Research on flood forecast of dashimen reservoir in xinjiang based on melting snow and runoff yield under excess infiltration

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Abstract. In China, the distribution of water resources is uneven in time and space. The effective allocation of water resources can realize the rational utilization of water resources. Reservoirs are an important part of the basin system, and the rational operation of reservoirs can realize the optimal allocation of water resources. Flood forecast is of great significance for reservoir operation. In order to realize the optimal operation of Dashimen reservoir in Xinjiang, aiming at the flood forecast in the dry area affected by melting snow, this paper expanded and improved the traditional hydrological forecast model, built the flood forecast model in the dry area with the coupling snowmelt based on the northern Shaanxi model and Elman neural network, and using the typical rainfall and runoff data in this area The results show that the relative error of the model is less than 10% and the accuracy is high, which can be used in the actual forecast. This model realizes the flood forecast in the drought area affected by snowmelt, and provides a new idea for the flood forecast of reservoir in the drought area affected by snowmelt, which has a certain guiding significance for the flood forecast in the drought area.

1. Introduction
In the basin of water resource is closely related to people's production and living within the region, has the characteristics of spatial and temporal distribution of water resource in China, coupled with climate change promote several processes led to a number of regional flood frequency increased [1-2], utilization of flood resources is the important way to alleviate the shortage of water resources [3], the water shortage will seriously restrict the development of social economy, flood utilization of flood resources can be very good ease regional water shortages [4-6], the effective allocation of water resources to realize the rational utilization of water resources, promote the sustainable development of social economy. As an important part of the basin system [7], reservoir is the main project of water resources allocation in the basin, and the spatial and temporal distribution of water resources can be redistributed [8-9]. The optimal allocation of water resources cannot be achieved without the rational
operation of reservoirs, and the effective utilization of water resources can be realized through the dynamic control of reservoir water level [10-13]. Due to the randomness of incoming runoff, reservoir operation decision making is a very complex process [14]. Optimal operation of reservoirs is closely related to accurate and timely flood forecasting [15]. Flood forecasting is based on the formation and movement rules of floods and USES the hydrometeorological data measured to predict the development of floods in the foreseeable period [16-17]. Flood forecast can provide early flood warning and prevent or reduce the flood damage [18 to 19], accurate, timely flooding on infrastructure operation and resource allocation of emergency decision-making is very important [20], flood forecast accuracy determines the precision of the reservoir scheduling results [21], hydrological models in runoff and flood forecasting plays an important role in [22], to solve the problem of reservoir scheduling and the production practice has important scientific significance and application value. The development range of hydrological models ranges from centralized models to semi-distributed models and fully distributed models [23]. It is an important task to select an appropriate hydrological model for the research area from numerous hydrological models, which determines the feasibility and accuracy of flood forecasting [24].

Northwest arid region small rainfall, high mountains snowmelt runoff is an important supply source [25], the influence of melting snow physical process compared with the rainfall runoff is relatively complex, coupled with the northwest region sparsely populated, hydrological station less lead to hydrological data is relatively lack, the traditional hydrological forecast method cannot have satisfied the requirements of the current production, so consider the northwest region of the influence of the snowmelt flood forecasting has been the difficulties of hydrological research [26]. The northern Shaanxi model is mainly used for flood forecasting in arid or super permeable areas, which has reasonable structure, few parameters, clear physical concept and simple calculation. As the calculation model of optimization, data driven model gradually get rapid development, the nonlinear function is constructed to describe the relationship between the input and output data to extract the system response to a particular input information, but it does not provide physical information of hydrological processes, coupled with the development and implementation is relatively quickly and easily, more and more widely applied in the flood forecast [27], neural network as a data-driven model has been widely used in hydrological forecasting and flood forecasting, become an important method in the field of hydrology research [28].

Dashimen reservoir located in qiemo river basin in xinjiang, away from the ocean, sufficient sunlight, temperature difference is bigger, precipitation, evaporation, river supply is given priority to with snowmelt, accurate forecast of runoff in the region is of great significance for big shimen reservoir scheduling, allowing them to better play its the comprehensive benefits of flood control, power generation, irrigation, [29]. In northwest arid region, considering the different regional runoff regularity and underlying surface conditions, the difference of the current model is generic, in this paper, and their big shimen reservoir basin of xinjiang as the research object, on the basis of model establishment in arid regions of shaanxi flood forecasting model, based on the Elman neural network model is established in the temperature - snowmelt model, considering the actual situation of the river basin, the flood forecasting model of the arid region is established to realize the flood forecasting of the arid region affected by the snowmelt, which is of great reference significance to the flood forecasting of the arid region in northwest China.

2. Study Area and Data

2.1. General situation of reservoirs and basins
Dashimen water control project is located on the Cheerchen River in Qiemo County, Bayingolin Mongolian Autonomous Prefecture, Xinjiang. The dam is a roller compacted asphalt concrete core dam. The dam site is located 300 meters downstream of the confluence of the Cherchen River and tuoqilisayi River, and is lower than the Qiemo hydrological station with a total reservoir capacity of 127 million cubic meters and a dam height of 132.8 meters, the annual power generation capacity of the hydropower
The station is expected to reach 170 million kwh, and the control basin area is 24692km². It is a key control key project in the Cherchen River Basin.

The Cheerchen river basin is located at 83 ° 30 ′ ~ 85 ° 15 ′ E and 36 ° 30 ′ ~ 39 ° 15 ′ n. It is connected with Taklimakan Desert in the north, karamiran River Basin in the west, Kunlun Mountain and Altun mountain range in the south, and Tarim River Basin in the northeast. The upper reaches of the basin are mainly mountainous areas with low temperature and more precipitation. The middle and lower reaches of the basin are blocked by high mountains, so it is difficult to reach the warm air flow. The precipitation is less and the evaporation is large. The snowmelt in the mountains is an important supplement to the runoff.

The location map of the study area is shown in Figure 1.

2.2. Data information
Through the preliminary design report of Dashimen water control project on Cherchen River in Xinjiang and China Meteorological data network, the data of temperature, rainfall monthly scale and daily scale of Dashimen station and Qiemo station, as well as hourly scale data of some periods are collected. The flood forecast of Dashimen reservoir can be preliminarily studied. The specific data are shown in Table 1.

Table 1. Collected research area data

| Serial number | Station   | Type of data       | Time Scale | length of time          |
|---------------|-----------|--------------------|------------|-------------------------|
| 1             | Dashimen Station | temperature, rainfall | daily scale | 2014.7.19-2014.12.31    |
| 2             | Dashimen Station | temperature, rainfall | daily scale | 2017.8.6-2019.11.28     |
3. Methods

3.1. Flood forecasting model in arid area
Dashimen reservoir basin is located in the inland arid area of Northwest China, which belongs to the over infiltration runoff, and the proportion of snowmelt runoff in flood season is not significant. Therefore, the commonly used rainfall runoff model in Northern Shaanxi is adopted. The Northern Shaanxi model is a conceptual rainfall runoff model established by studying the rainfall runoff process of the Loess Plateau in Northern Shaanxi, which can be used in arid and semi-arid areas such as the Loess Plateau.

In order to consider the non-uniformity of rainfall distribution and underlying surface distribution, the basin can be divided into several block unit areas in practical application.

3.1.1. Model principle and structure
The rainfall runoff model in Northern Shaanxi mainly includes three parts: calculation of runoff yield, slope confluence and river confluence, among which the calculation of runoff yield is the core part.

(1) calculation of runoff yield
Suppose that the rainfall intensity at any time period is $i$, the evapotranspiration is $E$, and the average infiltration rate of the basin is $f$, then:

$$R_1 = i - E$$

(2) runoff on pervious area $R_2$
If $i - E < f$, runoff is produced in part of the basin; if $i - E > f$, it is the whole basin runoff. That is:

$$R_2 = \begin{cases} 
(i - E - f) & i - E \geq f \\
E - f & i - E < f 
\end{cases}$$

(3) total basin yield $R$
$$R = R_1 \times FB + R_2 \times (1 - FB)$$

Considering the non-uniformity of infiltration capacity distribution, the above-mentioned runoff generation process becomes as follows:

Step1: Assuming the soil water content $\theta_1$ after $\Delta t$ ($t = t + \Delta T$), the infiltration capacity at the end of the first period can be obtained from $f = f_0 - K(\theta - f_0)$ and $f = f_0 + (f_0 - f) e^{-\lambda t}$.

Step2: Assuming a linear relationship, the average infiltration capacity ($\bar{f}_1$) of the first period can be obtained.

$$\bar{f}_1 = \frac{f + f_1}{2}$$

Step3: Comparing the average rainfall intensity ($\bar{i} - E$) with $f$ in the first period, if $\bar{i} - E < f$, the runoff is generated in part of the area; if $\bar{i} - E > f$, the runoff is generated on the whole runoff producing area. And the production flow is:
The infiltration capacity is:

\[
R_i = \begin{cases} 
(\bar{I}_i - E_i - \bar{F}) & \bar{I}_i - E_i \geq f_m \\
(\bar{I}_i - E_i - \bar{F}[1 - (1 - \frac{\bar{I}_i - E_i}{f_m})^{\mu_i + 1}]) & \bar{I}_i - E_i < f_m 
\end{cases}
\]  

(5)

Step 4: The moisture content of another soil at the end of the first period was calculated.

\[
\theta'_1 = \theta_1 - R_i - E_i
\]  

(6)

Step 5: Compare the size difference between θ1' and θ1. If it is less than the allowable error, return to step 1 to update the assumed θ1 at the beginning, and recalculate until both meet the iteration accuracy.

(2) Calculation of slope confluence

In the forecast model, the confluence of element area slope is combined with the method of linear reservoir and hysteresis calculation. The calculation formula is as follows:

\[
Q_t = CS \times Q_{c,1} + (1 - CS)I(t - L)
\]  

(8)

Where Q and I are respectively outflow and inflow processes (m³/s); CS is the surface runoff regression coefficient; (1-CS) is the surface runoff outflow coefficient; L is the time lag (number of time slots).

(3) Calculation of river confluence

The Muskingen piecewise continuous algorithm can be used to calculate river confluence in the prediction model, and the Muskingen flow calculus equation is:

\[
Q_{d,i} = C_0 Q_{a,i} + C_1 Q_{a,i} + C_2 Q_{a,i}
\]  

(9)

\[
C_0 = \frac{0.5\Delta t - kx}{k - kx + 0.5\Delta t} \quad C_1 = \frac{0.5\Delta t + kx}{k - kx + 0.5\Delta t} \quad C_2 = \frac{k - kx - 0.5\Delta t}{k - kx + 0.5\Delta t}
\]  

(10)

Where, C0, C1 and C2 are functions of k and x, and C0+C1+C2= L.

According to the inflow \(Q_{a,i}\), \(Q_{a,i}\) and the initial flow of the period \(Q_{d,1}\), the end flow \(Q_{d,2}\) of the period can be deduced from the above formula. By continuous calculation of each period, the outflow process line Qd (t) of the lower section can be obtained.

Therefore, for the total runoff yield of the arid area using the Northern Shaanxi model as the runoff generation model, the following equation can be obtained:

\[
Q = R + Q_t + Q_d(t)
\]  

(11)

Where: Q is the total runoff, R is the runoff, Qt is the slope catchment, Qd(t) is the river catchment.

3.1.2. Model parameters calibration

If the Holden infiltration equation is used in the runoff generation structure of the Northern Shaanxi model, There are 11 parameters such as evapotranspiration reduction coefficient KC, tension water storage capacity θm, basin impervious ratio FB, infiltration capacity f0 in the driest period, stable infiltration rate fc, coefficient K of Holden infiltration curve equation, parameter B of infiltration capacity distribution curve, surface runoff regression coefficient CS, concentration time L, muskingen parameter k and muskingen parameter x. In the study, the parameter calibration is carried out by discrete ergodic optimization within the feasible range. The steps are as follows:

Step 1: according to the actual situation, determine the approximate feasible value range of each parameter.

Step 2: determine a discrete precision, and discretize each parameter into a series of discrete values within the feasible range.
Step 3: Based on the principle of two-stage step-by-step optimization of classic dynamic programming algorithm POA, the objective is to minimize the sum of squares of errors between predicted and measured values to optimize each parameter.

Step 4: output the optimal parameters.

In the optimization process, it is assumed that the forecast flow series of the forecast section is \( Q_t \) \((t=1,2...,T)\), the corresponding measured incoming flow series is \( \tilde{Q}_t \) \((t =1,2...,T)\), then the objective function of parameter optimization can be expressed as:

\[
\text{Err} = \sum_{t=1}^{T} (Q_t - \tilde{Q}_t)^2, \quad t = 1,2...,T 
\]  \( (12) \)

Where \( T \) is the total forecast period.

3.2. Temperature - Snowmelt model

In the basin where The Dashimen Reservoir is located, there is less precipitation in the dry season, and the upstream flood gully dries up in the dry season. The runoff in the basin is mainly the groundwater that melts the upstream in front of the mountain and seeps into the slope, while the water in the downstream is exposed in the form of spring, and the change is relatively slow. In upstream uruk with Sue and alaa, rick river will shut above, due to the upstream will shut above higher elevation, river basin upstream snowmelt runoff is mainly is given priority to, change is slow, gentle fluctuation change, and closely related to the process of temperature rise, therefore can be based on neural network model to establish the upstream HuiGeKou flow section and the temperature of the relevant factors such as temperature, the early historical runoff - snowmelt model.

Compared with traditional forecasting methods, the application of neural network model in flood forecasting has the following advantages [30]: 1. The basin situation is complex and the boundary conditions are difficult to determine, and the neural network has strong adaptability to deal with the complicated situations such as ambiguous and incomplete information; 2. Flood forecasting involves many factors, and the neural network model can take into account the influence of various related factors as much as possible; 3. Affected by climate, engineering, riverbed, etc., the rule of reservoir inflow will also change accordingly The neural network can find a new weight to adapt to the changing demand by retraining the network under the condition of increasing data.

Common neural network models include Elman neural network, deep neural network, support vector machine, etc. Here, only the Elman neural network with good simulation results is introduced.

3.2.1. Model principle

The main goal of Elman neural network is to minimize the mean square deviation between the actual output and the expected output of the model. The error gradient distribution technique is adopted to search for the optimal connection weight of each neuron. There is a special middle layer in Elman neural network, which is called association layer (or connection unit layer). Each neuron of this layer is connected with a hidden layer neuron, whose main function is to retain the signal of the corresponding hidden layer neuron at the previous moment, and pass it into the hidden layer at the current moment, so as to complete the state feedback process and improve the learning efficiency and simulation accuracy of the model.

The topology of the model is shown in Figure 2.
In runoff forecasting, the output is only the predicted flow value, so the number of neurons in the output layer is 1. In the theoretical case, Elman neural network can achieve the fitting of all nonlinear relations, and the modeling process can be completed only according to the expected output of appropriate input factors.

3.2.2. Model structure

Assuming that in the Elman neural network, the number of neurons in the input layer is \( n \) and the number of neurons in the hidden layer is \( m \), the number of neurons in the associated layer is also \( m \), the input signal is \( x \), the time value is \( t \), the current time state of the hidden layer is \( s \), the previous time state of the hidden layer is \( S_c \), and the output signal is \( y \).

Then the output expression of neurons in the output layer of the model is:

\[
y(t) = g(w^3 s(t) + b_2)
\]

(13)

Where, \( g(.) \) is the operation function of the output layer, \( b_2 \) is the threshold value of the hidden layer neurons, \( w^3 \) is the weight of the hidden layer, \( s(t) \) is the output of the hidden layer neurons at time \( t \), and is expressed as:

\[
s(t) = f(w^1 s_c(t) + w^2 x(t - 1) + b_1)
\]

(14)

Where, \( w^1 \) is the weight of the associated layer, \( f(.) \) is the operation function of the hidden layer neurons, \( w^2 \) is the weight of the input layer, \( b_1 \) is the threshold value of the hidden layer neurons, \( S_c(t) \) is the state of the associated layer neurons at time \( t \), and can be expressed as:

\[
s_c(t) = s(t - 1)
\]

(15)

Elman neural network model uses the error gradient descent algorithm as the learning algorithm. Its purpose is to get the difference between the actual output and the expected output of the model. Through the gradient descent method, the connection weight and threshold value of each neuron are modified, so as to minimize the square sum of model error. Let the actual output of the model in the process of iteration \( t \) be \( y_d(t) \), then in the period \([0, T]\), the error function is defined as:

\[
E = \frac{1}{2} \sum_{t=0}^{T} [y_d(t) - y(t)]^2
\]

(16)

The partial derivative of the error \( E \) with respect to \( w^2 \) can be obtained, and the modified equation of the weight can be written:
Similarly, the partial derivative of the error $E$ with respect to $w_3$ can be obtained, and the modified equation of the weight can be written:

$$
\Delta w_3'(t+1) = (1 - mc)\eta(y_j(t) - y(t))f'(\chi)(t) + mc\Delta w_3(t)
$$

(18)

Where, $\eta$ is the learning rate and $mc$ is the momentum factor.

In order to improve the accuracy of the temperature-snow melting model, the effect of time delay should be considered in this process. The influence of time lag describes the influence of the time lag effect of outlet runoff relative recharge amount on the parameters of the temperature-snowmelt model [31]. As snowmelt runoff is characterized by daily fluctuation, the time lag length is obtained by comparing the measured air temperature series and flow process.

3.3. Flood forecasting model of Dashimen reservoir coupled with snow melting

3.3.1. Model principle

Because the Northern Shaanxi model is an over infiltration runoff model, only when the rainfall is greater than the infiltration, runoff will be generated. Therefore, when there is no rainfall, the runoff calculated by the model is zero, which obviously does not conform to the actual situation. The northwest arid area where Dashimen reservoir is located is a sensitive area of climate change. Water resources mainly come from rainfall and alpine snow melting affected by temperature. Temperature mainly affects the melting speed of alpine ice and snow, evapotranspiration on the basin surface, and the source form of river water volume. Therefore, when there is no rainfall, the river base flow in this area has a strong correlation with temperature.

Aiming at the situation of snow melting in arid areas of Northwest China, a flood forecasting model coupled with snow melting is established. The runoff calculated by the temperature snow melting model is taken as the base flow, and the discharge value calculated by the excess infiltration runoff generation model is taken as the final runoff.

Therefore, the flood forecasting model equation coupled with snow melting in arid area is as follows:

$$
R_{sum} = Q + y(t)
$$

(19)

Where: $R_{sum}$ is the total runoff, $Q$ is the runoff of the infiltration runoff model, $y(t)$ is the temperature snow melting model runoff.

3.3.2. Model structure

In this article, according to the distribution map of the stations of the Dashimen Water Conservancy Project's automatic hydrological forecasting system. The forecast area is divided into three parts with the upper reaches of the Uruksuhe River and Arayalike River junction, Qiqihalke and Dashimen Reservoir as the boundary. The temperature-snowmelt model is used to model the sections that are significantly affected by snowmelt, including Qiqihalke and the upstream confluence, and the interval of the forecast area is modeled based on the flood forecast model in arid areas, and finally the calculation results are superimposed to obtain Dashimen The flow process of the reservoir. The technical roadmap is shown in Figure 3.
4. Results and analysis

In this paper, based on the two typical rainfall runoff processes in the data, the parameters of the model are calibrated by using the flood forecasting model coupled with snow melting in arid area, and the quasi forecast calculation is carried out. The prediction results are compared with the measured results, and the relative error of prediction is calculated.

4.1. Flood forecasting model in arid area

Aiming at the Northern Shaanxi model in this model, 11 parameters such as evapotranspiration reduction coefficient (KC) were calibrated by using the collected data, and a better set of parameters were obtained. The parameter results after calibration are as follows:

| Serial number | Parameter | Optimized parameter values | Serial number | Parameter | Optimized parameter values |
|---------------|-----------|----------------------------|---------------|-----------|----------------------------|
| 1             | KC        | 0.25                       | 7             | B         | 2                          |
| 2             | 0m        | 80                         | 8             | CS        | 0.7                        |
| 3             | FB        | 0.7                        | 9             | L         | 2                          |
| 4             | f0        | 18                         | 10            | k         | 3                          |
| 5             | fc        | 80                         | 11            | x         | 0.2                        |
| 6             | K         | 0.9                        |               |           |                            |

For the temperature-snowmelt model, it is assumed that the daily temperature change rule in each month is basically unchanged, and the daily flood forecast model is established monthly. According to
the analysis of the actual situation of the river basin, the prediction impact factors selected for the model in the research work are:

① forecast before three days of traffic.
② the day before the interval temperature.
③ forecast ten-day average flow rate.

So the number of input layer neurons and selection of forecast factors corresponding to three. Numbers of hidden layer neurons to be determined by empirical formula, and then determined by experiment many times for 13, corresponding link layer neuron number for 13, because only a set of output as a result, the number of neurons in output layer is 1. The expected error threshold specified in the model is 0.001, the maximum number of iterations is 10,000, and the learning efficiency is 0.01.

Table 3. The number of neurons in each model layer of Elman neural network

| Input layer | Hidden layer | Link layer | Output layer |
|-------------|--------------|------------|--------------|
| 3           | 13           | 13         | 1            |

4.2. Model test

According to the optimization results of model parameters, the accuracy evaluation tables of medium and short-term prediction rates and inspection periods were obtained respectively, as shown in Table 4 and 5.

Table 4. Accuracy evaluation table for calibration and inspection periods of medium and long term forecast

| Model | Period   | Average relative error | Root-mean-square error | Certainty coefficient | Percent of pass |
|-------|----------|------------------------|------------------------|-----------------------|-----------------|
| ELman | Calibration period | 0.291 | 7.91 | 0.734 | 40.9% |
|        | Inspection period      | 0.264 | 13.71 | 0.633 | 42.5% |

Table 5. Accuracy evaluation table for calibration and inspection periods of short-term forecast

| Period       | Foresight period | Average relative error | Root-mean-square error | Certainty coefficient | Percent of pass |
|--------------|------------------|------------------------|------------------------|-----------------------|-----------------|
| Calibration period | 1d  | 0.04 | 1.36 | 0.83 | 100% |
|               | 2d  | 0.05 | 1.50 | 0.79 | 98%  |
|               | 3d  | 0.05 | 1.70 | 0.73 | 98%  |
| Inspection period | 1d  | 0.10 | 5.64 | 0.88 | 92%  |
|               | 2d  | 0.15 | 9.25 | 0.65 | 78%  |
|               | 3d  | 0.20 | 12.21 | 0.39 | 68%  |

Through the model, we can get the runoff process of Dashimen reservoir for calibration and inspection periods of medium and long-term forecast, as shown in Figure. 4 and Figure. 5.
Figure 4. Flow process diagram of Dashimen Reservoir for calibration periods of medium and long-term forecast

Figure 5. Flow process diagram of Dashimen Reservoir for inspection periods of medium and long-term forecast

It can be seen from Table 4 and Figure 3 and 4 that, for the medium and long term forecast of Dashimen Reservoir, the predicted flow for inspection periods almost coincides with the measured flow, and the fitting effect of flow process line during the inspection period is also good. The mean relative error and root-mean-square error in the inspection period are both small, and the certainty coefficient is above 0.6. For small river basins, the forecast effect is good, which can be used in the forecast.

The model is used to obtain the runoff process of Dashimen Reservoir for calibration and inspection periods of the short-term forecast, as shown in Figure 6 and 7.
Figure 6. Flow process diagram of Dashimen Reservoir for calibration periods of the short-term forecast
Figure 7. Flow process diagram of Dashimen Reservoir for inspection periods of the short-term forecast.
It can be seen from Table 5 and Figure 5 and 6 that, for the short-term forecast of Dashimen Reservoir, the predicted flow during the inspection period is in high agreement with the measured flow, and the prediction results of the inspection period have a large error, but the trend of flow change can be generally predicted, mainly because of the short data series and the low accuracy of the model.

4.3. Forecast results

The predicted runoff process and measured runoff process of the two rainfall events are shown in the figure below.

![Figure 8](image8.png)

**Figure 8** The forecasting process of the first typical rainfall and the measured runoff process

![Figure 9](image9.png)

**Figure 9** The forecasting process of the second typical rainfall and the measured runoff process

It can be seen from the above figure that in these two typical rainfall events, the prediction results calculated by the model are compared with the measured process of Dashimen reservoir, and it is found that the fitting accuracy of the forecast value and the measured value is good. Except for a few periods, the relative error of the forecast in other periods is within a certain range, and the relative error of the first rainfall runoff process is 3.0%. The average relative error of the second rainfall runoff process is 10.0%, the error is within 20%.
At the same time, the mathematical statistics method is used to evaluate the forecast results quantitatively. The forecast error indexes used include average relative error, average absolute error, certainty coefficient, root mean square error, etc. The forecast evaluation results are shown in Table 6.

| Forecast error index | Mean absolute error | Average relative error | Coefficient of certainty | Root mean square error |
|----------------------|---------------------|------------------------|--------------------------|------------------------|
| The first typical rainfall | 2.659               | 0.03                   | 0.999                    | 2.851                  |
| The second typical rainfall | 8.64                | 0.1                    | 0.99                     | 11.38                  |

It can be seen from the above table that the average absolute error, relative error and root mean square error are all small, and the certainty coefficient is very close to 1, which indicates that the prediction process has a high degree of coincidence with the measured process, the prediction error is small, and the accuracy is high, which can be used in the actual forecast operation.

5. Conclusions
In this paper, based on the coupled snowmelt flood forecasting model in arid areas, taking the typical rainfall runoff process of Dashimen reservoir in Xinjiang as an example, the flood forecasting results of the model are verified by the measured data. The results show that the relative prediction error is less than 10%, and the prediction error indicators show that the prediction process is consistent with the measured process. Compared with the traditional model, this model has obvious advantages and can be used in practical forecast. The flood forecasting model coupled with snow melting in arid areas further enriches the flood forecasting methods in northwest arid areas affected by snow melting, and provides new ideas and research methods for flood forecasting in this area, and has certain significance for flood forecasting research in Northwest China.

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References
[1] Tehranirad, B.; Herdman, L.; Nederhoff, K.; Erikson, L.; Cifelli, R.; Pratt, G.; Leon, M.; Barnard, P. Effect of Fluvial Discharges and Remote Non-Tidal Residuals on Compound Flood Forecasting in San Francisco Bay. Water 2020, 12, 2481.
[2] Taherkhani, M.; Vitousek, S.; Barnard, P.L.; Frazer, N.; Anderson, T.R.; Fletcher, C.H. Sea-level rise exponentially increases coastal flood frequency. Sci. Rep. 2020, 10, 1–17.
[3] Hua, L.; Wan, X.; Wang, X.; Zhao, F.; Zhong, P.; Liu, M.; Yang, Q. Floodwater Utilization Based on Reservoir Pre-Release Strategy Considering the Worst-Case Scenario. Water 2020, 12, 892.
[4] McFarlane, D.; Stone, R.; Martens, S.; Thomas, J.; Silberstein, R.; Ali, R.; Hodgson, G. Climate change impacts on water yields and demands in south-western Australia. J. Hydrol. 2012, 475, 488–498.
[5] Dettinger, M.D.; Ralph, F.M.; Das, T.; Neiman, P.J.; Cayan, D.R. Atmospheric rivers, floods and the water resources of California. Water 2011, 3, 445–478.
[6] Zhai, M.; Lin, Q.; Huang, G.; Zhu, L.; An, K.; Li, G.; Huang, Y. Adaptation of cascade hydropower station scheduling on a headwater stream of the Yangtze River under changing climate conditions. Water 2017, 9, 293.
[7] Windsor, J.S. Optimization model for the operation of flood control systems. Water Resour. Res. 1973, 9, 1219–1226.
[8] Huang Zengyu. Uniform design and its application in reservoir optimal dispatching [D]. Henan University, 2019.

[9] Liu Pan, Zhang Xiaqi, Deng Chao, Feng Maoyuan, Gao Shida, Zhang Wei. A preliminary study on the adaptive dispatching of reservoirs[J]. People's Yangtze River, 2019, 50(02): 1-5+12.

[10] Yun, R.; Singh, V.P. Multiple duration limited water level and dynamic limited water level for flood control, with implications on water supply. J. Hydrol. 2008, 354, 160–170.

[11] Diao, Y.; Wang, B. Scheme optimum selection for dynamic control of reservoir limited water level. Sci. China Technol. Sci. 2011, 54, 2605–2610.

[12] Zhou, Y.; Guo, S.; Chang, F.; Liu, P.; Chen, A.B. Methodology that improves water utilization and hydropower generation without increasing flood risk in mega cascade reservoirs. Energy 2018, 143, 785–796.

[13] Chang, J.; Guo, A.; Du, H.; Wang, Y. Floodwater utilization for cascade reservoirs based on dynamic control of seasonal flood control limit levels. Environ. Eath Sci. 2017, 76, 1–12.

[14] Guo Shenglian, Chen Jionghong, Liu Pan, Li Yu. Research progress and prospect of joint optimal operation of reservoir groups[J]. Advances in Water Science, 2010, 21(04): 496-503.

[15] Shen Huying, Qiu Hui, Xing Wenhui et al. Study and application of hydrological models for midterm forecasting of the inflow of the Three Gorges Reservoir[J]. Yangtze River, 2019, 50(10): 94-99+125.

[16] Bao Weimin. Hydrological forecasting [M]. Beijing: China Water Power Press, 2009.

[17] Zhang Jianyun. Review and reflection on the development of hydrological forecasting technology in China[J]. Advances in Water Science, 2010, 21(04): 435-443.

[18] Wang, Y.; Liu, R.; Guo, L.; Tian, J.; Zhang, X.; Ding, L.; Wang, C.; Shang, Y. Forecasting and providing warnings of flash floods for ungauged mountainous areas based on a distributed hydrological model. Water 2017, 9, 776.

[19] Chen, J.; Zhong, P.-A.; Wang, M.-L.; Zhu, F.-L.; Wan, X.-Y.; Zhang, Y. A risk-based model for real-time flood control operation of a cascade reservoir system under emergency conditions. Water 2018, 10, 167.

[20] Tehranirad, B.; Herdman, L.; Nederhoff, K.; Erikson, L.; Cifelli, R.; Pratt, G.; Leon, M.; Barnard, P. Effect of Fluvial Discharges and Remote Non-Tidal Residuals on Compound Flood Forecasting in San Francisco Bay. Water 2020, 12, 2481.

[21] Li Yan, Hu Jun, Wang Jinxing, Liu Song, Zhang Silong. Research on the application of river ensemble forecasting (ESP) in medium and long-term prediction of water resources[J]. Hydrology, 2008(01): 25-27.

[22] Liang Guohua, Zhang Wen, He Bin, Feng Jiaojiao. Research and application of watershed hydrological model identification method[J]. People's Yangtze River, 2019, 50(01): 53-57.

[23] Jabbari, A.; So, J.-M.; Bae, D.-H. Precipitation Forecast Contribution Assessment in the Coupled Meteo-Hydrological Models. Atmosphere 2020, 11, 34.

[24] Todini, E. Hydrological catchment modelling: Past, present and future. Hydrol. Earth Syst. Sci. 2007, 11,468–482.

[25] Zhang Yong, Liu Shiyin. Progress in the application of degree-day models in the study of glaciers and snow[J]. Glaciology and Geocryology, 2006(01): 101-107.

[26] Marks D, Kimball J, Tingey D, et al. The sensitivity of snowmelt processes to climate conditions and forest cover during rain-on-snow:A case study of the 1996 Pacific Northwest flood[J]. Hydrological Processes, 1998, 12 (10-11) :1569-1587.

[27] Kim, B.; Choi, S.Y.; Han, K.-Y. Integrated Real-Time Flood Forecasting and Inundation Analysis in Small–Medium Streams. Water 2019, 11, 919.

[28] Wang Sheng. Research on hydrological forecasting method based on neural network [D]. Huazhong University of Science and Technology, 2013.

[29] Mu Zhenxia, Jiang Huifang. Precipitation law and snowmelt runoff simulation in alpine mountainous area[M]. Beijing: China Water Power Press, 2015: 13.
[30] Xiao Xingtao, Zhang Shuxia. The application of neural network theory in the spring inflow forecast of Mopanshan Reservoir[J]. Heilongjiang Water Conservancy Science and Technology, 2011, 39(03): 266-267.

[31] Zhang Yichi, Li Baolin, Bao Anming, Zhou Chenghu, Chen Xi, Zhang Xueren. Simulation of snowmelt runoff in the Kaidu River Basin[J]. Science in China. Series D: Earth Science, 2006(S2): 24-32.