A web-based decision support system for smart dam operations using weather forecasts

Shahryar Khalique Ahmad and Faisal Hossain

ABSTRACT

A web-based open-source decision support system (DSS) was developed to facilitate real-world engagement with dam-operating agencies in the decision-making process involving atmospheric modeling, hydrologic modeling, and web technology. The development process was decoupled into the container (frontend) and the modeling framework for the content (backend), to arrive at an intelligent system that improves the productivity and independent reuse of each component. The backend framework uses the weather forecasts from Numerical Weather Prediction models, downscales to a finer resolution, and simulates hydrologic and data-based artificial neural network models to optimize operations. The frontend architecture disseminates the forecasted meteorological variables, reservoir inflow, optimized operations, and retrospective weekly assessment of forecasts and hydropower benefits. The framework is automated and operationalized over the Detroit dam (Oregon) to generate the daily optimized release decisions. However, backend scripts and frontend elements are flexible and customizable enough that the DSS can be reproduced for other dams. The optimization of reservoir operations based on weather forecasts results in significant additional hydropower benefit without compromising other objectives when compared to the conventional operations. More importantly, the platform helps visualize for the dam operator how much more 'smarter' operations can be if weather forecasts and open-source technology are used.

Key words | decision support system, hydropower maximization, Numerical Weather Prediction model, open source, smart operations, web-based

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INTRODUCTION

Management of water resources, in particular, dams and reservoirs, and ensuring sustainability in their operation is one of the most complex of the engineering problems that involve technical, social, economic, environmental, and legal issues (Global Water Partnership 2013). The complications in operating reservoirs for various stakeholder needs along with the various forms of associated uncertainties make the problem hard to tackle using solely human judgement. At the same time, the atmospheric and hydrological modeling techniques have improved in terms of accuracy and efficiency (Bauer et al. 2015). Not only have the forecasts improved over time, the observation network for various hydrometeorological variables in space

(satellites) or on the ground has become more widely accessible. The technological advances in sensor technology and high levels of integration of electronics and data communication have made the automation of hydrological and meteorological networks increasingly affordable around the globe (Biswas & Hossain 2017). Dams and reservoirs stand to benefit from such an extensive data availability and improved weather information.

However, the current state of reservoir operations has not changed much since they first came into existence (Alemu et al. 2011). The conventional reservoir operations, still practiced for a majority of dams (Jahanpour et al. 2014), are based on the rule curves that were designed

based on the climatology of historical flow observations and existing storage volumes (Yazicigil *et al.* 1983; Ficchì *et al.* 2015). An example of designing the reservoir-operating procedure, specifically for dam safety, was shown by Gabriel-Martin *et al.* (2017) considering incoming flood events of different return periods. The operating rules do not consider the alterations in the stakeholder demands and flow regimes since they were formulated (Lee *et al.* 2009; Hossain *et al.* 2012; Farmer & Vogel 2016). This has led to several instances of suboptimal operations that caused heavy damages, especially during the highly uncertain flood events. Examples include 1996 Willamette Valley flood in Oregon (Rose 2016), 2008 flood in Bihar, India (Mehta 2008), and recent 2018 flood in Kerala, India (Padmanabhan 2018). The operations based on static rule curves can also lead to missed hydroelectric energy (Miao *et al.* 2016). As energy demands grow rapidly with increasing population and urbanization, there is a need to meet those using clean sources of generation (Ellabban *et al.* 2014). The current state of hydropower production will soon be unable to cope unless consumer practices are changed. The developed world cannot expect any significant rise in hydropower capacity installation as most economical hydropower sites have already been explored in the past century (Labadie 2004). The developing nations have to face the increasing environmental and social costs from the numerous small- and large-scale hydropower dams that have been built recently or are planned for in the near future (Collier 2004; Yüksel 2009).

Thus, the existing (and future) hydropower infrastructure needs to improve its operational capacity to maximize energy production and reduce the impact and risks associated with the current policy of operations. One way is to utilize the information on forecast reservoir inflow in the reservoir-operating process (Georgakakos 1989; Zhao *et al.* 2011). The weather scale forecast fields of temperatures, wind, precipitation, and soil moisture are available publicly over the entire globe from the Numerical Weather Prediction (NWP) models from various meteorological agencies. Over the last decade, the accuracy of weather forecasting at the basin scale has witnessed significant improvement due to more reliable NWP models (Valeriano *et al.* 2010). According to Bauer *et al.* (2015), the skill in NWP forecasts at a lead time of 7 days has improved from around 50% in 1995 to more than 70% in 2015, where skills greater than 60% indicate a useful forecast. Various studies have demonstrated their ability to perform well in forecasting the streamflow (Habets *et al.* 2004; Collischonn *et al.* 2007; Zhou *et al.* 2011; René *et al.* 2013). Wang *et al.* (2014) presented the efficacy of using the quantitative precipitation forecasts (QPFs) in an integrated simulation and optimization system for optimizing dam releases in large river basins. However, the awareness and technical expertise required to process these forecasts for decision-making is mostly limited to the scientific community and does not extend to the application world. Also, multiple uncertainties exist in the optimal decision-making process presenting risks to the enduser decisions (Zhu *et al.* 2017). This limits the advancements in atmospheric modeling to benefit the water managers until creative and user-friendly solutions are devised to improve engagement and help managers understand the practical value of advancements. To empower and actively engage the dam operators, a dam user-driven decision support system (DSS) is needed that not only visualizes the weather forecast data, but one that forecasts the reservoir inflow, optimizes the release decisions and allows enough operator-driven flexibility to tweak constraints, and then predicts the optimized release and storage decisions. Valeriano *et al.* (2010) proposed a real-time-operating DSS specifically designed for flood management using QPFs and a hydrological model. The present study is inspired by the wide availability of NWP forecasts that can guide the water managers handling the dams if the information is synthesized and presented in a user-friendly environment.

A DSS, as defined by Loucks & da Costa (1991), is a 'computer-based tool having interactive, graphical and modeling characteristics to address specific problems and assist individuals in their study and search for a solution to their management problems'. The purpose of DSS is not to replace but rather to improve human decision-making in making informed choices to achieve a predefined objective (Ahmad & Simonovic 2006). A detailed overview on the DSS is provided by Loucks *et al.* (1985), Simonovic & Savic (1989), Teodosiu *et al.* (2009), and Zhang *et al.* (2014). Among the studies on water resources management, DSSs have been proposed for flood control (Cheng & Chau 2004; Abebe & Price 2005; Ahmad & Simonovic 2006), water supply (Westphal *et al.* 2003; Ge *et al.* 2013),

groundwater management (Aliyari *et al.* 2018), and irrigation requirements (Faye *et al.* 1998; Mateos *et al.* 2002). There are also studies on improving the hydropower generation using DSS-informed reservoir operations. Alemu *et al.* (2011) described a DSS that incorporated forecasts of streamflow and energy prices to generate reservoir-operating rules and optimize the economic value of the produced energy. The study obtained retrospective streamflow forecasts at weekly scale to perform the optimization at weekly intervals. Huang (1996) applied a DSS to the operation of a reservoir in Taiwan during the dry season, targeting the objectives of water supply, irrigation, and hydropower. Blanco *et al.* (2008) proposed a DSS to analyze micro-hydropower plants in the Brazilian Amazon under a sustainable development perspective. Another example is a DSS proposed for monthly operation planning of Dez and Karoon reservoirs in Iran with hydropower facilities by Karamouz *et al.* (2005). Despite the various efforts to formulate the DSS for hydropower operations, the literature still lacks the daily scale short-term advisory using the NWP fields.

Many of these studies have used commercial software packages for implementing the DSS, while others require specific desktop requirements to be able to use it. However, building cost-effective and easily accessible solutions that are sustainable in the settings of a dam-operating agency require a framework based on open-source/nonproprietary technology. Such a framework can enable the stakeholder and the end-user community that is more of a 'knowledge consumer' than its 'knower', to make the potential use of the advanced modeling techniques and software systems. Also, the nonproprietary tools allow to bypass cost-prohibitive proprietary software that might become an obstacle for the operating agencies. Web-based systems offer a solution that can be built using open-source tools and connect the complex models with an easy to use and follow frontend (Jahanpour *et al.* 2014). The technology has been widely incorporated for implementing the DSS. Biswas & Hossain (2017) built a web interface for facilitating water management in the developing world using satellite data. Zeng *et al.* (2012) developed a web-based DSS for a reservoir operations model with urban water demand forecasting, hydrological model, and water management model incorporated into the system. A flood control management system for small reservoirs was implemented using the

WebGIS technique by Chen *et al.* (2017) and applied on Hengshan Reservoir in the lower reaches of the Yangtze River. Cheng *et al.* (2005) also implemented a web-based flood control system for the reservoirs. Choi *et al.* (2005) described a conceptual web-based spatial DSS using Geographic Information Systems for watershed management.

In order to empower the stakeholder agencies with advancements in atmospheric science, modeling, and optimization techniques, the study has two-fold objectives – (i) to develop an open-source DSS that knits together the complex models and simulations running in the backend, with a frontend visualizer that is user-friendly and easy to follow, and (ii) to provide a continuous assessment of the modeled results that helps the decision-maker gauge the performance against the reference (observed) variables in the retrospective mode. The end goal is to help the dam operator realize 'smarter' dam operations by implementing such a DSS, so that the release decisions are optimal in satisfying different downstream stakeholder needs.

The rest of the paper is organized as follows. In the next section, we discuss the dam site to implement and operationalize the DSS, followed by a description of datasets used for setting up the backend. This is then followed by a detailed methodology and individual components of the DSS in the Methodology for DSS Development section. The backend framework is described in the Backend Architecture section followed by the frontend and its modules in the Frontend Architecture section. The case study results are presented in the Application over Detroit Dam section, showing a sample run produced by the DSS for Detroit dam, followed by discussion and concluding remarks.

STUDY SITE AND DATASETS

For the operationalization of the DSS conceptualized in this study, Detroit dam in Oregon was chosen based on its hydrologic characteristics and long record of the observed data. The storage dam, operated primarily for flood control and hydropower generation, forms Detroit lake over the North Santiam River with reservoir's storage capacity of 455,000 ac-ft (0.56 km^3). The storage capacity to annual inflow ratio is around 0.28, which makes the short-term forecasts meaningful for optimizing the reservoir operations

(Anghileri *et al.* 2016). The powerhouse contains two Francis turbine units with a hydraulic capacity of 5,340 cfs (1 cfs = 0.028 m³/s) and a combined nameplate capacity of 100 megawatts (MW). Furthermore, as the turbine-operating hours and the efficiency of operation usually vary during operations, linear regression was performed between the historical energy generation data (in megawatt-hours, MWh) and the product of hydraulic head and power release (converted to MW units) to obtain the turbine efficiency. The assumption made here is that the turbines will continue to operate in the near future with the same characteristics as obtained from the historical operations. The constant of the regression line was obtained as 19.72 h, which takes into account the turbine efficiency and the average number of operating hours. The dam is operated by U.S. Army Corps of Engineers (USACE) that posts real-time and historical operational data on a web-portal (Query Timeseries from USACE 2017). The flood season extends from November to March where the reservoir elevation is kept to a minimum while the conservation storage is provided from April to November. Figure 1 shows the location of dam, its reservoir, and the drainage basin.

The datasets used in the study include NWP forecast fields, hindcast forcings of precipitation, minimum and maximum temperature, and average wind speed for running the hydrological model. The NWP forecasts were obtained from the Global Forecast System (GFS) model at 0.25° resolution (Global Forecast System 2017). The hindcast forcings were obtained from the NCDC GSOD (Global Surface Summary of the Day 2017) data. The DSS also requires real-time and historical data on observed reservoir inflow, reservoir elevations, storage, and the hydroelectric energy generation. This was obtained from the query portal of USACE (Query Timeseries from USACE 2017). All the hydrometeorological datasets were resampled spatially and temporally to ensure compatibility with the hydrologic model's spatial and temporal resolution.

METHODOLOGY FOR DSS DEVELOPMENT

The premise of a DSS, according to Simon (1977), is based on four phases – providing intelligence in gathering of data and information, designing multiple solution options to resolve the problem, selecting the best alternative, and assessing whether the selected option is appropriate. In light of these, the following characteristics of the DSS were identified to fulfill the user's functional requirements and achieve the vital engagement with the stakeholder-operating agencies.
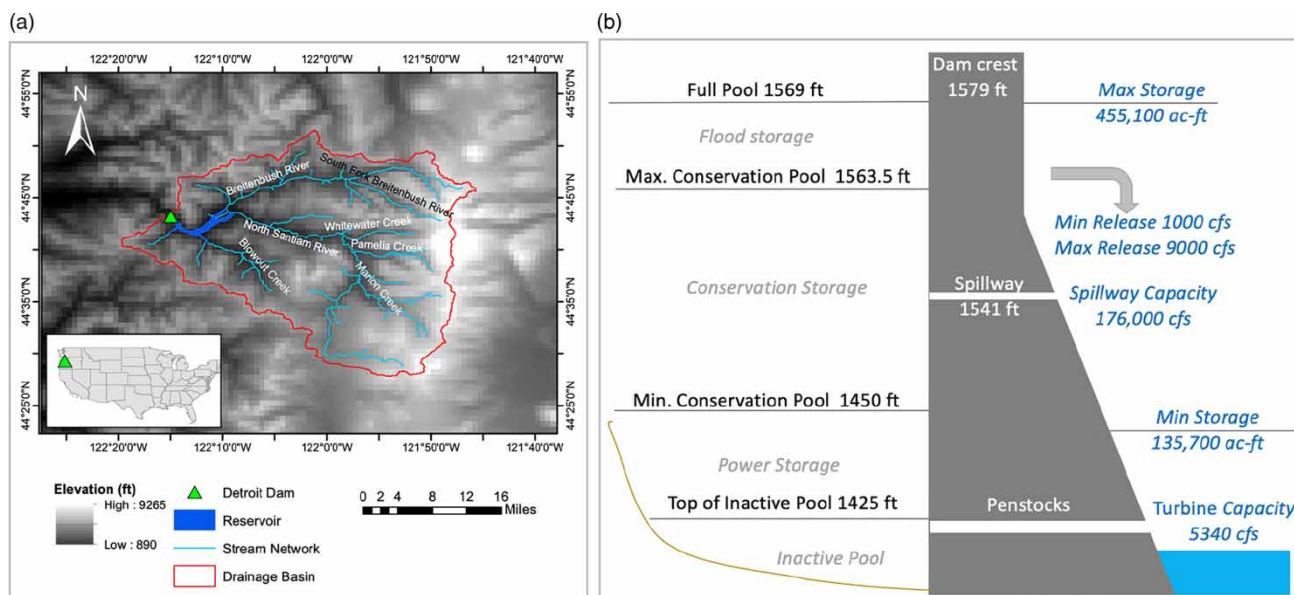

Figure 1 | (a) Detroit dam of Oregon, its reservoir, drainage basin, and stream network. The inset map shows the location of dam in CONUS. (b) Cross-section of Detroit dam (not to scale) showing relevant pool elevations in feet (from the mean sea level).

1. *User-friendly:* It should be easy to use and follow without the need of prior experience and advanced software handling skills.

2. *Accessible:* It should be easy to access and launch, without requiring any considerable workstation system resources or installation of commercial packages that might hamper their operationalization in resource-limited settings. This necessitates exploiting the open-source technology for building the entire framework.

3. *Fully integrated with the modeling framework:* The back-end of the DSS should process the required datasets and run all the necessary models to generate forecast inflow and optimized release decisions, without the user having to deal with the complexities involved therein.

4. *Rely on current system status:* The most current state of the reservoir should be assimilated for simulating the reservoir operations model to generate the future optimal releases. The system should also stream the actual operations.

5. *Continuous assessment:* The design of the DSS should also continuously assess and inform the user of the performance of the release decisions provided. The assessment should gage the end goal of the optimization (energy generation maximization or flood risk minimization), comparing the optimized and actual operations.

6. *Flexibility of backend:* The system should allow an easy way to customize the key constraints and dam characteristics in the scripts running at the backend, to be tailored for any other dam site of interest to the user.

7. *Customizability of frontend:* The frontend should stand as a generic template for numerous other dams that can benefit from the forecast-based optimized operations.

To fulfill these characteristics, we incorporate here the bipartite approach described by Gachet & Haettenschwiler (2003), for developing the DSSs, which decouple the process into the components of *decision support* and its *system*, or in other words, the *contents* and the *container*, respectively, of the DSS. Such an approach improves the independent reuse of the container and the contents, making it more productive, flexible, and easier to tailor for custom dam sites. This approach was implemented using the web-based technology where the frontend serves as the container, while the backend, that runs the modeling framework, provides

the necessary contents. The two components come together to provide the user with a useful application that supports the decision at hand and is accessible easily through internet technology (Marakas 1999). This bipartite architecture is shown in Figure 2, highlighting the interaction between the two top-level components along with their individual subconstituents. The resulting DSS is termed here as 'Intelligent Dam DEcisions and Assessment' (*i*-DDEA) and is described in detail in the following sections. The *i*-DDEA DSS is currently operational and hosted at http://depts. washington.edu/saswe/damdss/. To encourage the reproducibility of the DSS for other regions of interest and to provide a platform for assessing the necessary scripts for customization, a GitHub repository (https://github.com/ shahryaramd/iDDEA) has been set up for all the frontend script and libraries, and necessary scripts and model configuration files for the backend architecture, that anyone can download to start customizing the *i*-DDEA DSS.

Backend architecture

The backend of the DSS comprises of four different modules embedded into a framework, to produce optimized reservoir releases for 1–7 days lead time. The modules are coupled with each other, where one's output becomes the input to the next to generate the different results that serve as the content for the frontend template-based architecture. The scripts for automation of the framework were written in the Linux Operating System using Python scripting language (Van Rossum & Drake 1995). Because the DSS backend is designed to be model-agnostic, two different models were implemented for generating the reservoir inflow forecasts – one that uses a physically based hydrologic model, while the other using the data-based approach of artificial neural networks (ANNs). The four-model framework is illustrated in Figure 3 where the hydrologic model is used for forecasting. In the data-based approach for obtaining inflow forecasts, the hydrologic model is replaced by the ANN model as illustrated in Figure 5. The individual models are described below.

Weather forecast model

The GFS model, run by the National Oceanic and Atmospheric Administration (NOAA), produces global forecast
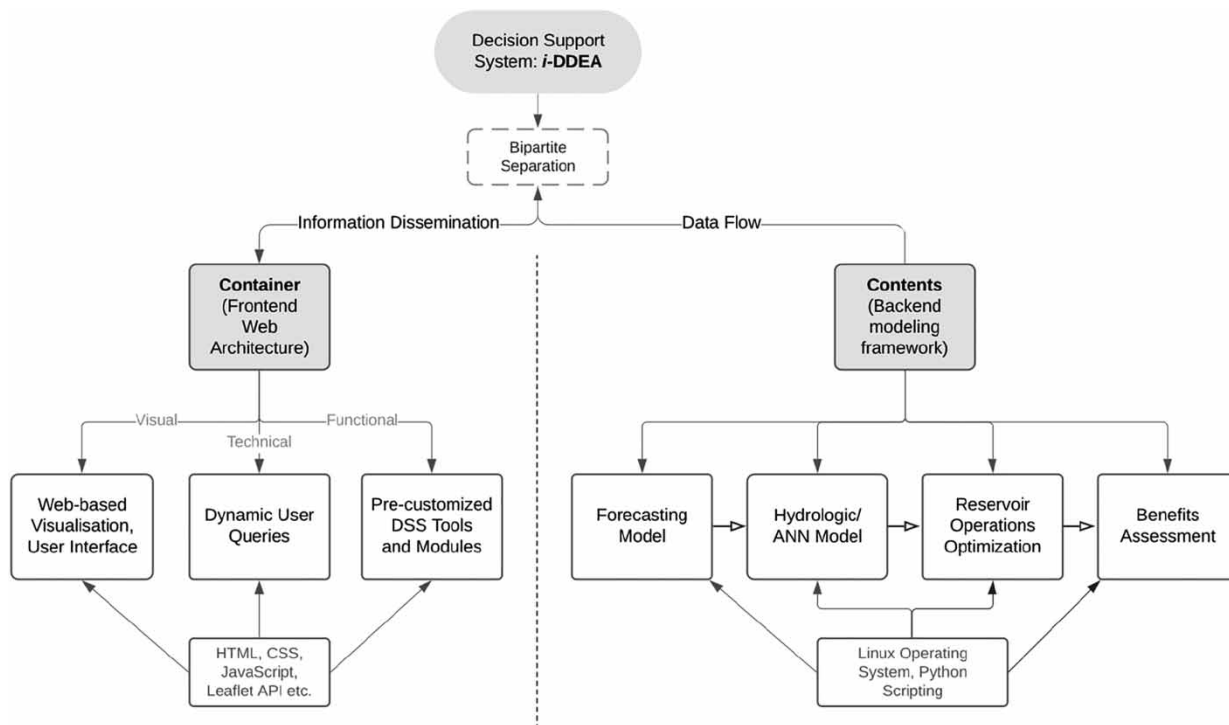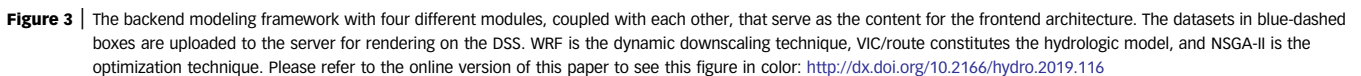
Figure 2 | The overall architecture for *i*-DDEA, based on a bipartite approach that separates the DSS into two major components – contents (here backend models) and container (the frontend web platform). The approach facilitates the independent reuse of the two components for easy customization. The DSS is hosted at http://depts.washington.edu/saswe/damdss/.

fields in almost real time for lead time of 1–16 days at each data assimilation cycle (00, 06, 12, and 18 UTC). However, the coarse resolution atmospheric forcings produced by the global-scale NWP models are often not detailed enough for the relatively small reservoir catchments. Thus, to resolve the atmospheric processes at finer scale, *dynamic downscaling* was performed using the Weather Research Forecasting (WRF) model (Skamarock *et al.* 2008). For details on the application of WRF, users can refer to Chen & Hossain (2016) and Sikder & Hossain (2016) which demonstrate the downscaling over USA and monsoonal regimes of South Asia, respectively. Two nested domains of 10 and 30 km were used for the Detroit dam. The model configurations were inherited from the forecast model runs of the Department of Atmospheric Sciences at the University of Washington (Pacific Northwest Mesoscale Model 2017). The gridded WRF-downscaled forcings of precipitation, temperature, and windspeed at 0.1° resolution were input to hydrologic model to obtain the forecasted streamflow. The WRF setup over the drainage basin of Detroit dam was evaluated (not shown here) against the reference Livneh dataset

(Livneh *et al.* 2013). The assessment of WRF-based downscaling over actual operations has been shown later in the 'Application over Detroit Dam' section.

Hydrologic model

For this study, the macroscale, distributed variable infiltration capacity (VIC) hydrologic model (Liang *et al.* 1994) was chosen to model the reservoir inflows. The time step of the VIC model simulation was selected as daily with a spatial resolution of 0.1°, considering the limitations of the user agency environment such as internet connectivity and restrictions in the computational power. The VIC model is forced with the NCDC hindcast forcings and WRF-downscaled GFS forecast forcings of precipitation, temperature, and wind speed at 0.1° resolution. Routing of streamflow was performed separately using the routing model of Lohmann *et al.* (1996). Following parameters of the VIC model were calibrated (calibrated values in brackets) – the fraction of maximum baseflow with nonlinear baseflow ($D_s = 0.39$), the fraction of maximum soil

Figure 3 │ The backend modeling framework with four different modules, coupled with each other, that serve as the content for the frontend architecture. The datasets in blue-dashed boxes are uploaded to the server for rendering on the DSS. WRF is the dynamic downscaling technique, VIC/route constitutes the hydrologic model, and NSGA-II is the optimization technique. Please refer to the online version of this paper to see this figure in color: http://dx.doi.org/10.2166/hydro.2019.116

moisture where nonlinear baseflow occurs ($W_s = 0.0028$), shape parameter of the VIC curve ($b_{inf} = 0.23$), and depth of soil layers 1 and 2 ($D_1 = 0.25$ m and $D_2 = 0.28$ m). The unit hydrograph in the routing model was also tailored to capture the fast response of Detroit basin. Model calibration was performed over 2009–2011, and the validation over 2013–2015, minimizing the root mean-squared error (RMSE) between the modeled and observed flow from USACE. Other metrics used for evaluation include Pearson correlation coefficient, Nash–Sutcliffe efficiency (NSE; Nash & Sutcliffe 1970), and Kling–Gupta

efficiency (KGE; Gupta *et al.* 2009). The first few months were ignored for evaluating the metrics, taking into account the model spin-up period. The results for calibration and validation are shown in Figure 4.

Data-based (ANN) forecast modeling

As the macroscale VIC model leaves room for improvement in the modeling of inflow, the data-based technique of ANN was implemented in the *i*-DDEA DSS as an alternative option for generating 1–7 days lead reservoir inflow
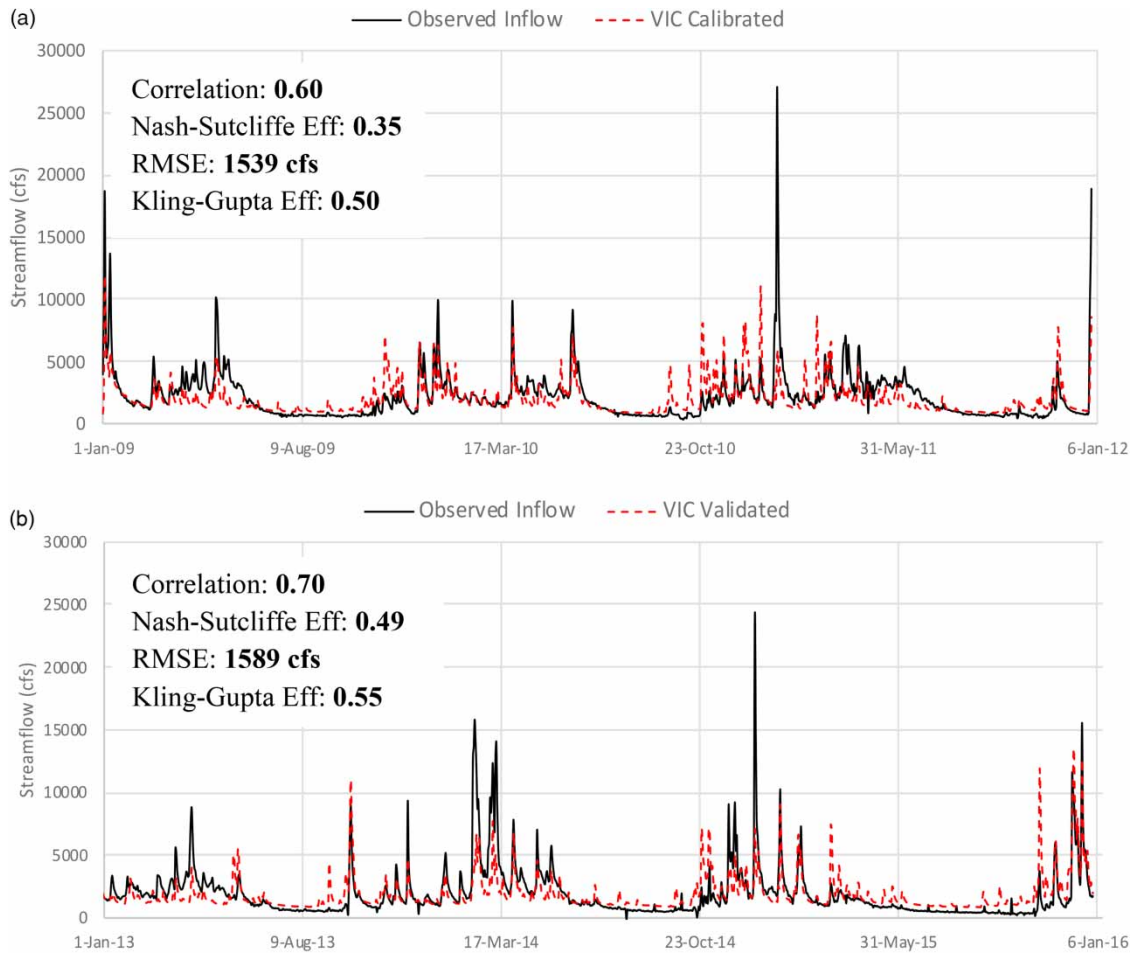
Figure 4 | (a) VIC calibrated and (b) validated streamflow, and observed flows at Detroit Dam, Oregon.
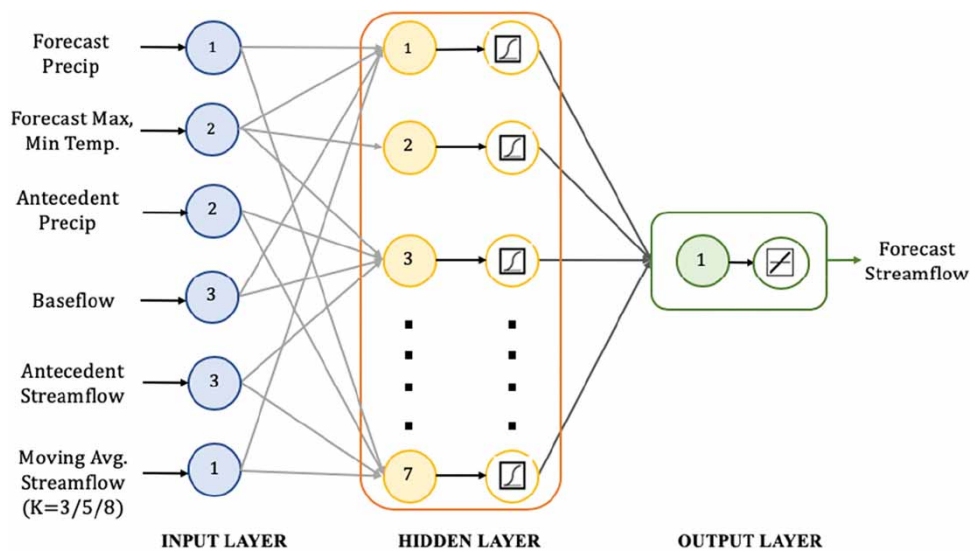

Figure 5 | Three-layered ANN architecture and the selected input nodes for hidden and output layers, respectively. Numbers on input nodes represent the selected number of antecedent/forecast days. K is the window length for moving average streamflow that is varied with lead time of forecasting (after Ahmad & Hossain 2019).

forecasts. An ANN, over the last two decades, has been established as an efficient choice for modeling water resource variables while capturing the nonlinearity in flow (Maier *et al.* 2010). A three-layered ANN was designed using antecedent precipitation (2 days), baseflow (3 days), streamflow (3 days; for lead times of 4–7 days), moving average streamflow (3-, 5- and 8-day window based on lead time), forecast precipitation (1 day), and forecast minimum/maximum temperature (1 day each) as the input predictors (Figure 5). A period of 9 years extending from January 2007 to August 2014 was used for training the ANN model, while the validation was performed over September 2014–December 2017. For further details on model setup, the reader is referred to Ahmad & Hossain (2019). The use of basin-averaged NWP fields from GFS model alleviates the need of computationally expensive dynamic downscaling using WRF.

Figure 6 shows the ANN-forecasted flow against the observed values over the validation period for lead times of 1, 4, and 7 days over Detroit dam. The metrics of NSE, correlation, and normalized RMSE are tabulated in Table 1.

Reservoir operation model

The reservoir operations were modeled at a time daily step to produce the optimized release policy over the forecast horizon of 7 days. A dam operator is very unlikely to be making decisions on reservoir releases for dams at frequencies higher than a day. As the forecast skill reduces with increasing lead time, the optimization model uses the updated flow forecasts (based on the VIC or ANN model) every other day. This strategy is called model predictive control (MPC) (Turner *et al.* 2017), which provides the optimal release policy over the forecast horizon. However, only the first two values of this policy are actually applied to the system, and the same optimization procedure is repeated using updated forecasts at the next time step over a forecast horizon shifted two steps ahead. We chose two steps to update considering the computational burden of running WRF downscaling every day which can become a constraint for the dam-operating agencies. The optimization was formulated as a multi-objective optimization problem with the objective functions of hydropower maximization and flood control (Madsen *et al.* 2009). The non-dominated sorting genetic algorithm (NSGA-II; Deb *et al.* 2000) was used to yield the optimal solutions from which an appropriate alternative was chosen at suitable satisfaction levels of both the objectives. The two objectives are formulated below.

1. Minimize the deficit in hydroelectric power production (MW) from the maximum generation capacity of the powerplant (HP_{max}) with turbine efficiency ϵ, operating
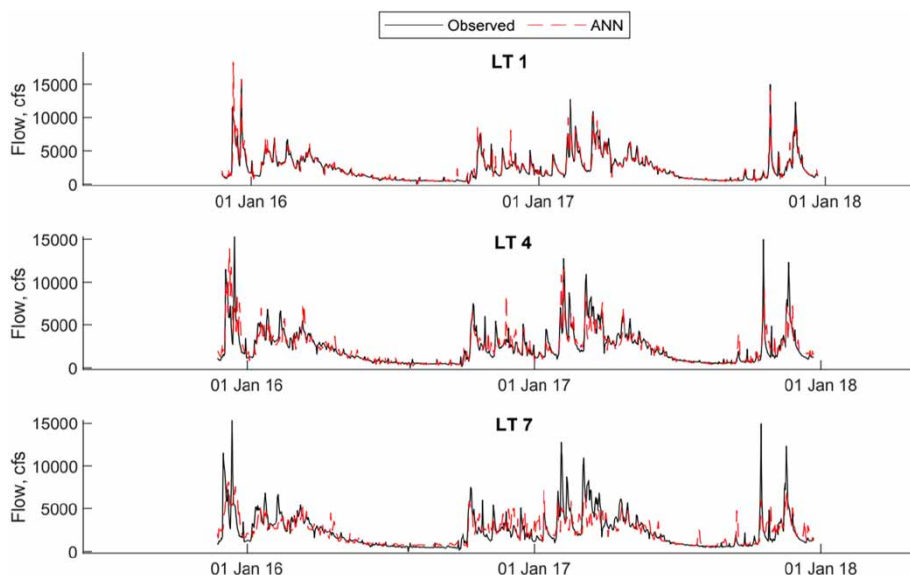

Figure 6 | ANN modeled flow plotted against observed values for lead times (LT) of 1, 4, and 7 days (LT 1, LT 4, and LT 7) over the validation period.

Table 1 | Evaluation metrics for the ANN-forecasted flow during validation for three lead times

	LT 1	LT 4	LT 7
NSE	0.84	0.72	0.60
Correlation	0.92	0.85	0.78
RMSE (cfs)	539.8	719.8	853.1
NRMSE	0.25	0.34	0.40

hours Δt_{turb}, power release R_p, and net elevation head ΔH.

$$\min f_1(\text{MW}) = \text{HP}_{max} - \sum_t \epsilon \cdot \Delta t_{turb} \cdot (\Delta H_t) \cdot R_{p,t} \qquad (1)$$

2. Minimize the absolute value of deviations of reservoir elevation (H) from the target rule curve level (T) over the optimization horizon. It is represented as follows:

$$\min f_2 \ (\text{ft}) = \sum_t |H_t - T_t| \qquad (2)$$

Several constraints were imposed on the optimization problem in the interest of downstream stakeholders and dam safety. The power release from the reservoir was limited by the turbine capacity, while following the storage volume continuity. In order to avoid excessive and infeasible rates of discharge via the spillway that can threaten downstream conditions, the spillway release rate was limited to a safe threshold of spillway capacity, for each day of the optimization horizon. The total release was bounded between the environmental flow limit and a safe threshold to prevent flooding at a downstream control station. The mathematical formulation of the constraints is given in Ahmad & Hossain (2019). The optimization routine was coded in the Python scripting language using open-source libraries. The script serves as a generic template, flexible to be tailored for operationalization of the concept over any other dam with varying characteristics, where none such solution exists in the current literature to the best of our knowledge.

Benefits assessment

The assessment of the optimized release decisions is performed against the observed operations without any optimization, on every day of the model run retrospectively over the past week. The *optimized hydropower benefits* are obtained using the optimized releases while passing the observed inflow into the system. These optimized releases are obtained from the MPC approach where the optimization is performed at every alternate step with the updated forecasts. The *observed hydropower benefits*, however, are computed from observed operations without any optimization/forecasts. The observed benefits correspond to the real-world power generation data obtained from the operating agency, USACE. The optimized hydropower benefits (MWh) are calculated as the product of hydraulic head and power release (via penstocks), considering the turbine efficiency, operating hours, and the capacity factor (ratio of actual hydropower produced to the maximum possible over a period).

Frontend architecture

The other primary component that serves as the link between the complex models running in the backend and the user (dam operator) is the frontend or the visualization framework of the i-DDEA DSS. This framework is organized into several modules to help achieve the desired characteristics of the DSS. The three main aspects of the user experience considered here are – visual, functional, and technical elements that are implemented using various open-source tools, libraries, and application program interfaces. The functional elements, as considered here, constitute the overall space, navigation, content and logos, and their respective formatting. The technical and visual aspects include the dynamic querying and visualization of timeseries/raster products on the web map, respectively. The schematic in Figure 7 illustrates the overall web architecture of the frontend. The description starts with the scripts and open-source tools used for designing the user interface, followed with the detailed explanation of each individual module.

Scripts and tools for user interface

Firstly, a local web server environment in the *localhost* was set up using the open-source software XAMPP
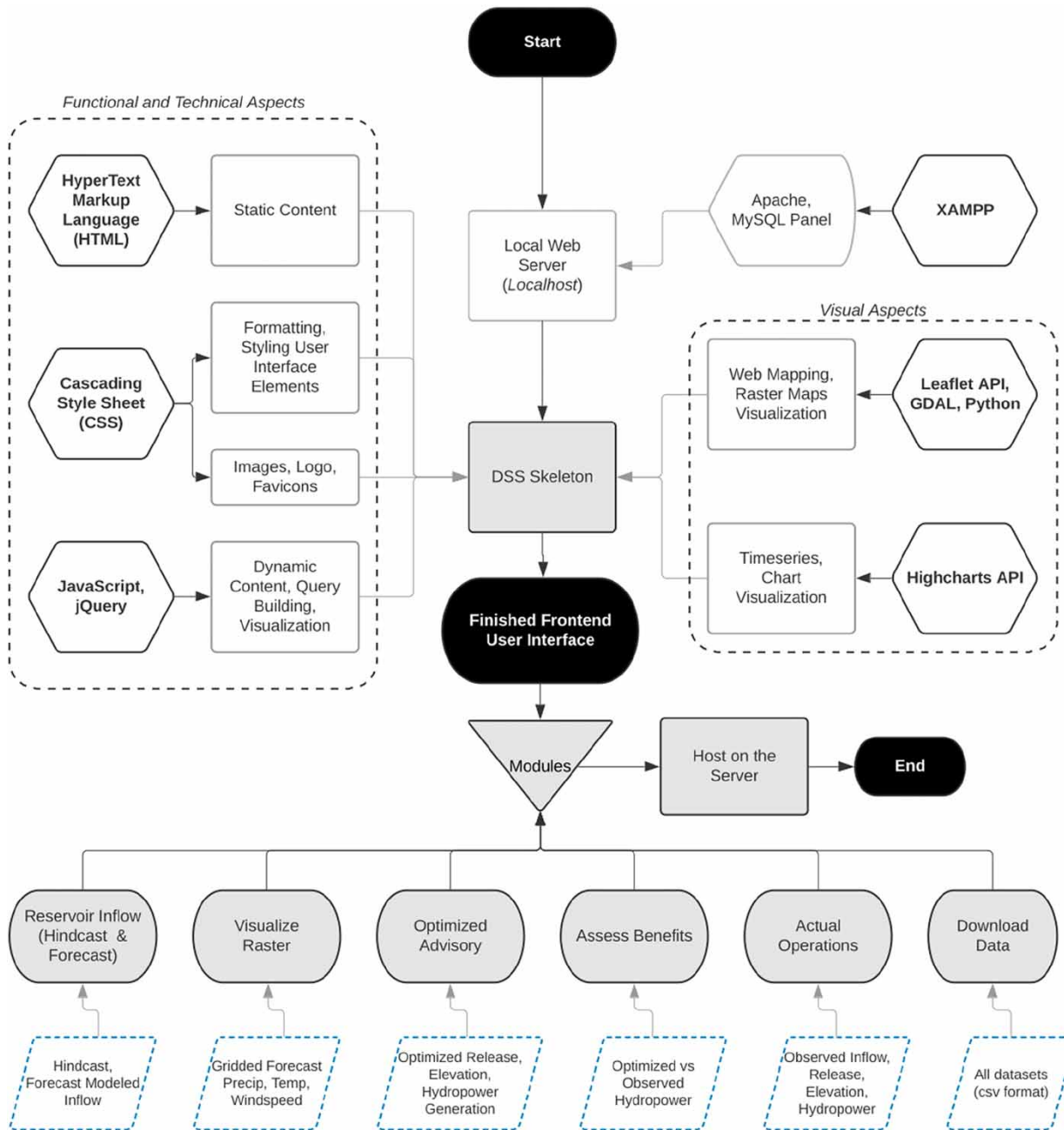
Figure 7 | The different components, necessary libraries, scripting languages, and modules embedded in the frontend web architecture of the DSS. The datasets at the bottom-most layer are processed and uploaded from the backend architecture.

(https://www.apachefriends.org/index.html). XAMPP stands for Cross-Platform (X), Apache (A), MariaDB (M), PHP (P), and Perl (P). The environment facilitates testing of the scripts and tools during the development phase on a local machine (local server) that mimics the real web server upon its deployment. For visualization of the gridded forecast datasets over

the basin, the web-mapping technology was utilized using an open-source JavaScript library called Leaflet (https://leafletjs.com/). It offers highly flexible and customizable mapping capabilities that can produce interactive maps for web and mobile applications. Another library called HighCharts (http://www.highcharts.com/) was used for publishing

interactive charts on the web-based DSS. The library is also written in pure JavaScript and offers an easy way of adding various charts such as line, spline, area, area-spline, column, bar, pie, and scatter. The Geospatial Data Abstraction Library (GDAL: https://www.gdal.org/) was used in the Linux Operating System to process the raw forecast fields to the GeoTIFF format for rendering on the web map. Finally, styling and event-handling libraries of Materialize (https://materializecss.com/) and jQuery (https://jquery.com/) were used to create a dynamic and interactive experience for the user. All these tools and libraries are open-source, nonproprietary that were identified through a web search for implementing the specific modules of the web framework.

Forecast visualization module

The first module of the frontend architecture is the advisory on processed forecasts for hydrological variables and inflow into the reservoir for 7 days lead time. The visualization informs the dam operator about the amount of water flowing into the system in the next 2 weeks and if any precautions are necessary in light of a potential flood event. The 'Reservoir Inflow' tab provides the user with two options to select from the source of modeled forecasts. First is the 'VIC-based forecasts' that downscale GFS forcings using WRF and generates 1–16 days lead forecasts. The plot shows the inflow timeseries for the past 2 months in hindcast and 16 days in forecast. The other option is 'Data-based (ANN) forecasts', which plots the 1–7 days forecast inflow along with the observed flow timeseries over the past 2 months. In future, other forecasting models/techniques can be added as options to choose from. The gridded forcing products of precipitation, minimum/maximum temperature, and average wind speed results are available from the 'Visualize' tab, with options to switch from lead times of 1, 4, 7, 10, and 15 days.

Optimized decision module

Based on the forecast inflow, the optimization model running in the backend produces an optimized set of releases to be made from the reservoir based on the current reservoir storage and future inflow. The user also has the option to visualize the corresponding forebay elevations of the reservoir and hydroelectric energy that could be produced (in MWh) by following the optimized release policy. This provides a real-time prospect to the dam operator in assessing the advisory to be followed.

Assessment module

The next module is developed to perform a retrospective assessment of the optimization-based decisions on the basis of additional energy benefits. The 'Assessment' tab presents the user with two options – 'Weekly Hydropower Assessment' and 'Weekly Forecast Assessment'. The hydropower assessment shows a bar chart comparing the hydroelectric energy (MWh) obtained from the observed observations (observed hydropower benefits) and those obtainable from the optimized releases (optimized hydropower benefits) using the VIC and ANN-based forecasts over the previous week of the model's simulation. The two scenarios for hydropower production are as follows:

1. *Optimized hydropower* – The hydropower that could have been generated, if the proposed optimal releases (updated every other day sequentially based on updated forecasts) were followed for the past week, starting from an initial observed storage of the reservoir. This scenario uses the observed inflow into the reservoir and optimized releases to calculate the optimized hydropower benefits.
2. *Observed hydropower* – The hydropower production based on the observed releases and inflows into the reservoir (with no optimization) over the previous week.

The forecast assessment provided on the DSS allows the user to compare the forecasts of inflow from the two models against the observed values over the selected week in retrospect. For a selected week of observed inflows, the user can choose the forecasts for any lead time (1–7 days), by specifying the date when the forecasts are produced.

Actual operations and data download module

Finally, the DSS allows the user to visualize the actual operations as streamed from the USACE's data portal. The 'Actual Operations' tab streams the variables of observed inflow, respective releases made from the reservoir, resulting reservoir elevations and the energy generation over the past 1 year. The module provides a quick way to visualize the

long-term trends of reservoir storage and hydropower gener-
ation which the optimized policy tries to improve upon.
Also, all the datasets are available for download to local
machines via the selection query located in the 'Download
Data' tab.

APPLICATION OVER DETROIT DAM

The DSS, operational over Detroit dam since December
2017, has been producing the forecasts and optimal release
decisions. The assessment of the modeled hindcast/forecast
flows and hydropower benefits is presented below for (a)
year-long simulation for 2018 and (b) over a specific peak
flow event, as generated by the DSS.

Year-long assessment using VIC and ANN-based forecasts

Firstly, to assess the NWP-based forecasts, the WRF-down-
scaled precipitation is compared against the CHIRPS dataset
(Funk *et al.* 2015) as precipitation plays a fundamental role in
the streamflow forecasts. The metrics of probability of detec-
tion (POD), false alarm rate, RMSE, and multiplicative bias
(explained in Appendix A, available with the online version
of this paper) are shown in Table 2, and the cumulative pre-
cipitation from the two sources are compared in Figure 8.

Forced with the downscaled forcings of precipitation,
temperature, and wind speed, the VIC model was simulated
to obtain the forecast flows, compared in Figure 9 against
the observed flow for 2018. The forecast flows show overesti-
mation in peak flow estimation and underestimation during
the low-flow season even after the possible VIC model cali-
bration. The underestimated flows are an artifact of the
macroscale VIC hydrologic model which is one of its limit-
ations in simulation over the small-scale basin of Detroit
dam. This remains an area of improvement which will be
considered in future work. The ANN modeled flows over
the same time period are also shown in Figure 9, highlighting
the improved predictive skill in capturing the peak and low
flows. The comparison metrics are summarized in Table 3.

The hydropower benefits obtained from the optimized
operations are compared with the observed power generation
data from USACE over the year 2018 in Figure 10, plotted

Table 2 │ Daily assessment of WRF-downscaled GFS precipitation for 2018, where 'LT' represents the lead time of forecasts

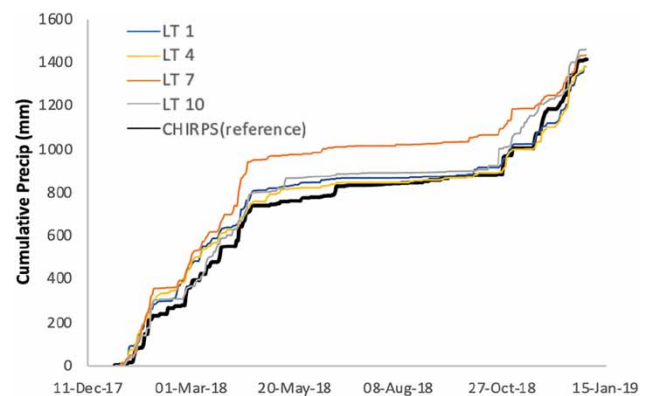|	Best value	LT 1	LT 4	LT 7	LT 10	LT 15
RMSE (mm)	0.0	9.63	9.63	10.19	13.05	11.93
NRMSE	0.0	0.94	0.94	0.99	1.27	1.16
POD-rain	1.0	0.74	0.76	0.63	0.52	0.41
POD-no rain	1.0	0.75	0.72	0.72	0.68	0.65
False alarm rate	0.0	0.25	0.28	0.28	0.32	0.35
Bias	1.0	1.58	1.62	1.46	1.34	1.21

Figure 8 │ Cumulative precipitation for the year 2018 using WRF downscaling compared with the CHIRPS dataset.

together with the respective inflow and release. The plots
are separated between the wet season (December–May) and
the dry season (June–November) for better assessment of
the tradeoffs in the optimal strategy. The plots suggest that
during the peak flow seasons, optimized policy results in
higher release ahead of the event leading to higher energy
generation. For low flows, the optimized release is con-
strained by the environmental flow limit of 800 cfs and
results in similar hydropower benefits as from the observed
operations, except for a few minor peaks whereby forecasting
early, additional energy generation is demonstrated (see
Figure 10(b)). The optimized and observed hydroelectric
energy benefits obtained using VIC and ANN forecasts
over the wet and dry seasons are summarized in Table 4.
The results suggest that the ANN-based optimized release
policy results in slightly higher benefits as compared to
those derived using VIC-based forecasts. This can be attribu-
ted to the underestimation of peak as well as low flows by the
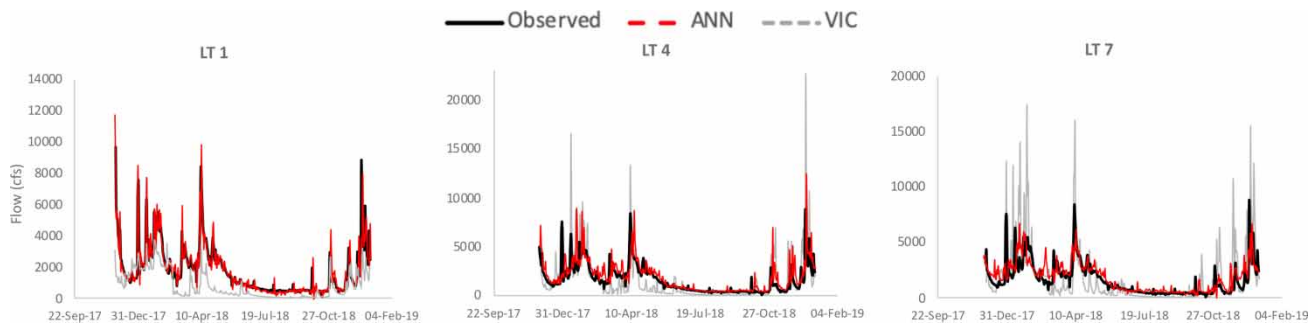VIC model (see Figure 9), which results in overly conservative

Figure 9 | Assessment of the modeled daily forecast flow using VIC and ANN models on DSS for the lead times (LT) of 1, 4, and 7 days for 2018 against observed data.

Table 3 | Assessment of daily forecast modeled flows using VIC and ANN models compared against observed flow data for 2018, where 'LT' denotes the lead time of forecasts

Dam name	VIC model			ANN model		
	LT 1	LT 4	LT 7	LT 1	LT 4	LT7
Correlation	0.65	0.37	0.39	0.88	0.73	0.73
NSE	0.05	−1.24	−1.73	0.74	0.40	0.51
RMSE (cfs)	1,507	2,306	2,492	786	1,186	1,080
NRMSE	0.86	1.31	1.42	0.45	0.67	0.62

lower releases leading to lower energy generation when compared to that possible using better-quality forecasts from ANN. Over the entire year under consideration, the additional energy benefit (difference of observed and optimized hydropower) amounted to 15,573 and 28,045 MWh from VIC and ANN-based forecasts, respectively. Also, the optimized operations satisfy the flood control objective by not exceeding the flood-safe release threshold of 9,000 cfs at all times. Thus, using the forecasts, that can capture the peak and low flows, to inform the operations at daily scale have the potential to
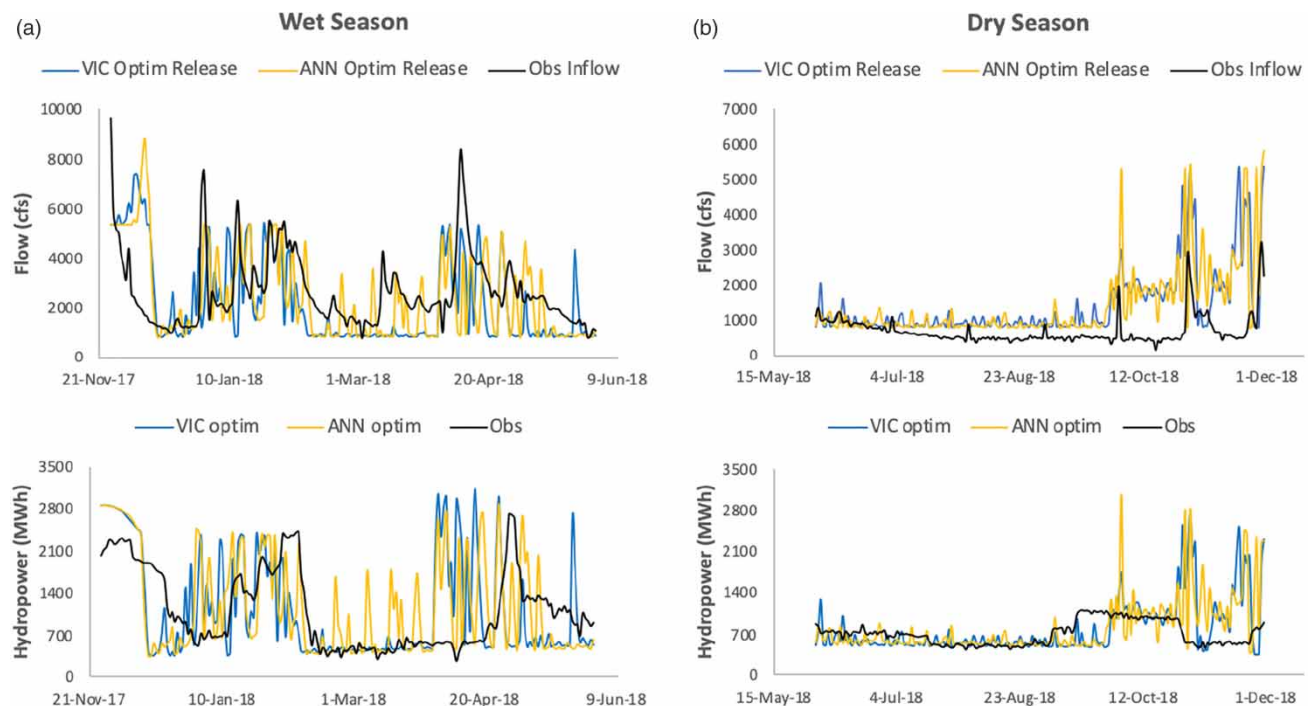

Figure 10 | Year-long assessment (over 2018) for the optimal release decisions using VIC and ANN-based forecast inflow for (a) the wet season from December to May (left panel) and (b) the dry season from June to November (right panel). The optimized release and observed inflow are shown in the top row, while the hydropower benefits from optimized and observed operations are compared in the bottom row.

Table 4 | Hydropower benefits over the wet and dry seasons of the year 2018 obtained by the optimal release decisions using VIC and ANN-based forecast inflow, compared with observed benefits (in MWh)

Season	Hydropower benefits (MWh)		
	VIC-based	ANN-based	Observed
Wet season (December–May)	212,017	224,167	209,022
Dry season (June–November)	141,809	142,131	129,232
Total	353,826	366,298	338,253

improve not only the energy generation but also meet the dam's other operating purposes with higher efficiency during different seasons.

Event-based assessment

To further underscore the value of optimized release decisions over the peak inflow/flood seasons, the assessment of the optimal policy derived using VIC-modeled flows was performed over one such event of 9 April 2018 with an observed peak of 8,400 cfs. The forecasted inflow obtained using the VIC model forced with WRF-downscaled forecasts for lead times of 1, 4, and 7 days over the selected event are shown in Figure 11(a). The forecast inflows were generated by the DSS on 8, 5, and 2 April 2018, respectively. The skill in forecast flow decreases with more overestimated peaks as lead time increases. The hindcast flows are underestimated, possibly due to the VIC model's limitation over small-scale basins as explained earlier. The respective optimized releases are shown in Figure 11(b), where the release was not allowed to exceed 9,000 cfs to prevent downstream flooding, while the minimum was set to 800 cfs considering environmental flow.

The resulting reservoir storage volumes based on the observed reservoir inflows and optimized releases for the respective lead times are shown in Figure 11(c). The
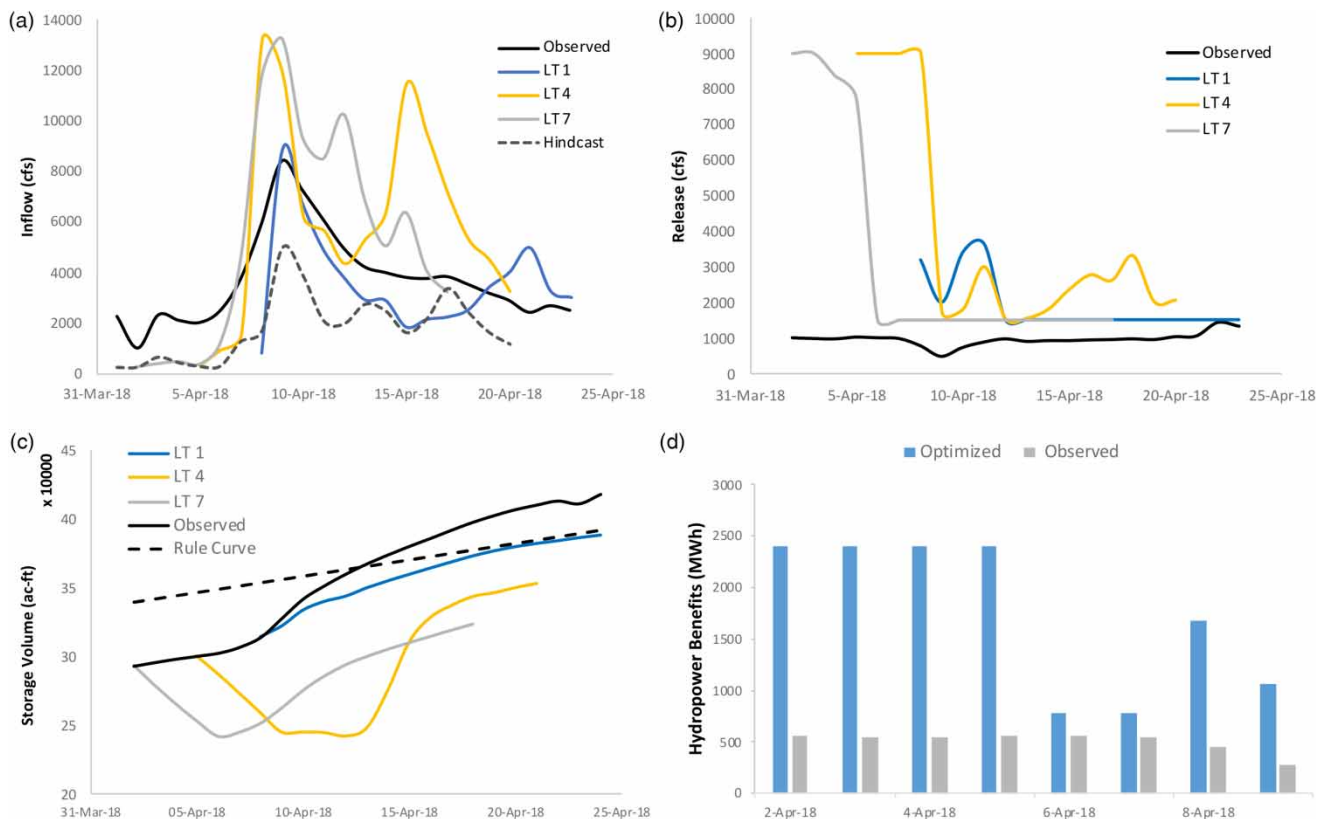

Figure 11 | (a) VIC-modeled forecast inflow using the WRF-downscaled forecast fields along with the modeled hindcast flow; (b) respective optimized releases based on the forecasts for lead times (LT) of 1, 4, and 7 days, with the respective observed values; (c) reservoir storage volume from the optimized operations based on observed inflows, and the rule curve; (d) comparison of hydropower benefits (MWh) using operations without optimization and those with the sequential (MPC) optimization, retrieved from DSS for the week ending on 10 April 2018.

reservoir, by early release of more water, creates enough storage to capture the peak flow before it hits the reservoir and then brings the levels closer to the rule curve after the peak inflow recedes. However, the overestimation in forecasts (e.g. in lead times of 4 and 7 days in Figure 11(c)) leads to excessive lowering of the reservoir levels within the specified bounds, due to which the reservoir is not able to fully recover under lower observed inflow. The observed elevations (without optimization) result in exceeding the rule curve level. The retrospective hydropower assessment over the week of peak flow comparing the energy production from optimized (MPC approach) and observed operations, as rendered on the 'Assessment' module of DSS, is shown in Figure 11(d). Over the week, optimized operations resulted in a weekly cumulative energy production of 13,895 MWh in comparison to 4,040 MWh from the current operations without any guidance from forecasts or optimization.

Ensemble forecasting

In order to incorporate the uncertainty in forecasts, an ensemble of forecast fields is needed to simulate the hydrologic model and obtain multiple realizations of future reservoir inflow. The Global Ensemble Forecasting System (GEFS) ensemble members issued by the NOAA at 1° resolution were used here for the purpose. The GEFS forecasts consist of 20 members of perturbed precipitation for the whole globe considering initial uncertainties by using the Ensemble Transform with Rescaling (ETR) technique (Cui et al. 2012). The data become available four times a day with a forecast horizon of 384 h at steps of 6 h. The mean, minimum, and maximum forecast flow using the VIC model forced with the respective ensemble forcings is shown in Figure 12. The plots suggest that the average GEFS scenario compares well with the observed flow, with its forecasting skill degrading with lead time.
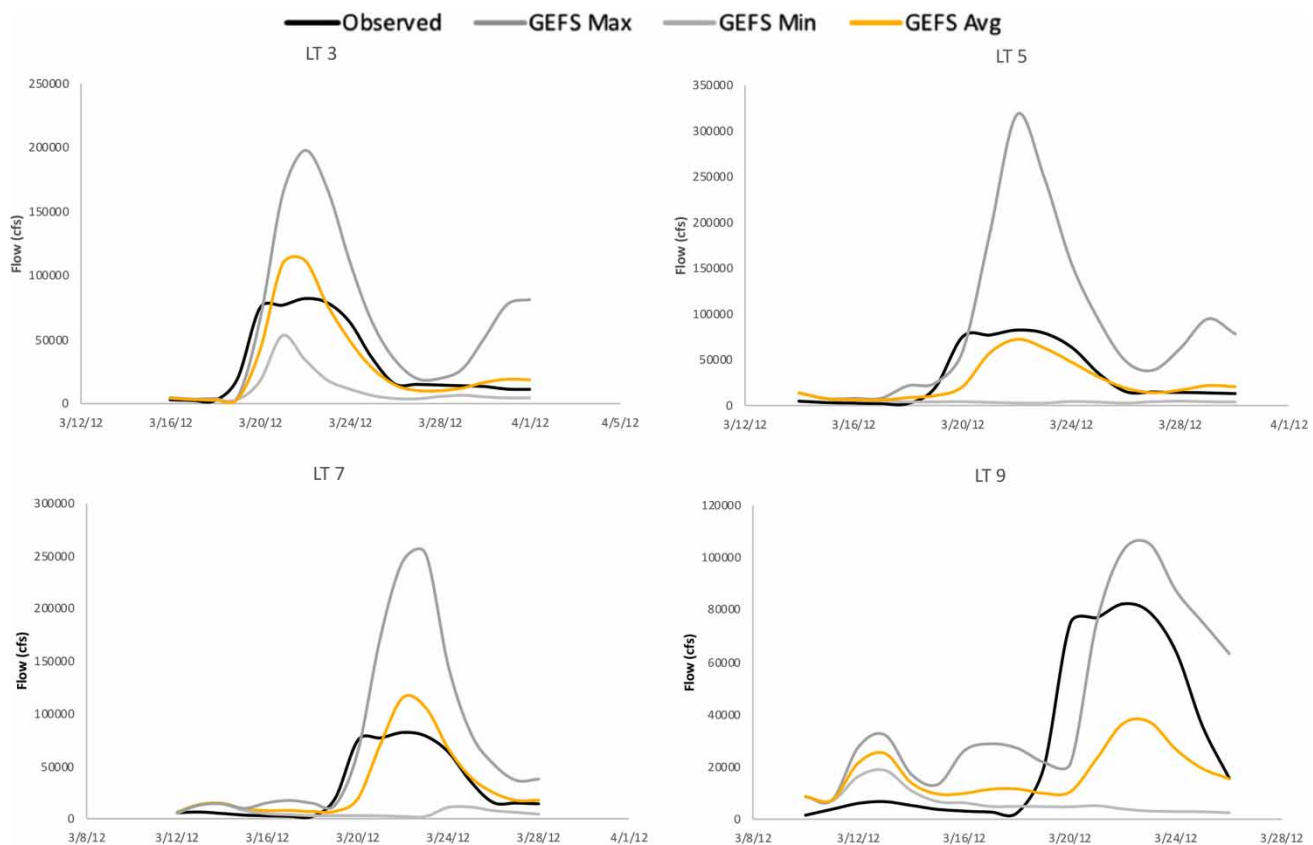

Figure 12 | Ensemble forecast streamflow corresponding to mean, minimum, and maximum of the GEFS ensemble forecast members for a peak flow event for lead times (LT) of 3, 5, 7, and 9 days.

These simulations demonstrate the possibility of integrating the GEFS-based ensemble forecasts within the operational framework of the DSS proposed here. The optimization model needs to be simulated for each of the forecast member realizations to obtain a range of optimized release decisions. However, due to limited computational resources in running the models for each member, ensemble forecasting has not been operationalized. The implementation of ANN-based ensemble forecasting is computationally feasible and will be considered in a future extension of this work.

DISCUSSION

The objective of the paper was to present a generic open-source DSS that engages the dam operator to leverage the advances in weather forecasting for improving the reservoir operations. The developed DSS, called *i*-DDEA, demonstrated here for the Detroit dam, exhibits the characteristics to achieve the required engagement with the stakeholder-operating agencies. For instance, the web-based portal, built entirely using the available nonproprietary tools and software, makes the *i*-DDEA user-friendly and accessible even for a semi- to low-skilled user. The front-end user interface is fully integrated with the complex models of weather forecast processing, hydrological modeling, and reservoir operation optimization to provide the enduser with an advisory that is easy to visualize and follow. The DSS also assimilates the current reservoir state posted publicly by the USACE. Another key feature that allows the user to gage the performance of the generated decisions is the 'Assessment' module of the DSS, continuously assessing the end goal of hydropower maximization as well as the performance of the forecast inflows using the NWP model in retrospect. The underestimation of VIC-modeled flows (as evidenced from year-long and event-based assessments), even after the extensive calibration procedure, remains a limitation of using the macroscale hydrologic model over the Detroit dam's small-scale basin. However, as demonstrated with the implementation of the data-based ANN technique that results in more skillful forecasts, the proposed web-based DSS for dam operations is model-agnostic and can be

operationalized with any modeling technique that performs best for the dam under consideration. Also, the use of better-quality forecasts from ANN that can capture the peak and low-flow patterns led to increased hydropower benefit over the course of both the wet and dry seasons. The future extension of this work will consider improving the forecast modeling component of the DSS by exploring other physical or data-based models as well as adding an ensemble forecasting technique to provide an estimate of the uncertainties in the modeled flow. Also, the uncertainty in VIC model's parameters needs to be considered in the modeling process as different sets of model parameters can produce a good model performance. The customizability of the frontend interface elements and backend scripts is discussed in the next section.

Customizability and scalability

The architecture of the DSS was designed to ensure customizability of the various components and interface elements. The generic framework, both in the backend and connecting frontend, allows even a semi- or low-skilled user to make small tweaks and additions tailored for any other dam site of interest to use the DSS. Some of the aspects of customizability in the frontend and backend scripts are as follows:

1. *Dam sites*: The web-based DSS, although currently operational for a single dam for the demonstration purpose, is designed to handle as many dams as possible without much changes required in the interface structure. The content–container organization facilitates adding more sites with only the source of content in a module to be changed for a particular dam.
2. *Forecasting technique*: In order to use a different forecasting technique, the 'Reservoir Inflow' tab can be modified to include that as an option in the dropdown menu. The backend should automate the forecast model processing to produce the timeseries of forecast inflow (and hindcast), which will be rendered by the frontend.
3. *Raster visualization:* More custom variables can be added under the 'Visualize' tab as pertinent to the forecasting technique used. The visualization only requires ASCII files to be provided for dynamically rendering as a raster image over the map.

4. *Optimized decisions and assessment:* The optimization routine is coded in the Python scripting language that makes it convenient to edit and customize for any other dam with varying characteristics and constraints. The required datasets include forecast inflow, current reservoir storage, and the rule curve elevations over the forecast horizon. The constraints, turbine characteristics, and parameters for the optimization technique (NSGA-II) can also be easily modified as per the requirements. The advisory is generated based on the optimized releases, resulting reservoir elevations and energy that could be produced based on the powerplant's characteristics. The assessment is then performed over the past week based on the hydroelectric energy that is produced. However, other variables can also be compared such as flood control benefits in terms of deviation from rule curve, post-flood damages, etc.

This generic DSS acts as a robust template, free and open-source that can be used for the vast number of powered dams to benefit from the forecast-based optimization and improve the hydropower generation scenario. The potential dam sites where the concept can be explored include the dams that are (i) powered, (ii) have small to medium reservoir storage capacity, and (iii) upstream in the dam network receiving unregulated flow, so that the hydrologic model has to model the natural flow received by the basin, free of human intervention from say, an upstream dam's release schedule. The third limitation can be addressed by considering a multi-dam network that integrates the hydrological model with upstream releases, which is out-of-scope for this study. An analysis over the US dams revealed 525 dams satisfying the three criteria, amounting to 23% of the 2,248 powered dams. We believe that the concept, if extended to a good fraction of such dams, has the potential to realize a smarter dam operational scenario producing an energy infrastructure independent of the fossil fuels and other nonrenewable sources.

CONCLUSIONS

Despite the state-of-the-art advancements in atmospheric sciences, numerical modeling, and data collection networks, most reservoirs are still operating based on the conventional methods. There exist plausible explanations for this such as predefined dam operation rules to be followed by dam operators to prevent extreme cases or to secure water resources based on their contract. Also, dam managers might not take a risk of using forecast information which usually entails uncertainty. However, even if the dam operators are willing to trust the forecasts (given the forecast models have undergone a significant improvement with higher confidence), one of the hurdles preventing the operational agencies from embracing them is the complexities involved in processing the forecasts and running models to extract meaningful information from the raw data. We have demonstrated a solution to this hurdle by building a web-based open-source platform that utilizes the publicly available weather forecasts, downscales to a finer resolution, couples it with hydrological modeling, and generates optimized release decisions. The performance assessment component integrated within the operational DSS builds confidence into the release policy being disseminated as the dam operators can assess the uncertainty in modeled results before acting on them. The bipartite approach of generic separation of the DSS into the container and the content helps realize an intelligent system that treats equally the high-level modeling tasks and the structural web design. The frontend offers a basic set of precustomized elements for decision-making and assessing the optimal decisions generated. When loading the data from the backend, the container simply fills those elements to delegate all the decision-making tasks. Such an approach also improves the independent reuse of the container and the contents.

The *i*-DDEA DSS, as demonstrated here for the Detroit dam in Oregon, has been automated to run operationally every day to communicate the advisory with all the necessary visualizations. Currently, there is no such consistent template, to the best of our knowledge, for delegating the reservoir operations informed with the short-term weather forecasts. We have presented a DSS architecture that is easily customizable by the semi-skilled or low-skilled user and can be incorporated for various other dams out there. The system is independent of the CPU or computational ability of the end-user, which makes it accessible for a large number of operating agencies, both in the developed and developing nations. It is worth mentioning that the

optimized release policy is able to improve the hydropower generation without compromising the flood control, especially during the flood seasons when uncertainty in the reservoir inflow is high causing overconservative operations by the dam operator. There are also the episodes, though less in number, when benefits from observed operations overweigh the optimized one. Nevertheless, the long-term benefits of maximizing the hydropower every day, even in small amounts, are a low-hanging fruit for the energy community that should not be overlooked. Also, better-quality flow forecasts can result in substantial benefits for various downstream stakeholders.

The take-home message from this work is that the development of open-source and nonproprietary tools has now made it possible for the water resources community to benefit from the advancements in the fields of atmospheric modeling, modeling, and optimization techniques. To ensure maximum uptake of science and models, a web-based DSS makes a perfect case to inform the dam operator about the most optimal set of decisions meeting the needs of different involved stakeholders of a hydropower infrastructure.

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