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The Value of Subseasonal Hydrometeorological Forecasts to Hydropower Operations: How Much Does Preprocessing Matter?

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Key Points:
- We jointly assess quality and value of subseasonal hydrometeorological forecasts for hydropower operations
- Using a preprocessing technique (in our case quantile mapping) is essential to improve both forecast quality and value
- The relationship between forecast quality and value is complex and strongly depends on the season and the metrics used to assess quality and value

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Abstract The quality of the forecasts, that is, the accuracy in predicting the observed streamflow, affects the decisions that can be taken thus determining the success or failure of hydropower operations, that is, the so-called forecast value. Although preprocessing techniques can be employed to improve forecast quality, the corresponding improvement in forecast value to hydropower is not straightforward to anticipate because of the complex relationship between quality and value, which depends on the hydrometeorological regime and water system features. The objective of this paper is to demonstrate the value to hydropower reservoir operations of preprocessed (i.e., bias corrected and downscaled) subseasonal forecasts and to compare the forecast quality and value across and within seasons. We use the forecast ensembles provided by the European Center for Medium-Range Weather Forecasts (ECMWF). We assess forecast quality in terms of bias, Continuous Ranked Probability Score (CRPS), and Continuous Ranked Probability Skill Score (CRPSS), and forecast value in terms of mean revenue and avoided unproductive spill. We consider daily subseasonal hydrometeorological forecasts covering lead times up to 1 month and a quantile mapping technique to preprocess the hydrometeorological forecasts. Forecasts are then used in a rolling horizon set up to optimize hydropower operations of the Verzasca hydropower system in the Alps (CH). Results show that preprocessing is essential to improve both forecast quality and value. Although hydropower reservoir operations benefit from considering forecasts all the yearlong, the relationship between forecast quality and value is complex and strongly depends on the metrics used to assess forecast quality and value and on the season.

1. Introduction

The ability of forecasting hydrometeorological variability has increased in recent years due to advancement in understanding of hydrometeorological processes, growing availability of observations (in particular due to remote sensing), the increase of computational power, and the associated development of high quality computer-based forecasting systems (Boughton & Droop, 2003). The improved forecasting capabilities have favored the use of meteorological and hydrological forecasts in many sectors, including water management.

Different research initiatives focus nowadays on the subseasonal time horizon for hydrometeorological forecasts (Hao et al., 2018; Robertson et al., 2015; Vitart et al., 2017; Vitart & Robertson, 2018; Yuan et al., 2015). Subseasonal forecasts are usually generated at weekly or biweekly intervals on lead times up to 5 weeks and cover the poorly investigated forecast horizon between the short- and medium-range weather forecast, that is, up to approximately 14 days lead time, and seasonal outlooks, that is, up to 12 months. The main challenge of using subseasonal hydrometeorological forecasts for specific water management applications is that the forecasts are usually provided at coarse spatial resolution (e.g., larger than 50 km) and often exhibit model specific biases (e.g., Bogner et al., 2018; Cloke & Pappenberger, 2009; White et al., 2017).

Various techniques can be applied to downscale hydrometeorological forecasts, thus enhancing their spatial resolution, and to bias correct them (e.g., Li et al., 2017). By *hydrometeorological forecasts* we mean forecast generated by the combination of a numerical weather prediction model and a hydrological model. From a hydrological perspective, the forecasts can be *preprocessed*, if the processing techniques are applied to the meteorological forecasts, or *postprocessed*, if the processing techniques are applied to the hydrological forecasts. In both cases, they are meant to minimize differences between the model outputs and the corresponding observations.

Many studies show that such preprocessing techniques can enhance the performance of short- to medium-range forecasts over Europe (Crochemore et al., 2016; Greuell et al., 2018; Lucatero et al., 2018a). For example, Crochemore et al. (2016) show the importance of preprocessing precipitation forecasts to enhance the forecast quality of runoff predictions for different catchments in France. Hegdahl et al. (2019) emphasize the importance of preprocessing temperature for catchments with seasonal snow cover in Norway. Similarly, recently published studies suggest that the performance of hydrometeorological predictions on the subseasonal time scale can be increased by preprocessing in different regions even if the performance of the forecasts as well as the effect of preprocessing highly depends on the catchment characteristics and location (e.g., Meissner et al., 2017; Shah et al., 2017; Schepen et al., 2018; Tian et al., 2017). Traditionally, forecasting systems are assessed in terms of forecast quality (or forecast skill), that is, how well they are able to anticipate hydrological conditions (e.g., Murphy, 1993). When forecasts are used to support water management, though, they should also be assessed in terms of forecast value, that is, in terms of how much they help to make better decisions (e.g., Anghileri et al., 2016; Turner et al., 2017; Weijs et al., 2010). The intuitive assumption that higher skill always leads to improved decisions has been disproved by studies in several different sectors, for example, for water management related to agricultural and health decision making (e.g., Chiew et al., 2003; Goddard et al., 2010). Indeed, depending on the application, the sensitivity of forecast value to forecast errors can be small, meaning that improved forecast quality does not necessarily mean improved forecast value. Therefore, it is of utmost importance to assess forecast quality and value together. In fact, while exhibiting a high forecast quality is important for the reliability of the forecasts, exhibiting a high value is fundamental to promote the use of forecasts in real-world applications by decision-makers and end-users (Block, 2011; Watkins & Wei, 2008; Whateley et al., 2014).

While a considerable research effort has been made to develop procedures to thoroughly assess the quality of hydrometeorological forecasts and quantify their uncertainty (e.g., Schaake et al., 2007; Laio & Tamea, 2007; Rossa et al., 2011; Sheffield et al., 2013), forecast value has not been investigated as thoroughly. Most of the studies focus on the value of forecasts on relatively short forecast horizons for flood control (e.g., Breckpot et al., 2013; Ficchì et al., 2016; Galelli et al., 2014; Wang et al., 2012). At a longer time scale and focusing specifically on hydropower operations, several authors assessed the economic value associated to using forecasts for improving reservoir operations. Hamlet et al. (2002) assessed the economic value of streamflow forecasts based on El Niño/Southern Oscillation (ENSO) and the Pacific Decadal Oscillation (PDO) to a series of hydropower reservoirs on the Columbia River (USA). Yao and Georgakakos (2001) compared a traditional management system to an adaptive forecast-decision system, which includes inflow forecasts and a multireservoir system operated for hydropower production and flood protection in California. Block (2011) analyzed the benefit of specifically tailored forecast for hydropower operations in the upper Blue Nile basin (Ethiopia) particularly focusing on the sensitivity of the hydropower performance on different forecast errors. Arsenault and Côté (2018) quantified the effects of forecast biases on Ensemble Streamflow Prediction (ESP) using different deterministic optimization methods to design the operations of a multireservoir hydropower scheme in Quebec (Canada). Boucher et al. (2012) analyzed the improvement in hydropower operations on the Gatineau River (Canada) achievable by using streamflow forecasts from an operational point of view. These works show that a combination of high quality forecasts and flexible decision making systems are key to increase the productivity and the economic value of hydropower systems around the world.

In this paper, we jointly assess quality and value of subseasonal hydrometeorological forecasts to improve the operations of an existing storage hydropower system in an Alpine region characterized by complex orography and mixed rain-snow-dominated hydrological regime. In particular, we focus on the role of quantile mapping (QM) as preprocessing technique for meteorological forecasts by comparing raw (i.e., non preprocessed) and preprocessed forecasts to quantify the improvements that preprocessing induces in terms of both hydrometeorological forecast quality and value across and within different seasons. The specific research questions are as follows:

- how much can preprocessing improve the quality of subseasonal hydrometeorological forecasts in an Alpine catchment characterized by complex terrain?

- what is the value of preprocessing to hydropower operations?
- in which conditions does an improvement in forecast quality translate into an improvement in forecast value?

We build a forecast-based adaptive management framework, which integrates hydrometeorological forecast and hydropower system optimization. The meteorological forecasts are a subseasonal meteorological forecast ensemble provided by the European Center for Medium-Range Weather Forecasts (ECMWF) with a spatial resolution of 50 km^2 and daily temporal resolution. Similarly to Monhart et al. (2019), the meteorological forecasts are preprocessed using QM with the double purpose of reducing the forecast errors (bias correction) and enhancing the spatial resolution (downscaling to 2-km × 2-km spatial resolution) to serve as input to the distributed Precipitation-Runoff-Evapotranspiration-Hydrotope (PREVAH) hydrological model. Finally, the hydrological forecasts are included into an optimal control problem to design the hydropower reservoir operations which guarantee the maximum hydropower revenue. Both the forecasts and the optimal release sequence are produced using a rolling horizon scheme characterized by a daily time resolution, a 1-month-long horizon, and a weekly update. Similarly to the framework proposed in Anghileri et al. (2016), we assess the value of the raw and preprocessed forecasts by comparing the performance of the hydropower system operations to lower and upper bound performances, corresponding, respectively, to using the climatological forecast (i.e., historical streamflow climatology) and the perfect forecast (i.e., hydrological simulation using observed meteorological data) into the optimization scheme.

The forecast-based adaptive management framework is tested on a real-world case study, the Verzasca hydropower system on the Swiss Alps. Subseasonal hydrometeorological forecasting is particularly challenging in this region because of the complex orography and the weaker effect of teleconnection patterns (e.g., the North Atlantic Oscillation) that influence the weather in the Europe (e.g., Domeisen et al., 2018) as for example compared to the El Niño/Southern Oscillation phenomenon in the tropics (e.g., Tang et al., 2018). Such teleconnection patterns are influenced by the sea surface temperature, the stratosphere dynamics, and the sea ice concentration, which are the main sources of predictability at the subseasonal to seasonal time scale. The Verzasca catchment is a mountainous and glacier-free catchment with highly varying runoff characteristics between seasons. During winter the precipitation is stored in the catchment as snow leading to reduced runoff. In contrast, precipitation in late summer to autumn directly contributes to runoff generation. Snow melt in spring and summer can further enhance the precipitation-driven runoff peaks. Because the processes generating runoff are different depending on the season, the quality of the hydrometeorological forecasts can significantly differ within the year. As a consequence, also the effect of the preprocessing can be different depending on the season (e.g., Monhart et al., 2019). The Verzasca hydropower system is composed of a regulated reservoir feeding a power plant. Because of the relative large streamflow volumes originated in spring by snow melt and in autumn by rain storms, the anticipation of streamflow peaks is critical for the hydropower system management, especially to minimize unproductive spills and maximize the electricity revenue.

The novelty of the paper consists in (i) the integration of existing models and approaches to demonstrate the economic value to hydropower reservoir operations of using hydrological forecasts which are based on bias corrected and downscaled subseasonal meteorological forecasts and (ii) the comparison between the improvements of forecast quality and value across and within seasons. Hence, we first provide a verification of the of preprocessed hydrometeological forecasts against hydropower reservoir inflow to assess their quality and, in a second step, their economic benefit thus quantifying the forecast value for the hydropower operations.

The paper is organized as follows. Section 2 describes in detail the forecast-based adaptive management framework. Section 3 describes the design of the experiments and the metrics used to assess forecast quality and value. Section 4 describes the hydropower system used to demonstrate the approach. Section 5 presents the results in terms of forecast quality and value and their relationship. Finally, section 6 summarizes the main contribution of the paper, discusses the limitations, and recommends directions for future work.

2. Methods

We use the forecast-based adaptive management framework shown in Figure 1. It is composed of (i) a numerical weather prediction model which provides meteorological (raw) forecasts, (ii) a preprocessing which downscales and bias corrects the raw forecasts, thus obtaining preprocessed meteorological forecasts, (iii) a hydrological model which produces streamflow forecasts, and (iv) a hydropower system optimization

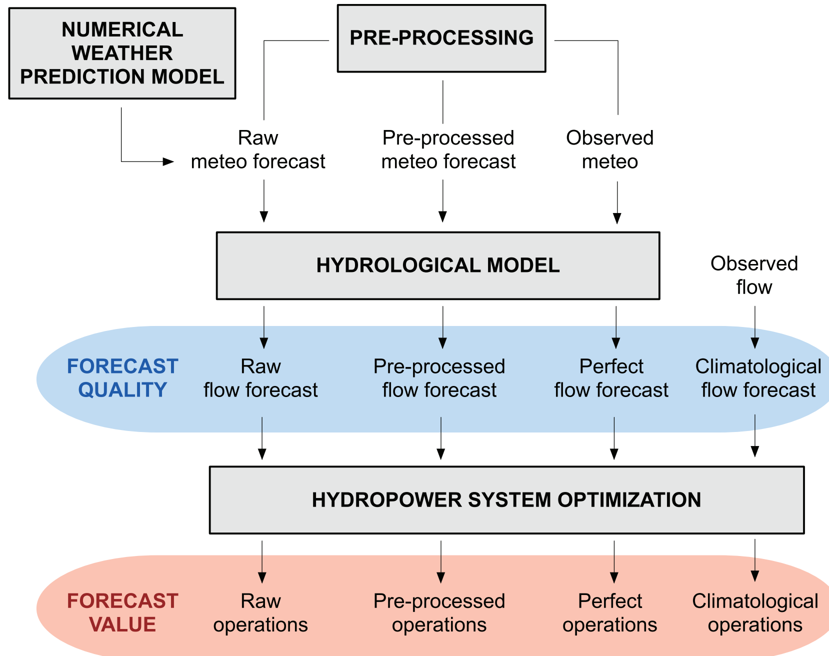

Figure 1. Forecast-based adaptive management framework composed of a numerical weather prediction model, preprocessing, a hydrological model, and a hydropower system optimization scheme. The experimental setting consists of four experiments which are based on two forecasts, raw (i.e., non preprocessed) and preprocessed forecasts, and two benchmarks including climatological forecasts (i.e., historical streamflow climatology) and perfect forecasts (i.e., hydrological simulations using observed meteorological data).

scheme which defines the optimal operations of the hydropower system. These modeling steps are described in detail in the following sections. The modeling choices we undertake in this work are meant to resemble the actual behavior of the hydropower operator, as we aim at demonstrating the value of subseasonal forecasts for practical water management applications.

2.1. Numerical Weather Prediction Model

We use the forecasts from the extended-range (i.e., subseasonal) Integrated Forecast System (IFS) provided by the European Center for Medium-Range Weather Forecasts (ECMWF). In particular, we use the output of the IFS model version CY40r1 that was operational from November 2013 to May 2015 (see ECMWF (2014) for the documentation of the specific model version). Along with the forecasts issued in the period 2013–2015, the IFS CY40r1 provides subseasonal ensemble reforecasts (i.e., retrospective forecasts for the period 1994–2015 that are generated with the same forecast system settings, that is, the same resolution, parametrizations, etc.) with five members, covering 32 days lead time, and issued every week. The forecasts and reforecasts have a spatial resolution of 50 km^2 and daily temporal resolution. A general description of the forecast system can be found in Vitart (2004) and Vitart et al. (2014).

In this work, we only use the reforecast on the period 2000–2014, because this is the period when the data concerning the hydropower system are available (see section 4). It is worth mentioning that this data set is unique because this model version was operational for more than a year, thus ensuring a proper comparison of the forecast quality across different seasons. Furthermore, using the reforecasts (and not the forecasts which are only available for one single year) ensures that we account for the year-to-year variability of specific weather patterns when computing the forecast quality and value. In the following sections of the manuscript, the term forecasts is used to refer to the reforecasts.

2.2. Preprocessing

The raw meteorological forecasts are preprocessed with the twofold purpose to reduce errors in the forecasts (bias correction) and to enhance their spatial resolution (downscaling). We apply an empirical QM technique, a simple and widely used technique for forecast preprocessing (e.g., Kang et al., 2010; Lucatero et al., 2018b; Verkade et al., 2013). The basic principle of the QM technique is to correct a given forecast so that the quantiles of the empirical cumulative distribution function (cdf) of the forecasts match the quantiles of the cdf of the historical observations. In particular, we use the methodologies presented in Monhart et al. (2018) and Monhart et al. (2019). They analyze respectively the effect of preprocessing from the meteorological perspective and from a hydrological perspective focusing on several catchments in Europe and in Switzerland.

Monhart et al. (2018) apply the framework on a wide data set comprising 1,637 surface meteorological observations over the European continent to determine the quality of the raw and preprocessed temperature and precipitation forecasts. Their results clearly show that preprocessing leads to improvements in the quality of subseasonal temperature and precipitation forecasts from a meteorological perspective. The improvement in forecast quality is especially relevant in areas characterized by complex terrain where the meteorological variables are impacted by local effects induced by the orography. Monhart et al. (2019) discuss the relative effect of preprocessing either temperature or precipitation only, showing that preprocessing both is essential to obtain high quality streamflow forecasts. Building from the results of these two studies, the focus of this paper is to analyze the effect of preprocessing for operational use for a specific hydropower system.

We use a gridded observational data set of 2-km × 2-km spatial resolution and daily temporal resolution from the Federal Office for Meteorology and Climatology (MeteoSwiss) to derive the cdf of the observed temperature and precipitation (Frei, 2014; Isotta et al., 2015; MeteoSwiss, 2016a, 2016b). Each forecast is corrected in a leave-one-year-out cross-calibration framework using the QM method to avoid introducing artificial skill in the forecasts. We preprocess the forecasts by applying a lead time and season dependent QM correction. The cdf of the forecast is computed from the data within a 7-day window centered around the value to be corrected, and the first 7 days of the previous and subsequent forecasts to obtain a larger data set (composed of a total of 21 days). The cdf of the observations is computed from the observed flow within a 21-day window centered around the day to be corrected.

We preprocess both temperature and precipitation, while the additional variables needed to drive the hydrological model (i.e., relative humidity, sunshine duration, surface albedo, and solar radiation, as detailed in section 2.3) are not preprocessed. Although these variables could benefit from a preprocessing step as well, we would require observations at high resolution and of good quality which are not available. Temperature and precipitation are also the key drivers of the hydrologic response in the considered Alpine region and their observations are available with temporal and spatial resolutions required by hydrological modeling. In addition, the effect of preprocessing temperature and precipitation on the quality and the value of subseasonal forecasts is still largely unknown and thus worth analyzing on its own.

2.3. Hydrological Model

We use a distributed version of the Precipitation-Runoff-Evapotranspiration-Hydrotope (PREVAH) model to produce the hydrological forecasts with a spatial resolution of 200-m × 200-m. The PREVAH model is a hydrological model specifically designed to capture hydrological processes that are important for catchments in complex terrain. The conceptual process-based approach of PREVAH represents relevant processes such interception, evapotranspiration, runoff and baseflow generation, groundwater, and, most importantly for Alpine regions, snow accumulation and snow melt. It takes precipitation, temperature, and additional meteorological variables, such as relative humidity, sunshine duration, surface albedo, and solar radiation, as input. The description of the original lumped model is included in Gurtz et al. (1999), Viviroli, Zappa, Schwanbeck, et al. (2009) and Zappa et al. (2003), while the extension to the fully distributed model used in this work is described in Speich et al. (2015) and Schattan et al. (2013). The model configuration specifically used in this work is described in detail by Orth et al. (2015) and Monhart et al. (2019).

We first run the model over the period 1991–2015 (including a spin-up time of 3 years) using observed meteorological variables as inputs. This run has a twofold purpose. First, it serves as perfect forecast in the experimental setting as further detailed in section 3. Second, it provides the initial conditions when the hydrological model is run in forecast mode using meteorological forecasts as input. In both cases, the input variables are downscaled to the 200-m × 200-m resolution of the hydological model by applying an interpolation based on inverse distance weighting as described in Viviroli, Zappa, Gurtz, et al. (2009). In addition, different height and terrain specific corrections are applied to the input variables, such as adiabatic lapse rate correction, aspect and slope corrections as described in Zappa et al. (2003). Similarly to many other distributed hydrological models, these corrections are computed internally to PREVAH as they depend on the model spatial resolution. They are particularly important to represent the hydrometeorological dynamics in catchments characterized by complex terrain, such as in Alpine environments, but they are intrinsically different from the statistical preprocessing we adopt for the temperature and precipitation forecasts.

2.4. Hydropower System Optimization

We adopt a Model Predictive Control (MPC) scheme where we define and solve a series of optimal control problems defined on a rolling horizon given a certain time series of forecasted reservoir inflow. The utility (or objective) function of each control problem has the form

$$\max_{r_{t+1},\dots,r_{t+H}} \left(\frac{1}{H} \sum_{\tau=t}^{t+H-1} U_\tau(s_\tau, r_{\tau+1}, a_{\tau+1}) + U^*_{(t+H) \bmod T}(s_{t+H}) \right) \tag{1}$$

and is based on the computation of the hydropower revenue $U_\tau(\cdot)$. The decision variables are the sequence of reservoir releases r_t at every time step within the optimization horizon. The length H of the optimization horizon corresponds to the length of the hydrometeorological forecast horizon, that is, 32 days. s_τ and $a_{\tau+1}$ are the reservoir storage and inflow, respectively. In this work, we compute the daily revenue [euro] by allocating the hydropower production in the most profitable hours of each day as follows

$$U_{t+1} = \sum_{j=0}^{n_{t+1}} \theta^j_{t \bmod T} G_{t+1} \tag{2}$$

where $\theta^j_{t \bmod T}$ [euro/MWh] is the spot price in the jth most profitable hour of day t and n_{t+1} [-] and G_{t+1} [MWh] are the daily number of hours in which the power plant is operated at full capacity and the electricity production, respectively (for more details see Anghileri, Botter, et al., 2018). The maximization of the revenue is a typical objective function adopted to represent the utility of a private company selling electricity in deregulated markets (see, e.g., Kern et al., 2012; Anghileri, Castelletti, et al., 2018). We assume that the electricity produced by the hydropower plant is sold on the electricity spot market (see section 6 for a discussion on the implications of this assumption). In order to avoid a premature emptying of the reservoir because of the finite and relatively short length of the optimization horizon H, the objective function accounts for a so-called penalty function $U^*_{(t+H) \bmod T}(s_{t+H})$. This represents the revenue that can be expected on average given a certain time $(t + H) \bmod T$ and a certain reservoir storage s_{t+H}. In our formulation, it expresses the benefit associated to keeping a certain water volume in the reservoir at the end of the rolling horizon. The notation $t \bmod T$ indicates the remainder of the division of the time t by the period T. In our case, T equals 364 days to account for the annual periodicity of the hydrometeorological processes and of the electricity price. In so doing, for example, the first Monday of each year is characterized by the same electricity price and penalty function and so on. More details on the penalty function are described toward the end of this section.

The constraints of the control problem include the storage mass balance equation

$$s_{t+1} = s_t + a_{t+1} - r_{t+1} \quad \forall t \in [0, 1, \dots, H] \tag{3}$$

where s_t [m^3] represents the reservoir storage at time t [day] and a_{t+1} [m^3] and r_{t+1} [m^3] are the inflow to the reservoir and the release from the reservoir occurring from t to $t+1$, respectively. The inflow is described as a deterministic time trajectory over the optimization horizon

$$a_{t+1} \quad \text{given} \quad \forall t \in [0, 1, \dots, H] \tag{4}$$

Depending on the experiment, it corresponds to a specific hydrological forecast (see Figure 1 and section 3 for more details).

The electricity spot price is modeled as a periodic deterministic trajectory

$$\theta^j_{t \bmod T} \quad \text{given} \quad \forall t \bmod T \in [0, 1, \dots, 364] \tag{5}$$

which is computed as a cyclostationary average from historical observations of the electricity price. The electricity price is thus the same for each first Monday in January, etc. In so doing we maintain the weekly and yearly periodicity typical of the electricity price. Accordingly with the objective of the paper, we intentionally do not consider electricity price forecasts to focus on the value of the hydrological forecasts only.

The reservoir release is bounded by the minimum and maximum feasible releases, which are defined as functions of the reservoir storage through the specific reservoir release-stage relationships

$$R_{t+1}^{\min}(s_t) \leq r_{t+1} \leq R_{t+1}^{\max}(s_t) \quad \forall t \in H \tag{6}$$

The definitions of the functions $R_{t+1}^{\min}\cdot$ and $R_{t+1}^{\max}\cdot$ account for the physical reservoir characteristics, thereby including intake, outlet, and spillway characteristics.

The penalty function $U^*_{t \bmod T}(\cdot)$ is computed by solving an additional stochastic optimization problem, similar to the one just described, where the reservoir inflow is not described as a deterministic trajectory, but as a sequence of lognormal probability distribution functions computed from the historical data. In this case, the optimal reservoir release sequence is the one which maximizes the expected average revenue over an infinite optimization horizon (see Anghileri et al., 2013; Castelletti et al., 2008; Soncini-Sessa et al., 2007). The function $U^*_{t \bmod T}(s_{t \bmod T})$ represents thus the revenue that can be expected on average given a certain time $t \bmod T$ and a certain reservoir storage $s_{t \bmod T}$.

We solve the optimization problem using Dynamic Programming using 38 and 26 discretization grid points for the storage and the release decision, respectively. The release discretization points are uniformly distributed between the minimum and maximum release. The storage discretization points are instead unevenly distributed between the minimum and maximum storage, with a more frequent sampling toward the maximum storage to allow for a more detailed and accurate representation of the storage dynamics in case spilling event would take place during the optimization and simulation. As we will discuss in section 6, an accurate representation of these events is critical to assess the forecast value.

3. Experimental Setting and Performance Metrics

We consider four different experiments in the present analysis (see Figure 1) where both the hydrometeorological forecasts and the optimal hydropower reservoir operations are produced at a daily temporal resolution, over a rolling horizon of 32 days, and updated weekly. Two experiments correspond to using raw and preprocessed hydrological forecasts to inform the hydropower reservoir operations. In order to match the ensemble forecasts and the deterministic optimization scheme (see section 2.4), we compute the median of the streamflow forecasts based on the cumulative flow. More precisely, (i) we compute the cumulative flow of each of the five ensemble members, (ii) we compute the median of the cumulative flows of the five ensemble members, and (iii) we reconstruct the median (non cumulative) trajectory to be used as input to the optimization (i.e., daily streamflow for each lead time) as the difference between consecutive days. Compared to the median computed directly from the (non cumulative) streamflow forecasts, this allows to better capture the variance of the ensemble, avoiding that large streamflow events forecasted in an individual ensemble member are excessively smoothed out. We acknowledge, however, that reservoir operation performances could increase when considering the entire ensemble within a probabilistic optimization approach (see, e.g., Boucher et al., 2012; Fan et al., 2016; Ficchí et al., 2016; Zhao et al., 2012). Nevertheless, we adopt the deterministic optimization approach described in section 2.4 because this is similar to the way most of the hydropower companies use hydrological forecasts in every day practice (Arsenault & Côté, 2018). We will further discuss the implications of selecting a deterministic optimization scheme in the concluding remarks (see Section 6).

The other two experiments correspond to benchmarks which are used to assess the forecast value. The perfect forecast is obtained by forcing the observed meteorological variables into the PREVAH hydrological model. This experiment represents the case in which the hydrometeorological forecasts have the highest quality and should drive to the highest hydropower performance. As such, this could be considered as an upper bound of the hydropower system performance. The climatological forecast, on the other hand, represents the lower bound performance, because the inflows are the median of the observed inflows over the period of analysis 2000–2014. To be consistent with the other experiments, the median is computed on the cumulative flows. Although Ensemble Streamflow Prediction (ESP) forecasts are a lower bound benchmark often used in the literature (e.g., Arsenault & Côté, 2018), we prefer to use the streamflow climatology because this is the most elementary piece of information that can be used to inform the operations of the hydropower system and actually the most used by the Swiss hydropower operators.

The quality of the forecasts is assessed in terms of (i) bias (i.e., the mean error) to assess systematic errors of the forecasts, (ii) Continuous Ranked Probability Score (CRPS) to assess the difference between the cdf of the forecasts and observations, and (iii) Continuous Ranked Probability Skill Score (CRPSS) to assess if the forecasts outperform a forecast based on climatology. The bias is defined as the difference between the ensemble mean of the forecasts and the corresponding observations and thus describes the systematic errors of the forecasts. The CRPS is a probabilistic verification score and takes into account the full ensemble, that is, the forecast spread and the forecast error, to assess how well the forecasts agree with the observations (Hersbach, 2000). The CRPS ranges from 0 to ∞ where a perfect forecast exhibits a CRPS equal to 0. The CRPSS compares the CRPS of a given forecast with the CRPS of a benchmark forecast and thus indicates to what degree the forecast under consideration outperforms the benchmark forecast. In our analysis, we use the climatology as benchmark forecast. More precisely, we treat each year of the observations in the period 2000–2014 for a given forecast date (and the subsequent 32 days to cover all lead times) as a climatological member to calculate the CRPS of the benchmark forecast. The CRPSS ranges from $-\infty$ to 1 with 1 being a perfect forecast and 0 indicating that the forecast under consideration is as good as the climatological benchmark forecast. Negative CRPSS indicate that the forecast is worse than the climatological benchmark forecast. Further technical details on the performance metrics can be found in Wilks (2011), Jolliffe and Stephenson (2012). It has been shown that the CRPS of an ensemble forecast depends on the size of the ensemble. To account for this effect, we use the framework of fair (i.e., de-bias) scores proposed by Müller et al. (2005) and Ferro (2014). The bias and the CRPS are computed individually for each forecast and lead time. These values are then averaged over all forecasts within the given season and the CRPSS is computed based on the average CRPS. For a thorough assessment of the forecast quality additional metrics could be taken into account (see, e.g., Monhart et al., 2019). As the main objective of this publication is to assess the value of the forecast for hydropower reservoir operations and how the forecast quality transfers into forecast value, we restrict the verification in this manuscript to the bias, the CRPS, and the CRPSS, which are all representative and meaningful characteristics to describe the forecast quality to a broad audience.

We choose two performance metrics to assess the value of forecasts to hydropower operations. These metrics are the spilled water volume (where a high forecast value corresponds to a low spilled water volume) and the revenue (where a high forecast value corresponds to a high revenue). These are the two metrics that the hydropower company takes into consideration when assessing effectiveness and efficiency of their operations. Avoiding spills is one of the priorities for hydropower companies. On the one hand, for a matter of security, on the other hand, spilled water is not turbined thus diminishing the production and the revenue. The two performance metrics are complementary as they are representative of two different management time scales. The reduction of the spill involves relatively short time scales as most of the reservoir inflow peaks can be managed on time scales ranging from hours to few days. The maximization of the revenue, instead, involves longer time scales as interseasonal reservoir management is needed to effectively match the electricity price dynamics which show significant seasonal fluctuations.

Figure 2 represents a sketch of the framework we adopt to analyze the relationship between forecast quality and value. We use the average CRPSS computed over all the lead times of the forecast horizon as metric for the forecast quality (represented on the x axis). As detailed above, a positive CRPSS indicates that the forecasts under consideration outperform the climatology and viceversa. We use either the revenue increase or the spill decrease with respect to the experiment using the climatological forecast as metrics for quantifying the forecast value (represented on the y axis). As for the previous case, a positive value of the metrics indicates that the forecast is more valuable than the climatological forecast for the water management purpose, that is, the hydropower reservoir operations in this case. We can then classify the forecasts according to four categories. Forecasts in the first quadrant (upper right) are better than the climatological forecast in terms of both quality and value. Forecasts in the second quadrant (upper left) are less skillful than the climatological forecast but are still valuable for water management. Forecasts in the third quadrant (lower left) are worse than the climatological forecast as for both quality and value. Forecasts in the forth quadrant (lower right) have better quality than the climatological forecast, but they are not valuable for water management.

4. Case Study

The forecast-based adaptive management framework is applied to the Verzasca hydropower system in Switzerland (Figure 3). The system is composed of a reservoir with a storage capacity of $105 \cdot 10^6$ m^3 which feeds a power plant with an average historical annual production of about 230 GWh. The dam is 220 m high, and the hydraulic head varies between approximately 200 m and 280 m. The installed power is 105 MW.

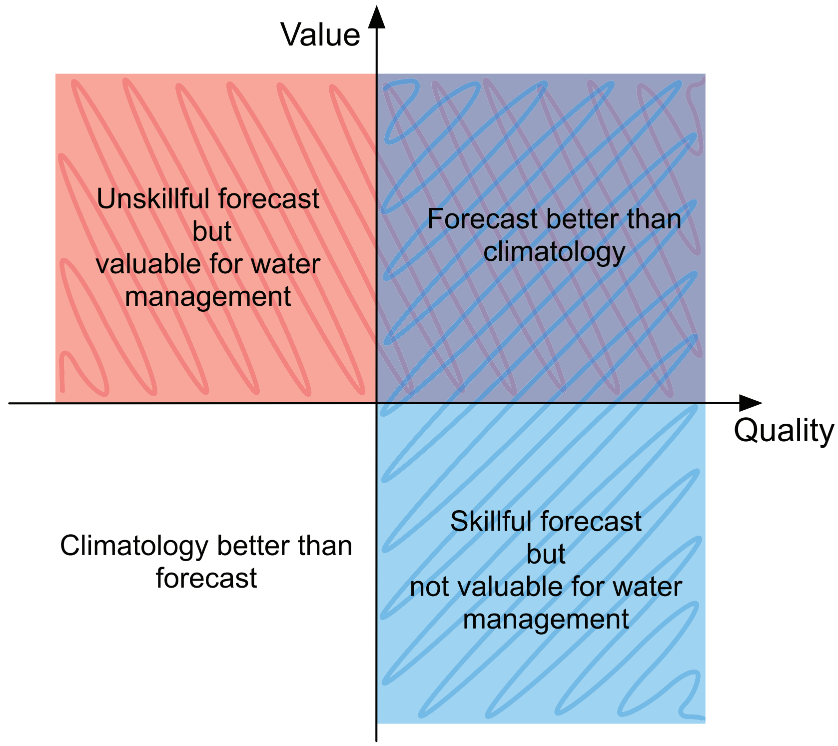

Figure 2. Sketch of the framework we adopt to compare forecast quality and value. Forecasts in the first quadrant (upper right) are better than the climatology in terms of both quality and value for water management. Forecasts in the second quadrant (upper left) are less skillful than climatology but still are valuable for water management. Forecasts in the third quadrant (lower left) are worse than climatology as for either quality and value. Forecasts in the forth quadrant (lower right) are more skillful than climatology, but they are not valuable for water management.

The catchment is located on the Southern Alps and is glacier free. It has a hydrological regime characterized by abundant snow melt in spring and summer (see Figure 3). Winter flows are usually low (less than 5 m^3/s) because most of the precipitation is stored as snow in the catchment (almost 25% of the annual precipitation falls as snow). Autumn may be characterized by intense rainfall events causing high peak flows (up to 120 m^3/s). The reservoir has a capacity-inflow ratio of 0.26, which corresponds to an average storage carry over of approximately 3 months. The capacity-inflow ratio is relatively small if compared to other Alpine hydropower reservoirs, which could go up to 0.9 (e.g., Anghileri et al., 2011; Denaro et al., 2017). The historical operations tend thus to compromise between the storage carryover from flow abundant periods (spring and autumn) to high electricity price periods (usually winter) and flood control to avoid unproductive spill events. Streamflow peaks originated either by intense precipitation events and/or rapid increase in temperature causing rapid snow melt can significantly impact reservoir operations especially in spring and autumn. Because of these events, the reservoir does not have a single draw down and refill cycle but might have more than one. The ability of timely and reliably forecasting these flow peaks is critical for the storage management, so to minimize unproductive spills and maximize the revenue. We will discuss more on these aspects in the next section when analyzing the optimization results.

As already mentioned in section 1, subseasonal hydrometeorological forecasting is particularly challenging in the study area because of the complex orography (the elevation ranges from 490 m to 2,864 m) and the convective precipitation events, which are hardly captured by the meteorological forecast. The numerical weather prediction model, preprocessing, and hydrological model (i.e., steps i to iii of the forecast-based adaptive management framework) follow the methodology described in Monhart et al. (2019). In this work, we take into account the full catchment area drained by the reservoir (233 km^2) and evaluate the forecasts against the net reservoir inflow provided by the hydropower operator for a period of 15 years (2000–2014). This time series, which is used for the forecast quality assessment (see section 5.1), is computed by the inversion of the reservoir mass balance starting from observations of reservoir storage and release. The net

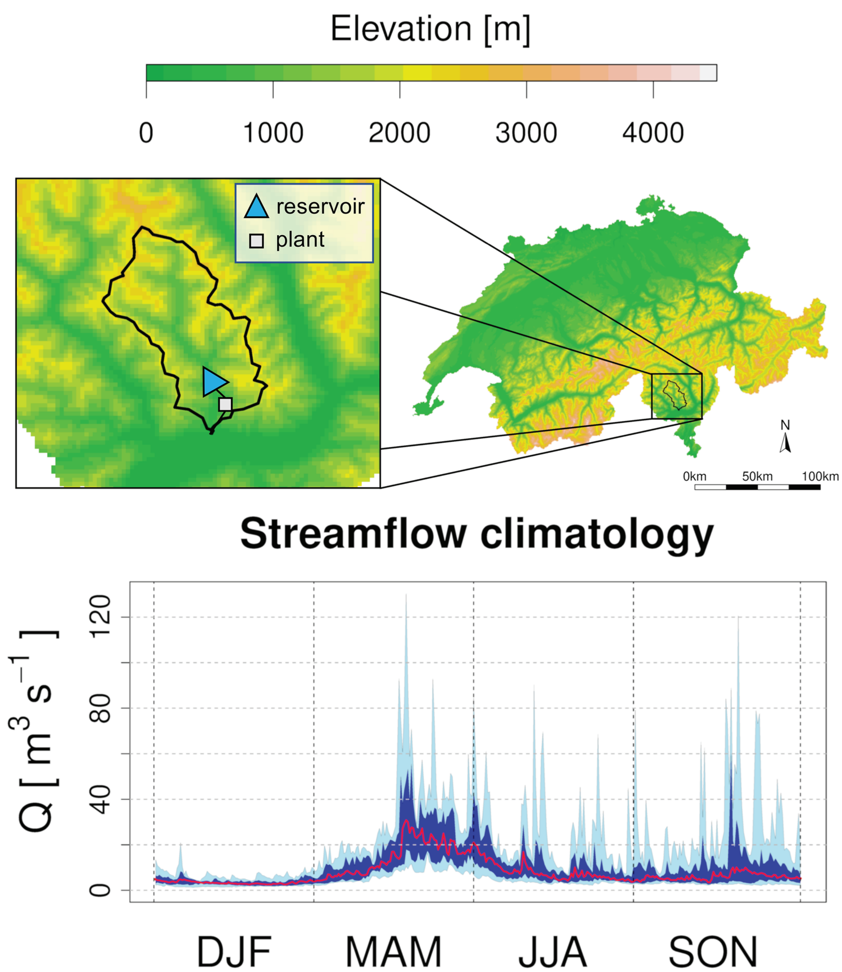

Figure 3. (upper panel) Study area and schemetic of the Verzasca hydropower system. (lower panel) Streamflow climatology (10th, 25th, 50th, 75th, and 90th percentiles).

reservoir inflow computed in this way is very reliable as the observations of reservoir storage and release are not subject to significant measurements errors.

5. Results and Discussion

5.1. Forecast Quality

In this section, we analyze the performances of the streamflow forecasts only, as streamflow is the variable affecting the hydropower system operations more closely. We refer the reader interested into the verification of the meteorological forecasts to Monhart et al. (2018). All streamflow forecasts within the period 2000–2014 are taken into account when computing the forecast quality presented in Figure 4. As mentioned in Section 3, we measure forecast quality in terms of bias, CRPS, and CRPSS. The raw ensemble streamflow forecasts show a general underestimation of the streamflow depicted by a negative bias for all lead times, with higher deviations on longer lead times. The bias is lower in winter (DJF) and summer (JJA) with values above -5 m^3/s and higher in spring (MAM) and autumn (SON) with a bias up to -10 m^3/s . The preprocessed forecasts clearly show a reduction of the bias for all seasons with a tendency to slightly overestimate the flows. The CRPS further emphasizes the importance of preprocessing and the dependence of the forecast quality on the season. The CRPS is below 3 m^3/s for all lead times in winter when low flows dominate in the Verzasca catchment indicating better quality of the forecasts compared to the other seasons. The forecasts in spring and autumn generally exhibit a lower quality with a CRPS around 10 m^3/s . The preprocessed forecasts clearly show an improvement in quality if the full year is considered (reduction of the CRPS by around 3 m^3/s). In summer and winter the improvements are marginal with an improvement in CRPS close

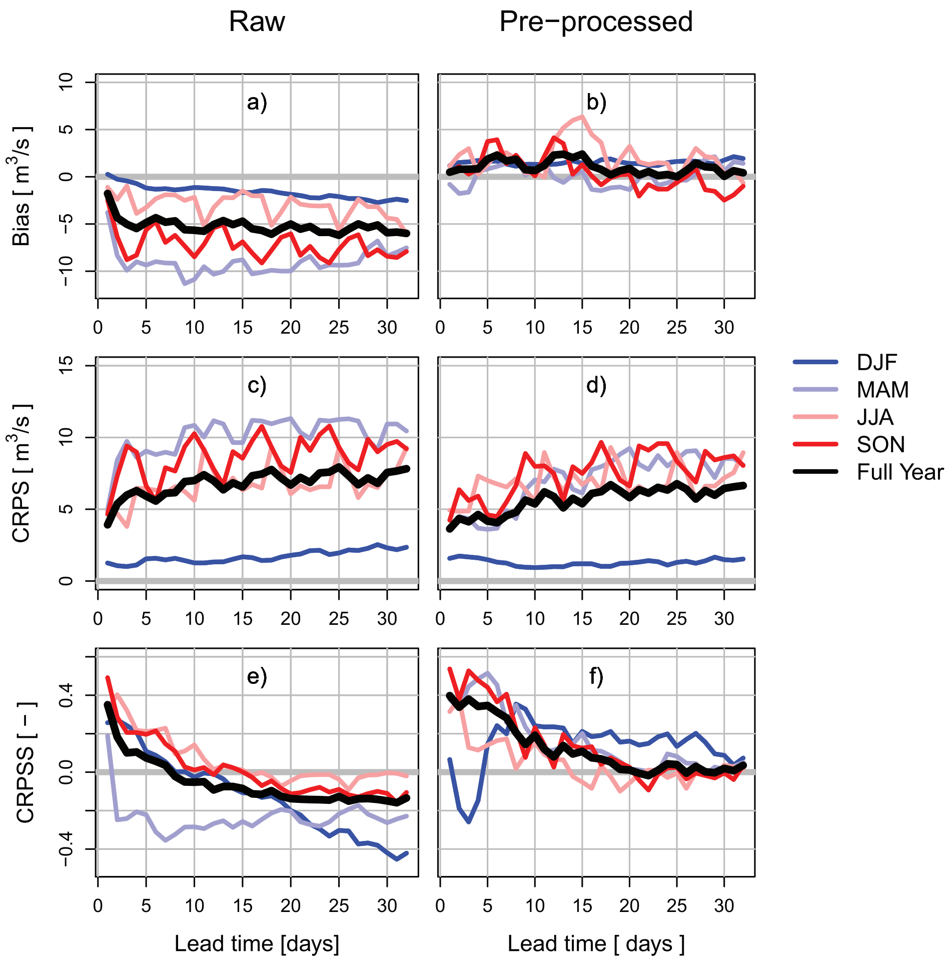

Figure 4. (a) Bias of the raw and preprocessed streamflow forecasts for the full year and the individual seasons, i.e., winter (December–February or DJF), spring (March–May or MAM), summer (June–August or JJA), and autumn (September–November or SON) within the period 2000–2014. (b) Same as in (a) but for the CRPS. (c) Same as in (a) but for the CRPSS. A perfect forecast would have a bias equal to 0, whereas a negative (positive) bias indicates underestimation (overestimation) of the streamflows. Similarly, a perfect forecast exhibits a CRPS equal to 0 with larger values indicating worse performance. A CRPSS equal to 1 indicates a perfect forecast and a CRPSS equal to 0 indicates that the performance is as good as the climatological forecast; negative values indicate that the forecast has less skill than the climatological forecast.

to 0 or even negative for some lead times, whereas spring and autumn show the largest improvements of up to 5 m^3/s.

In terms of the CRPSS, the forecasts clearly benefit from the preprocessing. The raw forecasts are worse than climatological forecasts (i.e., they have a negative CRPSS) after lead time equal to 8 days considering the CRPSS computed over the entire year, whereas the preprocessing allows the forecasts to be more informative than the climatology (i.e., CRPSS is positive) for 20 days. There are large seasonal variations in the CRPSS, as we already commented for the CRPS. In spring, the CRPSS of the raw forecasts suddenly drops below zero within few days lead time, but the CRPSS is positive for up to 20 days lead time after preprocessing. However, preprocessing does not always improve the forecast quality. The CRPSS of the raw forecasts is positive up to 8 days lead time in winter, but the performance reverses after preprocessing: the CRPSS is negative for short lead times and positive for long lead times. Summer shows a similar although weaker behavior. These results are in good agreement with a previous study in the same catchment by Monhart et al. (2019).

The good forecast quality in winter in terms of bias and CRPS can be explained by the independence of the streamflow on the precipitation forecasts. In most parts of the catchment, the precipitation occurs as snowfall and thus does not directly contribute to the runoff. In the other seasons (spring, summer, and autumn),

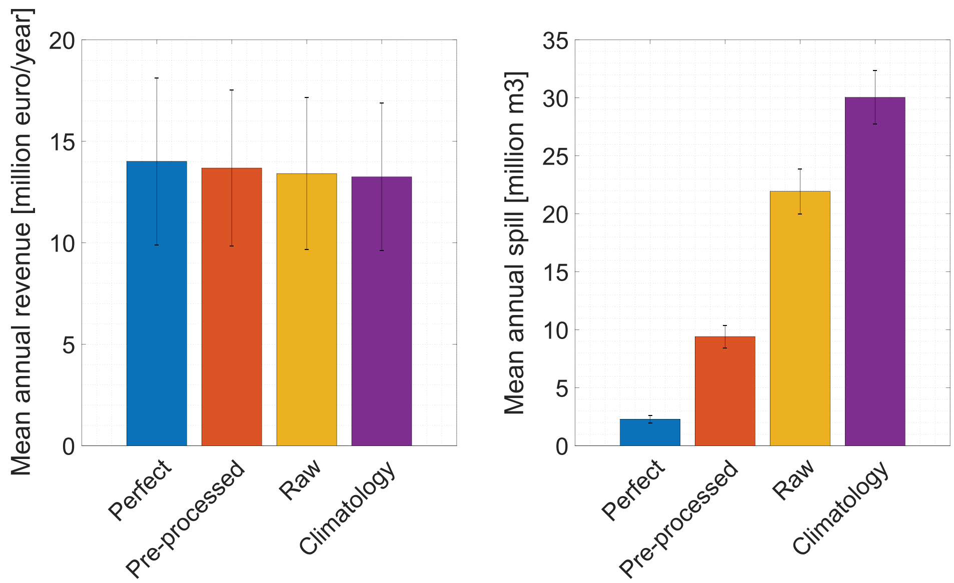

Figure 5. (a) Mean annual revenue and (b) mean annual spilled water volume corresponding to the four experiments computed over the horizon 2000–2014. The error bars represent ± the interannual standard deviation.

precipitation usually falls as rain, thus contributing to runoff directly. Runoff in spring is caused by the combined effect of precipitation and snow melt. Temperature is easier to forecast compared to precipitation and preprocessing does have a larger effect on temperature forecasts. Thus, in seasons when snow melt plays an important role (as in spring and partly in autumn) the quality of the forecasts can be significantly enhanced. In summer, when the streamflow depends mostly on precipitation, the underestimation of the streamflow can be corrected, but the quality in terms of both CRPS and CRPSS is only marginally improved. This can be related to the convective precipitation events in the catchment area which are not captured by the meteorological forecast and, by definition, can not be introduced with the QM technique. Indeed, QM suffers from some limitations, for example, it does not correct the spatial and temporal structures of the corrected time series and may underrepresent variability observed at the small scale (Maraun, 2013). In addition, Zhao et al. (2017) emphasize the inability of QM to provide fully reliable and coherent forecasts, that is, to ensure a full statistical consistency between the forecast and the observation. However, Monhart et al. (2018) suggest that QM, although simple, is a valuable method for bias correcting and downscaling the ECMWF extended-range forecast in an operational context. We will comment more on the suitability of QM for preprocessing in section 6.

The result showing that CRPSS in winter is worse after preprocessing can be explained by few events during the full period of the analysis. These events happen in winter and are characterized by temperature slightly below freezing level at the average catchment elevation in the raw forecasts and above freezing level after preprocessing causing low streamflow forecasts, in the first case, and high streamflow forecasts, in the second case. The observed runoff in these specific events is low than the one forecasted after preprocessing, thus leading to a large CRPS and therefore a low CRPSS. An extensive discussion of these events is included in Monhart et al. (2019).

All the lines in Figure 4 show a periodicity, which is especially evident in summer and autumn. This is an artifact caused by the fact that the forecasts are updated once a week. If an event with high streamflow occurred on a specific date, for example, on 31 April 2012, it would first appear in the score (most prominently in the CRPS) of the forecast issued on 3 April 2012 on lead day 28, it would then appear in the subsequent forecast issued on 10 April 2012 on lead time 21, etc. Hence, the corresponding score for the lead times 28, 21, 14, and 7 could highly deviate from the scores at other lead times. This effect would lead to a weekly cycle in the forecast quality. Similar issues on cycles in forecast verification (from hours to weeks) are reported by several other authors, (e.g., Addor et al., 2011; Bennett et al., 2014; Bogner et al., 2016, 2017).

In general, these results show that it is important to consider different verification measures to describe the performance of an ensemble forecast. In fact, the bias identifies only errors in the mean of the forecast,

Table 1
Forecast Value Measured in Terms of Increase of Revenue With Respect to the Experiment Considering Climatology

	Mean revenue [% increase w.r.t. climatology]				
	DJF	MAM	JJA	SON	Full Year
Perfect	−6.00	6.00	3.57	21.31	5.76
Preprocessed	−10.84	3.45	5.20	15.71	3.28
Raw	2.96	−0.18	1.11	1.22	1.22

Note. The mean values are computed over the entire time series (full year) and over the seasons: winter (December-February or DJF), spring (March-May or MAM), summer (June-August or JJA), and autumn (September-November or SON).

the CRPS and CRPSS do consider the forecast spread as well. For example, preprocessing shows greater improvement on the bias compared to the CRPS and the CRPSS in our case study. Thus, the impact of preprocessing depends on the verification metric used to characterize the performance.

5.2. Forecast Value

We assess the forecast value by computing two performance metrics: the mean annual revenue and the mean annual spilled water volume computed over the optimization horizon 2000–2014. Figure 5a shows the mean annual revenue associated to the different experiments described in section 3 and Figure 1. The difference between the two benchmarks, that is, perfect and climatological forecasts, represents an estimate of the maximum benefit, which can be potentially achieved by the inclusion of the forecasts in the design of the reservoir operations. Perfect forecasts allow on average for a 5.76% increase in the revenue with respect to considering the climatology (see Table 1), which corresponds to approximately 760,000 euros. More than half of this improvement can be obtained by considering the preprocessed forecasts (which allows for an average revenue increase of about 3.28% with respect to the experiment using climatology). Raw forecasts, instead, allow for a small improvement only (1.22% on average with respect to the experiment using climatology). Figure 5b shows the mean annual spilled volume of the different experiments. We obtain a reduction of −92.38% of the mean annual spilled water volume with respect to the climatology when considering the perfect forecast, −68.68% when considering the preprocessed forecast, and −26.98% when considering the raw forecast (see Table 2).

These results show that considering forecasts to inform hydropower operations is extremely beneficial. The reduction of spilled water is indeed key for the reservoir operations safety, on the one hand, and for increasing the production, on the other hand. The increase in revenue is also notable as, generally, hydropower systems are efficiently operated thus making additional improvements difficult to achieve. Our estimate is indeed in line with other works (e.g., Anghileri et al., 2013; Anghileri, Castelletti, et al., 2018; Gaudard et al., 2013), which achieve revenue increases between 2% and 5% by optimizing the operations of Alpine hydropower systems similar to ours (both in terms of the hydropower system configuration and the hydrological regime). The results also highlight that preprocessing is of fundamental importance to enhance the forecast value. The raw forecast experiment is indeed characterized by a systematic underestimation of the

Table 2
Forecast Value Measured in Terms of Reduction of Spilled Water Volume With Respect to the Experiment Considering Climatology

	Mean spill [% reduction w.r.t. climatology]				
	DJF	MAM	JJA	SON	Full Year
Perfect	80.14	100.00	96.65	91.73	92.38
Preprocessed	72.90	99.40	81.66	64.40	68.68
Raw	23.59	−1.09	49.80	23.25	26.98

Note. The mean values are computed over the entire time series (full year) and over the seasons: winter (December-February or DJF), spring (March-May or MAM), summer (June-August or JJA), and autumn (September-November or SON).

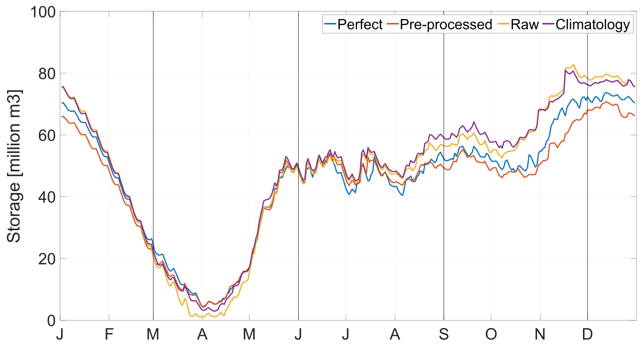

Figure 6. Reservoir storage pattern (50th percentile computed over the horizon 2000–2014 corresponding to the four experiments. The thick vertical lines highlight the extent of the seasons: winter (December-February or DJF), spring (March-May or MAM), summer (June-August or JJA), and autumn (September-November or SON).

reservoir inflows (see Figure 4a). This causes a tendency to underestimate the risk of spilling in the optimization. Indeed, the optimized storage is higher than in the other experiments (see Figure 6), which in turn leads to higher unproductive spill. The preprocessed forecasts allow to correct for the inflow underestimation (see Figure 4b), which results in the optimal operations being more conservative and maintaining a lower storage. Still, the results show that there is room for further improvement, as shown by the performance of the perfect forecast. However, despite the simplicity of the method, the significant gain in value underlines that even simple preprocessing techniques do have a large effect in both forecast quality and forecast value.

It is interesting to note that the benefits of considering the forecasts are more evident when the forecast quality is measured accounting for the reduced spilled volume (Table 2) than the increased revenue (Table 1) in this case study. The two performance metrics are indeed representative of two different management time scales. The mean annual revenue measures how effective the intra-annual storage management is. In fact, electricity prices are generally higher in winter when inflows are low, while water abundant seasons, such as spring and autumn, are characterized by lower prices. The best strategy to maximize the revenue would consist in shifting the use of water from the high flow seasons to the high price season. This is how most of the Alpine reservoirs are operated. However, in the Verzasca system, the relatively small storage capacity with respect to the reservoir inflow allows only for a moderate interseasonal storage carryover. The mean annual spilled water volume measures how effective the storage management is on shorter time scales. In fact, most of the reservoir inflow peaks can be managed on time scales ranging from hours to few days. The subseasonal forecasts adopted in this study are better suited to prevent spill events rather than maximizing revenue because their quality lasts for maximum 3 weeks.

Tables 1 and 2 report also the forecast value computed over the different seasons. Table 2 shows that the percentage improvement of the perfect forecasts is above 80% in all seasons. This means that most of the spill events could be avoided by making use of forecast that are able to properly anticipate the future inflows. The 100% improvement in spring has to be ascribed to the low number of spill events happening in that season because the reservoir storage is usually low (see Figure 6). The percentages in Table 1 are more difficult to interpret, because the maximization of the revenue involves time scales that are usually longer than just a season. The high revenue increase in autumn should be ascribed to the reduction of unproductive spills in that particular season. The revenue obtained using the perfect and the preprocessed forecasts in winter is lower than that obtained using the climatology forecast because the reservoir storage is generally lower, thus reducing the hydraulic head (Figure 6).

5.3. Relationship Between Forecast Quality and Value

Figure 7 shows the relationship between forecast quality and value computed when considering the raw and preprocessed forecasts. The metrics are computed over each season as well as over the entire year (as shown in Tables 1, 2, and 3). The CRPSS is better correlated to the spill reduction (Figure 7b—correlation coefficient equal to 0.89) rather than the revenue improvement (Figure 7a—correlation coefficient equal to 0.12) because, as commented before, the subseasonal forecasts considered in this paper are more informative for the time scale at which the reservoir is operated for reducing unproductive spill. The third quadrant in both plots is always empty meaning that both raw and preprocessed forecasts are always better than the climatological forecast in terms of either quality and value. All the metrics associated to the preprocessed forecasts are located upper right from the raw forecasts meaning that preprocessing is fundamental in improving both forecast quality or value.

In general, forecasts are always useful for the reservoir operations. In fact, the value is generally positive, with the exception of those cases when the revenue is computed over winter (Figure 7a), as commented in the previous section. The raw forecasts are less skillful than the climatological forecast when used in spring, winter, and over the full year, but they have anyhow some value for the hydropower management. The reason is that, although the forecasts are not skillful for most of the lead times, they are skillful at the

Table 3
Average CRPSS Computed Over the Forecast Horizon, That Is, 32 Days Lead Time Corresponding to the Raw and Preprocessed Forecasts

	Average CRPSS[computed over 32 days lead time]				
	DJF	MAM	JJA	SON	Full year
Preprocessed	14.29	15.94	4.83	13.81	12.05
Raw	−12.17	−23.84	6.20	1.02	−5.91

Note. The mean values are computed over the entire time series (full year) and over the seasons: winter (December-February or DJF), spring (March-May or MAM), summer (June-August or JJA), and autumn (September-November or SON).

beginning of the forecast horizon (see Figure 4). The optimization is capable of exploiting this skillful information to improve the reservoir operations. For a deterministic forecast, as the one used in optimization, the CRPS actually reduces to the mean absolute error (MAE). We thus repeated the analysis for the MAE and the corresponding mean absolute error skill score (in analogy to the CRPSS). Although the improvements in forecast quality are lower in terms of the MAE and mean absolute error skill score (MAESS) due to its deterministic character, the main characteristics of the relationship between quality and value remain unchanged (not shown).

The preprocessed forecasts show quite different forecast value in terms of reduced spill (approximately between +64 to +100%) for almost the same forecast quality (approximately between +12 to +16%). We already commented that the 100% improvement achieved in spring is due to the few spill events happening in spring, which can be fully eliminated when informing the reservoir operations with the preprocessed forecasts. Instead, it is interesting to compare the performances associated to summer and autumn. These are the two seasons characterized by the highest number of spill events. The preprocessed forecasts in autumn show higher quality but lower value with respect to the preprocessed forecasts in summer and vice versa. The reason is that the management in autumn is usually more critical because the reservoir storage is higher (see Figure 6). These results suggest that the relationship between quality and value is complex. It depends on both the metric chosen to represent the value and on the season.

6. Conclusions and Outlook

In this paper we assessed how much preprocessing subseasonal forecasts can simultaneously improve the quality and value of hydrometeorological forecasts for hydropower operations. We built a forecast-based adaptive management framework which utilizes IFS CY40r1 subseasonal meteorological forecasts provided

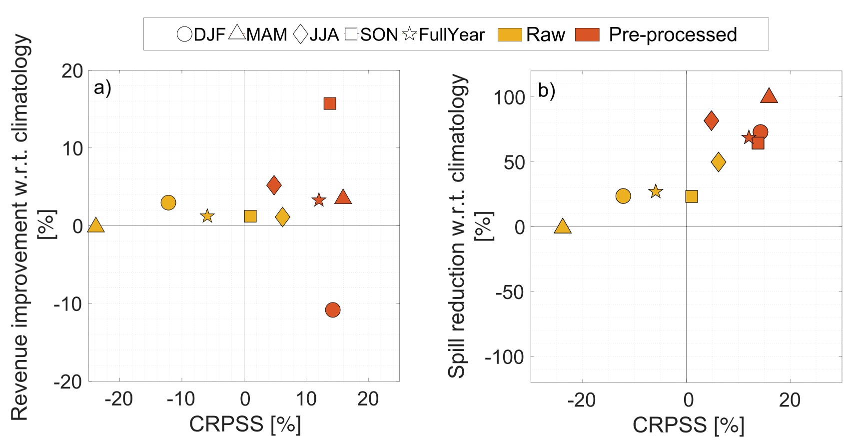

Figure 7. Comparison between forecast quality measured as CRPSS and value measured as (a) revenue improvement and (b) spill reduction with respect to climatology when considering the raw and preprocessed forecasts. The metrics are computed for the full period (full year) and the individual seasons, i.e., winter (December-February or DJF), spring (March-May or MAM), summer (June-August or JJA), and autumn (September-November or SON)) within the period 2000–2014.

by the ECMWF, QM as statistical preprocessing technique for precipitation and temperature, the hydrological model PREVAH to produce streamflow forecasts, and a Model Predictive Control optimization to design the hydropower system operations accordingly. The hydrometeorological forecasts as well as the optimal hydropower reservoir operations are produced at a daily temporal resolution, over a 32 days rolling horizon, and updated weekly. We applied the forecast-based adaptive management framework to the Verzasca hydropower system in the Swiss Alps and assessed the quality and value of the forecasts over the period 2000–2014.

Our results show that raw (i.e., non preprocessed) forecasts have a limited quality, but they are more valuable than the climatological forecast when designing the reservoir operations of the Verzasca hydropower system. Preprocessing clearly improves the quality of the streamflow forecast in terms of all the performance metrics we considered, that is, bias, CRPS, and CRPSS, as well as the value for hydropower operations in terms of increased mean revenue and reduction of unproductive spills. The effect of preprocessing strongly varies across the different seasons. CRPSS ranges from 5% to 16% on average depending on the seasons. Despite these variations, the preprocessed forecasts provide crucial information for improved hydropower operations. In particular, we obtain a reduction of unproductive spills of at least 64% depending on the season. The increase in mean annual revenue is about 3%, which although small is not insignificant and in line with other studies on Alpine hydropower systems (e.g., Anghileri et al., 2013; Anghileri, Castelletti, et al., 2018; Gaudard et al., 2013). When forecast quality and value are analyzed jointly, their relationship appears to be complex and dependent on both the metric chosen to represent the value and the season. For example, the subseasonal forecasts adopted in this study are better suited to prevent spill events because they span over 32 days maximum and because they have quality on 3 weeks at most. They have less impact in increasing the revenue, because this would require a reservoir management over longer lead times (intraseasonal management). Moreover, the relatively small reservoir capacity with respect to the mean annual inflow does not allow for protracted management. Turner et al. (2017) report similar considerations when comparing forecast quality and value for reservoirs operated for water supply and flood control. The results presented so far refer to the entire period of analysis 2000–2014. The effect of preprocessing might change depending on the hydrometeorological regime, for example, in wet years, the benefit of preprocessing might be higher if compared to dry years, due to the potentially higher number of high flow events. Unfortunately, the limited length of the time series (restricted to 15 years) does not allow to make a robust estimate of the effect of preprocessing across years with different regimes (e.g., wet and dry years).

We highlight that the results we obtained in this paper are specific for the Verzasca catchment and should be exported with care to other study sites. Indeed, many studies show that the effect of preprocessing hydrometeorological forecasts highly depends on the catchment characteristics and location (e.g., Meissner et al., 2017; Schepen et al., 2018; Shah et al., 2017; Tian et al., 2017) and that the value of the forecast depends on the water system features, especially on the water management purpose and the reservoir capacity-inflow ratio (e.g., Anghileri et al., 2016; Turner et al., 2017). It is, however, reasonable to expect that other sites in the Alpine environment, with similar characteristics in terms of hydrological regime and reservoir capacity-inflow ratio, would present similar hydrometeorological predictability patterns and reservoir operations dynamics. The general message of the paper, which holds for all these sites, is that the forecast quality and value are crucially enhanced by tailoring forecasts for the specific water management purpose and that hydropower operators should be encouraged to make use of subseasonal preprocessed forecasts. It is also extremely important to use multiple and complementary performance metrics to thoroughly characterize the relationship between forecast quality and value. In particular, to assess forecast value, it is key to adopt metrics that are meaningful to water managers to enhance the potential impact of the analysis.

While showing the unquestionable benefit of implementing forecast-driven reservoir operations, our results show also that there is still room for improvement regarding the hydrological forecast compared to the perfect forecast. Our work suffers from some limitations, which could be overcome in future studies as discussed in the following. The QM cannot correct the convective precipitation events in the catchment area, which are not originally captured by the meteorological forecasts. To this purpose, other preprocessing tools could be used, such as those based on a perfect prognosis approach (e.g., von Storch, 1999) or forecast techniques developed from stochastic weather generators (e.g., Volosciuk et al., 2017). For example, ensemble model output statistics combined with ensemble copula coupling (Schefzik, 2017) or an extension of the QM technique to a more advanced quantile regression neural network approach (Cannon, 2011) could be applied. Such techniques could provide the same degree of physical and multivariate consistency of the output as the member-by-member approach chosen in the current study (e.g., Schaeybroeck & Vannitsem, 2015) while considering also the correspondence between forecasts and observations. Furthermore, as outlined in section 1, postprocessing techniques can be applied to the resulting streamflow forecast to further enhance the quality of the forecasts, in addition to preprocessing hydrometeorological forecasts. For example, Bogner et al. (2018) analyses postprocessing tools based on wavelet transformation in combination with neural network and show that the performance of streamflow forecasts can be significantly enhanced if applied to subseasonal hydrometeorological forecasts. Such postprocessing techniques, and in particular the effect of the combination of preprocessing and postprocessing techniques, should be further investigated in future studies. As a final remark on the hydrometeorological forecasts, we stress the fact that hydrometeorological predictions have made great advances in predicting the weather more accurately over the past decades and these advances are expected to continue in future (Bauer et al., 2015). Hence, the quality of the hydrological predictions, and thus the full end-to-end prediction system for water management purposes, is expected to benefit from future advances in numerical weather prediction.

Another limitation of our approach is the use of deterministic optimization scheme. Based on other works (see, e.g., Boucher et al., 2012; Fan et al., 2016; Ficchí et al., 2016; Zhao et al., 2012), we expect that if the full streamflow forecast ensemble was used, for example, in a stochastic optimization scheme, the value could be further enhanced because the optimization could account for the entire uncertainty provided by the ensemble forecast. It would be also interesting exploring the relationship between forecast quality and value as a function of lead time, as the streamflow forecasts show decreasing quality with lead time and are generally skillful for 1 or 2 weeks depending on the season. To this end, a specific set of optimization experiments should be designed to isolate the relative contribution of different lead times on the forecast quality, as done, for example, in Anghileri et al. (2016), which analyze the contribution of the seasonal and interannual part of 1-year-long forecasts. As the forecasts seem to impact particularly the reduction of the spilled volume, we acknowledge that a more precise simulation of the spilled volume could be achieved by refining the simulation of the reservoir dynamics during the spilling events. The spilled volume is currently computed by integrating the reservoir spillway curves, which describe the instantaneous spilled flow as a function of the reservoir level, using a 1-hour integration time step for limiting the computational effort. A smaller integration time step would allow for more precise estimates. Also adopting hourly inflow forecasts, instead of daily forecasts, would improve the accuracy of the simulation of the catchment-reservoir system dynamics.

As for the metrics to compute the forecast quality, the revenues computed in the paper represent upper bound estimates of the actual revenues. Indeed, we assumed that the reservoir operations is optimized for the day-ahead electricity market and that the spot prices are known in advance. Moreover, we used a reference price trajectory (the average observed price) to calculate the revenue. In an operational and deregulated market setting, the prices may fluctuate significantly and the forecasting of electricity prices are likely to have a similar, if not greater, value in improving the real-time operations. The combined effect of price and streamflow forecasts on the hydropower operations is worth investigating in future studies. Finally, we also assume that the optimal reservoir operations do not account for any real-time network balancing. This last assumption is justified by the fact that the Verzasca hydropower system is one electricity generation source within a portfolio of sources owned by a unique power company. It is thus reasonable to isolate one system assuming that the other generation sources can be managed for meeting the expected production or to absorb the generation excess. As the balancing (or power reserve) markets are becoming increasingly important given the continuous expansion of variable renewable sources, such as wind and solar sources (e.g., Chazarra et al., 2016; Helseth et al., 2016; Kern et al., 2014), it would be interesting to analyze the operations of the hydropower system when accounting for a combination of day-ahead and balancing markets in future studies.

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References

Addor, N., Jaun, S., Fundel, F., & Zappa, M. (2011). An operational hydrological ensemble prediction system for the city of Zurich (Switzerland): Skill, case studies and scenarios. *Hydrology and Earth System Sciences*, *15*(7), 2327–2347. https://doi.org/10.5194/hess-15-2327-2011

Anghileri, D., Botter, M., Castelletti, A., Weigt, H., & Burlando, P. (2018). A comparative assessment of the impact of climate change and energy policies on Alpine hydropower. *Water Resources Research*, *54*, 9144–9161. https://doi.org/10.1029/2017WR022289

Anghileri, D., Castelletti, A., & Burlando, P. (2018). Alpine hydropower in the decline of the nuclear era: Trade-off between revenue and production in the Swiss Alps. *Journal of Water Resources Planning and Management*, *144*(8), 04018037. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000944

Anghileri, D., Castelletti, A., Pianosi, F., Soncini-Sessa, R., & Weber, E. (2013). Optimizing watershed management by coordinated operation of storing facilities. *Journal of Water Resources Planning and Management*, *139*(5), 492–500.

Anghileri, D., Pianosi, F., & Soncini-Sessa, R. (2011). A framework for the quantitative assessment of climate change impacts on water-related activities at the basin scale. *Hydrology and Earth System Sciences*, *15*(6), 2025–2038. https://doi.org/10.5194/hess-15-2025-2011

Anghileri, D., Voisin, N., Castelletti, A., Pianosi, F., Nijssen, B., & Lettenmaier, D. P. (2016). Value of long-term streamflow forecasts to reservoir operations for water supply in snow-dominated river catchments. *Water Resources Research*, *52*, 4209–4225. https://doi.org/10.1002/2015WR017864

Arsenault, R., & Côté, P. (2018). Analysis of the effects of biases in ESP forecasts on electricity production in hydropower reservoir management. *Hydrology and Earth System Sciences Discussions*, 1–29. https://doi.org/10.5194/hess-2018-236

Bauer, P., Thorpe, A., & Brunet, G. (2015). The quiet revolution of numerical weather prediction. *Nature*, *525*(7567), 47–55. https://doi.org/10.1038/nature14956

Bennett, J. C., Robertson, D. E., Shrestha, D. L., Wang, Q., Enever, D., Hapuarachchi, P., & Tuteja, N. K. (2014). A System for Continuous Hydrological Ensemble Forecasting (SCHEF) to lead times of 9 days. *Journal of Hydrology*, *519*, 2832–2846. https://doi.org/10.1016/J.JHYDROL.2014.08.010

Block, P. (2011). Tailoring seasonal climate forecasts for hydropower operations. *Hydrology and Earth System Sciences*, *15*(4), 1355–1368. https://doi.org/10.5194/hess-15-1355-2011

Bogner, K., Liechti, K., Bernhard, L., Monhart, S., & Zappa, M. (2018). Skill of hydrological extended range forecasts for water resources management in Switzerland. *Water Resources Management*, *32*(3), 969–984. https://doi.org/10.1007/s11269-017-1849-5

Bogner, K., Liechti, K., & Zappa, M. (2017). Technical note: Combining quantile forecasts and predictive distributions of streamflows. *Hydrology and Earth System Sciences*, *21*(11), 5493–5502. https://doi.org/10.5194/hess-21-5493-2017

Bogner, K., Liechti, K., Zappa, M., Bogner, K., Liechti, K., & Zappa, M. (2016). Post-processing of stream flows in Switzerland with an emphasis on low flows and floods. *Water*, *8*(4), 115. https://doi.org/10.3390/w8040115

Boucher, M. A., Tremblay, D., Delorme, L., Perreault, L., & Anctil, F. (2012). Hydro-economic assessment of hydrological forecasting systems. *Journal of Hydrology*, *416–417*, 133–144.

Boughton, W., & Droop, O. (2003). Continuous simulation for design flood estimation—A review. *Environmental Modelling & Software*, *18*(4), 309–318. https://doi.org/10.1016/S1364-8152(03)00004-5

Breckpot, M., Agudelo, O. A., Meert, P., Willems, P., & De Moor, B. (2013). Flood control of the Demer by using Model Predictive Control. *Control Engineering Practice*, *21*(12), 1776–1787.

Cannon, A. (2011). Quantile regression neural networks: Implementation in R and application to precipitation downscaling. *Computers and Geosciences*, *37*, 1277–1284. https://doi.org/10.1016/j.cageo.2010.07.005

Castelletti, A., Pianosi, F., & Soncini-Sessa, R. (2008). Reservoir control under economic, social and environmental constraints. *Automatica*, *44*(6), 1595–1607.

Chazarra, M., García-González, J., Pérez-Díaz, J. I., & Arteseros, M. (2016). Stochastic optimization model for the weekly scheduling of a hydropower system in day-ahead and secondary regulation reserve markets. *Electric Power Systems Research*, *130*, 67–77. https://doi.org/10.1016/j.epsr.2015.08.014

Chiew, F. H. S., Zhou, S. L., & McMahon, T. A. (2003). Use of seasonal streamflow forecasts in water resources management. *Journal of Hydrology*, *270*(1–2), 135–144. https://doi.org/10.1016/S0022-1694(02)00292-5

Cloke, H., & Pappenberger, F. (2009). Ensemble flood forecasting: A review. *Journal of Hydrology*, *375*(3-4), 613–626. https://doi.org/10.1016/j.jhydrol.2009.06.005

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

Denaro, S., Anghileri, D., Giuliani, M., & Castelletti, A. (2017). Informing the operations of water reservoirs over multiple temporal scales by direct use of hydro-meteorological data. *Advances in Water Resources*, *103*, 51–63. https://doi.org/10.1016/j.advwatres.2017.02.012

Domeisen, D. I., Badin, G., & Kosalka, I. M. (2018). How predictable are the Arctic and North Atlantic Oscillations? Exploring the variability and predictability of the Northern Hemisphere. *Journal of Climate*, *31*(3), 997–1014. https://doi.org/10.1175/JCLI-D-17-0226.1

ECMWF (2014). Part V: Ensemble prediction system (pp. 1–25). England: ECMWF Reading.

Fan, F. M., Schwanenberg, D., Alvarado, R., Assis dos Reis, A., Collischonn, W., & Naumman, S. (2016). Performance of deterministic and probabilistic hydrological forecasts for the short-term optimization of a tropical hydropower reservoir. *Water Resources Management*, *30*(10), 3609–3625. https://doi.org/10.1007/s11269-016-1377-8

Ferro, C. A. T. (2014). Fair scores for ensemble forecasts. *Quarterly Journal of the Royal Meteorological Society*, *140*(683), 1917–1923. https://doi.org/10.1002/qj.2270

Ficchí, A., Raso, L., Dorchies, D., Pianosi, F., Malaterre, P.-O., Overloop, P.-J. V., & Jay-Allemand, M. (2016). Optimal operation of the multireservoir system in the seine river basin using deterministic and ensemble forecasts. *Journal of Water Resources Planning and Management*, *142*(1), 05015005. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000571

Ficchì, A., Raso, L., Dorchies, D., Pianosi, F., Malaterre, P.-O., Van Overloop, P.-J., & Jay-Allemand, M. (2016). Optimal operation of the multireservoir system in the Seine River Basin using deterministic and ensemble forecasts. *Journal of Water Resources Planning and Management*, *142*(1), 05015005. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000571

Frei, C. (2014). Interpolation of temperature in a mountainous region using nonlinear profiles and non-Euclidean distances. *International Journal of Climatology*, *34*(5), 1585–1605. https://doi.org/10.1002/joc.3786

Galelli, S., Goedbloed, A., Schwanenberg, D., & van Overloop, P.-J. (2014). Optimal real-time operation of multipurpose urban reservoirs: Case study in Singapore. *Journal of Water Resources Planning and Management*, *140*(4), 511–523. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000342

Gaudard, L., Gilli, M., & Romerio, F. (2013). Climate change impacts on hydropower management. *Water Resources Management*, *27*(15), 5143–5156. https://doi.org/10.1007/s11269-013-0458-1

Goddard, L., Aitchellouche, Y., Baethgen, W., Dettinger, M., Graham, R., Hayman, P., et al. (2010). Providing seasonal-to-interannual climate information for risk management and decision-making. *Procedia Environmental Sciences*, *1*, 81–101. https://doi.org/10.1016/J.PROENV.2010.09.007

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

Gurtz, J., Baltenswieiler, A., & Lang, H. (1999). Spatially distributed hydrotope-based modelling of evapotranspiration and runoff in mountain basins. *Hydrological Processes*, *13*, 2751–2768. https://doi.org/10.1002/(SICI)1099-1085(19991215)13

Hamlet, A. F., Huppert, D., & Lettenmaier, D. P. (2002). Economic value of long-lead streamflow forecasts for {C}olumbia {R}iver hydropower. *Journal of Water Resources Planning and Management*, *128*(2), 91–101.

Hao, Z., Singh, V. P., & Xia, Y. (2018). Seasonal drought prediction: Advances, challenges, and future prospects. *Reviews of Geophysics*, *56*, 108–141. https://doi.org/10.1002/2016RG000549

Hegdahl, T. J., Engeland, K., Steinsland, I., & Tallaksen, L. M. (2019). Streamflow forecast sensitivity to air temperature forecast calibration for 139 Norwegian catchments. *Hydrology and Earth System Sciences*, *23*(2), 723–739. https://doi.org/10.5194/hess-23-723-2019

Helseth, A., Fodstad, M., & Mo, B. (2016). Optimal medium-term hydropower scheduling considering energy and reserve capacity markets. *IEEE Transactions on Sustainable Energy*, *7*(3), 934–942. https://doi.org/10.1109/TSTE.2015.2509447

Hersbach, H. (2000). Decomposition of the continuous ranked probability score for ensemble prediction systems. *Weather and Forecasting*, *15*, 559–570.

Isotta, F. A., Vogel, R., & Frei, C. (2015). Evaluation of European regional reanalyses and downscalings for precipitation in the Alpine region. *Meteorologische Zeitschrift*, *24*(1), 15–37. https://doi.org/10.1127/metz/2014/0584

Jolliffe, I. T., & Stephenson, D. B. (2012). Forecast verification: A practioner's guide in atmospheric science, (2nd ed.). Chichester UK: John Wiley and Sons.

Kang, T.-H., Young-Oh, K., & I1-Pyo, H. (2010). Comparison of pre- and post-processors for ensemble streamflow prediction. *Atmospheric Science Letters*, *11*(2), 153–159. https://doi.org/10.1002/asl.276

Kern, J. D., Characklis, G. W., Doyle, M. W., Blumsack, S., & Whisnant, R. B. (2012). Influence of deregulated electricity markets on hydropower generation and downstream flow regime. *Journal of Water Resources Planning and Management*, *138*(4), 342–355. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000183

Kern, J. D., Patino-Echeverri, D., & Characklis, G. W. (2014). An integrated reservoir-power system model for evaluating the impacts of wind integration on hydropower resources. *Renewable Energy*, *71*, 553–562. https://doi.org/10.1016/J.RENENE.2014.06.014

Laio, F., & Tamea, S. (2007). Verification tools for probabilistic forecasts of continuous hydrological variables. *Hydrology and Earth System Sciences*, *11*, 1267–1277.

Li, W., Duan, Q., Miao, C., Ye, A., Gong, W., & Di, Z. (2017). A review on statistical postprocessing methods for hydrometeorological ensemble forecasting. *Wiley Interdisciplinary Reviews Water*, *4*(6), e1246. https://doi.org/10.1002/wat2.1246

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

Lucatero, D., Madsen, H., Refsgaard, J. C., Kidmose, J., & Jensen, K. H. (2018b). On the skill of raw and post-processed ensemble seasonal meteorological forecasts in Denmark. *Hydrology and Earth System Sciences*, *22*(12), 6591–6609. https://doi.org/10.5194/hess-22-6591-2018

Maraun, D. (2013). Bias correction, quantile mapping, and downscaling: Revisiting the inflation issue. *Journal of Climate*, *6*(26), 2137–2143.

Meissner, D., Klein, B., & Ionita, M. (2017). Development of a monthly to seasonal forecast framework tailored to inland waterway transport in central Europe. *Hydrology and Earth System Sciences*, *21*, 6401–6423. https://doi.org/10.5194/hess-21-6401-2017

MeteoSwiss (2016a). Documentation of MeteoSwiss grid-data products daily mean, minimum and maximum temperature: TabsD, TminD , TmaxD, *Available at Meteoschweiz Kundendienst*, pp. 1–4.

MeteoSwiss (2016b). Documentation of MeteoSwiss grid-data products: Daily precipitation (final analysis): RhiresD, *Available at Meteoschweiz Kundendienst*, pp. 1–4.

Monhart, S., Spirig, C., Bhend, J., Bogner, K., Schär, C., & Liniger, M. A. (2018). Skill of subseasonal forecasts in Europe: Effect of bias correction and downscaling using surface observations. *Journal of Geophysical Research: Atmospheres*, *123*, 7999–8016. https://doi.org/10.1029/2017JD027923

Monhart, S., Zappa, M., Spirig, C., Schär, C., & Bogner, K. (2019). Subseasonal hydrometeorological ensemble predictions in small- and medium-sized mountainous catchments: benefits of the NWP approach. *Hydrology and Earth System Sciences*, *23*(1), 493–513. https://doi.org/10.5194/hess-23-493-2019

Müller, W. A., Appenzeller, C., Doble-Reyes, F. J., & Liniger, M. A. (2005). A debiased ranked probability skill score to evaluate probabilistic ensemble forecasts with small ensemble sizes. *Journal of Climate*, *18*, 1513–1523. https://doi.org/10.1175/JCLI3361.1

Murphy, A. H. (1993). What is a good forecast? An essay on the nature of goodness in weather forecasting. *Weather and Forecasting*, *8*(2), 281–293.

Orth, R., Staudinger, M., Seneviratne, S. I., Seibert, J., & Zappa, M. (2015). Does model performance improve with complexity? A case study with three hydrological models. *Journal of Hydrology*, *523*, 147–159. https://doi.org/10.1016/j.jhydrol.2015.01.044

Robertson, A. W., Kumar, A., Peña, M., & Vitart, F. (2015). Improving and promoting subseasonal to seasonal prediction. *Bulletin of the American Meteorological Society*, *96*(3), ES49–ES53. https://doi.org/10.1175/BAMS-D-14-00139.1

Rossa, A., Liechti, K., Bruen, M., Germann, U., Haase, G., Keil, C., & Krahe, P. (2011). The COST 731 Action: A review on uncertainty propagation in advanced hydro-meteorological forecast systems. *Atmospheric Research*, *100*(2-3), 150–167. https://doi.org/10.1016/J.ATMOSRES.2010.11.016

Schaake, J. C., Hamill, T. M., Buizza, R., Clark, M., Schaake, J. C., Hamill, T. M., et al. (2007). HEPEX: The hydrological ensemble prediction experiment. *Bulletin of the American Meteorological Society*, *88*(10), 1541–1548. https://doi.org/10.1175/BAMS-88-10-1541

Schaeybroeck, B. V., & Vannitsem, S. (2015). Ensemble post-processing using member-by-member approaches: Theoretical aspects. *Quarterly Journal of the Royal Meteorological Society*, *141*, 807–818. https://doi.org/10.1002/qj.2397

Schattan, P., Zappa, M., Lischke, H., Bernhard, L., Thurig, E., & Diekkruger, B. (2013). An approach for transient consideration of forest change in hydrological impact studies. *IAHS-AISH Proceedings and Reports*, *359*, 311–319.

Schefzik, R. (2017). Ensemble calibration with preserved correlations: Unifying and comparing ensemble copula coupling and member-by-member postprocessing. *Quarterly Journal of the Royal Meteorological Society*, *143*, 999–1008. https://doi.org/10.1002/qj.2984

Schepen, A., Zhao, T., Wang, Q. J., & Robertson, D. E. (2018). A Bayesian modelling method for post-processing daily sub-seasonal to seasonal rainfall forecasts from global climate models and evaluation for 12 Australian catchments. *Hydrology and Earth System Sciences*, *22*, 1615–1628. https://doi.org/10.5194/hess-22-1615-2018

Shah, R., Sahai, A. K., & Mishra, V. (2017). Short to sub-seasonal hydrologic forecast to manage water and agricultural resources in India. *Hydrology and Earth System Sciences*, *21*, 707–720. https://doi.org/10.5194/hess-21-707-2017

Sheffield, J., Camargo, S. J., Fu, R., Hu, Q., Jiang, X., Johnson, N., et al. (2013). North American Climate in CMIP5 Experiments Part II: Evaluation of historical simulations of intraseasonal to devadal Variability. *Journal of Climate*, *26*(23), 9247–9290. https://doi.org/10.1175/JCLI-D-12-00593.1

Soncini-Sessa, R., Castelletti, A., & Weber, E. (2007). *Integrated and participatory water resources management Theory*. Amsterdam, NL: Elsevier.

Speich, M. J., Bernhard, L., Teuling, A. J., & Zappa, M. (2015). Application of bivariate mapping for hydrological classification and analysis of temporal change and scale effects in Switzerland. *Journal of Hydrology*, *523*, 804–821. https://doi.org/10.1016/j.jhydrol.2015.01.086

Tang, Y., Zhang, R.-H., Liu, T., Duan, W., Yang, D., Zheng, F., et al. (2018). Progress in ENSO prediction and predictability study. *National Science Review*, *5*(6), 826–839. https://doi.org/10.1093/nsr/nwy105

Tian, D., Wood, E. F., & Yuan, X. (2017). CFSv2-based sub-seasonal precipitation and temperature forecast skill over the contiguous United States. *Hydrology and Earth System Sciences*, *21*, 1477–1490. https://doi.org/10.5194/hess-21-1477-2017

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

Verkade, J., Brown, J., Reggiani, P., & Weerts, A. (2013). Post-processing ECMWF precipitation and temperature ensemble reforecasts for operational hydrologic forecasting at various spatial scales. *Journal of Hydrology*, *501*, 73–91. https://doi.org/10.1016/j.jhydrol.2013.07.039

Vitart, F. (2004). Monthly Forecasting at ECMWF. *Monthly Weather Review*, *132*(12), 2761–2779. https://doi.org/10.1175/MWR2826.1

Vitart, F., Ardilouze, C., Bonet, A., Brookshaw, A., Chen, M., Codorean, C., et al. (2017). The subseasonal to seasonal (S2S) prediction project database. *Bulletin of the American Meteorological Society*, *98*(1), 163–173. https://doi.org/10.1175/BAMS-D-16-0017.1

Vitart, F., G. Balsamo, R. Buizza, L. Ferranti, S. Keeley, L. Magnusson, et al. (2014). Sub-seasonal predictions, ECMWF - Technical Memorandum, (738).

Vitart, F., & Robertson, A. W. (2018). The sub-seasonal to seasonal prediction project (S2S) and the prediction of extreme events. *npj Climate and Atmospheric Science*, *1*(1), 3. https://doi.org/10.1038/s41612-018-0013-0

Viviroli, D., Zappa, M., Gurtz, J., & Weingartner, R. (2009). An introduction to the hydrological modelling system PREVAH and its pre- and post-processing-tools. *Environmental Modelling & Software*, *24*(10), 1209–1222. https://doi.org/10.1016/j.envsoft.2009.04.001

Viviroli, D., Zappa, M., Schwanbeck, J., Gurtz, J., & Weingartner, R. (2009). Continuous simulation for flood estimation in ungauged mesoscale catchments of Switzerland—Part I: Modelling framework and calibration results. *Journal of Hydrology*, *377*(1-2), 191–207. https://doi.org/10.1016/j.jhydrol.2009.08.023

Volosciuk, C., Maraun, D., Vrac, M., & Widmann, M. (2017). A combined statistical bias correction and stochastic downscaling method for precipitation. *Hydrology and Earth System Sciences*, *21*(3), 1693–1719. https://doi.org/10.5194/hess-21-1693-2017

von Storch, H. (1999). On the use of 'inflation' in statistical downscaling. *Journal of Climate*, *12*(12), 3505–3506. https://doi.org/10.1175/1520-0442(1999)012<3505:OTUOII>2.0.CO;2

Wang, F., Wang, L., Zhou, H., Saavedra Valeriano, O. C., Koike, T., & Li, W. (2012). Ensemble hydrological prediction-based real-time optimization of a multiobjective reservoir during flood season in a semiarid basin with global numerical weather predictions. *Water Resources Research*, *48*, W07520.

Watkins, D. W., & Wei, W. (2008). The value of seasonal climate forecasts and why water managers don't use them. In *World Environmental and Water Resources Congress 2008* (pp. 1–5). Reston, VA: American Society of Civil Engineers. https://doi.org/10.1061/40976(316)550

Weijs, S. V., Schoups, G., & van de Giesen, N. (2010). Why hydrological predictions should be evaluated using information theory. *Hydrology and Earth System Sciences*, *14*(12), 2545–2558. https://doi.org/10.5194/hess-14-2545-2010

Whateley, S., Palmer, R., & Brown, C. (2014). Seasonal hydroclimatic forecasts as innovations and the challenges of adoption by water managers. *Journal of Water Resources Planning and Management*, *141*(5), 4014071. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000466

White, C. J., Carlsen, H., Robertson, A. W., Klein, R. J., Lazo, J. K., Kumar, A., et al. (2017). Potential applications of subseasonal-to-seasonal (S2S) predictions. *Meteorological Applications*, *24*(3), 315–325. https://doi.org/10.1002/met.1654

Wilks, D. S. (2011). Statistical methods in the atmospheric sciences. In *International Geophysics Series* (Chap. 8, 3rd ed., Vol. 100). London: Academic Press Inc.

Yao, H., & Georgakakos, A. (2001). Assessment of Folsom Lake response to historical and potential future climate scenarios: 2 Reservoir management. *Journal of Hydrology*, *249*(1-4), 176–196. https://doi.org/10.1016/S0022-1694(01)00418-8

Yuan, X., Wood, E. F., & Ma, Z. (2015). A review on climate-model-based seasonal hydrologic forecasting: physical understanding and system development. *Wiley Interdisciplinary Reviews Water*, *2*(5), 523–536. https://doi.org/10.1002/wat2.1088

Zappa, M., Pos, F., Strasser, U., Warmerdam, P., & Gurtz, J. (2003). Seasonal water balance of an Alpine Catchment as Evaluated by different methods for spatially distributed snowmelt modelling. *Nordic Hydrology*, *34*(3), 179–202.

Zhao, T., Bennett, J. C., Wang, Q. J., Schepen, A., Wood, A. W., Robertson, D. E., & Ramos, M. H. (2017). How suitable is quantile mapping for post-processing GCM precipitation forecasts. *Journal of Climate*, *30*(9), 3185–3196.

Zhao, T., Yang, D., Cai, X., Zhao, J., & Wang, H. (2012). Identifying effective forecast horizon for real-time reservoir operation under a limited inflow forecast. *Water Resources Research*, *48*, W01540. https://doi.org/10.1029/2011WR010623