Check for
updates

Reservoir Risk Operation of 'Domestic-Production-Ecology' Water Supply Based on Runoff Forecast Uncertainty

Tao Bai[1] · Qianglong Feng[1] · Dong Liu[1] · Chi Ju[2]

Abstract

Water supply operation of a reservoir group is a critical strategy for mitigating conflicts between water resource supply and demand in a basin. However, the uncertainty of runoff forecast presents significant challenges to this operation. To explore the risk laws of the complex water supply process, this study focuses on analyzing the three primary source streams and the main stream of the Tarim River, the largest inland river in China. Initially, a runoff forecast model is developed utilizing Long Short-Term Memory Artificial Neural Networks (LSTM-ANN) to generate runoff datasets. Subsequently, a theoretically optimal operation process for the reservoir group is derived through a long-series deterministic multi-objective operation, which establishes boundary constraints for water supply risk operation. Finally, the runoff forecast results are integrated into an uncertainty water supply risk operation model to assess the associated water supply risk. The results indicate that: 1) Due to varying guarantee rates and water supply priorities among different sectors, the risk of ecological water supply is the highest, followed by agriculture and then domestic-production. 2) Within an effective forecast range of 0% to 20%, the most significant increase occurs when the error ranges between 5 to 10%. 3) As the reservoir regulation capacity in mountainous areas increases, the average water supply risk value for agriculture decreases from 0.086 to 0.040, representing a 53.1% risk reduction. The research results are of great significance to the reservoir group risk operation and the water supply safety in the basin.

1 Introduction

Water resources are irreplaceable and valuable assets in the development of human society. However, with rapid development of social economy, the contradiction between the supply and demand of water resources in the basin is increasing (Peng et al. 2023), which seriously restricts the healthy development of society. In this regard, scholars have proposed many effective

✉ Dong Liu
Sunrise829@126.com

1   State Key Laboratory of Eco-Hydraulics in Northwest Arid Region of China, Xi'an University of Technology, Xi'an 710048, Shaanxi, China

2   Power China Kunming Engineering Corporation Limited, Kunming 650051, China

methods, among which reservoir group operation (Adams et al. 2017) is an important solution. Since the middle of the twentieth century, some scholars have started using mathematical methods to address the issue of water distribution in reservoir operation (Howard 1961) . However, traditional mathematical methods cannot address the curse of dimensionality in multi-objective optimization (Tilmant et al. 2002). Therefore, scholars from various countries have proposed new solutions. For example, SaberChenari et al. (2016) applied the Particle Swarm Optimization algorithm (PSO) to the short-term optimal operation of reservoirs. Sedighkia et al. (2022) integrated a mid-habitat hydraulic model with a heuristic optimization algorithm to mitigate the impact on the downstream ecological environment. Kosasaeng and Kangrang (2023) utilized the conditional atom search optimization method to enhance reservoir operation efficiency.

With the gradual maturity and improvement of reservoir operation theory, reservoir operation has evolved from the original deterministic operation to uncertain risk operation (Mufute et al. 2008). As of now, scholars from various countries have made important contributions to identifying risk factor, developing risk operation models, and establishing risk evaluation indexes. For example, Escuder-Bueno et al. (2016) used a risk analysis method to analyze and evaluate the uncertainty of downstream consequence assessment. Romano et al. (2017) considered extreme events in their risk analysis, quantifying the risk of water scarcity in water supply systems. Hariri-Ardebili (2018) systematically reviewed the fundamental components of uncertainty quantification and discussed their interrelationships. Celeste et al. (2020) proposed an operation model that takes into account the risk of failure and optimized the operation of reservoir water supply. Nabavi et al. (2021) discussed the role of sub-basin flood forecasting and reservoir dam site investigation in reducing flood risk. Li et al. (2022) discussed the simplification of flood control models for complex reservoir groups and the risk brought by simplified models. Zhang et al. (2023) analyzed the uncertainty between upstream water and natural precipitation in agricultural irrigation areas using Copula joint distribution. Yang et al. (2023) established a full-chain integrated system from hydrological response to final decision analysis to study the impact of significant climate change on the stability of water resources systems.

However, there are few studies on the complex process of water supply risk change and transmission from risk generation to water supply objects in the operation of water supply reservoir groups. Especially in the prediction model itself, which cannot fully reveal the reservoir inflow (Lian 2022) , this poses significant risk to the safety of water supply targets. In this paper, the research focuses on the three primary source streams and the main stream of the Tarim River. By establishing a runoff forecast model for the primary three sources of the Tarim River and a deterministic water supply operation model for the three primary source streams and the main stream of the Tarim River, the runoff input and boundary constraints under uncertain reservoir group operation are clarified. Based on this, a water supply risk operation model with uncertainty in runoff forecast is established. Spatial and temporal variations in water supply risk among different industries, including domestic, industrial, agricultural, and ecological, are quantitatively analyzed with the aim to minimize water supply risk. This analysis offers a risk prevention and control strategy for water supply operations in the Tarim River. The main content of this study is shown in Fig. 1.

2 Methodology

This section primarily introduces the method for establishing and solving models. The model establishment process comprises three key components: the uncertain annual runoff forecast model, the uncertain risk operation model, and the deterministic reservoirs operation model.
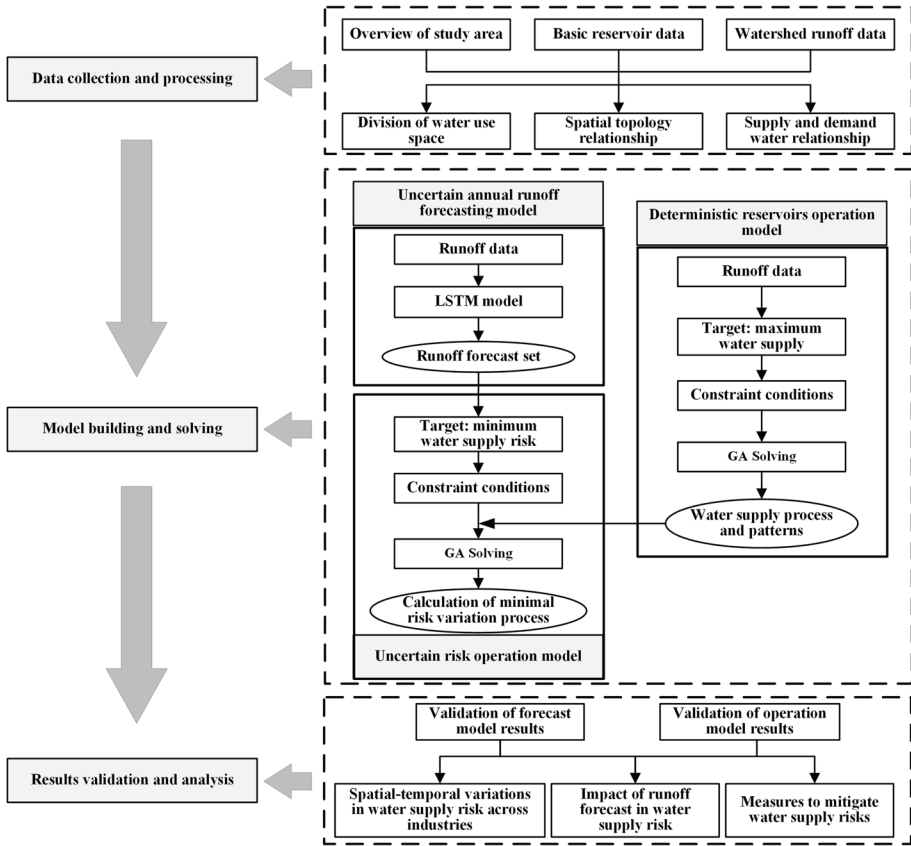
Fig. 1 Flowchart of the main content

2.1 Modelling

2.1.1 Uncertain Annual Runoff Forecast Model

With the advancement of computer science and innovative algorithms, the development of runoff forecasting has greatly benefited. Among numerous forecast models, Long Short-Term Memory (LSTM) model has proven effective in handling time-series data, effectively preserving the integrity of runoff information (Yu et al. 2019). LSTM is specialized recurrent neural network consisting of input layers, hidden layers, and output layers. It addresses the issues of memory loss and gradient vanishing that often occur with long sequence dependencies. Input layers receive and transmit the input data, while hidden layers process this data through various transformations, extracting features crucial for prediction. Finally, output layers produce the model's predictions based on the processed input data.

LSTM is particularly suitable for handling events with long time intervals and delays, effectively mitigating problems such as gradient explosion (Greff et al. 2016). Using various sequences as input to LSTM, it employs memory cells composed of input gates, output gates, and forget gates. Through these gate control units, LSTM reads and adjusts the hidden state

vectors and memory state vectors. The memory cell selectively forgets or adds some input data to the memory, enabling sequence prediction. The specific calculation process is as follows:

$$f_t = \delta(W_f x_t + U_f h_{t-1} + b_f) \tag{1}$$

$$i_t = \delta(W_i x_t + U_i h_{t-1} + b_i) \tag{2}$$

$$\widetilde{c}_t = \tanh(W_{\widetilde{c}} X_t + U_{\widetilde{c}} h_{t-1} + b_{\widetilde{c}}) \tag{3}$$

$$c_t = f_t c_{t-1} + i_t \widetilde{c}_t \tag{4}$$

$$o_t = \delta(W_o x_t + U_o h_{t-1} + b_o) \tag{5}$$

$$h_t = \tan h\,(c_t) o_t \tag{6}$$

where f_t is the forget gate at t moment, determining which runoff information should be forgotten in the LSTM unit.; δ is the Sigmoid function; W and U are weight matrices; x_t is the input at t moment, representing the runoff amount; h_t and h_{t-1} are the hidden layer state at t and $t-1$ moment, respectively, containing the model's memory from previous time steps and its understanding of the current time step; b is the offset vector, used to adjust the open or closed state of gates; i_t and o_t are input gate and output gate at t moment; $\tilde{c}_t$ is the memory update vector at time t, representing the update of memory at the current time step; c_t and c_{t-1} are the memory cell state variables at time t and $t-1$; $\tan h$ is hyperbolic cosine function.

2.1.2 Uncertain Risk Operation Model

Risk is the possibility of adverse events occurring following the interaction between risk sources and hazard-affected bodies. The calculation formula for risk is as follows:

$$V = \left| \frac{Q_{yc} - Q_{sc}}{Q_{sc}} * \Delta t \right| \tag{7}$$

$$P(X \le x_0) = \int_{-\infty}^{x_0} f(x) dx \tag{8}$$

$$R = V * P \tag{9}$$

where V is vulnerability, which is absolute value of relative error between forecasted and measured of water supply; Q_{yc} and Q_{sc} are forecasted and measured water supply flow; Δt is a time step of month scale; P is the probability of forecasted runoff; $f(x)$ is probability density of normal distribution function, which is more commonly used and has better fitting effect; R is water supply risk, which is the probability of a water shortage occurring in water supply objects within the basin.

Runoff forecast results are used as input, and minimizing water supply risk is considered the objective function. The objective function and constraint conditions are as follows:

(1) Objective function

$$\min R = \frac{1}{Z}\frac{1}{L}\sum_{z=1}^{Z}\sum_{l=1}^{L}R(z,l) \tag{10}$$

where $R(z,l)$ is the average water supply risk for various industries within the l interval (defined as the water use range divided according to the water conservancy project and water demand) under the z runoff forecast process; L and Z represent the total number of water use intervals and the size of runoff forecast set, respectively.

(2) Constraints and initial conditions

① Interval water balance constraint

$$W_{in}(z,l) + W_{under}(z,l) = W_g(z,l) + W_s(z,l) + W_{out}(z,l) + W_x(z,l) \tag{11}$$

where $W_{in}(z,l)$, $W_{under}(z,l)$, $W_g(z,l)$, $W_s(z,l)$, $W_{out}(z,l)$ and $W_x(z,l)$ represent the volume of surface water inflow, groundwater supply, total water supply, total water loss volume (including river loss, reservoir leakage, and evaporation loss), total water volume of outlet, and reservoir water storage in the l interval under the z set of runoff forecast operation.

② Reservoir water balance constraint

$$W_{ins}(z,i) = W_{outs}(z,i) + W_x(z,i) + W_s(z,i) \tag{12}$$

where $W_{ins}(z,i)$, $W_{outs}(z,i)$, $W_x(z,i)$ and $W_s(z,i)$ represent the volume of inflow runoff, reservoir discharge, reservoir storage, and reservoir loss of the i reservoir under the z set of runoff forecast operation.

③ Restriction of water level

$$Z_{max}(i,t) \geq Z(i,t) \geq Z_{min}(i,t) \tag{13}$$

where $Z_{max}(i,t)$, $Z_{min}(i,t)$ are the normal high water level and dead water level of the i reservoir at time t; $Z(i,t)$ is operating water level of the i reservoir at time t.

④ Storage capacity constraint

$$V_{max}(i,t) \geq V(i,t) \geq V_{min}(i,t) \tag{14}$$

where $V_{max}(i,t)$, $V_{min}(i,t)$ are the maximum storage capacity and dead storage capacity of the i reservoir at time t; $V(i,t)$ is the storage capacity of the i reservoir at time t.

⑤ Constraint on Guarantee Rate

$$P(l,n) \geq P_{min}(l,n) \tag{15}$$

where $P(l,n)$, $P_{min}(l,n)$ are actual guarantee rate (defined as the ratio of the time period when the actual water supply meets the design water supply to the total time) and industry requires a minimum guarantee rate of the l water supply interval of the n industry;

⑥ Discharge flow constraint

$$\overline{W}_d \geq c \tag{16}$$

where $\overline{W}_d$ is the average annual discharge of the reservoir at the end of the study area to protect the downstream ecological target; c is the upper limit of discharge.

⑦ Water supply constraints

$$W_{\max,l} \geq W_l(z,t) \geq 0 \tag{17}$$

where $W_{\max,l}$ is the total water requirement of interval l; $W_l(z,t)$ is the actual total water supply in the l interval under the z set of runoff forecast operation.

2.1.3 Deterministic Reservoirs Operation Model

To reduce the influence of initial parameters and boundary conditions on the uncertainty of run-off forecasts, the deterministic reservoirs operation model of water supply is developed with the objective of maximizing water supply. The objective function and constraints are as follows:

(1) Objective function

   Taking the monthly water level of each reservoir as the decision variable and the maximum water supply as the objective, the medium and long-term optimal operation model of the reservoir group is established as follows (18).

$$\max f = \sum_{l=1}^{L} \sum_{i=1}^{I} W(l,i) \tag{18}$$

   where $W(l,i)$ is water supply quantity of the l interval of the i industry.

(2) Constraint condition

   The model is to explore boundary of feasibility by dividing search space through historical water data. Therefore, the constraints of optimal operation of deterministic reservoir group water supply are consistent with Section 2.1.1.

2.2 Methods

2.2.1 Solution of Runoff Forecast Model

After considering the research area and multi-year historical runoff data, the solution process for the uncertain annual runoff forecast model is as follows:

Step 1: Input menstrual flow data, eliminate abnormal data, establish an input dataset, label the data according to the long series of monthly runoff data, and predict the next month's runoff by rolling the previous month's runoff;

Step 2: Normalize the runoff dataset, divide the runoff sequence into a training set and a test set according to the ratio of 8:2 (Sherstinsky 2020) to calibrate, test, and verify the parameters of the runoff forecast model;

Step 3: Create an LSTM regression network, specifying the maximum number of iterations of the model and the number of hidden units in the LSTM layer. Utilize a single-step runoff

time series forecast, where the current month runoff data is input and the next month runoff data is output.

Step 4: Fine-tune the LSTM parameters, select the model parameters with good forecast results, and input them;

Step 5: Execute the LSTM model to generate monthly runoff forecast results.

In order to evaluate the reliability of the LSTM forecast model results, the Nash–Sutcliffe efficiency coefficient (NSE) and the mean absolute error (MAE) are selected based on the model parameter calibration to assess the reliability of forecast results. The formulas are shown in (19) and (20).

$$NSE = 1 - \frac{\sum_{t=1}^{T} (Q_s(t) - Q_m(t))^2}{\sum_{t=1}^{T} (Q_s(t) - \overline{Q}_s)^2} \tag{19}$$

$$MAE = \frac{1}{T} \sum_{t=1}^{T} |Q_s(t) - Q_m(t)| \tag{20}$$

where $Q_s(t)$, $Q_m(t)$ and $\overline{Q}_s$ are measured flow, forecast flow and mean value of measured flow at t time, respectively.

2.2.2 Solution of Optimal Operation Model

Given the context of reservoir group water supply operations grappling with complex optimization problems that are large-scale, involve many variables (which is what is meant by high-dimensional), multiple constraints, and exhibit nonlinear characteristics, Genetic Algorithms (GA) show notable advantages (Bai et al. 2023). In this paper, the GA is utilized to solve the optimal operation problems of reservoir group water supply. By considering the water level of each reservoir in each month as the decision variable, the water supply guarantee rate of each industry, and the ecological water discharged by the reservoir as the penalty function, the optimal operation model is solved.

The operational objects and constraints of deterministic reservoir operation model and uncertain risk operation model are consistent, thus the reliability evaluation methods of the two are also consistent. The reliability evaluation method is based on the long series of operational results, and the water balance analysis of the reservoir and the water supply area is conducted on an annual scale.

3 Case Study

Taking the three primary source streams and the main stream of the Tarim River as examples, combined with incoming water characteristics, water demand, and model parameter selection, the rationality of the model and its output results are analyzed.

3.1 Study Area and Data

3.1.1 Regional Survey

Study area includes the three primary source streams and the main stream of the Tarim River. The three primary sources are the Aksu River, the Yarkand River, and the Hotan River. The Tarim River is in the hinterland of the mid-latitude Eurasian continent, surrounded by high mountains. It is a typical arid continental climate with an evaporation of 2380 mm, which is 47 times greater than the precipitation. The Tarim River is responsible for supplying water to 42 counties in 5 prefectures in southern Xinjiang, as depicted in Fig. 2. Under the dual influence of the uncertainty of runoff forecasts and the increasing demand for water supply, the water supply risk for various industries in the Tarim River has significantly increased.

3.1.2 Network Node Graph of Operation System

According to the layout of 7 water conservancy projects, the division of 12 water demand intervals (including 7 water demand intervals in the source area and 5 water demand intervals in the main stream area), and water demand of different industries, the operation
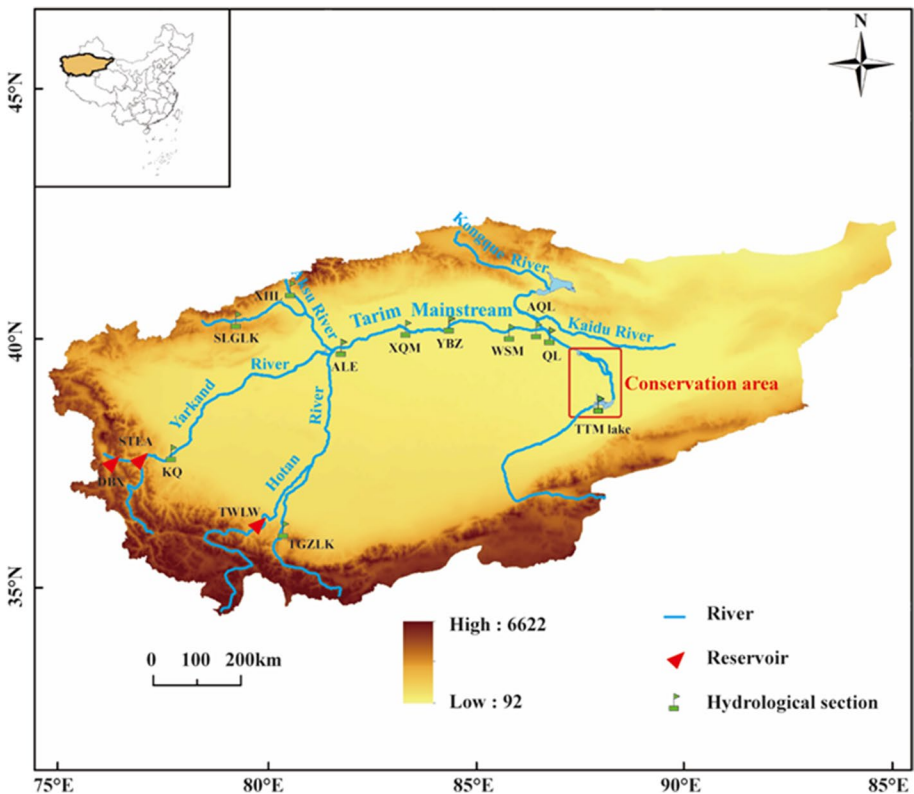

Fig. 2 Distribution map of water system and observation intervals in Tarim River

system in the Tarim River is determined, and the specific distribution is shown in Fig. 3. The system components of the Tarim River exhibit a hierarchical structure that ensures water allocation and management are conducted in a structured and organized manner.

The runoff data and reservoir data used in this paper are provided by the Tarim River Basin Management Bureau. The runoff data mainly consist of the natural runoff data from three primary sources: the Aksu River, the Yarkant River, and the Hotan River, as well as the Alar section of the main stream. The data spans from 1962 to 2016, totaling 55 years. The reservoir group consists of the DBX, STEA, TWLW source flow mountain water conservancy project, and the JRLK, DZ, QM, PM, KEQG, TLM main stream plain water conservancy project. The main reservoir data include tasks undertaken by the reservoir, dead water level, normal water level, water level storage capacity relationship, etc. Water demand data forms the basis for dividing it into 12 water demand intervals, which mainly include 'the rational allocation of water resources in Tarim Inland River', 'the impact of climate change on water resources management in Tarim River and adaptive countermeasures', 'the recent comprehensive management planning report of Tarim River'.

3.2 Principle of Allocation

(1) Principle of water resources allocation

① Strictly control the total amount of water resources development and utilization;
② Make full use of surface water and rationally exploit groundwater;
③ Save water, protect water resources.

(2) Water storage and supply method

Water supply method: The priority is to meet the production-domestic water demand, followed by meeting the agricultural irrigation water demand, and finally meeting the ecological water needs (defined in this paper as the ecological water demand outside the river). In addition, it is necessary to meet the discharge requirements of DXHZ reservoir.

Water storage strategy: Prioritize mountain reservoirs, situated in high-altitude areas and utilizing terrain slopes for water storage, over plain reservoirs located in lowland regions and relying on artificial irrigation. Mountain reservoirs are filled first due to their
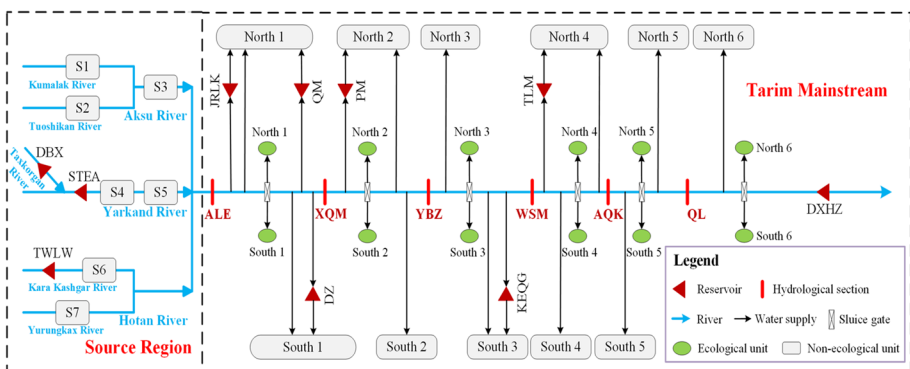

Fig. 3 Node diagram of reservoir group operation system in Tarim River

natural advantage in collecting rainwater or snowmelt. Plain reservoirs along main streams are consolidated based on water usage intervals. JRLK, DZ, and QM Reservoirs supply the ALE-XQM interval. PM Reservoir serves the XQM-YBZ interval, KEQG Reservoir caters to YBZ-WSM, and TLM Reservoir covers WSM-AQK.

3.3 Parameter Settings

3.3.1 Runoff Forecast Model

The three primary source streams and the main stream of the Tarim River are in China's inland arid region, where the runoff process is generated only in the source areas. Based on the division of training and testing datasets for the LSTM model's runoff sequence prediction, the period from 1962 to 2005 is selected as the model parameter calibration period, and the period from 2006 to 2016 is chosen as the validation period. The parameters of the LSTM model proposed in this article are shown in Table 1.

3.3.2 Reservoirs Operation Model

In the operation model, 55-year long series of runoff data from July 1962 to June 2016 were used, and the monthly calculation period is set. The starting time of the water conservancy year is July and the end time is the end of June of following year. In addition, through multiple adjustments to the GA parameters, the number of iterations, the initial population size, and the crossover probability respectively set 300, 200, and 0.7. According to industry norms, the minimum guarantee rate of domestic-production and agriculture is 95% and 75% respectively. The minimum guarantee requirement of the Tarim River ecology is to meet the ecological water demand of 350 million m^3 discharged by DXHZ reservoir.

4 Analysis and Discussion

According to model calculations and risk definitions, the temporal and spatial variations in water supply across different industries are analyzed based on risk value and vulnerability. Combined with various runoff forecast errors, this study discusses the impact of

Table 1 LSTM neural network model parameters

Main stream	Tributary	Num hidden units	Epochs	Learn rate
Aksu	Kumalak	100	100	0.005
	Tuoshikan	45	50	0.005
Yarkand	Taxkorgan	100	50	0.005
	Yarkand	55	60	0.005
Hotan	Kara Kashgar	300	500	0.005
	Yurungkax	100	180	0.005

The Num Hidden Units is the number of neurons or nodes in the hidden layer of the LSTM network; Epochs is the number of times the entire dataset is presented to the model for training; The Learn Rate is a hyperparameter that controls the step size of the updates made to the model's weights during training

runoff forecast errors on water supply risk and the transmission of risk within each interval. Finally, the method of reducing water supply risk is analyzed, and specific measures are provided.

4.1 Analysis of Model Rationality

4.1.1 Runoff Forecast Model

Runoff processes occur in the three primary source streams, so the runoff forecast focuses exclusively on the Tarim River source streams. The validation results for the Tarim River's various tributaries, as demonstrated in Fig. 4, providing the evaluation indicators for the forecast verification period, which are presented in Table 2.

Comparing the observed runoff processes with the runoff forecast results, it is evident that they exhibit consistent trends. Except for some extreme values where the forecast error is relatively large, the fit is generally favorable in other areas. The average values of MAE and NSE during the validation period are 23.21 and 0.88, respectively, indicating a good forecast performance.

4.1.2 Optimal Operation Model

Using the 2016 dispatch results for the Kara Kashgar River as an example, a water balance analysis is conducted for the TWLW reservoir operation and the S6 interval.
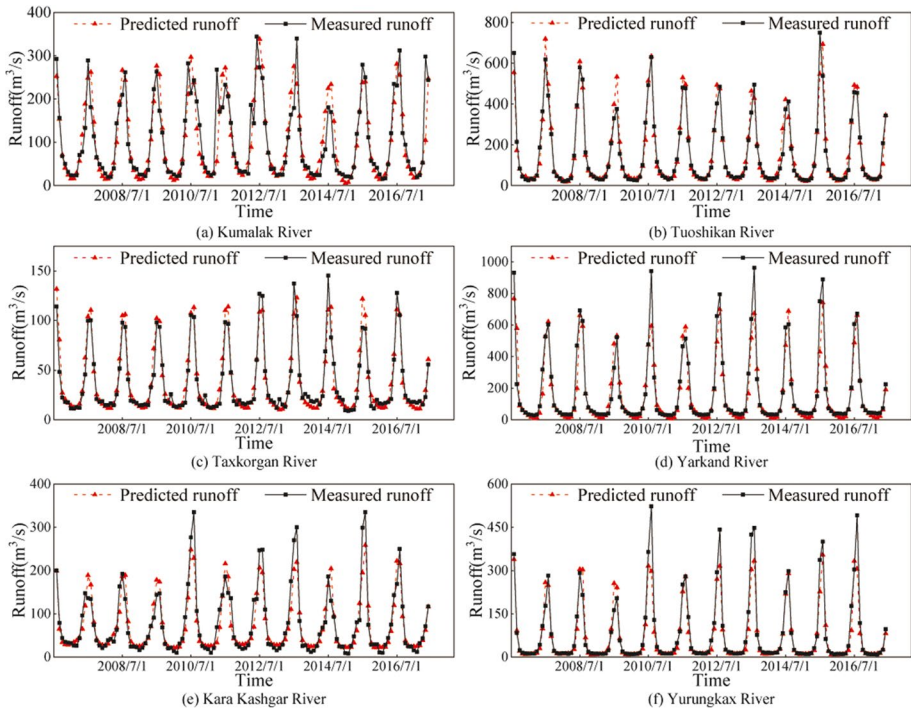
Fig. 4 Fitting process between forecasted runoff and measured runoff in source flow area

Table 2 Evaluation indices of runoff forecast verification period

Main stream	Tributary	MAE	NSE
Aksu	Kumalak	25.52	0.92
	Tuoshikan	26.44	0.78
Yarkand	Taxkorgan	6.97	0.91
	Yarkand	41.07	0.88
Hotan	Kara Kashgar	20.20	0.86
	Yurungkax	19.06	0.90

According to the test results in Table 3, the inflow of TWLW reservoir is 2.40 billion m^3 in 2016. At the end of the year, the change of storage capacity is 0.02 billion m^3, the loss is 0.02 billion m^3, and the discharge is 2.40 billion m^3, which met the water balance of reservoir operation. The inflow of interval S6 is 2.40 billion m^3, the loss of river channel is 0.32 billion m^3, the water supply of agricultural irrigation is 1.68 billion m^3, the water supply of production-domestic is 0.04 billion m^3, the water supply of groundwater is 0.38 billion m^3, and the discharge of interval S6 is 0.74 billion m^3. The rationality of establishment and solution of operation model is verified.

The operation process of the mountainous reservoir in the source flow area and the plain reservoir at each interval of the main stream in a 75% frequency dry year is shown in Fig. 5.

It can be seen from Fig. 5:

(1) Since the DBX is situated in the upper reaches of the Yarkant River, which has priority in water storage. The DBX reservoir stores water from the beginning of July to the end of August. From the beginning of September to the end of May, the water level has been consistently normal. From the beginning of June to the end of June, water is replenished to supplement the water used by downstream industries.;

(2) The STEA reservoir is situated downstream of the DBX reservoir and possesses a robust annual regulation capacity. It is impounded from the beginning of July to the end of August. It has been operating at a normal high-water level from the beginning of September to the end of October. The water is replenished from the beginning of

Table 3 Results of water allocation in TWLW reservoir and S6 interval of Kalakashi River

| Reservoir/interval	Water allocation object	Water supply (billion m^3)
TWLW reservoir	Inflow water	2.40
	Change of storage capacity	0.02
	Loss (river, reservoir leakage and evaporation)	0.02
	Discharge	2.40
S6 interval	Agricultural supply	1.68
	Production-domestic supply	0.04
	Groundwater extraction	0.38
	Loss (river, reservoir leakage and evaporation)	0.32
	Discharge	0.74
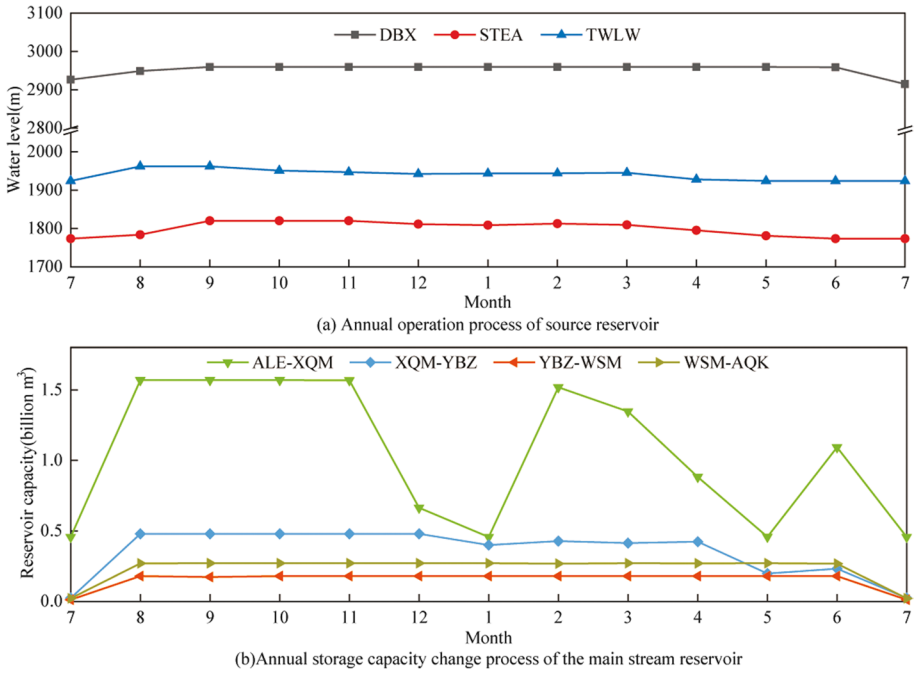
Fig. 5 Source and main streams reservoir operation process

November to the end of May to supplement the water used by various industries during the dry season;

(3) The TWLW reservoir regulates the incoming water of the Hotan River during dry years. It stores water from the beginning of July to the end of July, operates at a normal high water level from the beginning of August to the end of August, and replenishes water from the beginning of September to the end of April to supplement the water used by various industries during the dry season;

(4) The plain reservoirs in each interval of the main stream can effectively regulate the inflow of the main stream. They can store water during the wet season to supplement water usage for various industries during the dry season.

4.2 Water Supply Risk of Source and Main Streams

The source flow of the Tarim River is abundant in water, and the river ecosystem is stable (Li et al. 2021). The amount of water leaked from the river can meet the ecological water needs. However, the ecosystem of its main stream is fragile and requires artificial replenishment. Based on this, the risk operation results of each industry in each interval of source and main streams are shown in Table 4.

In the context of water supply priorities, the risk of water supply for production-domestic is deemed negligible, with a risk rating of 0.000 in both the water source and the main streams. However, for agriculture, the average risk of water supply in the source flow is measured at 0.057. When compared to the source flow, the maximum risk of water supply

Table 4 Risk operation results of various industries in source and main streams interval

Main stream/interval	Water supply risk		
	Production and living	Agricultural irrigation	Ecology
Aksu	0.000	0.076	—
Yarkand		0.025	—
Hotan		0.072	—
ALE-XQM		0.057	0.281
XQM-YBZ		0.007	0.281
YBZ-WSM		0.000	0.284
WSM-AQK		0.000	0.295
AQK-QL		0.000	0.293

"—" means that risk in industries corresponding to the interval are not considered

for agricultural irrigation in the main stream, under the management of the reservoir group, also stands at 0.057, which remains relatively low. Additionally, the risk of water supply in downstream areas tends to approach 0.000, and the risk associated with agricultural irrigation gradually diminishes from upstream to downstream. It's worth noting that ecological risk within each interval of the main stream are substantial, primarily influenced by the uncertainty of runoff forecasts. These ecological risks exceed 0.280 and demonstrate an upward trend along the spatial axis.

The comparison of risk and vulnerability between the source and main streams is shown in Figs. 6 and 7.

It can be seen from Figs. 6 and 7:

(1) The average water supply risk in the source streams is higher compared to the main stream. When comparing the probability of vulnerability occurrences, the probability of high vulnerability (greater than 0.5) is low.

Fig. 6 Risk comparison between the source and main streams of the Tarim River
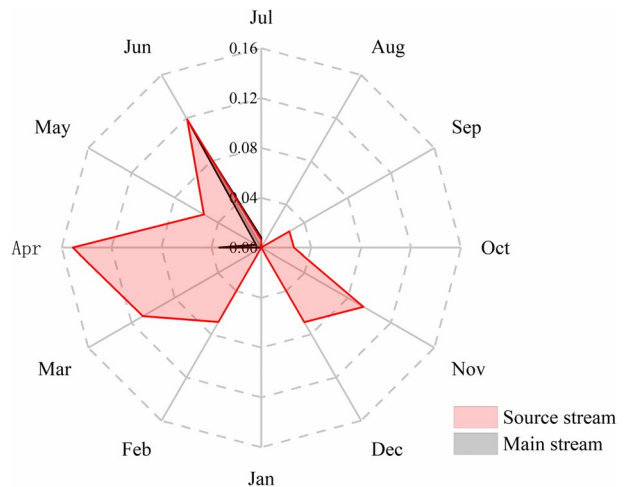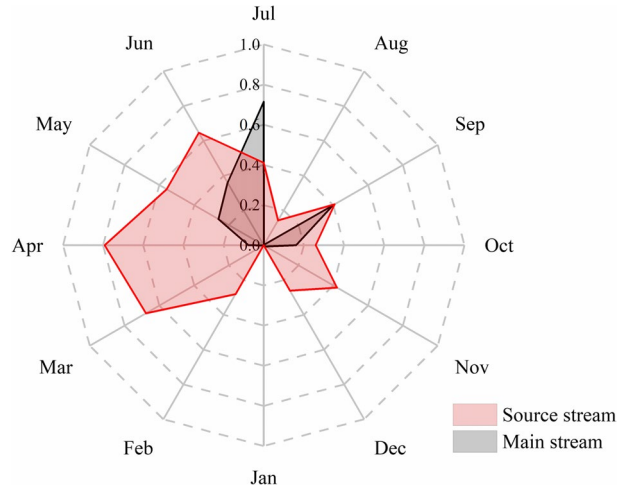
Fig. 7 Vulnerability comparison between the source and main streams of the Tarim River

(2) The water supply risk in the source stream is mainly concentrated from February to June and September to December, while in the main stream, it is primarily concentrated from April to June. Therefore, the source stream is more susceptible to water supply risk. The peak vulnerability in the source stream happens in April, whereas in the main stream, it occurs in July.

(3) Considering the reservoir group operation rule and water consumption patterns, the risk and vulnerability in each interval are relatively low during the dispatching period. Towards the end of the dispatching period, when water inflow decreases and reservoir storage is low, both the risk and vulnerability increase.

4.3 Influence of Forecast Error on Water Supply Risk

Considering the accuracy of runoff forecasts, analyze the variation pattern of water supply risk among different industries. The results are shown in Fig. 8.

With the increase in forecast error, the average water supply risk for each industry also increases. The largest increase occurs when the error falls between 5 and 10%. The risk of agricultural water supply increased from 0.003 to 0.032, a nine fold increase, while the risk of ecological water supply increased from 0.261 to 0.333, a 0.28-fold increase. Under different forecast accuracy, the transfer process of risk in each water supply interval is shown in Figs. 9 and 10.

It can be seen from Fig. 9 that water supply risk, caused by the uncertainty of runoff forecast, cannot be completely mitigated by regulating of mountainous reservoirs and plain reservoirs. Agricultural water supply risk increases with the rise in forecast error. The agricultural water supply of the main stream is more affected by forecast accuracy than that of the source streams. Furthermore, there is a notable phenomenon of the transmission of agricultural water supply risk between upstream and downstream regions of both the source and main streams. It can be seen from Fig. 10 that the ecological water supply order in the main stream is low. Forecast errors result in a significant increase in the risk of ecological water supply, but the spatial distribution remains relatively stable.
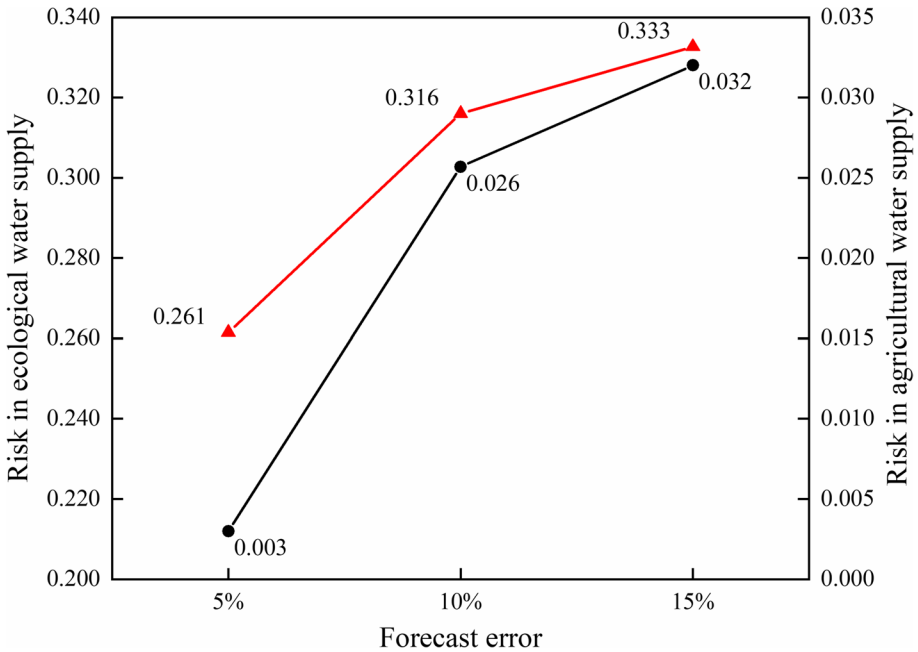
Fig. 8 Average water supply risk of each industry under different forecast accuracy
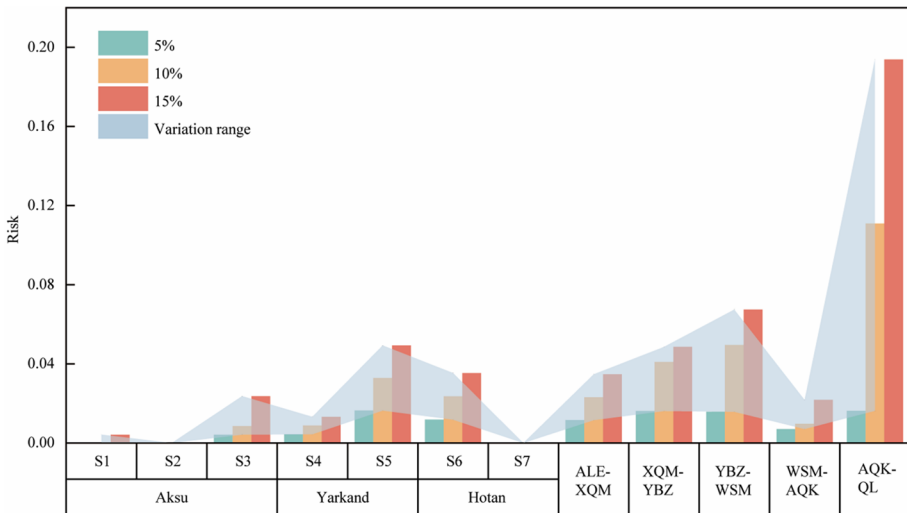

Fig. 9 Risk of agricultural water supply in each interval under different forecast accuracy

4.4 Risk Reduction Capacity Considering Mountainous Reservoirs

The mountainous reservoirs in the Tarim River have a high storage capacity, and the water loss due to evaporation and leakage is lower compared to plain reservoirs (Zhao et al.
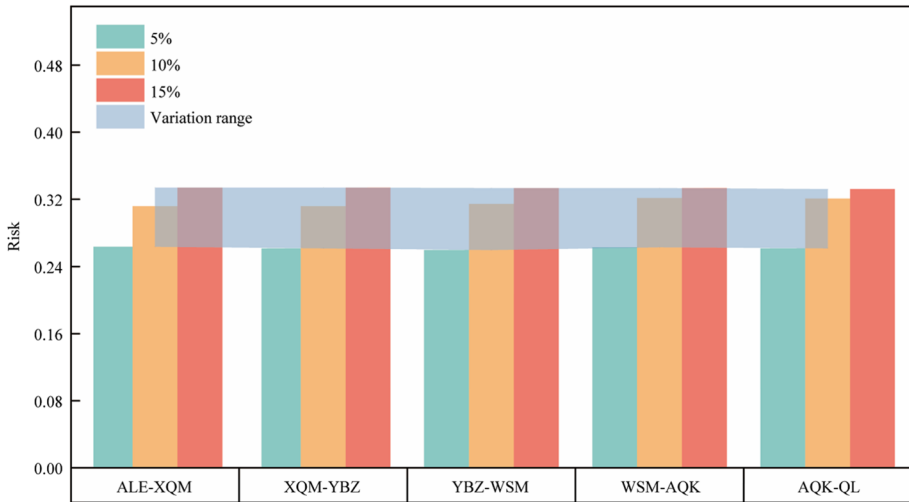
Fig. 10 Risk of ecological water supply in each interval under different forecast accuracy

2022). Utilizing the regulation capacity of mountainous reservoirs is the primary option to mitigate the risk associated with water supply. The risk reduction capacity of mountainous reservoirs in the Tarim River is shown in Table 5.

In the case of a 75% frequency drought year, the average water supply risk for agriculture and ecology are 0.086 and 0.291, respectively. With an increase in the adjustable reservoir storage capacity, the average water supply risk for agriculture and ecology decreases to 0.040 and 0.287, respectively, representing reductions of 53.1% and 1.4%. During drought years in the Tarim River, the importance of agricultural water supply surpasses that of the ecological water supply. As a result, the reduction in the average water supply risk for agriculture is significantly greater than the average water supply risk for ecology.

5 Conclusion and Suggestion

This study focuses on the three primary source streams and the main stream of the Tarim River. It involves establishment of the LSTM runoff forecast model, the deterministic optimization model for reservoir group water supply operation, and the determination of inputs

Table 5 Risk reduction capacity of reservoirs in mountainous areas of Tarim River

Reservoir	Number	Risk		Risk reduction rate	
		Agriculture	Ecology	Agriculture /%	Ecology /%
Without reservoir	0	0.086	0.291	—	—
DBX	1	0.079	0.289	8.4	0.7
DBX、STEA	2	0.048	0.288	44.4	1.4
DBX、STEA、WTWL	3	0.040	0.287	53.1	1.4

and boundary conditions for the water supply risk optimization model. To minimize the risk of water supply, the temporal and spatial variation of water supply risk in dry years and the transfer law of risk among different industries are studied. The main conclusions are as follows:

(1) Under reservoir group dispatching, the production-domestic water supply, given its higher priority, has a water supply risk of 0, indicating that it is well-assured. The ecology in source areas remains stable without the need for supplementary water, resulting in an average agricultural water supply risk of 0.057. For the main stream, the risk of agricultural water supply is relatively low, thank to regulation by multiple reservoirs, averaging 0.013.

(2) Risk follows a spatial pattern of decreasing from upstream to downstream. In contrast, the ecological water supply risk in various sections of the main stream is significantly higher, exceeding 0.280, with risk primarily influenced by runoff forecast uncertainty. Overall, there is a rising trend of ecological water supply risk in space along the main stream.

(3) Within the range of effective forecast errors, as the forecast error increases, the average water supply risk for various industries also increases, with the largest increase observed when the error exceeds 5%. Agricultural water supply risk increased from 0.003 to 0.032, a nine fold increase, while ecological water supply risk rose from 0.261 to 0.333, marking a 0.28-fold increase.

(4) In addition to enhancing the accuracy of runoff forecasts, the ability to reduce water supply risk can also be improved by utilizing the regulating capacity of mountain reservoirs. In a 75% frequency drought year, the average water supply risk for agriculture is 0.086. With an increase in the adjustable reservoir storage capacity, the average water supply risk for agriculture can be reduced to 0.040, leading to a 53.1% decrease in risk.

Compared with the risk analysis of water demand processes (Bai et al. 2021), this study further focuses on identifying the causes of risks and analyzing the spatial and temporal changes of water supply risks from the source to various water demand industries. However, due to the diversity and complexity of risk factors and risk receptors in the Tarim River, there are still many areas for improvement in research. The first is to continue conducting in-depth research on water distribution in a variety of risk sources. The second is that this paper only considers source stream mountain reservoirs and main stream plain reservoirs that have already been constructed. The next step is to consider the impact of the reservoir under construction on the water supply risk operation of the entire basin.

Declarations

Ethics Approval There are no relevant waivers or approvals.

Consent to Participate Authors consent to their participation in the entire review process.

Consent to Publication Authors allow publication if the research is accepted.

Competing Interests 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.

References

Adams LE, Lund JR, Moyle PB et al (2017) Environmental hedging: a theory and method for reconciling reservoir operations for downstream ecology and water supply. Water Resour Res 53(9):7816–7831. https://doi.org/10.1002/2016wr020128

Bai T, Yu J, Jin W et al (2021) Study on risk analysis of Sanhekou Reservoir operation based on different water demand processes. J Hydroelectric Eng 40(8):12–22 (in Chinese)

Bai T, Yu J, Jin W et al (2023) Multi-objective and multi-scheme research on water and sediment regulation potential of reservoirs in the upper Yellow River. Int J Sedim Res 38(2):203–215. https://doi.org/10.1016/j.ijsrc.2022.10.004

Celeste AB, Cai X, Ponnambalam K et al (2020) New considerations for a reservoir capacity optimizer that accounts for failure risks. J Water Resour Plan Manag 146(5):06020003. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001199

Escuder-Bueno I, Mazzà G, Morales-Torres A et al (2016) Computational aspects of dam risk analysis: findings and challenges. Engineering 2(3):319–324. https://doi.org/10.1016/j.eng.2016.03.005

Greff K, Srivastava RK, Koutník J et al (2016) LSTM: a search space odyssey. IEEE Trans Neural Netw Learn Syst 28(10):2222–2232. https://doi.org/10.1109/tnnls.2016.2582924

Hariri-Ardebili MA (2018) Risk, Reliability, Resilience (R3) and beyond in dam engineering: a state-of-the-art review. Int J Disaster Risk Reduct 31:806–831. https://doi.org/10.1016/j.ijdrr.2018.07.024

Howard RA (1961) Dynamic programming and Markov processes. Math Gaz 3(358):120. https://doi.org/10.2307/1266484

Kosasaeng S, Kangrang A (2023) Optimum reservoir operation of a networking reservoirs system using conditional atom search optimization and a conditional genetic algorithm. Heliyon 9(3). https://doi.org/10.1016/j.heliyon.2023.e14467

Li W, Huang F, Shi F et al (2021) (2021) Human and climatic drivers of land and water use from 1997 to 2019 in Tarim River basin, China. Int Soil Water Conserv Res 9(4):532–543. https://doi.org/10.1016/j.iswcr.2021.05.001

Li J, Zhong P, Wang Y et al (2022) Risk analysis for the multi-reservoir flood control operation considering model structure and hydrological uncertainties. J Hydrol 612:128263. https://doi.org/10.1016/j.jhydrol.2022.128263

Lian L (2022) Runoff forecasting model based on CEEMD and combination model: a case study in the Manasi, China. Water Supply 22(4):3921–3940. https://doi.org/10.2166/ws.2022.021

Mufute NL, Senzanje A, Kaseke E (2008) The development of a risk of failure evaluation tool for small dams in Mzingwane Catchment, Zimbabwe. Phys Chem Earth Parts A/B/C 33(8–13):926–933. https://doi.org/10.1016/j.pce.2008.06.029

Nabavi E, Sabour M, Dezvareh GA et al (2021) Predicting and routing the sub-basin floods and investigating the reservoir dam location in flood risk reduction (case study, Zolachai Dam in West Azerbaijan). Model Earth Syst Environ:1–19. https://doi.org/10.1007/s40808-021-01330-1

Peng J, Liu T, Chen J et al (2023) The conflicts of agricultural water supply and demand under climate change in a typical arid land watershed of Central Asia. J Hydrol Reg Stud 47:101384. https://doi.org/10.1016/j.ejrh.2023.101384

Romano E, Guyennon N, Bon AD et al (2017) Robust method to quantify the risk of shortage for water supply systems. J Hydrol Eng 22(8). https://doi.org/10.1061/(ASCE)HE.1943-5584.0001540

SaberChenari K, Abghari H, Tabari H (2016) Application of PSO algorithm in short-term optimization of reservoir operation. Environ Monit Assess 188(12). https://doi.org/10.1007/s10661-016-5689-1

Sedighkia M, Datta B, Abdoli A (2022) Reducing the conflict of interest in the optimal operation of reservoirs by linking mesohabitat hydraulic modeling and metaheuristic optimization. Water Supply 22(2). https://doi.org/10.2166/ws.2021.373

Sherstinsky A (2020) Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network. Physica D 404:132306. https://doi.org/10.1016/j.physd.2019.132306

Tilmant A, Faouzi EH, Vanclooster M (2002) Optimal operation of multipurpose reservoirs using flexible stochastic dynamic programming. Appl Soft Comput J 2(1). https://doi.org/10.1016/s1568-4946(02)00029-7

Yang Z, Wang Y, Song S et al (2023) Multi-objective operation-decision-making-risk propagation analysis for cascade reservoirs affected by future streamflow process variations. J Hydrol 620:129518. https://doi.org/10.1016/j.jhydrol.2023.129518

Yu Y, Si X, Hu C et al (2019) A review of recurrent neural networks: LSTM cells and network architectures. Neural Comput 31(7):1235–1270. https://doi.org/10.1162/neco_a_01199

Zhang S, Kang Y, Gao X et al (2023) Optimal reservoir operation and risk analysis of agriculture water supply considering encounter uncertainty of precipitation in irrigation area and runoff from upstream. Agric Water Manag 277. https://doi.org/10.1016/j.agwat.2022.108091

Zhao M, Liu Y, Wang Y et al (2022) Effectiveness assessment of reservoir projects for flash flood control, water supply and irrigation in Wangmo Basin, China. Sci Total Environ 851:157918. https://doi.org/10.1016/j.scitotenv.2022.157918