

Exploring the value of seasonal flow forecasts for drought management in South Korea

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Abstract.

Drought poses significant challenges across various *water-dependent* sectors. In the past few decades, numerous devastating droughts have been reported worldwide including in South Korea. A recent drought in South Korea, which lasted from 2014 to 2016, led to significant consequences including water restrictions and nationwide crop failures. Historically, reservoirs have played a crucial role in mitigating hydrological droughts by *increasing* water supply stability. With exacerbating intensity and frequency of droughts, *enhancing the operational efficiency of existing reservoirs* becomes increasingly important. This study examines the value of Seasonal Flow Forecasts (SFFs) in informing reservoir operations *during three historical drought events, with a focus on two key reservoir systems in South Korea. For these events, we simulate what would have happened if the reservoir managers had optimised operations using SFFs. For comparison, we also simulate the effect of reservoir operations optimised using two deterministic scenarios (worst-case and 20-year return period drought) and another ensemble forecasts product (Ensemble Streamflow Prediction, ESP). We repeat our simulation experiments by varying the key choices in the experimental set-up, i.e. the forecast lead time, decision-making time step, and the method for selecting a compromise solution between conflicting objectives. We then propose a new, simple and intuitive method for measuring the value of the different scenarios/forecasts, based on the frequency of outperforming (in a Pareto-dominance sense) the historical operation across such experiments. Our findings indicate that while deterministic scenarios show higher accuracy, forecast-informed operations with ensemble forecasts tend to yield greater value. This highlights the importance of considering forecast uncertainty in optimising reservoir operations. Although SFFs generally show higher accuracy than ESP, the difference in value is small. Last, sensitivity analysis shows that the method used to select a compromise release schedule between competing operational objectives is a key control of forecast value, implying that the benefits of using seasonal forecasts may vary widely depending on how priorities between objectives are established.*

Keywords: drought, reservoir operations, seasonal weather forecasts, seasonal flow forecasts, ensemble streamflow prediction, multi-objective optimisation, multi-criteria decision-making

1. Introduction

Drought stands as one of the major natural disasters with devastating impacts for various sectors including agriculture, water resources, environment and energy (Mishra and Singh, 2010; Schwalm et al., 2017; Zhang et al., 2022). The severity of droughts is anticipated to escalate in the future under a warmer climate, but there is plenty of evidence to suggest that this increase may already be underway (Sheffield et al., 2012). In South Korea, a severe drought event, prolonged from 2014 to 2016, caused substantial consequences, such as water restrictions in certain regions and nationwide crop failures (K-water, 2018). Reservoirs have played a crucial role in mitigating drought impacts by *stabilising* water supply and compensating for hydrological variability (Goldsmith and Hildyard, 1984). However, the increasing frequency and intensity of extreme droughts are posing greater challenges for reservoir operators (Sheffield et al., 2012; Schwalm et al., 2017). On the other hand, the construction of new reservoirs has become increasingly controversial in many countries, including South Korea, mainly due to concerns about the socio-economic costs and undesirable environmental impacts of reservoir development (Ehsani et al., 2017). This highlights the growing significance of enhancing the operation of existing reservoirs to mitigate drought damages. A key contribution to this end may come by improving flow forecasting systems and their use in support of decision-making under extreme weather conditions (Turner et al., 2017).

Advancements in numerical weather prediction systems over the past decade have significantly improved forecasting performance at longer time scales (Bauer et al., 2015; Alley et al., 2019). Seasonal weather forecasts, which provide predictions of weather variables (e.g. precipitation, temperature) for the next several months, have gained interest among researchers for their potential in enhancing water resources management. Accordingly, numerous studies have been conducted to transform seasonal weather forecasts into more relevant Seasonal Flow Forecasts (SFFs) across various regions of the world (e.g. Prudhomme et al., 2017; Arnal et al., 2018; Greuell et

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87 al., 2018; Lucatero et al., 2018; Hurkmans et al., 2023). In many countries, however, practical reservoir operations
88 still make limited use of SFFs. Even when water resource modelling is used to inform operational decisions,
89 reservoir operators tend to run these models against deterministic scenarios such as the worst-case scenario (Yoe,
90 2019) or against Ensemble Streamflow Prediction (ESP) (Day, 1985). The worst-case scenario mimics the most
91 extreme historical event to hedge risks associated with uncertainties in water management, whereas ESP generates
92 an ensemble of flow forecasts by forcing a hydrological model with historical meteorological observations (Baker
93 et al., 2021). Previous studies have identified as primary obstacles to the use of SFFs by water managers their
94 tendency to adopt a risk-adverse approach (Block, 2011), the lack of experience in handling SFFs products and
95 the perceived low reliability of SFFs (Millner and Washington, 2011; Soares and Dessai, 2016; Jackson-Blake et
96 al., 2022). Indeed, previous studies have shown that SFFs provide more accurate forecast than ESP only for the
97 first or second months ahead (Yossef et al., 2013; Crochemore et al., 2016; Lucatero et al., 2018) and their
98 performance decreases with increasing lead time (Greuell et al., 2018; Pechlivanidis et al., 2020).

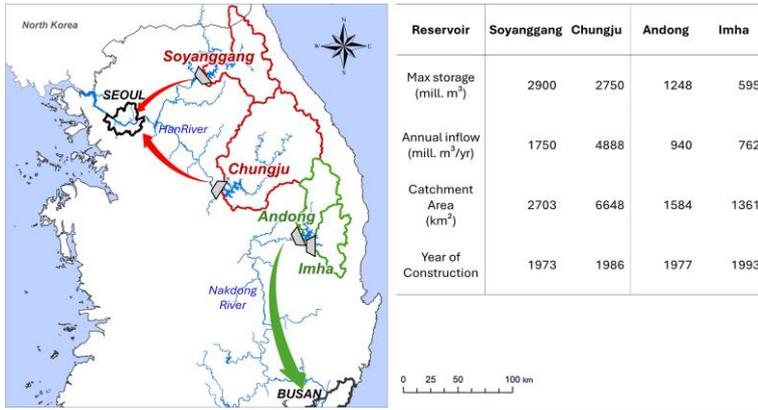
99 In perspective of reservoir operations, however, more than the forecast accuracy, i.e. how well hydrological
100 forecasts replicate observations, the attention should be directed to the forecast value, i.e. the benefits of using
101 forecasts to inform operational decisions (Turner et al., 2017; Peñuela et al., 2020a). Assessing forecast value may
102 reveal situations where using forecasts enhances water management even if the accuracy is relatively low (Rougé
103 et al., 2023). With this idea in mind, several studies have utilised model simulations to assess how using SFFs
104 could have improved reservoir operations during past events. To achieve this, these studies feed SFFs into a
105 reservoir operation optimisation model to find the “optimal” release schedule based on those flow predictions and
106 then assess the effects of the optimal schedule by simulating it against the actual observed flows. The process is
107 repeated for as many decision time-steps as needed throughout the historical event. The performances of such
108 forecast-informed operations are then summarised through a set of performance indicators and compared to the
109 performances obtained with a benchmark approach, such as optimising against a deterministic scenario or using
110 prescribed operation rules. The increase in performance with respect to the benchmark is regarded as the value of
111 the SFFs. For example, Chiew et al. (2003) investigated the value of SFFs for agricultural supply from a reservoir
112 in Australia, a region affected by El Nino/Southern Oscillation (ENSO) teleconnections. They found that release
113 schedule informed by SFFs can yield modest benefits compared to using a predefined reservoir operation rule.
114 Peñuela et al. (2020a) assessed the forecast value for reservoir operations in the UK, focusing on maximising
115 water supply and minimising pumping energy cost. They found that using ensemble forecasts can significantly
116 enhance operational efficiency compared to relying on a deterministic worst-case scenario, whereas ESP is a hard-
117 to-beat benchmark. Crippa et al. (2023) assessed the value of SFFs for agricultural water supply in Greece and
118 found that SFFs can marginally improve reservoir operations with respect to using a simple reservoir operation
119 rule. However, they solely utilised the median of the SFFs ensemble, hence leaving open the question of whether
120 using the full ensemble and allowing for uncertainty in the optimisation process could bring more obvious
121 advantages, as found in Peñuela et al. (2020a).

122 This paper investigates the value of SFFs for informing reservoir operations in South Korea by assessing their
123 potential to mitigate the impacts of three major historical drought events. We build on our previous works on the
124 skill of seasonal precipitation and flow forecasts across catchments in South Korea, indicating that SFFs can be
125 particularly suitable for predicting droughts. Specifically, in Lee et al. (2023), we compared the performance of
126 precipitation forecasts from various forecasting centres and found that the European Centre for Mid-range
127 Weather Forecasting (ECMWF) provides the most accurate forecasts in South Korea and particularly during dry
128 years. Our subsequent research on translating seasonal weather forecasts into flow forecasts (Lee et al., 2024),
129 demonstrated that SFFs are generally more accurate than ESP up to 3 months ahead and at even longer lead times
130 in dry years. In this study, we focus on two reservoir systems, Soyanggang-Chungju and Andong-Imha, which
131 serve as crucial water sources for the country, including densely populated metropolitan areas such as the capital
132 city of Seoul, and three recent major droughts in 2001-02, 2008-09, and 2004-16. To identify the optimal ‘forecast-
133 informed’ reservoir operations during these drought events, we employ a multi-objective optimisation approach
134 driven by SFFs. For comparison, we also optimise against ESP and two deterministic scenarios currently utilised
135 by the national water agency in charge of reservoir operations (K-water). To increase the robustness of our
136 conclusions, simulation experiments are repeated with different choices of the forecast lead time, the method for
137 selecting a compromise solution between the two conflicting objectives pursued by the reservoir managers
138 (minimising short-term supply deficit versus maximising the storage volume at the end of the hydrological year),
139 and the temporal resolutions for repeating the multi-objective optimisation, i.e. the decision-making time step.
140 Finally, for each flow scenario/forecast, we synthetically measure the value of the scenario/forecast as the chances
141 of achieving better operational outcomes compared to historical operations (i.e. Pareto-dominating historical
142 operations) across all the simulation experiments. This new approach to measuring value is useful because it
143 acknowledges the uncertainty in the simulation results due to experimental set-up choices while also capturing
144 the trade-offs between the conflicting objectives in a simple, synthetic way.

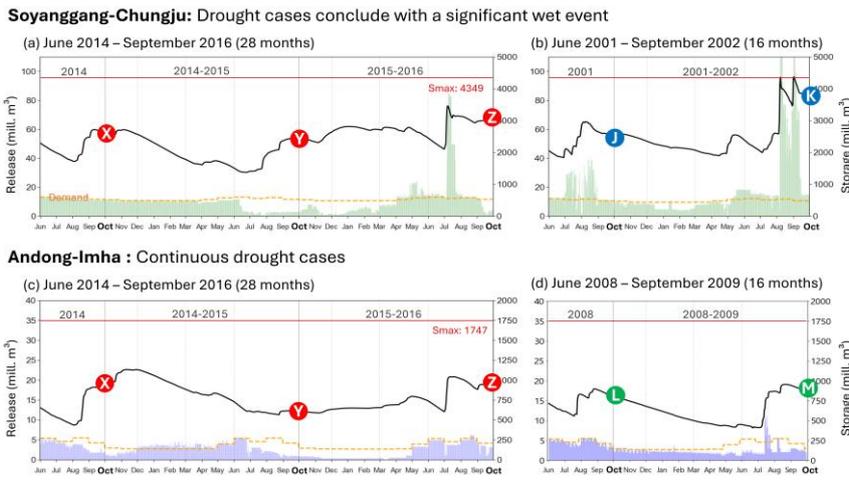
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A key contribution of this paper lies in introducing a new methodology for quantifying forecast value and analysing its sensitivity to key experimental choices.

184 2. Study area and available data

185 2.1 Case study reservoirs and drought events



187 Figure 1: Location and properties of the studied reservoirs and their catchments. The green and red arrows represent
188 the regions supplied by those reservoirs.



189 Figure 2: Daily reservoir operation records for the studied drought events (K-water, 2023). Points X, Y, Z, J, K, L, M
190 represent the ends of the hydrological years (September 30th) which will be used as points in time for the forecast value
191 assessment.
192

193 Currently, there are 20 multipurpose reservoirs in operation across South Korea, each playing a vital role in
194 national water resources management and the mitigation of water-related disasters (Park and Kim, 2014). This
195 study specifically focuses on two reservoir systems: Soyanggang-Chungju and Andong-Imha. The Soyanggang
196 and Chungju reservoirs have the largest storage capacity in South Korea (Figure 1). They are positioned upstream
197 of the Han River and serve as primary water sources for Seoul's metropolitan area, with a population of
198 approximately 23 million people (K-water, 2023). In terms of total storage capacity, these two reservoirs also
199 stand as the two largest across the country. The Andong and Imha reservoirs are located in northernmost region
200 of the Nakdong River and supply water to plenty of cities alongside the river, including Busan, the second-largest
201 city in the country.

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224 The Soyganggang and Chungju reservoirs are operated conjunctively by the national water resources corporation,
225 K-water, effectively functioning as a single reservoir. For instance, during periods when one reservoir (e.g.
226 Soyganggang) experiences reduced storage volume, the other reservoir (e.g. Chungju) supplements the water
227 supply. A historical example of this conjunctive operations is provided in Figure S1 in the supplementary material.
228 A similar approach is used for the Andong and Imha reservoirs. Here again conjunctive operations are important
229 for mitigating drought damage. Therefore, in this study, we treat Soyganggang-Chungju as one integrated two-
230 reservoir system, and the same for Andong-Imha. The catchments feeding these systems exhibit similar
231 hydrological regimes, with approximately 70% of annual inflow occurring during the wet season (June to
232 September) due to monsoons and typhoons, and low inflows in the dry season (December to February) caused by
233 lower temperatures and reduced precipitation. Reservoir releases follow a weekly schedule which is revised by
234 K-water every month based on projections of future storages for the upcoming 3 to 6 months derived using a low
235 inflow scenario (specifically, the 20-year return period drought further described in Section 3.1.1).

236 Figure 2 illustrates the daily reservoir operation records (storages and releases) during the historical drought events
237 analysed in this study. The very severe 2014-16 drought event is included in the analysis for both reservoir systems.
238 This event caused severe damages such as regional water restrictions and nationwide crop failures (K-water, 2018).
239 During this period, the aggregated storage volume for Soyganggang-Chungju reached its lowest in record (1373
240 million m³, corresponding to 24.3% of storage capacity) and its third lowest record for Andong-Imha (434 million
241 m³, 23.5%). Additionally, we analysed the drought event from 2001 to 2002 for Soyganggang-Chungju and the
242 event from 2008 to 2009 for Andong-Imha. The drought events show distinct characteristics: both droughts in
243 Soyganggang-Chungju (Figure 2(a, b)) conclude with a large inflow (and outflow) event in the subsequent wet
244 season, while in Andong-Imha relatively low flow conditions persist into the wet season (Figure 2(c, d)).

245 2.2 Observational data and seasonal weather forecasts

246 This study utilises quality-controlled daily precipitation data from 49 in-situ stations distributed within the
247 catchments, as provided by K-water, along with daily temperature data from 37 in-situ stations managed by the
248 Korean Meteorological Administration (KMA). Unlike precipitation and temperature, potential
249 evapotranspiration (PET) data were computed based on the standardised Penman-Monteith method suggested by
250 the United Nations Food and Agriculture Organisation (Allen et al., 1998). We used the Thiessen polygon method
251 to calculate the mean areal data for each reservoir. For reservoir operation modelling, we used quality-controlled
252 daily reservoir operation records provided by K-water, including the storage volume, inflow and water supply. In
253 generating these records, K-water utilises a water balance equation, considering reservoir volume changes from
254 water level fluctuations and supplies. These reservoir inflow data are not corrected for removing the effect of
255 evaporation losses from the reservoirs.

256 For generating SFFs, we employed the seasonal weather forecasts provided by ECMWF (system 5). This choice
257 was based on our prior research, which demonstrated that generally ECMWF offers the most accurate precipitation
258 forecasts across South Korea (Lee et al., 2023). ECMWF provides 25 ensemble forecasts from 1993 to 2016 and
259 51 ensembles since 2017 on a monthly basis, with a lead time extending up to 7 months ahead. To ensure
260 consistency with our previous works, we obtained ECMWF's seasonal weather forecasts datasets for precipitation,
261 temperature and PET with a spatial resolution of 1×1°. We downloaded forecast data from the Copernicus Climate
262 Data Store every month in the period of the three drought events of Figure 2. Additionally, we downloaded
263 forecast data for the available period from 1993 to 2010 to compute bias correction factors (as detailed in Section
264 3.1.1).

265 3. Methodology

266 3.1 Simulating forecasts-informed operations during a past drought event

267 Figure 3 schematically outlines our methodology for simulating reservoir operations during a past drought event,
268 and each compartment of the figure corresponds to a sub-section from 3.1.1 to 3.1.4. We begin by compiling four
269 distinct flow scenarios/forecasts (Worst-Case Drought (WCD), 20-Year return period Drought (20YD) / ESP, SFFs)
270 using historical observational data and seasonal weather forecasts from ECMWF system5 (Section 3.1.1).
271 For each of this flow scenario/forecast, we generate a set of Pareto optimal weekly release schedules, taking into
272 account two conflicting objectives: securing storage volume and minimising supply deficit (Section 3.1.2). A
273 single compromise release schedule within this set is then selected using a Multi-Criteria Decision-Making
274 (MCDM) methods (Section 3.1.3). We then simulate the evolution of the reservoir systems until the next decision-
275 making time step by feeding the chosen release schedule into a reservoir simulation model forced by observed
276 inflow data (Section 3.1.4). The aforementioned process is iteratively repeated until the end of the simulation

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period (i.e. the end of the historical drought event as shown in Figure 2). As highlighted in Figure 3, the key choices in setting-up each simulation experiment are: the type of flow scenario/forecast and relevant lead time; the MCDM method used to select a compromise schedule; and the decision-making time step, i.e. the frequency with which release schedules are re-optimised. Note that the forecast lead time can be chosen to be longer than the decision-making time step, in which case only the first part of the optimised release schedule is applied before being re-optimised.

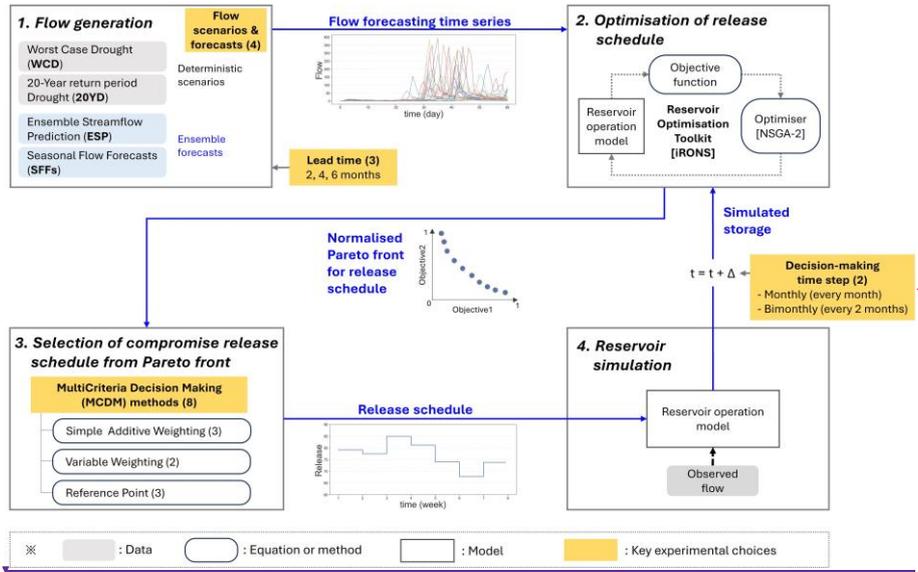


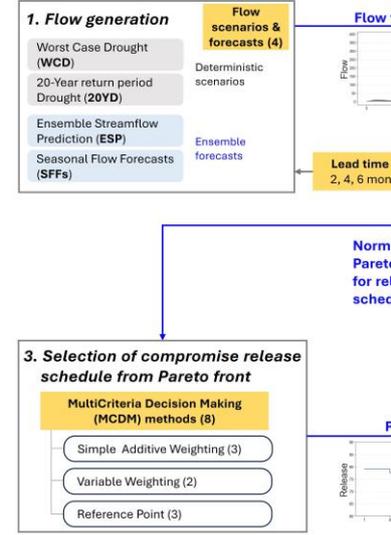
Figure 3: Schematic diagram illustrating the reservoir simulation methodology employed in this study to simulate forecast-informed reservoir operations during a drought event.

3.1.1 Generation of deterministic flow scenarios and ensemble flow forecasts

In this study, we considered two deterministic scenarios, WCD and 20YD, alongside two ensemble forecasts products, ESP and SFFs. All scenarios and forecasts are generated at daily resolution (i.e. the resolution of the hydrometeorological data and weather forecasts) and then aggregated to weekly resolution (the resolution for reservoir simulation). In our simulation experiments, we tested scenarios/forecasts with lead times of 2, 4, or 6 months. An example of reservoir simulation process, with various experimental choices such as flow scenario/forecast, lead time and decision-making time step, is illustrated in Figure S2. The WCD scenario was generated by analysing historical flow records and identifying the lowest observed inflows for each reservoir. The 20YD scenario, which is the scenario currently employed in practical reservoir operations in South Korea, was obtained from K-water. To derive this scenario, K-water conducts a low-flow frequency analysis of historical inflow records spanning over 30 years (Ryoo et al., 2009; Jung et al., 2012). We built an ensemble for each weather variable (precipitation, temperature and PET) based on historical observations from 1966 to 2010 and fed it into the Tank hydrological model (Sugawara et al., 1986, 1995) to generate ESP flow ensemble with 45 members (Lee et al., 2024). The Tank model is a lumped conceptual rainfall-runoff model, widely used in South Korea and many other countries (Goodarzi et al., 2020; Ou et al. 2017). We calibrated and validated the model using observations for the period 2001-2010 and 2011-2020, respectively. Lastly, we generated an ensemble of SFFs using ECMWF's seasonal weather forecasts (system 5) as input for the same Tank model (25 ensemble forecasts until 2016 and 51 since 2017). Given the coarse spatial resolution (1°x1°) of the seasonal weather forecast data compared to the reservoir's catchment areas, we applied the linear scaling method to correct biases. Bias correction factors were derived by comparing weather forecasts with observations over the period 1993-2010. We made this choice to maximise the chances of getting robust estimates for the bias correction factors (Maraun et al., 2010; Johnson and Sharma, 2012), although this may lead to an overestimation of the SFFs performance during the 2001-02 and the 2008-09 drought events, given that observations for those events contributed to the bias correction process. Further details regarding the structure, parameter calibration,

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validation and performance of the Tank model, as well as the linear scaling method used for bias correction, are comprehensively documented in our previous paper (Lee et al., 2024).

To assess the accuracy of flow forecasts, we employed the Mean Error (ME) of monthly flow averaged across the entire simulation period. In calculating ME for ensemble forecasts, we considered their ensemble median. It is calculated as:

$$\text{Mean Error} = \frac{1}{N} \sum_{i=1}^N (Q_i^{\text{Forecast}} - Q_i^{\text{Observation}}) \quad (1)$$

where, N represents the total number of timesteps (months) in the simulation periods. Q_i^{Forecast} and $Q_i^{\text{Observation}}$ are forecasted and observed monthly flow at time i (month), respectively. When the ME is negative (positive), the forecast tends to underestimate (overestimate) the flow.

While ME is a simple measure of forecast accuracy, it does not account for the contributions of each member within the ensemble. Therefore, we also computed the forecast skill using the Continuous Ranked Probability Score (CRPS) and the Continuous Ranked Probability Skill Score (CRPSS), developed by Matheson and Winkler (1976). While CRPS measures the absolute performance (score), CRPSS represents the relative performance (skill) with respect to a benchmark, in our case the ESP. These metrics are computed as follows:

$$\text{CRPS} = \int [F(x) - H(x \geq y)]^2 dx \quad (2)$$

$$\text{CRPSS} = 1 - \frac{\text{CRPS}^{\text{SFFs}}}{\text{CRPS}^{\text{ESP}}} \quad (3)$$

where $F(x)$ represents the cumulative distribution of the SFFs ensemble, x and y are the forecasted and observed flow. H is called the 'Heaviside (or Indicator) function' and is equal to 1 when $x \geq y$ and 0 when $x < y$. CRPS values range from 0 to infinity and the lower CRPS the higher forecasting performance. CRPS^{SFFs} and CRPS^{ESP} are the CRPS of SFFs and ESP, respectively. When the CRPSS is positive ($0 < \text{CRPSS} \leq 1$), SFFs have skill with respect to ESP, when it is negative, ESP outperforms SFFs. If the CRPSS equals zero, the performance of SFFs is equivalent to that of ESP.

To exhibit the skill more intuitively, we employed the concept of 'overall skill', as introduced in our previous research (Lee et al., 2023; 2024). It represents the frequency with which SFFs outperform the benchmark (ESP) over a specific period and can be expressed as:

$$\text{Overall skill (\%)} = \frac{\sum_{i=1}^N [H(\text{CRPSS}(i))] }{N} \times 100 (\%) \quad (4)$$

where N is the total number of months in the periods, i.e. the analysed drought event in our case. Again, the Heaviside function (H) is equal to 1 when $\text{CRPSS}(i) > 0$ and 0 when $\text{CRPSS}(i) \leq 0$. If the overall skill is greater than 55%, SFFs generally have skill with respect to ESP across the period. However, if it is less than 45%, ESP outperforms SFFs. When the overall skill is between 45% to 55%, we consider them to have an equivalent level of performance (Lee et al., 2024).

3.1.2 Multi-objective optimisation of release schedule

Reservoir operations inherently involve managing multiple objectives often in conflict with each other (Zhou et al., 2011; Vassoney et al., 2021). In terms of drought management, the amount of supply deficit shows an inverse correlation with both the secured reservoir storage at the initial stage of the hydrological year (October 1st) and the total inflow into the reservoir across the hydrological year (from October 1st to the subsequent September 30th). In other words, inadequate storage at the outset of the hydrological year leads to substantial disruptions in water supply and the severity of these shortages further increases when the inflow is insufficient. These relationships are evident in historical records, as illustrated in Figure S3.

To account for both the need of ensuring supply and of securing storage for the next hydrological year, we established two operational objectives in our optimisation: to minimise the mean Squared Supply Deficit (SSD, [million m³]²) over the optimisation period and to minimise the Storage Volume Difference (SVD, million m³) relative to the reservoir's capacity at the end of the hydrological year. The rationale for squaring the supply deficit is to incorporate risk hedging principles, aimed at strategically allocating water resources over time (You, 2013; Shiau, 2022). These two objectives are formulated as:

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$$444 \quad SSD = \frac{1}{T} \sum_{t=0}^T [\text{Max}(0, d(t) - Q(t))]^2 \quad (5)$$

$$445 \quad SVD = \text{Max}(0, S_{max} - S) \quad (6)$$

446 where T is the total number of weeks for which the flow forecast is available (i.e. T equals the lead time in months
 447 $\times 4$), $d(t)$ and $Q(t)$ represent water demand and supply at week t , respectively. S_{max} is the storage capacity of
 448 the reservoir (million m^3) and S is the storage volume (million m^3) at the end of the hydrological year. When the
 449 end of hydrological year is not included in the optimisation period, S is set to the storage at the end of optimisation
 450 period. By definition, superior performance is associated with smaller objectives (SSD and SVD).

451 For the reservoir operation modelling and the optimisation of release schedules, this study utilises the ‘interactive
 452 Reservoir Operations Notebooks and Software’ (iRONS) toolbox developed by Peñuela et al. (2021). This toolbox
 453 offers a set of Python functions, and a Jupyter Notebook based environment to simulate and optimise reservoir
 454 operations. In iRONS, the reservoir model, based on a mass balance equation, is linked to an optimiser that utilises
 455 the Non-dominated Sorting Genetic Algorithm (NSGA-II) for the multi-objective optimisation. Given that in
 456 multi-objective optimisation problems, a single optimal solution that satisfies all objectives simultaneously is
 457 unattainable (Lu et al., 2011; Malekmohammadi et al., 2011), NSGA-II identifies a set of non-dominated solutions
 458 whose performance realise different Pareto optimal trade-offs between the two objectives. The performances
 459 associated with these solutions visualised in the objective space constitute the so called ‘Pareto front’ (Giagkiozis
 460 and Fleming, 2014; Ni et al., 2022). The SSD and SVD are used as objective functions to generate a Pareto front.
 461 We set the number of solutions to be evolved by the NSGA-II algorithm (so called ‘population’ size) to 100, and
 462 the number of iterations to 100000, leading to a total of ten million model evaluations for each optimisation run.
 463 When optimising against ensemble forecasts, the two objective functions (Eqs. 5 and 6) are evaluated against each
 464 ensemble member, and the average is taken as the final objective value and passed on to the NSGA-II optimiser.

465 3.1.3 Selection of a compromise solution from the Pareto front

466 Since the Pareto front, delivered by the multi-objective optimisation (Section 3.1.2), comprises multiple release
 467 schedules, a critical decision must be made to select one compromise release schedule from that Pareto front. The
 468 methodology for this selection will be referred to as Multi-Criteria Decision-Making (MCDM) from now on, as
 469 described in some of the previous literature (e.g. Wang and Rangaiah, 2017; Ni et al., 2022). In other context,
 470 MCDM methods are presented to support decision makers in selecting compromise alternatives for complex water
 471 management issues (Afshar et al., 2011; Malekmohammadi et al., 2011; Zhu et al., 2017; Vassoney et al., 2021).
 472 In this study, the MCDM method is employed as a way to mimic the selection that, in real world, would be made
 473 by the reservoir operator when running forecasts through a reservoir operation optimisation model and being
 474 returned a Pareto front. Given the significant uncertainty regarding how the operator would make this selection,
 475 considering multiple MCDM methods provides a means to address this uncertainty in our assessment of forecast
 476 value.

477 Various MCDM methods have been developed and utilised over the last several decades (Velasquez and Hester,
 478 2013). Among them, this study employed eight distinct methods, which can be systematically categorised into
 479 three groups: Simple Additive Weighting (SAW), variable weighting and reference point methods. Firstly, the
 480 SAW method, which is frequently employed in decision-making (Arsyah et al., 2021), ranks the alternatives based
 481 on their weighted sum performance (Fishburn, 1967). In this study, we consider the ‘balanced’ method where
 482 equal weights are assigned to each objective, as well as the ‘storage-prioritised’ and ‘supply-prioritised’ methods,
 483 which prioritise storage and supply, respectively.

484 Secondly, we propose the ‘variable weighting’ method, which reproduces more closely the thought process of
 485 reservoir operators, who weight supply more when the storage is abundant and less when storage is scarce. We
 486 applied this method in two ways: the ‘simple selective’ method, which adopts the same weights as in the SAW
 487 methods but varying them depending on storage status and the ‘multi-weight’ method, which applies more detailed
 488 procedure to allocate weights based on storage status.

489 Lastly, the reference point method identifies the compromise solution on a Pareto front by measuring the distance
 490 from a reference point. In this study, we applied three approaches: the ‘utopian point’, ‘knee point’ and ‘TOPSIS’
 491 methods. The utopian point method selects the solution on the Pareto front that minimises the Euclidean distance
 492 from the utopian (or ideal) point, which represents the theoretical perfect solution (Lu et al., 2011). The knee point
 493 method selects the knee point, which is a point where the curvature of the Pareto front is maximum (Das, 1999).
 494 Among various methods for detecting the knee point, we employed the Minimum Manhattan Distance method
 495 which is known for its simplicity and robustness (Chiu et al., 2016; Li et al., 2020). The TOPSIS method selects
 496 a point with the shortest Euclidean distance from the ideal point and the longest distance from the anti-ideal point
 497 as the compromise solution (Hwang and Yoon, 1981; Liu, 2009). This is a widely chosen method (Tzeng and

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- Deleted: NSGA-II optimization with one million iterations for each Pareto front generation, using the two objectives defined in Eqs. 5 and 6 to optimize the weekly release schedule. We set the number of NSGA- II iterations for each Parto front generation to one million.
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535 Huang, 2011; Wang and Rangaiah, 2017) including the United Nations Environmental Program (Chen, 2000; Zhu
 536 et al., 2015).
 537 Detailed information on the MCDM method and normalisation of a Pareto front, including equations, merits and
 538 demerits, is provided in the supplementary material (Section S1 and S2).

539 **3.1.4 Reservoir simulation against observed inflows**

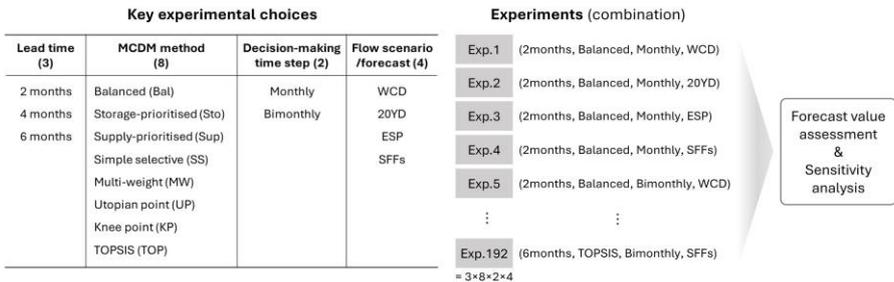
540 Once a Pareto-optimal release schedule is selected, the final step of our simulation methodology is to evaluate
 541 what would have been achieved if that schedule had been implemented. To this end, we simulate how the reservoir
 542 storage would have evolved under the selected release schedule and against observed inflows. The reservoir
 543 simulation is based on the repeated application of the following water balance equation:

544
$$S_{t+1} = S_t + I_t - R_t \quad t = 0, \dots, T-1 \quad (7)$$

545 where S_t is the simulated storage, I_t the observed inflow and R_t the optimised release for week t . Eq. 7 is repeated
 546 from time $t=0$, corresponding to the week when the scenarios/ forecasts are generated and the optimisation is run,
 547 until the time when the generation/optimisation process is run again, i.e. time $T=4$ (weeks) in the case of monthly
 548 decision-making time-step or $T=8$ (weeks) in case of bimonthly. The final simulated storage S_T is then used as
 549 the initial storage for the next multi-objective optimisation run and subsequent simulation (see Figure 3).

550 **3.2 Measuring the forecast value and its sensitivity to experimental choices**

551 For each drought event, the reservoir simulation of the forecast-informed operations described in Section 3.1, is
 552 repeated using different scenario/forecast products and with various combinations of key experimental choices.
 553 These choices include the forecast lead time, the MCDM method and the decision-making time step, as
 554 summarised in Figure 4. Therefore, the total number of experiments for each drought event amounts to 192 (3
 555 lead times \times 8 MCDM methods \times 2 decision-making time steps \times 4 flow scenarios/forecasts).



556 **※ MCDM:** MultiCriteria Decision-Making
WCD: Worst Case Drought, **20YD:** 20-Year return period Drought, **ESP:** Ensemble Streamflow Prediction, **SFFs:** Seasonal Flow Forecasts

557 **Figure 4: Key experimental choices for simulating forecast-informed reservoir operations. Each of the 192 simulation**
 558 **experiments is conducted according to Figure 3.**

559 For each experiment, we computed two performance indicators, representing supply deficit (SSD) and storage
 560 volume (SVD) as in Eqs. 5 and 6 but using the simulated storage and release time series from the simulation
 561 against observed inflows (step 4 in Figure 3). We then calculated the same indicators using the observed storage
 562 and release, to quantify the performance of the historical operations, which we use as a benchmark. Unlike
 563 previous studies (e.g. Turner et al., 2017; Peñuela et al., 2020a; Crippa et al., 2023) that analysed improvements
 564 in performance indicators separately, here we propose a new and simple way to take into account the improvement
 565 in both indicators simultaneously. In fact, performance indicators generally exhibit a trade-off relationship with
 566 each other, so that an improvement with respect to the benchmark for one indicator may come at the price of a
 567 loss in the other. Analysing them independently from one another obscures these trade-offs.

568 To overcome this issue, here we calculated the difference in each indicator (simulated - historical) in each
 569 experiment and defined the forecast value as the number of experiments where this difference is negative for both
 570 indicators. In fact, since we aim to minimise both indicators, negative differences in both indicate that the
 571 simulated operations outperform the historical operation. This method provides an intuitive and practical
 572 understanding of forecast value, as it directly relates to the chances of achieving better operational outcomes

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Key experimental choices			
Lead time (3)	MCDM method (8)	Decision-making time step (2)	Flow /sc
2 months	Balanced (Bal)	Monthly	
4 months	Storage-prioritized (Sto)	Bimonthly	
6 months	Supply-prioritized (Sup)		
	Simple selective (SS)		
	Multi-weight (MW)		
	Utopian point (UP)		
	Knee point (KP)		
	TOPSIS (TOP)		

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Key experimental choices			
Lead time (3)	MCDM method (8)	Decision-making time step (2)	Flow /sc
2 months	Balanced (Bal)	Monthly	
4 months	Storage-prioritized (Sto)	Bimonthly	
6 months	Supply-prioritized (Sup)		
	Simple selective (SS)		
	Multi-weight (MW)		
	Utopian point (UP)		
	Knee point (KP)		
	TOPSIS (TOP)		

※ MCDM: MultiCriteria Decision-Making
 WCD: Worst Case Drought, 20YD: 20-Year return period

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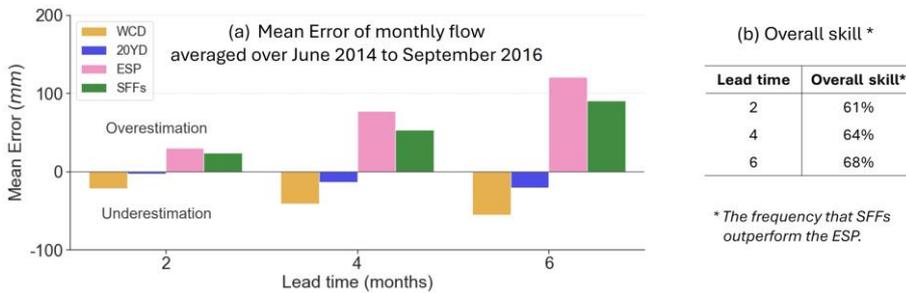
593 compared to historical operation, taking into account operational trade-offs and factoring in the uncertainty in the
 594 key experimental set-up choices. Last, we analysed the sensitivity of forecast value to those key experimental
 595 choices. This analysis serves as a useful tool in pinpointing the primary determinant of forecast value and offering
 596 insights for optimising setup choices to maximise the value for drought management.

597 **4. Results**

598 For clarity of illustration, in Section 4.1, we first present the results for one event and reservoir system: the drought
 599 that occurred in Soyanggang-Chungju from 2014 to 2016 (Figure 2). In Section 4.2, we expand our results to
 600 include other reservoir systems and events, aiming to explore to what extent our conclusions on the value of SFFs
 601 and its key controls can be generalised.

602 **4.1 Simulation results for the 2014-2016 drought in Soyanggang-Chungju reservoirs**

603 **4.1.1 Accuracy and skill of seasonal flow forecasts**



604 **Figure 5:** (a) Mean Error of monthly flow (simulated – observed) for Soyanggang-Chungju reservoir system averaged
 605 from June 2014 to September 2016 for different scenarios/forecasts (2-month lead time). (b) The overall skill of SFFs,
 606 which represents the frequency of SFFs outperforming ESP across the simulation period.

608 Figure 5(a) illustrates the Mean Error of monthly flow (see Eq. 1) for lead times of 2, 4, 6 months and different
 609 type of flow scenario/forecast (WCD: yellow, 20YD: blue, ESP: pink, SFFs: green). As shown in the figure,
 610 deterministic scenarios (WCD and 20YD) exhibit smaller errors compared to the ensemble forecasts. This is not
 611 surprising, as the WCD and 20YD scenarios are designed to mimic dry conditions and we are now evaluating
 612 accuracy on a severe drought event. Ensemble forecasts, particularly, show a systematic bias towards
 613 overestimating flows, with this tendency being more pronounced in ESP compared to SFFs. This pattern is
 614 consistently observed across different reservoir systems and events, as further illustrated in Figure S4.

615 Figure 5(b) shows the overall skill (see Eq. 4), indicating the frequency with which SFFs outperform ESP across
 616 the simulation period. In this specific event, the overall skill exceeds 60% at all lead times, indicating that SFFs
 617 generally perform better compared to ESP. However, results from different reservoir systems and events (reported
 618 in Figure S4), show lower overall skill, and decreasing with lead time. Our additional analysis of cumulative flow
 619 observations and forecasts for the period 2014-16, presented in Figure S5, indicates that this drought event was
 620 more severe than the 20-year return period drought for nearly two years – until the high inflows of July 2016.
 621 Given that reservoirs in South Korea are designed to supply water for a year under a drought with a 20-year return
 622 period, this event posed significant challenges to reservoir operators.

623 **4.1.2 Reservoir simulations and their performances**

624 The simulated reservoir operation results are illustrated in Figure 6, showing the storage volume (a) and
 625 cumulative squared supply deficit (b) generated using WCD (yellow), 20YD (blue), ESP (pink) and SFFs (green).
 626 For each flow scenario/forecast, there are 48 simulation outcomes resulting from different combinations of the
 627 experimental choices (3 lead times × 8 MCDM methods × 2 decision-making time steps). Higher storage volume
 628 compared to historical operation (black line) is preferable and vice versa for cumulative squared supply deficit.

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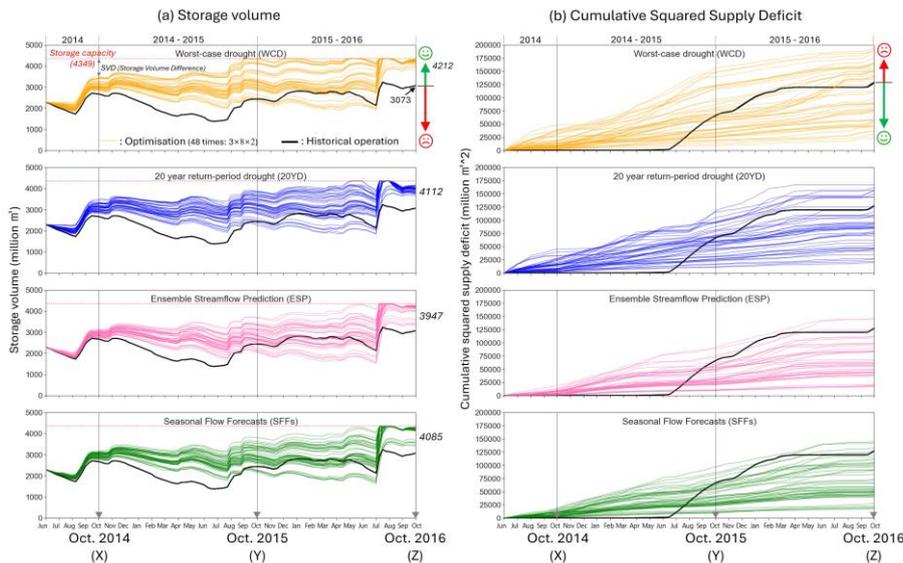
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Deleted: (see Figure S5), shows that the mean overall skill decreases from 54% to 53% and 46% for 2, 4, and 6 months of lead time, respectively. This suggests that SFFs do not consistently outperform ESP and the overall skill typically decreases as lead time increases.

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Figure 6: Simulated reservoir operation results for Soygangg-Chungju from June 2014 to September 2016 in terms of (a) storage volume and (b) cumulative squared supply deficit. From top to bottom, the rows represent simulation of the forecast-informed operations using WCD (orange), 20YD (blue), ESP (pink) and SFFs (green), respectively. Each sub-figure has 48 simulated results (coloured lines, 3 lead times \times 8 MCDM methods \times 2 decision-making time steps) and a single historical operation (black line). The numbers on the right end of Figure 6(a) represent the mean storage volume (million m^3) across all 48 simulations at the end of the simulation period (September 30th, 2016).

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As shown by the black lines in Figure 6, the reservoir operators seemed to be unaware of the impending drought event until June 2015, as up to that point they continued to supply the demand (causing no deficit) while storage level declined. Subsequently, their operational focus shifted to managing storage availability, which led to significant supply deficits beginning in July 2015. Compared to this historical operations, most of the forecast-informed reservoir operations achieve higher storage volumes throughout the event (Figure 6(a)). By the end of the simulation period (September 30th, 2016), all forecast-informed operations replenish the reservoir system more than the historical operations did. Operations informed by deterministic scenarios (upper two rows) offer slightly superior results for securing storage volume compared to ensemble forecasts (lower two rows), as shown by average final storage values reported at the right end of Figure 6(a), but they produce larger supply deficits than ensemble forecasts (Figure 6(b)). This trend arises from the underestimation of flows by deterministic scenarios (see Figure 5(a)), which results in reduced releases and increased supply deficits. (Further results for other reservoir systems and drought events also depicted in Figure S6.)

In particular, many of the ensemble members of SFFs produced in June 2016 anticipated the high flow event that occurred in July 2016 (see Figure S7). This led the multi-objective optimisation informed by SFFs to suggest higher releases, in contrast to the (unnecessarily) low releases designed when using the worst case or 20-year return period drought scenario.

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4.1.3 Value of seasonal flow forecasts

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Figure 7 depicts the differences in achieved performance indicators (SSD and SVD) between simulated operations and historical operation at distinct points in time (X, Y and Z in Figure 6), corresponding to the end of hydrological years (September 30th). Coloured circles in the figure denote the type of flow scenario/forecast used in simulations (following the same colour coding as in Figure 6) and there are 48 circles ($3 \times 8 \times 2$) in each colour, corresponding to the combinations of 3 lead times, 8 MCDM methods and 2 decision-making time steps. Circles positioned below (above) zero for both the x and y axes, i.e. within the green (red) shaded area, indicate experiments where reservoir simulations achieve better (worse) performance compared to historical operation. The count of circles within the green shaded area (bottom-left quadrant) represents the forecast value, indicating the chances of simulated reservoir operations outperforming historical operation, as detailed in Section 3.2.

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In summary, forecast-informed operations using deterministic scenarios generally do better at securing storage volume while using ensemble forecasts is better for minimising supply deficit. This result is further corroborated by our additional analysis across different events and reservoir systems, as depicted in Figure S5.

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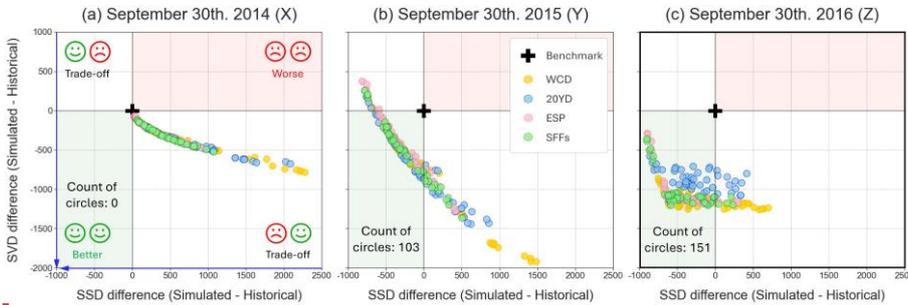
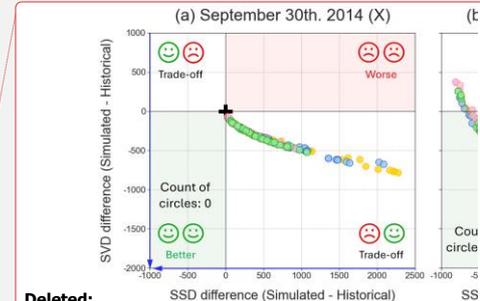


Figure 7: Difference in SSD (x-axis) and SVD (y-axis) between historical operation (black cross) and simulated operations using different flow scenarios/forecasts (coloured circles) in Soyanggang-Chungju during the 2014-2016 drought. Performances are calculated on September 30th in (a) 2014, (b) 2015 and (c) 2016. Each sub-figure shows 48 points for each flow scenario/forecast (WCD, 20YD, ESP, SFFs), resulting from different combinations of key experimental choices (3 lead times × 8 MCDM methods × 2 decision-making time steps).

At the initial stage of simulation, as shown in Figure 7(a), simulated forecast-informed operations only exhibit a trade-off relationship with historical operation. All circles are distributed in the bottom-right quadrant, indicating that the historical operation prioritised water supply over storage volume until the end of September 2014 (X). However, as the impact of forecast-informed operations accumulates (i.e. the period of simulation moves from X to Z), more circles tend to fall in the green shaded area where simulated operations outperform historical operation. This result suggests that the model-based reservoir operation optimisation has the potential to improve the management of prolonged drought events. Specifically, as shown in Figure 7(c), the majority of simulations not falling within the green shaded area by the end of the simulation (September 30th, 2016 (Z)), are associated with deterministic scenarios (yellow and blue circles). These findings are consistently demonstrated with our experiments applied to other drought events and reservoir systems, as presented in Figure S8.

4.1.4 Sensitivity of forecast value to key experimental choices

The top row of Figure 8 presents a figure similar to Figure 7(c), but with distinct colour codes assigned to different experimental choices for each category. The bottom row of Figure 8 illustrates the sensitivity of forecast value (y-axis) to the choice of forecast lead time (a), MCDM method (b), decision-making time step (c) and type of flow scenario/forecast (d) for September 30th, 2016, (corresponding to Figure 7(c)). The maximum number on the y-axis in each sub-figure represents the total number of simulation experiments conducted for a particular experimental set-up choice. The forecast value (hollow circle) represents the number of experiments that the reservoir simulation outperforms historical operation for both objectives (SSD and SVD). For example, in the bottom row of Figure 8(a), the lead time is fixed at 2, 4 or 6 months (horizontal axis) and for each of these choices there are 64 experiments (see range of vertical axis), resulting from the combination of 8 MCDM methods, 2 decision-making time steps and 4 flow scenarios/forecasts. When an experimental choice (x-axis) correlates with a higher forecast value (y-axis), it indicates that using that specific experimental choice can lead to greater operational benefits for managing droughts.



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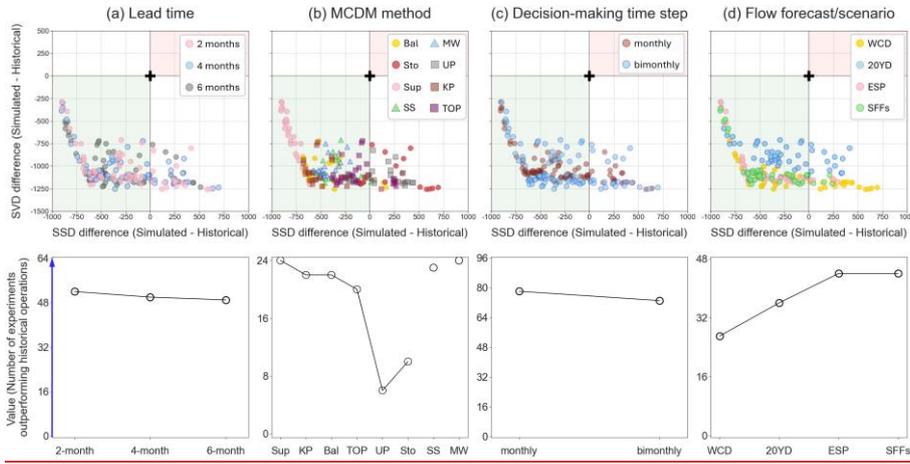
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773 **Figure 8: Top row: Difference in SSD (x-axis) and SVD (y-axis) between historical operation (black cross) and simulated operations using different experimental choices: (a) forecast lead time, (b) MCDM method, (c) decision-making time step and (d) type of flow scenario/forecast. Bottom row: Forecast value (y-axis) plotted against the same experimental choices for the same reservoir system and date. The MCDM methods are ordered from left to right with increasing importance to storage availability, along with two variable weighting methods (SS and MW). All results refer to Soygangang-Chungju reservoir system on September 30th, 2016.**

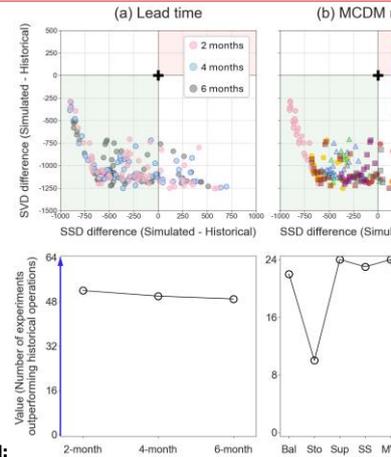
780 As shown in Figure 8(b), the number of experiments outperforming historical operations varies significantly depending on the MCDM method used for selecting a compromise solution from the Pareto front, suggesting that this choice is a key control of forecast value. In this specific drought event, using the storage-prioritised (Sto) and utopian point (UP) methods leads to a much lower forecast value compared to using the other methods. Note that, with our problem formulation, the storage-prioritised and utopian point methods are the ones that give more weight to conservation of storage volumes, at the expenses of supply deficits (see Figure S9 for further details). Importantly, Figure 8(d) demonstrates that the value is also influenced by the type of flow scenario/forecast used to inform the reservoir operations optimisation. In this case, a higher value is attained using ensemble forecasts (ESP, SFFs) than deterministic scenarios (WCD, 20YD), but there is no difference in forecast value between ESP and SFFs.

790 Additionally, we applied a bootstrapping technique to test the impact of using different sample sizes across the plots in Figure 8 (bottom row) and found that the impact of sample sizes on sensitivity result is negligible (see Figure S10).

793 **4.2 Simulation results for other reservoir systems and drought events**

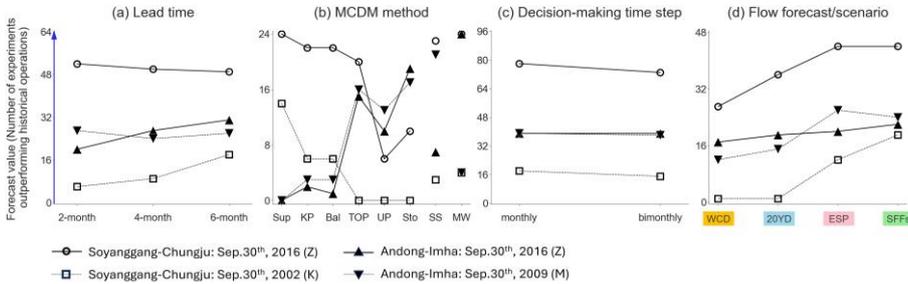
794 **4.2.1 Sensitivity of forecast value to key experimental choices**

795 Having analysed the forecast value and its key controls for one drought event in one reservoir system, Figure 9 illustrates whether similar or contrasting results are found in the other three events and reservoir systems considered in this study (see Figure 2 for a description of these events; intermediate results, i.e. simulated storages and releases, and difference in both objectives for these reservoir systems and events are reported in Figure S6 and Figure S8). Note that Figure 9 incorporates the result from Soygangang-Chungju for the 2014-2016 drought event already shown in Figure 8 (white circles connected by solid line).



Deleted: Figure 7: (first row) The difference of SSD (x-axis) and SVD (y-axis) between historical operation (black cross) and simulated operations using different experimental choices: (a) forecast lead time, (b) MCDM method, (c) decision-making time step and (d) type of flow forecast/scenario in Soygangang-Chungju on September 30th, 2016. (second row) Forecast value (y-axis) plotted against the same experimental choices for the same reservoir system and date. (Refer to Figure 3 for the acronyms corresponding to the MCDM methods.)

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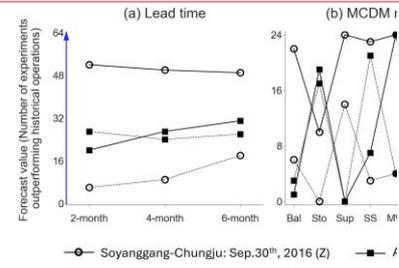
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836 **Figure 9: Forecast value (y-axis) against key experimental choices including (a) lead time, (b) MCDM method, (c)**
 837 **decision-making time step and (d) type of flow scenario/forecast for Soyganggang-Chungju (○, □) and Andong-Imha**
 838 **(▲, ▼) at the end of different drought events (points Z, K, M in Figure 2). The MCDM methods are ordered the same**
 839 **as in Figure 8.**

840 Figure 9(b) confirms the substantial influence of the choice of MCDM method on forecast value. However, it also
 841 highlights that which method deliver more values varies with the event and reservoir system. As already noted, in
 842 the Soyganggang-Chungju reservoir system, the forecast value increases with MCDM methods that prioritise
 843 avoiding supply deficits (i.e. Sup, KP and Bal). This is likely due to the fact that the two drought events analysed
 844 for this system end with a large inflow event (see Figure 2), therefore the emphasis on minimising supply deficits,
 845 combined with the forecast ability to anticipate the upcoming inflows (as discussed in Sec. 4.1.2), enable to fully
 846 exploit the natural replenishment of storage from the wet event that occurs at the end of the simulation period.
 847 The opposite is observed in Andong-Imha system, where the analysed drought events persist into the upcoming
 848 wet season, and therefore MCDM prioritising storage conservation (UP, Sto) tend to deliver more value.
 849 The higher value of ensemble forecasts (ESP and SFFs) is also confirmed in Figure 9(d), particularly in
 850 Soyganggang-Chungju reservoir system, whereas their advantage over deterministic scenarios (WCD and 20YD)
 851 is less pronounced in Andong-Imha. Lastly, Figure 9(a,c) indicate that increasing the forecast lead time or
 852 decreasing the decision-making time step slightly improves forecast value. Yet again, this improvement appears
 853 relatively marginal when compared to the impact of the chosen MCDM method or flow scenario/forecast.

854 **4.2.2 Relationship between forecast accuracy and value**

855 Figure 10 illustrates the overall relationship between the accuracy of each flow scenario/forecast (x-axis) and its
 856 value computed over the 8 MCDM methods (y-axis) in informing decision-making for enhanced drought
 857 management. For this figure, we only used experiments with a 6-month lead time and monthly decision-making,
 858 to closely mimic current reservoir operations practices in South Korea. Note that excluding other options for these
 859 two experimental choices should not undermine the robustness of our conclusions as the sensitivity analyses in
 860 previous sections have shown that these choices have low impact on forecast value. Red symbols represent the
 861 simulation results when using observations of future flows as if they were 'perfect' forecast (note that, by
 862 construction, this scenario is associated with zero error on the horizontal axis of Figure 10).



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 Figure 8: Forecast value (y-axis) against key experimental choices including (a) lead time, (b) MCDM method, (c) decision-making time step and (d) type of flow forecast/scenario for Soyganggang-Chungju (○) and Andong-Imha (■) at the end of different drought events (points Z, K, M in Figure 1(b)). ¶

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Deleted: the significant variability with events and reservoir systems. For example, the multi-weight method (MW) leads to a high value during the 2014-2016 drought event for both reservoir systems but a low value for the other events. Or the TOPSIS method (TOP) generally provides relatively higher forecast value for three events but a notably low value during the 2001-2002 drought in Soyganggang-Chungju. ¶

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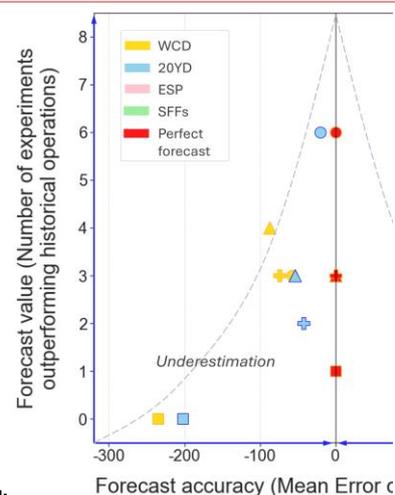
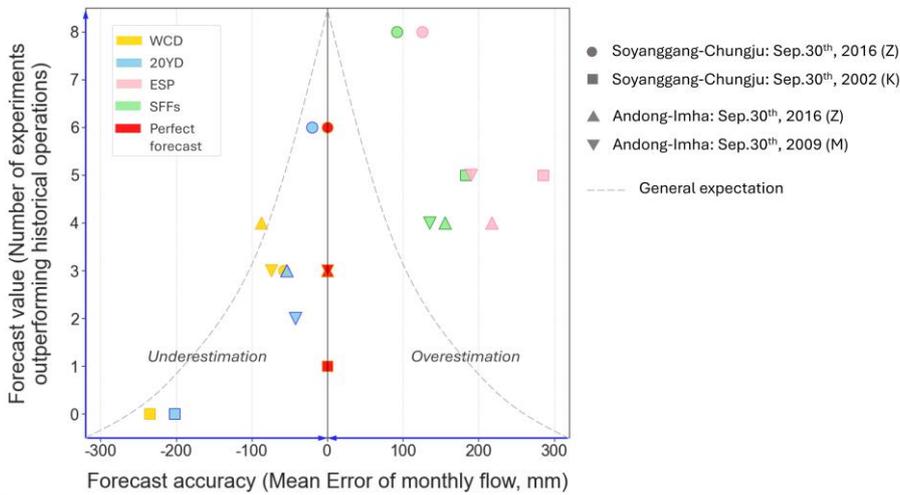
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883 **Figure 10:** Relationship between forecast accuracy (Mean Error of monthly flow, x-axis) and value (calculated over
 884 the 8 MCDM methods, y-axis) at the end of the simulation period for different drought events and reservoir systems.
 885 For each event and system, the figure shows five points corresponding to the simulated forecast-informed operations
 886 using different scenarios/forecasts (orange: WCD, blue: 20YD, pink: ESP, green: SFFs, red: perfect forecast). The
 887 perfect forecast scenario was generated using actual flow observations as future forecasts. The direction of the blue
 888 arrows indicates higher performance (high value, low error). The grey dashed lines conceptually illustrate the general
 889 expectation on the relationship between forecast accuracy and value.

890 Figure 10 demonstrates that despite the higher accuracy of deterministic scenarios, as evidenced by general
 891 proximity of the yellow and blue points to zero on the x-axis, ensemble forecasts (pink and green points) result in
 892 a higher value. The Pearson's correlation coefficient between the accuracy and value for the datapoints of Figure
 893 10 is approximately -0.2, indicating a very weak relationship. These findings deviate somewhat from the general
 894 expectation on the relationship between forecast accuracy and value, that higher accuracy would lead to higher
 895 value (this assumed relationship is represented in Figure 10 by the dashed grey lines). When comparing the
 896 accuracy between ensemble forecasts, SFFs demonstrate a slight advantage over ESP, with a tendency for smaller
 897 overestimations. In terms of forecast value, however, there are no significant differences between them, indicating
 898 the operational benefits obtained from using SFFs and ESP appear to be comparable.

899 Figure 10 also includes the value obtained from optimising operations against the perfect forecast scenario,
 900 depicted by red symbols. Surprisingly, this figure indicates that the value of perfect forecast in our experiments is
 901 lower than that of ESP and SFFs. This counterintuitive result stems from the fact that even with perfect knowledge
 902 of flows within the optimisation horizon (i.e. the forecast lead time), perfect forecast does not resolve the
 903 uncertainty about future flows beyond that horizon. Therefore, acknowledging uncertainty during the optimisation
 904 horizon, as done when using ensemble forecasts, yields more cautious operations that in the long-term prove to
 905 be more robust against adverse events not seen during the optimisation.

906 **5. Discussion**

907 **5.1 Value of SFFs in informing decision-making for managing droughts**

908 Our findings highlight the higher value of ensemble forecasts (ESP, SFFs) over deterministic scenarios (WCD,
 909 20YD), aligning with several previous studies. For example, Peñuela et al. (2020a) demonstrated that employing
 910 ensemble forecasts can yield higher operational benefits compared to using deterministic (worst-case) scenario in
 911 a water supply reservoir system in the UK. The higher value of ensemble forecasts for informing flood control
 912 decisions was also demonstrated by Fan et al. (2016). They compared the value using the ensemble mean versus
 913 using the full SFFs ensemble and found that the latter notably enhanced forecast value. However, our research
 914 also revealed that the extent to which ensemble forecasts yield higher value can vary significantly depending on
 915 the reservoir systems, as the enhancement of operational benefits was more evident in the Soyanggang-Chungju
 916 than in the Andong-Imha reservoir system. It is also notable that even a perfect forecast with zero forecasting

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939 error did not achieve a higher value compared to the ensemble forecasts (ESP and SFFs). The lower performance
940 of the perfect forecast scenario is counterintuitive but can be attributed to its finite lead time. In other words,
941 accounting for uncertainty within the optimisation horizon, as done by ESP and SFFs, indirectly helps to better
942 handling the uncertainty about inflows beyond that horizon (refer to Figure S11). Few previous studies also
943 reported that forecast-informed operations forced by ensemble forecasts often deliver comparable or higher
944 performance compared to the perfect forecast scenario (Zhao et al., 2011; Fan et al., 2016; Ficchi et al., 2016).
945 While our findings emphasise the importance of considering forecast uncertainty when optimising reservoir
946 operations, no significant difference in value was found between the two ensemble forecasts (ESP and SFFs). This
947 is consistent with the findings of Peñuela et al. (2020a), who similarly observed no notable difference in the value
948 of ESP and SFFs. Given the lower computational cost and higher practical experiences of generating ESP, the
949 latter remains a hard-to-beat reference.

950 For analysing the relationship between forecast performance and value, we only evaluated two attributes of the
951 forecast performance (i.e. accuracy and skill). Our results showed that the relationship between the forecast
952 performance and value is not significant. To further explore this relationship, additional attributes, such as
953 correlation, variance and reliability may also be considered. These attributes might yield different outcomes when
954 comparing forecast products and could provide new insights into the relationship between performance (i.e., the
955 level of agreement between forecasts and observations) and value (i.e., their usefulness in informing decisions).

956 This study includes a sensitivity analysis that examines how forecast lead time, MCDM method, decision-making
957 time step and type of flow scenario/forecast affect value. Although we found some improvements in forecast value
958 with longer lead times, their impact was generally marginal. A prior study by Yang et al. (2021) also evaluated
959 the influence of lead time, ranging from 10 to 30 days, on forecast value for hydropower and water supply. They
960 argued that considering a longer lead time for forecast-informed operations may enhance the value. However, the
961 lead times they examined were considerably shorter than those in our study, which makes direct comparisons with
962 our study challenging. To further validate the relationship between lead time and forecast value, it is essential to
963 conduct additional research involving a broader range of reservoirs and drought events.

964 The highly variable performance of MCDM methods depending on reservoir systems and drought events (see
965 Figure 9(b)) emphasises the significance of using ensemble forecasts in reservoir operations, as they consistently
966 bring operational benefits (see Figure 9(d)). While identifying an optimal MCDM method which could offer the
967 best solution across all drought events was not possible in this study, practical guidelines can be offered for
968 applying each method based on their inherent characteristics. Firstly, the SAW method is straightforward to apply
969 and may be particularly advantageous for reservoirs with obvious operational purposes or characteristics.
970 Specifically, the supply-prioritised method might be well-suited for a reservoir with ample storage capacity but
971 lower demand. On the other hand, the storage-prioritised method would be useful for reservoirs with a high risk
972 of causing significant economic or social damage when facing a substantial supply deficit over short periods. This
973 method helps mitigate the risk of extreme storage shortages, thereby reducing the likelihood of accidental supply
974 failure (e.g. zero supply for certain periods). Secondly, the performance of the variable weighting method can be
975 highly dependent on subjective choices in determining the appropriate weights and storage ranges. Therefore,
976 sufficient operational records are essential for effectively applying this method. Conversely, the reference point
977 method, offering a geometric estimation of the compromise solution, may prove advantageous for reservoirs with
978 limited operational history.

979 Bias correction of seasonal weather forecasts, such as precipitation, is a widely addressed issue concerning the
980 performance of SFFs (Shrestha et al., 2017). In this study, we utilised bias-corrected SFFs, building on our
981 previous findings that demonstrated the effectiveness of bias correction in improving the accuracy of SFFs (Lee
982 at al., 2023b). While the positive impact of bias correction on SFFs is widely documented in the literature (e.g.
983 Lucatero et al., 2018; Tian et al., 2018; Pechlivanidis et al., 2020), a previous study noted that bias correction may
984 potentially reduce performance under extreme conditions (Crochemore et al., 2016). Our supplementary
985 experiment, presented in Figure S12, investigates the influence of bias correction on forecast value. The result
986 indicates that bias-corrected SFFs generally yield higher value compared to SFFs without bias correction.
987 However, to fully validate the impact of bias correction on the value, further research applying our methodology
988 across diverse reservoirs and drought events is necessary.

989 5.2 Limitations and directions for future research

990 A key limitation of our study is the limited range of drought events analysed. While we assessed forecast value
991 across two reservoir systems and three historical drought events, these samples are still limited to draw general
992 conclusions. This limitation is difficult to overcome given the infrequent occurrence of extreme drought events

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Deleted: We also found that It is also notable that even a perfect forecast with zero forecasting error did not achieve a higher value compared to the ensemble forecasts (ESP and SFFs). using ensemble forecasts, despite their limited accuracy, yields more benefits than using deterministic scenarios, even the perfect forecast. The lower performance of the perfect forecast scenario can be attributed to its finite lead time and its reliance on a single flow scenario without accounting for uncertainty. Few previous studies also reported that forecast-informed operations forced by ensemble forecasts often deliver comparable or higher performance compared to the perfect forecast scenario (Zhao et al., 2011; Fan et al., 2016; Ficchi et al., 2016).¶

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Deleted: Our findings show that the MCDM method used to select a compromise solution from the Pareto front is a key determinant of forecast value, but no single MCDM method that consistently performs best across different events and reservoir systems was identified in this study. Previous research also has demonstrated that different MCDM methods have distinct performance characteristics (Velasquez and Hester, 2013; Taherdoost and Madanchian, 2023). The highly variable performance of MCDM methods depending on reservoir systems and drought events emphasizes the significance of using ensemble forecasts in reservoir operations, as they consistently bring operational benefits.

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Deleted: This study provides valuable insights into the value of SFFs in informing decision-making for managing droughts; however, it is essential to acknowledge several limitations. Firstly,

and the limited availability of seasonal forecast data, which only became available in 1993. Since our results have shown the dependency of forecast value on reservoir systems and events, more assessments are needed to establish more general patterns in the relationship between accuracy and value, as well as to compare the performance between different forecast products. We hope that the methodology and open-source code developed for this study will enable potential users to replicate our experiments and validate our provisional results across other regions around the world.

Secondly, in assessing forecast value, we use historical operational performance as a benchmark. While it offers more intuitive value comparison, it is important to recognise that historical operations may have been influenced by a range of internal and external circumstances not captured by our model and performance indicators. For example, reservoir release decisions may be adjusted based on additional water supplies from external sources such as neighboring reservoirs or rivers. Additionally, our proposed method only looks at whether the historical performance is Pareto-dominated, but it does not account for the magnitude in differences between historical and simulated performances. Incorporating hypervolume, defined as the space enclosed by a set of points in a multi-dimensional space (While et al., 2006; Sanchez-Gomez et al., 2019), could enhance this method to better quantify the value.

Last, our modelling of the reservoir systems is based on several simplifying assumptions. A key simplification is that evaporation from reservoirs is not considered. In South Korea, direct measurements of reservoir evaporation are rarely conducted, which poses challenges to ensuring the reliability of indirect evaporation estimation. Recent research by Park et al. (2024) introduced an empirical formula to estimate reservoir evaporation specifically for Yongdam Reservoir, which is uniquely equipped with direct evaporation measurements. The study highlighted the importance of validating this formula for its applicability to other reservoirs. However, reservoir evaporation tends to intensify during extreme droughts, resulting in increased loss of storage volume (Wurbs and Ayala, 2014; Shah et al., 2024). Thus, further studies incorporating reservoir evaporation based on reliable estimating formulas are necessary. A second simplification is that we only used two operational objectives: securing storage and minimising water deficit, to centre our attention on reservoir operations. However, there are various other objectives worth considering for simulating reservoir operations, such as potential economic damages from droughts or benefits of risk hedging. Although quantifying those objectives is challenging, incorporating them into a multi-objective approach for drought management could significantly assist water managers.

6. Conclusions

This study explores the potential usefulness of SFFs in informing reservoir operations for managing droughts in South Korea. While deterministic scenarios (WCD, 20YD) exhibited higher accuracy, the value achieved from using ensemble forecasts (ESP, SFFs) was higher. This result emphasises the significance of considering flow forecast uncertainty when optimising reservoir operations and demonstrates that higher forecast accuracy does not necessarily translate into higher value. Our study also suggests that forecast-informed operations using ensemble forecasts can reduce supply deficit and increase storage conservation compared to historical operations during past drought events. However, no clear evidence was found supporting that SFFs can lead to greater value over conventional ESP at present. As seasonal weather and flow forecasting technology continuously evolves and improves, this conclusion is provisional, and it will be important to continue to assess the performance of SFFs in enhancing reservoir operations as new forecasting products become available. Our sensitivity analysis also shows that the MCDM method used to select a compromise release schedule from a Pareto front is a key control of forecast value. This suggests that the operator's prioritisation of competing objectives is crucial in determining forecast value.

By analysing multiple reservoirs and drought events within the same region, our study takes an initial step toward systematising the forecasts performance and value assessment. While this effort is still incomplete, it serves as a beginning to move beyond the "single case study" approach that has dominated previous research in this area. We hope that the workflow and open-source code developed in this study will help researchers and water managers in South Korea as well as other countries in conducting further research and expanding the practical application of SFFs to enhance drought management. In particular, we proposed a new simple method to assess the forecast value that simultaneously takes into account the trade-offs between operational objectives and the uncertainty stemming from key set-up choices for the simulation experiments. This is achieved by counting the number of simulation experiments that outperform benchmark operations (the historical operations in our case) for both objectives. This straightforward performance metric may be useful for quantifying forecast value in a practical and intuitive manner across a wide range of water resources management studies, beyond drought management, including hydropower, flood control and other applications.

Code and data availability. The iRONS package used for reservoir operation modelling, optimisation and value assessment is available at <https://doi.org/10.5281/zenodo.4277646> (Peñuela and Pianosi, 2020b). The SEAFLOW

Deleted: in assessing forecast value, we proposed a methodology that uses historical operational result as a benchmark. While it offers more intuitive value comparison, it is important to recognize that this benchmark may be influenced by complex decisions considering various internal and external circumstances. For example, decisions on water releases may be adjusted based on additional water supplies from external sources such as neighboring reservoirs or rivers.¶

Deleted: , while we assessed forecast value across two reservoir systems and historical drought events, these case studies may not be sufficient to draw general conclusions. Since our results have demonstrated the dependency of forecast value on reservoir systems and events, it is crucial to continue further application efforts to establish more general patterns in the relationship between accuracy and value, as well as to compare the performance between different forecast products.

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Deleted: Considering the ongoing escalation in the frequency and severity of drought events worldwide, including South Korea, our effort is both timely and essential for finding novel solutions to mitigate future drought damages. Beyond our specific results, this study also proposed a new simple method to assess the forecast value that simultaneously takes into account the trade-offs between operational objectives and the uncertainty stemming from key set-up choices for the simulation experiments. This is achieved by counting the number of simulation experiments that outperform benchmark operations (the historical operations in our case) simultaneously for two objectives. This straightforward performance metric may be useful for quantifying forecast value in a practical and intuitive manner across a wide range of studies for water resources management, beyond drought management, such as hydropower, flood control and others.¶

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1155 (SEAsonal FLOW forecasts) and SEAFORM (SEAsonal FORecast Management) Python packages are available
1156 at <https://doi.org/10.5281/zenodo.12800811> (University of Bristol, 2023a) and
1157 <https://doi.org/10.5281/zenodo.128009> (University of Bristol, 2023b), respectively. ECMWF's data are available
1158 under a range of licenses (Copernicus, 2024). Reservoir and flow data are made available by the K-water and can
1159 be downloaded from <https://www.water.or.kr> (K-water, 2023).

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1160 *Author contributions.* YL designed the experiments, with suggestions from co-authors. YL developed the
1161 workflow and performed the simulation. FP and MARR participated in the discussions on the interpretations of
1162 results and suggested ways of moving forward in the analysis. AP provided YL with modelling technical support.
1163 All authors reviewed and contributed to the writing of the manuscript.

1164 *Competing interests.* The contact author has declared that none of the authors has any competing interests.

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1168 01).

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1169 References

- 1170 Afshar, A., Mariño, M.A., Saadatpour, M. and Afshar, A.: Fuzzy TOPSIS multi-criteria decision analysis
1171 applied to Karun reservoirs system, *Water Resources Management*, 25(2), 545–563,
1172 <https://doi.org/10.1007/s11269-010-9713-x>, 2011.
- 1173 Allen, R.G., Pereira, L.S., Raes, D. and Smith, M.: *Crop evapotranspiration: Guidelines for computing crop*
1174 *water requirements*. United Nations Food and Agriculture Organization, Irrigation and drainage paper 56,
1175 Rome, Italy, 1998.
- 1176 Alley, R.B., Emanuel, K.A. and Zhang, F.: Advances in weather prediction. *Science*, [online] 363, 342–344,
1177 <https://doi.org/10.1126/science.aav7274>, 2019.
- 1178 Arnal, L., Cloke, H.L., Stephens, E., Wetterhall, F., Prudhomme, C., Neumann, J., Krzeminski, B. and
1179 Pappenberger, F.: Skilful seasonal forecasts of streamflow over Europe?, *Hydrology and Earth System Sciences*,
1180 22(4), 2057–2072, <https://doi.org/10.5194/hess-22-2057-2018>, 2018.
- 1181 Arsyah, U.I., Jalinus, N., Syahril, Ambiyar, Arsyah, R.H and Pratiwi, M.: Analysis of the Simple Additive
1182 Weighting method in educational aid decision making, *Turkish Journal of Computer and Mathematics*
1183 *Education*, 12(14), 2389–2396, <https://doi.org/10.17762/turcomat.v12i14.10664>, 2021.
- 1184 Baker, S.A., Rajagopalan, B. and Wood, A.W.: Enhancing ensemble seasonal streamflow forecasts in the upper
1185 Colorado river basin using multi-model climate forecasts, *Journal of the American Water Resources*
1186 *Association*, 57, 906–922, <https://doi.org/10.1111/1752-1688.12960>, 2021.
- 1187 Bauer, P., Thorpe, A. and Brunet, G.: The quiet revolution of numerical weather prediction. *Nature*, 525, 47–55,
1188 <https://doi.org/10.1038/nature14956>, 2015.
- 1189 Block, P.: Tailoring seasonal climate forecasts for hydropower operations, *Hydrology and Earth System*
1190 *Sciences*, 15(4), 1355–1368, <https://doi.org/10.5194/hess-15-1355-2011>, 2011.
- 1191 Chen, C.-T.: Extensions of the TOPSIS for group decision-making under fuzzy environment, *Fuzzy Sets and*
1192 *Systems*, [online] 114(1), 1–9, [https://doi.org/10.1016/s0165-0114\(97\)00377-1](https://doi.org/10.1016/s0165-0114(97)00377-1), 2000.
- 1193 Chiew, F.H.S., Zhou, S.L. and McMahon, T.A.: Use of seasonal streamflow forecasts in water resources
1194 management, *Journal of Hydrology*, 270(1-2), 135–144, [https://doi.org/10.1016/s0022-1694\(02\)00292-5](https://doi.org/10.1016/s0022-1694(02)00292-5), 2003.
- 1195 Chiu, W.-Y., Yen, G.G. and Juan, T.-K.: Minimum Manhattan distance approach to multiple criteria decision
1196 making in multiobjective optimization problems, *IEEE Transactions on Evolutionary Computation*, 20(6), 972–
1197 985, <https://doi.org/10.1109/tevc.2016.2564158>, 2016.
- 1198 Copernicus: Climate Data Store, <https://cds.climate.copernicus.eu/> (last access: 19 May 2024), 2024.
- 1199 Crippa, N., Grillakis, M.G., Tsilimigkras, A., Yang, G., Giuliani, M. and Koutroulis, A.G.: Seasonal forecast-
1200 informed reservoir operation, Potential benefits for a water-stressed Mediterranean basin, *Climate Services*, 32,
1201 100406–100406, <https://doi.org/10.1016/j.cliser.2023.100406>, 2023.

1205 Crochemore, L., Ramos, M.-H. and Pappenberger, F.: Bias correcting precipitation forecasts to improve the skill
1206 of seasonal streamflow forecasts, *Hydrology and Earth System Sciences*, 20(9), 3601–3618,
1207 <https://doi.org/10.5194/hess-20-3601-2016>, 2016.

1208 Das, I.: On characterizing the ‘knee’ of the Pareto curve based on normal-boundary intersection, *Structural*
1209 *Optimization*, 18(2), 107–115, 1999.

1210 Day, G.N.: Extended streamflow forecasting using NWSRFS, *Journal of Water Resources Planning and*
1211 *Management*, 111(2), 157–170, [https://doi.org/10.1061/\(asce\)0733-9496\(1985\)111:2\(157\)](https://doi.org/10.1061/(asce)0733-9496(1985)111:2(157)), 1985.

1212 Ehsani, N., Vörösmarty, C.J., Fekete, B.M. and Stakhiv, E.Z.: Reservoir operations under climate change:
1213 Storage capacity options to mitigate risk, *Journal of Hydrology*, [online] 555, 435–446,
1214 <https://doi.org/10.1016/j.jhydrol.2017.09.008>, 2017.

1215 Fan, F.M., Schwanenberg, D., Alvarado, R., Reis, A.A., Collischonn, W. and Naumman, S.: Performance of
1216 deterministic and probabilistic hydrological forecasts for the short-term optimization of a tropical hydropower
1217 reservoir, *Water Resources Management*, 30, 3609–3625, <https://doi.org/10.1007/s11269-016-1377-8>, 2016.

1218 Ficchi, A., Raso, L., D Dorchie, Pianosi, F., Malaterre, P.-O., van Overloop, P.-J. and Jay-Allemand, M.:
1219 Optimal operation of the multireservoir system in the Seine River basin using deterministic and ensemble
1220 forecasts, *Journal of Water Resources Planning and Management*, 142(1),
1221 [https://doi.org/10.1061/\(asce\)wr.1943-5452.0000571](https://doi.org/10.1061/(asce)wr.1943-5452.0000571), 2016.

1222 Fishburn, P.C.: Additive utilities with finite sets: Applications in the management sciences, *Naval Research*
1223 *Logistics Quarterly*, 14(1), 1–13, <https://doi.org/10.1002/nav.3800140102>, 1967.

1224 Giagkiozis, I. and Fleming, P.J.: Pareto front estimation for decision making, *Evolutionary Computation*, 22(4),
1225 651–678, https://doi.org/10.1162/evco_a_00128, 2014.

1226 Goldsmith, E. and Hildyard, N.: *The Social and Environmental Effects of Large Dams*, Random House (NY),
1227 1984.

1228 ~~Goodarzi, M., Jabbarian Amiri, B., Azarneyvand, H., Khazaei, M. and Mahdianzadeh, N.: Assessing the~~
1229 ~~performance of a hydrological Tank model at various spatial scales, *Journal of Water Management Modeling*,~~
1230 ~~29, 1–8, <https://doi.org/10.14796/jwmm.c472>, 2020.~~

1231 ~~Greuell, W., Franssen, W.H.P., Biemans, H. and Hutjes, R.W.A.: Seasonal streamflow forecasts for Europe –~~
1232 ~~Part I: Hindcast verification with pseudo- and real observations, *Hydrology and Earth System Sciences*, 22(6),~~
1233 ~~3453–3472, <https://doi.org/10.5194/hess-22-3453-2018>, 2018.~~

1234 Hurkmans, R.T.W.L., Hurk, B., Schmeits, M., Wetterhall, F. and Pechlivanidis, I.G.: Seasonal streamflow
1235 forecasting for fresh water reservoir management in the Netherlands: An assessment of multiple prediction
1236 systems, *Journal of Hydrometeorology*, 24(7), 1275–1290, <https://doi.org/10.1175/jhm-d-22-0107.1>, 2023.

1237 Hwang, C.L. and Yoon, K.: *Multiple attribute decision making: methods and applications, A state-of-the-art*
1238 *survey*, Springer-Verlag, New York, 1981.

1239 Jackson-Blake, L., Clayer, F., Haande, S., James E.S. and Moe, S.J.: Seasonal forecasting of lake water quality
1240 and algal bloom risk using a continuous gaussian bayesian network, *Hydrology and Earth System Sciences*,
1241 26(12), 3103–3124, <https://doi.org/10.5194/hess-26-3103-2022>, 2022.

1242 ~~Johnson, F. and Sharma, A.: A nesting model for bias correction of variability at multiple time scales in general~~
1243 ~~circulation model precipitation simulations, *Water Resources Research*, 48(1), 1–16,~~
1244 ~~<https://doi.org/10.1029/2011wr010464>, 2012.~~

1245 Jung, Y., Nam, W.S., Shin, H. and Heo, J.-H.: A study on low-flow frequency analysis using dam inflow,
1246 *Journal of The Korean Society of Civil Engineers*, 32(6B), 363–371,
1247 <https://doi.org/10.12652/ksce.2012.32.6b.363>, 2012.

1248 ~~K-water (Korea Water Resources Corporation): *My water*, [online] www.water.or.kr. Available at:~~
1249 ~~<http://www.water.or.kr> [Accessed 10 May. 2023], 2023.~~

1250 K-water (Korea Water Resources Corporation): *2013-2018 Sustained drought analysis and assessment report*,
1251 South Korea, 2018.

1252 Lee, Y., Peñuela, A., Pianosi, F. and Rico-Ramirez, M.A.: Catchment-scale skill assessment of seasonal
1253 precipitation forecasts across South Korea, *International journal of climatology*, 43(11), 5092–5111,
1254 <https://doi.org/10.1002/joc.8134>, 2023.

Deleted: ¶

Formatted: Font: Italic

Formatted: Font: (Asian) Malgun Gothic, (Asian) Korean

Deleted: Kwon, H.-H., Lall, U. and Kim, S.-J.: The unusual 2013–2015 drought in South Korea in the context of a multicentury precipitation record: Inferences from a nonstationary, multivariate, Bayesian copula model, *Geophysical Research Letters*, 43(16), 8534–8544, <https://doi.org/10.1002/2016GL070270>, 2016.¶

1261 Lee, Y., Pianosi, F., Peñuela, A. and Rico-Ramirez, M. A.: Skill of seasonal flow forecasts at catchment-scale:
 1262 an assessment across South Korea, *Hydrology and Earth System Science*, 28, 3261–3279,
 1263 <https://doi.org/10.5194/hess-28-3261-2024>, 2024.

1264 Li, W., Zhang, G., Zhang, T. and Huang, S.: Knee point-guided multiobjective optimization algorithm for
 1265 microgrid dynamic energy management, *Complexity*, 2020, 1–11, <https://doi.org/10.1155/2020/8877008>, 2020.

1266 Liu, P.: Multi-attribute decision-making method research based on interval vague set and TOPSIS method,
 1267 *Technological and Economic Development of Economy*, 15(3), 453–463, <https://doi.org/10.3846/1392-8619.2009.15.453-463>, 2009.

1269 Lu, L., Anderson-Cook, C.M. and Robinson, T.J.: Optimization of designed experiments based on multiple
 1270 criteria utilizing a Pareto frontier, *Technometrics*, 53(4), 353–365, <https://doi.org/10.1198/tech.2011.10087>,
 1271 2011.

1272 Lucatero, D., Madsen, H., Refsgaard, J.C., Kidmose, J. and Jensen, K.H.: Seasonal streamflow forecasts in the
 1273 Ahlergaarde catchment, Denmark: the effect of preprocessing and post-processing on skill and statistical
 1274 consistency, *Hydrology and Earth System Sciences*, 22(7), 3601–3617, <https://doi.org/10.5194/hess-22-3601-2018>, 2018.

1276 Malekmohammadi, B., Zahraie, B. and Kerachian, R.: Ranking solutions of multi-objective reservoir operation
 1277 optimization models using multi-criteria decision analysis, *Expert Systems with Applications*, 38(6), 7851–7863,
 1278 <https://doi.org/10.1016/j.eswa.2010.12.119>, 2011.

1279 Matheson, J.E. and Winkler, R.L.: Scoring rules for continuous probability distributions, *Management Science*,
 1280 22(10), 1087–1096, <https://doi.org/10.1287/mnsc.22.10.1087>, 1976.

1281 ~~Maraun, D., Wetterhall, F., Ireson, A.M., Chandler, R.E., Kendon, E.J., Widmann, M., Brienen, S., Rust, H.W.,
 1282 Sauter, T., Themeßl, M., Venema, V.K.C., Chun, K.P., Goodess, C.M., Jones, R.G., Onof, C., Vrac, M. and
 1283 Thiele-Eich, I.: Precipitation downscaling under climate change: Recent developments to bridge the gap
 1284 between dynamical models and the end user, *Reviews of Geophysics*, 48(3), 1–34,
 1285 <https://doi.org/10.1029/2009rg000314>, 2010.~~

1286 Millner, A. and Washington, R.: What determines perceived value of seasonal climate forecasts? A theoretical
 1287 analysis, *Global Environmental Change*, 21(1), 209–218, <https://doi.org/10.1016/j.gloenvcha.2010.08.001>,
 1288 2011.

1289 Mishra, A.K. and Singh, V.P.: A review of drought concepts, *Journal of Hydrology*, [online] 391(1-2), 202–216,
 1290 <https://doi.org/10.1016/j.jhydrol.2010.07.012>, 2010.

1291 Ni, X., Dong, Z., Jiang, Y., Xie, W., Yao, H. and Chen, M.: A subjective-objective integrated multi-objective
 1292 decision-making method for reservoir operation featuring trade-offs among non-inferior solutions themselves,
 1293 *Journal of Hydrology*, 613, 128430, <https://doi.org/10.1016/j.jhydrol.2022.128430>, 2022.

1294 ~~Ou, X., Gharabaghi, B., McBean, E. and Doherty, C.: Investigation of the Tank model for urban storm water
 1295 management, *Journal of Water Management Modeling*, 25, 1–5, <https://doi.org/10.14796/jwmm.c421>, 2017.~~

1296 Park, J.Y. and Kim, S.J.: Potential impacts of climate change on the reliability of water and hydropower supply
 1297 from a multipurpose dam in South Korea, *Journal of the American Water Resources Association*, 50(5), 1273–
 1298 1288, <https://doi.org/10.1111/jawr.12190>, 2014.

1299 Park, M., Lee, J.H., Lim, Y.K. and Kwon, H.H.: Estimation of evaporation from water surface in Yongdam dam
 1300 using the empirical evaporation equation, *Journal of Korea Water Resources Association*, 2, 139–150, 2024.

1301 Pechlivanidis, I.G., Crochemore, L., Rosberg, J. and Bosshard, T.: What are the key drivers controlling the
 1302 quality of seasonal streamflow forecasts?, *Water Resources Research*, 56(6),
 1303 <https://doi.org/10.1029/2019wr026987>, 2020.

1304 ~~Peñuela, A., Hutton, C. and Pianosi, F.: Assessing the value of seasonal hydrological forecasts for improving
 1305 water resource management: insights from a pilot application in the UK, *Hydrology and Earth System Sciences*,
 1306 24(12), 6059–6073, <https://doi.org/10.5194/hess-24-6059-2020>, 2020a.~~

1307 ~~Peñuela, A. and Pianosi, F.: iRONS (interactive Reservoir Operation Notebooks and Software), Zenodo,
 1308 <https://doi.org/10.5281/zenodo.4277646>, 2020b.~~

1309 Peñuela, A., Hutton, C. and Pianosi, F.: An open-source package with interactive Jupyter Notebooks to enhance
 1310 the accessibility of reservoir operations simulation and optimization, *Environmental Modelling & Software*, 145,
 1311 105188, <https://doi.org/10.1016/j.envsoft.2021.105188>, 2021.

Deleted: ,

Formatted: Font: (Asian) Malgun Gothic, (Asian) Korean

Deleted: Mathew, M., Sahu, S. and Upadhyay, A.: Effect of normalization techniques in robot selection using weighted aggregated sum product assessment, *International Journal of Innovative Research and Advanced Studies*, 4(2), 59–63, 2017.

Formatted: Font: Italic

Formatted: Font: (Asian) Malgun Gothic, (Asian) Korean

Deleted: Nam, W.-H., Hayes, M.J., Svoboda, M.D., Tadesse, T. and Wilhite, D.A.: Drought hazard assessment in the context of climate change for South Korea, *Agricultural Water Management*, 160, 106–117, <https://doi.org/10.1016/j.agwat.2015.06.029>, 2015.

Formatted: Font: (Asian) Malgun Gothic, (Asian) Korean

Deleted: ¶

1322 Prudhomme, C., Hannaford, J., Harrigan, S., Boorman, D., Knight, J., Bell, V., Jackson, C., Svensson, C., Parry,
1323 S., Bachiller-Jareno, N., Davies, H., Davis, R., Mackay, J., McKenzie, A., Rudd, A., Smith, K., Bloomfield, J.,
1324 Ward, R. and Jenkins, A.: Hydrological Outlook UK: an operational streamflow and groundwater level
1325 forecasting system at monthly to seasonal time scales, *Hydrological Sciences Journal*, 62(16), 2753–2768,
1326 <https://doi.org/10.1080/02626667.2017.1395032>, 2017.

1327 Rougé, C., Penuela-Fernandez, A., Pianosi, F.: Forecast families: A new method to systematically evaluate the
1328 benefits of improving the skill of an existing forecast, *Journal of Water Resources Planning and Management*,
1329 149(5), <https://doi.org/10.1061/JWRMD5.WRENG-5934>, 2023.

1330 Ryoo, K.-S., Lee, H.-G., Park, J.-H. and Hur, Y.-T.: Improvement of estimation method on the low flow
1331 frequency inflow for the optimal reservoir operation, *Journal of Water Resources Planning and Management*,
1332 1287–1291, 2009.

1333 [Sanchez-Gomez, J., Vega-Rodríguez, M.A. and Pérez, C.: Comparison of automatic methods for reducing the
1334 Pareto front to a single solution applied to multi-document text summarization, *Knowledge-Based Systems
1335 journal*, 174, 123–136, <https://doi.org/10.1016/j.knosys.2019.03.002>, 2019.](#)

1336 Schwalm, C.R. anderegg, W.R.L., Michalak, A.M., Fisher, J.B., Biondi, F., Koch, G., Litvak, M., Ogle, K.,
1337 Shaw, J.D., Wolf, A., Huntzinger, D.N., Schaefer, K., Cook, R., Wei, Y., Fang, Y., Hayes, D., Huang, M., Jain,
1338 A. and Tian, H.: Global patterns of drought recovery, *Nature*, 548(7666), 202–205,
1339 <https://doi.org/10.1038/nature23021>, 2017.

1340 Shah, D., Zhao, G., Li, Y., Singh, V.P. and Gao, H.: Assessing global reservoir-based hydrological droughts by
1341 fusing storage and evaporation, *Geophysical Research Letters*, 51(1), 1–11,
1342 <https://doi.org/10.1029/2023gl1106159>, 2024.

1343 Sheffield, J., Wood, E.F. and Roderick, M.L.: Little change in global drought over the past 60 years, *Nature*,
1344 [online] 491(7424), 435–438, <https://doi.org/10.1038/nature11575>, 2012.

1345 Shiau, J.-T.: Risk-aversion optimal hedging scenarios during droughts, *Applied Water Science*, 13(1), 1–14,
1346 <https://doi.org/10.1007/s13201-022-01817-x>, 2022.

1347 Shrestha, M., Acharya, S.C. and Shrestha, P.K.: Bias correction of climate models for hydrological modelling -
1348 are simple methods still useful?, *Meteorological Applications*, 24(3), 531–539,
1349 <https://doi.org/10.1002/met.1655>, 2017.

1350 Soares, B.M. and Dessai, S.: Barriers and enablers to the use of seasonal climate forecasts amongst
1351 organisations in Europe, *Climatic Change*, 137(1-2), 89–103, <https://doi.org/10.1007/s10584-016-1671-8>, 2016.

1352 Sugawara, M., Watanabe, I., Ozaki, E. and Katsuyama, Y.: *Tank model programs for personal computer and the
1353 way to use*, National Research Centre for Disaster Prevention, Japan, 1986.

1354 Sugawara, M.: “*Tank model.*” *Computer models of watershed hydrology*, V. P. Singh (Ed.), Water Resources
1355 Publications, Highlands Ranch, Colorado, 1995.

1356 Tian, F., Li, Y., Zhao, T., Hu, H., Pappenberger, F., Jiang, Y. and Lu, H.: Evaluation of the ECMWF system 4
1357 climate forecasts for streamflow forecasting in the Upper Hanjiang River basin, *Hydrology Research*, 49(6),
1358 1864–1879, <https://doi.org/10.2166/nh.2018.176>, 2018.

1359 Turner, S.W.D., Bennett, J.C., Robertson, D.E. and Galelli, S.: Complex relationship between seasonal
1360 streamflow forecast skill and value in reservoir operations, *Hydrology and Earth System Sciences*, 21(9), 4841–
1361 4859, <https://doi.org/10.5194/hess-21-4841-2017>, 2017.

1362 Tzeng, G.H. and Huang, J.: *Multiple attribute decision making: methods and applications*, Boca Raton (Florida):
1363 Crc Press, 2011.

1364 [University of Bristol: SEAFORM, Zenodo \[code\], <https://doi.org/10.5281/zenodo.12800811>, 2023a.](#)

1365 [University of Bristol: SEAFLOW, Zenodo \[code\], <https://doi.org/10.5281/zenodo.12800917>, 2023b.](#)

1366 Vassoney, E., Mammoliti Mochet, A., Erika, D., Negro, G., Pilloni, M.G. and Comoglio, C.: Comparing multi-
1367 criteria decision-making methods for the assessment of flow release scenarios from small hydropower plants in
1368 the alpine area, *Frontiers in Environmental Science*, 9, 1–20, <https://doi.org/10.3389/fenvs.2021.635100>, 2021.

1369 Wang, Z. and Rangaiah, G.P.: Application and analysis of methods for selecting an optimal solution from the
1370 Pareto-optimal front obtained by multiobjective optimization, *Industrial & Engineering Chemistry Research*,
1371 56(2), 560–574, <https://doi.org/10.1021/acs.iecr.6b03453>, 2017.

Formatted: Font: (Asian) Malgun Gothic, (Asian) Korean

Deleted: Taherdoost, H. and Madanchian, M.: Multi-Criteria Decision Making (MCDM) methods and concepts, *Encyclopedia*, [online] 3(1), 77–87, <https://doi.org/10.3390/encyclopedia3010006>, 2023.¶

Deleted: Vafaei, N., Ribeiro, R.A. and Camarinha-Matos, L.M.: Assessing Normalization Techniques for Simple Additive Weighting Method, *Procedia Computer Science*, 199, 1229–1236, <https://doi.org/10.1016/j.procs.2022.01.156>, 2022.¶

Deleted: Velasquez, M. and Hester, P.T.: An analysis of multi-criteria decision-making methods, *International Journal of Operations Research*, 2, 56–66, 2013.¶

- 1383 While, L., Hingston, P., Barone, L. and Huband, S.: A faster algorithm for calculating hypervolume, *IEEE*
 1384 *Transactions on Evolutionary Computation*, 10(1), 29–38, <https://doi.org/10.1109/tevc.2005.851275>, 2006.
- 1385 Wurbs, R.A. and Ayala, R.A.: Reservoir evaporation in Texas, USA, *Journal of Hydrology*, [online] 510, 1–9,
 1386 <https://doi.org/10.1016/j.jhydrol.2013.12.011>, 2014.
- 1387 Yang, G., Guo, S., Liu, P. and Block, P.: Sensitivity of forecast value in multiobjective reservoir operation to
 1388 forecast lead time and reservoir characteristics, *Journal of Water Resources Planning and Management*, 147(6),
 1389 [https://doi.org/10.1061/\(asce\)wr.1943-5452.0001384](https://doi.org/10.1061/(asce)wr.1943-5452.0001384), 2021.
- 1390 Yoe, C.E.: *Principles of risk analysis: decision making under uncertainty*, Boca Raton, FL: Crc Press, Taylor
 1391 And Francis, 2019.
- 1392 You, G.J.-Y.: Hedging Rules for the operation of lake Okeechobee in Southern Florida, *Journal of the American*
 1393 *Water Resources Association*, 49(5), 1179–1197, <https://doi.org/10.1111/jawr.12078>, 2013.
- 1394 Yossef, N.C., Winsemius, H., Weerts, A., van Beek, R. and Bierkens, M.F.P.: Skill of a global seasonal
 1395 streamflow forecasting system, relative roles of initial conditions and meteorological forcing, *Water Resources*
 1396 *Research*, 49, 4687–4699, <https://doi.org/10.1002/wrcr.20350>, 2013.
- 1397 Zhang, X., Hao, Z., Singh, V.P., Zhang, Y., Feng, S., Xu, Y. and Hao, F.: Drought propagation under global
 1398 warming: Characteristics, approaches, processes and controlling factors, *Science of The Total Environment*,
 1399 [online] 838, 156021, <https://doi.org/10.1016/j.scitotenv.2022.156021>, 2022.
- 1400 Zhao, T., Cai, X. and Yang, D.: Effect of streamflow forecast uncertainty on real-time reservoir operation,
 1401 *Advances in Water Resources*, 34(4), 495–504, <https://doi.org/10.1016/j.advwatres.2011.01.004>, 2011.
- 1402 Zhou, A., Qu, B.-Y., Li, H., Zhao, S.-Z., Suganthan, P.N. and Zhang, Q.: Multiobjective evolutionary
 1403 algorithms: A survey of the state of the art, *Swarm and Evolutionary Computation*, 1(1), 32–49,
 1404 <https://doi.org/10.1016/j.swevo.2011.03.001>, 2011.
- 1405 Zhu, F., Zhong, P., Sun, Y. and Xu, B.: Selection of criteria for multi-criteria decision making of reservoir flood
 1406 control operation, *Journal of Hydroinformatics*, 19, 558–571, <https://doi.org/10.2166/hydro.2017.059>, 2017.
- 1407 Zhu, F., Zhong, P., Xu, B., Wu, Y. and Zhang, Y.: A multi-criteria decision-making model dealing with
 1408 correlation among criteria for reservoir flood control operation, *Journal of Hydroinformatics*, 18(3), 531–543,
 1409 <https://doi.org/10.2166/hydro.2015.055>, 2015.

Formatted: Font: (Asian) Malgun Gothic, (Asian) Korean