Journal of Renewable and Sustainable Energy ARTICLE scitation.org/journal/rse

Forecast-informed hydropower optimization at long and short-time scales for a multiple dam network

Cite as: J. Renewable Sustainable Energy **12**, 000000 (2020); doi: 10.1063/1.5124097
Submitted: 11 August 2019 · Accepted: 31 January 2020 ·
Published Online: 0 Month 0000

View Online Export Citation CrossMark

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ABSTRACT

This study presents a scheme for co-optimizing the long-term (seasonal) reservoir operating objectives with the short-term (daily) objectives for multi-dam networks to maximize hydropower generation. Long-term optimal reservoir storage provides temporal space to optimize operation of the dams at short-term based on forecasted reservoir inflow. This study asks if there is an added benefit of co-optimization of operations at long- and short-term scales for hydropower generation. The multi-objective optimization problem at both the temporal scales was simultaneously solved considering Pareto optimality between conflicting objectives. Constraints pertaining to flood control, dam safety, and environmental flow were imposed. The proposed scheme was implemented over a network of Blue Mesa, Morrow Point, and Crystal dams in the Upper Colorado Basin. Ensemble forecast forcings from publicly available numerical weather prediction and climate models were used as inputs for the daily and monthly scale inflow forecasts. The results show improvements of 41%, 27%, and 15% in hydropower generation using the co-optimization during wet, moderate, and dry years, respectively, against a benchmark that neglects inflow forecasts. This study demonstrates added benefit of co-optimizing the operations for hydropower generation based on short- and long-term forecasted reservoir inflow. Given that most dams today operate as a network in a river basin, we recommend moving away from single dam and single time scale optimization to a multiple-dam with long- and short-term scale co-optimization-based operations to make renewable energy generation more efficient.

I. INTRODUCTION

One of the least expensive and stable sources of energy with significant operational flexibility and instant power generation capability is conventional hydropower (Holmes and Papay, 2011). Hydropower has experienced comparatively fewer periods of fluctuations in yield, unlike wind or solar, which are dependent on geographic location and ambient weather conditions (DOE, 2016). To reduce the dependence on fossil fuels and promote the use of clean and renewable energy sources, the operations of hydropower dams (used here interchangeably with "reservoirs") need to play a critical and central role. Hydropower dams that already exist are not getting phased out globally anytime soon despite the well-known costs to the environment and ecosystem services (Ligon *et al.*, 1995; Tilt *et al.*, 2009). Thus, efficiently managing such a resource has the potential to not only expand clean (i.e., non-fossil fuel) energy generation but also provide resilience against extreme hydrological events, drought management, and flood protection (Yang *et al.*, 2017). As the growing population's demand for water and the resulting water stress continues to increase, building newer dam infrastructure is not a fool-proof solution and is much debated in the literature (Manyari and de Carvalho, Jr., 2007; Tilt *et al.*, 2009). Rather, if the existing dams are operated more efficiently, higher energy benefits can be achieved without building new hydropower dams. In other words, improved performance of hydropower operations can generate more energy from fewer dams, while providing the planned hydropower systems with smarter expansion plans (Marques and Tilmant, 2013).

Researchers and policy makers, over the past century, have been attempting to improve the reservoir operations to better satisfy the demands of stakeholders. A major challenge toward improving the operational effectiveness of reservoirs is to integrate the forecast of weather and climate information with real-time operating policies (Dong *et al.*, 2006). A distinction is generally made concerning the temporal scale of forecasts where short-term forecasts (daily to weekly scale) are incorporated to optimize for short-term (tactical) operational

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purposes while medium to long-term forecasts (monthly or seasonal scale) are used for long-term (strategic) objectives (Anghileri *et al.*, 2016). Although this is a common notion for using forecast information to optimize reservoir operations, it suffers from drawbacks. Losses can occur to the specified operating purpose due to optimization addressing only the short or long-term objectives but not both (Sreekanth *et al.*, 2012). Real-time operations typically rely on forecasts with a horizon of only a few days because of degrading skill in forecasts with the increasing lead time (Celeste *et al.*, 2008). However, relying only on the short-term forecasts for reservoir operation optimization results in a short-sighted policy that does not dovetail the longer-term goals. Such release decisions optimal over short-term are prone to sub-optimality when the performance is assessed over the seasonal or annual scale (Xu *et al.*, 2015; Sreekanth *et al.*, 2012). Likewise, when the optimization problem addresses only the long-term planning of the reservoir operations, it uses seasonal hydro-climatic information that can introduce large inflow uncertainty at shorter time scales. Bias in long-term forecasts of inflow and conflicts between long and short-term operation goals can again lead to a suboptimal policy over the long-term as well as over episodic extreme events (Xu *et al.*, 2015). Therefore, it is imperative now to achieve a balance between the immediate and potential future benefits, satisfying both the short and long-term optimality in operations. Large dams that operate as a network can optimize their monthly storage and release based on seasonal (long-term) forecast of inflow. Such long-term optimization provides temporal solution space to optimize and tailor the operations of the dams at short-term (daily) scales based on reservoir inflow using weather-forecasts. We demonstrate this concept schematically in Fig. 1.

Dams are seldom operated individually and are usually connected in a network, often to form a multi-reservoir system with a cascade of reservoirs in series and occasionally in parallel. Operating the entire system in coordination with each dam is essential for improving the operational efficiency and maximizing the overall benefits to the stakeholder with conflicting interest (Xu *et al.*, 2015). Joint operation considers the storage variation in each linked reservoir and subsequently results in a set of optimal releases with simultaneous evaluation of numerous trade-offs in the best interest of each reservoir. Operating rule curves are often used to guide the operations of system of dams outlining the reservoir storage targets to be met at specific times of the year. The rules are historically developed by respective operating agencies using historical reservoir inflows, physical constraints (e.g., downstream channel capacity), and historical operating objectives (Anghileri *et al.*, 2016). A number of reservoir planning and operation studies have optimized the rules based on the operating purpose and type of reservoir network. Lund and Guzman (1999) reviewed a variety of derived real-time operating policies for multiple reservoir networks operated for water supply, flood control, hydropower, water quality, and recreation and presented conceptual optimal rules for series and parallel reservoir networks. Marques and Tilmant (2013) underscored the economic value of coordination in a large-scale multi-reservoir system in Brazil. Zhou *et al.* (2016) derived optimal operating rules for a multi-reservoir system in China by combining the water and power operating rules to coordinate operations. However, most of these published rules are static "thumb rules" that cannot be relied upon when the circumstances change. For example, during extreme events of unprecedented magnitude, relying upon such rules does not guarantee the best degree of resilience or downstream safety. This necessitates a scheme of operations, which is dynamically updated at shorter timescales and adjusts itself accordingly without the need to refer to static rules.

The dimensionality problem in optimizing larger systems is tackled using the aggregation of multiple reservoirs to convert into an equivalent single-reservoir optimization problem (Liu *et al.*, 2011). This is then followed by a disaggregation scheme to obtain solutions for single reservoirs (Saad *et al.*, 1994). Fang *et al.* (2014) proposed the hedging rule based on an aggregated reservoir and the storage allocation rule to specify release from each reservoir. Archibald *et al.* (1997) included a two-dimensional representation of the rest of the system to the equivalent aggregated reservoir. Another commonly applied approach is to optimize the released and stored energy instead of the

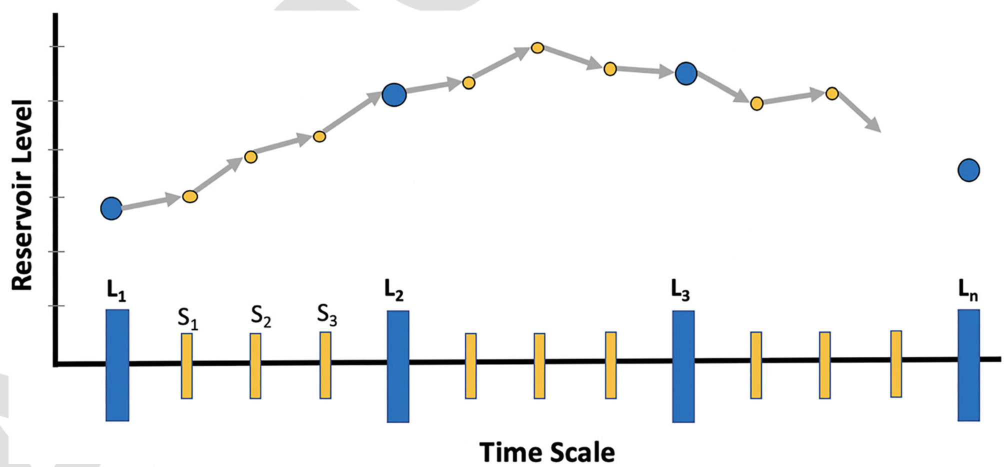

FIG. 1. Schematic showing the concept of co-optimization where the long-term optimal goals are dovetailed with the short-term optimal reservoir operations. Blue bars (L_1, …, L_n) are long-term forecast horizon units (or lead times) for obtaining storages optimized for long-term benefits, while yellow bars (S_1, …, S_n) denote the short-term optimization horizon. The corresponding short-term optimal operations (gray arrows) result in the levels (yellow circles) that are also optimal with the long-term goals (blue circles). The co-optimization uses temporal solution space to tailor the short-term operating policy within the long-term horizon.

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objective or cost function. For example, Becker and Yeh (1974) and Li *et al.* (2012) proposed the optimal operation model that minimized the loss of released or stored energy. Furthermore, a general rule for increasing hydropower is to prioritize storage in reservoirs with the highest energy production (Marques and Tilmant, 2013). However, such an approach is biased as the most "efficient" reservoir that needs the least amount of release per unit energy generated always gets more load, leading to faster storage depletion and reducing its productivity (Xu *et al.*, 2015).

A vast majority of literature on deriving optimal operation rules has paid attention to either short-term or long-term forecast-based optimization. The value of long-term inflow forecasts (monthly to seasonal scale) has been demonstrated for flood control operations (Anghileri *et al.*, 2016), hydropower operations (Hamlet *et al.*, 2002; Block, 2011; Maurer and Lettenmaier, 2004; Alemu *et al.*, 2011), irrigation and water supply (Sankarasubramanian, 2009; Georgakakos *et al.*, 2005), and drought management (Golembesky *et al.*, 2009). On the other hand, a few of the studies on short-term (daily to weekly) forecasts, specifically for hydropower maximization, include Ahmad *et al.* (2020), Monteiro *et al.* (2013), Madsen *et al.* (2009), and Fan *et al.* (2016). There are only a handful of studies that have focused on integrating the long-term optimization module with the short-term (daily) operations as a co-optimization strategy.

One of the first efforts to integrate the optimization models at different temporal scales was proposed by Becker *et al.* (1976) and Yeh (1979) for the operation of the California Central Valley Project. The procedure optimizes a monthly model over one year and uses the monthly ending storages into a daily model followed by using the daily releases into an hourly model. Georgakakos (2006) used a similar concept for developing the multilayer operation model for Nile Basin. Dong *et al.* (2006) assessed the effect of flow forecasting quality on the benefits of single-reservoir operation. The ending monthly storage from a long-term optimization model was input as constraints to the short-term daily model. However, the long-term model uses the monthly average of the observed flow series, which results in a single static long-term policy and is not updated as the optimization progresses in time. Also, different levels of noise were added synthetically to the observed inflow to obtain the short-term forecasts. Synthetic forecasts render the optimization results sensitive to the added noise, which are not representative of the actual value in the concept when it is operationalized. Celeste *et al.* (2008) integrated daily and monthly optimization models over a single reservoir operated for water supply. A deficit term was obtained from the long-term release policy representing how well the demands are met so as to trigger hedging during the short-term operations. This approach does not guide the short-term policy at each time step of the optimization horizon; rather, the operations are only affected when the deficit exceeds a certain threshold. Sreekanth *et al.* (2012) generated synthetic forecast flows to demonstrate the nesting of long-term optimization with the short-term model at a time step of five days over a single reservoir in South India. Simple linear constraints were used for using the information from the long-term model into the short-term optimization procedure. Xu *et al.* (2015) established a short-term operation model first to minimize the operation cost, and then the non-dominated set of solutions was used as input to a long-term model to select the best strategy for both the temporal scales. Again, historical inflows were used to represent the possible flow scenarios to occur in the future.

Given the history of multi-reservoir optimization, there still remain a few gaps that necessitate attention from the scientific community:

(a) there are hardly any studies that integrate the short and long-term operating objectives simultaneously as a co-optimization problem while updating the optimal polices at both time scales for a multi-reservoir system, specifically for hydropower operations;
(b) the existing studies on co-optimization at the two timescales have only used synthetically generated forecasts by adding noise to the observed inflow time series, which does not represent the true value in such a concept when applied operationally; and
(c) although there have been efforts to study the effect of the quality of flow forecasts on the resulting optimal policy, no comprehensive framework has been developed to assess the added value in co-optimization of the operating policy at short and long-term scales against a conventional baseline with no optimization for multiple dam networks.

To address these unresolved issues for hydropower generation in the context of renewable energy sustainability, the present study uses a real-time weather forecasting model at short-term (daily) and a seasonal climatic model at long-term (monthly) temporal scales to obtain flow forecasts for the co-optimization model.

The specific research questions addressed here are (1) what is the added value of co-optimization in time and space dimension over a multi-dam network operated for hydropower operations? (2) How sensitive is the optimal reservoir operating policy to the skill in short and long-term flow forecasts?

The rest of this paper is organized as follows. In Sec. II, the selected site and necessary datasets for the application of the proposed technique are described. This is then followed by a detailed description of the forecasting and reservoir operation optimization model as well as the evaluation framework in Sec. III. The case study results of the application of short- and long-term forecasts for optimization using different strategies for evaluation are presented in Sec. IV. A sensitivity analysis of the skill of long-term forecasts is also included, followed by discussion and concluding remarks in Sec. V. AQ2

II. STUDY SITE AND DATASETS

A. Multi-dam network and its operations

The dam network chosen for the demonstration of the proposed technique is one of the four units of the Colorado River Storage Project called Wayne N. Aspinall Unit. The unit is composed of a series of three dams—Blue Mesa (BM) Dam, Morrow Point (MP) Dam, and Crystal (CR) Dam in the Upper Colorado Basin along the Gunnison River, which flows further down into the Colorado River. The dams were constructed between 1963 and 1977 and are operated by the U.S. Bureau of Reclamation (USBR). A schematic of the reservoir connections and relevant hydrological stations is shown in Fig. 2 (USBR, 2004). The drainage basin of the Blue Mesa dam used for reservoir inflow modeling is also shown. Table I summarizes the characteristics of dams and power plants in the Unit.

The upstream-most and largest reservoir, Blue Mesa, is responsible for the primary water storage in the system. The power plants at

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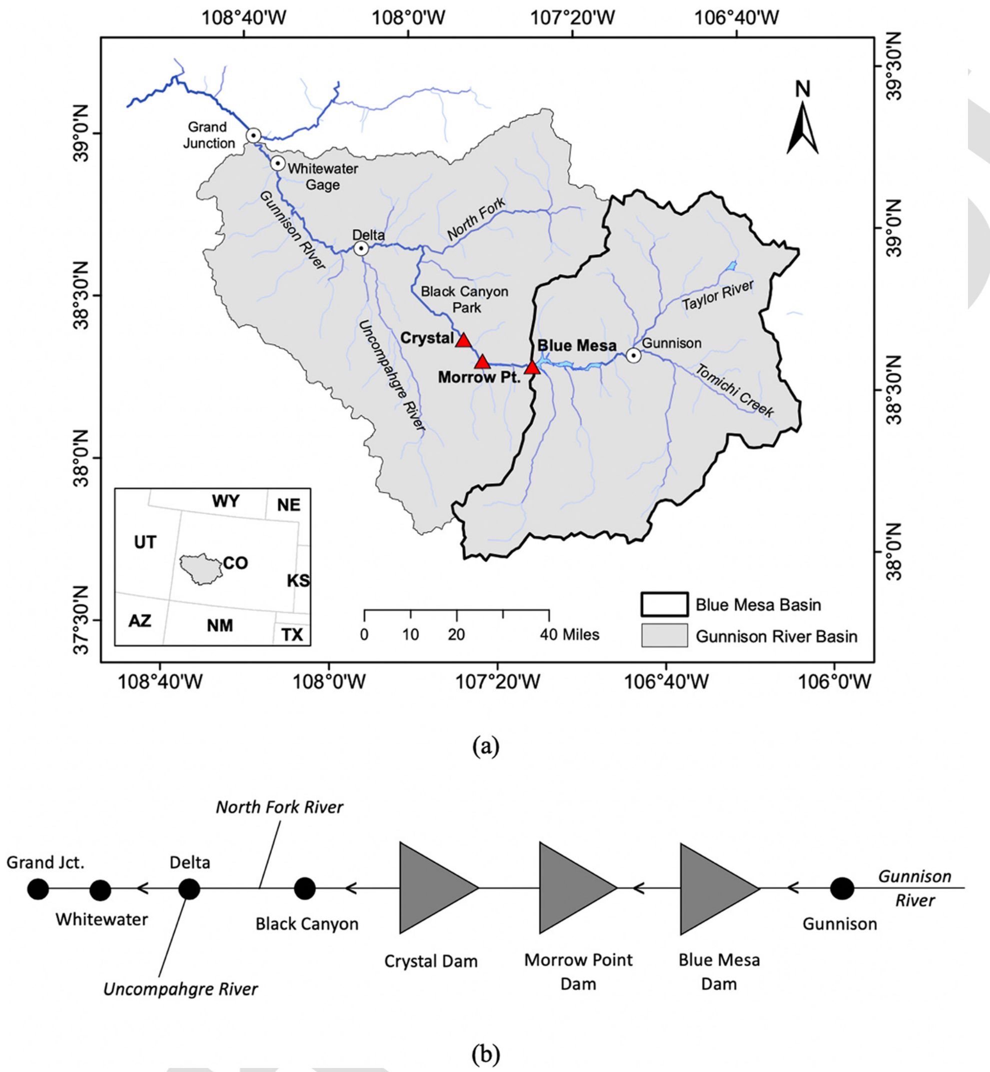

FIG. 2. (a) Dams in the Aspinall Unit, pertinent hydrological stations, Gunnison River, and Blue Mesa drainage basins; (b) simplified schematic showing the dam connections and relevant stations (not to scale). Arrows show the flow direction (upstream to downstream).

Blue Mesa and Morrow Point are highly flexible with the release rates and can be operated to provide peaking power. The five turbines at the three dams are capable of generating up to 291 MW of electricity. The power plant at the Morrow Point produces the largest amount of energy, around twice as much as Blue Mesa. The crystal reservoir serves as a regulation reservoir to stabilize flows to the Gunnison River and is usually operated under constraints to regulate downstream flows. The dam releases can be made via powerhouses/penstocks, bypass, or spillway routes. The USBR manages the releases within certain sideboards that include annual snowpack conditions, senior water rights, minimum downstream flow requirements, power plant and outlet capacities, reservoir elevation goals, fishery management recommendations, dam safety, and other considerations. Certain operational goals are mandated to honor these sideboards, which were used to design constraints for the optimization model. These goals include but are not limited to the following (see Fig. 2 for hydrological stations):

(a) the desired Whitewater gage peak flow (USGS station 09152500) to be obtained every year based on the April–July forecasted inflow into the Blue Mesa reservoir;
(b) flow at the Gunnison River above the confluence with the Uncompahgre River to be kept below 15 000 cfs;
(c) peak releases be typically made between May 10th and June 1st, giving priority to power plants followed by bypasses and spillways;
(d) Blue Mesa Reservoir to be kept at or below 7490 feet (580 000 acre-feet live storage) by December 31st to provide storage for next spring's runoff and minimize upstream icing;
(e) minimum downstream flow through the Black Canyon of the Gunnison National Park and Gunnison Gorge National

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TABLE I. Relevant characteristics of the dams, reservoirs, and power plants in the Aspinall Unit.

Dam, reservoir, and power plant characteristics	Blue Mesa	Morrow point	Crystal
Dam type	Earthfill embankment	Double-curvature thin-arch	Double-curvature thin-arch
Dam height (ft)	502.0	468.0	323.0
Spillway crest elevation[a] (ft)	7487.9	7123.0	6756.0
Crest elevation[a] (ft)	7528.0	7165.0	6772.0
Total storage capacity (acre-ft)	940 700	117 190	25 240
Total installed capacity (MW)	86.4	173.3	32.0
Production mode	Peaking	Peaking	Base load
Number of turbines	2	2	1
Turbine flow capacity (cfs)	3400	5400	2150
Bypass capacity (cfs)	4500	1500	1900
Spillway capacity (cfs)	34 000	41 000	41 350

[a]Above the mean sea level.

Conservation Area is 300 cfs, except in severe drought when flow may be reduced;

(f) maximum releases from the Crystal Dam, outside of the peak flow period, be limited to the 2150 cfs power plant capacity; and

(g) daily ramping rates at the Crystal Dam limited to the increase in 500 acre-ft and the decrease of 400 acre-ft per day.

B. Operational and hydrometeorological data

The observed operational data for the Aspinall Unit were obtained from the USBR's data portal (https://www.usbr.gov/rsvrWater/HistoricalApp.html; Aspinall Unit Water Operations, 2019), which include observed inflows, releases, reservoir elevation, storage, and hydropower generated. The operational data were used for setting up the optimization model as well as in calibration and validation of the forecasting models. The hydro-meteorological forecast forcings, basin's antecedent conditions, and current reservoir state (from USBR) were inputs to the inflow forecasting model. The forecast fields of precipitation, temperature, and windspeed were acquired from the Global Forecast System (GFS) global-scale numerical weather prediction (NWP) model at 0.5° for a lead time of 7 days with a 3-h temporal resolution. To include the uncertainty estimates in the forecast flow, National Oceanic and Atmospheric Administration's (NOAAs) Global Ensemble Forecasting System Reforecast (version 2) dataset (GEFS/R) (Hamill *et al.*, 2013) with an 11-member ensemble of forecasts at 1° resolution was used. The average scenario of the ensemble members was used for optimizing the reservoir operations. The antecedent basin precipitation was obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) gridded rainfall time series at a resolution of 0.05° (Funk *et al.*, 2015). The gridded datasets were converted into basin-averaged estimates for inputs to the forecasting model.

For the monthly scale long-term forecasting model, in addition to the antecedent monthly streamflow, the ensemble seasonal forecast forcings from the climate model suite of North American Multi-Model Ensemble (NMME) were used (Kirtman *et al.*, 2014). The diversity of models in NMME provides a superior representation of multi-model uncertainty in seasonal forecast skill, on average, relative to other seasonal prediction systems. Because it is computationally challenging to use each of the ensemble models present in the NMME suite for optimization, two models were chosen to obtain enough ensemble members that are representative of the uncertainty in modeled forcings. These were (i) Climate Forecast System version 2 (CFSv2) for monthly precipitation fields (Saha *et al.*, 2014) and (ii) Geophysical Fluid Dynamics Laboratory (GFDL) CM2.1 model for sea surface temperature fields (Delworth *et al.*, 2006). An additional predictor of the SST anomaly based index of Niño 3.4 was also used AQ3 for the monthly forecast model, retrieved from the National Oceanic and Atmospheric Administration Earth System Research Laboratory (NOAA-ESRL) (http://www.esrl.noaa.gov/psd/data/climateindices/list/). The period of analysis used to setup the long-term forecasting model extended from 1980 to 2018, while that for short-term weather forecasting ranged from 2007 to 2018.

III. METHODS

The general approach followed in this study and the experimental components are schematically shown in Fig. 3. The following sections AQ4 describe the methodological components in detail.

A. Short-term ensemble flow forecasting

To obtain the short-term forecasts for the lead time of 7 days for inflow into each of the three reservoirs in the dam network, two kinds of models were incorporated: (i) data-based artificial neural network (ANN) model for the Blue Mesa dam, which is the most upstream in the multi-dam network and (ii) linear regression model for the Morrow Point and Crystal dams, which lies downstream. The ANN model was specifically chosen for the Blue Mesa dam because it receives most of the unregulated flow and the nonlinearities in the hydrological response are most suited for a complex model like ANN. However, for the next two downstream dams, the inflows are highly dependent on the release from the upstream dam and hence do not require complex modeling exercise. Ashe skill in modeling the system inflow is mostly driven by the most upstream Blue Mesa dam; the focus was to improve the quality of Blue Mesa's forecast inflow using ANN. The specifications of the ANN model are described next

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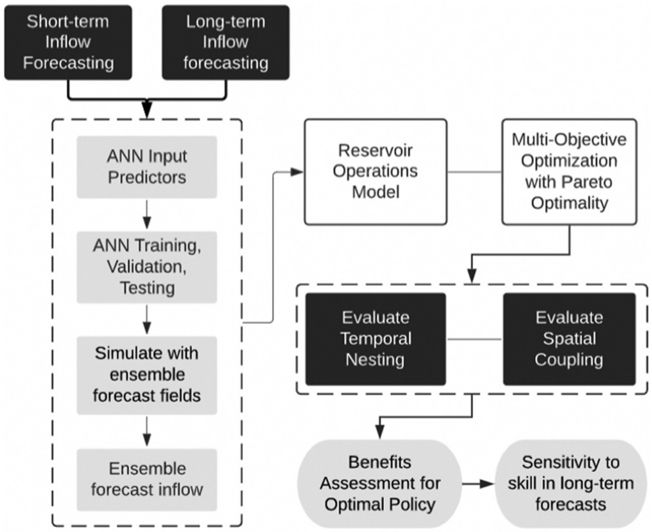

FIG. 3. Schematic of the approach showing key experimental components of the study. See Table IV for explanation of the evaluation framework strategies.

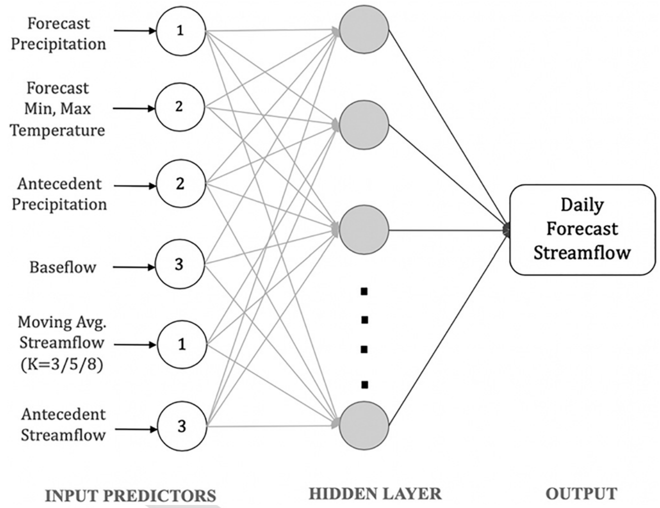

FIG. 4. ANN model configuration with the selected input predictors for daily streamflow forecasting over the Blue Mesa dam. Log sigmoid and linear transfer functions were used for hidden and output layers, respectively. The number of antecedent/forecast days for each node is also shown. K is the window length for moving average streamflow that varies with the forecast lead time.

followed by the linear regression model and ensemble forecast processing.

1. ANN model for daily flow forecasting

The daily forecasting model is based on a feedforward neural network involving input, hidden, and output layers. Considering the reservoir and basin characteristics, the candidate input layer nodes were identified as: (i) forecast fields of precipitation and temperature, obtained from the GFS model at a resolution of 0.5°; (ii) antecedent precipitation over the basin; (iii) antecedent streamflow into the reservoir; and (iv) antecedent baseflow. A procedure was followed similar to that used by Ahmad and Hossain (2019) for selecting the optimal set of input predictors to this ANN model. The final predictor set included antecedent precipitation (2 days), antecedent baseflow (3 days), antecedent inflow (1/2/3 days based on the lead time), antecedent moving average inflow (3/5/8-day window based on the lead time), forecast precipitation (1 day), and forecast min/max temperature (1 day each). The configuration of the short-term ANN model is shown in Fig. 4. The ANN was trained using the Levenberg–Marquardt (LM) method, and measures of early stopped training (STA) and regularization were taken to avoid overfitting and lack of generalization (underfitting). The period of Jan 2007 to Aug 2014 was used as the *training set*, while the *validation* and *testing sets* were selected as Sep 2014–Oct 2015 and Nov 2015–Dec 2017, respectively.

2. Linear regression model for downstream dams

Using the modeled inflow into the most upstream dam, a linear regression model was developed to route the release from upstream dams to inflow into the downstream reservoirs. The linear regression model was deemed to be fit for the purpose as the two downstream dams, Morrow Point and Crystal, mostly receive regulated flow with minimal contribution from the intermediate tributaries. The two sets of linear regression models were developed: (a) between Blue Mesa release and Morrow Point inflow and (b) between Morrow Point release and Crystal inflow. The linear relationships and the respective correlations are shown in Fig. 5.

3. Ensemble forecast processing

After the base reservoir inflow models (ANN-based for Blue Mesa and linear regression-based for other two dams) were developed to obtain deterministic inflow forecasts for the lead time of 1–7 days, the uncertainty in forecasts was modeled next for the Blue Mesa dam inflow. The trained ANN model was fed with 11 ensemble scenarios of the forecast forcings from the GEFS model to result in the ensemble inflow forecast. Given that the reservoir operation model was designed to use a deterministic optimization technique, the average scenario of the ensemble forecast members was used in the optimization model (see Sec. III C). The average of the ensemble flow forecasts showed higher skill compared to the deterministic forecasts obtained using GFS forcings (see Table V). The higher skill in the average scenario of GEFS-based ensemble forecast flow as compared to the deterministic daily forecasts from GFS was also confirmed in a study by Ahmad and Hossain (2019) for multiple dams in US.

B. Long-term ensemble flow forecasting

For nesting the short-term optimization model with long-term operations, the long-term flow forecast model was developed to result in monthly inflow forecasts for up to 7-months in the future. Similar to the short-term forecasting, a feedforward ANN model with one hidden layer was designed to forecast the inflow into the most upstream Blue Mesa dam. However, an entirely different set of input predictors from the NMME climate model outputs suitable to capture seasonal

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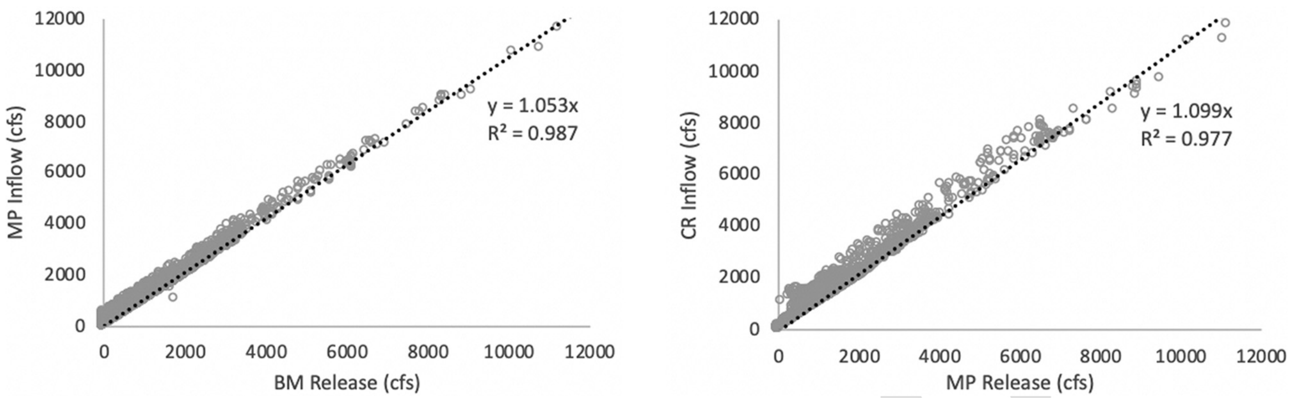

FIG. 5. Scatter plots showing linear regression between release and inflow of the upstream–downstream dam pairs of Blue Mesa (BM)–Morrow Point (MP) and Morrow Point (MP)–Crystal (CR) dams.

variations in seasonal runoff was developed. Based on a predictor selection analysis similar to that for the short-term ANN model, the input predictors were forecast precipitation (1 month; from the CFSv2 model), forecast sea surface temperature (1 month; from the GFDL CM2.1 model), antecedent inflow (1/2/3 months based on the lead time), antecedent baseflow (3 months), antecedent moving average flow (3/5/8-month window based on the lead time), and Niño 3.4 index (1 month). The climate models in NMME contain 12 ensemble members (realizations) for each variable, which were used to train the ANN model. The average trace of the forecast flow was used for optimization. For the other two downstream dams, the linear regression model for daily forecasting was used under the assumption that inflow contributions from tributaries at the monthly scale are insignificant. The available dataset was divided into *training*, *validation*, and *test* sets extending from 1981 to 2007, 2008 to 2011, and 2012 to 2018, respectively.

C. Reservoir operation optimization

The forecast flow information obtained from short and long-term forecasting models was used as input to the optimization model for obtaining optimal release decisions. The focus of this study was on hydropower maximization, which was formulated as the major objective. Other constraints were incorporated into the model representing flood control, environmental flow concerns, and dam safety. The short-term optimization model was setup with a daily temporal scale over the 7-day horizon, while the long-term model was developed to output optimal release decisions at the monthly scale with the optimization horizon of 7 months. The nesting of the two optimization models was carried out by using the long-term optimal reservoir state to formulate a complementary objective function into the short-term model at every time step of the horizon. Different operation strategies were devised to evaluate the value in co-optimization. The long-term optimization model is described next, which is the basis for the nesting procedure, followed by short-term optimization and evaluation strategies.

1. Long-term optimization model

The optimization model for monthly release decisions is based on two objective functions, maximizing the total hydropower generation from all power plants in the system and minimizing the deviation of elevation of the Blue Mesa dam at the end of year from a required target level. As the skill in long-term forecasts degrades with the increasing lead time, the model predictive scheme (MPC) was employed at the monthly scale, which updates the flow forecasts at every step of the optimization horizon (Turner *et al.*, 2017; Ahmad and Hossain, 2020). The spread of the ensemble flow forecasts was ignored in the deterministic optimization procedure so that it can provide a clear indication of the contribution of forecasts to the optimal operation performance (Turner *et al.*, 2017).

The two objectives are formulated below:

1. Maximizing hydroelectric power production (MW) from the system's three power plants,

$$\max f_1(MW) = \sum_n \sum_t \epsilon^n \cdot \Delta t^n_{turb} \cdot \left(HF^n_t - HT^n_t\right) \cdot R^n_{p,t}, \qquad (1)$$

   where t is the optimization horizon of 7 months, n is the index for the reservoir in consideration, $n = 1, 2, 3$, HF and HT are the reservoir forebay and tailrace water levels (ft), ϵ is the turbine efficiency, Δt_{turb} denotes the turbine operating hours, and R_p is the power release from turbines (cfs).
2. Minimizing the absolute value of deviation of reservoir elevation from the target level (T) in the month of December (H_{Dec}) for the Blue Mesa dam. This is to satisfy the requirement for the Blue Mesa dam to return to 7490 ft on December 31st to provide storage for next spring's runoff and minimize upstream icing. Under the MPC scheme of optimization, the objective is only implemented for horizons containing the month of December.

$$\min f_2(ft) = . \qquad (2)$$

The energy production function in Eq. (1) requires the knowledge of turbine efficiency and the number of operating hours for everyday operations. Because the turbine operating characteristics usually vary over the year and within any day of operations, a regression model was developed for estimating energy generation. Linear regression was performed between the observed hydropower (in MWh) and the product of hydraulic head ΔH and power release R_p based on the historical data. The obtained regression constant captures the

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unknown turbine efficiency ϵ and operating hours Δt_{turb}. The constants were obtained as 17.02 h, 18.64 h, and 12.22 h for Blue Mesa, Morrow Point, and Crystal dams, respectively. Multiple constraints were imposed on the long-term optimization model considering flood control, dam safety, environmental flow requirements, and operational restrictions for Aspinall reservoirs specified in the control manuals. Various operational restrictions specified by the control manuals (USBR, 2004, 2012a, 2012b) (see Sec. II A) were considered for setting up the constraints as summarized in Table II.

2. Short-term daily optimization model

The daily-scale multi-objective optimization model using the MPC scheme was setup to generate optimal release decisions for one week ahead in the future. The primary and secondary objectives varied with the strategy of optimization (see Table IV). The ensemble forecast spread was ignored during the optimization for reasons mentioned under the long-term optimization model. The constraints for optimization were tailored to account for the daily-scale reservoir operations of the three dams. In addition to the constraints for the long-term optimization model, the daily ramping rates for Crystal dam release and daily maximum change in the Crystal reservoir forebay elevations were constrained by the values specified in the control manuals and are summarized in Table III.

3. Optimization algorithm

The multi-objective optimization problem was solved using deterministic genetic algorithm-based optimization. Due to the conflicting nature of objective functions, a non-dominated or Pareto set of solutions is needed where one objective function cannot be improved further without violating the other. To implement the Pareto optimality, the Non-dominated Sorting Genetic Algorithm (NSGA-II; Deb *et al.*, 2002) was used. Open-source library *platypus* (https://platypus.readthedocs.io) was incorporated to formulate the multi-dam optimization problem. The algorithm produces a set of Pareto optimal solutions (with the user-defined size of Pareto optimal set), from which the dam operator can choose the preferred solution based on which objective function receives priority according to the situation at hand. For the sake of this study, a balanced optimal solution was selected on the Pareto front that gives equal weightage to both the objectives. Pareto optimization allows for different units of objective functions without the need to transform to consistent units, which is often difficult to achieve (Madsen *et al.*, 2009).

TABLE II. Dam-specific and general constraints imposed on the monthly optimization model.

Dam-specific constraints	Value
Blue Mesa Dam	
Minimum elevation	7393.0 ft
Maximum elevation (Jan–Mar)	7490.0 ft
Maximum elevation (Apr–Dec)	7519.4 ft
Elevation on Dec 31	7490.0 ft
Morrow point dam	
Minimum elevation (Jun–Sep)	7151.0 ft
Minimum elevation (Oct–May)	7143.0 ft
Maximum elevation	7160.0 ft
Crystal dam	
Minimum elevation	6725.0 ft
Maximum elevation	6772.0 ft
General constraints	
Minimum monthly release	2500 cfs
Maximum monthly release	64 500 cfs
Maximum monthly release (May 10–Jun 1)	220 000 cfs

TABLE III. Additional constraints imposed on the daily scale short-term optimization model.

Dam-specific constraints	Value
Crystal dam	
Maximum elevation change (Apr–Jun)	4 ft per day
Maximum elevation change (Jul–Mar)	10 ft per day
Daily ramping rate—increase	500 acre-ft per day
Daily ramping rate—decrease	400 acre-ft per day
Morrow point dam	
Daily ramping rate—increase/decrease	2000 acre-ft per day
Blue Mesa dam	
Daily ramping rate—increase/decrease	2000 acre-ft per day
General constraints	
Minimum daily release	300 cfs
Maximum daily release	2150 cfs
Maximum daily release (May 10–Jun 1)	12500 cfs

D. Co-optimization at long-term and short-term scales

The proposed strategy optimizes the operations of the cascade of dams in tandem while considering the long-term benefits for short-term optimality. We coin this co-optimization as *temporal nesting with spatial coupling* (TeNeSC). TeNeSC-based optimization is carried out in two steps; first, the long-term model, as described in Sec. III C 1, is used to obtain monthly optimal release decisions over an optimization horizon of seven months into the future. The monthly optimal operations yield the optimal reservoir states at the end of each month. The end-of-month reservoir storages over the 7-month horizon are linearly interpolated to result in the daily levels that form the boundary conditions or constraints for the short-term daily scale optimization model. The small storage of dams in consideration (capacity to the annual inflow ratio close to 1) results in variability in the reservoir state at daily scales and justifies the daily time step for short-term optimization (Anghileri *et al.*, 2016). Furthermore, the “coupled” component in the TeNeSC scheme signifies the joint operation of the dam network, where the co-optimization is carried out by simultaneously considering releases from all the dams. The water released from the upstream dam reaches the downstream reservoir with a certain delay equal to the flow travel time along the reach. The delay time usually ranges from several hours and extends to days only when the flow travel time is long enough in large multi-reservoir systems (Souza and Diniz, 2012; Ge *et al.*, 2014). Given that the present study considers daily scale operations over medium scale inter-reservoir reaches, the

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delay time was neglected in the routing of streamflow. A schematic illustrating the temporal nesting of the optimization models is shown in Fig. 6.

The boundary conditions were used to formulate the secondary objective for the short-term optimization model where the primary goal is hydropower maximization across all the dams in the network. The objective was set to minimize the deviation of elevation from the boundary conditions (or target elevation) reflecting the long-term optimal conditions over the short-term optimization horizon. Because the main purpose of the Crystal dam is to act as a regulator of the upstream releases, there is a lesser flexibility left for the optimal reservoir level for hydropower maximization. This was taken into consideration by obtaining the deviation of reservoir levels only on the first day of the optimization horizon. The higher weight is indirectly assigned to the secondary objective as the MPC scheme only considers the first day's optimal release and discards the rest. However, for Blue Mesa and Morrow Point dams, the deviation was obtained at the last (seventh) day of the horizon as they are operated for peaking power and permit higher flexibility in operations. Mathematically, the secondary objective is formulated as

$$\min f_2(ft) = \left|H_7^1 - T_7^1\right| + \left|H_7^2 - T_7^2\right| + \left|H_1^3 - T_1^3\right|, \tag{3}$$

where H_t^n is the nth reservoir's storage (numbered from the upstream to downstream dam) at time step t. The optimization problem was bound by the fundamental long and short-term constraints on reservoir storages and releases described in Secs. III C 1 and III C 2. Apart from those, the continuity constraints for the three reservoirs over each time step t of the optimization horizon can be mathematically stated in vector form as

$$\boldsymbol{S_i}(t+1) = \boldsymbol{S_i}(t) + \boldsymbol{I_i}(t) + \boldsymbol{M}.\boldsymbol{R_i}(t), \tag{4}$$

where $\boldsymbol{S_i}(t)$ is the vector of storages in reservoirs $i = 1, \ldots, n$; $\boldsymbol{I_i}(t)$ and $\boldsymbol{R_i}(t)$ are vectors of inflows into and release from each reservoir; and $\boldsymbol{M}$ is an $n{*}n$ square matrix representing the indices of reservoir connections,

$$\boldsymbol{M} = \begin{bmatrix} -1 & 0 & 0 \\ 1 & -1 & 0 \\ 0 & 1 & -1 \end{bmatrix}.$$

For the continuity constraints, storage-elevation relations were obtained as second-order polynomial equations for each reservoir using 15 years of historical data (2004–2018) using which the storage at each time step was converted to the respective reservoir level. The coupled optimization model solves a giant matrix for all the reservoirs to derive the optimal reservoir release decisions and their respective states at each time step.

E. Evaluation framework for co-optimization

To answer the first research question of this study and establish the efficacy of co-optimization, several strategies of optimization were implemented under an evaluation framework. The objective is to separately underscore the value in two different facets of co-optimization for maximizing hydropower: (a) nesting of short- and long-term objectives in time and (b) coupling of reservoirs in space. Tables IV(a) and IV(b) summarize the specifications of each strategy for evaluating temporal nesting and spatial coupling.

An additional aspect that needs consideration for demonstrating the robustness of this concept is the value of the real-time forecasting model in improving the operational benefits of the dam network. Our study accomplishes this by considering two different scenarios of obtaining the inflow forecasts:

(a) *perfect forecast scenario* that stands as a hypothetical benchmark of maximum attainable benefits using the different strategies described above. Here, the observed inflow is used as a proxy to the forecasts over the desired optimization horizon to simulate the perfect forecast scenario.

(b) *operational forecast scenario* where the reservoir inflow forecasts are obtained using the short- and long-term forecasting models developed in Secs. III A and III B. This scenario is the representative of the practically possible benefits using an

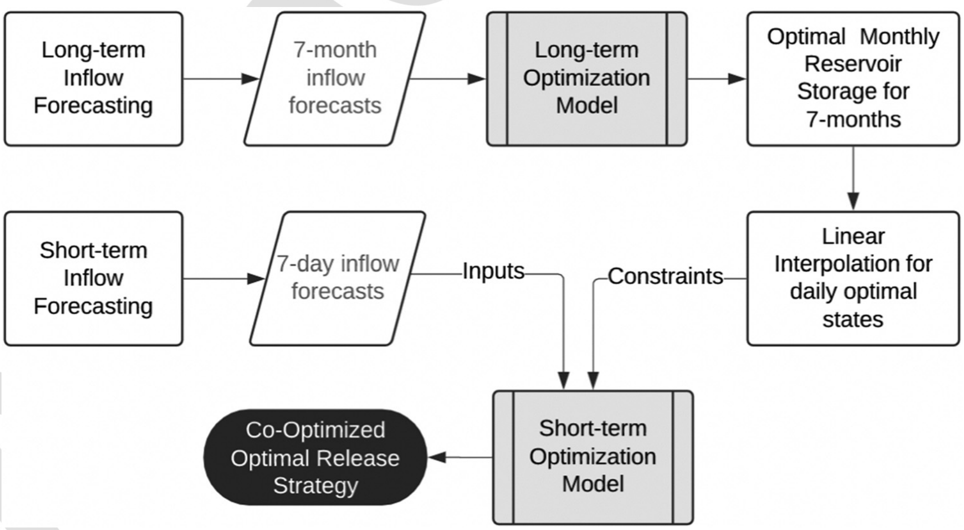

FIG. 6. Schematic explaining the procedure of co-optimization with the long- and short-term objectives.

TABLE IV. (a) Specifics of strategies under the framework to evaluate the value in temporal nesting, formulated as the multi-objective problem. (b) Specifics of strategies under the framework to evaluate the value in spatial coupling.

Strategy	Formulation	Description	Objective
(a) All Spatially Coupled			
TeNeSC	Short + long	• Uses nested co-optimization at long and short-term scales • Continuity constraints formulated as one giant matrix [Eq. (4)]	*Primary*: maximize hydropower *Secondary*: minimize the deviation of reservoir elevation from target levels based on long-term optimality [Eq. (3)]
T1	Short-only	• No use of nested co-optimization • Continuity constraints the same as TeNeSC	*Primary*: maximize hydropower *Secondary*: minimize the absolute deviation between reservoir release and turbine capacity: $\min f_2(cfs) = \sum_{i=1}^{n}\sum_{t=1}^{T} \lvert R_t^i - T_{cap}^i \rvert$ (n: number of reservoirs; T : short-term horizon of 7 days).
T2	Long-only	• No use of nested co-optimization • Considers long-term optimality only during daily optimization • Continuity constraints the same as TeNeSC	*Primary*: minimize the absolute deviation of reservoir elevation H from target levels based on long-term optimality T for the first day of horizon $\min f_1(ft) = \sum_{i=1}^{n} \lvert H_1^i - T_1^i \rvert$ (n: number of reservoirs) *Secondary*: the same as the secondary objective in T1
(b) Both Temporally Nested			
TeNeSC	Coupling	• The same as in Table IV(a)	Same as in Table IV(a)
C1	No coupling	• No coordination among reservoir release decisions. • Separate optimization models developed for each reservoir; the regression model converts upstream release into downstream inflow	*Primary*: maximize hydropower *Secondary*: the same as TeNeSC, deviation calculated individually for each reservoir in the respective optimization model

operational flow forecasting. The technique is operational for real-time reservoir inflow forecasts for Ganges and Brahmaputra river basins (Ahmad and Hossain 2019; http://depts.washington.edu/saswe/datavis_Timeseries.html).

F. Benchmark scheme

To obtain the actual value in using forecast information for realizing optimal operations, a benchmark operating scheme is necessary that by itself neither uses any forecast information nor is based upon any co-optimization at different timescales. Rather, the benchmark scheme should be reflective of control rules designed with respect to certain operating objectives that the dam operator follows in practice. Thus, to setup a fair benchmark, a customized control-rule based operation scheme was designed to specifically address the hydropower maximization objective (Turner *et al.*, 2017), which is also the basis of strategies described under the evaluation framework. The control rules were designed in the form of lookup table where the optimal release is specified as a function of two state variables: reservoir storage and season of year, as proposed by Turner *et al.* (2017). The stochastic dynamic programming (SDP)-based optimization procedure coded in the R package *reservoir* (Turner and Galelli, 2016) was incorporated to optimize for these rules. The observed inflows for 15-year period (2004–2018) were used for each dam as input to the SDP model, including the reservoir and objective function specifications. Three separate sets of control rules were obtained for each reservoir at the monthly time step, with no coupling between the operations of adjacent reservoirs. To assess the benefits against this benchmark, a metric called *percent improvement over benchmark* (IB) was formulated as

$$IB\,(\%) = \frac{HP_{optim} - HP_{bm}}{HP_{bm}} \times 100, \tag{5}$$

where HP_{optim} and HP_{bm} are the total hydropower production (HP) from the three dams of the Aspinall Unit using optimized and benchmark reservoir operating schemes.

G. Effect of skill in long-term forecasts

The skill in long-term monthly flow forecasts usually degrades rapidly as compared to that in the short-term daily-scale forecasts. As the temporal nesting uses long-term forecasts as the boundary

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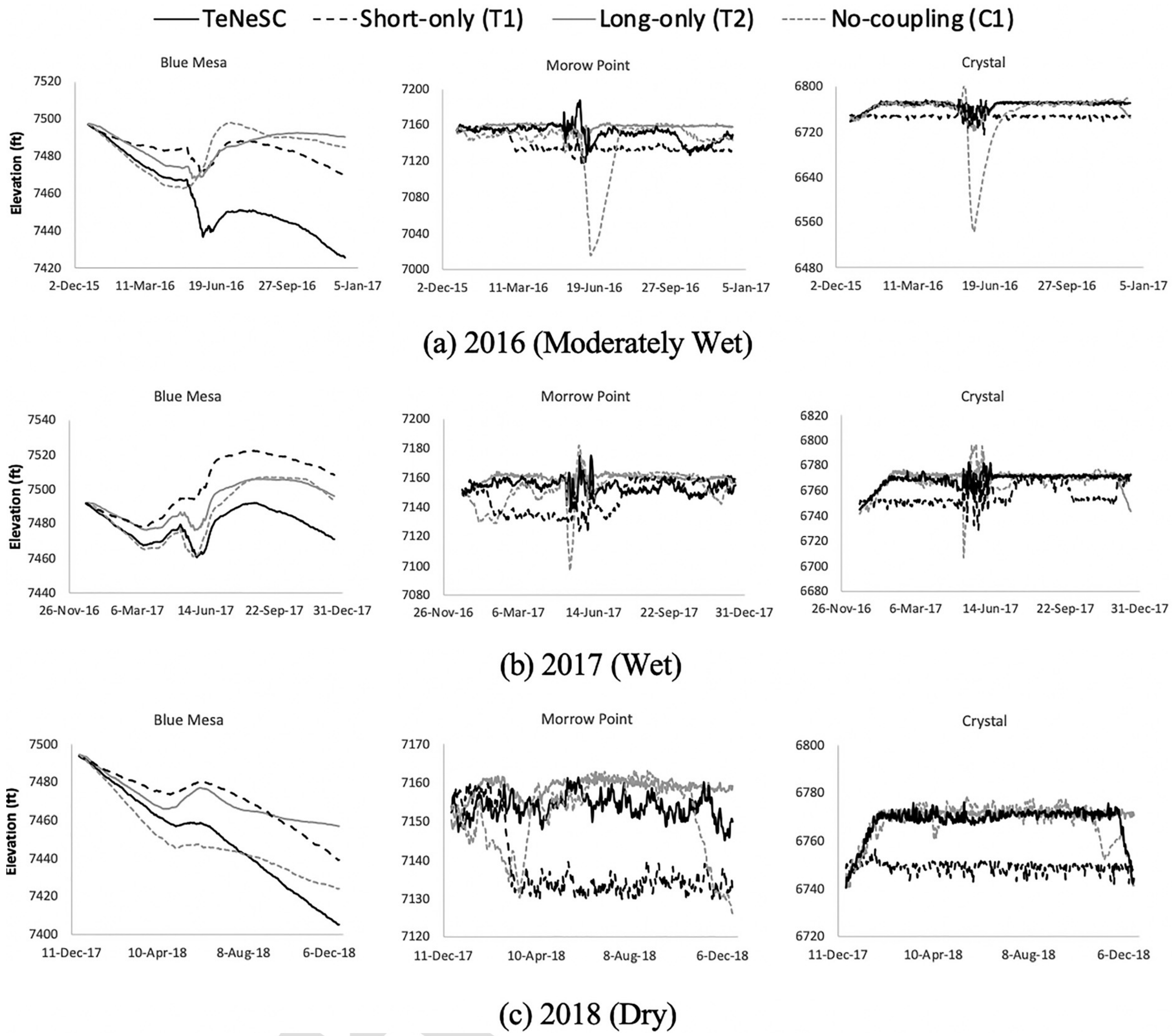

FIG. 7. Optimal reservoir elevations from the different strategies using the perfect forecast scenario for the three dams over the three years with different flow characteristics.

condition for the daily-scale optimization model, the performance is primarily driven by the skill in the long-term forecasts. For instance, any major error in predicting the onset of flood or drought season can cause the short-term release decisions to be optimized toward an objective function that does not reflect long-term optimality. This can potentially result in sub-optimal operations in both the short and long terms. Hence, it is imperative to assess how the skill in monthly ANN-based forecasts affects the resulting optimal reservoir operation policy.

The observed monthly inflow data were synthetically corrupted to simulate underestimation and overestimation in the flow forecasts. Six perturbed monthly inflow timeseries were generated by adding multiplicative bias with six different constants, three of which simulated underestimation (multiplicative constant < 1), while the rest simulated overestimation in the predicted inflow (multiplicative constant > 1). The multiplicative factors simulate the worst-case scenarios of consistent over- or under-prediction of the flows across the period of analysis. Also, as the forecast error is more likely to increase for higher river flows (Montanari and Grossi, 2008), the proposed factors were able to replicate increasing bias in forecasts for higher inflow. Perturbed monthly inflow timeseries were used to carry out the co-optimization (TeNeSC) using the perfect short-term inflow forecasts. The resulting reservoir elevations and hydropower benefits were compared across the different perturbed scenarios to assess the effect of degrading skill in long-term predictions.

IV. CASE STUDY RESULTS

A. Reservoir operation optimization

The proposed concept of co-optimization and strategies for evaluation were implemented over the selected multi-dam network of the Aspinall Unit of Blue Mesa, Morrow Point, and Crystal dams. Three years (2016–2018) with different inflow characteristics were selected for the analysis. While 2016 was a moderately wet year with the annual

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inflow of 441 535 cfs into the system, 2017 and 2018 experienced anomalously wet and dry conditions with the annual inflow of 629 083 cfs and 211 853 cfs, respectively. The different flow conditions were chosen to further underscore the robustness of this technique under different seasons of dam operations. The detailed results are described in the following sections. The assessment of the forecast skill in short and long-term ANN flow forecasting models is described in detail in Appendix for the interested readers.

1. Evaluation framework

The long-term optimal policy derived from the monthly scale optimization model was used for the strategies that nest long-term benefits with short-term optimization (i.e., TeNeSC and C1). For the other strategies used for evaluation, either only the short-term forecasts (T1) or long-term forecasts (T2) were used for the optimization. Figure 7 shows the optimal reservoir elevations using these strategies using perfect forecasts for the three years, while Fig. 8 shows the corresponding optimal elevations obtained using the operational forecasts (ANN-based for Blue Mesa and regression-based for the others). The long-term optimal policy of operations is also shown alongside in each plot.

When the optimization model uses temporal nesting and considers the three reservoirs as a network (TeNeSC), the reservoir levels from the short-term optimization model are adjusted according to closely follow the long-term optimality. The long-term optimal policy tends to maximize the reservoir storage for the downstream two dams, where the upstream Blue Mesa dam acts as buffer for maximizing the energy generation. The resulting flexibility in the operation of upstream dams enables them to provide peaking power, while the Crystal dam traces the long-term optimal levels with minimal changes in reservoir levels. Considering the strategies used to evaluate TeNeSC, the short-term optimization (T1) results in lower storage levels for the downstream dams, resulting in lower hydropower benefits in the long-run due to its myopic nature. In contrast, the long-term only strategy (T2) tends to closely trace the monthly target levels but loses additional

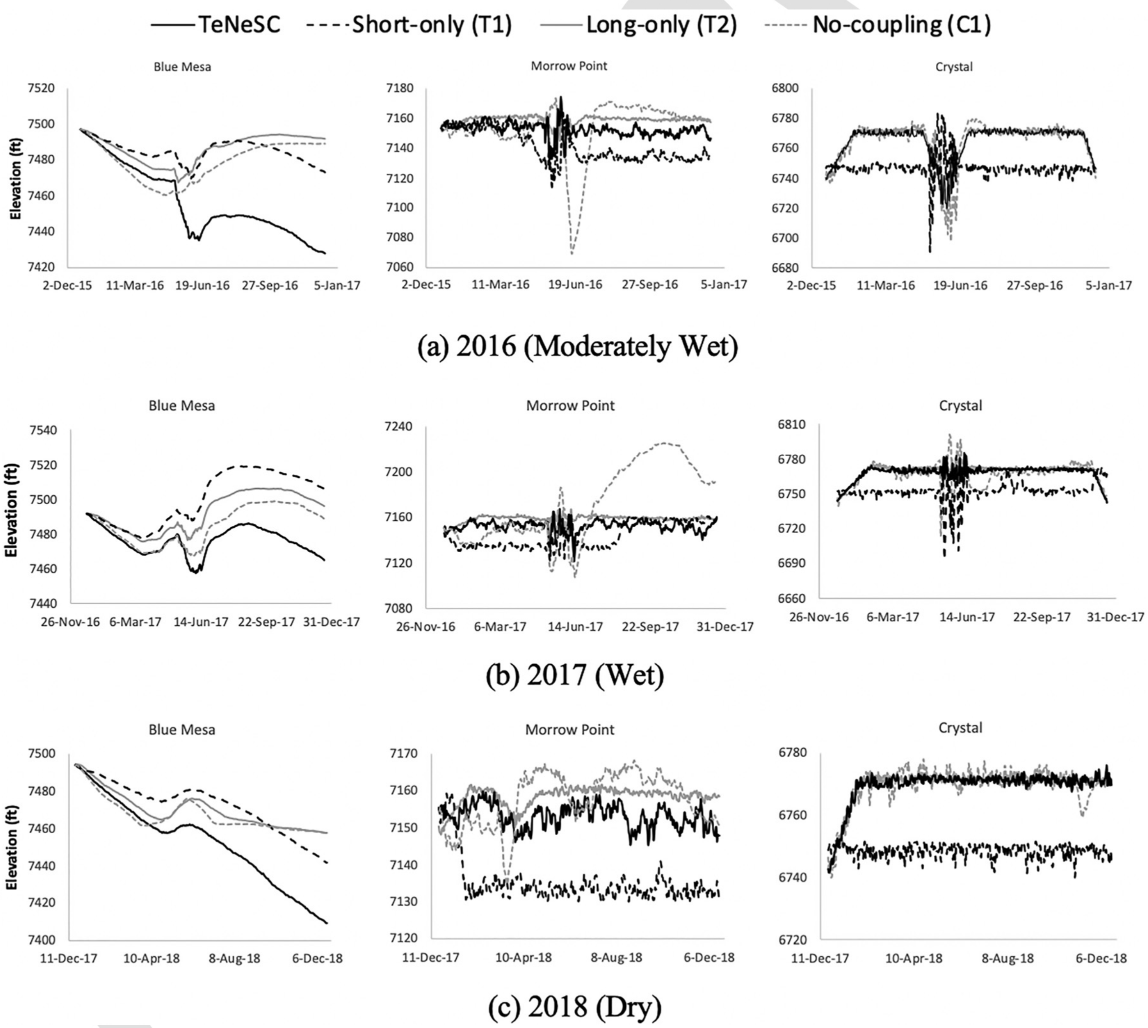

FIG. 8. Optimal reservoir elevations from different strategies using operational forecasts (ANN/linear regression-based) for the three dams.

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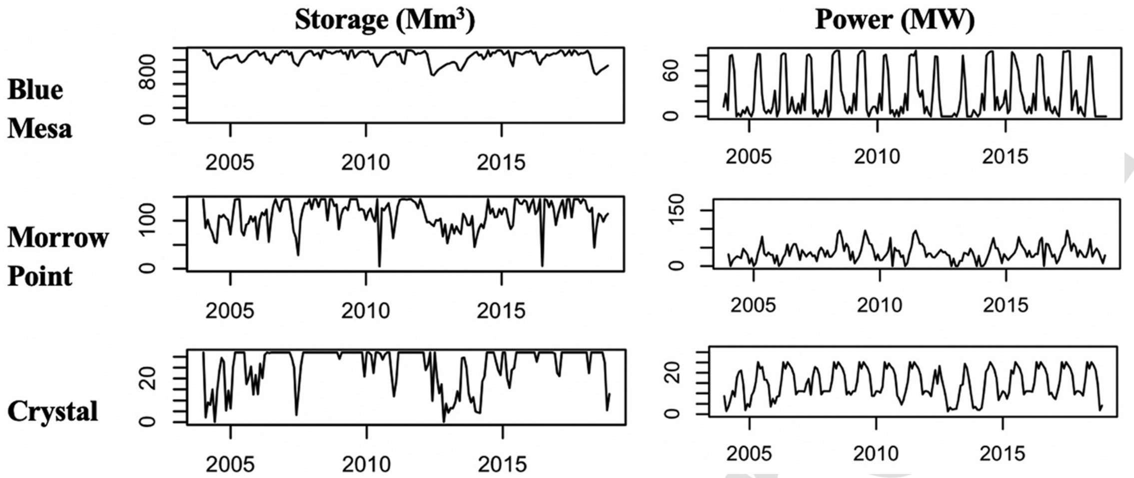

FIG. 9. Benchmark control rules designed specifically for hydropower maximization using the R package *reservoir* for the dams in the Aspinall Unit during the period 2004–2018 at the monthly scale (after Turner and Galelli, 2016).

hydropower benefits in short-term possible by tweaking the daily release decisions accordingly (Table V).

Further, the value in spatial coupling was assessed separately by comparing TeNeSC with the no-coupling scenario (no co-ordination among reservoir release decisions; C1). The results from C1 suggest that one of the two downstream dams undergoes major fluctuations in reservoir levels, even violating the storage constraints for a few days irrespective of co-optimization at the long- and short-term scales. The fluctuations primarily occur during the peak flow season of wet years. In contrast, spatial coupling of dams further facilitates in keeping the reservoir levels within safe bounds and prevents violation of the storage constraints. TeNeSC helped avoid any sudden surge or steep dip in the reservoir levels during the wet and dry years. Finally, the high accuracy of operational forecasts leads to optimal policies similar to those obtained by the use of perfect forecasts (see Fig. 8).

2. Benchmark scheme

The reservoir storage and resulting hydropower generation (MW) using the benchmark scheme are shown in Fig. 9 for the three dams. The scheme is derived individually for each dam in the network based on the observations over 2004–2018, without using any forecast information.

3. Hydropower benefit assessment

The hydropower benefits harnessed from each strategy over the three years and using the two forecast scenarios are shown in Table V. The benefits from the perfect forecast scenario set bounds to maximum attainable benefits, which cannot be exceeded by the optimal policy under the operational forecast scenario. Hydropower generation (MWh) using observed real-world operations (obtained from USBR) is also shown in Table V for comparison.

The high skill in ANN forecasts resulted in benefits similar and lesser to those from the perfect forecast scenario for all the strategies. Considering the different years of analysis, the proposed approach of TeNeSC, which answers the key research question of our study, is more advantageous during the dry and moderate years (2016 and 2018) as compared to the wet year (2017).

Within the strategies evaluating values in temporal nesting, both the short-term-only (T1) and long-term-only (T2) optimization result in lower benefits in hydropower when compared against the proposed benchmark. TeNeSC, on the other hand, generates benefits of 14%–41% over the different seasons for the perfect forecast scenario. Further, using the short-only optimization (T1) was most beneficial for drier years, while the long-term only optimization (T2) produced more benefits for the wetter year. This stresses the value in incorporating both the strategic and tactical planning for robustly efficient operations across different years. Next, the value in spatial coupling is underscored by comparing TeNeSC against strategy C1 with no coupling. The latter again falls short of the hydropower benefits compared to the former. This is because when the optimization considers only the individual reservoirs without any coordination in release decisions, the optimal policy for one dam leads to other dams performing sub-optimally, leading to an overall reduced performance of the system. The hydropower generation from real-world observed operations, although not used for assessment as mentioned in Sec. III F, was comparable to those from the benchmark scheme.

B. Effect of skill in long-term forecasts

The perturbed inflow forecasts for the Blue Mesa dam were obtained for the moderately wet year of 2016 to study the effect of skill in monthly forecasts on the optimal operations. Figure 10(a) shows the perturbed inflow time series using six different constants of multiplicative bias. The long-term optimization model was first used to obtain monthly optimal policies for the three dams. Figure 10(b) shows the optimal long-term policy for the Blue Mesa dam for the corresponding perturbed inflow time series.

The long-term optimal elevations were then used to constrain the short-term optimization under the TeNeSC scheme. The hydropower benefits using the optimal operating policy from different underestimation and overestimation scenarios are summarized in Table VI. Comparing the outputs from different scenarios of perturbation, a

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TABLE V. Assessment of hydropower production (HP) benefits over the Aspinall unit using different strategies compared against benchmark and observed benefits over three years; IB is the improvement in production over the benchmark scheme. Comparing TeNeSC with T1 and T2 gives values in temporal nesting, while comparing with C1 gives values in spatial coupling.

Year	Strategy	Formulation	HP (GWh-perfect forecast)	IB (%)	HP (GWh-operational forecast)	IB (%)
2017 (wet)	TeNeSC	Short + long + coupled	1028	14.8	1021	14.1
	T1	Short-only	893	−0.3	877	−2.0
	T2	Long-only	934	4.3	929	3.8
	C1	Uncoupled	921	2.8	915	2.2
		Benchmark Observed	*895* *812*		… …	
2016(moderate wet)	TeNeSC	Short + long + coupled	974	26.9	948	23.5
	T1	Short-only	837	9.0	821	7.0
	T2	Long-only	759	−1.1	750	−2.3
	C1	Uncoupled	807	5.2	780	1.7
		Benchmark Observed	*767* *761*		… …	
2018 (dry)	TeNeSC	Short + long + coupled	847	41.5	829	38.5
	T1	Short-only	684	14.3	669	11.8
	T2	Long-only	603	0.6	599	0.1
	C1	Uncoupled	702	17.2	652	8.9
		Benchmark Observed	*599* *609*		… …	

higher bias of the inflow forecasts toward over- or underestimation generally results in lower energy benefits relative to the perfect forecast benefits. The effect of degrading skill is more prominent for the overestimation scenarios where the optimization strategy results in the over-conservative release policy, leading to lower energy production. The underestimation scenarios, on the other hand, yield relatively high releases and generate more energy when assessed over the entire year. However, the overall difference among the resulting optimal policies and respective hydropower benefits was insignificant. This is partly because the long-term forecasts are not directly utilized for arriving at the final optimized releases; rather, the first step of long-term optimization leads to the monthly optimal release policy, which then feeds the daily optimization. Thus, the effect of poor skill in monthly forecasts is, to some extent, compensated for by the more accurate short-term forecasts while deriving the final daily optimal releases. This is advantageous in the case when long-term forecasts are not very skillful as demonstrated here with heavy over/underestimation, further underscoring the value of co-optimization at long- and short-time scales.

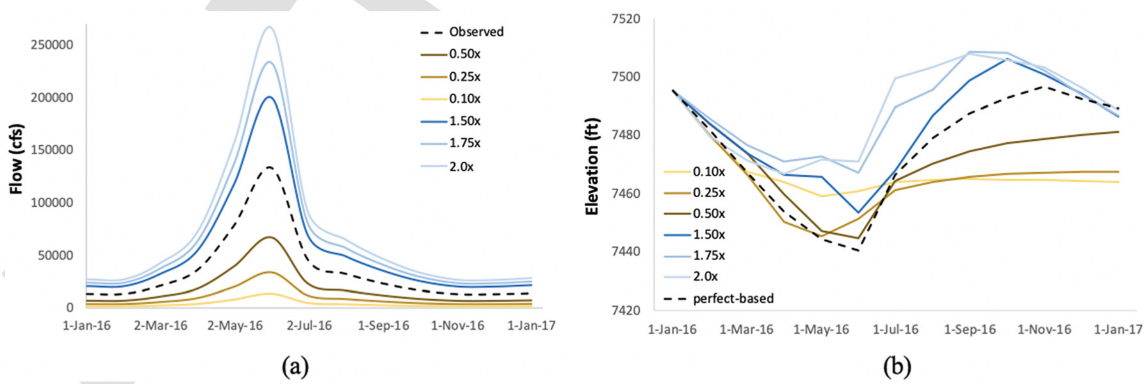

FIG. 10. (a) Perturbed inflow timeseries for the Blue Mesa dam over 2016 to be used for the TeNeSC scheme; (b) optimal monthly elevations for the Blue Mesa dam using the long-term optimization model based on the different perturbed forecast inflow time series; the black dashed line is based on perfect forecasts (i.e., observed inflow).

TABLE VI. Hydropower benefits obtained with TeNeSC using different perturbed inflow scenarios, "Nx" represents the perturbed inflow scenario obtained by multiplying the observed inflow timeseries by constant "N."

Underestimation scenario	Hydropower (GWh)	Overestimation scenario	Hydropower (GWh)
0.10×	968.1	1.50×	949.4
0.25×	973.4	1.75×	949.9
0.50×	960.8	2.0×	937.9
Perfect forecast	*973.8*		

V. DISCUSSION AND CONCLUSIONS

The smart use of skillful forecasts at weather and climate scales can potentially make the operation of existing dams more efficient. As forecast systems require fewer resources and manpower than building new energy infrastructure (Turner *et al.*, 2017), a major implication of using the forecasts is the improved efficiency of operations instead of building new hydropower dams to satisfy the same energy demands. To realize this potential toward energy generation, we have demonstrated a scheme that integrates the long-term benefits with the short-term optimization model to achieve optimality at both the time scales for a multiple dam network. The findings presented here are globally applicable, where energy demands and the need for greener and cleaner energy production are simultaneously escalating.

As a first step, to model the reservoir short-term (daily) and long-term (monthly) inflow forecasts, we used a numerically efficient and skillful data-based technique of ANN for the most upstream dam that receives unregulated natural flow. The publicly available NWP forecast forcings at the weather scale and the climate model outputs at the climate scale currently represent an underutilized resource for the energy and water resource community. The data-intensive and skillful ANN modeling technique was only employed for the most upstream dam of the three-dam network that brings natural inflow into the system. However, for the downstream reservoirs whose inflow is serially correlated with releases from the respective upstream dams, a linear regression model was found to be suitable for modeling the cascading inflow. This concept can be useful even for more complex multi-dam networks such as a parallel or combination of series-parallel networks, where only the most upstream reservoirs (one or more) need a skillful forecasting technique.

Our study shows that using the long-term optimal policy as a guide to the short-term optimization model aids the reservoir in avoiding any sudden surge or dip in the levels that might occur in extreme seasons. In particular, this is valuable for the wet season when an inflow peak with high uncertainty can leave the dam operator with a small temporal window to pre-release and adjust the reservoir levels when using short-term forecasts. With a skillful monthly forecast of the inflow volume from climate models, the temporal window of operations extends manifold giving the operator enough room to adjust the levels with minimal spells of heavy spillway release. Similarly, during the extremely dry seasons, long-term forecasts of drier years can keep the storage levels within safe bounds for a relatively unvarying energy supply (satisfying the baseload demands). The Pareto optimality in multi-objective optimization provides flexibility to the dam operator to choose an appropriate solution based on the prevailing circumstances and trade-offs between the two conflicting objectives.

The other component of co-optimized operations is the spatial coupling of reservoirs where the connected dams are operated and optimized for in tandem. The results suggest that benefits to the dam operator offered by coordination in release decisions depend on the characteristics of the reservoirs in the network. A diverse network comprising reservoirs and power plants with varying characteristics can potentially use the spatial coupling for the release policy tailored to each dam. Thus, if a dam is assigned to meet base load demands, its optimal release policy should allow for minimum changes in reservoir levels while, for the dams whose purpose is to provide peaking power during certain operational hours/days, the release policy can be adjusted accordingly to maintain the requirements for other baseload-providing reservoirs. This, when integrated with temporal nesting, has far-reaching implications for the numerous small and large multi-dam networks that were constructed in the previous centuries with long service lives but are suffering from fading efficiencies. Our proof-of-concept implies that smart use of seasonal and short-term forecasts can compensate for the losses in performance and generate more energy.

The quantification of benefits under the evaluation framework was performed by comparing them against a benchmark scheme that completely neglects the forecasts. The study showed 14%–41% of improvements in energy benefits from the co-optimized scheme against the benchmark over years with different flow characteristics. In general, the dry and medium years showed higher energy improvements than the considered wet year. A similar conclusion was also reported by Xu AQ6 *et al.* (2014) who obtained long-term energy generation as a function of short-term operations. As Xu *et al.* (2014) suggest, the objective of maximizing the hydropower or stored energy favors the long-term energy production under drier conditions by maintaining higher storage levels. This leads to relatively high overall improvements on nesting the short and long-term optimality. However, wetter conditions demand higher release, leading to a loss to the storage maximization objective in the long term and hence comparatively lesser improvements to hydropower.

This study specifically focused on the application of forecast-based reservoir operations at different temporal scales for improving upon the hydropower generation. The technique involves components of flow forecasting and optimization, which require *in situ* data on reservoir operations and inflow for setting up the models. For operationalizing the concept over other dam networks across the globe, the forecasting models can rely on inputs from the global NWP model and satellite remote sensing. However, the optimization model needs to be setup in conditions of scarce *in situ* data on dam operations. We hope to consider this in a future study. Moreover, with improved efficiency of reservoir operations, any excess energy generation can be wasted if there is not enough demand for dispatching the power to the grid, or in case, there is no provision for excess energy storage. Thus, another logical future extension of this work is to integrate energy demand forecasting and excess energy storage with the co-optimized-based reservoir operations. The utility of nesting the weather forecasts within the climate forecast-based operations not only is limited to hydropower but can also benefit other renewables such as solar and wind energy generation. Future endeavors on fostering the clean energy generation should aim toward an integrated hydro-wind-solar based energy framework.

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ACKNOWLEDGMENTS

This work was supported by the NASA Applied Science Program grant in Water Resources Nos. NNX15AC63G and NNX16AQ54G (Program Manager Dr. Bradley Doorn).

APPENDIX: SKILL ASSESSMENT IN FLOW FORECASTING MODELS

1. Short-term inflow forecasts

Using the selected ANN architecture, the training, validation, and testing of the ANN base model were performed using the GFS forecast forcings for the Blue Mesa dam. The trained ANN model was then forced with 11-member ensemble forecast forcings from the GEFS model to result in the ensemble streamflow forecasts for lead times of 1–7 days. The GEFS-based ensemble flow forecasts obtained using the trained ANN model are shown in Fig. 11 for the period of analysis 2016–2018. The selected period of analysis included anomalously dry, intermediate, and anomalously wet years. The performance of the average scenario of GEFS-based ensemble forecasts is compared against that obtained using GFS-based forecast. The evaluation metrics of Nash-Sutcliffe Efficiency (NSE), Correlation, Root Mean Squared Error (RMSE), and RMSE normalized with the mean of observed inflow (NRMSE) were used. The metrics are shown in Table VII.

TABLE VII. Evaluation metrics comparing the GEFS-average and GFS based flow forecasts for lead times of 1, 4, and 7 days against the observed inflow for the Blue Mesa dam.

	GEFS average scenario			GFS		
Metric	L1	L4	L7	L1	L4	L7
NSE	0.971	0.923	0.912	0.972	0.921	0.888
Correlation	0.986	0.963	0.956	0.986	0.960	0.943
RMSE (cfs)	215.1	350.9	375.6	188.7	313.5	368.1
NRMSE	0.120	0.196	0.209	0.120	0.199	0.233

The high accuracy exhibited by ANN flow forecasts results in a narrow spread of the GEFS-based ensemble forecasts. The average scenario of the ensemble has slightly higher skill as compared to that obtained from the GFS-based forecasts and hence was used as input to the short-term optimization model.

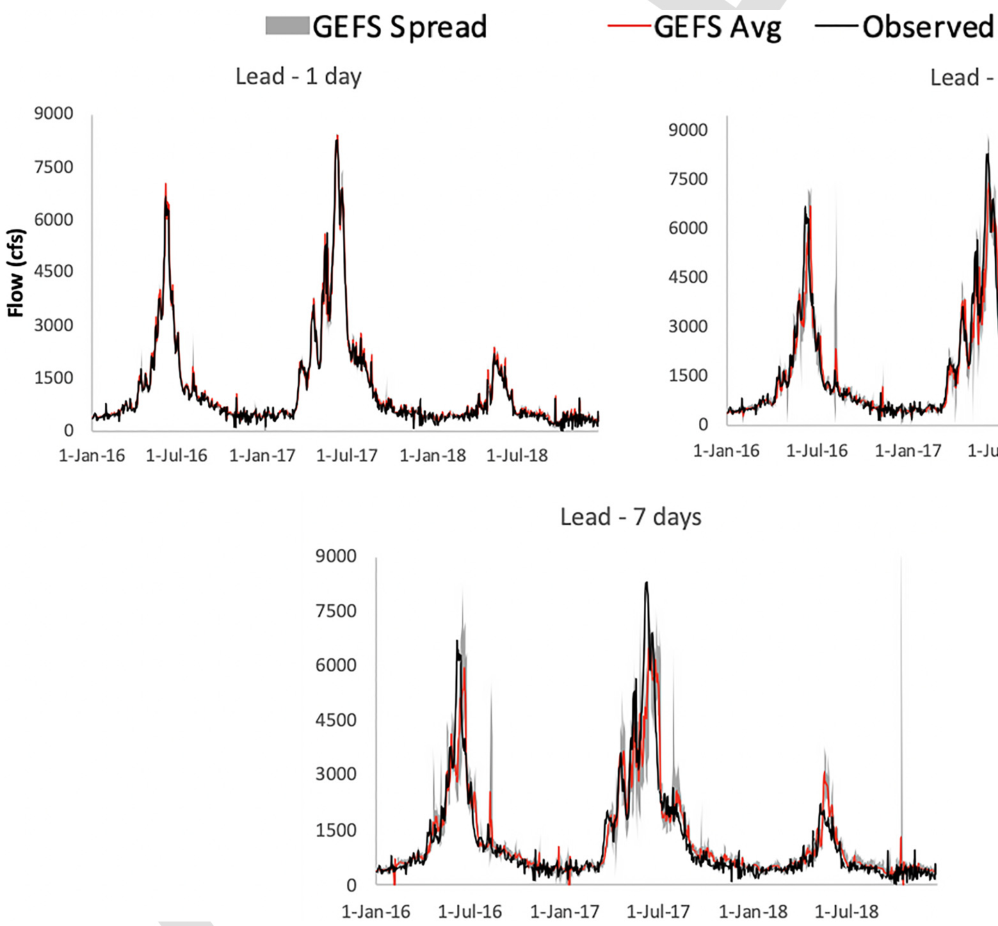

FIG. 11. Daily ensemble inflow forecasts along with the observed flow and average scenario of the 11-member ensemble for the Blue Mesa dam over 2016–2018.

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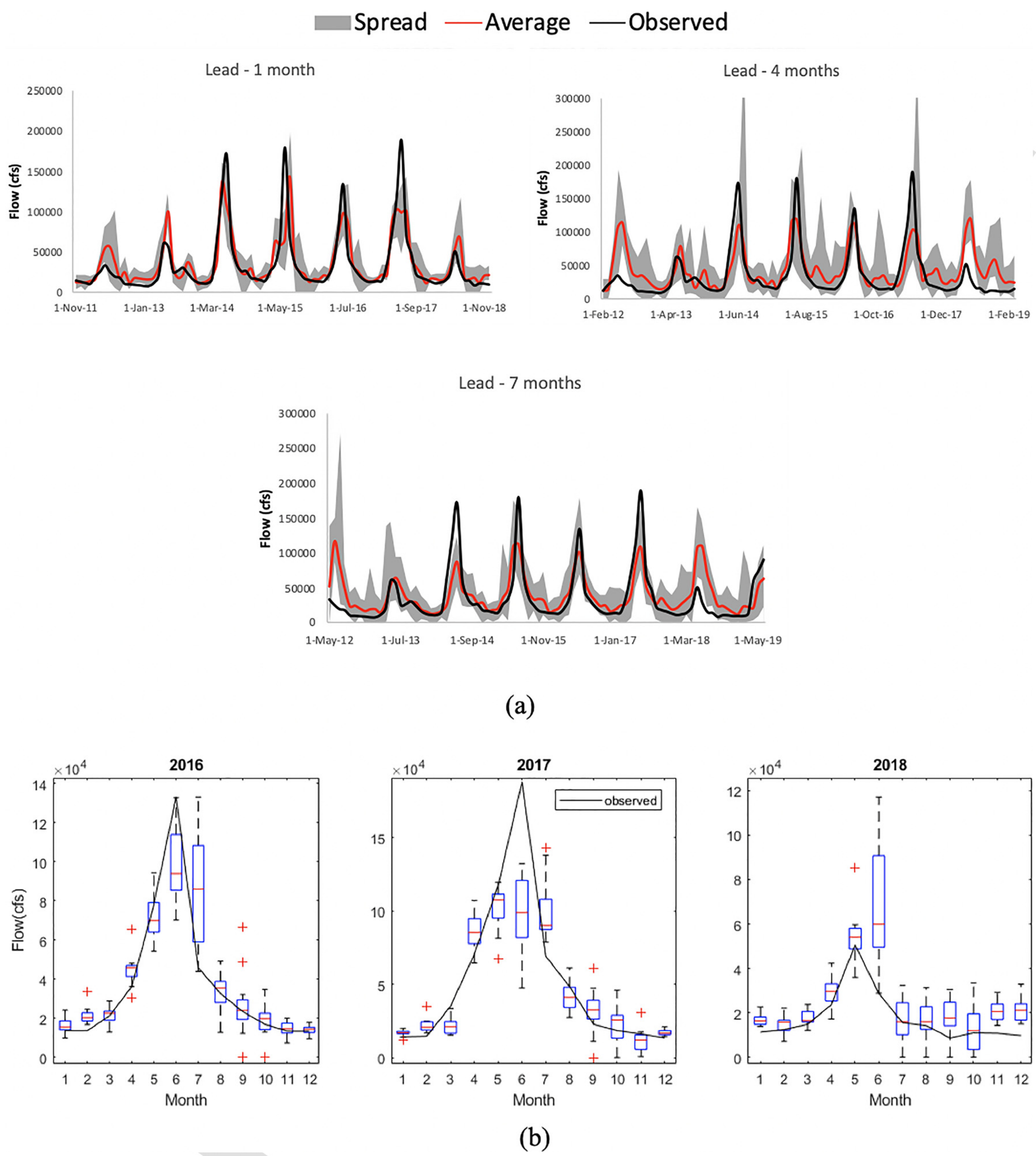

FIG. 12. (a) Ensemble monthly flow forecasts using the ANN model compared against the observed inflows over the testing period for lead times of 1, 4, and 7 months; (b) box-plots of the ensemble flow forecasts for 2016–2018 showing the spread in the forecasts for the lead time of 1-month.

TABLE VIII. Evaluation metrics for assessing the performance of the average scenario from the ensemble of monthly flow forecasts over the testing period of the ANN model.

Metric	Lead 1 month	Lead 4 months	Lead 7 months
NSE	0.63	0.53	0.58
Correlation	0.80	0.75	0.77

2. Long-term inflow forecasts

The long-term ANN model was trained using the selected predictors, and ensemble forecast forcings were used to result in the ensemble of flow forecasts. The modeled monthly flow forecasts over the testing period are compared with the observed inflow in Fig. 12(a). The spread in the ensemble forecasts for the lead time of 1 month for Blue Mesa dam is shown as the box-plot in Fig. 12(b).

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The average forecast scenario was used for performing the deterministic genetic algorithm-based optimization. The metrics evaluating the performance of average monthly forecast scenario against the observed values are tabulated in Table VIII.

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