Research and application of an intelligent networking model for flood forecasting in the arid mountainous basins

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Abstract
Storm floods occur frequently and have complex characteristics in arid mountainous areas, which for a long time has been a weak link in flood forecasting. The application of an artificial intelligent model and physically-based hydrological model has some limitations on flood forecasting in arid mountainous areas with scarce data. In this article, the ANN model and Muskingum-Cunge method are combined to propose an intelligent networking model for flood forecasting (FFIN model) in arid mountainous areas with scarce data, which BR-ANN model is used to forecast the flood in the catchment sub-basin with runoff data, while the General Regression Neural Network model is used to carry out flood parallel forecast in the catchment sub-basin without runoff data. The Muskingum-Cunge method is used to connect the sub-basins and form a confluence network, so as to simulate the flood routing process in river. The verification and comparison results in study area show that the FFIN model has a superior overall forecasting ability. For the forecasting period, the evaluation index Kling-Gupta efficiency is 0.88, Nash efficiency coefficient is 0.982 and forecasting deviation of flood peak flow is 7.15%. The FFIN model can be effectively applied to flood forecasting in arid mountainous areas with scarce runoff data.

KEYWORDS
arid mountainous basins, flood forecasting, forecast factors, intelligent networking

1 INTRODUCTION

Floods are one of the most frequent and destructive natural disasters in the world (Noji & Lee, 2005). After floods occur, the impacts include direct casualties, loss of agricultural production, destruction of infrastructure (Pant, Thacker, Hall, Alderson, & Barr, 2018), disruption of commerce and education and indirect social impacts on communities (Lindell & Prater, 2003) and human health (Du, FitzGerald, Clark, & Hou, 2010; Jonkman & Vrijling, 2008). Particularly in arid mountainous areas, where the rainfall intensity is high, very dry and crusted soil can rapidly convert rainfall to runoff, resulting in higher flood risks and destructiveness (Kundzewicz et al., 2014; Sen et al., 2013). At the same time, flash floods in these areas are likely to be accompanied by a series of geological disasters such as landslides and debris flows (Van Tu, Duc, Tung, & Cong, 2016). Accurate flood forecasting can effectively support the early adoption of flood warning, flood control and other flood mitigation
measures so as to reduce flood losses (Guven, 2009; Yaseen, El-shafie, Jaafar, Afan, & Sayl, 2015), and is also of great significance for regional planning, irrigation water intake, sediment transport and other hydrological applications (Araghinejad, Burn, & Karamouz, 2006; Danandeh Mehr, Kahya, Şahin, & Nazemosadat, 2015; Solomatine & Shrestha, 2009). However, floods in arid mountainous areas remains a weak link in disaster forecasting and prevention throughout the world (Zhang, Lin, et al., 2018; Zhang, Yu, et al., 2018). The main sources of forecast difficulty include the uncertainty of transmission loss (Al-Qurashi, McIntyre, Wheater, & Unkrich, 2008), spatial heterogeneity and non-stationarity of model parameters (Beven, 2001; Beven, 2006), and impact of human activities on runoff. Unfortunately, the validity and accuracy of flood forecasting in these areas are further limited by hydrological station networks and meteorological data (Sorman & Abdulrazzak, 1993; Younis, Anquetin, & Thielen, 2008). These challenges make it necessary to design new models or methods by which to predict floods more accurately.

Flood simulation and forecasting modelling systems are classified into two main groups, namely, physically-based hydrological models (process-based models) and artificial intelligence models (data-based models) (Adamowski, Chan, Prasher, & Sharda, 2012; Baratti et al., 2003). The physically-based hydrological models have clear physical meaning and are important in understanding hydrological processes, yet their calibration is costly, time consuming and difficult to calibrate in regions where data are scarce (Kan et al., 2019). The AI models do not have clear physical significance, only depends on the correlation between data (Yaseen et al., 2015). With the development of AI technology, many AI models have been applied in the prediction and simulation of nonlinear hydrology (Yaseen et al., 2016; Zhang, Lin, et al., 2018; Zhang, Yu, et al., 2018). Among these models, artificial neural networks (ANNs) are very commonly used models for hydrological forecasting (Adamowski et al., 2012). Many scholars have used their learning abilities to build ANN models for runoff or flood forecasting under different conditions, thereby proving the applicability of ANN models in rainfall–runoff forecasting (De Vos & Rientjes, 2007; Dou, Chen, Bao, & Li, 2011; Ghorbani, Zadeh, Isazadeh, & Terzi, 2016; Lin & Chen, 2008; Yaseen et al., 2016).

Among the existing ANN models, Bayesian regularisation ANN (BR-ANN) possesses a rather strong non-linear forecast ability, which overcomes the over-fitting problem of backpropagation ANN model training, and improves the robustness of the model (Burden & Winkler, 2008). The BR-ANN has been widely used for nonlinear function fitting and prediction, and has shown good prediction capabilities (Alp & Cigizoglu, 2007; Burden & Winkler, 2008; El-Bakry, 2003; Ticknor, 2013). The General Regression Neural Network (GRNN) is also a widely used model in ANN models. It does not need to go through the training iteration process of backpropagation ANN, which extracts function values directly from the input dataset, and has a lower requirement on the number of input learning samples (Danandeh Mehr et al., 2015; Specht, 1991). Many scholars use the GRNN to construct the rainfall–runoff forecasting model, and to forecast the river runoff (Awchi, 2014; Hu, Lam, & Ng, 2005; Kisi, 2008; Singh & Deo, 2007; Turan & Yurdusev, 2009). Although ANNs are widely used in runoff or flood forecasting, they have no clear physical significance, which limits their further development. Furthermore, if human activities cause changes in the confluence characteristics of a certain catchment area, the application of ANNs is greatly restricted (Baratti et al., 2003).

In view of this, some scholars have combined the two methods in hydrological forecasting to improve the forecasting effect. Chu (2009) used the Neuro-Fuzzy approach to estimate the parameters of the Muskingum model more accurately. Chua and Wong (2010) used a combined artificial neural network-kinematic wave (ANN-KW) approach to simulate rainfall–runoff processes. They implemented an estimated discharge obtained from the KW model as the input to the ANN, then used the ANN to account for the difference between the estimated and measured discharges, which can be considered to be equivalent to a loss rate. Latt (2015) examined the application of an ANN approach in the Muskingum flow routing, by estimating the Muskingum parameters by using ANN. The above studies have made corresponding progress, yet did not strictly construct a rainfall–runoff coupling model for the basin. In addition, at present the existing studies have not combined the two methods for flood forecasting in areas where runoff data are scarce. In this article, the ANN model and Muskingum-Cunge method are combined to construct an intelligent networking model for flood forecasting (i.e., the FFIN model), which is available for application in arid mountainous areas for which data are scarce in some areas. Based on ANN models to forecast the catchment of sub-basins, the Muskingum-Cunge method is then used to simulate the flood routing process, and the flood flow of basin is predicted. This grants the intelligent model with several physical properties, transforming the “black box” model into the “grey box” model. Finally, in the study area, the forecasting effects of the FFIN model and GRNN, BR-ANN, BP-ANN and Linear models are compared, and the characteristics and potential of the FFIN model are summarised in detail.
2 | STUDY CASE AND RESEARCH DATA

2.1 | Study case

In this article, the Rujigou Basin of the Helan Mountains in China is selected as the research object. The basin has an area of 74.80 km², altitude of 1,180–2,346 m, valley length of 15.8 km and the average gradient of the valley is 23.5‰ (Figure 1). The Rujigou Basin is part of the Yellow River Basin, with a slope of 6°–45° and vegetation coverage rate of about 30%. The Rujigou Basin is located in the middle-temperature drought climate region with a drought index of 6.5 (Wang, 2018). Heavy storms and floods have occurred frequently in the Rujigou Basin. Since 1958, more than 40 major floods have occurred there, with a wide range of impacts on the downstream.

According to the topographic characteristics of the Rujigou Basin, it is divided into 13 catchment sub-basins (Figure 1). After precipitation occurs, floods in each sub-basin converge to the river network, and propagate to the outlet of the basin.

2.2 | Research data

Due to the fact that the FFIN model aims to predict the sudden and large flood in arid mountainous area, the runoff data from 2006 to 2011 with frequent floods are used to verify and evaluate the model. All of the data used in the model are daily data. In order to evaluate the prediction ability of the FFIN model for large floods, the flood with the greatest discharge in 2006 was selected as the forecast flood, while the data from 2007 to 2011 were used for the model training and testing. In addition, it should be noted that the model has no limitations on the prediction time scale, which is depends entirely on the data. The precipitation data were obtained by the interpolation of data from three weather stations, that is, Xigoumen, Huangcaotan and Rujigou. Other meteorological data were sourced from weather stations and CMADS (Meng & Wang, 2017). The runoff process at the outlet of each sub-basin was simulated by the distributed hydrological model of the Rujigou Basin, and this used as the research data of the FFIN model. In this article, sub-basin1–8 is set to be the catchment area with runoff data,
3 | MODELS AND METHODS

3.1 | Studied framework of the FFIN model

The FFIN model, applied in arid mountainous basins, is a coupling model, which combines the ANN model and Muskingum-Cunge method. Firstly, the sub-basins are divided according to topographic characteristics and the distribution of hydrological stations in basin, and the key forecast factors of the FFIN model are identified. Secondly, the flood forecasting of the sub-basins is carried out. The BR-ANN model is constructed for each sub-basin with runoff data. The parallel forecasting is performed for sub-basins without runoff data, by using the GRNN model with results for the forecasting period of the BR-ANN model as input. Finally, based on the sub-basins model results as the boundary conditions, the Muskingum-Cunge method with clear physical significance is used to the floods routing simulation of river network. The studied framework of the FFIN model is shown in Figure 2.

3.2 | Identification and analysis of forecast factors

As the ANN is designed to fit the correlation between the input and output series, its forecasting accuracy can be improved by using superior correlation series for input, and eliminating inferior correlation series. The Pearson correlation coefficient is used to evaluate the correlation between runoff series and each factor, which may affect the basin runoff, so as to identify the key forecast factors of the FFIN model. The calculation formula is as follows:

$$R = \frac{\sum_{i=1}^{T} (Q_{o,i} - \bar{Q}_o) \sum_{i=1}^{T} (Q_{s,i} - \bar{Q}_s)}{\sqrt{\sum_{i=1}^{T} (Q_{o,i} - \bar{Q}_o)^2 \sqrt{\sum_{i=1}^{T} (Q_{s,i} - \bar{Q}_s)^2}$$

where $Q_{o,i}$ and $Q_{s,i}$ are the observed and simulated ith value of the flood flow, $\bar{Q}_{o,i}$ and $\bar{Q}_{s,i}$ are the average of observed and simulated $Q$.

The BR-ANN models of sub-basin 1–8 are trained by using the meteorological and runoff data, and the forecast dataset was input for flood forecasting. A total of nine meteorological factors are selected for correlation analysis to identify the forecast factors. These factors are the precipitation (Prep), antecedent precipitation (Pa), arid-area antecedent precipitation (Arid-Pa), antecedent one-day precipitation (Prep-1), antecedent two-day precipitation (Prep-2), antecedent three-day precipitation (Prep-3), average temperature (Ave-Temp), average humidity (Ave-Hum) and average wind (Ave-Win). Among them, the mathematical expression of $P_a$ for arid areas is as follows (Zhan & Ye, 2007):

$$P_{a,t} = K(P_{a,t-1} + P_{t-1})$$

where $P_{a,t}$ and $P_{a,t-1}$ are the antecedent precipitation on the day of $t$, $t - 1$; $P_{t-1}$ is the precipitation on the day of $t - 1$; and $K$ is the daily recession coefficient of the soil water content, which is usually in the range of 0.5–0.8 in arid areas; $K = 0.5$ is used in the study area in this article. In arid mountainous areas, the soil evapotranspiration volume is high after precipitation, and the soil water content recedes quickly (Ivanov et al., 2010; Sela, Svoray, & Assouline, 2012). Therefore, an improved calculation method based on $P_{t-1}, P_{t-2}$ and $P_{t-3}$ for the antecedent precipitation in arid mountainous areas is proposed. The
expression of the arid-area antecedent precipitation \( (P'_{a,t}) \) is as follows:

\[
P'_{a,t} = K[P_{t,1} + K(P_{t,2} + KP_{t,3})]
\]

For the identification of forecast factors of the GRNN model, the storm flood of 2009 (July 7–10) and confluence characteristic parameters of the sub-basins are selected for analysis. The eight factors, namely area, precipitation (Prep), arid-area antecedent precipitation (Arid-Pa), length, slope, average confluence length (Con-length), confluence accumulation (Con-acc) and confluence shape coefficient (Con-shape) are selected to calculate their correlation coefficients with flood series in space. Among them, the Con-length and the Con-acc are calculated by means of hydrological analysis. The Con-shape is a dimensionless coefficient added to characterise the flood confluence shape of the sub-basins. The mathematical expression is as follows:

\[
C = \frac{L_s}{W_s}
\]

where \( C \) is the Con-shape of the sub-basin, \( L_s \) is the length of the confluence channel in the sub-basin and \( W_s \) is the confluence width relative to the direction of \( L_s \).

### 3.3 BR (Bayesian regularisation)-ANN model

Bayesian regularisation can overcome the remaining deficiencies of ANN, and the models it produces are robust and well matched to the data, which lead to optimal predictions (Burden & Winkler, 2008; Caballero & Fernández, 2006). Based on this advantage of BR-ANN, it is adopted as the flood prediction method of sub-basin with runoff data in the FFIN model. In general, the training step aims at reducing the sum squared error of the model output and target value (Ticknor, 2013), while the Bayesian regularisation adds an additional term to this equation:

\[
F = \beta E_D + \alpha E_W; E_W = \sum_{i=1}^{m} w_i^2
\]

where \( F \) is the objective function, \( \alpha \) and \( \beta \) are objective function parameters \( E_D \) is the sum of squared errors, and \( E_W \) is the sum of square of the network weights, with \( m \) being the number of weights (MacKay, 1992a).

In the Bayesian framework, the weights are considered random variables in the learning process, and assigned a probability distribution that represents the relative degrees of belief in the different values. This function is initially set to some prior distribution. Once the data have been observed, they can be converted to a posterior distribution using Bayes’ theorem (Bishop, 1995; Foresee & Hagan, 1997):

\[
P(w|D, \alpha, \beta, M) = \frac{P(D|w, \alpha, \beta, M)P(w|\alpha, M)}{P(D|\alpha, \beta, M)}
\]

where \( w \) is the vector of network weights, \( D \) represents the data vector and \( M \) is the neural network model being used. \( P(w|D, \alpha, \beta, M) \) is the posterior probability, namely the plausibility of a weight distribution considering the information of the dataset in the model used. \( P(w|\alpha, M) \) is the prior density, which represents our knowledge of the weights before any data are collected. \( P(D|w, \beta, M) \) is the likelihood function, which is the probability of the data occurring, given the weights. \( P(D|\alpha, \beta, M) \) is a normalisation factor, which guarantees that the total probability is 1 (Caballero & Fernández, 2006; Foresee & Hagan, 1997). Considering that the noise in the training set data is Gaussian and that the prior distribution for the weights is Gaussian, the posterior probability fulfils the relation:

\[
P(w|D, \alpha, \beta, M) = \frac{1}{Z_F} \exp(-F)
\]

where \( Z_F \) depends on objective function parameters. Therefore, under this framework, minimization of \( F \) is identical to finding the \( Z_F \) (locally) most probable parameters (MacKay, 1992b).

Based on the identification results of the forecast factors (see Section 4.1), the Prep and Arid-Pa series of sub-basin1–8 during the training period are selected as the input, while the runoff series is selected as the output (1,550 sets of data), so as to construct the rainfall–flood forecast models of sub-basin1–8, respectively, and train them.

### 3.4 GRNN model

The GRNN has a strong non-linear mapping ability, flexible network structure and high fault tolerance and robustness (Cigizoglu & Alp, 2006; Specht, 1991). The GRNN model is suitable for solving non-linear problems, and can extract the function trend directly from the training input data. At the same time, the GRNN model has less restriction on the volume of the input sample data of
the model, and can still guarantee the forecast effect when the sample data volume is small (Kisi, 2007). For these reasons, the GRNN model is used for parallel forecasting of flood process in sub-basins without runoff data. Its applicability will be demonstrated later in this article.

GRNN consists of four layers: the input layer, mode layer, summation layer and output layer (Figure 3). The number of neurons in the input layer is equal to the number (n) of training samples. The summation layer is the weighted sum of the neurons in all model layers to calculate the output value. The output layer receives the calculation results of the summation layer (Cigizoglu, 2005). The theoretical basis of GRNN is non-linear regression analysis. The regression analysis of non-independent variable Y relative to independent variable x is actually the calculation of Y with the highest probability value. The formula for calculating Y relative to the model input X is as follows:

\[
\mu(X) = \frac{\sum_{i=1}^{n} Y_i \exp\left[-D(X,X_i)\right]}{\sum_{i=1}^{n} \exp\left[-D(X,X_i)\right]} \quad (8)
\]

\[
D(X,X_i) = \left(\frac{X-X_i}{\sigma}\right)^2 \quad (9)
\]

where \(X_i\) and \(Y_i\) are the sample observation values of the random variable \(x\) and \(y\); \(\sigma\) is the smoothing factor; and \(D\) represents the distance function of RBF kernel. The estimated value \(\mu(X)\) is the weighted average of all sample observation values, and the weight factor of each observation value \(Y_i\) is the exponent of the square of the Euclidian distance between the corresponding samples \(X_i\) and \(X\).

According to the identification results of the forecast factors (see Section 4.1), Prep, Arid-pa, Area, Slope, Con-length and Con-shape of sub-basin1–8 in the forecasting period are used as the input, while the BR-ANN model forecasting results are used as the output to construct a GRNN model for flood parallel forecasting in the sub-basin without runoff data (Figure 3). As the GRNN model has poor forecasting effect outside the sample range, the data of study basin historical floods and adjacent basin floods are added to the model dataset. In order to further analyse the advantages and potential of GRNN for flood parallel forecasting, the prediction effects of BR-ANN and GRNN are compared in Section 4.3 (Table 5).

### 3.5 Construction of the FFIN model

After the flood process at the outlet of all sub-basins is predicted, the Muskingum-Cunge method is used to connect the sub-basins, and to simulate the river flood routing. The Muskingum-Cunge method is an improved method based on the principle of water balance and the Muskingum method of tank storage equation (Cunge, 1969). It introduces the channel parameters with clear physical significance, so that the model can more accurately reflect the flood routing characteristics of natural rivers. The method is based on the continuous equation and momentum equation in diffusion form:

\[
\frac{\partial A}{\partial t} + \frac{\partial Q}{\partial x} = q_L \quad (10)
\]

\[
S_f = S_0 - \frac{\partial y}{\partial x} \quad (11)
\]

where \(A\) is the cross-section area of the river; \(Q\) is the flow rate of the river; \(q_L\) is the lateral inflow of the river; \(t\) is the time; \(S_f\) is the friction ratio; \(S_0\) is the bottom slope; \(x\) is the distance along the direction of the river flow; and \(y\) is the water depth. The convection diffusion equation (Miller & Cunge, 1975) is obtained by combining Equations (10) and (11), and using linear approximation:

\[
\frac{\partial Q}{\partial t} + c \frac{\partial Q}{\partial x} = \mu \frac{\partial^2 Q}{\partial x^2} + cq_L \quad (12a)
\]

\[
c = \frac{dQ}{dA} \quad (12b)
\]

\[
\mu = \frac{Q}{2BS_0} \quad (12c)
\]

where \(c\) is the wave velocity; and \(\mu\) is the hydraulic diffusivity.
Based on the BR-ANN, GRNN and Muskingum-Cunge methods, the FFIN model of the Rujigou Basin was established, and the river network flood routing was simulated (Figure 4). The Rujigou river section is trapezoidal in shape, and the changes in the section is small. The percolation method is used for calculating the river seepage. The Muskingum-Cunge simulation parameters of the main reaches of the model are shown in Table 2, among them, Manning's $n$ is determined after the calibration using historical floods (Yuan, 2014). The reliability of all parameters is verified in the Results section (Section 4.4).

### Table 2 Parameters of the Muskingum-Cunge method in the main reaches

| Reach | Length (m) | Wide (m) | Slope | Percolation channel loss rate | Manning's $n$ | Side slope |
|-------|------------|----------|-------|-------------------------------|---------------|------------|
| 3     | 2,730      | 60       | 0.0317| 0.003                         | 0.045         | 0.502      |
| 5     | 1,300      | 60       | 0.0317| 0.003                         | 0.045         | 0.502      |
| 9     | 1,210      | 60       | 0.0317| 0.003                         | 0.045         | 0.502      |
| 11    | 5,070      | 56.6     | 0.0283| 0.003                         | 0.0283        | 0.6        |
| 12    | 2,417      | 67.3     | 0.02  | 0.0027                        | 0.02          | 0.6        |
| 14    | 430        | 60       | 0.0317| 0.0027                        | 0.0317        | 0.502      |
| 15    | 290        | 67.3     | 0.02  | 0.0027                        | 0.02          | 0.6        |
| 16    | 1,420      | 67.3     | 0.02  | 0.0027                        | 0.02          | 0.6        |
| 18    | 371        | 70.4     | 0.0218| 0.003                         | 0.0218        | 0.51       |
| 19    | 3,820      | 70.4     | 0.0218| 0.003                         | 0.0218        | 0.51       |

Based on the BR-ANN, GRNN and Muskingum-Cunge methods, the FFIN model of the Rujigou Basin was established, and the river network flood routing was simulated (Figure 4). The Rujigou river section is trapezoidal in shape, and the changes in the section is small. The percolation method is used for calculating the river seepage. The Muskingum-Cunge simulation parameters of the main reaches of the model are shown in Table 2, among them, Manning’s $n$ is determined after the calibration using historical floods (Yuan, 2014). The reliability of all parameters is verified in the Results section (Section 4.4).

### 3.6 Evaluation index of the model forecast effect

The Nash efficiency coefficient ($NSE$), Root Mean Squared Error ($RMSE$), Correlation coefficient ($R$) and Percent bias ($PBIAS$) are selected as the single index by which to evaluate the performance of the model:

\[
NSE = 1 - \frac{\sum_{i=1}^{T}(Q_{o,i} - Q_{s,i})^2}{\sum_{i=1}^{T}(Q_{o,i} - \bar{Q}_{o,i})^2} \tag{13}
\]

\[
RMSE = \sqrt{\frac{1}{T} \sum_{i=1}^{T}(Q_{o,i} - Q_{s,i})^2} \tag{14}
\]

\[
R = \frac{\sum_{i=1}^{T}(Q_{o,i} - \bar{Q}_{o,i}) \sum_{i=1}^{T}(Q_{s,i} - \bar{Q}_{s,i})}{\sqrt{\sum_{i=1}^{T}(Q_{o,i} - \bar{Q}_{o,i})^2 \sum_{i=1}^{T}(Q_{s,i} - \bar{Q}_{s,i})^2}} \tag{15}
\]

\[
PBIAS = \frac{\sum_{i=1}^{T}(Q_{o,i} - Q_{s,i})}{\sum_{i=1}^{T}Q_{o,i}} \tag{16}
\]

where $T$ is the total number of sample pairs, $Q_{o,i}$ and $Q_{s,i}$ are the observed and simulated $i$th value of the flood discharge, $\bar{Q}_{o,i}$ and $\bar{Q}_{s,i}$ are the average of observed and simulated $Q$. For the overall forecasting effect of the FFIN model, the KGE’ (modified Kling-Gupta Efficiency) (Kling, Fuchs, & Paulin, 2012) is selected as the comprehensive evaluation index. The KGE’ is a recent
performance indicator based on the equal weighting of linear correlation ($R$), bias ratio ($\beta$) and variability ($\gamma$):

$$KGE' = 1 - \sqrt{(R-1)^2 + (\beta-1)^2 + (\gamma-1)^2} \quad (17)$$

The hydrological performance can be classified using $KGE'$ as follows (Kling et al., 2012): good ($KGE' \geq 0.75$); intermediate ($0.75 > KGE' \geq 0.5$); poor ($0.5 > KGE' > 0.0$) and very poor ($KGE' \leq 0.0$).

### 4 | RESULTS

#### 4.1 | Forecast factors of FFIN model

In this study, the Prep has the best correlation with run-off series (Figure 5). The correlation coefficient ranges between .6 and .8. The average correlation coefficient of the Prep-1, Prep-2 and Prep-3 are .12, .09 and .04, thus indicating that the correlation between these three series and the runoff series is very weak. The average correlation coefficients of the Pa and Arid-Pa are .12 and .17, respectively, which are greater than those of the Prep-1, Prep-2 and Prep-3. This shows that Arid-Pa has a higher correlation with the runoff series. For Ave-Tem, Ave-Hum and Ave-Win, the correlation with runoff series is weak. These meteorological factors have less significant influence on runoff, and are thus not used as the input forecast factors of the model. For these reasons, Prep and Arid-Pa are selected as the input factors for the flood forecasting of sub-basin1–8.

Table 3 shows the correlation coefficients between the parallel forecast factors and flood series in the identification period (July 7–10, 2009). The correlation coefficients of Prep and Arid-pa are above .4 and .3, respectively, which have a stable correlation with flood flow in the sub-basins. Area, Con-length and Con-shape have a high correlation with flood flow, with the correlation coefficient being above .75. Among them, the Con-length is the highest, and is significantly greater than Length, with a correlation coefficient of .5–.8. The average correlation coefficient of the Slope is .46, which is an important factor affecting the convergence of mountainous areas. For the Con-acc, its correlation with flood series is unstable. Therefore, Prep, Arid-pa, Area, Slope, Con-length and Con-shape are selected as the key forecast factors for parallel forecasting in the GRNN model.

#### 4.2 | Flood forecasting of sub-basins with runoff data

Table 4 shows the results of the training, testing and forecasting of sub-basin1–8. With the exception of sub-basin1, whose model training NSE is 0.88 and PBIAS is $-14.18\%$, the training NSE are all greater than 0.9, and their PBIAS are less than $\pm 10\%$. The mean of $R$ of all sub-basin models training results is .95, while the RMSE are small, and the mean of $R$ in the testing period is 0.75.
The training effects of each sub-basin model are shown to be superior, and testing results also shows that the models are reliable. Next, the Prep and Arid-pa were input into each model for flood forecasting of sub-basin 1–8 in the forecasting period (July 6–20, 2006).

The results of forecasting period show that the effects of each sub-basin model are all good, NSE and R are very high, and RMSE is small. In particular, the forecasting of flood peak flow is very accurate. However, minor errors in the flood recession period lead to greater PBIAS in some sub-basins (sub-basin4, sub-basin7 and sub-basin8; Figure 6). This is due to the fact that the daily runoff in the study area is small, and the correlation between the Arid-Pa and runoff series is weak, thus making it difficult

### TABLE 4  Evaluation index value of model training, testing and forecasting effect

| Sub-basin Structure | 1  2,10,10,1 | 2  2,5,5,1 | 3  2,5,5,1 | 4  2,5,5,1 | 5  2,10,10,1 | 6  2,10,10,1 | 7  2,5,10,5,1 | 8  2,5,10,5,1 |
|---------------------|---------------|------------|------------|------------|---------------|---------------|----------------|---------------|
| Training            | NSE | 0.883 | 0.973 | 0.991 | 0.869 | 0.985 | 0.978 | 0.989 | 0.926 |
|                     | PBIAS | −14.18% | −3.01% | 4.11% | 5.57% | 2.63% | −2.41% | −5.70% | −3.59% |
|                     | RMSE | 0.015 | 0.004 | 0.002 | 0.011 | 0.004 | 0.004 | 0.014 | 0.003 |
|                     | R | .94 | .96 | .95 | .93 | .94 | .98 | .93 | .93 |
| Testing             | NSE | 0.126 | 0.277 | 0.502 | 0.556 | 0.382 | 0.380 | 0.673 | 0.428 |
|                     | PBIAS | −16.96% | −40.23% | −0.69% | −1.24% | −22.92% | −12.56% | 0.68% | 7.07% |
|                     | RMSE | 0.007 | 0.002 | 0.001 | 0.001 | 0.002 | 0.002 | 0.006 | 0.002 |
|                     | R | .73 | .68 | .84 | .81 | .75 | .79 | .83 | .69 |
| Forecasting         | NSE | 0.945 | 0.978 | 0.994 | 0.997 | 0.992 | 0.986 | 0.993 | 0.96 |
|                     | PBIAS | −8.97% | −3.60% | −0.39% | 11.36% | −6.61% | −3.02% | 12.95% | 28.12% |
|                     | RMSE | 0.193 | 0.07 | 0.034 | 0.03 | 0.064 | 0.068 | 0.201 | 0.097 |
|                     | R | .97 | .99 | .99 | .99 | .99 | .99 | .99 | .98 |

Note: In order to ensure the training effect of the model, the data from 2007 to 2009 including multiple floods are used for the model training, while the last 15% of the data from 2007 to 2011 are used for the model testing. During the testing period, no flood occurred, thus the runoff is small, and the slight deviation in the forecasting results cause its evaluation indexes to perform poorly. However, the trend of forecasting runoff is accurate and the correlation coefficient is greater, this can ensure that the model is reliable under test.

**FIGURE 6** Comparison of forecasted and observed discharge (m³/s) for the forecasting period in sub-basin 1 (a), sub-basin 4 (b), sub-basin 7 (c) and sub-basin 8 (d)
to avoid the forecast error in the process of flood recession.

4.3 Flood forecasting of sub-basins without runoff data

For the sub-basins without runoff data, sub-basin9 and sub-basin10 are used to determine the Speard coefficient and validate the model. The flood parallel forecast of sub-basin11, sub-basin12 and sub-basin13 are performed after reasonable validation. In order to verify the applicability of the GRNN for flood parallel forecasting in the sub-basin without runoff data, the model was constructed using the training dataset. The sub-basin9 flood series was used to calibrate the Speard coefficient to .25, and the sub-basin10 flood was parallel forecasted. Table 5 lists the forecast evaluation index values of sub-basin9 and sub-basin10 during the training period. Among them, the NSE and $R$ are shown to be superior. The RMSE is 0.016 and 0.017 m$^3$/s, and the PBIAS is $-59.02\%$ and $-57.68\%$, respectively. The main reason for the higher PBIAS is that the runoff of sub-basin9 and sub-basin10 are smaller during periods of no rainfall, thus a small amount of deviation in the long series will easily cause an increase of PBIAS. The greater NSE and $R$ values indicate that the flood peak flow forecast is accurate, and the deviation during the no-rainfall period has less impact on the flood forecast effect of the model. Therefore, it is feasible to use GRNN for flood parallel forecasting in the FFIN model.

For the flood in the forecasting period, the forecast dataset (196 sets of data) was input to construct and train the model. Next, the sub-basin9 flood process was used to determine that the Speard parameter to be 0.3, then the floods of sub-basin10–13 were parallel forecasted. It should be noted that when the parallel forecast dataset has good representativeness, the Speard parameter can be directly used for multiple floods prediction after one calibration. Table 5 lists the forecast evaluation indexes of sub-basin9 and sub-basin10 during the forecasting period: NSE and $R$ are greater than 0.92, the PBIAS are less than 15%, and the RMSE are 0.245 and 0.102 m$^3$/s, respectively. The results show that the parallel forecast capability of the model is strong, yet there is a small amount of deviation during the flood recession period (Figure 7). At the same time, the comparison of forecasting effects between GRNN and BR-ANN also shows that the former can accurately forecast sub-basin floods without runoff data.

4.4 FFIN model flood forecasting in the Rujigou Basin

Firstly, the flood routing parameters of the FFIN model were verified using dataset of training period (Figure 8). The forecast result NSE is 0.964, $R$ is .972, PBIAS is 33.11% and RMSE is 0.193 m$^3$/s, thereby indicating that the flood forecasting is accurate. The KGE' of forecasting in the 2009 (July 3–17) is 0.73. The results show that the
flood routing parameters of the FFIN model are reliable, and that the flood forecast effect is good.

After validating the model, the flood process of each sub-basin in the forecasting period is input (the BR-ANN forecast results of sub-basin1–8, as well as the GRNN forecast results of sub-basin9–13), so as to perform a networking forecast for floods in Rujigou Basin. In order to further compare and analyse the forecasting effect of the FFIN model, the BR-ANN, BP-ANN, GRNN and Linear forecasting results are added. The forecasting results of the FFIN model during the forecasting period are shown to be close to those of the observed values. The NSE is 0.982, R is .993, PBIAS is 10.65%, RMSE is 2.22 m³/s and KGE’ is 0.88. The forecast discharge of flood peak is 64.15 m³/s, observed discharge is 69.08 m³/s, and forecast deviation is 7.14%. This reveals that the flood forecasting of the sub-basin is reliable, and that the Muskingum-Cunge method with physical meaning can accurately simulate the flood routing process of the river network. The comparison of the BR-ANN, BP-ANN, GRNN and Linear forecast results show that the forecast effect of the FFIN model is obviously better than other models, and it has better flood forecast ability. During the flood rising period (July 12–13th) and recession period (July 15–17), there are some deviation in the forecasting of the FFIN model. During the rising period, the forecasting is smaller than the observations, and during the recession period, the forecasting is greater than the observations. However, the flood peak prediction effect of the FFIN model is satisfactory, that these deviation does not affect the actual application potential of the model.

5 | DISCUSSION

The FFIN model was constructed based on the BR-ANN, GRNN and Muskingum-Cunge methods, and verified in the study area. For the forecast factors for sub-basin1–8, rainfall (Prep and Arid-Pa) is the most important. This is consistent with the existing research conclusions (Chen, Chen, & Li, 2013). In arid areas, infiltration excess runoff is common during heavy rainfall (Descroix, Viramontes, Estrada, Gonzalez Barrios, & Asseline, 2007; Wang, Li, & Bao, 2010), and especially in small basins, the base flow is very small, thus the immediate rainfall directly determines the flood process. For these reasons, the correlation between other meteorological factors and the runoff is poor. There have studies which have also shown that temperature (Zhang & Govindaraju, 2000), evaporation (Kingston, Maier, & Lambert, 2005) and other meteorological factors are not important in runoff forecasting using ANN models. The parallel forecast factors show that, in addition to rainfall, there are many factors, which are also related to flooding in space, such as Area, Con-length, Con-shape and Slope, which have corresponding physical significances, and their correlation with runoff is very stable.

The flood forecasting effect of sub-basin1–8 is very good (Table 4). This benefits from the division of sub-basins, which enhances the correlation between input and runoff. It is clear in hydrological simulation that the subdivision of the river basin can be used to obtain more accurate results (Rezaei Sadr, 2020). The verification results of the parallel forecast show that the flood forecasting results of the sub-basins without runoff data are reliable (Table 5). At the same time, the comparison
The results of this study show that the forecasting effect of FFIN model is satisfactory, and that the forecasting deviation of flood peak is small. The FFIN model provides a better fit ability to the complex hydrological process than the BR-ANN, BP-ANN, GRNN and Linear models (Figure 9). The FFIN model can be used for storm floods forecasting in arid mountainous areas where data are scarce, and can guarantee the forecast accuracy. At the same time, the forecast ability of the FFIN model for runoff process dominated by light precipitation and antecedent precipitation is not outstanding, which resulted in some deviations during the flood rising and recession periods. This may have been due to the fact that the representativeness of the forecast dataset is not strong, and that the correlation between the Arid-Pa and runoff series is unstable. In fact, many potential factors are involved in runoff generation (Bafithile & Li, 2019), thus the forecasting deviations are unavoidable, and there are many reasons for these deviations. It is worth noting that the model does not select the soil surface characteristics as input factors, which has an impact on runoff generation (Ribolzi et al., 2007), and may even exceed the slope (Descroix, Gonzalez Barrios, Vandervaere, Viramontes, & Bollery, 2002). Although the study area is small and the data time scale is short, it clearly biases the prediction results. However, the flood peak discharge in arid mountainous areas is great, while the discharge in the rainless period is very small. In practical applications, a small amount of deviation in flood rising and recession periods does not affect the overall advantages or potential of the model. Therefore, the FFIN model is reliable for flood forecasting and can provide support for flood emergency decision-making in arid mountainous areas with scarce data. In addition, if human activities in a catchment area lead to changes in runoff and confluence conditions (Islam, Sikka, Saha, & Singh, 2012), then the FFIN model can alter the Muskingum-Cunge confluence input of a specific sub-basin in order to respond. The other advantages of the FFIN model can be further assessed in terms of its flexibility and generalisation capabilities.

The main significance of this article lies in providing a network-based flood forecasting framework. The method in the FFIN model is not limited to the method used in this article, and superior methods can be selected according to the regional characteristics, so as to increase the prediction accuracy of the model.

6 | CONCLUSIONS

Flood forecasting in arid mountainous areas has high uncertainty, accuracy is difficult to guarantee, and it is often limited by forecasting data. In this article, according to the characteristics of the ANN and Muskingum-Cunge method, an FFIN model is proposed by combining these two methods, which can be use for flood forecasting in arid mountainous areas with scarce data, and it has been verified in the Rujigou Basin of the Helan Mountains in China. Based on the results of the study described above, the advantages and disadvantages of the FFIN model are summarised and analysed.

For the study basin, the forecast factors of the model in catchment areas with runoff data are Prep and Arid-pa, while those for catchment areas without runoff data is Prep, Arid-pa, Area, Slope, Con-length and Con-shape. No other factors are necessary to operate the FFIN model. The division of catchment sub-basins increases the rainfall-flood correlation, so that the BR-ANN flood forecasting models of the sub-basin with runoff data have better forecast effects. Especially for single-peak rainstorm floods, the deviation of the peak forecast is very
small. The NSE of the forecasting period is greater than 0.94, and the mean RMSE is 0.039 m³/s. At the same time, the verification and comparison results show that the GRNN is applicable for flood parallel forecasting in the sub-basin without runoff data, and that it can guarantee the accuracy of the forecast. During the forecasting period, the NSE of flood forecasting for sub-basin 9 and sub-basin 10 are 0.925 and 0.988, and the RMSE are 0.245 and 0.102 m³/s, respectively.

Finally, the flood prediction effect of the FFIN model is satisfactory, and upon comparison with the BR-ANN, BP-ANN, GRNN and Linear models, it also shows stronger forecasting capability. Therefore, it is concluded the FFIN model provides a superior method by which to perform the flood forecasting in basins with scarce runoff data compared to the traditional method. The forecast result KGE' is 0.88, NSE is 0.982, and flood peak deviation is 7.14%. Due to the limitations of the dataset and forecast factors, the FFIN model may be insensitive or over sensitive to light precipitation and early precipitation, thereby resulting in some deviations during the flood rising and recession periods. However, the slight deviation in this period does not affect the potential of the model in practical applications, and this problem may be effectively solved when forecasting in other basins, or when the dataset is representative. The flood or hydrological forecasting framework of the FFIN model is worthy of further discussion and research, and it is of great significance to build a network model with stronger forecast capabilities based on regional characteristics.

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DATA AVAILABILITY STATEMENT
The runoff data that support this study are available from the Ningxia Water Conservancy. Restrictions apply to the availability of these data, which were used under licence for this study. Data are available from the authors with the permission of the Ningxia Water Conservancy. Meteorological data of 2008–2011 is available from CMADS at the following url: http://westdc.westgis.ac.cn/data/6aa7fe47-a8a1-42b6-ba49-62fb33050492.

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