System response curve correction method of runoff error for real-time flood forecast

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ABSTRACT

Multiple factors including rainfall and underlying surface conditions make river basin real-time flood forecasting very challenging. It is often necessary to use real-time correction techniques to modify the forecasting results so that they reach satisfactory accuracy. There are many such techniques in use today; however, they tend to have weak physical conceptual basis, relatively short forecast periods, unsatisfactory correction effects, and other problems. The mechanism that affects real-time flood forecasting error is very complicated. The strongest influencing factors corresponding to this mechanism affect the runoff yield of the forecast model. This paper proposes a feedback correction algorithm that traces back to the source of information, namely, modifies the watershed runoff. The runoff yield error is investigated using the principle of least squares estimation. A unit hydrograph is introduced into the real-time flood forecast correction; a feedback correction model that traces back to the source of information. The model is established and verified by comparison with an ideal model. The correction effects of the runoff yield errors are also compared in different ranges. The proposed method shows stronger correction effect and enhanced prediction accuracy than the traditional method. It is also simple in structure and has a clear physical concept without requiring added parameters or forecast period truncation. It is readily applicable in actual river basin flood forecasting scenarios.

Key words | correction method, error distribution, hydrologic forecast, real-time forecasting, system response curve, unit hydrograph

HIGHLIGHTS

- From the perspective of system theory, an RSCR method to modify production flow is proposed.
- This method uses the system response curve feedback of the production flow in each period to correct the production flow in each period.
- The validity and practicability of the method are proved by numerical simulation experiments with different random distribution errors.

INTRODUCTION

When a hydrological model is directly applied for flood forecasting, observation errors, model structure errors, parameter selection errors, and initial state errors degrade the forecast accuracy below relevant requirements (Yapo et al. 1996; Yu & Chen 2005; Bao 2006; Giulia & Fabio 2017). It is necessary to ensure accurate real-time correction of flood forecast errors to resolve this problem (Goswani et al. 2005; Liu 2012; Wang et al. 2017).
Real-time flood forecast error correction serves to resolve the error factors in real-time which would alter the representation of the actual flood in the hydrological model for a river basin (Broersen & Weerts 2005; Moradkhani et al. 2012; Liu & Han 2013). This correction system can be used to obtain real-time information regarding rainfall, flooding, and all other available factors. Real-time information corrects forecast errors in real time (Hartnett & Nash 2017). The structure, parameters, state variables, or input values of the original model are constantly corrected and updated based on new information so that the forecast results gradually approximate the true values (Qin et al. 2018a, 2018b).

Today’s commonly used correction methods include the autoregressive correction technique, Kalman filter correction, wavelet analysis, artificial neural network (Babovic et al. 2001; Trushnamayee et al. 2019), and chaos theory (Bogner & Kalas 2008; Pagano et al. 2011). These methods can process the latest forecast errors of hydrological systems in real time and use them as the basis for correcting the model parameters, states, and forecasted output values to allow the system to quickly adapt to the current situation (Jiang et al. 2016). The methods are effective to some extent for the real-time correction of flood forecasting errors (Madsen & Skotner 2005; Looper & Vieux 2012; Li et al. 2016; Si et al. 2019) but show some persistent deficiencies.

1. **Deficient theoretical basis.** Existing algorithms center on the differences between measured and calculated values at the exit section of the basin, that is, the residuals. For example, the autoregressive correction technique works based on the correlation between a series of residuals; it is believed that there is a correlation between the previous residual series and the following residual series. There is also a p-order autoregressive (AR) model available for error estimation. In a real-time flood forecasting scenario, however, errors occurring at different times do not meet such assumptions. For example, near the peak of the flood, there will be sudden changes in the flow and the errors are not related. If the AR model is used for correction, the result will not be ideal.

2. **Truncated forecast period.** Using the information from the errors between the measured and calculated flow at the exit section to establish an AR model (Todini & Jones 1977) and further correcting the flow calculation process severely shortens the forecast period.

3. **Additional parameters are necessary.** The newly established error correction AR model requires that new parameters be introduced in addition to the structure of the prediction model. The additional parameter estimation creates new parameter estimation errors.

4. **Insufficient information available for error correction.** Many of the algorithms mentioned above are widely used in fields other than flood forecasting error correction. The Kalman filtering technique (Kalman 1960; Wood & Szollosi 1978), for example, is mainly used in communication and industrial automatic control applications. This method is highly complex and can accommodate a large amount of information but rarely provides sufficient information for real-time flood forecasting correction (Qu & Bao 2005; Weerts & El 2006; Wu et al. 2013). In this context, it performs similarly to the simple AR correction model, which greatly restricts its practical use.

There is a demand for an effective error correction technique with physical meaning to support accurate real-time flood forecasting. Errors emerge in the real-time flood forecasting system for many reasons and the mechanism that affects these errors is complicated. Inductive analysis of these factors suggests that most of them affect the runoff yield of the forecast model. In view of this, a feedback correction method was established in this study that traces back to the source of information.

The concept of the response curve of the linear confluence model system was developed first. The resultant linear response model system response matrix feedback was then used to correct the outlet cross-section flow error. In other words, the runoff yield of the basin period was corrected and the corrected runoff was substituted into the model to recalculate the flow correction result of the river basin outlet section. It is important to emphasize that this method uses runoff as an input variable; each stage after runoff is a distinct system and the output is the streamflow of the outlet. The key to operating this method is to replace the correction of flow error of the outlet with the correction of the runoff process.
METHODOLOGY

Introduction to flow concentration system

The river basin flow concentration can be regarded as a system. The input is the net rain process and the output is outlet section flow process (Figure 1).

In this system, the flow process at the catchment outlet can also be referred to as the response of the basin to the process of net rainfall, or simply, the ‘river basin response’. The relationship between river basin response \( Q(t) \) and net rainfall input \( I(t) \) can be expressed as follows:

\[
Q(t) = \Phi[I(t)]
\]

where \( \Phi \) is an operator denoting the operational relationship between the system input and response (Bao 2006).

Basin runoff is the first link in the formation of flow. It is a dynamic concept that presents spatial-temporal changes including the spatial development of runoff yield area at different times, as well as changes in runoff generation intensity over time as rain falls. The runoff is generated mainly on the slope of the basin; its role in the system may be very complicated (Zhao 1992). The proportions of the slope area are different in different basins as well. Various factors that influence the runoff generation on the slope, including vegetation, soil, slope ratio, land use, slope area, and location perform differently in basins of different sizes.

Therefore, there are many influencing factors in the runoff model simulation and the errors are complicated.

As shown in Figure 2, after runoff is generated in the river basin, the runoff yield \( R \) enters the confluence stage. The confluence stage can be divided into two sub-stages: overland confluence and river network confluence. To facilitate the simplification of the confluence structure, before the overland confluence, the runoff yield \( R \) is divided into surface water, subsurface water, and groundwater portions each with different respective confluence characteristics; they participate in the calculation independently. Finally, they converge into the river basin outlet section at the river network confluence stage.

Runoff correction method based on the system response curve (RSRC)

The confluence part of the hydrological forecast model is regarded as a system. The response function of the system can be expressed as follows:

\[
Q(t) = Q(X(t), \theta, t)
\]

where \( X(t) \) represents various variables in the model (input variables, intermediate state variables of the model) and \( \theta \) represents parameters of the model. The parameters \( \theta \) of the model can be adjusted to simulate the hydrological response characteristics of a basin, and, once calibrated, generally do not change in the short term (Bárdossy & Singh 2008; Smith et al. 2014). The variable \( t \) represents time. Any change in the parameters or variables in the above formula influences the flow at the outlet section of
the basin, that is, there is a response process. The parameters of the model do not change within any certain period of time.

Only the system response caused by the changes in the runoff yield \( R \) was considered in this study; no response caused by other variables is discussed here. Formula (2) can thus be rewritten as:

\[
Q(t) = Q(R, \theta, t)
\]

where \( R = [r_1, r_2, r_3, \ldots, r_n]^T \) indicates the runoff yield series. After performing total differential equation of the above system response functions, then:

\[
dQ = \frac{\partial Q}{\partial R} dR
\]

where \( R = [r_{C1}, r_{C2}, r_{C3}, \ldots, r_{Cn}]^T \) is the initial series value of the calculated runoff yield, \( \Delta R = [\Delta r_1, \Delta r_2, \Delta r_3, \ldots, \Delta r_n]^T \) is the error value of the runoff yield, \( Q(R, \theta, t) \) is the measured flow process \( Q_O \), and \( Q(R_C, \theta, t) \) is the calculated flow process \( Q_C \) at the outlet section of the basin.

\[
\begin{align*}
Q_R(R_C, \theta, t)\Delta R &= \left. \frac{\partial Q(R, \theta, t)}{\partial r_1} \right|_{R=R_C} \Delta r_1 + \left. \frac{\partial Q(R, \theta, t)}{\partial r_2} \right|_{R=R_C} \Delta r_2 + \cdots + \left. \frac{\partial Q(R, \theta, t)}{\partial r_n} \right|_{R=R_C} \Delta r_n
\end{align*}
\]

(5)

It is assumed that the length of the sample series is \( T \) and \( Q(t) = [Q_1, Q_2, Q_3, \ldots, Q_T]^T \). \( T \) is substituted into Formula (5) to obtain:

\[
\begin{align*}
Q(R, \theta, 1) &= Q(R_C, \theta, 1) + \left. \frac{\partial Q(R, \theta, 1)}{\partial r_1} \right|_{R=R_C} \Delta r_1 + \left. \frac{\partial Q(R, \theta, 1)}{\partial r_2} \right|_{R=R_C} \Delta r_2 + \cdots + \left. \frac{\partial Q(R, \theta, 1)}{\partial r_n} \right|_{R=R_C} \Delta r_n \\
Q(R, \theta, 2) &= Q(R_C, \theta, 2) + \left. \frac{\partial Q(R, \theta, 2)}{\partial r_1} \right|_{R=R_C} \Delta r_1 + \left. \frac{\partial Q(R, \theta, 2)}{\partial r_2} \right|_{R=R_C} \Delta r_2 + \cdots + \left. \frac{\partial Q(R, \theta, 2)}{\partial r_n} \right|_{R=R_C} \Delta r_n \\
&\vdots \\
Q(R, \theta, T) &= Q(R_C, \theta, T) + \left. \frac{\partial Q(R, \theta, T)}{\partial r_1} \right|_{R=R_C} \Delta r_1 + \left. \frac{\partial Q(R, \theta, T)}{\partial r_2} \right|_{R=R_C} \Delta r_2 + \cdots + \left. \frac{\partial Q(R, \theta, T)}{\partial r_n} \right|_{R=R_C} \Delta r_n
\end{align*}
\]

(6)

The matrix form of Formula (6) is:

\[
Q(R, \theta, t) = Q(R_C, \theta, t) + U\Delta R + E
\]

(7)

where \( \Delta R \) is the magnitude of error of the runoff yield to be solved. \( E = [e_1, e_2, e_3, \ldots, e_T]^T \) is the error term and the white noise vector. The expression of the \( U \) matrix is:

\[
U = \begin{bmatrix}
\frac{\partial Q(R, \theta, 1)}{\partial r_1} & \cdots & \frac{\partial Q(R, \theta, 1)}{\partial r_n} \\
\frac{\partial Q(R, \theta, 2)}{\partial r_1} & \cdots & \frac{\partial Q(R, \theta, 2)}{\partial r_n} \\
\vdots & \ddots & \vdots \\
\frac{\partial Q(R, \theta, T)}{\partial r_1} & \cdots & \frac{\partial Q(R, \theta, T)}{\partial r_n}
\end{bmatrix}
\]

(8)

Each term in the \( U \) matrix of the above formula can be solved by the difference approximation of the following formula:

\[
\frac{\partial Q(R, \theta, t)}{\partial r_i} = Q(r_1, \ldots, r_i + \Delta r_i, \ldots, \theta, t) - Q(r_1, \ldots, r_i, \ldots, \theta, t)
\]

(9)

where \( t = 1 \ldots T, \ i = 1 \ldots n \). When \( i \) does not change and \( t \) changes from 1 to \( T \), the \( T \) term difference value is a column in the \( U \) matrix. This column is exactly the system response series corresponding to the unit variation of runoff yield \( r_i \), which is referred to here as the system response curve corresponding to the runoff yield \( r_i \). This response curve is influenced by the runoff yield values in other periods. The runoff yield series changes in real time over time, so the system response curve corresponding to the runoff yield \( r_i \) also changes dynamically.
The formula for calculating the correct amount of the runoff yield from Formula (6) is:

$$\Delta R = (U^T U)^{-1} U^T (Q(R, \theta, t) - Q(R_c, \theta, t))$$

(10)

and the corrected runoff yield series is:

$$R_c = R_c + \Delta R$$

(11)

where $R_c$ must satisfy $R_c' \geq 0$ and when $PE > 0$, $R_c' \leq PE$.

$R_c$ in Equation (11) can be substituted into the calculation model for recalculating. The final correction result can then be obtained as follows:

$$Q'(R, \theta, t) = Q(R_c, \theta, t) + U \Delta R$$

(12)

$\partial Q / \partial R$ in Equation (4) is the system response curve. The $U$ matrix in Equation (8) is a system response matrix composed of the system response curve of the number of correction periods. Equations (11) and (12) constitute the runoff error correction model (RSRC).

The system response curve starts from the structure of the calculation model. Only the runoff errors were considered in the model calculation in this study. The outlet section flow error series calculated by the model corrects the runoff yield in each period through the system response curve feedback of the runoff yield in each period.

The final confluence error process is typically the only process utilized and is also the largest source of calculation errors in the model. The method proposed in this paper (RSRC) brings the correction one step closer to the runoff generation correction, which fundamentally resolves problems inherent to traditional real-time correction methods. RSRC is based on the model structure itself and has a physical basis. It makes full use of real-time forecasting information for the purpose of correction without losing the model’s forecast period and without necessitating additional parameters.

**NUMERICAL SIMULATION AND ANALYSIS**

**Numerical simulation case**

As discussed below, an ideal model with a unit hydrograph of confluence as the structure was used to verify the correctness, rationality, and effectiveness of the proposed runoff correction method. The ‘ideal model’ is one in which all terms of inputs, outputs, and errors are known (Bao et al. 2013a, 2013b). The structure of the ideal model is shown below.

As shown in Figure 3, with the system response curve matrix composed of the unit hydrograph, the runoff $R$ is converted into an outlet flow process. This can be expressed as follows:

$$Q = U \times R$$

(13)

where

$$Q = \begin{bmatrix} q_1 \\ q_2 \\ \vdots \\ q_m \end{bmatrix}; \quad U = \begin{bmatrix} u_1 & 0 & \cdots & \cdots & 0 \\ u_2 & u_1 & \cdots & \cdots & \cdots \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ u_p & u_{p-1} & \cdots & \cdots & u_1 \end{bmatrix}; \quad R = \begin{bmatrix} r_1 \\ r_2 \\ \cdots \\ r_p \end{bmatrix}$$

$Q$ is the flow process of the outlet; $U$ is a matrix composed of the unit hydrograph of the confluence curve and each column in the matrix is the confluence curve of the basin. $R$ is the runoff yield vector. $U$ is an $m \times p$-dimensional matrix composed of the unit hydrograph ordinates; the matrix is a lower triangular matrix.

The runoff depths of six periods were used as the model inputs. The single unit hydrograph and double unit hydrograph with the period rainfall as the variable were used as
the confluence structures that were substituted into the model for calculation. The calculated value output by the model is a true value. The errors of different distributions were added to the true value. Based on the system response curve, the runoff yield was corrected by the error series feedback of the basin outlet with different probability distributions.

**Case for single system response curve (RSRC-S)**

The unit hydrograph does not consider the uniformity of the net rain and the underlying surface and regards the basin as a whole. The system response of the runoff yield per period is the unit hydrograph itself. The unit hydrograph selected for this analysis is shown in Figure 4. An ideal model was obtained to calculate the process line (Figure 5) based on the unit hydrograph and the net rain depth series of the six periods (Table 1).

Four error models were set for the runoff errors $\Delta R$, so four error models were used to validate the proposed method.

1. Uniform random distribution of error variation (−10% to +10% range);
2. Normal distribution with the mean of 0 and standard deviation of 0.05;
3. Uniform random distribution of error variation (−20% to +20% range);
4. Normal distribution with the mean of 0 and standard deviation of 0.1.

The four error models randomly generated 15 sets of samples as the measured flow series for the runoff generation error correction calculation. The error correction effects $Q(R, \theta, t)$ under different error distributions and the same error distribution with different amplitudes of variation were checked. The true value series were calculated by the true value of the runoff generation and the true value of the unit hydrograph. The system white noise, in this case, was a random sequence with a mean value of 0 and a range of ±10% of the flow value.

**Case for double system response curve**

Under a single system response curve, the linear system is a practical and effective method for runoff yield feedback correction. At this point, the results have yet to be verified for a changing system response curve. Runoff served as a variable for the purposes of this analysis. The criteria for the two unit hydrograph models varying with runoff in the study basin were established as follows:

- When $R \leq 10$ mm, unit hydrograph 1 was used;
- When $R > 10$ mm, unit hydrograph 2 was used.
Unit hydrographs 1 and 2 are shown in Figure 6. The unit hydrograph model and net rain depth series in six periods (Tables 6 and 7) form an ideal model to calculate the flow process line, as shown in Figure 7.

The errors uniformly and randomly distributed at (−20% to +20%) and those subject to N(0, 0.12) normal distribution were used as the variation range of calculation errors. Fifteen sets of samples were generated randomly as the respective measured flow series for the same correction calculation for runoff generation errors. The effectiveness of the fed-back corrected runoff with error series with different error distributions was tested under the double system response curve.

Real study case

The correction results of the actual basin flood using RSRC were analyzed to further validate the proposed correction method. The basin subjected to this case study is Qilijie Station, located in the northwest of Minjiang Basin. It features a drainage area of 14,787 km², a total river length of 215 km, and a river slope is 0.8‰. The average flow concentration time is about 15 h and the maximum value can reach 20 h. The climate is relatively humid and belongs to a semi-humid region. Per an analysis of given measurement data, 68.9% of the mean annual rainfall falls between March and June and evaporation is greatest between May and September. The average annual mean runoff is 15.9 billion m³ with a runoff depth of 1,076 mm.

 Twelve years of historical data (1988–1999) including hourly precipitation, pan evaporation, and discharge were used in this study. Hydrological data were used for the case study including daily and hourly rainfall/runoff and daily evaporation rate. The runoff data were calculated based on the change in the water level of the reservoirs. The rainfall data were obtained from rain gauges near the dams. The daily evaporation data were obtained by using daily evaporation pan data from an evaporation station near the dams. Hourly (30 flood event) data were used to test the performance of the flood forecasting correction method.

Evaluation criteria

In order to assess the accuracy of modeling results, several statistical indices were selected to judge the correction method performance including the Nash–Sutcliffe Efficiency (NSE)
coefficient (Nash & Sutcliffe 1970), the relative flood volume error ($\Delta W$), and the relative flood peak error ($\Delta TP$). The INS (percentage improvement of NSE, INS) was also computed as proposed by Si et al. (2015) to assess improvements to the NSE value resulting from the proposed method.

NSE:

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{LT} (QC_i - Q_i)^2}{\sum_{i=1}^{LT} (Q_i - \bar{Q})^2}$$  \hspace{1cm} (14)$$

Relative error of flood volume ($\Delta W$):

$$\Delta W = \frac{(W - W_m)}{W_m} \times 100\%$$  \hspace{1cm} (15)$$

Relative error of flood peak ($\Delta TP$):

$$\Delta TP = \frac{(TP - TP_m)}{TP_m} \times 100\%$$  \hspace{1cm} (16)$$
INS:

\[ \text{INS} = \frac{|\text{NSE}_t - \text{NSE}_{0t}|}{\text{NSE}_{0t}} \times 100\% \quad (17) \]

where \( Q_C \) and \( Q_t \) are the calculated and measured flow, respectively; \( Q \) is the average value of the flow and \( LT \) is the number of calculation periods. \( W_m \) is the measured flood volume; \( W \) is the calculated flood volume. \( TP_m \) refers to the measured flood peak and \( TP_t \) to the calculated flood peak. \( \text{NSE}_t \) indicates the NSE without correction and \( \text{NSE}_{0t} \) means the NSE with correction.

The relative flood volume error (\( \Delta W \)) and relative flood peak error (\( \Delta TP \)) measure the bias of model performance. The optimal value is 0.0, which means that the model has an unbiased flow simulation. An NSE value close to 1 means the model is of high quality and is highly reliable; NSE close to 0 means that the simulation results are close to the average value of the observed values, that is, the overall result is reliable, but the process simulation error is large. When NSE is far less than 0, the model is not credible.

### NUMERICAL RESULTS AND DISCUSSION

#### Single system response curve case

The errors generated by the four different distribution functions and the correction calculation results of the last 15 samples are shown in Tables 2–5.

The original model effect, corrected model effect, and correction effect were analyzed separately. \( \text{NSE}_{0t} \) represents the original model effect, indicating that from the perspective of the model alone, the fitting effect of model calculation and the measured series are uncorrelated with the real-time correction method. \( \text{NSE}_t \) represents the corrected model effect, i.e., the forecast effect of error correction performed by the model calculation plus real-time information (RSRC). As

#### Table 2 | Runoff correction results based on single system response curve with random distribution of error variation (±10%)  

| Measured value | Uncorrelated | Correlated |
|----------------|--------------|------------|
| \( W_m \) (mm) | \( TP_m \) (m\(^3\)s\(^{-1}\)) | \( W_t \) (mm) | \( TP_t \) (m\(^3\)s\(^{-1}\)) | \( \Delta W \) (%) | \( \Delta TP \) (m\(^3\)s\(^{-1}\)) | \( TP_t \) (m\(^3\)s\(^{-1}\)) | \( \Delta TP_t \) (%) | \( \text{NSE}_t \) | \( \text{NSE}_{0t} \) | \( \text{INS} \) |
|----------------|--------------|------------|----------------|----------------|----------------|----------------|----------------|---------------|----------------|----------------|----------------|
| 76.1           | 46,784       | 73         | −4.12          | 44,930         | −3.96          | 0.959          | 75.6           | −0.66         | 46,558         | −0.48          | 0.998          | 4.07           |
| 74.4           | 45,976       | 73         | −1.86          | 44,930         | −2.28          | 0.963          | 74.9           | 0.72          | 45,456         | −1.13          | 0.998          | 3.63           |
| 76.2           | 46,787       | 73         | −4.12          | 44,930         | −3.97          | 0.956          | 75.8           | −0.53         | 46,560         | −0.49          | 0.997          | 4.11           |
| 75.7           | 46,737       | 73         | −3.63          | 44,930         | −3.87          | 0.957          | 75.2           | −0.73         | 46,715         | −0.05          | 0.998          | 4.28           |
| 69.3           | 39,205       | 73         | 5.32           | 44,930         | 14.60          | 0.954          | 69.6           | 0.45          | 39,772         | 1.45           | 0.999          | 4.72           |
| 73.6           | 45,963       | 73         | −0.85          | 44,930         | −2.25          | 0.964          | 74.0           | 0.53          | 45,623         | −0.74          | 0.999          | 3.63           |
| 72.9           | 41,788       | 73         | 0.10           | 44,930         | 7.52           | 0.962          | 73.0           | 0.09          | 41,947         | 0.38           | 1.000          | 3.95           |
| 72.6           | 46,521       | 73         | 0.55           | 44,930         | −3.42          | 0.955          | 73.5           | 1.24          | 45,676         | −1.82          | 0.993          | 3.98           |
| 73.5           | 45,743       | 73         | −0.74          | 44,930         | −1.78          | 0.961          | 74.1           | 0.71          | 45,281         | −1.01          | 0.998          | 3.85           |
| 73.4           | 45,309       | 73         | −0.53          | 44,930         | −0.84          | 0.966          | 74.0           | 0.86          | 44,664         | −1.42          | 0.998          | 3.31           |
| 71.6           | 42,786       | 73         | 1.92           | 44,930         | 5.01           | 0.962          | 71.8           | 0.19          | 43,044         | 0.60           | 1.000          | 3.95           |
| 72.0           | 44,492       | 73         | 1.34           | 44,930         | 0.98           | 0.967          | 71.9           | −0.16         | 44,368         | −0.28          | 1.000          | 3.41           |
| 74.6           | 45,033       | 73         | −2.12          | 44,930         | −0.23          | 0.964          | 74.5           | −0.08         | 44,992         | −0.09          | 1.000          | 3.73           |
| 70.2           | 43,826       | 73         | 4.04           | 44,930         | 2.52           | 0.962          | 69.8           | −0.51         | 43,228         | −1.36          | 0.999          | 3.85           |
| 70.1           | 39,813       | 73         | 4.13           | 44,930         | 12.85          | 0.959          | 70.2           | 0.12          | 39,657         | −0.39          | 1.000          | 4.28           |

Notes: \( W_m \) is the measured flood volume; \( W_t \) is the calculated flood volume without correction; \( W_{0t} \) is the calculated flood volume with correction; \( TP_m \) refers to the measured flood peak; \( TP_{0t} \) refers to the calculated flood peak without correction; \( TP_t \) refers to the calculated flood peak with correction; the relative error between the computed and measured flood volume without correction \( \Delta W_t = (W_t - W_{0t})/W_{0t} \times 100\% \); the relative error between the computed and measured flood volume with correction \( \Delta W_t = (W_t - W_{0t})/W_{0t} \times 100\% \); the relative error between the flood peak of the computed and the measured flood volume without correction \( \Delta TP_t = (TP_t - TP_{0t})/TP_{0t} \times 100\% \); the relative error between the flood peak of the computed and the measured flood volume with correction \( \Delta TP_t = (TP_t - TP_{0t})/TP_{0t} \times 100\% \); \( \text{NSE}_t \) is the deterministic coefficient without correction; \( \text{NSE}_{0t} \) is the deterministic coefficient with correction. The following tables are the same.
mentioned above, the effect coefficient INS indicates whether the correction effect is good or poor, that is, the effect relative to the original model error.

From the perspective of model calculations, Tables 2–5 show that after the four distribution functions produce errors. The model calculation results have an average

| Table 3 | Runoff correction results based on single system response curve with random distribution of error variation (EX – 0, σ – 0.052) |
|---------|---------------------------------------------------------------|
| Measured value | Uncorrelated | Correlated |
| Wm (mm) | Tpm (m³s⁻¹) | Wm (mm) | Wm (%) | Tpm (m³s⁻¹) | ΔTpm (%) | NSEo |
| 75.9 | 47,870 | 73 | -3.85 | 44,930 | -6.14 | 0.949 |
| 69.7 | 43,104 | 73 | 4.74 | 44,930 | 4.24 | 0.949 |
| 73.4 | 41,355 | 73 | 0.50 | 44,930 | 8.64 | 0.953 |
| 75.6 | 46,661 | 73 | -3.46 | 44,930 | -3.71 | 0.952 |
| 74.2 | 44,380 | 73 | -1.61 | 44,930 | 1.24 | 0.958 |
| 75.2 | 46,251 | 73 | -2.90 | 44,930 | -3.42 | 0.949 |
| 75.0 | 46,167 | 73 | -2.61 | 44,930 | -2.68 | 0.954 |
| 72.3 | 41,068 | 73 | 0.98 | 44,930 | 9.40 | 0.956 |
| 75.5 | 44,898 | 73 | -3.36 | 44,930 | 0.07 | 0.954 |
| 74.1 | 45,840 | 73 | -1.46 | 44,930 | -1.99 | 0.953 |
| 75.2 | 45,631 | 73 | -2.89 | 44,930 | -1.54 | 0.956 |
| 70.7 | 41,792 | 73 | 3.27 | 44,930 | 7.51 | 0.954 |
| 73.6 | 47,361 | 73 | 0.75 | 44,930 | -5.13 | 0.952 |
| 70.6 | 40,927 | 73 | 3.42 | 44,930 | 9.78 | 0.956 |
| 73.8 | 47,378 | 73 | -1.04 | 44,930 | -5.17 | 0.949 |

| Table 4 | Runoff correction results based on single system response curve with random distribution of error variation (±20%) |
|---------|---------------------------------------------------------------|
| Measured value | Uncorrelated | Correlated |
| Wm (mm) | Tpm (m³s⁻¹) | Wm (mm) | Wm (%) | Tpm (m³s⁻¹) | ΔTpm (%) | NSEo |
| 78.5 | 50,662 | 73 | -7.01 | 44,930 | -11.31 | 0.935 |
| 79.3 | 50,757 | 73 | -7.92 | 44,930 | -11.48 | 0.932 |
| 75.8 | 49,023 | 73 | -3.66 | 44,930 | -8.35 | 0.933 |
| 74.3 | 48,995 | 73 | -1.68 | 44,930 | -8.30 | 0.933 |
| 77.6 | 47,298 | 73 | -5.92 | 44,930 | -5.01 | 0.927 |
| 76.2 | 47,135 | 73 | -4.15 | 44,930 | -4.68 | 0.929 |
| 66.7 | 39,579 | 73 | 9.47 | 44,930 | 13.52 | 0.929 |
| 73.8 | 47,687 | 73 | -1.05 | 44,930 | -5.78 | 0.898 |
| 76.3 | 47,229 | 73 | -4.32 | 44,930 | -4.87 | 0.934 |
| 76.0 | 51,432 | 73 | -3.94 | 44,930 | -12.64 | 0.932 |
| 70.2 | 42,761 | 73 | 3.92 | 44,930 | 5.07 | 0.93 |
| 74.1 | 48,555 | 73 | -1.47 | 44,930 | -7.47 | 0.934 |
| 65.6 | 35,577 | 73 | 11.23 | 44,930 | 26.29 | 0.935 |
| 75.1 | 47,937 | 73 | -2.79 | 44,930 | -6.27 | 0.935 |
| 71.1 | 46,172 | 73 | 2.73 | 44,930 | -2.69 | 0.927 |
deterministic coefficient above 0.9. For the first two distribution functions, the model calculation results with the errors uniformly distributed at ±10% and the errors subject to the N (0, 0.05²) normal distribution show a deterministic coefficient over 0.95. However, the forecast error of flood peaks uniformly distributed at ±20% and that subject to the normal distribution of N (0,0.12) reach −15 and −20% (Tables 4 and 5, ΔTPo). Those of flood volume reach −7 and −11% (Tables 4 and 5, ΔWo), respectively. The flood peak forecast errors at ±10% uniform distribution and that subject to the N (0, 0.12) normal distribution reach −10 and −9.5% (Tables 2 and 3, ΔTPo), respectively, while those of flood volume reach −4 and −4% (Tables 2 and 3, ΔWo). In effect, the unit hydrograph forecasting model is applicable under the given assumptions for the basin but must be further corrected in real time during the forecasting process.

The real-time correction results indicate that regardless of the distribution random errors, the simulation results of the 60 sets of samples plus the corrected runoff yield have substantial improvement. The flood peak and flood volume forecasts were also improved significantly after operating the proposed method. The forecast errors of the flood peaks uniformly distributed at ±20% and subject to the N (0, 0.12) normal distribution are only −2.76 and −3.25% (Tables 4 and 5, ΔTPo); those of the flood volume are −1.54 and −1.41% (Tables 4 and 5, ΔWo). The forecast errors of the flood peaks uniformly distributed at ±10% and subject to N (0, 0.05²) normal distribution reach −1.82 and −1.45% (Tables 2 and 3, ΔTPo) while those of the flood volume reach −0.66 and −1.24% (Tables 2 and 3, ΔWo), respectively.

The four distribution functions generated errors which were effectively corrected and the model calculation results show an average deterministic coefficient (NSEo) of more than 0.998. Overall, the INS statistic indicates a 3.9% improvement for the errors uniformly distributed at ±10%, a 4.9% improvement using N (0, 0.05²) normal distribution, a 7.6% improvement for the errors uniformly distributed at ±20% and N (0, 0.01²) normal distribution. Regardless of the type of random error added, the effect of the model using the proposed correction method is favorable.

The samples of each distribution are listed here. Model calculations, measurements, and correction comparison hydrograph are provided in Figures 8. The two types of four distribution functions present different errors and the samples are diverse. Some measured peaks are excessively large while others are too small. The peaks appear earlier

### Table 5 | Runoff correction results based on single system response curve with random distribution of error variation (EX = 0, σ = 0.12)

| Measured value | Uncorrelated | Correlated |
|----------------|--------------|------------|
| Wm (mm) | TPm (m³ s⁻¹) | Wm (mm) | ΔWm | TPm (m³ s⁻¹) | ΔTPm (%) | NSEo | Wm (mm) | ΔWm (%) | TPm (m³ s⁻¹) | ΔTPm (%) | NSEo | INS |
| 70.4 | 42,181 | 73 | 3.65 | 44,930 | 6.52 | 0.912 | 70.0 | −0.66 | 41,369 | −1.93 | 0.995 | 9.10 |
| 77.0 | 50,231 | 73 | −5.24 | 44,930 | −10.55 | 0.865 | 75.9 | −1.54 | 49,147 | −2.16 | 0.901 | 4.16 |
| 78.2 | 50,511 | 73 | −6.69 | 44,930 | −11.05 | 0.892 | 77.4 | −1.13 | 49,160 | −2.67 | 0.993 | 11.32 |
| 77.3 | 48,062 | 73 | −5.58 | 44,930 | −6.52 | 0.923 | 77.3 | 0.01 | 48,088 | 0.05 | 1.000 | 8.34 |
| 74.8 | 45,738 | 73 | −2.35 | 44,930 | −1.77 | 0.897 | 75.7 | 1.29 | 44,902 | −1.83 | 0.98 | 9.25 |
| 77.9 | 49,687 | 73 | −6.32 | 44,930 | −9.57 | 0.913 | 77.9 | −0.07 | 49,939 | 0.51 | 1.000 | 9.53 |
| 70.6 | 47,085 | 73 | 3.43 | 44,930 | −4.58 | 0.92 | 71.0 | 0.65 | 46,597 | −1.04 | 0.954 | 3.70 |
| 68.4 | 44,808 | 73 | 6.70 | 44,930 | 0.27 | 0.923 | 67.9 | −0.69 | 45,495 | 1.53 | 0.991 | 7.37 |
| 75.5 | 48,845 | 73 | −3.37 | 44,930 | −8.02 | 0.905 | 75.3 | −0.39 | 48,289 | −1.14 | 0.992 | 9.61 |
| 77.1 | 47,034 | 73 | −5.37 | 44,930 | −4.49 | 0.943 | 76.9 | −0.34 | 46,720 | −0.69 | 0.990 | 4.98 |
| 71.5 | 43,018 | 73 | 2.07 | 44,930 | 4.44 | 0.941 | 71.8 | 0.35 | 43,412 | 0.92 | 0.984 | 4.57 |
| 77.1 | 48,307 | 73 | −5.32 | 44,930 | −6.99 | 0.909 | 76.9 | −0.31 | 47,994 | −0.65 | 0.992 | 9.13 |
| 73.1 | 48,384 | 73 | −0.16 | 44,930 | −7.14 | 0.916 | 73.5 | 0.48 | 47,942 | −0.91 | 0.996 | 8.73 |
| 71.8 | 40,088 | 73 | 1.69 | 44,930 | 12.08 | 0.897 | 72.2 | 0.62 | 40,636 | 1.37 | 0.990 | 10.37 |
| 72.9 | 46,331 | 73 | 0.17 | 44,930 | −3.02 | 0.952 | 72.0 | −1.22 | 45,052 | −2.76 | 0.994 | 4.41 |
or later in time and the resulting peak shapes also fluctuate. The hydrograph shown in Figure 8 also indicates that the corrected streamflow obtained using the proposed correction method is closer to the observed streamflow than that without correction.

Based on the above results, the proposed correction method, which seeks the feedback corrected runoff based on the model structure from the perspective of a single system response curve, is reasonable and effective with relatively high calculation accuracy under different variation ranges of the same distribution or different characteristic value distributions. The results also suggest that the correction effect improves as the random error increases.

Double system response curve case

Based on the errors generated by the two different distribution functions, Formulas (3)–(16) were used alongside Matlab support to inversely calculate the corrected runoff for each of the respective 15 samples. The results of the correction calculation are shown in Tables 6 and 7. Due to space limitations, example results are given for only eight samples of the two distributions. Model comparison, actual measurement, and correction comparison diagrams are given in Figure 9.

As shown in Tables 6 and 7, the flood peak value of the original model is too small. The uncorrected calculation errors corresponding to the two distributions are $-3.0$ and $5.7\%$. The flood peak errors of $(-20\%, 20\%)$ uniform distribution are $-15.50$ and $20.34\%$ (Table 6, $\Delta TP_o$) and the flood peak errors of normal distribution $N(0, 0.1^2)$ fall between $-54.91$ and $10.53\%$ (Table 7, $\Delta TP_o$). This indicates that the model performs well in simulating low-level floods but produces large errors in simulating high-level floods, which is related to the calculation results of the ideal model.
However, after the runoff yield correction, the simulated uniform distribution subject to (−20%, 20%) and the normal distribution subject to $N(0, 0.1^2)$ improved substantially. The flood peak errors (−20%, 20%) of uniform distribution are −3.52 and −3.54%. The errors of flood volume are −1.51 and −1.49%. The flood peak errors of normal
distribution of \( N(0, 0.1^2) \) are \(-4.53\) and \(-2.21\%\) and the flood volume errors fall between \(-2.13\) and \(1.29\%\). The average values of the flood peak errors of the two decreased to \(-0.56\) and \(-1.15\%\), respectively; the average values of flood volume errors of the two decreased to \(0.10\) and \(-0.14\%\), respectively. The average deterministic coefficients

Figure 9 | Comparison of the hydrographs obtained using RSRC-D with two random distribution of error: (a) with random distribution of error variation (\( \pm 20\% \)), (b) random distribution of error variation \( (EX = 0, \sigma = 0.1^2) \).

Figure 10 | The comparison chart of the relative flood volume error (\( \Delta W \)) before and after correction with RSRC-S. (a) with random distribution of error variation (\( \pm 10\% \)); (b) random distribution of error variation \( (EX = 0, \sigma = 0.05^2) \); (c) random distribution of error variation (\( \pm 20\% \)); (d) random distribution of error variation \( (EX = 0, \sigma = 0.1^2) \).
(NSE) increased from 0.898 and 0.92 to 0.996 and 0.997, respectively. The average INS of the two reaches 10.93 and 8.42%, respectively.

As shown in Figure 9, the errors plus the error simulation effects of two different distributions were ultimately improved by the correction method based on the system response curve feedback to correct the runoff yield, especially in the vicinity of the flood peak. The proposed method, based on the feedback correction of the system response curve, remains feasible and effective as the system response curve changes.

**Numerical results**

Figure 10 shows the relative flood volume error ($\Delta W$) of four error models with correction compared with without correction in a single system response curve (RSRC-S). As shown in Figure 10, for the single system response curve case, the relative flood volume error ($\Delta W$) has an average decrease of 78.5% with correction (Figure 10(a)), 86.6% (Figure 10(b)), 83.1% (Figure 10(c)), and 83.2% (Figure 10(d)).

The relative flood peak error ($\Delta TP$) is shown in Figure 11. Comparison between the correction result and the $\Delta TP$ value reveals a small range from 0.59 to 1.3%, while relative flood peak error ($\Delta TP$) decreases by 79.2% on average compared with the uncorrected value.

Figure 12 shows the relative flood volume error ($\Delta W$) and the relative flood peak error ($\Delta TP$) of two error models with and without correction in the double system response curve (RSRC-D). The $\Delta W$ and $\Delta TP$ show an average decrease up to 85 and 82%, respectively.
In summary, as shown in Figures 10–12, the relative error is restricted to narrow range near zero. The flood peak flow and flood simulation accuracy are greatly improved when the proposed correction method is used. Figure 13(a) shows the streamflow performance NSE values before and after correction with four random error distributions in a single system response curve case (RSRC-S), that is, in the double system response curve case (RSRC-D) is displayed in Figure 13(b). For the first two distribution functions, the NSE with the errors uniformly distributed at ±10% and the errors subject to the $N(0, 0.05^2)$ normal distribution increased by 3.6 and 4.8% to reach 0.996 and 0.999. The NSE increased by 7.6% with the flood peak errors ($-20\%$, $20\%$) and $N(0, 0.1^2)$ of the uniform distribution. Errors distributed at ±10% and $N(0, 0.05^2)$ are lower than that at ±20% and $N(0, 0.1^2)$. Thus, the correction effect improves as the model error increases.

In Figure 14, with error distributed at ±20%, the average INS is 7.58 for the case in single system response curve, compared with 10.93 in the double case. With respect to error distributed at $N(0, 0.1^2)$, the average INS is 7.64 (RSRC-S) and 8.43(RSRC-D), respectively. The INS statistic with error distributed at ±20% indicates a 44% improvement using the double system response curve (RSRC-D) and a 10% improvement with $N(0, 0.1^2)$. The double system response curve correction method provides better results for real-time correction. This is mainly because this approach uses more information about the unit hydrograph. Under the same error distribution, it can obtain better results than a method with a single curve.

Figure 12 | The performance of the relative error of two error models with RSRC-D compared with uncorrected. (a) random distribution of error variation ($\pm$ 20%); (b) random distribution of error variation ($\Delta$ $\pm$ 0.1%$^2$).
Real study results

Detailed results obtained by the application of the RSRC in an actual basin are provided in Table 8 in the supporting information; the results for all 30 flood events were examined here.

A test was run on the data for 30 floods in Qilijie Station, Minjiang River Basin to find that the INS of all the events improved. The average effect coefficient was 11.604, making for quite obvious correction effects. From the perspective of flood volume, over a maximum of 905,523, the relative error of the calculated flood volume was 13.45%. After correction, $\Delta W_t$ was only 3.16% marking a decrease of 10.29%. The relative error of flood volume did not decrease in certain floods but rather may have increased (e.g., 970,702, 960,328, 950,625, 940,425, 920,704). The relative error of flood volume calculated by the original model was small in these cases but the certainty coefficient was below 0.900, which suggests that the model simulation was relatively balanced in terms of the total amount but it was unsatisfactory from the start of the process. After correction, the relative error of the flood volume did not significantly increase. The revised flood volume was still below 3% and the certainty coefficient significantly improved, indicating that the overall process simulation improved compared to that before the correction.

The proposed method produced marked effects in the actual data for Qilijie Station. Under the model response theory, the proposed runoff correction is reasonable and effective in terms of the physical cause mechanism and yields highly accurate calculations in terms of actual watershed inspection precision.

CONCLUSIONS

Traditional correction models are not sufficient for real-time flood forecasting. Models which generalize the real-world scenario have simple mathematical expressions but result in various errors in the real-time flood forecasting
context. It is necessary to introduce an error correction technique to the real-time flood forecasting system.

The concept of basin linear confluence system was utilized in this study to construct a conceptual runoff error correction model. A model system response curve correction method was established accordingly which corrects the runoff by the model system response curve feedback based on the errors between the calculated and measured flow results. An error correction theory was also developed based on the structure itself, which has a physical basis. The proposed method enhances forecasting accuracy without truncating the forecast period or requiring additional parameters.

For verification based on the ideal model, the linear system ideal model was first divided into single system

Table 8 | Runoff correction results in Qilijie basin

| Flood code | Observed value $W_o$ (mm) | Uncorrelated | Correlated |
|------------|--------------------------|--------------|------------|
|            | $W_r$ (mm)  | $\Delta W_o$ (%) | NSE_o       | $W_r$ (mm)  | $\Delta W_r$ (%) | NSE_t       | INS |
| 990715     | 84.9        | 80.8          | 4.79        | 0.944       | 83.6         | 1.59        | 0.976  | 3.390 |
| 990523     | 95.0        | 82.2          | 13.45       | 0.910       | 92.0         | 3.16        | 0.981  | 7.802 |
| 990515     | 63.4        | 63.6          | -0.30       | 0.954       | 64.3         | -1.42       | 0.991  | 3.878 |
| 990415     | 52.8        | 52.1          | 1.53        | 0.952       | 51.7         | 2.07        | 0.998  | 4.832 |
| 980611     | 655.5       | 664.1         | -1.31       | 0.925       | 652.9        | 0.40        | 0.940  | 1.622 |
| 980509     | 80.5        | 93.0          | -15.49      | 0.884       | 79.2         | 1.65        | 0.996  | 12.670 |
| 980303     | 137.8       | 132.9         | 3.56        | 0.944       | 136.3        | 1.04        | 0.975  | 3.284 |
| 980215     | 34.9        | 40.3          | -15.35      | 0.787       | 35.5         | -1.72       | 0.991  | 25.921 |
| 970808     | 35.9        | 39.3          | -9.49       | 0.575       | 35.8         | 0.31        | 0.986  | 71.478 |
| 970702     | 134.6       | 133.7         | 0.62        | 0.875       | 140.2        | -4.16       | 0.906  | 3.543 |
| 970620     | 59.5        | 52.8          | 11.34       | 0.851       | 59.3         | 0.40        | 0.995  | 16.921 |
| 970605     | 60.2        | 68.8          | -14.41      | 0.944       | 59.6         | 0.93        | 0.996  | 5.508 |
| 960530     | 73.6        | 81.2          | -10.37      | 0.907       | 74.2         | -0.88       | 0.998  | 10.033 |
| 960328     | 29.2        | 29.0          | 0.72        | 0.781       | 29.6         | -1.27       | 0.987  | 26.376 |
| 950813     | 40.7        | 46.0          | -12.97      | 0.654       | 40.7         | 0.12        | 0.972  | 48.624 |
| 950625     | 137.4       | 139.1         | -1.20       | 0.898       | 140.5        | -2.22       | 0.933  | 3.898 |
| 950502     | 83.2        | 83.2          | 0.10        | 0.958       | 82.8         | 0.58        | 0.981  | 2.401 |
| 940425     | 95.4        | 95.4          | 0.03        | 0.910       | 96.6         | -1.20       | 0.955  | 4.945 |
| 930630     | 86.6        | 84.5          | 2.36        | 0.941       | 83.4         | 3.68        | 0.985  | 4.676 |
| 920704     | 182.4       | 184.0         | -0.87       | 0.898       | 191.4        | -4.93       | 0.986  | 9.800 |
| 920616     | 72.3        | 71.6          | 0.94        | 0.897       | 72.5         | -0.32       | 0.996  | 11.037 |
| 920501     | 34.0        | 33.3          | 2.06        | 0.963       | 33.6         | 1.38        | 0.991  | 2.908 |
| 910526     | 78.9        | 76.1          | 3.60        | 0.670       | 80.9         | -2.55       | 0.982  | 46.567 |
| 900611     | 69.5        | 73.3          | -5.53       | 0.952       | 68.7         | 1.17        | 0.981  | 3.046 |
| 890618     | 79.9        | 77.7          | 2.73        | 0.907       | 79.3         | 0.71        | 0.987  | 8.820 |
| 890527     | 84.3        | 87.2          | -3.38       | 0.976       | 84.8         | -0.63       | 0.996  | 2.049 |
| 890521     | 56.5        | 55.0          | 2.60        | 0.704       | 57.1         | -1.17       | 0.995  | 41.335 |
| 880520     | 180.6       | 193.5         | -7.16       | 0.949       | 181.7        | -0.60       | 0.996  | 4.953 |
| 880405     | 37.5        | 40.7          | -3.86       | 0.925       | 38.1         | -1.41       | 0.990  | 7.027 |
| 880228     | 97.2        | 105.9         | -8.95       | 0.944       | 101.0        | -3.93       | 0.994  | 5.297 |
| Average    | 100.5       | 102.0         | -2.16       | 0.879       | 100.9        | -0.31       | 0.981  | 11.604 |
response curve and double system response curve. The method where the model response curve is used to feedback the corrected runoff yield achieved the desired results, regardless of whether the distribution was normal or uniform. The average relative error of flood volume is reduced by 83.2%, the relative error of the flood peak decreased by 74.1%, the average value of INS was greater than 5%, and the NSE value was close to 1. In the real model case, the NSE of all floods increased to above 0.95 and the mean INS value was 11%. To this effect, the proposed method is valid. The method presented in this paper is one of the few error correction models that has a physical formation mechanism and requires no additional model parameters to operate. The method is readily applicable. However, the applicability of the correction method to areas with significant nonlinearity in the basin confluence system still needs further research.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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