https://doi.org/10.5194/egusphere-2025-4739
Preprint. Discussion started: 28 October 2025

Forecast-based operation of re-purposed small reservoirs for floods, farms, and (low) flows

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Abstract.

The increased frequency and intensity of hydrological extremes, including drought, due to anthropogenic climate change will drive the need for enhanced water supply resilience, even in water-rich countries. Previous studies have shown that small reservoirs have considerable potential for expanding water supply for various purposes, including when repurposed from flood-only reservoirs for both flood and drought protection. However, whether these repurposed reservoirs retain the same flood protection ability when operating under forecasts is still unclear, as reservoir operation under forecasts has primarily been researched in the context of large reservoirs. In this study, we investigated potential operating rules under forecasts for 30 small-to-midsize flood reservoirs to a) determine if the uncertainty introduced by forecasts degrades the performance of repurposed reservoirs so significantly as to render the concept unusable, b) identify patterns in the relationship between forecast accuracy and optimal reservoir performance, and c) identify patterns in optimal reservoir operation rules, under the constraint that flood protection should not be compromised. Performance is determined by the modelled ability to either supplement streamflow to avoid low flows or to provide water for irrigation purposes in the area of the reservoir. 1000 combinations of three operation parameters—the warning threshold at which flood pre-release begins, the rate at which water is released from the reservoir for flood pre-release, and the inflow at which the reservoir begins storing water—were tested for maintenance of flood protection (viability) and benefit for the reservoir's additional uses. While some reservoirs indeed were no longer beneficial when optimized to operate under forecasts, many still maintained benefits above 40%, with a couple even surpassing their performance under perfect knowledge. Comparing changes in benefit from the perfect-knowledge operation to forecast accuracy indicated that high rates of hits, false alarms and misses, and misses (HFM) could explain the largest decreases in performance, while other forecast accuracy metrics were less impactful. However, even if HFM were low but nonzero, a poorly-timed false alarm could drain a reservoir's storage before a spike in demand, causing a noticeable loss in performance. Investigation of reservoirs' potential benefits under forecasts should therefore be done via simulation rather than approximated via characterizing indices. Optimal operation rules tended to be those that most closely mimicked the perfect knowledge operation, i.e. aggressive storage thresholds and a tendency to hold onto the water storage for as long as is safe, but more conservative operating rules were also able to provide benefits as well. The models for forecast operation and optimization

produced for this study can be used by water managers to assess if existing small flood reservoirs can feasibly be used to increase water supply resilience in a changing world.

1 Introduction

Droughts have long been recognized as significant natural hazards that impose severe impacts on multiple sectors worldwide. Shortages in water, coupled with higher temperatures, reduce crop yields and can even impact livestock mortality, ultimately resulting in massive economic losses (Caretta et al., 2022; Matiu et al., 2017). The increasing frequency and severity of droughts due to climate change exacerbate these challenges (Spinoni et al., 2017), posing substantial threats to food security as agricultural droughts become a major driver of yield reduction worldwide (Lesk et al., 2016; Naumann et al., 2021). Prolonged lower river levels as a result of hydrological drought can affect river ecology—for example, low flow indices are commonly part of an assessment of flows for ecological protection (Poff et al., 2017; Yarnell et al., 2020; Vigiak et al., 2018). Lower river levels can also limit or reduce riverine transport, which may have significant effects on the economy (Christodoulou et al., 2020; Jonkeren et al., 2007).

Small reservoirs have often been named as a potential decentralized solution to water scarcity in regions across the globe, such as Italy, Slovakia, Ghana, Burkina Faso, Zimbabwe, and Brazil (Wisser et al., 2010; Jurík et al., 2018; Casadei et al., 2019; Liebe et al., 2007; Mady et al., 2020; Şen, 2021; Owusu et al., 2022). These are reservoirs typically defined as having a dam height of ≤15 m, a surface area of < 0.1 km^2, and / or a storage volume of up to 1-2 million m^3 (Jurík et al., 2018; Casadei et al., 2019). Because they are smaller, they are cheaper to construct and maintain, and can be implemented in otherwise remote locations (Qadir et al., 2007). They can also be much more easily adapted to local conditions and can be managed locally (Venot and Krishnan, 2011). Research has suggested that recommissioning small reservoirs could maintain or even increase crop yields in an uncertain future (Heinzel et al., 2022), which could be a reason behind the high increase in the number of remotely-sensed reservoirs in water-stressed Europe (Aminzadeh et al., 2024). As climate change impacts destabilize traditional water availability patterns, decentralized small-scale solutions such as small reservoirs may play a leading role in mitigating drought effects in more temperate regions of the globe.

Droughts are not the only natural hazards affected by reservoirs—in many temperate regions around the globe, the primary hydrological hazard has long been floods. The disastrous floods in Germany, Belgium, and the Netherlands in 2021 (Ludwig et al., 2023; Mohr et al., 2023)remain heavy on the public conscience, and many flood reservoirs have been built specifically for this purpose. Bartholomeus et al. (2023) argue, however, that over-preparing for floods may have left these countries underprepared for drought, and call for resilience measures that enable an integrated approach for managing both floods and droughts. The combination of the two objectives in reservoir operations is difficult due to their inherently competing nature, but can be effective when done correctly (Chang et al., 1995; Balley, 1997). Recent research in the state of Baden-Württemberg, Germany, has suggested that repurposing small flood reservoirs for drought under perfect-knowledge conditions

https://doi.org/10.5194/egusphere-2025-4739
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can be quite impactful for satisfying local agricultural irrigation demand and for improving low-flow conditions in rivers (Ho et al., 2025; Ho and Ehret, 2025). However, their performance when operating under forecasts remains unproven.

The impact of forecasts in reservoir operation and optimization has been an active topic. Forecasted reservoir operations have often relied on the concept of hedging—in other words, that an increase in short-term risks, e.g. by continuing to keep water storage despite incoming floods, can increase long-term benefits by increasing water supply (Zhao et al., 2014; Draper and Lund, 2004; Hui et al., 2016). Many studies report that reservoir operations benefit from (or at the very least, are not negatively affected by) operation under forecasts in comparison to the case where no future information is available (Delaney et al., 2020; Chen et al., 2016; Mostaghimzadeh et al., 2022; Schwanenberg et al., 2015). The value of these forecasts are affected by two factors: forecast uncertainty and forecast horizon (the time into the future which is forecasted). Zhao et al. (2011) found that reservoir performance generally decreases with increasing uncertainty, but that the magnitude of this decrease depends on the type of forecasting product used (probabilistic, deterministic, or semi-probabilistic forecasts). Forecast uncertainty tends to increase with increasing forecast horizon; however, studies have shown that a balance between forecast uncertainty and horizon can be achieved to benefit performance (Zhao et al., 2012; Zhao et al., 2019). Turner et al. (2017) argued that, when operating for demands for water, this relationship breaks down—high forecast accuracy no longer necessitates improvement. Further research suggests that the value of the forecasts may decrease or disappear altogether, depending on the specific objectives and constraints (Doering et al., 2021). These results, however, are primarily in the context of large reservoirs. Given the potential benefits of small repurposed flood reservoirs for drought resilience under perfect knowledge, the value of forecasts in the operation of these reservoirs should be investigated.

This study aims to demonstrate the potential benefits of repurposing small flood reservoirs for drought protection when operating under forecasts in comparison to perfect-knowledge scenarios,, particularly under the constraint that the reservoir flood protection function should not be compromised. Specifically, we optimize the operation rules of 30 reservoirs in southwest Germany, modified from Ho et al. (2025) for irrigation demand fulfilment and Ho and Ehret (2025) for streamflow supplementation, to make decisions based on available streamflow forecasts without increasing downstream flooding. The results aim to answer the following questions:

- Q1: Does the uncertainty introduced by using forecasts for decision-making significantly decrease the performance of repurposed small reservoirs' operation such that it is no longer beneficial?
- Q2: What is the relationship between forecast accuracy and decrease in optimal performance between the perfect-knowledge and forecasting operations?
- Q3: What operating rules are most likely to be optimal, and how do these differ from current operation rules?

We begin with an overview of the study area and reservoirs selected for study, then describe the methods used to generate the historical streamflow forecasts, inflow time series, streamflow supplementation demand and irrigation demand time series for each reservoir. We continue with an explanation of the forecast operation model for optimization, the metrics for which the reservoirs are optimized, and the metrics for comparing with perfect-knowledge optimization. Finally, results are presented in the context of the three questions above and are discussed accordingly.

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2 Data and Methods

2.1 Study Area

The German state of Baden-Württemberg is in the southwest of Germany and shares borders with France and Switzerland. The majority of the state belongs to subcatchments of the Rhine, with the rest belonging to those of the Danube catchments. Two climate regimes dominate, according to the Köppen-Geiger classification (Beck et al., 2023). A temperate oceanic climate (Cfb) covers the majority of the state, including most of the Black Forest and the major cities, such as Karlsruhe, Stuttgart, and Freiburg im Breisgau. A humid and warm continental climate (Dfb) covers the Swabian Alb and the eastern parts of the Black Forest. Average annual precipitation from 1991-2022 ranges from 600-1200 mm in the majority of the state, though precipitation in the Black Forest is significantly higher (1400-2100 mm). Typical reference evapotranspiration in the same time period ranges from 450 mm per year in the Black Forest and Swabian Alb to 700 mm per year in the Rhine Valley and urban areas.

This study builds on previous work on the potential of flood reservoirs for drought protection (Ho and Ehret, 2025; Ho et al., 2025). The curious reader may refer to these works for detailed discussion on the reservoir selection process. While the selected reservoirs (Table 1) are small and at most mid-size on the global scale, they are named in this study by size according to the German standard DIN19700 (Lubw, 2007), in which large reservoirs have a capacity of over 1 million cubic meters, medium reservoirs a capacity of 100,000-1 million cubic meters, and small a capacity of 50,000-100,000 cubic meters, and by current usage (flood-only or multipurpose). These reservoirs are currently primarily operated for flood protection, impounding floods once the flooding limit Q_{crit} is exceeded, and are modelled in this work as individual reservoirs without regards to their function in a system.

Table 1. The 30 reservoirs from Ho and Ehret (2025), along with their operating parameters (the operating capacity and the flooding limit Q_{crit}), investigated in this study. ID numbers have been added for clarity. The maximum of the Q_{70} low-flow time series (section 2.3) is included as an indicator of the river regime.

Category	Inundation Type	Name	ID Number	Operating Capacity [m^3]	Q_{crit} [m^3s^{-1}]	Max(Q_{70}) [m^3s^{-1}]
LF	Operational	Bernau	1	1,020,000	22.00	1.013
		Gottswald	2	4,720,000	830.00	20.619
		Mittleres Kinzigtal	3	2,700,000	860.00	16.988
		Wolterdingen	4	3,000,000	75.00	4.602
LM	Permanent	Federbach	5	652,652	0.400	0.090
		Fetzachmoos	6	3,500,000	15.00	1.518
		Nagoldtalsperre	7	1,741,000	15.00	0.865
		Rehnenmuehle	8	2,930,000	7.00	0.523
MF	Operational	Schwaigern	9	151,880	3.32	0.134

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		Seckach	10	64,000	50.30	0.747
		Seebaechle	11	33,112	0.10	0.014
		Unterbalbach	12	210,000	6.33	0.156
	Permanent	Doertel	13	168,400	0.79	0.060
		Lindelbach	14	172,000	0.50	0.014
		Weissacher Tal	15	185,000	2.41	0.070
MM	Operational	Heinzental	16	310,000	1.09	0.059
		Hofwiesen	17	335,210	10.68	0.171
		Wustgraben	18	276,181	0.50	0.053
	Permanent	Fischbach	19	181,625	3.70	0.101
		Huettenbuehl	20	32,000	4.00	0.227
		Kressbach	21	233,780	0.70	0.050
		Michelbach	22	81,728	1.00	0.036
		Salinensee	23	188,000	3.60	0.069
SF	Operational	Duffernbach	24	31,143	1.55	0.031
		Goettelfinger Tal	25	83,400	4.10	0.154
		Mittelurbach	26	60,000	0.50	0.092
		Wollenberg	27	30,200	3.37	0.063
SM	Permanent	Hoelzern	28	7,703	1.50	0.003
		Lennach	29	9,600	2.10	0.004
		Nonnenbach	30	3,759	0.17	0.029

2.2 Weather and Streamflow Forecasts

2.2.1 Historical Weather Forecasts

To reproduce the exact forecasting situation of operational flood forecasting for the period 2010 through 2021, the original weather forecast datasets archived by the flood forecasting center of Baden-Württemberg were used for this re-simulation (Table 2). This meteorological dataset combines three forecasting products supplied by the German Meteorological Service (DWD), namely COSMO-DE (Baldauf et al., 2016), COSMO-D2 (Baldauf et al., 2018), and ICON-D2 (Reinert et al., 2025), which at the time were the most advanced products available for hydrological water-balance forecasting. Missing variables were substituted with observed weather data at the time of forecasting. Further differences in these products are horizontal and vertical model resolution and further optimization of meteorological sub-processes.

Table 2. Weather forecast products and variables used to generate the historical streamflow forecasts.

Years	Product	Forecast Variables	Spatial Resolution	Forecast Horizon	Updating Interval
2010-2017	COSMO-DE	Precipitation	2.8 km	27 hrs	3 hrs
2018-2020	COSMO-D2	Precipitation, air temperature, global radiation, wind speed, air pressure, relative humidity	2.2 km	27 hrs	3 hrs
2021	ICON-D2	Precipitation, air temperature, global radiation, wind speed, air pressure, relative humidity	2 km	Up to 48 hrs	3 hrs

2.2.2 Historical Streamflow Forecasts and Inflow Time Series

The historical streamflow forecasts were generated using the process-oriented water balance Large Area Runoff Simulation Model, also known as LARSIM (Bremicker, 2000; Haag and Luce, 2008; Bremicker et al., 2013; Haag et al., 2022), and is currently used operationally in several countries in Europe, including the study area Baden-Württemberg. Discharge concentration and river routing are simulated in hourly resolution and on a 1 x 1 km grid, whereas evapotranspiration, snow dynamics, the soil water balance and runoff generation are modelled using hydrological response units. For this evaluation, the models were re-run in the same configuration currently used at the federal flood forecasting center of Baden-Württemberg to produce deterministic forecasts and inflow time series for each reservoir. The forecast horizon was limited to a maximum of 24 hours to limit forecast uncertainty, with a new forecast initiated every hour of the evaluation period (2010–2021) using the most recent meteorological forecast.

At the transition point from measured data to actual forecasts, the model is automatically optimized at the gauge catchment level on the basis of comparing simulated and measured discharge. If the configuration files allow optimization for the current discharge range, and if deviations between simulated and observed discharge exceed a predefined threshold (5%), multiple optimization routines are triggered. The system then automatically selects the most plausible adjustment process as described in detail by Luce et al. (2006). When discrepancies are caused by localized rainfall or snowmelt errors, a correction factor modifies the water supply over the forecast period. If mismatches instead result from storage dynamics (e.g. recession after a flood peak), the model updates the filling levels of its hydrological storages (interflow, direct runoff, groundwater). These corrections are constrained within predefined ranges of adjustment factors (Luce et al., 2006). Due to these corrections, however, the resulting modelled streamflow for each reservoir differs slightly from those used in Ho and Ehret (2025) and Ho et al. (2025).

2.3 Streamflow Demand Time Series

Streamflow demand is based on the hourly 70th percentile exceedance flow (Q_{70}) of the reservoir's inflow time series. This Q_{70} is calculated following the adjusted method of Cammalleri et al. (2016) presented in Ho and Ehret (2025) (Figure 1). For each time step *t* within a year, we collect a 721 x *n* matrix of discharge values: 721 represents all the hourly time steps in a 30-day

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Preprint. Discussion started: 28 October 2025

moving window (with an additional value to center the window on *t*), which is applied to all the years in the dataset (*n*). The cumulative distribution function curves for discharge, and then the percentile exceedance curves, are derived based on the values in this matrix. The threshold value at each timestep is the discharge corresponding to the chosen percentile exceedance.

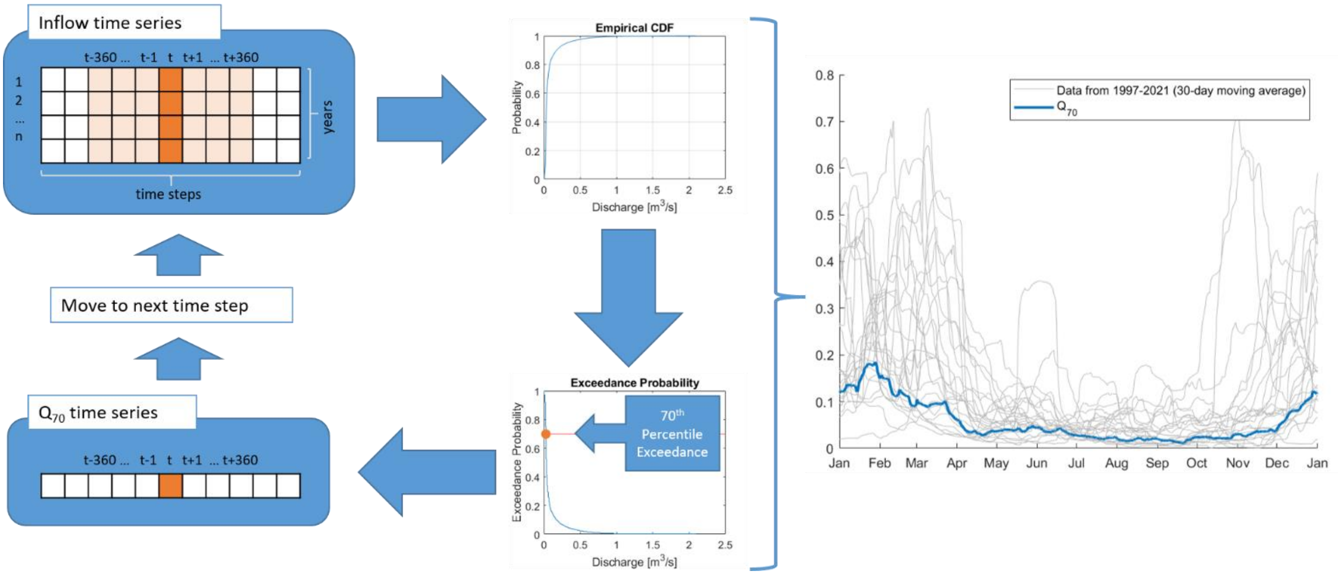

Figure 1. Example calculation of the Q_{70} time series, reprinted with permission from Ho and Ehret (2025).

2.4 Irrigation Demand Time Series

Time series of irrigation demand for each reservoir were taken from Ho et al. (2025). These were calculated for a 5 km^2 square-shaped region around each reservoir for a variety of different crops. Crop cover and soil texture maps were obtained from Schwieder et al. (2024) and Düwel et al. (2007), respectively, and used to identify agricultural response units (ARUs)—areas of the same crop and soil cover within a region. The irrigation demand (AID) of each ARU was calculated using the FAO-56 method (Allen et al., 1998) using a collection of plant growth and soil parameters from various sources (Allen et al., 1998; Pereira et al., 2021a; Pereira et al., 2021b; Rallo et al., 2021; Ad-Hoc-Arbeitsgruppe, 2005). For more details, please refer to Ho et al. (2025). The total AID time series of each reservoir is the sum of each ARU's AID:

$$AID = \sum_{ARU=1}^{m} AID_{ARU} \qquad \textbf{(1)}$$

2.5 Forecast Operation Model

The reservoir's operation under forecasts (Figure 2) is modelled by running forward in time by comparing various state variables and threshold parameters (Table 3):

1. If the current inflow Q_{in} is above the flooding limit Q_{crit}, it impounds the floods by storing flow above the flooding limit (flood operation module) until the operating capacity C is reached; else, it makes a decision based on the most recent forecast.

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2. If a forecast is unavailable, the reservoir repeats the previous operation module.
3. If the highest forecasted value is larger than the flooding limit ($max(Q_{in,forecast}) > Q_{crit}$), the reservoir releases volume such that the outflow is Q_{crit} (flood pre-release module).
4. If the highest forecast value is greater than the warning threshold Q_{thresh} ($max(Q_{in,forecast}) > Q_{thresh}$), the reservoir releases volume such that the outflow is $Q_{release}$ (partial pre-release module).
5. If the forecast fails both of these conditions, the model operates based on the current inflow Q_{in}—if Q_{in} is greater than the retention flow Q_r, the reservoir will store water such that the outflow is Q_r (drought fill module).
6. If there is a need for water—either Q_{in} is below the streamflow drought threshold or there is irrigation demand—the reservoir will release volume to meet the demand.

The model can be operated for either streamflow or irrigation operation (it cannot do both at the same time) and is a modified version of the models in Ho et al. (2025) and Ho and Ehret (2025). For either use, the model is optimized for highest benefit by adjusting Q_r (as in the aforementioned studies), the Q_{thresh}, and/or the $Q_{release}$ using the following variables:

1. percQ_thresh, which is the threshold percentage of the flooding limit (Q_{crit}) which we will indicate as a forecast warning level (Q_{thresh}):

$$Q_{thresh} = percQ_{thresh} \times Q_{crit} \quad \textbf{(2)}$$

2. percQ_release, which is the percentage of Q_{crit} that will be released to pre-empty the reservoir at the rate $Q_{release}$:

$$Q_{release} = percQ_{release} \times Q_{crit} \quad \textbf{(3)}$$

Table 3. Key variables for the forecast operation model.

Abbreviation	**Description**
C	Operational capacity of the reservoir (full minus permanent inundation volume)
Q_{crit}	Flooding limit; critical flow above which reservoir impounds floods
$Q_{in,t}$	Inflow to the reservoir at time t
$Q_{in,forecast}$	Forecasted inflow to the reservoir
$Q_{70,t}$	70^{th} percentile exceedance flow at time t
AID_t	Agricultural irrigation demand of the reservoir's area at time t
Q_{thresh}	Warning flow at which partial pre-release module begins
$Q_{release}$	Reservoir outflow during the partial pre-release module
Q_r	Retention flow at which water is stored in the reservoir; optimization variable
$percQ_{thresh}$	Q_{thresh} expressed as a percentage of Q_{crit}; optimization variable
$percQ_{release}$	$Q_{release}$ expressed as a percentage of Q_{crit}; optimization variable

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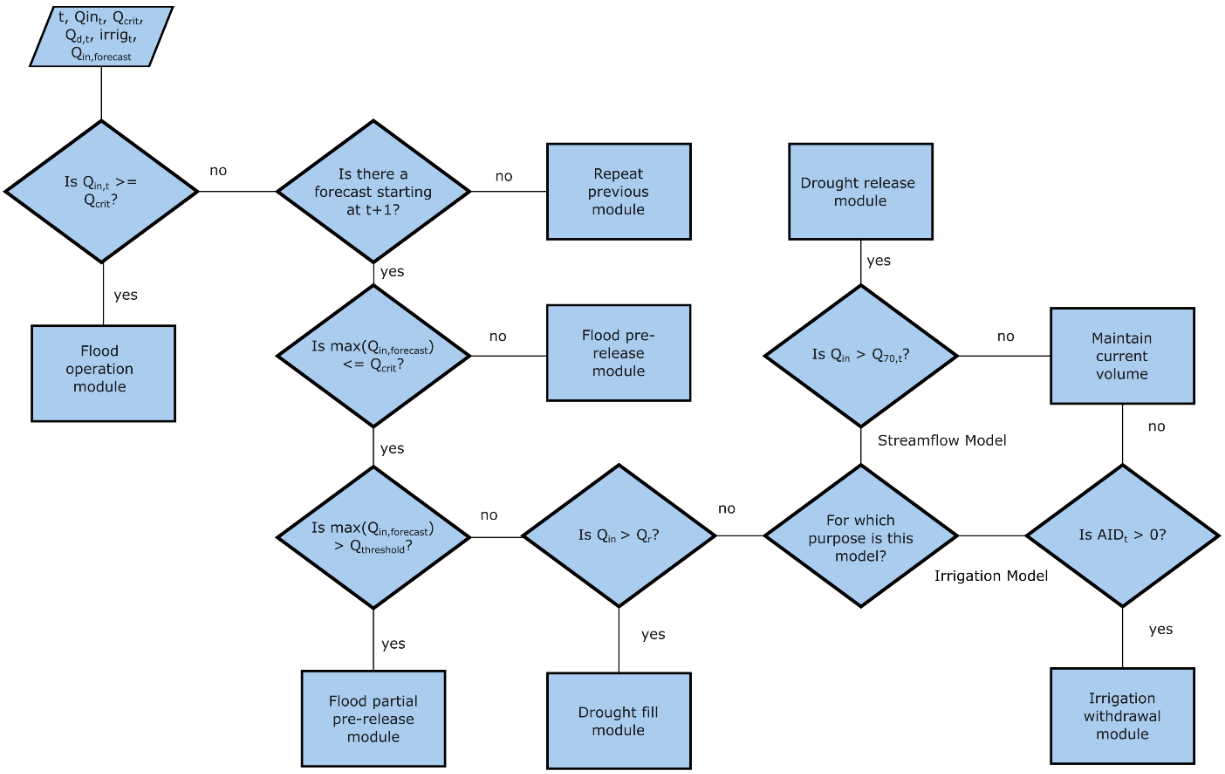

Figure 2. The decision tree for the forecast operation model.

2.6 Metrics for Comparison & Evaluation

2.6.1 Determination of Benefit

Benefits in this study are expressed as percent reduction of a negative outcome, which are in turn expressed via penalty functions.

2.6.1.1 Flood Protection Benefit

Flood protection remains the cornerstone of the reservoir's operation—in no circumstances are increases of flooding volume acceptable. Flood penalty is simply defined in Ho and Ehret (2025) as

$$P_{f,t} = \begin{cases} 0, & Q_{out,t} \leq Q_{crit} \\ -5\left(Q_{out,t} - Q_{crit}\right), & Q_{out,t} > Q_{crit} \end{cases} \quad (1)$$

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and expresses the amount of water above Q_{crit} that the reservoir cannot impound, multiplied by a scalar (here chosen arbitrarily as 5).

Because the in-situ reservoir operation rules are currently optimized for flood protection, no increase in flood protection (i.e. no flood protection benefit) is expected using the forecast operation model. However, in all optimization efforts, only parameter sets that do not increase flood penalty shall be considered.

2.6.1.2 Streamflow Supplementation – Penalty Benefit

The streamflow penalty P_d and the streamflow benefit B_p are metrics developed for evaluating a reservoir's performance for streamflow supplementation in Ho and Ehret (2025).

The streamflow benefit B_p refers to the reservoir's ability to provide water and reduce streamflow penalty, represented as the percentage of penalty reduced by the operation (ranging from 0 to 100%, where higher is better). This is based on the difference between the penalty in the flood-only (i.e. current) operation and the penalty in a combined (flood and streamflow supplementation) operation scheme:

$$B_p = 100 \times \frac{\sum P_{d,flood-only} - \sum P_{d,combined\ operation}}{\sum P_{d,flood-only}} \quad \textbf{(4)}$$

2.6.1.3 Agricultural Irrigation Demand – Irrigation Benefit

The benefit from the reservoir in the case of irrigation demand is summarized as the percentage of the irrigation demand that the reservoir can supply (ranging from 0 to 100%, where higher is better):

$$B_{ID} = 100 \times \frac{\sum AID_{fulfilled}}{\sum AID_{total}} \quad \textbf{(2)}$$

The AID_{total} is the sum of the irrigation demand time series for all crops within a reservoir's area, and the $AID_{fulfilled}$ is the water withdrawn for irrigation purposes by the irrigation model.

2.7 Optimization for Forecast Operation

The forecast operation models were tested using 1,000 different parameter sets consisting of combinations of 10 values each of Q_r, percQ_thresh, and percQ_release. These parameters were constrained as follows:

$$\max(Q_{70}) < Q_r < Q_{crit} \quad \textbf{(3)}$$

$$\max(Q_{70}) < Q_{crit} \times percQ_{thresh} < Q_{crit} \quad \textbf{(4)}$$

$$0.05 \leq percQ_{thresh}, percQ_{release} \leq 1 \quad \textbf{(5)}$$

For comparing values of Qr across reservoirs, we normalize the optimal Qr with the reservoir's Qcrit:

$$percQ_{crit} = {Q_r}/{Q_{crit}} \quad \textbf{(6)}$$

Each parameter set was tested in both the irrigation and streamflow cases to determine changes in flood penalty; i.e., if there was any increase in flood volume that was not retained by the reservoir. Viable parameter sets were those that had no increase

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in flood penalty, and the optimal parameter set was the viable parameter set that had the highest benefit for the use case. It is likely that a reservoir could have more than one optimal parameter set (i.e. a Pareto front).

2.7.1 Forecast Accuracy

The quality of forecasts for a given reservoir is evaluated based on their accuracy in comparison to the inflow time series, i.e. the percentage of forecasts that correctly predict floods (hits; H), incorrectly predict floods (false alarms; F), incorrectly predict no floods (misses; M), and correctly predict no floods (correct rejections; R). For this purpose, any instance of $Q_{in,forecast}$ greater than or equal to Q_{crit} will result in a flood forecast, regardless of forecast horizon. A high rate of F+R indicates that the reservoir did not have many flooding events. High percentages of H+F trigger frequent flood pre-release; in other words, there will be less water available for the intended usage. A relatively high MM would likely indicate that the reservoir's priority should remain flood protection, as an empty reservoir would reduce the risk of flood damage due to faulty forecasts.

The quality of these forecasts can be further described using additional variations of the confusion matrix. The critical success index (CSI) describes the rate of successful event identification over both forecasted and missed events, ranging from 0 (worst) to 1 (best):

$$CSI = \frac{H}{H + M + F} \quad \textbf{(7)}$$

The precision of the forecast describes the rate of successful flood forecasts compared to all predicted floods, where a higher score (maximum 1, minimum 0) indicates that if a flood is forecasted, it is more often correct:

$$\text{precision} = \frac{H}{H + F} \quad \textbf{(8)}$$

The recall of the forecast describes the rate of successful flood forecasts compared to all true floods, where a higher score (maximum 1, minimum 0) indicates that more of the flood events were identified:

$$\text{recall} = \frac{H}{H + M} \quad \textbf{(9)}$$

The F1 score is the harmonic mean between precision and recall, allowing for a balanced representation of both, where a higher score (maximum 1, minimum 0) indicates better performance:

$$\text{F1} = \frac{2 \times (\text{precision} \times \text{recall})}{\text{precision} + \text{recall}} \quad \textbf{(10)}$$

Thus, the forecasts for the sample event (Figure 3) have a CSI of 0.474, a precision of 0.750, a recall of 0.563, and an F1 score of 0.643. This could be interpreted as having a moderate ability of forecasting an event (medium CSI), a high accuracy when predicting flood events (high precision), a moderate ability to identify an actual event (medium recall), and a moderate-to-high overall accuracy (F1 score).

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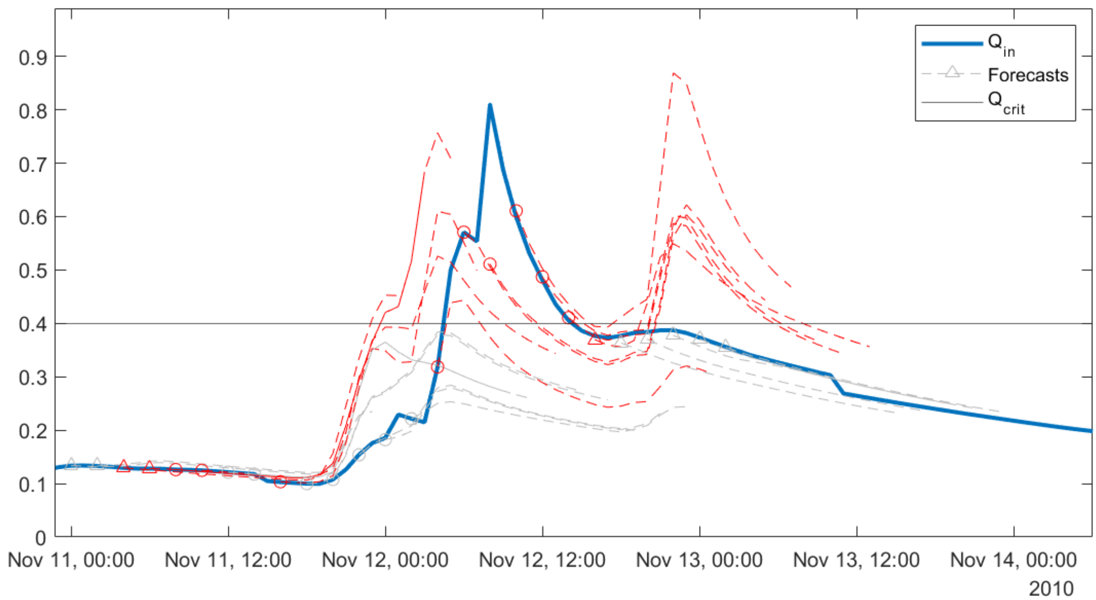

Figure 3. A three-day sample of forecasts generated by LARSIM for Federbach reservoir (for clarity, only every other forecast is shown). The marker, placed at the first value of each forecast, is a circle if a flood occurred during the forecast horizon and a triangle if no flood occurred. Red color indicates the forecast predicted a flood event; gray indicates no flood predicted. In this sample, there are 9 hits, 7 misses, 3 false alarms, and 7 correct rejections.

2.7.2 Comparison with the Perfect Knowledge Scenario

The forecast model benefits for each reservoir is evaluated in comparison to its perfect-knowledge scenario to determine the impact of forecasts in operation. Ho and Ehret (2025) and Ho et al. (2025) provide perfect-knowledge scenarios for the streamflow and agricultural reuse models; however, due to differences in the model setup (see 2.2.2), the reservoir inflow time series—and therefore the benefits—are different. Therefore, the perfect-knowledge benefits have been rerun with the new inflow time series using the methods presented in Ho and Ehret (2025) and Ho et al. (2025).

3 Results

3.1 Optimization Results

The number and performance of resulting viable parameter sets varied greatly, with some reservoirs having no viable parameter sets and others having more than 900 (Figure 4). The optimal parameter set is the one with the highest benefit—for some reservoirs, there are multiple optimal sets (i.e. Pareto-optimal sets). Small reservoirs have considerably lower benefits, especially those that are currently multipurpose reservoirs, as they often struggled to store water. Mid-sized and large multipurpose reservoirs perform overall quite well; however, many non-optimal parameter sets still provide considerable

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benefit to both use cases. Should an optimal parameter set be deemed unfeasible for other reasons (e.g. a need to increase flood safety margins), there remain many other viable options.

The distribution of the benefits can also be informative. Some reservoirs have large gaps between clusters of equally-performing parameter sets, resulting in a very discontinuous distribution. In the irrigation usage case, this may not be too surprising, as the demand itself is quite disjointed: due to the assumptions when calculating the demand time series, water for an entire ARU is requested on the same day and is not staggered. Its fulfilment on any given day is also limited by the reservoir's volume—once the entire volume is given for the season, there are rarely additional increases in benefit. In the streamflow usage case, however, this could indicate forecasts that require frequent pre-releases or consistent water shortages limiting the overall viability of the reservoir.

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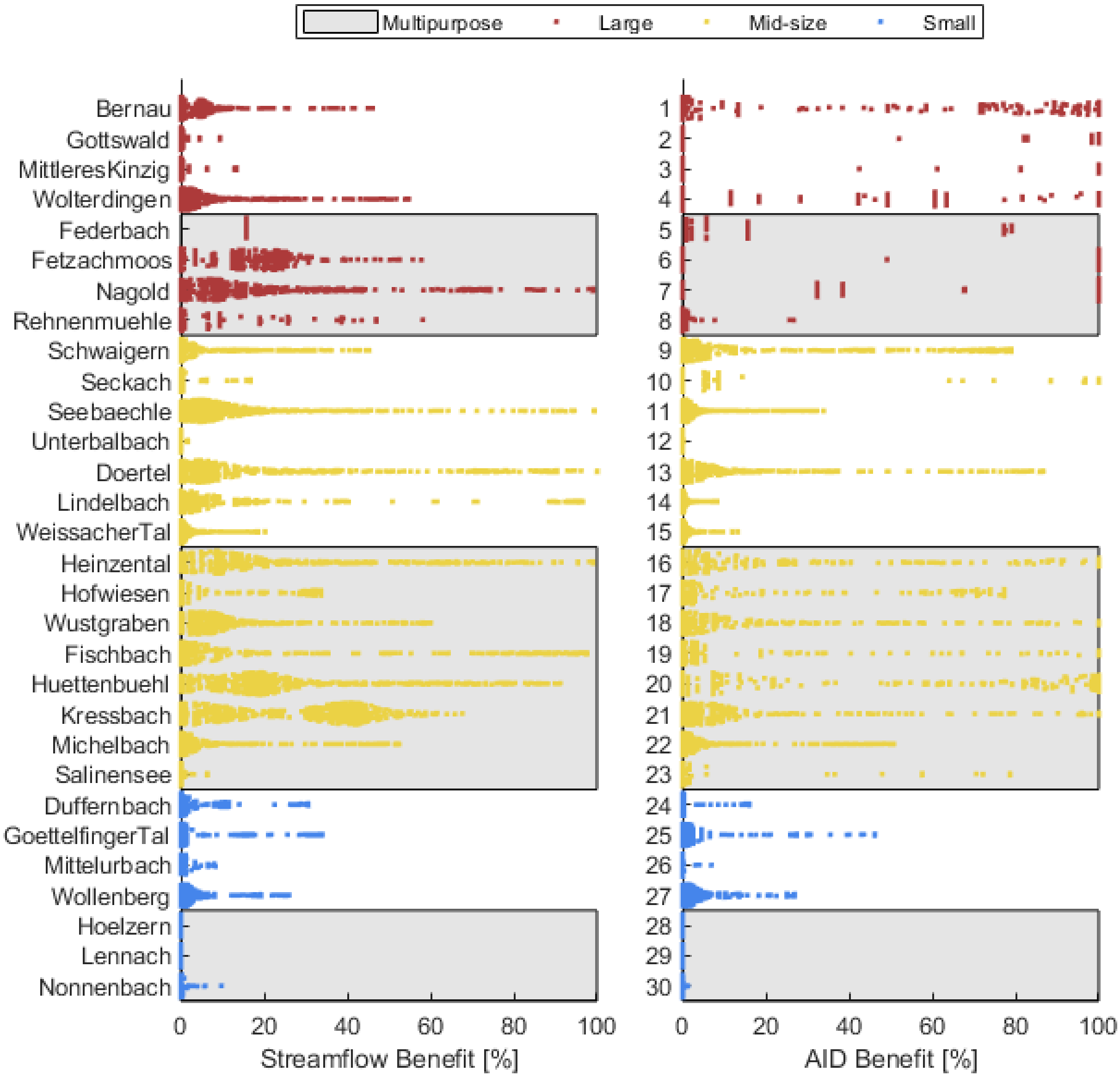

Figure 4. Distributions of the performance of viable parameter sets for the selected reservoirs.

The frequency patterns of successful viable parameter combinations differ considerably from those of optimal parameter
280 combinations (Figure 5, Figure 6). In both use cases (streamflow and irrigation), the frequency hotspots of viable parameter sets indicate highly conservative rules: low warning thresholds (percQ_thresh), high release rates (percQ_release), and high storage thresholds (percQ_crit) resulting in reduced storage serve to minimize volume stored and maximize volume released

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before a flood. These rules are similar to the in-situ operation rules (store only flood waves and release volume as soon as possible) and are therefore most likely to result in no increased flood penalty; however, they are less likely to produce any benefit (see A) due to reduced water storage.

In contrast, frequency hotspots of pareto-optimal sets indicate highly aggressive rules: high warning thresholds and low storage thresholds serve to maximize volume stored and hold it for as long as possible. These mimic the optimal rules found in the perfect-knowledge scenarios. This is also reflected in heatmaps of average benefit for parameter combinations (see Appendix A). Indeed, in both uses, the vast majority of pareto-optimal sets occur when percQ_thresh is between 0.8 and 1.0 and percQ_crit is between 0.1 and 0.2 (values under 0.1 are not permitted). An exception can be found in streamflow optimal sets at percQ_thresh between 0.2 and 0.3—this is due to large multipurpose reservoirs, such as Federbach, which tend to have a low Qcrit relative to its volume and thus need more time (enabled by a lower warning threshold) for a successful pre-release. This is not reflected in irrigation due most likely to the shorter time series and the seasonal nature of the demand. The relatively high occurrence frequencies at percQ_crit are due to reservoirs that experience little to no benefit. The variety of high performing release rates indicate that this parameter will be the most impactful in the optimization scheme.

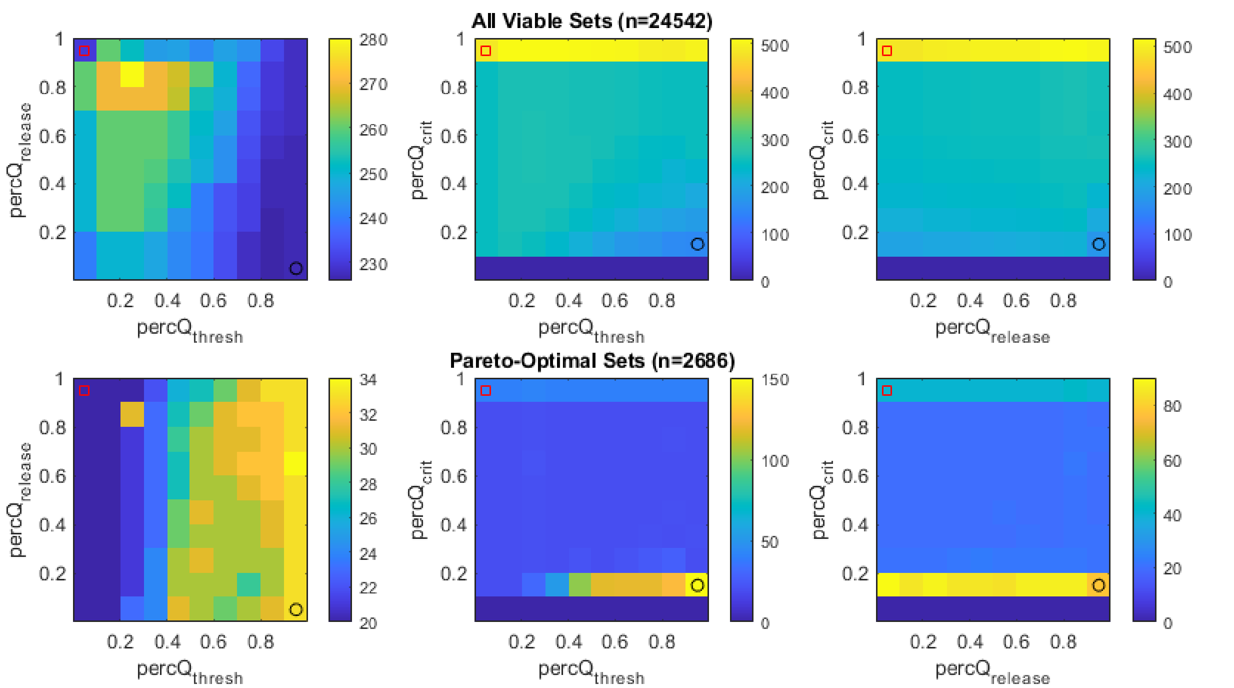

Figure 5. Color indicates frequency of a given parameter combination in either all viable parameter sets or pareto-optimal sets for streamflow-optimized forecast operation. The red square indicates the current (flood-optimized) operation rules, whereas the black circle indicates the perfect-knowledge operation rules.

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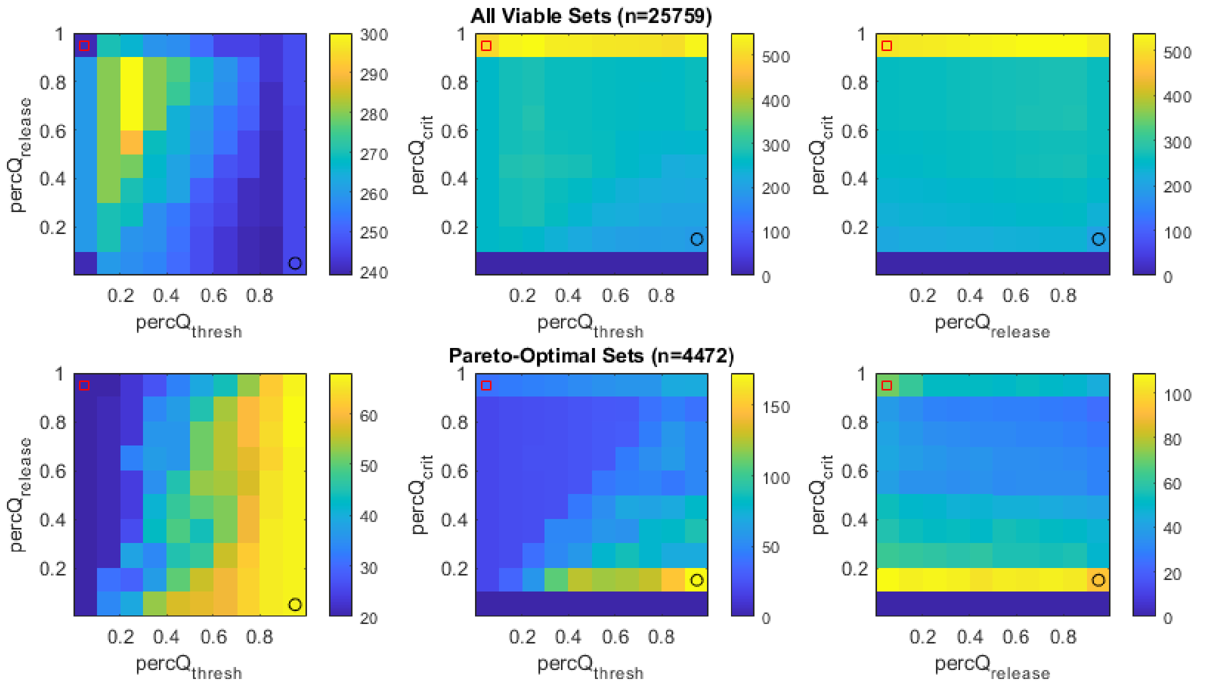
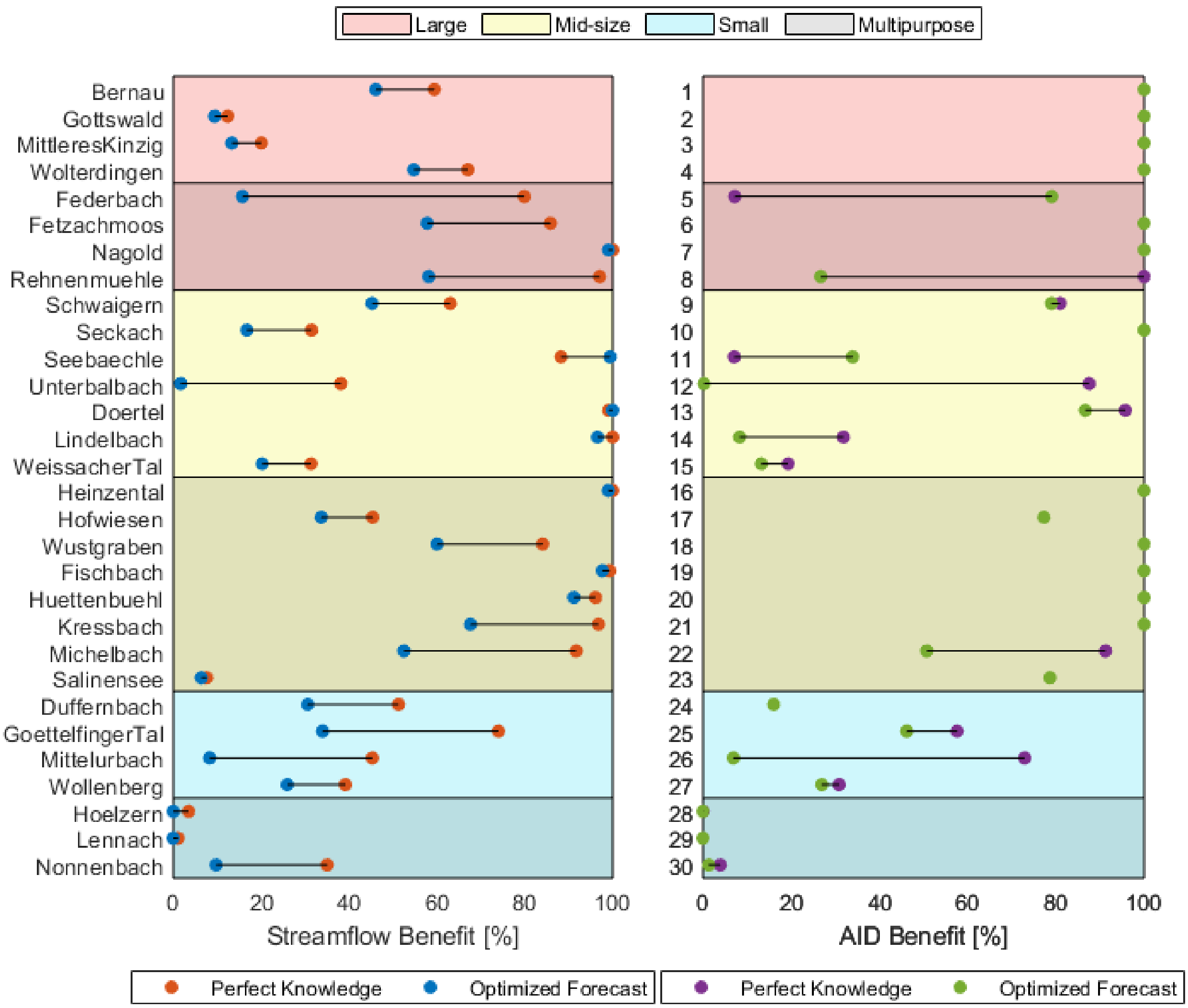


Figure 6. Color indicates frequency of a given parameter combination in either all viable parameter sets or pareto-optimal sets for irrigation-optimized forecast operation. The red square indicates the current (flood-optimized) operation rules, whereas the black circle indicates the perfect-knowledge operation rules.

3.2 Comparing Forecasted to Perfect-Knowledge Conditions

The agricultural and streamflow benefits from the optimal parameter sets were compared with those from the perfect-knowledge conditions (Figure 7). In most cases, and as to be expected, the perfect-knowledge operation for resulted in higher benefits than the optimized forecast operation, with a median difference of 13% (mean 17%) for streamflow supplementation and a median difference of 0% (mean 8.5%) for irrigation demand—while surprising, this is because 15 reservoirs maintained their performance when operated for irrigation. Seven reservoirs operated for streamflow and 15 operated for irrigation still maintain a benefit greater than 70% (compared to 14 for streamflow and 20 for irrigation in the perfect-knowledge scenario). In fact, in some cases the reservoir's performance actually increased under forecast operation—this occurred in two reservoirs (Seebaechle and Doertel) in the streamflow operation case, and two (Federbach and Seebaechle) in the irrigation case. This is because of a slight nuance in the partial pre-release module: in the perfect-knowledge optimization, the reservoir is required to be completely empty before a flood. In contrast, the optimized forecast only requires that flooding conditions do not increase, effectively increasing the flexibility of the reservoir and allowing water to remain in the reservoir before a flood. In reservoirs with frequent flooding, this increases the water available for drought, as water storage is carried over from one flood event to the next.



320 **Figure 7. Differences in performance between the optimal performance under perfect knowledge and uncertain forecasts. If only the optimized forecast is visible, the optimized forecast and perfect knowledge performed equally well; if only the perfect knowledge is visible, there were no viable parameter sets for operation under forecasts.**

3.3 Influence of Forecast Accuracy

The accuracy of the reservoir forecasts from 2010-2021 was rather varied (Table 4). Forecasts at nine reservoirs correctly
325 found no flooding events. Of the remaining 20 reservoirs, seven had forecasts with F1 scores of less than 0.5 (indicating poor performance), seven had forecasts with F1 scores between 0.5 and 0.75 (indicating good performance), and six had forecasts with F1 scores of at least 0.75 (indicating high performance).

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One could expect that high occurrence rates of H, F, and / or M would significantly impact benefits, as these would incur action from the reservoir. Indeed, reservoirs with a change in benefit of at least 50% (Rehnenmuehle, Unterbalbach, Federbach, and Mittelurbach) do have among the highest rates of HFM (Figure 8)—though in the case of Federbach's irrigation optimization, this benefit is in the positive direction. High HFM, however, is not a prerequisite for a large change in benefit—other reservoirs with large changes (20-40%) have HFM of less than 2%, indicating that low flooding rates does not mean that benefits will remain unchanged. Other accuracy metrics (CSI and F1 score) seem to have less of an explanatory impact, as the four reservoirs with the greatest changes in benefit scored high in both CSI and F1.

Table 4. Forecast accuracy statistics (hits, H; misses, M; false alarms, F; correct rejections, R; critical success index, CSI = H/(H+F+M), precision, H/(H+F); recall, H/(H+M); and F1 score, 2/(recall^{-1}+precision^{-1})) at all reservoir locations. The names of reservoirs with changes in benefit of more than 50% are bolded.

	Reservoir	H [#]	M [#]	F [#]	R [#]	CSI	Precision	Recall	F1
1	Bernau	54	42	18	105079	0.47	0.75	0.56	0.64
2	Gottswald	0	0	0	105193	-	-	-	-
3	MittleresKinzig	0	0	0	105193	-	-	-	-
4	Wolterdingen	234	40	92	115159	0.64	0.72	0.85	0.78
5	**Federbach**	6406	1648	1123	96016	0.70	0.85	0.80	0.82
6	Fetzachmoos	1183	524	416	103068	0.56	0.74	0.69	0.72
7	Nagold	48	16	25	105102	0.54	0.66	0.75	0.70
8	**Rehnenmuehle**	67828	2026	1407	33932	0.95	0.98	0.97	0.98
9	Schwaigern	5	19	19	105150	0.12	0.21	0.21	0.21
10	Seckach	1155	571	194	103273	0.60	0.86	0.67	0.75
11	Seebaechle	0	0	0	105193	-	-	-	-
12	**Unterbalbach**	62825	1854	973	39539	0.96	0.98	0.97	0.98
13	Doertel	41	34	13	105103	0.47	0.76	0.55	0.64
14	Lindelbach	2	22	6	105163	0.07	0.25	0.08	0.13
15	WeissacherTal	0	0	0	105193	-	-	-	-
16	Heinzental	140	72	88	104891	0.47	0.61	0.66	0.64
17	Hofwiesen	0	0	3	105188	0.00	0.00	-	0.00
18	Wustgraben	0	0	0	105192	-	-	-	-
19	Fischbach	30	43	125	104995	0.15	0.19	0.41	0.26
20	Huettenbuehl	416	329	188	104260	0.45	0.69	0.56	0.62
21	Kressbach	1205	669	388	102931	0.53	0.76	0.64	0.70
22	Michelbach	6	64	12	105111	0.07	0.33	0.09	0.14
23	Salinensee	0	0	0	105192	-	-	-	-

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24	Duffernbach	0	0	0	105193	-	-	-	-
25	GoettelfingerTal	0	0	15	105178	0.00	0.00	-	0.00
26	**Mittelurbach**	646	339	118	104089	0.59	0.85	0.66	0.74
27	Wollenberg	15	38	2	105138	0.27	0.88	0.28	0.43
28	Hoelzern	0	0	0	105193	-	-	-	-
29	Lennach	0	0	0	105193	-	-	-	-
30	Nonnenbach	512	0	0	105193	1.00	1.00	1.00	1.00

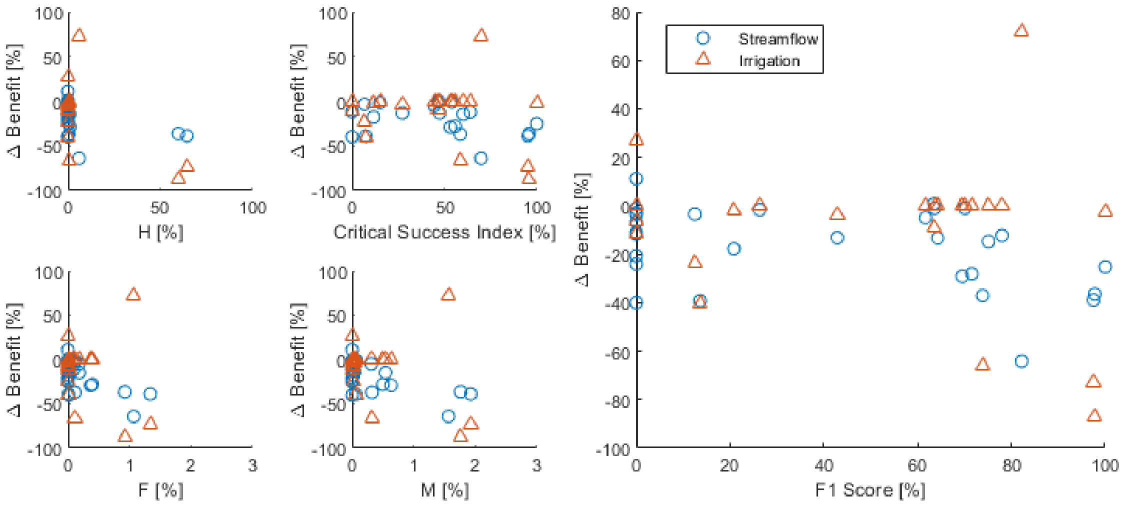

Figure 8. Relationships between different accuracy metrics and change in benefit for each reservoir and use case.

4 Discussion

The primary finding of the study is that, even when operating in a more realistic scenario (i.e. with uncertain forecasts), the concept of repurposing small flood reservoirs for irrigation or/and streamflow supplementation as presented in Ho and Ehret (2025) and Ho et al. (2025) can still provide significant benefits in a range of viable parameter sets. Though the performance of most reservoirs was noticeably affected by the forecasts (indeed, some reservoirs were no longer beneficial to a particular purpose), many were able to maintain benefits above 40%. These were generally reservoirs that did not experience a flood event during the observation period and had well-performing forecasts. Small reservoirs—in particular, small multipurpose reservoirs—had very little benefits whereas large and mid-size reservoirs generally performed quite well, which is consistent with previous findings (Ho et al., 2025; Ho and Ehret, 2025). Ideal parameter sets were those that imitated the operation rules under perfect knowledge: to store water at a storage threshold as low as possible, and to hold onto the water as long as is safe.

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Although these aggressive parameter sets were typically the highest-performing, more conservative rulesets could also viably provide some benefit as well.

While forecast quality remains the biggest uncertainty in this study, as LARSIM is not typically used to model small catchments (and forecasting in small catchments is already quite tricky), these are the best forecasts that we can currently generate for most of these reservoirs: the model setup is the same as the current operational setup in use in the study area, and the forecast horizon is a brief 24 hours. Our results showed that typical forecast metrics—namely the critical success index (CSI) and the F1 score—alone did not explain large changes in reservoir benefits from the perfect knowledge case. Indeed, it seemed that flood occurrences were the deciding factor here. Reservoirs with high HFM in their forecasts were emptied frequently for flood protection and thus have the greatest change in reservoir benefits—if this is the only (or the biggest) reservoir in this basin, this may make the reservoir critical for flood protection, and could potentially be deprioritized as a candidate for scope expansion on the basis of flood safety and reduced benefit. On the other hand, while most reservoirs with low HFM in their forecasts had little change in their benefit, others still had noticeable decreases in performance. This is primarily due to timing—a loss of water storage due to HFM before an incurrence of demand means that less demand can be fulfilled. Thus, although high HFM is generally indicative of frequent pre-release and therefore lowered benefit, low HFM does not necessarily mean high benefit, a finding that is consistent with Turner et al. (2017), who found that high forecast accuracy (i.e. low HF) had diminishing returns in reservoirs operated for water demand. Because the success of a reservoir is effectively decoupled from these quality metrics, investigations of a reservoir's potential should thus be conducted via simulations as outlined in this study and not estimated on the basis of forecast quality.

5 Conclusion

This study demonstrated that, with modified operating rules, small flood reservoirs can be converted to additionally provide streamflow or irrigation supplementation—even when operating under uncertain forecasts, and without compromising flood protection. This approach can also be applied to other regions to help water managers evaluate potential changes to their reservoirs as well. In particular, the three questions posed in the introduction can be answered as follows:

- Q1: For most reservoirs tested, the use of forecasts still resulted in tangible benefits for reservoirs optimized for streamflow or irrigation supplementation.
- Q2: Two common forecast metrics—critical success index (CSI) and F1 score—were shown to be less impactful for explaining drops in reservoir success than simple flood occurrence statistics (i.e. the ratio of hits, misses, and false alarms, HFM). Although high HFM was shown to noticeably change the benefits gained from a reservoir, low HFM is not a guarantee that benefits will remain unchanged. The timing of the flood events is also important.
- Q3: The operating rules that are most optimal are aggressive rules that mimic the rules found in Ho and Ehret (2025) and Ho et al. (2025)— rules that maximize water stored and that maximize how long the water is held. Current rules are, in contrast, those that minimize water storage and maximize the time the reservoir is empty.

The presented results can also be used to guide selection of future rulesets. Because the performance distributions of viable rulesets are rather discontinuous for some reservoirs, it is more advisable to optimize a reservoir individually using the

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developed toolbox than to attempt to pick a ruleset based on previous reservoirs. The computational resources consumed in this endeavor depends on the volume of forecasts available and the number of parameter sets tested. However, an optimal ruleset may ultimately be undesirable for other reasons—for example, if increased safety margins are desired to account for future river regime changes due to climate change, more conservative rulesets might be better. Understanding whether a ruleset is aggressive or conservative can guide the decision in the proper direction for its usage.

Ultimately, whether or not a small flood reservoir should be converted for either of these purposes is a subjective question. While this study attempts to solve for the water supply benefit part of this equation, other considerations (such as impacts to water quality and downstream ecosystems, cost, and necessary safety margins) must be taken into account when deciding on potential scope expansion of a reservoir. Indeed, research has suggested that a reservoir effect (i.e. dependability of water infrastructure drives increased demand, analogous to the levee effect in flood protection) may, in the long term, result in worsened water shortages in the future (Di Baldassarre et al., 2018). We hope, however, that the tools and results presented in this study enable water managers to initiate informed discussions about using their existing reservoirs to enhance water supply resilience.

6 Appendix

A. Heatmaps of Benefit

Heatmaps of the average benefit, where the color indicates the average benefit of the parameter combination across all reservoirs, reveal that aggressive parameter sets are higher-performing. Given that they are more frequently optimal, this should not be surprising; however, these plots indicate that a variety of parameter combinations can yield similar benefits.

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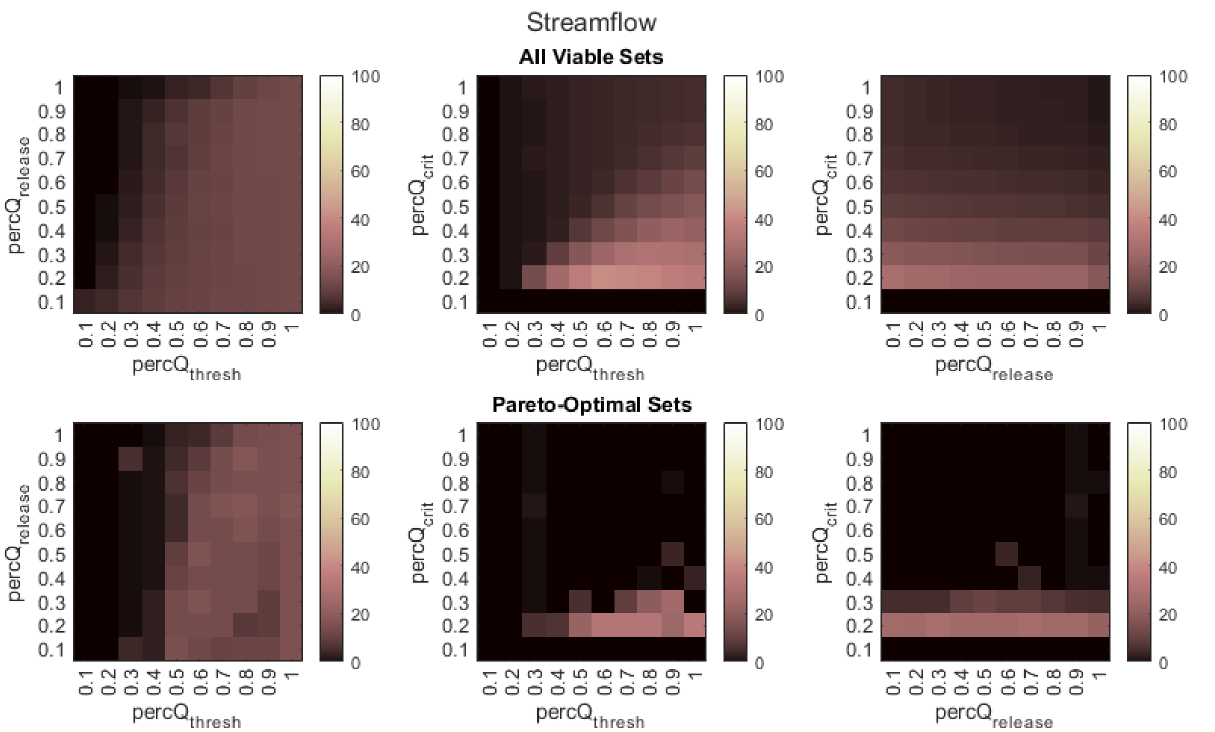

Figure A1. Average streamflow benefit of each parameter combination.

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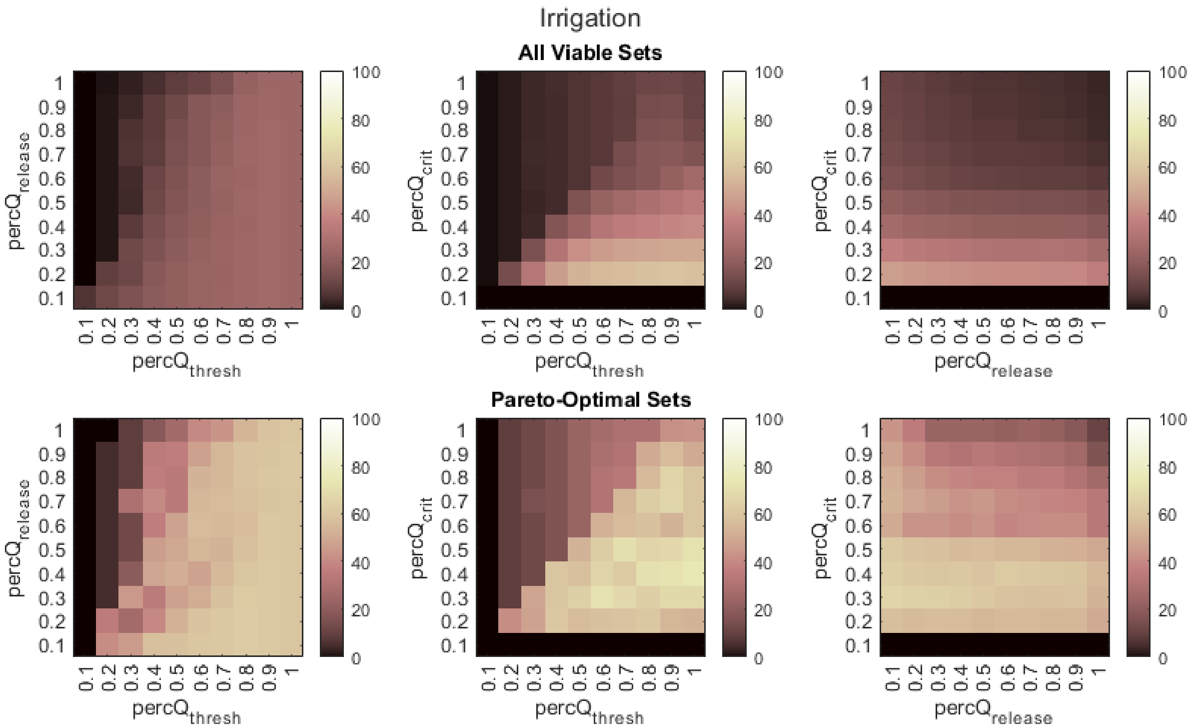

Figure A2. Average streamflow benefit of each parameter combination.

7 Code and Data Availability

The data and MATLAB scripts developed to run these models—along with a detailed documentation package—can be downloaded at doi:10.5281/zenodo.17183389.

8 Author Contribution

SQH and UE conceived and designed the methodology and reservoir models, which was coded, implemented, and executed by SQH. SQH wrote the initial draft of the paper with assistance from RL. RL produced the forecast data for the analysis and contributed to the improvement of the paper. Data analysis was performed by SQH, with input and guidance from UE. UE supervised the research and contributed to the improvement of the paper.

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9 Competing Interests

The authors declare that they have no conflict of interest.

10 Acknowledgements

We would like to thank our colleagues Chantal Kipp and Dr. Gabriel Fink at the Landesanstalt für Umwelt Baden-Württemberg and Dr. Ingo Haag at HYDRON for their support. Finally, we would like to thank the people of Baden-Württemberg who, through their taxes, provided the basis for this research.

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Preprint. Discussion started: 28 October 2025

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