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

**Tristan D. J. Graham[1], Quan J. Wang[2], Yating Tang[3], Andrew Western[4], Wenyan Wu[5], Guy Ortlipp[6], Mark Bailey[7], Senlin Zhou[8], Kirsti Hakala[9], Qichun Yang[10]**

[1]Research Fellow, Department of Infrastructure Engineering, The University of Melbourne, Parkville, VIC. 3010, Australia (corresponding author). ORCID: https://orcid.org/0000-0001-8272-0594. Email: Tristan.Graham@unimelb.edu.au

[2]Professor, Department of Infrastructure Engineering, The University of Melbourne, Parkville, VIC. 3010, Australia. ORCID: https://orcid.org/0000-0002-8787-2738. Email: Quan.Wang@unimelb.edu.au

[3]Modeller, NSW Department of Planning and Environment, Paramatta, NSW. 2150, Australia. Email: Yating.Tang@dpie.nsw.gov.au

[4]Professor, Department of Infrastructure Engineering, The University of Melbourne, Parkville, VIC. 3010, Australia. ORCID: https://orcid.org/0000-0003-4982-146X. Email: A.Western@unimelb.edu.au

[5]Senior Lecturer, Department of Infrastructure Engineering, The University of Melbourne, Parkville, VIC. 3010, Australia. ORCID: https://orcid.org/0000-0003-3907-1570. Email: Wenyan.Wu@unimelb.edu.au

[6]Coordinator, River Operations, Goulburn-Murray Water, Tatura, VIC. 3616, Australia. Email: Guy.Ortlipp@gmwater.com.au

[7]Manager, Water Resources, Goulburn-Murray Water, Tatura, VIC. 3616, Australia. Email: Mark.Bailey@gmwater.com.au

[8]Senior Hydrologist, Water Forecasting Team, Bureau of Meteorology, Docklands, VIC. 3008, Australia. Email: Senlin.Zhou@bom.gov.au

[9]Research Fellow, Department of Infrastructure Engineering, The University of Melbourne, Parkville, VIC. 3010, Australia. ORCID: https://orcid.org/0000-0002-4914-8845. Email: Kirsti.Hakala@unimelb.edu.au

[10]Research Assistant Professor, Thrust of Earth, Ocean and Atmospheric Sciences, Hong Kong University of Science and Technology (GZ), Guangzhou, China, 511453. ORCID: https://orcid.org/0000-0002-8689-2550. Email: QichunYang@hkust-gz.edu.au

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

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

*Ensemble inflow climatology*

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

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

***Case study***

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

*Water allocation algorithm*

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

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

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

*Ensemble seasonal inflow forecasts and ensemble seasonal inflow climatology*

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

Because the BoM forecasts have a horizon of three months, climatology was used to extend the application to the end of the irrigation season. This climatology was derived from the same BJP models by simply taking the marginal distributions in the absence of predictor variables. Since these forecasts and climatology were produced independently by site and by 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

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

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

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

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

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

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

*Outlook accuracy*

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

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

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

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

*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 $\mathbf{1.3858}/\sqrt{\boldsymbol{n}}$, 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 years. We would expect, therefore, that our results would show greatest improvement if the period considered is dry. Within the three-year period considered in this study, the first year was the wettest, reaching entitlement by December. Neither of the other two years reached full entitlement by February. In wet years the method could be used instead to produce outlooks of low reliability water share (LRWS) or risk of spill.

*Necessity for skilful seasonal streamflow forecasts*

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

*Use of method in other regions or applications*

The Goulburn region was selected for this case study due to its complexity, allowing identification of more hurdles to implementation than in a simple system. Allocations in the Goulburn must consider trade and inter-seasonal accounting, including management of multiple reservoirs. This system complexity necessitates a complex water allocation algorithm, which in this case was in the form of an Excel workbook with dozens of worksheets and several macro modules. Automation of the workflow in Python requires interaction with the Excel workbook, including updating macros and formulas, importing forecasts, running Excel calculations, and extracting results. Macros were first replaced by a modified version, then spreadsheets were updated and recalculated. In several instances users of the workbook had added rows or columns, so it was important in the automation to correctly identify components in the worksheets rather than assuming them all to have the same structure. The total run time to process outlooks from a single issue date was 6 minutes, almost all of which was calculations within Excel. A much faster option, and likely future direction, would be to convert the entire process to Python. Prior to uptake, however, it makes more sense to allow current practices to continue and run the script over the existing workbook. Within half a day the script was successfully updated for application in a simpler system.

## Summary and conclusions

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

We observed improvements to outlooks informed by seasonal streamflow forecasts. These improvements were not evenly distributed through time, with the greatest gains 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 model for Goulburn system was provided by Goulburn-Murray Water (GMW): https://www.g-mwater.com.au/.

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

1) Historical seasonal streamflow forecasts for Lake Eildon and Goulburn Weir (provided by BoM).
2) Historical seasonal streamflows for Lake Eildon and Goulburn Weir (provided by BoM).
3) Historical determinations (provided by Goulburn-Murray Water and available from: https://nvrm.net.au/seasonal-determinations/history).
4) Historical outlooks for the Goulburn system (available from: https://nvrm.net.au/outlooks/historical-outlooks).

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

## References

Alemu, E.T., Palmer, R.N., Polebitski, A., Meaker, B., 2011. Decision Support System for Optimizing Reservoir Operations Using Ensemble Streamflow Predictions. J. Water Resour. Plan. Manage.-ASCE, 137(1): 72-82. DOI:10.1061/(asce)wr.1943-5452.0000088

Anghileri, D. et al., 2016. Value of long-term streamflow forecasts to reservoir operations for water supply in snow-dominated river catchments. Water Resources Research, 52(6): 4209-4225. DOI:10.1002/2015wr017864

Australian Bureau of Meteorology, 2023. "National Summary (Model Performance): Seasonal Streamflow Forecasts". Accessed March 17, 2023.

Bennett, J.C., Wang, Q.J., Li, M., Robertson, D.E., Schepen, A., 2016. Reliable long-range ensemble streamflow forecasts: Combining calibrated climate forecasts with a conceptual runoff model and a staged error model. Water Resources Research, 52(10): 8238-8259. DOI:10.1002/2016wr019193

BoM, 2022. Seasonal Streamflow Forecasts: Water Information: Bureau of Meteorology. Australian Bureau of Meteorology.

Boucher, M.A., Tremblay, D., Delorme, L., Perreault, L., Anctil, F., 2012. Hydro-economic assessment of hydrological forecasting systems. Journal of Hydrology, 416-417: 133-144. DOI:10.1016/j.jhydrol.2011.11.042

Chiew, F.H.S., Piechota, T.C., Dracup, J.A., McMahon, T.A., 1998. El Nino/Southern Oscillation and Australian rainfall, streamflow and drought: Links and potential for forecasting. Journal of Hydrology, 204(1-4): 138-149. DOI:10.1016/s0022-1694(97)00121-2

Clark, M., Gangopadhyay, S., Hay, L., Rajagopalan, B., Wilby, R., 2004. The Schaake Shuffle: A Method for Reconstructing Space–Time Variability in Forecasted Precipitation and Temperature Fields. Journal of Hydrometeorology, 5(1): 243-262. DOI:10.1175/1525-7541(2004)005<0243:Tssamf>2.0.Co;2

DELWP, 2022. Victorian Water Register. Victorian State Government, Department of Envirnonment, Land, Water, and Planning.

Feikema, P.M. et al., 2018. Service and Research on Seasonal Streamflow Forecasting in Australia, World Scientific Series on Asia-Pacific Weather and Climate. DOI:10.1142/9789813235663_0010

Goulburn Broken Catchment Management Authority, 2017. Regional irrigated land and water use mapping in the Goulburn Murray Irrigation District.

Hamlet, A.F., Lettenmaier, D.P., 1999. Columbia River streamflow forecasting based on ENSO and PDO climate signals. J. Water Resour. Plan. Manage.-ASCE, 125(6): 333-341. DOI:10.1061/(asce)0733-9496(1999)125:6(333)

Kaune, A., Chowdhury, F., Werner, M., Bennett, J., 2020. The benefit of using an ensemble of seasonal streamflow forecasts in water allocation decisions. Hydrology and Earth System Sciences, 24(7): 3851-3870. DOI:10.5194/hess-24-3851-2020

Laio, F., Tamea, S., 2007. Verification tools for probabilistic forecasts of continuous hydrological variables.

Lu, M., Lall, U., Robertson, A.W., Cook, E., 2017. Optimizing multiple reliable forward contracts for reservoir allocation using multitime scale streamflow forecasts. Water Resources Research, 53(3): 2035-2050. DOI:10.1002/2016wr019552

MDBA, 2020. How allocations work inthe Murray-Darling Basin. Murray Darling Basin Authority (MDBA).

NVRM, 2022. Outlooks. Northern Victoria Resource Manager.

Regonda, S., Zagona, E., Rajagopalan, B., 2011. Prototype Decision Support System for Operations on the Gunnison Basin with Improved Forecasts. J. Water Resour. Plan. Manage.-ASCE, 137(5): 428-438. DOI:10.1061/(asce)wr.1943-5452.0000133

Robertson, D.E., Wang, Q.J., 2012. American Meteorological Society A Bayesian Approach to Predictor Selection for Seasonal Streamflow Forecasting. Journal of Hydrometeorology, 13(1): 155-171. DOI:10.2307/24912755

Troin, M., Arsenault, R., Wood, A.W., Brissette, F., Martel, J.L., 2021. Generating Ensemble Streamflow Forecasts: A Review of Methods and Approaches Over the Past 40 Years. Water Resources Research, 57(7). DOI:10.1029/2020wr028392

Victorian Department of Environment, L., Water, and Planning, 2021. Consolidated Bulk Entitlement (Eildon-Goulburn Weir) Conversion Order 1995 as at 30 June 2021.

Wang, Q.J., Robertson, D.E., 2011. Multisite probabilistic forecasting of seasonal flows for streams with zero value occurrences. Water Resources Research, 47(2). DOI:10.1029/2010wr009333

Wang, Q.J., Robertson, D.E., Chiew, F.H.S., 2009. A Bayesian joint probability modeling approach for seasonal forecasting of streamflows at multiple sites. Water Resources Research, 45(5). DOI:10.1029/2008wr007355

Wang, Q.J. et al., 2019. An evaluation of ECMWF SEAS5 seasonal climate forecasts for Australia using a new forecast calibration algorithm. Environmental Modelling & Software, 122. DOI:10.1016/j.envsoft.2019.104550

Winsemius, H.C. et al., 2014. The potential value of seasonal forecasts in a changing climate in southern Africa. Hydrology and Earth System Sciences, 18(4): 1525-1538. DOI:10.5194/hess-18-1525-2014

Young, M.D., 2014. Designing water abstraction regimes for an ever-changing and ever-varying future. Agricultural Water Management, 145: 32-38. DOI:10.1016/j.agwat.2013.12.002

Zaerpour, M., Papalexiou, S.M., Nazemi, A., 2021. Informing Stochastic Streamflow Generation by Large-Scale Climate Indices at Single and Multiple Sites. Advances in Water Resources, 156. DOI:10.1016/j.advwatres.2021.104037

## Statements and declarations

The authors declare that there is no real or perceived conflict of interest regarding the publication of this article. This study is funded by the ARC Linkage Project (LP170100922). Wenyan Wu acknowledges support from the Australian Research Council via the Discovery Early Career Researcher Award (DE210100117). The seasonal streamflow forecasts can be found from the website of the Australia Bureau of Meteorology (BoM, 2022). The water balance model for Goulburn system was provided by Goulburn-Murray Water (GMW): https://www.g-mwater.com.au/.

## 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.