

24 ⁸Senior Hydrologist, Water Forecasting Team, Bureau of Meteorology, Docklands, VIC.
25 3008, Australia. Email: Senlin.Zhou@bom.gov.au

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

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

32

33 **Abstract**

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

57

58 **Keywords**

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

61

62 **Practical applications**

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

73

74 **Introduction**

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

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

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

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

116 Currently, allocation outlooks are generally produced based on inflow estimates from
117 historical observations of the system, combined with current storage volume information. To
118 provide a range of possible outcomes, scenario cases (e.g., dry, average, or wet) may be
119 developed corresponding to probabilities of exceedance in the historical record (e.g., NVRM,
120 2022). Unfortunately, these allocation outlooks tend to have large uncertainties, limiting their
121 usefulness. The use of improved inflow assumptions informed by seasonal streamflow
122 forecasts has the potential to both improve the accuracy of outlooks and reduce the
123 uncertainty (Kaune et al., 2020).

124 Seasonal inflow forecasts have been used for various applications, such as to support
125 reservoir operations (Alemu et al., 2011; Anghileri et al., 2016; Boucher et al., 2012), and
126 inform the development of early flood warning systems (Winsemius et al., 2014). However,
127 their use for informing seasonal water allocation outlooks has received little attention. A
128 recent theoretical application of ensemble inflow forecasts to improve water supply (Lu et al.,
129 2017) illustrates their potential to improve accuracy. Their use to improve allocation outlooks
130 is also supported (Kaune et al., 2020); however, work to date has not made use of an
131 operational allocation algorithm, nor has it compared outlooks using seasonal forecasts with
132 outlooks using current operational methods, instead comparing them to actual determinations
133 (assuming an extreme dry scenario). These works support the use of seasonal inflow forecasts
134 but have not developed tools that can be directly implemented by water agencies with real
135 allocation rules.

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

144 **Materials and methods**

145

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

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

151

152 ***Producing allocation determinations and outlooks***

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

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

163

164 ***Incorporating ensemble inflow forecasts***

165 Future flow estimates could be better informed using existing skilful forecasts of
166 seasonal streamflows. These forecasts are based on some understanding about catchment and
167 climate conditions and are therefore expected to produce more accurate and less uncertain
168 allocation outlooks. An overview of the process is presented in Figure 2. Streamflow
169 forecasts for all relevant sites are combined with climatology beyond the forecast horizon
170 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 an 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 ($>10^6$ km²), 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 (100x10⁹ 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

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

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

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

287

288 *Producing seasonal allocation outlooks*

289 Incorporation of the inflow climatology or forecast ensemble discussed above allowed

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

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

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

309

310 *Evaluation of outlooks*

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

313 to the development of several useful tools for assessing probabilistic forecasts (Wang et al.,
 314 2009). Our evaluation includes a side-by-side comparison of outlooks, and comparisons of
 315 uncertainty sharpness, accuracy, and reliability (using PIT uniform variate plots). Since the
 316 current GMW outlooks are scenario based rather than full probability distributions (or
 317 ensembles), we only show them in visual comparisons. For other comparisons we instead use
 318 the climatology-based ensemble outlook as a proxy for the current method.

319

320 *Side-by-side comparison of outlooks*

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

327 *Outlook sharpness*

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

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

332 Where $P^{-1}(0.10)$ and $P^{-1}(0.99)$ represent the determinations corresponding to the 10th and 99th
 333 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 (**CRPS_{clim}**) to that of the ensemble
364 forecast-based outlook (**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

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

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

$$SS_{\mathbf{CRPS}} = (\overline{\mathbf{CRPS}_{clim}} - \overline{\mathbf{CRPS}_{fcst}}) / \overline{\mathbf{CRPS}_{clim}} \quad (5)$$

371 *Outlook reliability*

372 The reliability of ensemble outlooks was evaluated using a probability integral
 373 transform (PIT) uniform probability plot (Laio and Tamea, 2007; Wang et al., 2009; Wang et
 374 al., 2019). The PIT is defined as the CDF value corresponding to an observed inflow. A
 375 reliable forecast should have a uniform distribution, so plotting the observed CDF against a
 376 uniform distribution CDF should result in a 1:1 line. As values of 100% determination were
 377 censored, a random value was generated in the range 0 to the minimum point corresponding
 378 to 100% determination, giving pseudo-PIT values (Wang and Robertson, 2011). A perfectly
 379 reliable forecast should follow the 1:1 line, while the test is passed if all points fall within the
 380 Kolmogorov confidence bands. For the Kolmogorov confidence bands, a confidence level of
 381 $\alpha = 0.05$ was used, resulting in a width of $1.3858/\sqrt{n}$, where n is the number of data points
 382 used in the plot. The distribution of the points relative to the 1:1 line indicates whether the
 383 forecast probability distributions are too high, too low, too wide, or too narrow. PIT plots
 384 were produced for outlooks with one-month, two-month, three-month, and five-month lead
 385 times, allowing comparison of the reliability across the four lead times.

386

387 **Results and discussion**

388 *Side-by-side comparison of outlooks*

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

397

398 *Sharpness*

399 Most sharpness values for each irrigation season were less than 1, indicating an
400 overall improvement in outlook sharpness, or a narrowing of the uncertainty, when ensemble
401 forecast inflows are used, compared with the proxy using ensemble climatology inflows
402 (Figure 8). Generally, the best performing outlooks are those with short lead times,
403 corresponding to the period with the greatest contributed portion of forecast data, while the
404 ensemble forecast-based outlooks with long lead times generally show similar performance to
405 the ensemble climatology-based outlooks. A marked improvement is also observed from
406 September, corresponding to higher skill in the inflow forecasts (see Supplementary Material
407 2).

408

409 *Accuracy*

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

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

421

422 ***Reliability***

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

428

429 ***Limitations and broader application***

430 *Use of method in dry vs. wet years*

431 Outlooks of water allocation are useful only until determinations reach full entitlement, or
432 more precisely, when there is uncertainty in future determinations. Here we have considered
433 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.

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

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

501

502 **Data Availability Statement**

503 The seasonal streamflow forecasts used can be found from the website of the Australia
504 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://nvrn.net.au/seasonal-determinations/history>).

516 4) Historical outlooks for the Goulburn system (available from:
517 <https://nvrn.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

521 **References**

- 522 Alemu, E.T., Palmer, R.N., Polebitski, A., Meaker, B., 2011. Decision Support System for Optimizing
523 Reservoir Operations Using Ensemble Streamflow Predictions. *J. Water Resour. Plan. Manage.-*
524 *ASCE*, 137(1): 72-82. DOI:10.1061/(asce)wr.1943-5452.0000088
525 Anghileri, D. et al., 2016. Value of long-term streamflow forecasts to reservoir operations for water
526 supply in snow-dominated river catchments. *Water Resources Research*, 52(6): 4209-4225.
527 DOI:10.1002/2015wr017864
528 Australian Bureau of Meteorology, 2023. "National Summary (Model Performance): Seasonal Streamflow
529 Forecasts". Accessed March 17, 2023.

- 530 Bennett, J.C., Wang, Q.J., Li, M., Robertson, D.E., Schepen, A., 2016. Reliable long-range ensemble
 531 streamflow forecasts: Combining calibrated climate forecasts with a conceptual runoff model and
 532 a staged error model. *Water Resources Research*, 52(10): 8238-8259.
 533 DOI:10.1002/2016wr019193
- 534 BoM, 2022. Seasonal Streamflow Forecasts: Water Information: Bureau of Meteorology. Australian
 535 Bureau of Meteorology.
- 536 Boucher, M.A., Tremblay, D., Delorme, L., Perreault, L., Anctil, F., 2012. Hydro-economic assessment of
 537 hydrological forecasting systems. *Journal of Hydrology*, 416-417: 133-144.
 538 DOI:10.1016/j.jhydrol.2011.11.042
- 539 Chiew, F.H.S., Piechota, T.C., Dracup, J.A., McMahon, T.A., 1998. El Nino/Southern Oscillation and
 540 Australian rainfall, streamflow and drought: Links and potential for forecasting. *Journal of*
 541 *Hydrology*, 204(1-4): 138-149. DOI:10.1016/s0022-1694(97)00121-2
- 542 Clark, M., Gangopadhyay, S., Hay, L., Rajagopalan, B., Wilby, R., 2004. The Schaake Shuffle: A Method
 543 for Reconstructing Space–Time Variability in Forecasted Precipitation and Temperature Fields.
 544 *Journal of Hydrometeorology*, 5(1): 243-262. DOI:10.1175/1525-
 545 7541(2004)005<0243:Tssamf>2.0.Co;2
- 546 DELWP, 2022. Victorian Water Register. Victorian State Government, Department of Environment,
 547 Land, Water, and Planning.
- 548 Feikema, P.M. et al., 2018. Service and Research on Seasonal Streamflow Forecasting in Australia, World
 549 Scientific Series on Asia-Pacific Weather and Climate. DOI:10.1142/9789813235663_0010
- 550 Goulburn Broken Catchment Management Authority, 2017. Regional irrigated land and water use
 551 mapping in the Goulburn Murray Irrigation District.
- 552 Hamlet, A.F., Lettenmaier, D.P., 1999. Columbia River streamflow forecasting based on ENSO and PDO
 553 climate signals. *J. Water Resour. Plan. Manage.-ASCE*, 125(6): 333-341.
 554 DOI:10.1061/(asce)0733-9496(1999)125:6(333)
- 555 Kaune, A., Chowdhury, F., Werner, M., Bennett, J., 2020. The benefit of using an ensemble of seasonal
 556 streamflow forecasts in water allocation decisions. *Hydrology and Earth System Sciences*, 24(7):
 557 3851-3870. DOI:10.5194/hess-24-3851-2020
- 558 Laio, F., Tamea, S., 2007. Verification tools for probabilistic forecasts of continuous hydrological
 559 variables.
- 560 Lu, M., Lall, U., Robertson, A.W., Cook, E., 2017. Optimizing multiple reliable forward contracts for
 561 reservoir allocation using multitime scale streamflow forecasts. *Water Resources Research*,
 562 53(3): 2035-2050. DOI:10.1002/2016wr019552
- 563 MDBA, 2020. How allocations work in the Murray-Darling Basin. Murray Darling Basin Authority
 564 (MDBA).
- 565 NVRM, 2022. Outlooks. Northern Victoria Resource Manager.
- 566 Regonda, S., Zagana, E., Rajagopalan, B., 2011. Prototype Decision Support System for Operations on the
 567 Gunnison Basin with Improved Forecasts. *J. Water Resour. Plan. Manage.-ASCE*, 137(5): 428-
 568 438. DOI:10.1061/(asce)wr.1943-5452.0000133
- 569 Robertson, D.E., Wang, Q.J., 2012. American Meteorological Society A Bayesian Approach to Predictor
 570 Selection for Seasonal Streamflow Forecasting. *Journal of Hydrometeorology*, 13(1): 155-171.
 571 DOI:10.2307/24912755
- 572 Troin, M., Arsenault, R., Wood, A.W., Brissette, F., Martel, J.L., 2021. Generating Ensemble Streamflow
 573 Forecasts: A Review of Methods and Approaches Over the Past 40 Years. *Water Resources*
 574 *Research*, 57(7). DOI:10.1029/2020wr028392
- 575 Victorian Department of Environment, L., Water, and Planning, 2021. Consolidated Bulk Entitlement
 576 (Eildon-Goulburn Weir) Conversion Order 1995 as at 30 June 2021.
- 577 Wang, Q.J., Robertson, D.E., 2011. Multisite probabilistic forecasting of seasonal flows for streams with
 578 zero value occurrences. *Water Resources Research*, 47(2). DOI:10.1029/2010wr009333
- 579 Wang, Q.J., Robertson, D.E., Chiew, F.H.S., 2009. A Bayesian joint probability modeling approach for
 580 seasonal forecasting of streamflows at multiple sites. *Water Resources Research*, 45(5).
 581 DOI:10.1029/2008wr007355
- 582 Wang, Q.J. et al., 2019. An evaluation of ECMWF SEAS5 seasonal climate forecasts for Australia using a
 583 new forecast calibration algorithm. *Environmental Modelling & Software*, 122.
 584 DOI:10.1016/j.envsoft.2019.104550
- 585 Winsemius, H.C. et al., 2014. The potential value of seasonal forecasts in a changing climate in southern
 586 Africa. *Hydrology and Earth System Sciences*, 18(4): 1525-1538. DOI:10.5194/hess-18-1525-
 587 2014
- 588 Young, M.D., 2014. Designing water abstraction regimes for an ever-changing and ever-varying future.
 589 *Agricultural Water Management*, 145: 32-38. DOI:10.1016/j.agwat.2013.12.002

590 Zaerpour, M., Papalexiou, S.M., Nazemi, A., 2021. Informing Stochastic Streamflow Generation by
591 Large-Scale Climate Indices at Single and Multiple Sites. *Advances in Water Resources*, 156.
592 DOI:10.1016/j.advwatres.2021.104037
593

594 **Statements and declarations**

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

602

603 **CRedit authorship contribution statement**

604 **Tristan D. J. Graham:** Software, Formal analysis, Visualisation, Writing – original draft
605 and editing. **Quan J. Wang:** Conceptualization, Funding acquisition, Methodology,
606 Software, Writing – review and editing. **Yating Tang:** Software, Formal analysis, Writing –
607 original draft.
608 **Andrew Western:** Conceptualization, Funding acquisition, Methodology, Writing – review.
609 **Wenyan Wu:** Writing – review. **Guy Ortlipp:** Data curation, Writing – review. **Mark**
610 **Bailey:** Data curation. **Senlin Zhou:** Data curation. **Kirsti Hakala:** Writing – review.
611 **Qichun Yang:** Writing – review.

612

613 **Supplementary material**

614 Supplementary Material 1:

615 File name: Supplementary_Material_1_mean_monthly_flows.tif

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

617 to 2020.

618

619 Supplementary Material 2:

620 File name: Supplementary_Material_2_inflow_forecast_skill_scores.tif

621 Caption: Median **CRPS** skill scores (%) for 1-month, 2-month, and 3-month

622 streamflow volumes from the forecast month, as provided by the Bureau of Meteorology.