AGU PUBLICATIONS

Water Resources Research

RESEARCH ARTICLE

10.1002/2015WR017864

Key Points:

- Flow forecast value to reservoir operation judged considering forecast skill and reservoir features
- Seasonal (SC) versus inter-annual (IAC) component of ESP forecast to the overall value is isolated
- The IAC contributes 20–60% of the total value and perfect SC would improve the total value by 15–20%

Supporting Information:

- Supporting Information S1

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

Received 18 JUL 2015
Accepted 6 APR 2016
Accepted article online 12 APR 2016
Published online 2 JUN 2016

Value of long-term streamflow forecasts to reservoir operations for water supply in snow-dominated river catchments

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Abstract We present a forecast-based adaptive management framework for water supply reservoirs and evaluate the contribution of long-term inflow forecasts to reservoir operations. Our framework is developed for snow-dominated river basins that demonstrate large gaps in forecast skill between seasonal and inter-annual time horizons. We quantify and bound the contribution of seasonal and inter-annual forecast components to optimal, adaptive reservoir operation. The framework uses an Ensemble Streamflow Prediction (ESP) approach to generate retrospective, one-year-long streamflow forecasts based on the Variable Infiltration Capacity (VIC) hydrology model. We determine the optimal sequence of daily release decisions using the Model Predictive Control (MPC) optimization scheme. We then assess the forecast value by comparing system performance based on the ESP forecasts with the performances based on climatology and perfect forecasts. We distinguish among the relative contributions of the seasonal component of the forecast versus the inter-annual component by evaluating system performance based on hybrid forecasts, which are designed to isolate the two contributions. As an illustration, we first apply the forecast-based adaptive management framework to a specific case study, i.e., Oroville Reservoir in California, and we then modify the characteristics of the reservoir and the demand to demonstrate the transferability of the findings to other reservoir systems. Results from numerical experiments show that, on average, the overall ESP value in informing reservoir operation is 35% less than the perfect forecast value and the inter-annual component of the ESP forecast contributes 20–60% of the total forecast value.

1. Introduction

Both flood control and drought management can benefit from weather and streamflow forecasts such as when anticipating hazards and increasing the potential buffering capacity of water storing facilities [*Yao and Georgakakos*, 2001; *Faber and Stedinger*, 2001; *Franz et al.*, 2003]. Intuitively, the more accurate the forecasts are, the more effective the decisions based on them will be. Yet, improved accuracy may not fully translate into improved operational performance [*Chiew et al.*, 2003; *Watkins and Wei*, 2008; *Boucher et al.*, 2012]. For example, if a flood is forecasted with sufficient lead time, reservoir outlets can be operated to reduce the peak flow rate [*Saavedra Valeriano et al.*, 2010; *Zhao and Zhao*, 2014], but, even if perfectly forecasted, the flood peak may not be attenuated if the reservoir is structurally unable to promptly adapt to the forecasted conditions, e.g., its outlets are too small or its storage capacity is limited.

The term *forecast value* is used in the literature to indicate the operational value of using a forecasting system to support water management, that is, a forecast's effectiveness in informing decisions. The forecast value is measured in terms of system performance improvement as defined by the operating objectives [*Murphy*, 1993; *Laio and Tamea*, 2007]. Forecast value differs from *forecast quality*, which indicates how well the forecast matches reality [*Murphy*, 1993]. Obviously, the two are related: forecast value is expected to increase with forecast quality, but it may also vary based on other factors such as reservoir capacity and the operating objectives [*Andersen et al.*, 1971; *Yao and Georgakakos*, 2001; *Hamlet et al.*, 2002; *You and Cai*, 2008; *Rosenberg et al.*, 2011]. A strong relationship exists between forecast time horizon, reservoir characteristics, and operating objectives. Generally speaking, short-term forecasts are more valuable when the reservoir has a capacity smaller than its annual inflow volume, and it is operated for short-term operation purposes such as flood protection [*Saavedra Valeriano et al*., 2010]. Long-term forecasts are more valuable for large reservoirs with medium to long-term operating objectives, e.g., hydropower generation and water supply [*Maurer and Lettenmaier*, 2004; *Sankarasubramanian et al*., 2009a]. The forecast value also depends on the flexibility of the decision-making procedures, which might be able to exploit the information provided by the forecasts to different degrees [*Yao and Georgakakos*, 2001; *Faber and Stedinger*, 2001; *Whateley et al*., 2014]. For example, if a reservoir must be operated according to a predefined rule curve, the release decision is determined by the current state of the reservoir relative to the rule curve, and is insensitive to streamflow forecast [*Soncini-Sessa et al*., 2007].

Multiple approaches are available to forecast seasonal reservoir inflows, from regression relationships between observed snowpack and reservoir inflow [e.g., *Pagano et al*., 2004], to forcing a properly initialized hydrology model with climate forecasts [e.g., *Wood et al*., 2002; *Wood and Lettenmaier*, 2006]. Climate forecasts are available from a number of sources, including resampling from historic climate observations [*Day*, 1985], downscaled numerical climate model forecasts, e.g., CFSv2, [e.g., *Yuan et al*., 2011], or stochastic climate generators [e.g., *Caraway et al*., 2014]. Longer lead time forecasts are sometimes possible if inter-seasonal to inter-annual climate variations such as El Nino Southern Oscillation (ENSO) lead to local predictability [e.g., *Hamlet and Lettenmaier*, 1999; *Pagano et al*., 2001]. However, the use of these forecasts poses implementation challenges because it requires increased communication and coordinated risk mitigation between stakeholders [*Pagano et al*., 2014].

The source of hydrometeorological predictability, and forecast quality, depends on the catchment type, the forecasted season, and the forecast horizon [*Shukla and Lettenmaier*, 2011]. For instance, reservoir inflow forecasts in snow-dominated river basins may perform well with respect to both timing and magnitude at short lead times, but, usually, at most only the seasonal volumetric forecast has skill at the seasonal time scale. Beyond the snowmelt period, seasonal forecasts typically have limited skill. In snow-dominated river basins, the forecast horizon for seasonal flow forecasts is often extended using climatology for the period beyond which the forecast is skillful [*Wood and Lettenmaier*, 2006] to provide a complete input flow series for reservoir optimization (for example a full year). This climatological component affects storage management for inter-seasonal and inter-annual carryover.

Because of the limited long-term skill of streamflow forecasts, attention has been focused on the value of short-term forecasts for flood control operation [e.g., *Breckpot et al*., 2013; *Wang et al*., 2012]. At a longer time scale, numerous studies have investigated the value of forecasts, and predictable inter-annual variability when available, for hydropower generation [e.g., *Hamlet et al*., 2002; *Maurer and Lettenmaier*, 2004; *Koskela*, 2009; *Voisin et al*., 2006; *Kim and Palmer*, 1997; *Alemu et al*., 2010]. A few studies have focused on the forecast value for irrigation or municipal supply [e.g., *Yao and Georgakakos*, 2001; *Georgakakos et al*., 2005; *Sankarasubramanian et al*., 2009b; *Georgakakos and Graham*, 2008; *You and Cai*, 2008]. At the seasonal scale, most studies use synthetic forecasts generated by adding an error term to observed streamflow time series [e.g., *Maurer and Lettenmaier*, 2004; *Sankarasubramanian et al*., 2009b; *Georgakakos and Graham*, 2008]. At longer scales, climatic teleconnections, such as El Nino Southern Oscillation (ENSO), Pacific Decadal Oscillation (PDO), and Sea Surface Temperature (SST) are considered to predict inter-annual variability when available [e.g., *Graham et al*., 2006; *Hamlet and Lettenmaier*, 1999]. Streamflow forecasts are frequently used to design reservoir operations at monthly or seasonal time resolution, often by performing an offline optimization for a fixed time horizon and setting a constraint on the end-of-period reservoir storage [*Zhao et al*., 2012; *Georgakakos and Graham*, 2008] or by using adaptive management systems [e.g., *Georgakakos et al*., 2012, 2005; *Yao and Georgakakos*, 2001]. These studies concluded that there is often a mismatch between the information needed for reservoir operations and the skillful lead time of the reservoir inflow forecast.

In this paper, we build upon previous adaptive management framework analyses. Rather than evaluating the impact of varying error characteristics of the overall forecast, we explore how temporal components of long-term forecasts influence adaptive management toward water supply operations in snow-dominated river basins, or locations with large discrepancies in forecasting skill over different seasons. We argue that the value of long-term reservoir inflow forecasts, which are inconsistent in their skill for seasonal and inter-annual forecast lead times, depends on how much of the skillful forecast is used in reservoir optimization and how the forecast information translates into reservoir operation's performance. Our paper addresses the following general questions:

1. What is the operational value of long-term inflow forecasts for reservoirs operated for water supply in a snow-dominated river basin?
2. How is the information provided by the inflow forecasts exploited by the operating policies?
3. What are the potential and actual contributions of the seasonal and inter-annual components of the long-term inflow forecasts to reservoir operations?
4. How does the forecast value vary based on reservoir characteristics?

The objective of this paper is to bound the benefit, or value, that a long-term reservoir inflow forecast might bring to reservoir operations, when used to inform an adaptive reservoir management system. These findings can inform what components of a long-term reservoir inflow forecast need to be improved and how to improve the optimization based on the added information of different skill over different horizons, thus improving communication between forecasters and reservoir operators. To the best of our knowledge, no other papers have addressed this temporal aspect of the forecast value for improving reservoir operation.

Our methodology consists of adopting a *forecast-based adaptive management* framework to explore the potential for long-term reservoir inflow forecasts, issued on a weekly basis, to inform the daily operation of water supply reservoirs in snow-dominated river basins and correspondingly assess the forecast value in terms of system performance improvement. We use the Ensemble Streamflow Prediction (ESP) approach [*Day*, 1985] as our forecasting approach. We combine the Variable Infiltration Capacity (VIC) hydrology model [*Liang et al*., 1994] and historical weather records to generate a set of one-year-long streamflow forecasts conditioned on the initial state of the catchment (ESP approach [*Day*, 1985]). We chose the ESP approach for multiple reasons specific to the bounding objective of the paper. First, the approach is widely used across the western U.S. [*Wood and Lettenmaier*, 2006] and it is a central component of National Weather Service water supply forecasting activities in the western U.S. [*Rosenberg et al*., 2011]. This is a representative forecast for operational conditions. Second, the ESP-based flow forecast typically owes its skill to the hydrological initial conditions which not only is a leading source of skill in the Spring for snowmelt controlled basin [*Shukla and Lettenmaier*, 2011], but also implies that the skill is very seasonal and the inter-annual component contribution is zero with respect to climatology. Those specific characteristics will allow us to disaggregate the contribution of seasonal and inter-annual forecast in the value assessment. Reservoir release decisions are then determined by using Model Predictive Control (MPC) [e.g., *Mayne et al*., 2000; *Scattolini*, 2009], a flexible and adaptive optimization scheme, that (i) solves multiple optimization problems defined over a finite rolling horizon, and (ii) assimilates a description of future hydrological conditions as produced by the forecasting system [*Breckpot et al*., 2013; *Galelli et al*., 2014]. MPC accounts for both short-term and long-term effects of the release decisions and periodically revises the decisions to include the most up-to-date streamflow forecasts. The contribution of the paper is not in developing either novel long-term forecasts or optimization methods, but to combine forecasting method (i.e., ESP) and optimization method (i.e., MPC) in a forecast-based adaptive management framework and to use this framework to:

1. Compute the ESP forecast value by comparing the system performances with the two classical benchmarks of perfect forecast and climatology;
2. Assess the relative contribution of the seasonal and inter-annual forecast skill to the overall forecast value by considering another benchmark (called hybrid forecasts) specifically designed to isolate the two contributions.

Another contribution is the recommendation of a new forecast evaluation framework for application to reservoir optimization. Typical measures that have been used for forecast evaluation include correlation, RMSE, etc. over multiple lead times. Instead, our experiment highlights the need to evaluate forecasts for their seasonal and inter-annual components.

We first apply our methodology to a specific case study, the Oroville Reservoir in California, then we modify the characteristics of the reservoir and the demand to demonstrate the robustness and transferability of the findings to other reservoir systems sharing the same main operating objective, i.e., water supply, and hydrological regime, i.e., snow-dominated.

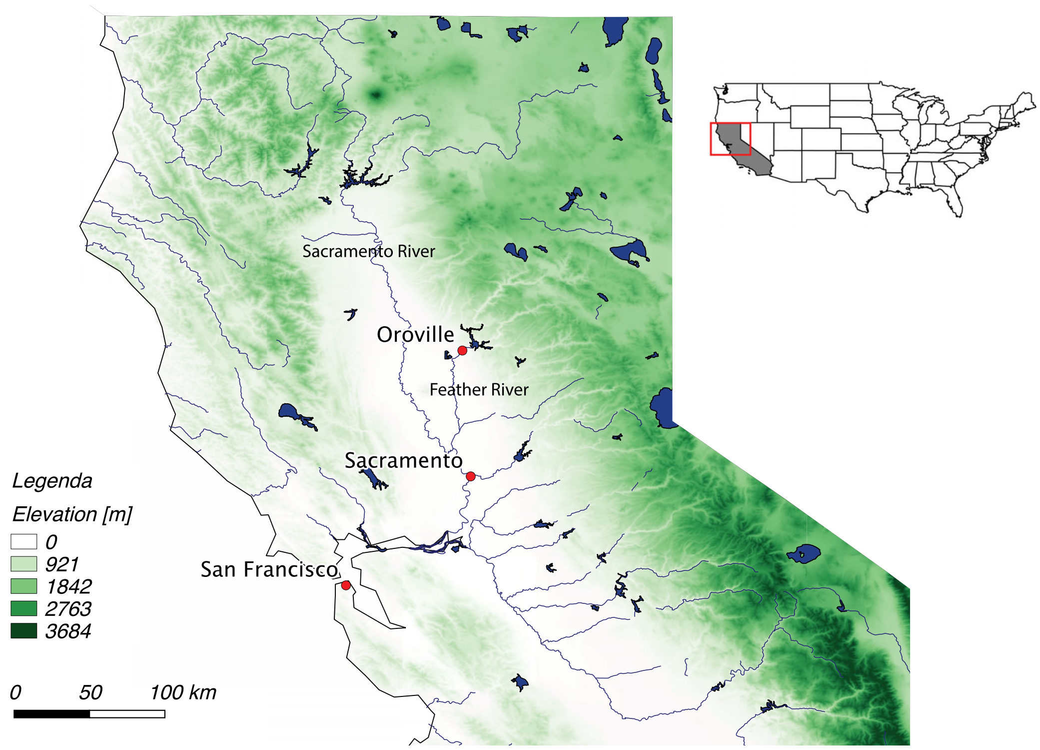

Figure 1. Case study area comprising the Oroville Reservoir, the Feather River, and the San Francisco Bay Area.

The paper is organized as follows. We first present the domain of application and the modeling framework, i.e., the forecast-based adaptive management scheme. We follow with the description of the experimental approach to evaluate streamflow forecast quality and its value to reservoir operation. We discuss the results, highlighting the reservoir operation performance achieved by consideration of the perfect forecast and climatological information only, then by isolating the contributions of seasonal and inter-annual forecast skill in ESP forecasts. We conclude the paper by summarizing the main results, commenting on limitations, and presenting further research directions.

2. Study Site

The Oroville-Thermalito reservoir complex (Figure 1) is a water storage and delivery system of reservoirs, canals, power, and pumping plants located on the Feather River in California. It is composed of three reservoirs among which Oroville is the largest with a storage capacity of almost 4.4 km^3. The other two, i.e., Thermalito Forebay and Afterbay, have considerably smaller capacities and are not accounted for in this study (for more details, see section 3.2).

The Oroville Reservoir is supplied by the Feather River which collects water from a catchment of about 10,000 km^2 with a mean annual inflow volume of almost 5 km^3. The climate of the area is Mediterranean, consisting of wet winters and warm, dry summers, with most of the precipitation during the cold season, from November to March. Similar to many catchments in the western U.S., it is a mixed snow-rain catchment with most of the water flowing into the reservoir during winter and spring. However, inter-annual variability in precipitation and temperature is large, which leads to inter-annual differences in timing and quantity of snowmelt and, therefore, streamflow [*Kalra et al.*, 2012].

Along with many other reservoirs located in California, the Oroville Reservoir is part of the California State Water Project, whose main purpose is to satisfy urban, agricultural, and environmental water demands in California, in general, and the San Francisco Bay area, in particular. In addition, the Oroville Reservoir is operated for hydropower generation and flood control for the Feather River and the Sacramento River. Its

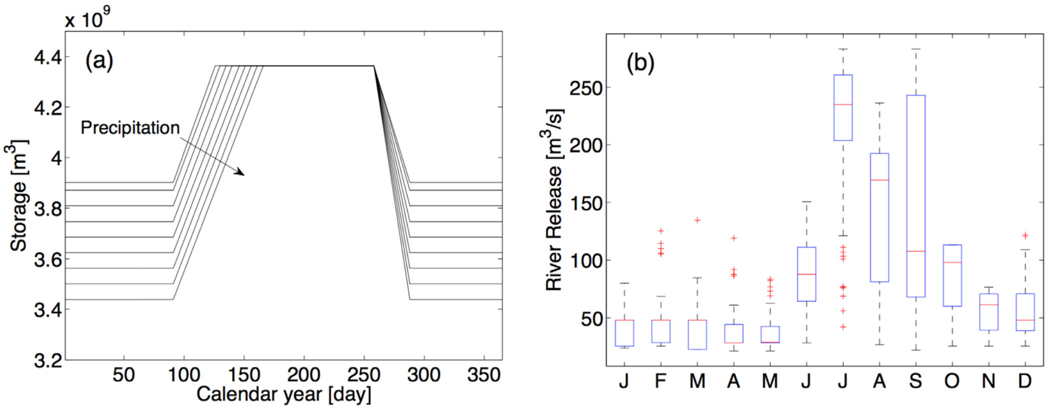

Figure 2. (a) Flood rule curves used in the actual operation of the Oroville Reservoir as function of time and precipitation. (b) Monthly boxplot of the flow released in the Feather River simulated by the CalSim model over the historical period 2000–2010.

current operation is based on the flood-control rule curves shown in Figure 2a. The curves divide the reservoir capacity into two pools: the flood control pool indicated by the area above the curves, and the conservation pool, which is the volume that can be filled for all other purposes. For each day of the year, the flood pool is defined as a function of the weighted accumulated precipitation over the catchment (the higher the precipitation, the bigger the flood control pool). The curves, developed by the United States Army Corps of Engineers in 1971, are based on historical reservoir inflows, physical constraints (e.g., downstream channel capacity), and historical operating objectives (mainly flood protection and water supply). The actual water needs of the downstream users are assessed annually. For example, crop selections are made in November, based on existing reservoir storage and projections of reservoir inflows. The selection is updated in May, when more realistic streamflow forecasts are available, based on snowpack measurements and updated reservoir storage conditions [*Rosenberg et al*., 2011]. The water demand is then dynamically partitioned among the reservoirs of the California State Water Project, based on the water availability of each reservoir in the network.

Because we only examine Oroville Reservoir, we estimated the historical water demand that this reservoir was required to supply during our analysis period. Unfortunately, records of past planning decisions are not readily available. For this reason, the entire network of reservoir is simulated over our study period (2000–2010) using the California water resources management model CalSim [*Draper et al*., 2004]. We obtained the CalSim simulations from the California Department of Water Resources (June 2013). They represent the release time series of the Oroville Reservoir when it is operated as part of the entire system. We, then, consider this time series as a proxy for the share of the total water demand assigned to the Oroville operation only (Figure 2b). As expected, this time series shows a significant inter-annual variability. We compute the 10th, 25th, 50th, 75th, and 90th percentiles, resulting in five trajectories that we used as reference annual demand patterns in our subsequent analysis. These trajectories correspond to demand-storage ratios of 0.54, 0.7, 0.89, 1.06, and 1.17, respectively.

3. Forecast-Based Adaptive Management

Reservoir release decisions for long-term operations, such as water supply, must account for impacts on both short-term and long-term time horizons. That is, they should aim to meet the water demand for the current time period without compromising the ability to meet the water demand in the future. This decision process may be enhanced by consideration of long-term streamflow forecasts. However, since forecast quality tends to decrease with lead time, the forecasts need to be updated frequently as new streamflow forecasts and new knowledge about the state of the reservoir become available. In this study, we adopt an adaptive management scheme in which both the forecasts and the decisions are periodically revised based on newly available information.

The adaptive management scheme works as follows. At time $\bar{t}$, a forecasting model produces a long-term forecast F_0 of the future reservoir inflows. The forecast F_0 is a sequence of inflows q_0 over the finite horizon

$[\bar{t}, \bar{t}+h]$, i.e., $F_0 = \{q_0(\bar{t}), q_0(\bar{t}+1), \cdots, q_0(\bar{t}+h)\}$. The forecasting model used in our study (described in section 3.1) produces inflows with a daily time step ($\Delta t=1$ day) over a one-year lead time ($h = 1$ year). The forecast F_0 is then used to feed a Model Predictive Control (MPC) optimization algorithm (described in section 3.2), which provides a sequence OP_0 of h operating rules m_0, i.e., $OP_0 = \{m_0(\bar{t}, s), m_0(\bar{t}+1, s), \cdots, m_0(\bar{t}+h, s)\}$, one for each day of the time horizon. Each operating rule $m(\cdot)$ provides the optimal reservoir release decision for a given time t as a function of the reservoir storage s. In principle, these operating policies can be used to operate the reservoir over the entire forecast horizon $[\bar{t}, \bar{t}+h]$. However, at time $\bar{t}+\tau$, a new forecast $F_1 = \{q_1(\bar{t}+\tau), q_1(\bar{t}+\tau+1), \cdots, q_1(\bar{t}+\tau+h)\}$ is issued (with the model used here, forecasts are issued once a week, i.e., $\tau = 7$ days). Therefore, a new MPC optimization can be run and a new sequence of operating policies $OP_1 = \{m_1(\bar{t}+\tau, s), m_1(\bar{t}+\tau+1, s), \cdots, m_1(\bar{t}+\tau+h, s)\}$ is computed. From this moment onward, at each time $t \geq \bar{t}+\tau$, two operating policies are available, one from the sequence OP_0 and one from OP_1. Among the two, the latter should be preferred because it is based on the updated forecast F_1, which is supposed to be more reliable than F_0. The operating policies OP_1, in their turn, will be used until a new forecast F_2 is issued at time $t = \bar{t}+2\tau$ and updated operating policies are generated, and so on. Consequently, the forecast-based adaptive management scheme guarantees that the reservoir is operated based on the most updated streamflow forecasts at each time step. The next paragraphs describe the forecasting approach and the MPC optimization routine in more detail.

3.1. The ESP-VIC Forecasting Approach

In the western U.S., where streamflow is largely snow-dominated, the skill in seasonal streamflow forecasts is derived mostly from the initial conditions, i.e., the amount of water stored in the snowpack and in the soil at the beginning of the melting period. Skillful climate forecasts will complement the predictability based on initial conditions and extend the skillful horizon of the forecast [*Shukla and Lettenmaier*, 2011].

Our objective is to quantify how differences in forecast skill over multiple key forecast horizons influence the adaptive optimization of reservoir operations. In addition, we aim to quantify the relative contribution of these different forecast periods to the overall value of the forecast. More specifically, we want to estimate the range of values of forecast skill for different forecast time horizons and demonstrate the need to evaluate and communicate this time-varying skill for use in adaptive optimization.

We might have used synthetic forecasts with different error characteristics across multiple horizons according to our analysis objectives. However, ESP (resampling of previous climate with perfect knowledge of initial conditions) provides a simple and intuitive forecast, which allows for the isolation of the seasonal and inter-annual forecast components. The skill of the ESP forecasts relies on the model initial conditions, i.e., snowpack and soil moisture storage. ESP forecasts have little skill in forecasting inter-annual water availability. ESP is widely used by numerous water management agencies, including the United States National Weather Service River Forecast Centers and the United States Bureau of Reclamation [*Rosenberg et al*., 2011]. ESP forecast skill often is comparable to seasonal forecasts from other sources. For example, the skill of the National Center for Environmental Prediction (NCEP) Climate Forecast System version 2 (CFS v2) [*Saha et al*., 2014] seasonal climate forecast does not significantly surpass that of ESP for seasonal volumetric snowmelt in the western U.S. [*Yuan et al*., 2011; *Shukla and Lettenmaier*, 2011]. We could use CFSv2 forecasts as well, but the implications are out of the scope of this paper with respect to our objective to assess the upper and lower values of different forecast horizons. The use of CFSv2-based flow forecast would lead to more investigation on the source of the skill for each horizons, i.e., initial hydrologic conditions or climate for seasonal component [*Li et al*., 2009; *Sinha and Sankarasubramanian*, 2013] and climate for the inter-annual component, and how it affects the carryover in our optimization. We assume that the seasonal and inter-annual flow forecasts based on climate forecast (CFSv2) are bounded by our ESP and perfect long-term flow forecast, which is a reasonable assumption [*Yuan et al*., 2011; *Luo et al*., 2007].

In the first step of the forecast-based adaptive management scheme, we produce a retrospective hydrologic forecast data set using the ESP approach and the VIC hydrology model as developed and applied in the WestWide Seasonal Flow Forecast system [*Wood and Lettenmaier*, 2006]. VIC is a physically based, semidistributed hydrology model that closes the energy and water balances and includes subgrid variability in elevation, vegetation, and infiltration with an explicit snow model. The setup used in this analysis uses a 1/8° spatial resolution and a daily time step [*Maurer et al*., 2002].

Table 1. Performance Indicators of the VIC Hydrology Model Over the Calibration (2000–2005) and Validation Data Set (1990–2000)

Performance Indicator	Calibration (2000–2005)	Validation (1990–2000)
Annual relative bias	0.00	0.00
Daily correlation	0.91	0.93
Daily NSE	0.81	0.84
Daily NSE (log flow)	0.84	0.79
RMSE/Obs mean	0.46	0.67
MSE/Obs mean	0.19	0.16

The forecast process consists of two steps: a *nowcast mode* to derive initial conditions on the day of the forecast and a *forecast mode* to derive the 365-days-long streamflow forecasts. The VIC model is first run in *nowcast mode* until the forecast day to obtain an estimate of the hydrological initial conditions based on observed gridded meteorological forcings [*Maurer et al.*, 2002]. In *forecast mode*, the hydrology model is initialized with the hydrological conditions from the nowcast run and is further forced with a 49-member, 365 day long, ensemble climate forecast, which is resampled from the existing 1960–2010, long-term, gridded, observation-based meteorological data set using a leave-one-year-out approach. For example, the first member of the climate forecast for 1 April 2006 corresponds to the meteorological sequence from 1 April 1960 to 31 March 1961, the second member corresponds to 1 April 1961 to 31 March 1962, and so on until 2009. However, 1 April 2006 to 31 March 2007 is removed from the ensemble.

Calibration of the VIC model over the Feather River Basin was performed using the Multi-Objective Complex Evolution method from the University of Arizona (MOCOM-UA) [*Yapo et al.*, 1998], as applied by *Voisin et al.* [2011]. Soil and routing parameters are both optimized at the daily time step for daily and long-term volume and timing. Four metrics are used in the calibration: the explained variance, the relative bias, the relative standard deviation difference, and the absolute value of the annual mean volume error, as suggested by *Gupta et al.* [2009]. The performance of the simulated streamflow is evaluated with respect to the naturalized daily streamflow at Oroville Dam (station code ORO on http://cdec.water.ca.gov). Table 1 presents measures of model performance for the calibration period (2000–2005) and the validation period (1990–2000) for the following components: correlation, Nash Sutcliff Efficiencies (NSEs), and raw and relative Root-Mean-Square Errors (RMSEs) and Mean Square Errors (MSEs). Model performance for both periods (calibration and validation) is very similar, with slightly higher correlation and NSEs, but also RMSE, during the validation period. This performance, over the validation period, represents accuracy of the representation of initial conditions for the flow forecasting system as well as the best forecast benchmark.

3.2. The Model Predictive Control (MPC) Optimization

In the second step of the forecast-based adaptive management scheme, reservoir release decisions are determined by Model Predictive Control (MPC) to account for both short-term and long-term effects of the release decisions. The decisions are periodically revised to include the most up-to-date streamflow forecasts.

In this study, we average the original flow forecast ensemble members to one trace and use a deterministic optimization method, i.e., Deterministic Dynamic Programming. Generally speaking, reservoir operation performances could benefit from the consideration of the entire ensemble within a probabilistic optimization approach [e.g., *Yao and Georgakakos*, 2001; *Franz et al.*, 2003; *Boucher et al.*, 2012], but in this paper, we instead explore how forecasts with different skill over different horizons may affect the design of reservoir operation, without focusing on how forecast uncertainty affects reservoir operation design. We will further discuss the implications of this assumption in the conclusions.

We consider two operating objectives: flood control and water supply. The latter is used for irrigation, municipal supply, and environmental conservation both in the Feather River and in the San Francisco Bay area. We do not consider hydropower production because the hourly dynamic of the hydropower plants cannot be properly described at the daily time step. For the same reason, we consider only the Oroville Reservoir, disregarding the smaller Thermalito Forebay and Afterbay reservoirs, which are mainly used for pumped storage and for temporary storage to fill irrigation canals. The Oroville Reservoir is represented by a mass balance model. Evaporation losses are modeled as a function of reservoir storage and time of the year, and are calibrated based on historical records. Reservoir releases are constrained by physical reservoir characteristics, e.g., spillway rating curves and maximum outlet flow. The mass balance model is validated against historical reservoir storage observations. The coefficient of determination is 0.98 on a daily basis, with a mean daily relative bias ranging from −0.5% to 2%.

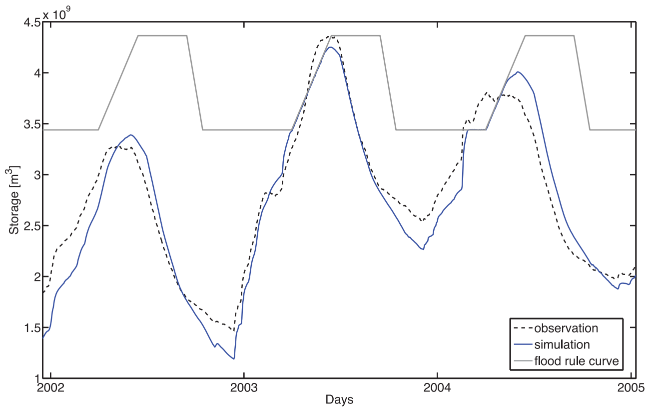

Figure 3. Validation of the optimal control problem: comparison of the observed (black dashed line) and simulated (blue solid line) storage trajectory. The latter is obtained by solving a deterministic Model Predictive Control (MPC) problem on the horizon 2000–2010, using the 50th percentile of downstream demand (corresponding to a 0.89 demand-storage ratio) and the historical time series of reservoir inflows. The grey solid line represents the flood rule curve used in the optimal control problem formulation.

Flood control is included as a constraint to the MPC problem by using the most conservative flood rule curve as an upper bound on reservoir storage (the lowest curve in Figure 2a). By so doing, we ensure that flood risk is minimized based on the actual operating policies. Water supply, instead, is included in the objective function J_{irr}, which is formulated as the squared deficit volume with respect to the downstream demand

$$J_{irr}=\sum_{t=\bar{t}}^{\bar{t}+h-1}\left[\max\left(w_t-r_t,0\right)\right]^2 \qquad (1)$$

where r_t is the average daily release from Oroville Reservoir, w_t is the downstream water demand, and h is the length of the optimization horizon, i.e., 365 days. The downstream water demand w_t is the sum of two components: the 7-days moving average of the observed flow diverted from Thermalito Afterbay and the 10th, 25th, 50th, 75th, and 90th quantiles of the releases simulated by the CalSim model (boxplot of Figure 2b). We use the resulting five demand trajectories to assess the forecast value under different demand stresses (see section 6.2). In each experiment, we use one of the five reference patterns to design the optimal reservoir operation. The same reference pattern is then used to compute the reservoir operation performance and, as a consequence, the forecast value. The squared term in the objective function places a higher penalty on a single large deficit event than on a sequence of smaller deficit events (of the same overall volume) and therefore induces the MPC optimization to distribute supply deficits over time. The squared deficit from a target release is a commonly used objective function for long-term operation and for the design of hedging rules [*Neelakantan and Pundarikanthan*, 1999; *You and Cai*, 2008; *Draper and Lund*, 2004]. The objective function can also be considered as a minimization of the vulnerability of the reservoir operation, as defined by *Hashimoto et al*. [1982], because it tends to minimize the consequences of supply failures. We consider a single objective problem to focus explicitly on the forecast value for water supply. In a multiobjective framework, this issue would be complicated by the presence of multiple tradeoffs, which may shift the forecast value toward other reservoir operating objectives. On the other hand, we include a constraint on flood protection to explicitly distinguish between long-term and short-term objectives and, thus, between different time scales in reservoir operation.

The reservoir model, the formulation of the objective function, and the MPC problem constraints (see the supporting information for their complete formulation) represent a realistic description of the actual reservoir management. Figure 3 compares the time series of observed reservoir storage with the time series obtained by solving a deterministic MPC problem on the optimization horizon 2000–2010, using the 50th percentile of downstream demand (corresponding to a demand-storage ratio equal to 0.89) and the historical observed time series of reservoir inflows. The comparison results in a Nash-Sutcliffe efficiency of 0.82, computed on a daily basis. Overall, the model mimics reasonably well the actual reservoir operation. In particular, the simulated reservoir drawdown is comparable to the observed drawdown. The differences in the upper storage result from a constraint imposed in the optimal control problem formulation: the actual rule curve for the flood control pool varies annually and is updated throughout the season based on daily hydrological observations, while we always adopt the most conservative pool for the entire simulation period in the MPC formulation.

4. Experimental Approach

Our experimental approach is represented in Figure 4. We compare the benefit of considering ESP forecasts with two literature benchmarks. The first benchmark uses a perfect forecast, i.e., daily reservoir inflow simulated using observed weather, consisting of perfect seasonal and inter-annual flow forecast components.

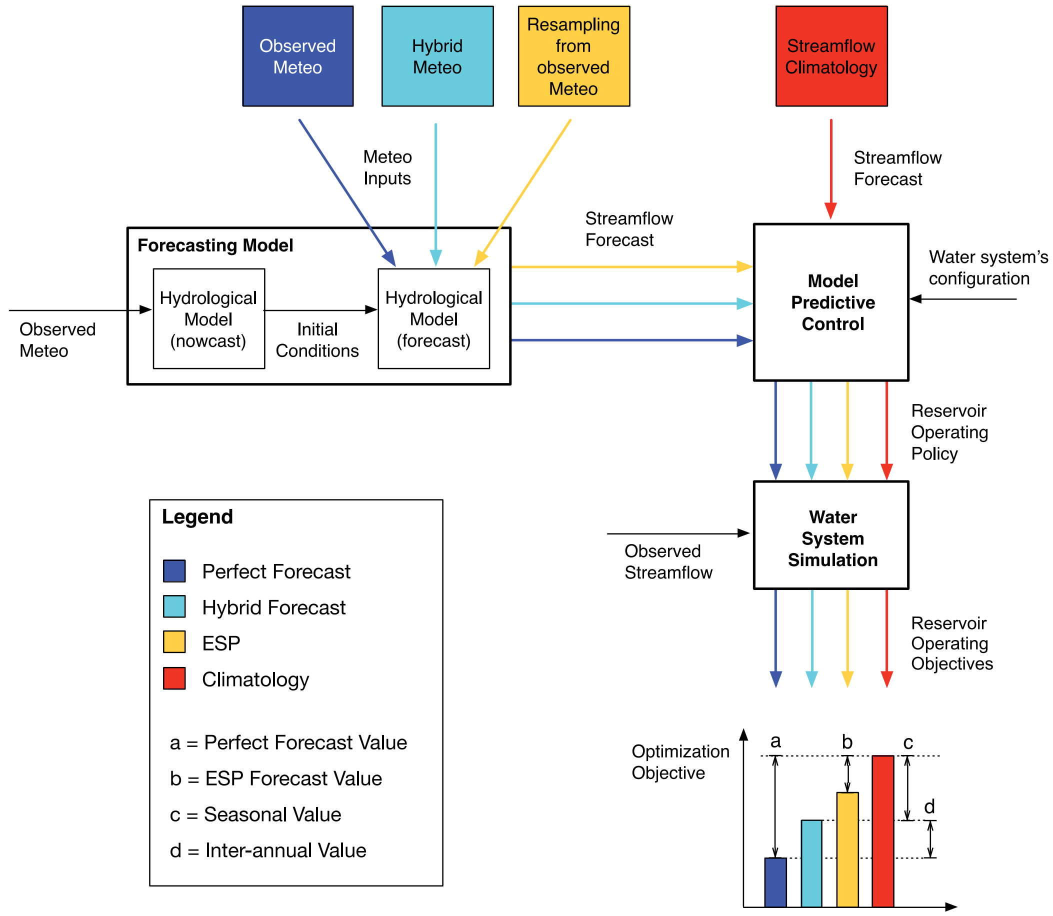

Figure 4. Forecast-based adaptive management framework composed of a forecasting model (a spun-up hydrological model forced with long-term forecasts) and a Model Predictive Control optimization scheme. The experimental setting consists of different benchmark forecasts (perfect forecast, climatology, and hybrid forecast) that are compared with an ESP forecast to determine the value of the seasonal and inter-annual forecast components. The value of the different components is measured by the reservoir operating objective.

This represents the upper bound that can be achieved both from the point of view of forecast quality and forecast value. The second benchmark is streamflow climatology, i.e., no skill in seasonal or inter-annual components. In this case, climatology (computed as the 1960–2010 daily average simulated reservoir inflow) leads to the operational performance that can be achieved in the absence of specific knowledge about next year's weather. Both the climatology and the perfect forecast are obtained by running the VIC model forced with the observed meteorology. We do not use observed streamflow, but rather streamflow simulated with the VIC model using observations. The reason for this is to assure that the two benchmarks were consistent with the ESP approach (which requires the VIC model simulation as well) and to isolate our quantification of forecast quality and value from hydrological modeling errors. Stated otherwise, this approach avoids any confounding of our results with VIC model biases.

We, then, assess the ESP forecast value by comparing the reservoir operating performances with the two benchmarks. ESP provides a representative long-term forecast with reasonably skillful (depending on date of forecast) seasonal, and unskilled inter-annual components. We assess both the quality and the value of the ESP forecasts. To further analyze the source of the ESP forecast value, we construct a set of hybrid forecasts by merging perfect forecasts until the end of the water year with climatology afterward, resulting in a perfect seasonal forecast component and an unskillful inter-annual component. When compared with the two benchmarks, the hybrid forecasts allow us to isolate and quantify the contributions of the seasonal and inter-annual forecast components to the overall forecast value.

We first apply the forecast-based adaptive management framework to the Oroville Reservoir in California. We then modify the reservoir and demand characteristics to demonstrate the robustness and transferability

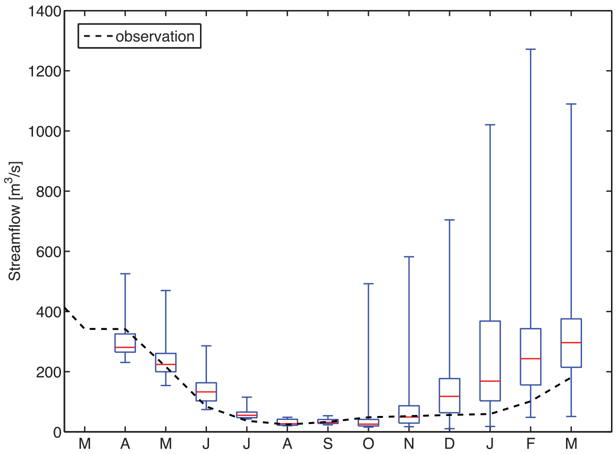

Figure 5. Example of ESP forecast quality: streamflow forecast ensemble on 1 April 2000. The boxes show the 25th, 50th, and 75th percentiles, while the whiskers represent the minimum and maximum ensemble members, thus indicating the full range of uncertainty. The black dashed line represents the observations. The forecast quality is highest for April–July volumetric streamflow, while the forecast quality is significantly reduced after the summer.

of our findings to other reservoir systems that share the same main operating objective (water supply) and hydrological regime (snow-dominated).

5. Forecast Quality

The ESP forecast data set consists of a 49-member ensemble of 365 day long streamflow forecasts. As explained in section 3.1, the ensemble is simulated using the VIC hydrology model by resampling from the 1960–2010 observed meteorological data set using a leave-one-year-out approach. We evaluate the forecast quality by comparing the forecasted monthly flow volume with the observed flow volume [*Wood and Lettenmaier*, 2006]. Figure 5 represents the typical seasonal ESP flow forecasts issued at the onset of snowmelt at Oroville (similar results apply for other snow-dominated catchments). It represents, as an example, the 365 day flow forecasts issued on 1 April 2000. The figure shows that the forecast quality is highest for April–July volumetric streamflow. The forecast uncertainty is relatively small during these months and the observed trajectory lies not far from the center of the box plot. After the summer, the forecast quality is significantly reduced. The observed trajectory lies below the 25% of the ensemble in almost every month as a result of a systematic high bias in the forecasts. After the end of the water year, when the effect of spring initial conditions has disappeared, the information in the streamflow forecast is the same in each year and corresponds to climatology. The inter-annual component of the ESP forecast has thus little skill, because inter-annual hydroclimatological forecasts are driven by climate conditions rather than by hydrological initial conditions.

Figure 6 shows the monthly Mean Square Errors (MSEs) divided by the variance for the different experiments (perfect forecasts, climatology, ESP, and hybrid forecasts), as a function of the lead time (months) and the month during which the forecast is issued. The ratio represents the ability of the forecast to predict the monthly flow with respect to climatology. A value of 1 indicates no improvement with respect to climatology. Values below 1 indicate forecasts that are more informative than climatology. The perfect forecast ratios present an upper bound on the forecast skill. The figure clearly shows that the forecasts do not provide useful information (compared to climatology) during fall and winter when the flow is low. The ratios for the climatology forecasts are all close to one (they are not exactly one because the climatology used for the forecast is based on the 1960–2010 period while the climatology used for verification is based on the 2000–2010 period). The ESP forecast shows greater skill than climatology during winter and spring season, while the skill is similar to climatology right at and after the start of the new water year. The hybrid forecast experiment represents the upper bound for forecast quality that an ESP forecast can achieve.

6. Forecast Value

We define *forecast value* as the performance gain in reservoir operation obtained by including the forecasts into the decision-making system. Thus, unlike forecast quality, which is independent of how the forecasts are used, forecast value is dependent on the forecast application. The performance is measured by the objective function used in the MPC optimization, i.e., by the squared supply deficit, which is computed based on the optimal operating policies for each forecast and the observed reservoir inflow time series. The ESP forecast value is computed as the improvement in reservoir operating performance compared to the case in which climatology is used (segment *b* in Figure 4). The maximum potential value is obtained by comparing the two extreme cases of using a perfect forecast and a climatology forecast (segment *a* in Figure 4). The ESP forecast value gives insight into the operational value of the forecasts, while the perfect

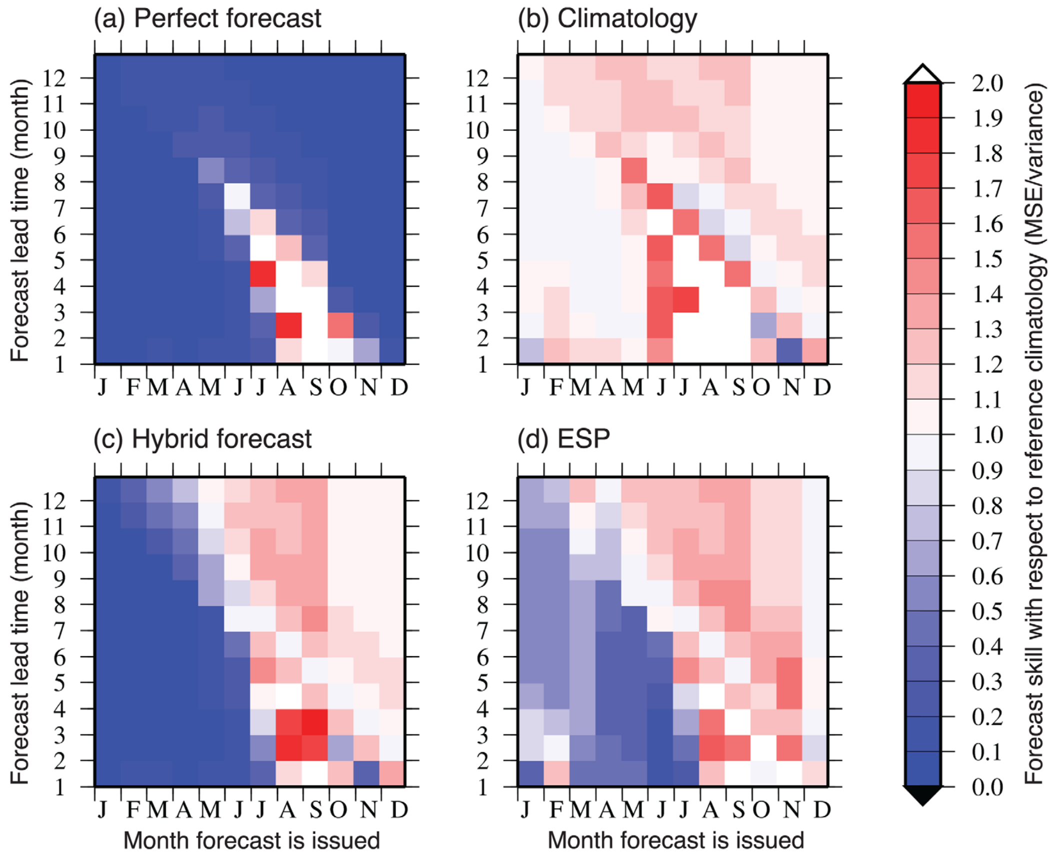

Figure 6. Monthly mean square errors over the variance for the different experiments; (a) perfect forecast, (b) climatology, (c) hybrid forecast (i.e., merged perfect forecast with climatology), (d) ESP, as a function of the month when the forecast is issued and the lead time (months). A value of 1 indicates no improvement with respect to climatology. Values below 1 indicate useful information.

forecast value quantifies the theoretical improvement that could be potentially achieved. We bound the value of the seasonal component of the ESP forecast by comparing the reservoir operating performances obtained when considering the hybrid forecast with that of the climatology forecast (segment *c* in Figure 4). This also represents the upper bound value that an ESP forecast can achieve, for example, by improving the definition of the soil moisture or snow water equivalent state. Finally, we bound the value of the interannual component of the ESP forecast by comparing the reservoir operating performances obtained when considering the hybrid forecast with that of the perfect forecast (segment *d* in Figure 4). This component of the overall value could only be achieved by consideration of climatic teleconnections where and when they exist.

In the following paragraphs, we assess the forecast values from the two benchmarks, ESP and hybrid experiments for the Oroville operation. Next, we change the water system configuration to explore how other factors, beyond forecast quality, can affect forecast value.

6.1. ESP Forecast Value

Figure 7 shows the squared supply deficit for the period 2000–2010, computed with respect to the 50th percentile of the downstream demand. Overall, the perfect forecast benchmark produces smaller deficits than the climatology benchmark, which means that knowledge of future inflows is valuable for reservoir operations. The improvement is noticeable when prolonged dry spells occur, e.g., during 2001–2002 and 2007–2009. During these years, the annual reservoir inflow volume is 10%–40% smaller than the active reservoir capacity (Figure 7a). As a result, the reservoir cannot be filled completely and optimal operating

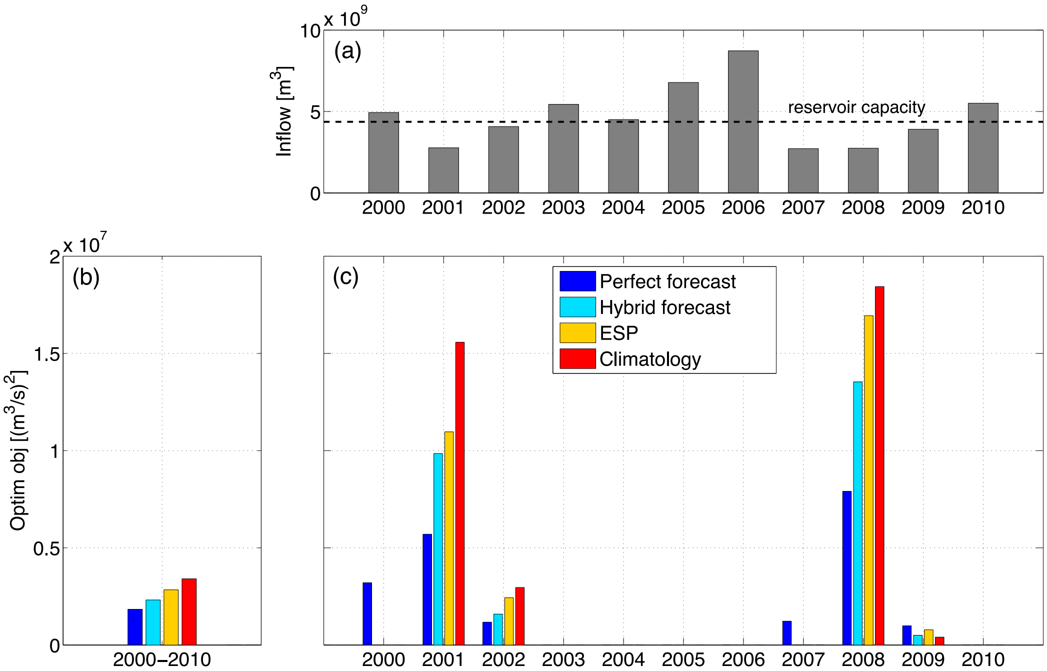

Figure 7. (a) Annual observed inflow volume to the Oroville Reservoir (the active capacity of the reservoir is represented with the dashed line). (b and c) Reservoir operation performances measured by the objective function used in the MPC optimization, i.e., the squared supply deficit. Performances are computed with respect to the 50th percentile of the downstream demand (corresponding to 0.89 demand-storage ratio), based on the optimal operating policies for each forecast (i.e., perfect forecast, hybrid forecast, ESP forecast, and climatology) and the observed reservoir inflow time series on the period 2000–2010.

policies are extremely important to satisfy the demand. Moreover, because the Oroville Reservoir has the potential to carryover water storage from one year to the next, the reservoir operator should decide whether to satisfy the current demand or curtail supply in the current year and store water for the next year. The use of an ESP forecast gives performances very similar to the ones obtained using climatology (Figure 7). The loss in value compared to the perfect forecast stems from the lack of information in the ESP forecast beyond the seasonal volumetric forecast, while the adaptive management optimization evaluates the forecast value over an entire year. Figure 8 provides more insight into the use of forecast information by the operating policies by analyzing reservoir releases in 2000 and 2001. The ESP and climatology forecasts are close to the perfect forecast for most of 2000, which is a normal year. In contrast, both the climatology and ESP forecast systematically overestimate the streamflow in 2001, which is a dry year with a dry fall and winter. Based on the perfect forecast, the optimization process results in policies that incur a deficit in year 2000 to mitigate the accumulated deficit over both years (Figure 8).

To better assess the contribution of knowledge of reservoir inflows in the next water year (or inter-annual component of the forecast) to the overall forecast value, we analyze the performances based on the hybrid forecasts. The difference between the perfect forecast and the hybrid forecast measures the loss in value due to not knowing the next year's water status. The difference between the hybrid forecast and ESP indicates the value that could be potentially gained by improving the ESP seasonal volumetric forecast. Figure 7b shows that the inter-annual component of the forecast contributes about 30% of the total forecast value over the entire horizon 2000–2010. If we consider only the two dry spells of the period under analysis, i.e., 2000–2002 and 2007–2009 in Figure 7c, the contribution of the inter-annual component increases to 45%.

6.2. Effects of Water System Features on ESP Value

Forecast value depends not only on forecast quality but also on the characteristics of the reservoir system. As a result, identical forecasts may be valued differently for different reservoir systems. Forecast value for a given reservoir may also change over time, because both the hydrological conditions and reservoir operation needs may evolve. In this section, we explore the sensitivity of forecast value, especially their seasonal and inter-annual components, to changes in the water system demand and supply features. This analysis

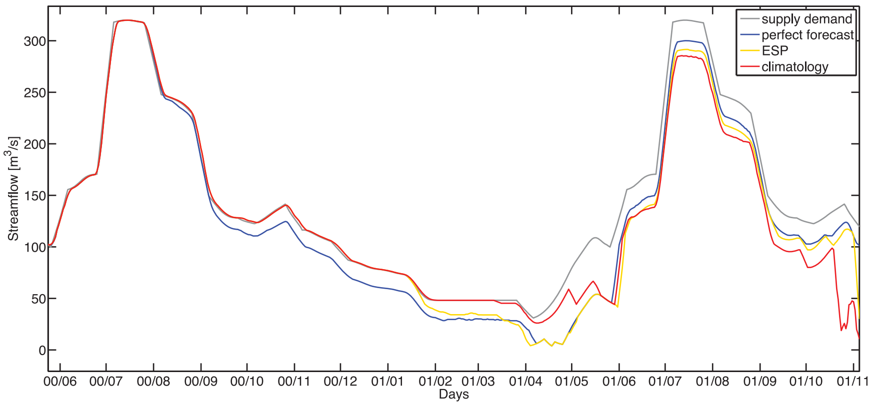

Figure 8. Reservoir release trajectories obtained when simulating the optimal operating policy derived considering the perfect forecast, the ESP forecast, and the climatology. The water demand to be supplied is represented by the grey solid line. When considering the perfect forecast, the optimized reservoir policy produces a controlled deficit in year 2000 to mitigate the accumulated deficit over both years 2000–2001. When considering the ESP forecast and the climatology, instead, the optimized reservoir policy produces a larger deficit in year 2001.

allows us to extend our findings to other reservoir systems that share the same main operating objective (water supply) and hydrological regime (snow-dominated).

Figure 9 provides a qualitative interpretation of forecast value as a function of demand and capacity-inflow ratio. The different water demands represent different potential levels of stress on the system. Increasing ratios of reservoir capacity over reservoir inflow represent an increasing ability of the system to store the inflow and meet the demand. Figure 9a shows the value of a perfect forecast. The forecasts have no value at all in two cases. In the first case, the downstream demand is high and the capacity-inflow ratio is low, maximizing the potential for water stress. Here, the reservoir is not properly designed to supply the demand and its operation cannot benefit from the use of forecasts. In the second case, the downstream demand is low and the capacity-inflow ratio is high, which means that the reservoir is oversized. Under these circumstances, every operating policy is able to meet the demand and once again the forecasts do not improve the operation. Forecasts become valuable in cases that fall between these two extremes. In reality, forecasts

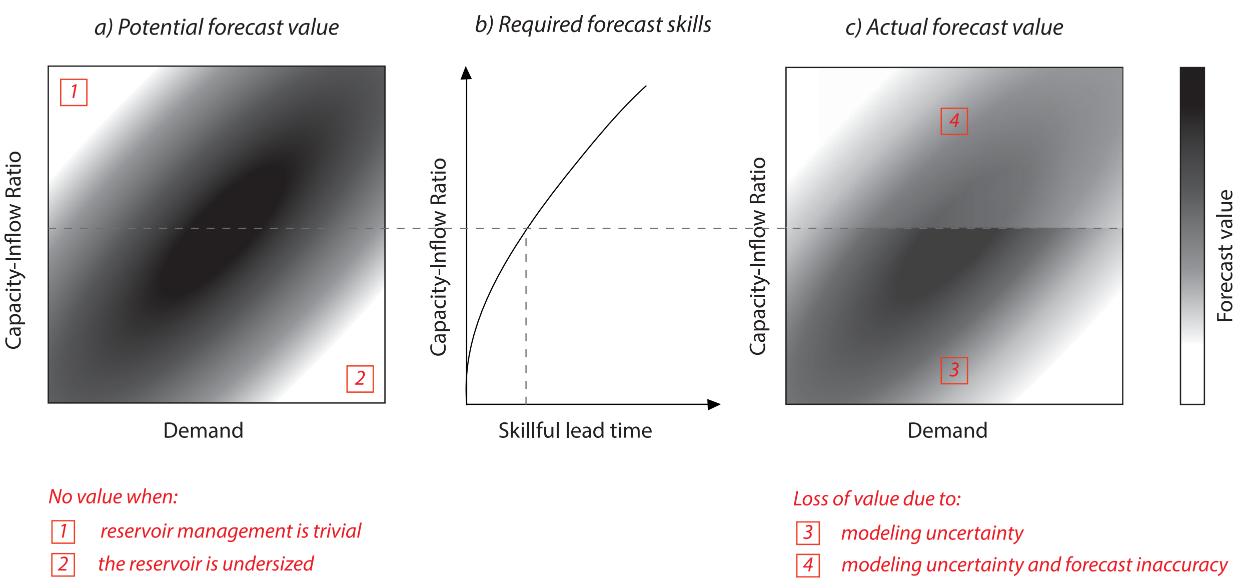

Figure 9. Sketch of the value of streamflow forecast as a function of supply demand and capacity-inflow ratio. (a) Potential value achievable using a perfect forecast: the forecasts have no value when the reservoir is undersized, maximizing the potential for water stress, or when the demand is small and the reservoir operation becomes trivial. (b) Relationship between the capacity-inflow ratio and the required forecast skillful lead time: the larger the capacity-inflow ratio, the longer the lead time on which forecast should be skillful to effectively inform reservoir operation. (c) Actual value achievable using a realistic forecast: the value decreases over the entire parameter space because of modeling uncertainty, and, even further on the upper part, because of a lack of forecast skill at long lead times.

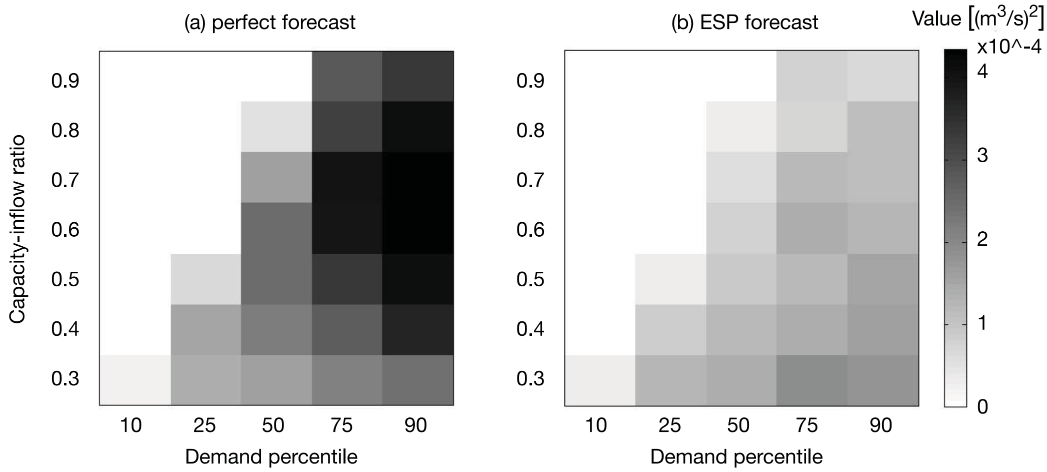

Figure 10. Numerical value of streamflow forecast as a function of supply demand and capacity-inflow ratio: (a) potential value achievable using a perfect forecast and (b) actual value achievable using ESP forecast.

have limited skill, especially for long lead times. This reduces the forecast value especially when the capacity-inflow ratio is large [*You and Cai*, 2008]. As a result, the more realistic representation of the forecast value is the one sketched in Figure 9c. The value decreases over the entire parameter space because of modeling uncertainty, and, even further on the upper part, because of a lack of forecast skill at long lead times.

To evaluate these effects quantitatively, we apply the forecast-based adaptive management scheme for different levels of demand and supply characteristics, obtained by perturbing the Oroville water system's configuration. We consider the five different downstream demand scenarios described in section 3.2. The scenarios differ in the annual water volume and in the seasonal pattern (see Figure 2b). We also consider seven different capacity-inflow ratios from 0.3 to 0.9, where 0.7 is approximately equal to the actual ratio of the Oroville Reservoir. Technically, we modify the ratio by changing the reservoir active storage, but keeping the same capacity and time pattern of the flood pool, so that the reservoir's ability to buffer floods is not altered. For each new water system configuration, we apply the forecast-based adaptive management scheme to obtain different operating policies, which are then simulated, as before, for the period 2000–2010.

The resulting forecast values are shown in Figure 10. Figure 10a represents the upper bound for the forecast values, computed as the difference between the reservoir operation performances based on the climatology and perfect forecast benchmarks. Figure 10b shows the actual value, which is computed as the difference between the performances of the climatology benchmark and the ESP forecasting system. The performance is computed as the mean daily squared supply deficit over the entire simulation horizon 2000–2010. The numerical results quantitatively substantiate the qualitative description given above. Notice, however, that Figures 9a and 10a are not directly comparable because in the latter the forecasts are perfect, but only have a fixed lead time of 365 days (rather than an infinite horizon). The value of the inflow forecast increases as the reservoir becomes unable to meet the demand. This happens for every capacity-inflow ratio when the demand is high, i.e., 75th and 90th percentiles, and for increasingly smaller capacities for lower demand percentiles. When the demand is low, forecasts have no value because many reservoir configurations can be considered oversized and the operation can easily supply the demand, even during dry years. Moving from perfect forecast (Figure 10a) to ESP forecast (Figure 10b), the forecast value decreases over the entire domain, as expected. On average, the actual ESP forecast value is 35% less than the potential value. The decrease is more pronounced (up to 80%) when the capacity-inflow ratio is large, because ESP forecasts are only skillful on the seasonal scale and not for longer lead times, as required by the reservoir operation. In the hybrid forecast experiment (not shown), the loss of value compared to the maximum value is 20% on average (and 60% at maximum). This means that improving the current seasonal skill of ESP can contribute to an increase in the forecast value of between 15 and 20%.

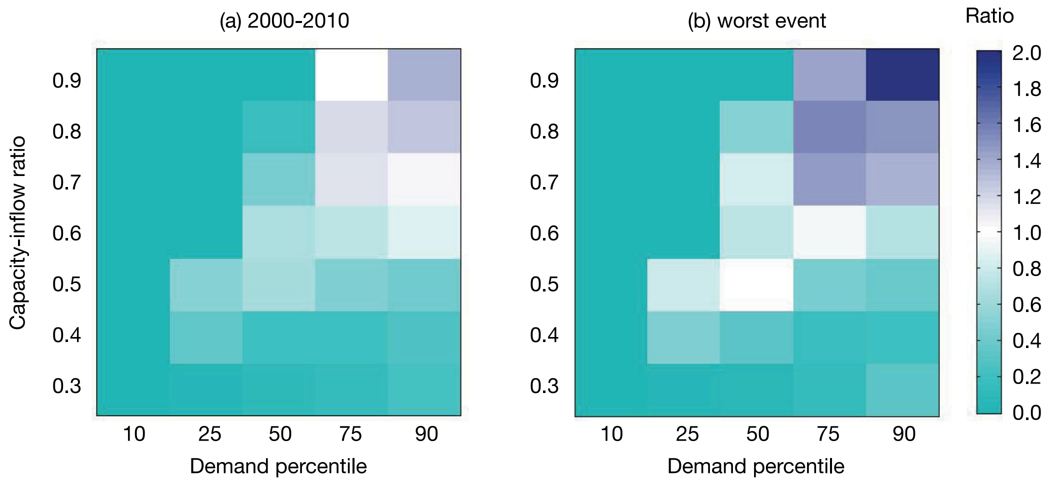

Figure 11. Ratio between the value of the inter-annual and seasonal components, obtained considering the hybrid forecast, as a function of supply demand and capacity-inflow ratio: (a) average value over the entire horizon 2000–2010 and (b) value over the worst dry event.

The relative contribution of the seasonal and inter-annual components of the forecasts also varies depending on the reservoir characteristics. Figure 11a shows the ratio between the inter-annual value and the seasonal value (as defined in the previous paragraph) for each combination of reservoir capacity-inflow ratio and water demand. It shows clearly that the inter-annual component of the forecasts is more important when the reservoir is large, either in absolute terms or relative to the demand. The value of the seasonal streamflow forecast increases with a decrease in the capacity-inflow ratio. As already noted, these numbers are computed over the entire evaluation horizon and thus summarize the usefulness of the forecasts in both wet and dry years. There were two major dry events in the 10 year period, i.e., in 2000–2002 and 2007–2009. The figures computed over the worst event among the two shows that the ratio goes up to 2 (Figure 11b), meaning that, during situations of particularly high water stress, an accurate inter-annual streamflow forecast is about twice as important as an accurate snowmelt volumetric forecast.

7. Discussion and Conclusions

In this paper, we assess the value of long-term streamflow forecasts in designing reservoir operations for water supply in snow-dominated river basins using a forecast-based adaptive control framework. At first, we analyze the Oroville reservoir system in the western U.S., an inter-annual reservoir operated for flood control and municipal and irrigation supply. The analysis quantifies the value of the inter-annual forecast component especially during prolonged dry spells, when the potential to store water from one year to the next can be exploited. ESP forecasts have only limited value for Oroville operations, because the forecast skill in this snow-dominated catchment is seasonal and limited to spring, while optimal adaptive reservoir operation for Oroville requires reliable water availability information at longer lead times. We estimate that the inter-annual component of the forecast contributes about 30–45% of the total forecast value, depending on the hydrological conditions (normal or dry).

The forecast value depends also on the reservoir operation objectives, the hydrological features, and other structural characteristics of the water system. We explore the effect of water demand and storage capacity-inflow ratio on the value of a given forecast. In so doing, we investigate different potential stress situations, from almost no stress, e.g., when the reservoir is large and the demand is low, to very high stress, e.g., when the reservoir is small and the demand is high. This analysis allowed us to obtain more general results beyond the specific study site, and to examine how the value of the forecast for the Oroville Reservoir may change in the future, under the pressure of evolving hydrological conditions and reservoir operation needs. Perfect forecasts are valuable when the water system is under stress, i.e., large supply demand with respect to reservoir capacity, or the reservoir is operated for inter-annual carryover. Conversely, seasonal ESP forecast value is highest when the demand is medium-high and the reservoir is relatively small, because in this case, the reservoir can only shift water on a seasonal basis. Inter-annual forecasts are needed in case of large reservoirs (large in absolute terms or with respect to the demand they need to supply), while their contribution is negligible for small reservoirs. Finally, if the demand is only a small portion of the reservoir inflow and storage, streamflow forecasts have little value.

On average, the ESP value is 35% less than the perfect forecast value. The inter-annual component of the ESP forecast contributes 20–60% of the total forecast value, depending on the hydrological conditions (normal or dry). Improvements in the seasonal component of the ESP forecast would increase the overall ESP forecast value between 15 and 20%. These results, obtained by considering multiple capacity-inflow ratios and different demands, are applicable to other snow-dominated river basins with similar operating objectives (water supply) and forecast skill (seasonal versus inter-annual). The findings should motivate more collaborative research between forecasters and reservoir operators.

An ensemble-based optimization scheme that explicitly accounts for the uncertainty embedded in the ESP ensemble when designing the reservoir operation policies may improve reservoir operation performance [e.g., *Yao and Georgakakos*, 2001; *Franz et al.*, 2003; *Boucher et al.*, 2012]. The resulting improvements are likely most pronounced at short rather than long (e.g., inter-annual) lead times, because the initial conditions of the hydrological model influence the forecasts only until the end of the summer. As a consequence, the entire forecast ensemble (just as the ensemble average) does not contain information about the next water year and cannot inform the optimization procedure about the proper amount of carryover. A detailed analysis of the value of the full ensemble is beyond the scope of this paper and remains a topic for future research.

Acknowledgments
The authors wish to thank Michael Anderson, California State climatologist, for his insightful feedbacks and Aaron Miller and Lek Boone at California Department of Water Resources for their collaboration on providing water demand data and feedbacks on initial setups. Nathalie Voisin was partially supported by the United States Department of Energy, Water Use Optimization Toolset project. Bart Nijssen was supported in part through the United States Department of Energy, Wind and Water Power Program under contract DE-AC06-76RLO with Pacific Northwest National Laboratory via task order 108989 to the University of Washington. The analysis output is available upon request from the corresponding author.

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