumstances. The largest
216 land use groups in the Goulburn Murray Irrigation District are cropping (260,000 ha), and
217 dairy (235,000 ha), followed by non-dairy grazing (135,000 ha) and horticulture (40,000 ha)
218 (Goulburn Broken Catchment Management Authority, 2017).

219

220 *Water allocation algorithm*

221 The Goulburn system is managed according to the Bulk Entitlements (Eildon –
222 Goulburn Weir) Conversion Order 1995 and amendments made to it (Victorian Department
223 of Environment, 2021). Calculation of available water in the system starts with current
224 storage levels and a conservative estimate of inflows over the next 6 weeks, along with
225 considerations for dead storage that is inaccessible. This is followed by adjustments for water
226 transfers with neighbouring systems, evaporation, headworks, and river losses, commitments
227 for power generation, urban bulk entitlements, domestic and stock supply, trade to the
228 Murray, and carryover commitments. Some of these adjustments are dependent on the state
229 and accounts of neighbouring systems.

230 Water holders within the system may hold permanent water shares known as
231 *entitlements* which can be of various priority levels. In essence, these are various types of
232 shares of the bulk water entitlement. As water availability in the system increases, *allocation*
233 *determinations* (the proportion of entitlements that are made accessible) increase, first for the
234 highest priority entitlements and subsequently for lower priority entitlements (see Figure 4).
235 Entitlements that are most commonly affected by restrictions in dry years are the *high*
236 *reliability water shares* (HRWS), and in wet years the *low reliability water shares* (LRWS)
237 may provide water to irrigators. In this case, HRWS of the current year are first allocated up
238 to 25%, then water is split between HRWS of the current and subsequent irrigation seasons
239 (August to May) until the latter reaches 50%. HRWS of the subsequent season are filled to
240 100% following the current year and prior to any LRWS. From 1978 to 2006, full (100%)
241 HRWS allocations were achieved every year, except 2003. From 2007 to 2020, however, full
242 HRWS allocations were only achieved in 7 out of the 14 years. In this example, we focus on

243 HRWS for the current year, over the three irrigation seasons 2017/2018 to 2019/2020. HRWS
244 allocation trade in the Greater Goulburn has averaged $74 M per year since 2007/2008,
245 peaking at $190 M in the 2011/2012 irrigation season.

246

247 *Ensemble seasonal inflow forecasts and ensemble seasonal inflow climatology*

248 The inflow forecasts we utilize were produced by the Australian Bureau of
249 Meteorology (BoM) for both Lake Eildon and Goulburn Weir. These forecasts are standalone
250 ensembles, produced for each site and each month separately, each with a forecast horizon of
251 three months and consisting of 5,000 members. As mentioned above, various approaches may
252 be used to produce the forecasts. In this case, they were produced using the Bayesian Joint
253 Probability (BJP) statistical modelling approach (Wang & Robertson, 2011; Wang,
254 Robertson, & Chiew, 2009; Zhao, Schepen, & Wang, 2016) with inflow and precipitation
255 from the previous months as antecedent catchment predictors, and derived climate indices as
256 climate predictors. The specific predictors used varied by site and by month, and were
257 derived using data from 1950 to 2008 (Robertson and Wang, 2012). The forecasts have
258 previously been demonstrated to be skilful and reliable (Feikema et al., 2018). The six
259 months June to November are typically the wettest, with average monthly inflows exceeding
260 100 GL (100×10^9 litres) at both Lake Eildon and Goulburn Weir, peaking at 290 GL and 235
261 GL respectively in August (see Supplementary Material 1).

262 Because the BoM forecasts have a horizon of three months, climatology was used to
263 extend the application to the end of the irrigation season. This climatology was derived from
264 the same BJP models by simply taking the marginal distributions in the absence of predictor
265 variables. Since these forecasts and climatology were produced independently by site and by
266 lead-time, linking of corresponding members of each dataset in their existing orders may

result in unrealistic patterns across time or space. To ensure realistic patterns in the final ensemble, we applied the Schaake Shuffle (Clark et al., 2004), copying patterns in the historical record. Details of the procedure are as follows.

We used an arbitrarily chosen 50-year period of historical inflows up to 2016, the year before our analysis starts, to construct a template for shuffling the ensemble members of the forecasts. The historical data were sorted by the magnitude of inflows at Lake Eildon for the first month, and the order of inflows across all other months and at Goulburn Weir were noted. As the forecasts have 5,000 ensemble members and the template has only 50 years of data, the 5,000 members were randomly shuffled then divided into 100 blocks of 50 members. The 50 members in each block were reordered (Schaake shuffled) to match the order in the template. If for example the high observed inflows at one site occur simultaneously to high inflows at a second site, this pattern will now be seen in the recorded ensemble as well. Likewise, if dry summers are typically paired with wet winters in the historic record, this will be true in the recorded ensemble. This Schaake shuffle process is repeated for each of the 100 blocks, forming a large ensemble of 5,000 members. The complete procedure is illustrated in Figure 5.

For producing ensemble climatology-based outlooks, we follow the same procedure as for constructing the ensemble inflow forecast except that the first three months of independent forecast ensembles are replaced with respective climatology ensembles at the beginning step of Figure 5.

Producing seasonal allocation outlooks

Incorporation of the inflow climatology or forecast ensemble discussed above allowed

ensemble outlooks to be generated through to the end of the season. Each outlook has 5,000 members, corresponding to the 5,000 members of the inflow ensemble. Typically, outlooks are produced in the middle, and occasionally at the start, of each issuing month (February, May, July, August, September, October, November, December).

In practice, the water authority (GMW) follows a slightly different methodology in producing climatology-based outlooks. Rather than using an ensemble seasonal inflow climatology, the water managers define four scenario conditions: wet, average, dry, and extreme dry, corresponding roughly to the 10%, 50%, 90%, and 99% probabilities of exceedance from the historical inflow records for Lake Eildon and Goulburn Weir. For each of these scenarios, the outlooks are produced through the irrigation season to February in the following year, providing entitlement holders an indication of future allocation uninformed by catchment and climate conditions, and with broad uncertainty. The current water allocation algorithm has calculations that vary by probability of exceedance from the historical record. This required that each ensemble inflow member had to be also converted to a probability of exceedance.

As our ensemble outlooks are not directly comparable to the scenario-based method currently used by GMW, the climatology-based ensemble outlook was used as a proxy for the current method in the evaluations. We have evaluated the forecast-based outlook by comparing it against the climatology-based outlook.

Evaluation of outlooks

While the BJP inflow forecast inputs used are demonstrated to be skilful and reliable, it is important to evaluate the outputs of the water allocation algorithm. Recent work has led

to the development of several useful tools for assessing probabilistic forecasts (Wang et al., 2009). Our evaluation includes a side-by-side comparison of outlooks, and comparisons of uncertainty sharpness, accuracy, and reliability (using PIT uniform variate plots). Since the current GMW outlooks are scenario based rather than full probability distributions (or ensembles), we only show them in visual comparisons. For other comparisons we instead use the climatology-based ensemble outlook as a proxy for the current method.

Side-by-side comparison of outlooks

A plot of allocation outlooks for each issue date was produced, showing reported exceedance levels (i.e., 10%, 50%, 90%, 99%) corresponding to the G-MW scenario outlooks along with the corresponding final determinations. These were used to check that the climatology was an appropriate proxy for the current scenario method, as well as to visually check outlook accuracy and sharpness. Outlooks with medians closer to the final determinations and narrower uncertainty suggest an improvement in the method.

Outlook sharpness

For each irrigation season, a heatmap was produced showing the sharpness of the ensemble outlooks. The sharpness of a single date is the distance between ensemble forecast-based outlook percentiles divided by the corresponding distance between ensemble climatology-based outlook percentiles, that is

$$Sharpness = \frac{P_{fcst}^{-1}(0.10) - P_{fcst}^{-1}(0.99)}{P_{clim}^{-1}(0.10) - P_{clim}^{-1}(0.99)} \quad (1)$$

Where $P^{-1}(0.10)$ and $P^{-1}(0.99)$ represent the determinations corresponding to the 10th and 99th percentiles (10% and 99% probability of exceedance) from the outlook ensemble,

334 respectively. The subscripts "clim" and "fcst" identify those using the ensemble climatology-
335 based method and ensemble forecast-based method, respectively. A sharpness value of 1
336 indicates that the outlooks have the same uncertainty, while a value less than 1 indicates a
337 narrowing or sharpening of the uncertainty bands.

338 This sharpness calculation considers the 89% of ensemble members between the 10th
339 and 99th percentiles. However, once the 10th percentile reaches 100% allocation the
340 proportion of ensemble members considered reduces, making the comparison invalid. To
341 resolve this issue, when the 10th percentile reaches 100% for ensemble outlooks produced
342 from either the ensemble climatology-based method or ensemble forecast-based method, the
343 upper bound (P*) as defined in equation (2) is used in the modified sharpness equation (3).
344 For example, if the ensemble climatology-based and ensemble forecast-based outlooks
345 reached 100% allocation at the 25th and 10th percentiles, respectively, P* would be 0.25
346 (Figure 6).

$$P^* = max\{P_{clim}(100\%), P_{fcst}(100\%)\} \quad (2)$$

$$Sharpness^* = \frac{P_{fcst}^{-1}(P^*) - P_{fcst}^{-1}(0.99)}{P_{clim}^{-1}(P^*) - P_{clim}^{-1}(0.99)} \quad (3)$$

347 This sharpness calculation becomes increasingly sensitive to differences in the drier
348 tail during wet seasons, partially due to the differences introduced by the random shuffling of
349 ensemble members prior to the application of the Schaake Shuffle. To overcome the
350 sensitivity of this test to random seeds, the outlooks were developed with 10 random seeds,
351 and the results were averaged to produce the final sharpness values.

352

353 *Outlook accuracy*

354 A skill score based on the continuous ranked probability score (**CRPS**) was used as a
355 measure of model accuracy (Wang et al., 2009). The **CRPS** in our case (as shown in equation
356 (4)) represents the area between the cumulative distribution function (CDF) of our
357 probabilistic ensemble outlook (q) and the Heaviside function (H) representing an observed
358 determination q_{obs} (i.e., 0 for $q < q_{obs}$, 1 for $q \geq q_{obs}$). A value of 0 indicates a perfectly
359 accurate model, with all ensemble members correctly predicting the allocation determination.
360 Larger values indicate an offset of the ensemble median, or an uncertainty spread that is too
361 wide or narrow.

362 The skill score (as shown in equation (5)) shows the proportional reduction in **CRPS**
363 from the reference ensemble climatology-based outlook ($\mathbf{CRPS_{clim}}$) to that of the ensemble
364 forecast-based outlook ($\mathbf{CRPS_{fcst}}$), where the overbar indicates averaging over the irrigation
365 seasons. A negative skill score indicates the model is less skilful than the reference, a positive
366 number indicates the model is more accurate and/or better distributed than the reference, and
367 perfect skill is represented by a maximum value of 1. This skill score was calculated for each
368 issue and target month. Due to the limited number of seasons available (2-3), the values of

this skill score were also sensitive to individual outlooks, and thus the same averaged ensembles were used for the calculation as in the sharpness calculation.

$$\mathbf{CRPS} = \int [CDF(q) - H(q - q_{obs})]^2 dq \quad (4)$$

$$SS_{\mathrm{CRPS}} = (\overline{\boldsymbol{CRPS_{clim}}} - \overline{\boldsymbol{CRPS_{fcst}}})/\overline{\boldsymbol{CRPS_{clim}}} \quad (5)$$

Outlook reliability

The reliability of ensemble outlooks was evaluated using a probability integral transform (PIT) uniform probability plot (Laio and Tamea, 2007; Wang et al., 2009; Wang et al., 2019). The PIT is defined as the CDF value corresponding to an observed inflow. A reliable forecast should have a uniform distribution, so plotting the observed CDF against a uniform distribution CDF should result in a 1:1 line. As values of 100% determination were censored, a random value was generated in the range 0 to the minimum point corresponding to 100% determination, giving pseudo-PIT values (Wang and Robertson, 2011). A perfectly reliable forecast should follow the 1:1 line, while the test is passed if all points fall within the Kolmogorov confidence bands. For the Kolmogorov confidence bands, a confidence level of $\alpha = 0.05$ was used, resulting in a width of $\boldsymbol{1.3858/\sqrt{n}}$, where n is the number of data points used in the plot. The distribution of the points relative to the 1:1 line indicates whether the forecast probability distributions are too high, too low, too wide, or too narrow. PIT plots were produced for outlooks with one-month, two-month, three-month, and five-month lead times, allowing comparison of the reliability across the four lead times.

Results and discussion

Side-by-side comparison of outlooks

The ensemble climatology-based outlook shows some differences to the Goulburn-Murray Water (GMW) scenarios but were mostly consistent (Figure 7, left column). This confirms that ensemble climatology-based outlook was an appropriate proxy for the current GMW process in comparisons with the ensemble forecast-based outlook. For the 2019-2020 irrigation season, the ensemble forecast-based outlook (Figure 7, right hand side) median value was visibly closer to the final determinations (black crosses) from the August issue onwards, and the probability distribution narrowed in comparison to both the GMW scenarios and ensemble climatology results, particularly from September onwards.

Sharpness

Most sharpness values for each irrigation season were less than 1, indicating an overall improvement in outlook sharpness, or a narrowing of the uncertainty, when ensemble forecast inflows are used, compared with the proxy using ensemble climatology inflows (Figure 8). Generally, the best performing outlooks are those with short lead times, corresponding to the period with the greatest contributed portion of forecast data, while the ensemble forecast-based outlooks with long lead times generally show similar performance to the ensemble climatology-based outlooks. A marked improvement is also observed from September, corresponding to higher skill in the inflow forecasts (see Supplementary Material 2).

Accuracy

All **CRPS** skill scores were positive, indicating the ensemble forecast-based outlooks were more accurate than the ensemble climatology-based outlooks (Figure 9). Higher skill

scores were observed where there were short lead times and for those issued later in the season, corresponding to inflow forecasts with greater skill. Outlooks that made use of the skilful forecasts from the first months of the year (i.e., Issued from November to January for February) all had skill scores above 40%. This means the outlook skill can exceed the skill of underlying forecasts. The outlooks with the longest lead times (top right in Figure 9) showed the lowest accuracy, suggesting those outlooks were very similar to the climatology outlooks. When **CRPS** skill scores are calculated for small datasets, they are sensitive to individual data points. Here we only have three seasons to compare. A discussion of the impact of dry and wet years is provided below in *Limitations and broader application*.

Reliability

The PIT values for one, two, and three-month lead times all remain within the Kolmogorov 5% significance bands, indicating they are reliable (Figure 10). A five-month lead time produces unreliable results, with points lying outside the bottom significance band, indicating the forecast is too high. The one-month lead time resulted in the narrowest spread from the 1:1 line, suggesting that outlooks with shorter lead times are more reliable.

Limitations and broader application

Use of method in dry vs. wet years

Outlooks of water allocation are useful only until determinations reach full entitlement, or more precisely, when there is uncertainty in future determinations. Here we have considered outlooks of high reliability water share (HRWS), which are particularly important in dry

434 years. We would expect, therefore, that our results would show greatest improvement if the
435 period considered is dry. Within the three-year period considered in this study, the first year
436 was the wettest, reaching entitlement by December. Neither of the other two years reached
437 full entitlement by February. In wet years the method could be used instead to produce
438 outlooks of low reliability water share (LRWS) or risk of spill.

439

440 *Necessity for skilful seasonal streamflow forecasts*

441 We have presented a method to translate skilful seasonal streamflow forecasts into improved
442 outlooks. Availability of streamflow forecasts is therefore a necessity when applying the
443 method elsewhere. While streamflow forecast skill is not expected to linearly effect outlook
444 skill (Regonda et al., 2011), use of unskilful forecasts is unlikely to provide any improvement
445 over current practices that only consider historical flow probabilities. Hence, the variability in
446 streamflow predictability with hydroclimate (e.g., Australian Bureau of Meteorology, 2023)
447 would lead to spatial patterns in the applicability of this method.

448

449 *Use of method in other regions or applications*

450 The Goulburn region was selected for this case study due to its complexity, allowing
451 identification of more hurdles to implementation than in a simple system. Allocations in the
452 Goulburn must consider trade and inter-seasonal accounting, including management of
453 multiple reservoirs. This system complexity necessitates a complex water allocation
454 algorithm, which in this case was in the form of an Excel workbook with dozens of
455 worksheets and several macro modules. Automation of the workflow in Python requires
456 interaction with the Excel workbook, including updating macros and formulas, importing

457 forecasts, running Excel calculations, and extracting results. Macros were first replaced by a
458 modified version, then spreadsheets were updated and recalculated. In several instances users
459 of the workbook had added rows or columns, so it was important in the automation to
460 correctly identify components in the worksheets rather than assuming them all to have the
461 same structure. The total run time to process outlooks from a single issue date was 6 minutes,
462 almost all of which was calculations within Excel. A much faster option, and likely future
463 direction, would be to convert the entire process to Python. Prior to uptake, however, it
464 makes more sense to allow current practices to continue and run the script over the existing
465 workbook. Within half a day the script was successfully updated for application in a simpler
466 system.

467

468 **Summary and conclusions**

469 With demand for water often exceeding supply in developed systems across the
470 world, water managers must prioritize and regulate water allocation. Allocation
471 determinations are necessarily highly conservative, to avoid over commitment, leading to a
472 pattern of increasing allocations through the irrigation season. As a result, water users rely on
473 experience, or where available, on allocation outlooks to inform the water they will have
474 available through to the end of the year. Current methods to produce these outlooks rely
475 solely on historical flows and have wide uncertainty. While streamflow forecasts are
476 available across much of Australia, and even globally, they have not yet been integrated into
477 allocation outlook workflows.

478 We observed improvements to outlooks informed by seasonal streamflow forecasts.
479 These improvements were not evenly distributed through time, with the greatest gains
480 observed for short lead times (a few months ahead) and outlooks issued later in the season.

The relatively lower skill with long lead times is likely associated with the increasing proportion of inflow information coming from climatology, while reduced forecast skill with lead time may also contribute. Improved skill through the irrigation season, on the other hand, corresponds to the main inflow season, which has a relatively big impact on final allocation determinations, and with the inclusion of highly skilled underlying forecasts for the start of the year. Sites with skilful forecasts for the wetter months are likely to benefit most from their incorporation into allocation outlook calculations, as the allocation outlook skill relates to total volumes over the period considered. Our example implementation has demonstrated the methods ability to improve sharpness, accuracy, and reliability of outlooks.

The observed improvements in outlooks from inclusion of ensemble forecast-based inflows suggests that the method could be beneficial elsewhere if skilful forecasts are available. Similarly, further improvements may be possible through improvements to the inflow forecasts themselves, or with extensions to the inflow forecast horizon beyond the 3 months used in this implementation (Bennett et al., 2016). While we have only evaluated the incorporation of inflow forecasts here on high-reliability water shares (HRWS) in the Goulburn system, it could be equally useful in other water manager decisions such as other water shares or risk of spill (when water must be released to reduce storage levels causing forfeiture of carryover water). Likewise, it could be applied to other systems where skilful inflow forecasts are available. Broader integration of seasonal inflow forecasts can reduce uncertainty, allowing better management of risks, and in turn increase water use efficiency.

Data Availability Statement

The seasonal streamflow forecasts used can be found from the website of the Australia Bureau of Meteorology (http://www.bom.gov.au/water/ssf/index.shtml). The water balance

505 model for Goulburn system was provided by Goulburn-Murray Water (GMW):
506 https://www.g-mwater.com.au/.

507

508 The following data was used in the preparation of this study, and are made available in the
509 supplementary material:

510 1) Historical seasonal streamflow forecasts for Lake Eildon and Goulburn Weir
511 (provided by BoM).

512 2) Historical seasonal streamflows for Lake Eildon and Goulburn Weir (provided by
513 BoM).

514 3) Historical determinations (provided by Goulburn-Murray Water and available from:
515 https://nvrm.net.au/seasonal-determinations/history).

516 4) Historical outlooks for the Goulburn system (available from:
517 https://nvrm.net.au/outlooks/historical-outlooks).

518 The water balance models are protected and may only be accessed with permission from
519 Goulburn-Murray Water.

520

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CRediT authorship contribution statement

Tristan D. J. Graham: Software, Formal analysis, Visualisation, Writing – original draft and editing. **Quan J. Wang:** Conceptualization, Funding acquisition, Methodology, Software, Writing – review and editing. **Yating Tang:** Software, Formal analysis, Writing – original draft.

Andrew Western: Conceptualization, Funding acquisition, Methodology, Writing – review.

Wenyan Wu: Writing – review. **Guy Ortlipp:** Data curation, Writing – review. **Mark Bailey:** Data curation. **Senlin Zhou:** Data curation. **Kirsti Hakala:** Writing – review.

Qichun Yang: Writing – review.

Supplementary material

Supplementary Material 1:

File name: Supplementary_Material_1_mean_monthly_flows.tif

Caption: Mean monthly inflows (GL) at Lake Eildon and Goulburn Weir from 1900 to 2020.

Supplementary Material 2:

File name: Supplementary_Material_2_inflow_forecast_skill_scores.tif

Caption: Median **CRPS** skill scores (%) for 1-month, 2-month, and 3-month streamflow volumes from the forecast month, as provided by the Bureau of Meteorology.