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Research papers

A hybrid hydrologic modelling framework with data-driven and conceptual reservoir operation schemes for reservoir impact assessment and predictions

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ABSTRACT

Reservoirs have been built worldwide to address the water-related issues. To fully understand their potential impacts on the hydrologic regime, explicitly parameterizing reservoir operation in hydrologic models is often required. In this study, two data-driven reservoir operation schemes based on extreme gradient boosting (XGBoost) and artificial neural network (ANN) are respectively developed to predict the reservoir release and storage in hydrologic models for reservoirs with historic in-situ inflow, storage, release data. Then, a hybrid modelling framework is proposed by coupling a high-resolution (3 km) hydrologic model with (1) the developed data-driven reservoir operation schemes and (2) a calibration-free conceptual reservoir operation scheme designed for data-scarce reservoirs. This allows quantitative assessment of the cumulative impacts of dam operation on the hydrologic regime under different reservoir data availability. The framework is applied to the Upper Yangtze River Basin (UYRB) in China that is one of the most regulated river basins across the country due to extensive reservoir construction. Results indicate that both data-driven reservoir operation schemes can well reconstruct the reservoir releases and storage in the UYRB (daily NSE of ~ 0.9), and the XGBoost performs slightly better than ANN. By coupling reservoir operation, the model shows a remarkably improved performance in reconstructing the daily streamflow of the basin. The major reservoirs in the UYRB can redistribute excessive water in the wet season to the dry season and attenuate the high and low flows, leading to enhanced water security along the river. Our approach provides a practical framework for reservoir impact assessment and predictions.

1. Introduction

For the past few decades, the increasing need for water resources has continued to pose threats to achieving the sustainable development goal of the United Nations in the context of population growth and climate warming (O'Neill et al., 2017; Liu et al., 2017). It has been reported by the United Nations that over 20 % of the global population are expected to be living in regions with absolute water scarcity by 2030 (Gain et al., 2016; Wada et al., 2016; Omer et al., 2020). To alleviate the water shortage at local, regional and national levels, planning and construction of water infrastructures, for example, man-made dams, is one of the most practical strategies, which has been continuously adopted by decision makers. By far, the global reservoir capacity has exceeded 8,000 km^3, equivalent to one-sixth of the river discharge to oceans (Boulange et al., 2021).

Hydrologic models with varying degree of complexity of anthropogenic disturbance representations have been employed for assessing the planned and existing water infrastructures on alternations of hydrologic regimes, redistributions of water resources, and modifications of biodiversity and ecological services (Wada et al., 2011, 2017; Veldkamp

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et al., 2018; Voisin et al., 2013). These often include parameterization of dam operation, water withdrawal, irrigation, and other human activities at basin scales (Zhao et al., 2016; Räsänen et al., 2017; Wang et al., 2017; Wang et al., 2019), national scales (Shin et al., 2019), and global scales (Wisser et al., 2010; Wada et al., 2016; Hanasaki et al., 2006; Hanasaki et al., 2018). Efforts in further extending hydrologic models have been made in, such as, coupling hydrological processes with thermo-dynamical processes at the land surface (Clark et al., 2021), and coupling human impacts with surface water hydrodynamics (Shin et al., 2019) and groundwater hydrodynamics (Wei et al., 2021). Recently, Fleischmann et al. (2021) coupled a hydrodynamic model with a hydrologic model for describing the river-reservoir-floodplain continuum. Moreover, numerous modeling studies about climate change impact have proposed alternative adaptation measures of reservoir operation and planning for mitigating risks of, such as, floods and irrigation failures, for basins in different climate region (Ehsani et al., 2017; Arheimer et al., 2017; Boulange et al., 2021).

In addition, hydrologic models with reservoir operation have been further developed to address reservoir-related water issues, for example hydroelectric power generation (Grill et al., 2014; Giuliani et al., 2016; Arheimer et al., 2017; Hoang et al., 2019). For instance, Wan et al. (2021) developed a hydroelectricity production (HP) model and reproduced the global hydropower production trend and its seasonal and interannual variability for the period 1975–2016. Such offline integration between outputs of hydrologic models and parameterizations of hydropower production has been adapted for studying, for example, impacts of droughts on hydroelectricity production at regional scales. For example, the Variable Infiltration Capacity (VIC) model with an offline reservoir operation scheme have been employed by Zhao et al. (2021) and Zhong et al. (2020) to investigate the sensitivity of the potential hydropower generation of the upper Yangtze River basin to different climate warming scenarios.

With the focus on representations of reservoir operation in hydrologic models, two kinds of approaches are commonly employed. One is the data-driven reservoir operation scheme that learns the relationship between inflow, release, and storage through the training of data-driven models against a large amount of data. For example, Coerver et al. (2018) demonstrates the capability of neural network (NN) based fuzzy rules to derive the reservoir operation rules and the reservoir release. Similarly, Ehsani et al. (2016) employed the NN model to describe the function between reservoir release, and achieved satisfactory reservoir operation simulations of 17 reservoirs. Recently, Yang et al. (2019) combined two recurrent neural networks, namely nonlinear autoregressive model with exogenous input (NARX) and long short-term memory (LSTM) model, with a distributed hydrologic model to forecast the reservoir release and downstream streamflow in a real-case application. While these data-driven models show promising results, they require sufficient historic reservoir operation data (inflow, release, storage, etc.) for model training, which may not be available at large scales and limits the applicability of these models (Akter and Babel, 2012; Lu et al., 2021). To minimize the data requirement, conceptual reservoir operation schemes have also been developed and used, which generally establishes empirical reservoir operation functions (Hoang et al., 2019, Yassin et al., 2019). For example, Dong et al. (2022) recently proposed a conceptual operation scheme for ungauged reservoirs and achieved satisfactory results for China's largest reservoirs.

Despite the progress made by the existing literature, there are a few open issues that deserve further investigation. For example, there lacks a well-established hydrologic modelling framework to the quantify the cumulative impacts of a reservoir group with distinct data availability. Also, the potential of different data-driven approaches in capturing the behavior of China's reservoirs has not been well investigated. To this end, the aims of this study are (1) to develop data-driven reservoir operation schemes based on XGBoost and ANN algorithms to predict the reservoir release and storage in the hydrologic models for data-rich reservoirs; (2) to establish a hybrid hydrologic modelling framework with the joint use of data-driven and conceptual reservoir operation schemes under different reservoir data availability; (3) to quantify the cumulative impacts of reservoir operation on the hydrologic regime.

In this study, we choose the Upper Yangtze River basin (UYRB) in China as our target region. Our choice here is because (1) the UYRB is part of the longest river in Asia, namely, the Yangtze River, and changes in water resources of the UYRB can affect water resources in downstream regions of Asia (Gu et al., 2018; Liu et al., 2019); and (2) several largest dams of China have been built in this region to alleviate the water and energy shortage of the country, making the UYRB an ideal area for reservoir impact simulations and assessment.

2. Methodology

2.1. Data-driven reservoir operation scheme for data-rich reservoirs

2.1.1. eXtreme gradient boosting (XGBoost) decision trees

XGBoost (Chen and Guestrin, 2016) is an implementation of the gradient boosting decision tree (GBDT) proposed by Friedman (2001), which is currently-one of the fastest and best-integrated decision tree algorithms. The algorithm utilizes the CART as the base learner. The result is jointly determined by multiple correlated decision trees, as the input sample of the next decision tree will be related to the results of the previous decision tree. Specifically, XGBoost presents a new loss function with regularization, which can efficiently use sparse data without overfitting compared with traditional GBDT (Zhan et al., 2023). XGBoost is a highly flexible and versatile tool that can solve most regressions and classifications, as well as user-created objective functions.

In this study, six booster hyperparameters, namely the learning rate, the number of decision trees, the maximum depth of a tree, the minimum sum of weights of all observations required in a child, the fraction of observations to be randomly samples for each tree, the subsample ratio of columns when constructing each tree, are selected to be automatically optimized through the Bayesian Optimization (BO) approach. BO is a sequential design strategy for global optimization of black-box functions that does not assume any functional forms and have been widely used in hyperparameter optimization of machine learning models. A fivefold cross-validation is performed during the training process to reduce the risk of overfitting.

2.1.2. Artificial neural network (ANN)

ANN is a widely used machine learning model formulated in an interconnected node structure (Haykin, 1998). Typically, an ANN consists of an input layer, one or more hidden layers, and an output layer. In this study, an ordinary, simple ANN architecture consisting of an input layer, a hidden layer, and an output layer with rectified linear unit (ReLu) activation function is employed. Two hyperparameters, namely the number of nodes in the hidden layer and the regularization term strength, are selected to be automatically optimized through the BO approach. A fivefold cross-validation is performed during the training process to reduce the risk of overfitting.

2.1.3. Development of data-driven reservoir operation schemes

In this section, we aim to develop two data-driven reservoir operation schemes based on XGBoost and ANN, respectively, to predict the reservoir releases and storage in hydrologic models at the daily scale, when driven by the reservoir inflow. In reality, reservoir operation is often guided by prescribed reservoir operation rules that can be illustrated by a set of reservoir operation curves in a reservoir operation chart. When the current storage rises above an operation curve, the release tends to increase, preventing the storage overfilling at an inappropriate time, and vice versa (Dong et al., 2022, 2023). This relates the reservoir release to the current water storage (V) and the month of the year (M). The reservoir release is also related to the inflow (I) through the water balance. For large, important reservoirs, the release decision can also be guided by inflow forecasts in the future, thus considering the inflow at the next timestep in the reservoir operation simulations is reasonable. In addition, we consider the reservoir releases (Q) at previous timesteps also indicative of current reservoir release. This is because the reservoir release is temporarily autocorrelated, as the operation of reservoir sluices and floodgates are continuous in time.

Given the above consideration, we create the input dataset of the XGBoost/ANN regression model as an inflow vector, namely [I_{t+1}, I_t, I_{t-1}], a release vector, namely [Q_{t-1}, Q_{t-2}], storage [V_t], and month [M_t], with t representing the current timestep. The predictand [Q_t] is the reservoir release at the current time. In our study, a daily timestep is adopted. The XGBoost/ANN regression model can then be expressed as,

$$Q_t = f(I_{t+1}, I_t, I_{t-1}; V_t; Q_{t-1}, Q_{t-2}; M_t)$$

where f represents the reservoir operation function, which can be learnt by the XGBoost/ANN algorithms. Then, the XGBoost and ANN models are respectively trained using the historical inflow, release, storage, and month data.

The respective XGBoost/ANN model is the core of our proposed reservoir operation scheme. The simulation workflow is designed as a closed loop form, which is presented in Fig. 1 and is elaborated as follows.

1) Standardize the data. All of the data are standardized in the following form:$Q' = Q\cdot\frac{86400}{V_f}$;$I' = I\cdot\frac{86400}{V_f}$;$V' = V\cdot\frac{1}{V_f}$;$M' = M\cdot\frac{1}{12}$, where the superscript denotes standardization, V_f is the upper water level of the flood control storage, 86,400 is the total seconds of a day.
2) Predict with the trained XGBoost/ANN regression model. The predictors are input in the trained XGBoost/ANN model to generate the predictand, i.e., the reservoir release at the current day Q_t.
3) Update the reservoir storage. The reservoir storage at the current timestep is updated from the predicted reservoir release and the current inflow through the water balance equation.

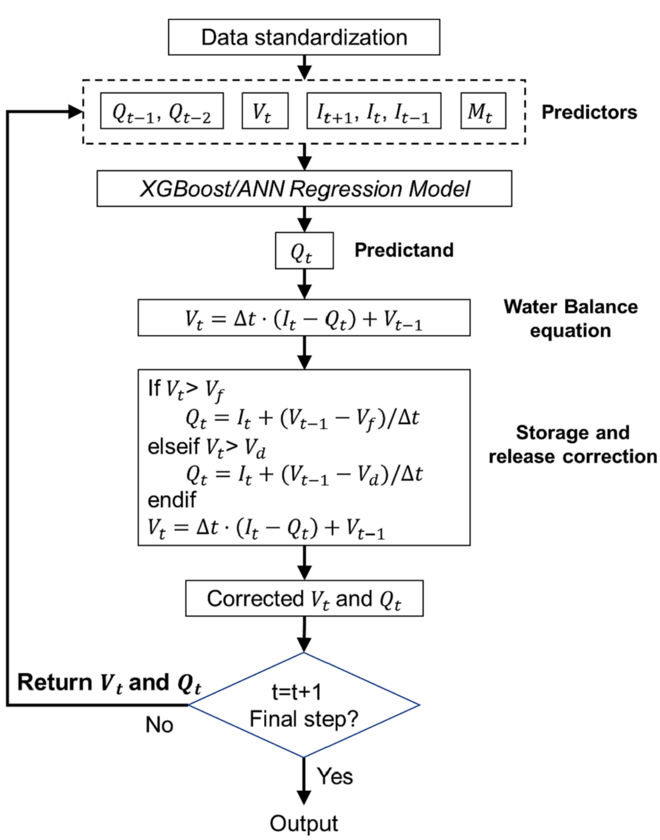

Fig. 1. The modelling workflow of the data-driven reservoir operation schemes.

4) Correct the predicted release and storage. Additional storage constraints are imposed on the reservoir operation scheme to avoid unrealistic storage conditions – the updated storage in Step 3) should be neither larger than V_f, the upper water level of the flood control storage, nor smaller than V_d, the upper level of the inactive storage. Therefore, if such constraints are violated in Step 3), the release is recalculated so that the storage constraints are met.
5) Take the predicted release and storage as the predictors in the next timestep. The predicted release and storage at the current step recurrently serve as the input of the XGBoost/ANN regression model in the next step until the simulation reaches the last step.

2.2. A calibration-free conceptual operation scheme for data-scarce reservoirs

A calibration-free conceptual operation scheme (Dong et al., 2022, 2023) is employed to estimate the release and storage variation of reservoirs with no historic operation data. The release of reservoirs, Q_t, is calculated as follows,

$$Q_t = \begin{cases} \min\left(Q_{\min},\ \dfrac{V_t}{\Delta t}\right) & (V_t \leqslant V_d) \\ \max(Q_{\min},\ r\cdot U_t) & (V_d < V_t \leqslant V_c) \\ r\cdot U_t + (Q_s - r\cdot U_t)\cdot\left(\dfrac{V_t - V_c}{V_f - V_c}\right)^k & (V_c < V_t \leqslant V_f) \\ \max\left(Q_s, \dfrac{V_t - V_f}{\Delta t}\right) & (V_t > V_f) \end{cases}$$

where V_t, V_d, V_c and V_f are the water storage of reservoirs at the model time step t, at the dead level, conservation level, and high flood level, respectively. Q_{min} is the minimum release; r is time-varying parameter to reflect the storage condition; U_t is the human water demand at the model time step t; Q_s is the maximum acceptable release for flood control purposes; k ($k \leq 1$) is a flood indicator equal to the ratio of Q_s to the inflow.

In this scheme, parameters such as Q_{min}, Q_s, U_t and r need to be determined. Specifically, Q_{min} and Q_s are estimated as the 10th and 99th percentile of non-exceedance probabilities of simulated streamflow in the local grid cell, respectively. The parameter r is determined at a monthly scale based on the difference between the current storage and the target storage (V_{tar}), a time-dependent storage level often prescribed in the operation rules or expected in the actual reservoir operation (Neitsch et al., 2011). Here, V_{tar} is empirically derived from linear interpolation between V_{cd} at the beginning of dry season and V_d at the beginning of wet season. r at the time t is expressed as,

$$r_t = 1 + c\cdot\frac{V_t - V_{tar}}{V_{cd} - V_d}$$

with

$$c = \min\left(\frac{I_a}{3\cdot(V_{cd} - V_d)}, 1\right)$$

where V_{cd} is the water storage at the dry-season conservation level, i.e., the maximum normal operating level; V_{tar} is the target storage; I_a is the mean annual inflow. The human water demand of reservoirs U_t is determined according to the designed functionality of reservoirs and the monthly water demand of the area. More details on the determination of U_t and on the reservoir operation scheme is provided in Dong et al., 2022, 2023.

2.3. High-resolution coupled land surface-hydrologic modelling

In this study, we employ the CLHMS model as the base model for hydrologic simulation, which couples a land surface scheme and surface and subsurface water routing (Dong et al., 2022, 2023). The land surface scheme (LSX) consists primarily of a six-layer soil module, a two-layer vegetation module, a two-layer snow module and a glacier/icesheet module, and is capable of solving the water and energy balance in the snow-vegetation-soil continuum and on the glacier areas, thus providing the the source terms of runoff, infiltration, and evapotranspiration for the diffusion wave equation for surface routing and the 2-D boussinesq equation for groundwater routing at a raster grid basis (Yang, 2009; Yang et al., 2010, 2012,2013; Wagner et al., 2016). The model runs at a spatial resolution of 3 km and a 1-hour timestep,

The meteorological data needed to drive the CLHMS consist of the CN05.1 dataset for precipitation and the NCEP/NCAR reanalysis data for temperature, wind speed, radiation, pressure and humidity. The CN05.1 dataset published by China Meteorological Administration is a $0.25^{\circ}\times0.25^{\circ}$ gridded precipitation dataset interpolated from the observed precipitation of ~ 2,400 rain gauges nationwide. The specific yield of aquifer and the aquifer thickness required for the groundwater module is collected from the China National Geologic Survey Dataset from the National Earth System Science Data Center.

3. Case study of the Upper Yangtze River basin

3.1. Study area

The Upper Yangtze River Basin (UYRB) refers to the basin above the Yichang hydrologic station in the mainstream Yangtze River and has a drainage area of 1.0 million km^2, accounting for about 12 % of China's total land area. The basin is mostly dominated by subtropical and temperate climate and is strongly influenced by the East Asia monsoon. The mean annual precipitation is about 1000 mm with strong seasonal variability, and about 75 % of the precipitation occur between May and September.

The UYRB is a major economic, agricultural, and industrial hub of China and currently accounts for about one-six of the country's population and gross domestic product. To alleviate the water and energy shortage across the area, a large number of reservoirs have been continuously built since late 1990 s. As of 2020, there have been more than ten thousand reservoirs over the basin, with a total capacity of around 130 km^3. Reservoirs can significantly disrupt the natural hydrologic processes of the basin and bring a challenge to the sustainable management of the basin. Major hydrologic stations of the basin include Shigu, Ertan, Gaochang, Pingshan, Wulong, Beibei, Cuntan and Yichang (Fig. 2).

3.2. Reservoir information and operation data

While there are a large number of reservoirs in the UYRB, most of them are either with a small capacity or unable to regulate the streamflow beyond daily scales, thus having a trivial impact on the streamflow of downstream areas. As shown in Fig. 2, we identify and incorporate a total of 10 reservoirs in our study that (1) have a capacity larger than 1 km^3, and (2) have a considerable ability to regulate the local streamflow at the monthly scale, namely-Three Gorges, Xiluodu, Jinping I, Goupitan, Ertan, Pubugou, Tingzikou, Baozhusi, Zipingpu, and Changheba. These 10 reservoirs have a total capacity of 92 km^3, accounting for nearly 3/4 of the combined capacity of all operational reservoirs in the UYRB as of 2019.

We collect the daily in-situ inflow, storage, and release of Three Gorges, Xiluodu, Jinping I and Ertan, which are then fed into the data-driven reservoir operation scheme for training, testing and predicting (Table 1). The combined capacity of these 4 reservoirs accounts for nearly 80 % of the total capacity of the 10 reservoirs. For other reservoirs, no in-situ reservoir operation data is available, and the release of these reservoirs are simulated with the calibration-free conceptual reservoir operation scheme.

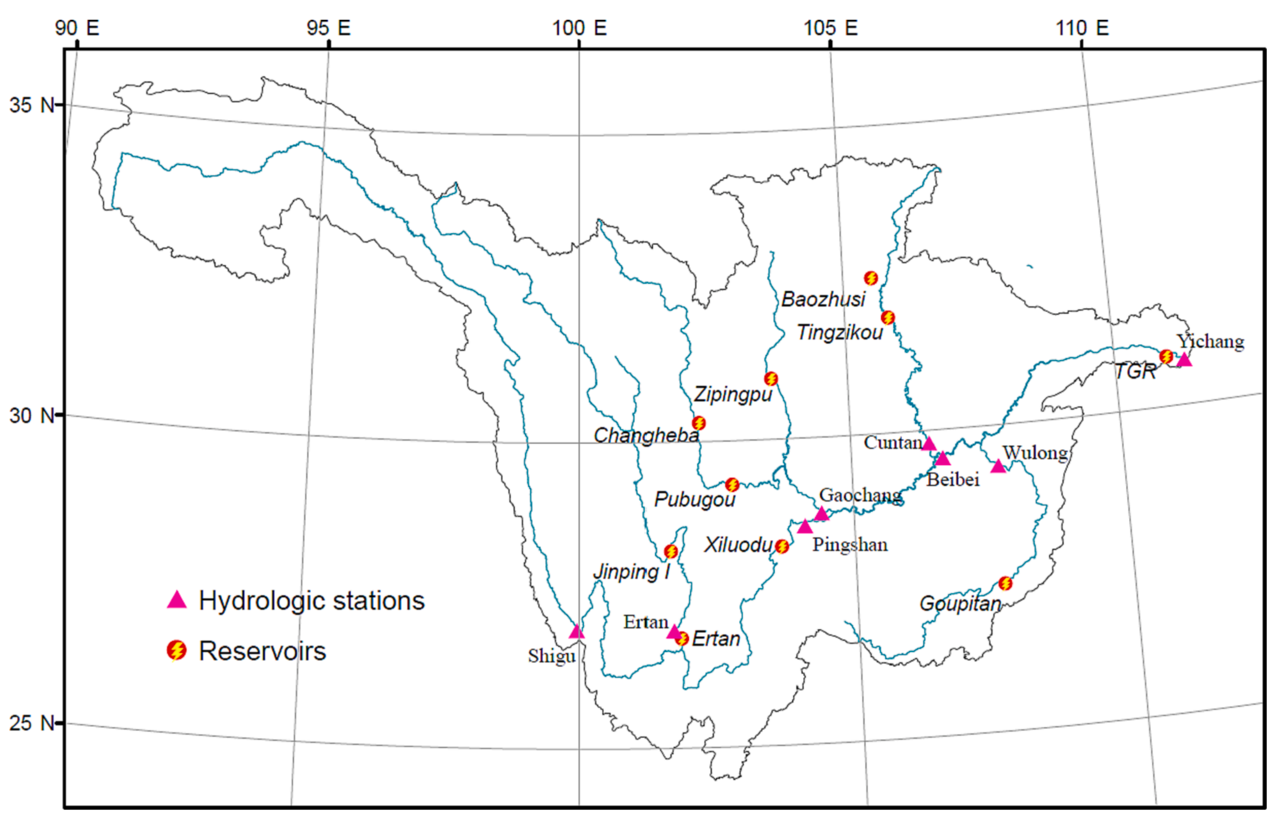

Fig. 2. The Upper Yangtze River Basin and the hydrologic stations and reservoirs considered in this study. TGR – Three Gorges Reservoir.

Table 1
Summary of reservoirs considered in this study.

Reservoir	Basin	Capacity/km^3	Operational year	Modelling approach	Data period
Three Gorges	Mainstream	45.1	2009	data-driven	2009–2019
Xiluodu	Jinshajiang	12.7	2013	data-driven	2014–2019
Jinping I	Yalong	8.0	2013	data-driven	2015–2018
Goupitan	Wujiang	6.5	2008	conceptual	/
Ertan	Yalong	6.1	1998	data-driven	2010–2018
Pubugou	Minjiang	5.3	2009	conceptual	/
Tingzikou	Jialingjiang	4.1	2013	conceptual	/
Baozhusi	Jialingjiang	2.6	1996	conceptual	/
Zipingpu	Minjiang	1.1	2005	conceptual	/
Changheba	Minjiang	1.1	2016	conceptual	/

3.3. Streamflow data

In this study, the daily in-situ streamflow data at the Shigu, Ertan, Gaochang, Pingshan, Wulong, Beibei, and Cuntan stations (Fig. 2) during 1961–1995 are collected. The daily in-situ streamflow data at the Yichang station during 1961–2020 are collected. These data are used for calibration and validation of the hydrologic model.

3.4. Experimental design

To understand the impact of reservoir operation on the hydrologic regime of the UYRB, we set up three simulation scenarios, namely *Natural flow*, *Actual reservoirs*, and *All Reservoir*. A 10-year simulation for the historic period of 2011–2020 is conducted for each scenario. This period is selected because most of the reservoirs were put into operation around 2010.

- *Natural flow* scenario. This scenario refers to hydrologic simulations with no account of reservoirs to represent the natural flow regimes of the UYRB.
- *Actual reservoirs* scenario. This scenario refers to hydrologic simulations taking account of reservoir operation according to the operation date of each reservoir, i.e., a reservoir is not activated during a model simulation until the simulation reaches the time point where that reservoir was completed in the real world. This scenario is set to represent the 'actual' streamflow regime of the UYRB, which is then compared with the *Natural flow* scenario to manifest the improvement of model performance by taking account of the reservoirs in the hydrologic simulations.
- *All reservoirs* scenario. This scenario refers to hydrologic simulations taking account of the operation of all 10 reservoirs. This scenario represents the flow regimes of the UYRB under the full impact of reservoirs, which is then compared with the *Natural flow* scenario to quantify the impact of reservoir operation on the streamflow regime of the UYRB.

In the *Actual reservoirs* scenario and the *All reservoirs* scenario, the reservoir operation is represented by the XGBoost-based data-driven reservoir operation scheme for the Three Gorges, Xiluodu, Ertan and Jinping I Reservoir. This selection is based on the evaluation results in Section 4.1. For the other 6 reservoirs, the reservoir operation is represented by the conceptual reservoir operation scheme.

4. Results

4.1. Reservoir operation simulations with data-driven reservoir operation scheme

To accurately depict the hydrological impact of reservoirs, we train, cross-validate, and test the two data-driven reservoir operation schemes (Section 2.1) for the Three Gorges, Xiluodu, Ertan and Jinping I Reservoir using the historic in-situ reservoir operation data. The training period and the testing period for each reservoir are same for XGBoost and ANN, which are shown in Fig. 3.

Fig. 3 depicts the daily observed and simulated release and storage of the four reservoirs, respectively. In general, the accuracy of the release and storage simulation is rather satisfactory for both XGBoost- and ANN-based reservoir operation schemes. For the XGBoost-based scheme, the daily Nash-Sutcliffe efficiency (NSE) values of simulated storage of Three Gorges Reservoir are 0.96 (0.96) over the training (testing period), and the daily NSE values of simulated release are 0.92 (0.93) over the training (testing period) (Table 2). The daily NSE values of simulated storage of Xiluodu Reservoir are 0.90 (0.88) over the training (testing period), and the daily NSE values of simulated release are 0.93 (0.91) over the training (testing period). These results are similar for the other two reservoirs, as the daily NSE values of simulated storage (release) over the training and testing periods are all above 0.90 (0.85) (Table 2). For the ANN-based scheme, the accuracy is slightly lower than the XGBoost-based scheme. For example, the daily Nash-Sutcliffe efficiency (NSE) values of simulated storage of Three Gorges Reservoir are 0.93 (0.90) over the training (testing period), and the daily NSE values of simulated release are 0.88 (0.84) over the training (testing period). In general, our results suggest that both of the developed data-driven reservoir operation schemes are able to accurately represent the operation of the investigated four reservoirs. Due to the relatively better accuracy, the XGBoost-based scheme is selected to simulate the reservoir operation in the following sections.

4.2. Reservoir operation simulations with calibration-free conceptual operation scheme

The operation of other reservoirs, on the other hand, are all represented by the calibration-free conceptual reservoir operation scheme (Section 2.2). To assess the validity of the calibration-free operation scheme in simulating the operation of no-data reservoirs, here we drive this scheme with the in-situ inflow of Three Gorges, Xiluodu, Ertan and Jinping I Reservoir and apply this scheme to each of these reservoirs for evaluation. Note that the in-situ reservoir release and storage are not used for calibration but for evaluation only.

Fig. 4 shows the simulated water storage and release of the four reservoirs, respectively. For these reservoirs, the conceptual reservoir operation scheme can generally well capture the variation of water storages, with the daily NSE values of water storage ranging from 0.72 to 0.80 (Table 2). This is similar for the reservoir release, as the daily NSE values ranges from around 0.7 to 0.9 for these reservoirs. These results highlight the applicability of the conceptual operation scheme in ungauged reservoir simulations, suggesting that the employed conceptual operation scheme can serve as a reliable tool to simulate the reservoir operation process without historic operation records for reservoir impact assessment in ungauged basins.

4.3. Improved hydrologic simulations considering reservoir operation

To reproduce the natural flow regime of the UYRB, the hydrologic

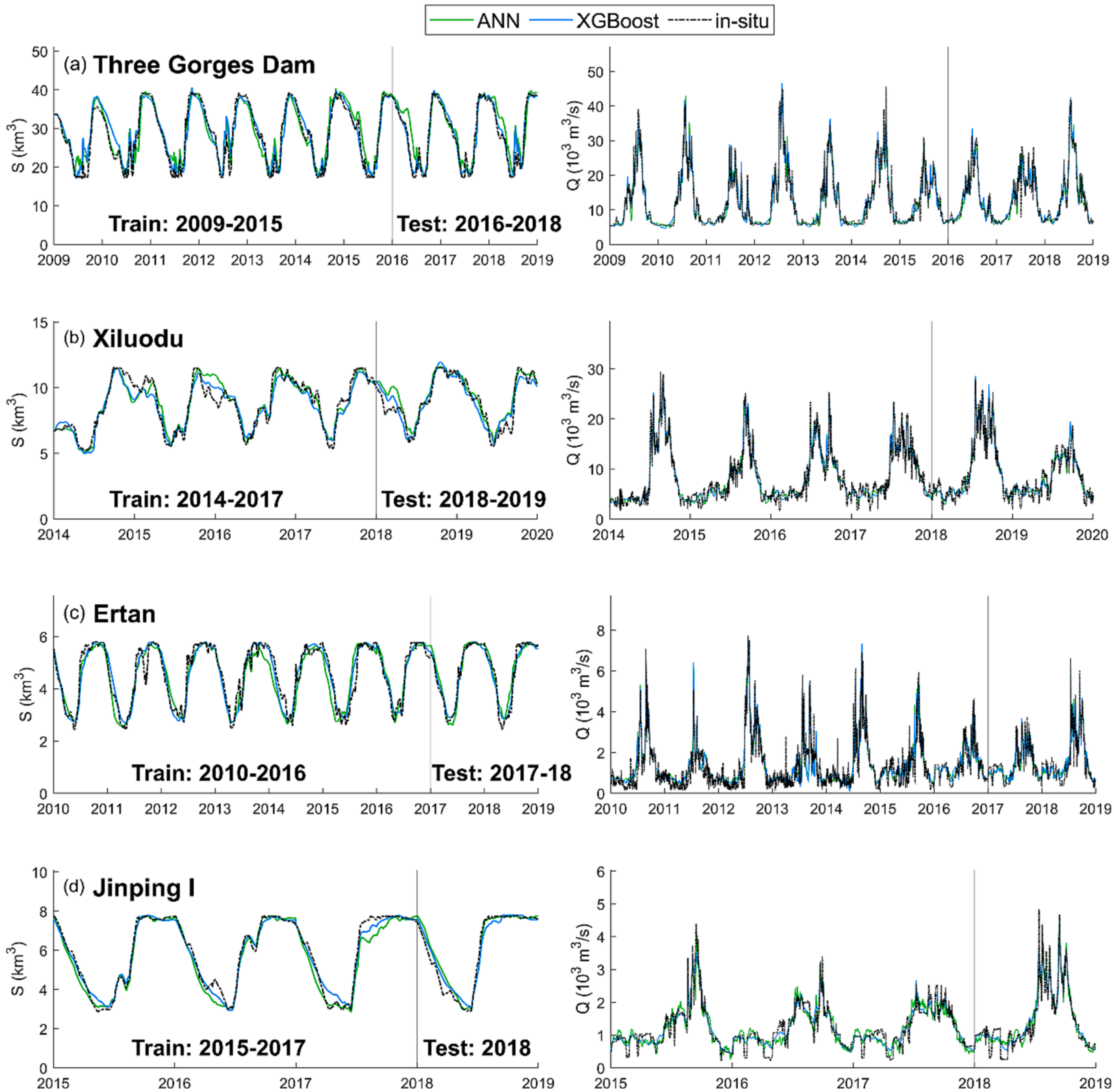

Fig. 3. Daily storage (left) and release (right) simulations of the (a) Three Gorges, (b) Xiluodu, (c) Ertan, and (d) Jinping I with the XGBoost- and ANN-based data-driven reservoir operation schemes.

Table 2
Metrics of reservoir operation simulations with data-driven and conceptual schemes.

Reservoir	Release			Storage		
	XGBoost training/testing	ANN	Conceptual	XGBoost training/testing	ANN	Conceptual
Three Gorges	0.92/0.93	0.93/0.90	0.86	0.96/0.96	0.88/0.84	0.77
Xiluodu	0.93/0.91	0.92/0.90	0.88	0.90/0.88	0.87/0.83	0.76
Jinping I	0.90/0.88	0.82/0.85	0.65	0.98/0.97	0.92/0.93	0.80
Ertan	0.86/0.85	0.83/0.80	0.78	0.93/0.95	0.85/0.90	0.72

model with no account of reservoirs is calibrated against the daily streamflow of Shigu, Ertan, Gaochang, Pingshan, Wulong, Beibei, Cuntan, and Yichang for the period of 1961–1985 and is validated for the period of 1986–1995. The calibration and validation periods are selected as such since most of the reservoirs upstream of the stations were put into operation only after 1995. Fig. 5 presents the calibration

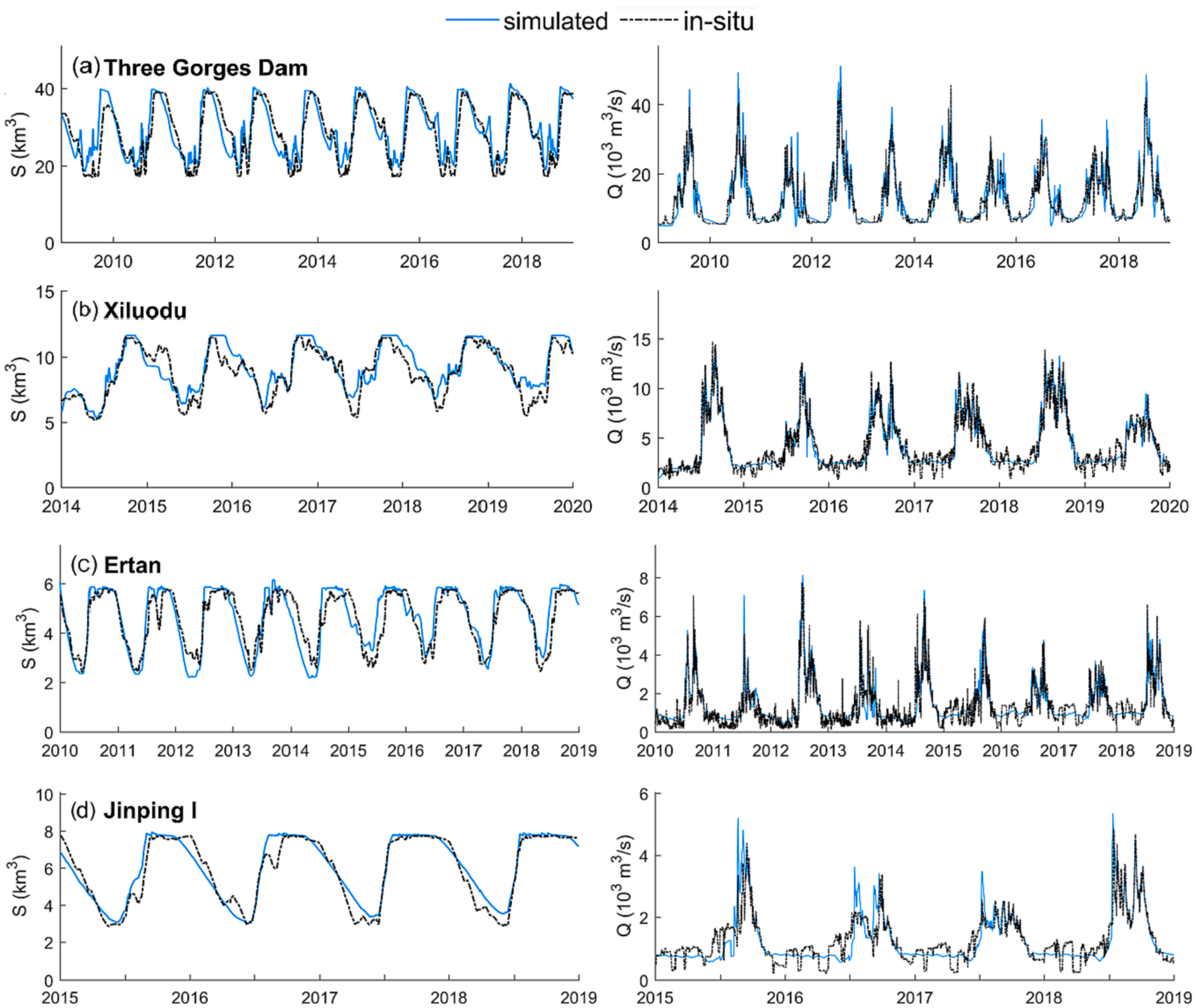

Fig. 4. Daily storage (left) and release (right) simulations of the (a) Three Gorges, (b) Xiluodu, (c) Ertan, and (d) Jinping I with the calibration-free conceptual operation scheme. Note that the observed data are not used for calibration but for comparison only.

and validation results with the daily NSE values. It shows that the performance of the hydrologic model with no account of reservoirs is quite satisfactory, with most of the daily NSE values over 0.9 in the mainstream and over 0.7 in the tributaries. This result indicates that our model is able to well depict the natural hydrologic processes of the UYRB.

After the model calibration and validation, we continue the simulations to the period of 2011–2020. Notably, the streamflow simulated by the hydrologic model without reservoirs shows a daily NSE of 0.64 during 2011–2020. This can possibly be explained by the fact that several large mainstream and tributary reservoirs in the UYRB were put into operation in the past decades, yet the hydrologic simulation without reservoirs is unable to account for the impact of reservoirs on the streamflow during this period.

To confirm if the lack of reservoir operation is the major cause of the degraded model accuracy during this period, we perform a hydrologic simulation in which the reservoir operation is represented by the XGBoost-based data-driven reservoir operation scheme for the Three Gorges, Xiluodu, Ertan and Jinping I Reservoir and by the conceptual reservoir operation scheme for other 6 reservoirs. Fig. 6 depicts the daily streamflow simulations under *Natural flow* scenario (orange) and the *Actual reservoirs* scenario (blue) compared with observations (black). In general, we find that integrating reservoirs in the hydrologic model can improve the model performance in the streamflow simulation during 2011–2020, as the daily NSE at Yichang is significantly enhanced from 0.64 to 0.90 during this period. This indicates that the reservoir-represented CLHMS model allows accurately quantifying the hydrological impact of reservoirs.

4.4. Impact of reservoir operation on the flow regime

Fig. 7 depicts the monthly streamflow at the Yichang station and its differences under the *Natural flow* and the *All reservoirs* scenarios, respectively. For the *All reservoirs* scenario, reservoirs are found able to significantly decrease the seasonal flow variability, as the average streamflow is decreased from by 3150 m^3/s (13 %) for the wet season (June to October) and increased by 2214 m^3/s (32 %) for the dry season (November to May). Reservoirs can also reduce the interannual variations of monthly streamflow, and the monthly streamflow interval between the 90 % and 10 % percentile averaged over a year is reduced from ~ 5980 m^3/s to ~ 4880 m^3/s. In particular, the streamflow during the wet season is more stabilized over a multi-year period, with the 10–90 interval reduced from ~ 10920 m^3/s to ~ 9520 m^3/s.

To further investigate the impact of reservoir operation on the hydrologic extremes of the UYRB, the multi-year averaged maximum/minimum 1-day (MAX1/MIN1), 3-day (MAX3/MIN3), 7-day (MAX7/MIN7), 30-day (MAX30/MIN30), and 90-day (MAX90/MIN90) streamflow simulated by the hydrologic model are compared between the *All reservoirs* scenario and the *Natural flow* scenario at the Yichang station. Fig. 7b depicts the variations of extreme hydrologic indicators induced

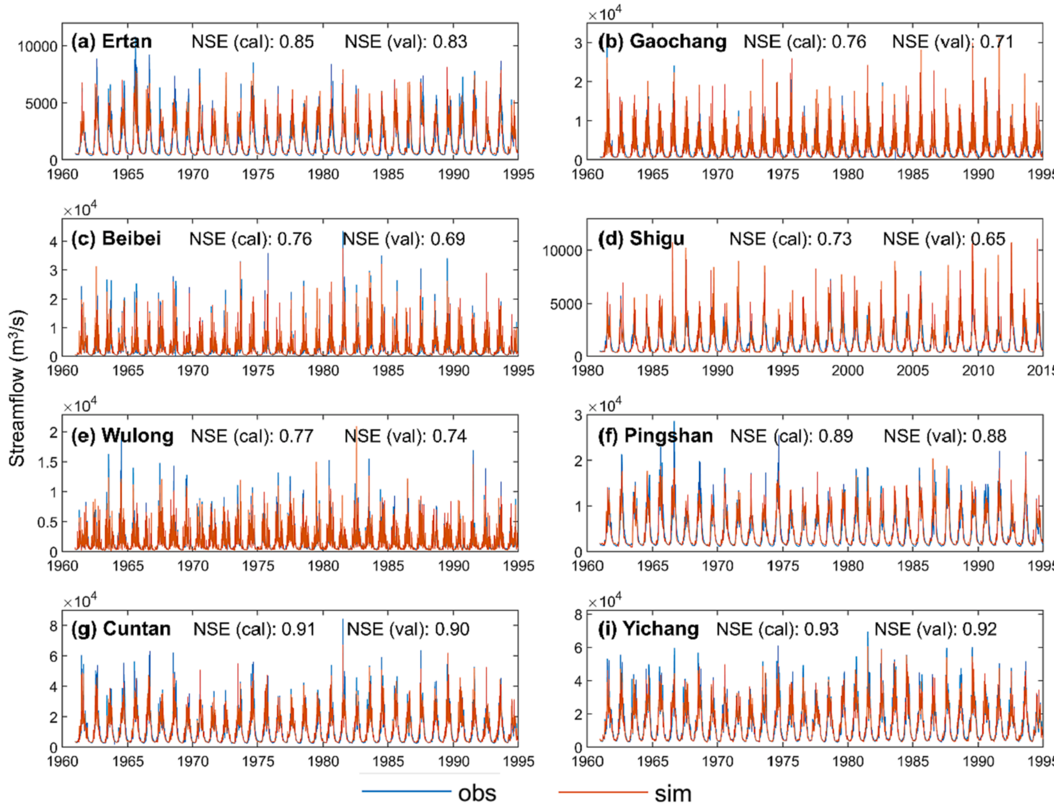

Fig. 5. The simulated and observed daily streamflow at 8 hydrologic stations.

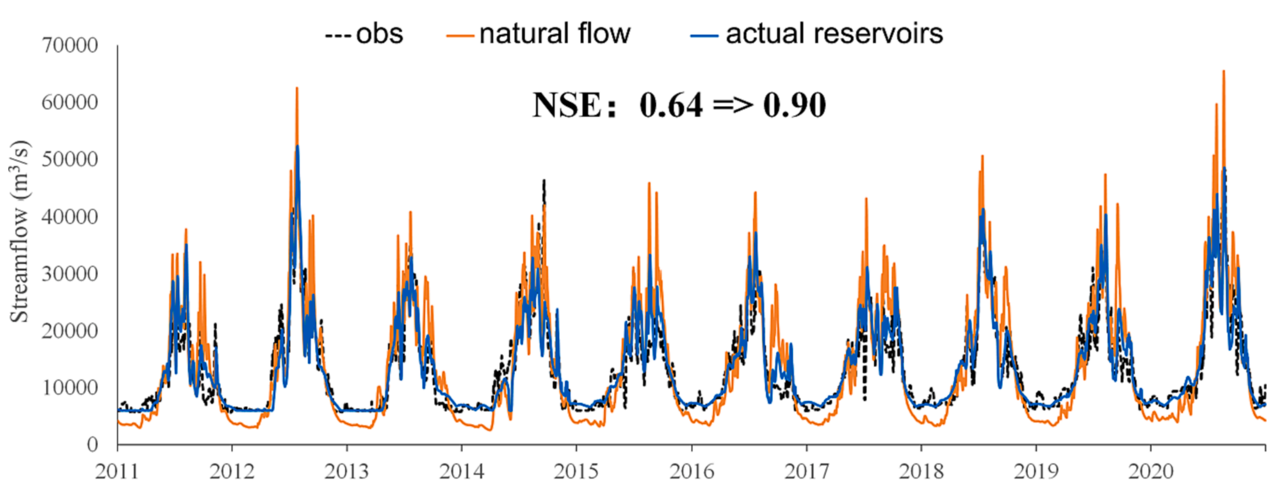

Fig. 6. Daily streamflow simulations at Yichang station during 2011–2020 under the *Natural flow* scenario and the *Actual reservoirs* scenario.

by reservoirs. It is noted that reservoir operation can reduce the flood magnitudes by reducing the multi-year averaged maximum 1-day, 3-day 7-day, 30-day, and 90-day streamflow by 21 %, 19 %, 14 %, 9 % and 9 %, respectively. Similarly, reservoir operation can significantly alleviate the drought condition by increasing the multi-year averaged minimum 1-day, 3-day 7-day, 30-day, and 90-day streamflow by 101 %, 101 %, 100 %, 91 % and 79 %, respectively.

Fig. 8a depicts the multi-year averaged simulated natural streamflow of the UYRB at the 3 km resolution. Fig. 8b and 8c depicts the relative difference of the simulated dry-season and wet-season streamflow between the *All reservoirs* scenario and the *Natural flow* scenario. It can be seen that tributary reservoirs can greatly impact the streamflow at local scales, for example the Jinping I Reservoir can reduce the streamflow in the wet season by 11 % (Fig. 8c) while increasing the streamflow in the dry season by over 40 % (Fig. 8b). Due to the lateral flow downstream of the dam, the impact of individual tributary reservoirs diminishes towards downstream areas, yet their cumulative effect can still stretch further downstream to the mainstream. The mainstream reservoirs can have a cumulative, prominent effect on the downstream streamflow along the mainstream, especially for the Xiluodu Reservoir, which releases 6 % less water during the wet season but releases 13 % more water during the dry season compared with the inflow. For the most downstream reservoir of the UYRB, i.e., Three Gorges Reservoir, the reservoir release is 2215 m^3/s (32 %) higher in the dry season and 3150 m^3/s (13 %) lower in the wet season under the *All reservoirs* scenario than the *Natural flow* scenario.

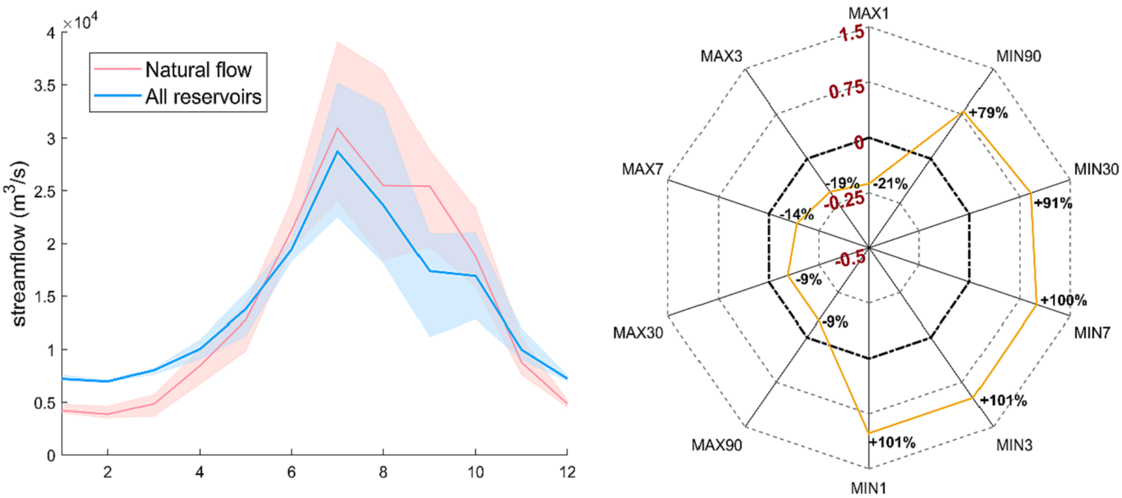

Fig. 7. (a) The average monthly streamflow at the Yichang station and (b) the difference in the extreme flow indicators between the *All reservoirs* scenario and the *Natural flow* scenario over the simulation period. The shaded area refers to the 10–90 percentile interval.

5. Discussion

5.1. Prospects and possible limitations of data-driven reservoir operation simulations

As an estimated 2.8 million reservoirs have been constructed globally, recent research efforts in improving the representations of reservoir operation in hydrologic models are flourishing (Veldkamp et al., 2018; Turner et al., 2020; Boulange et al., 2021). As a powerful ensemble learning algorithm, the XGBoost has been one of the most popular machine learning methods to overcome difficulties in a variety of earth system modelling applications. In this study, we developed two data-driven reservoir operation schemes based on XGBoost and ANN, respectively, to predict the reservoir release and storage in the hydrologic models. In general, both algorithms exhibit satisfactory results in modelling reservoir operation based on historic in-situ reservoir operation data. In particular, compared with the ANN based scheme, the XGBoost based scheme shows a slightly better predicting accuracy of reservoir releases and storages (daily NSE around ~ 0.9 for all of the reservoirs), which is comparable to those reported by other studies (Ehsani et al., 2016; Coerver et al., 2018). This implies that XGBoost can be applicable in hydrologic simulations and predictions in reservoir-regulated basins.

The proposed hybrid hydrologic modelling framework also has the potential for improving real-time streamflow forecasting. For example, hydrologic models can be driven by future meteorologic forecast to generate future reservoir inflow forecasts (Yang et al., 2019). The inflow can then be input to the data-driven and conceptual reservoir operation schemes to predict the future reservoir releases, allowing the information of inflow forecasts to be reasonably transferred downstream.

An issue associated with the data-driven reservoir model is its fundamentally black-box nature, which may be subject to a degraded performance in extrapolation beyond the training data. To alleviate this problem, several storage constraints are applied to the machine learning algorithms in this study, forming up a physics-informed data-driven approach. If the calculated storage fails to meet the constraints, the predicted release in this step is recalculated via the reservoir water balance equation (Fig. 1). This approach is similar to that adopted by Gangrade et al. (2022), who used a few empirical equations to constrain the predicted results of their proposed long-short term memory model (LSTM) based reservoir operation scheme. However, it is also worth noting that the simulation accuracy reported in their study is somewhat lower than those reported in the existing literature, which could be due to the exclusion of reservoir release in the predictors of the regression model. This suggests that inclusion of reservoir release in a closed loop form may help achieve more accurate predictions with data-driven reservoir operation schemes.

5.2. Possible future directions of data-driven reservoir operation simulations

Often, the lack of reservoir operation data limits the use of machine learning in reservoir modelling, leaving the conceptual reservoir operation scheme the only choice in hydrologic models, as in our hybrid modelling framework. However, we believe there is room for improvement of machine learning approaches with respect to 'ungauged' reservoirs. Notably, recent studies have attempted to employ the LSTM model to predict streamflow in ungauged basins (Arsenault et al., 2023; Kratzert et al., 2019). This was done by (1) training the machine learning model using the long-term meteorological data and static features of the basin as predictors and streamflow as the predictand for a large number of basins (usually greater than 100) and (2) testing the model in other basins that are in the test samples (which are a proxy for ungauged basins). By doing so, both Arsenault et al., 2023; Kratzert et al., 2019 have reported superior accuracies of LSTM model in simulating the streamflow in these test basins over the traditional hydrologic model, even if the traditional models are well calibrated in these basins. Such an idea could be transferrable to operation simulations of reservoirs without historic operation data. This will be one of our future research directions.

6. Conclusions

In this study, two data-driven reservoir operation schemes based on XGBoost and ANN are developed to predict the reservoir release in hydrologic models for reservoirs with historic operation data. Then, a hybrid hydrologic modelling framework is proposed by using the data-driven reservoir operation scheme in a high-resolution (3 km) hydrologic model together with a calibration-free conceptual reservoir operation scheme designed for data-scarce reservoirs. This allows quantitative assessment of the cumulative impacts of dam operation on the hydrologic regime under different reservoir data availability.

As a test application, the proposed hybrid modelling framework is applied to the Upper Yangtze River Basin where ten major operational reservoirs are taken into consideration (i.e., Three Gorges, Xiluodu, Jinping I, Goupitan, Ertan, Pubugou, Tingzikou, Baozhusi, Zipingpu, and Changheba). By comparing with the in-situ reservoir releases and storage, we show that both of the developed XGBoost- and ANN- based

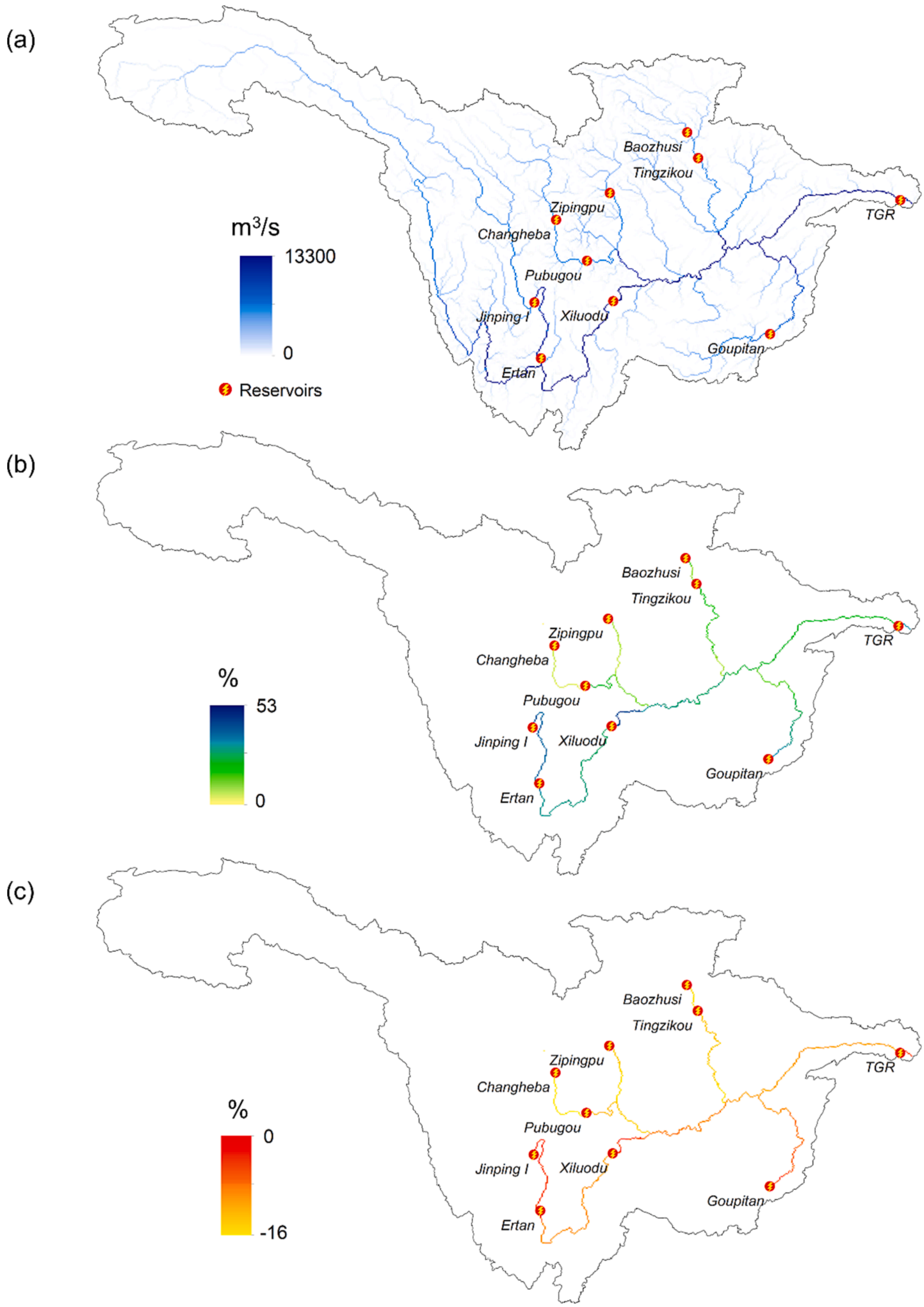

Fig. 8. (a) the spatial distribution of the simulated natural streamflow at the 3 km resolution averaged over 2011–2020, (b) the simulated relative difference of dry-season streamflow induced by reservoirs, and (c) the simulated relative difference of wet-season streamflow induced by reservoirs.

reservoir operation schemes trained from the historic in-situ reservoir operation data (i.e., inflow, release, storage) can accurately reconstruct the reservoir releases and storage considered in our study. The XGBoost generally shows a slightly superior accuracy over ANN, with all of the daily NSE values of simulated releases and storage are over 0.85. The calibration-free conceptual reservoir operation scheme, despite exhibiting a lower simulation accuracy, can generally capture the release and storage variations of the major reservoirs in the UYRB, which suggests this scheme can be used for simulations of reservoirs without reservoir operation data. By coupling the XGBoost-based reservoir operation scheme and the calibration-free conceptual reservoir operation scheme with the hydrologic model, the model shows a remarkably improved performance in reconstructing the historic streamflow at the Yichang station, i.e., the outlet of UYRB.

On its basis, four sets of 10-year (2011–2020) simulations with a spatial resolution of 3 km are conducted to analyze the likely streamflow variations under the cumulative impacts of the operation of 10 major reservoirs in the UYRB. Simulation results show that the mainstream and tributary reservoirs have a notable, cumulative impact on the hydrologic regime at the local scale and the regional scale by redistributing the excessive water resources in the wet season to the dry season, leading to an improved level of water security especially along the mainstream. Reservoirs also attenuate the high flows and low flows along the river, with the maximum 1-day to 90-day streamflow reducing by 9 %~21 % and the minimum 1-day to 90-day streamflow increasing by 79 %~101 %, respectively.

This study proposes a hybrid hydrologic modelling framework with the combined use of data-driven and conceptual reservoir operation schemes that can be applicable worldwide. Future research directions include the development of a generalized data-driven reservoir operation modelling framework that can be applied to reservoirs in ungauged basins.

CRediT authorship contribution statement

Ningpeng Dong: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Funding acquisition. **Wenhai Guan:** Writing – review & editing. **Jixue Cao:** Writing – review & editing. **Yibo Zou:** Writing – review & editing. **Mingxiang Yang:** Writing – review & editing. **Jianhui Wei:** Writing – review & editing. **Liang Chen:** Writing – review & editing. **Hao Wang:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The reservoir operation data is available at https://doi.org/10.5281/zenodo.7190469 with the consent of the corresponding author.

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