Integrated neural networks for monthly river flow estimation in arid inland basin of Northwest China

Zailin Huoa, Shaoyuan Fenga,b,*, Shaozhong Kanga, Guanhua Huanga, Fengxin Wanga, Ping Guoa

a Centre for Agricultural Water Research in China, China Agricultural University, Beijing 100083, PR China
b College of Water Science and Engineering, Yangzhou University, Yangzhou 225009, PR China

SUMMARY

Streamflow model including rainfall–runoff and river flow models play an important role in water resources management, especially in arid inland area. Traditional conceptual models have disadvantage of requirement of spatial variations parameters about physical characteristics of the catchments. To overcome this difficult, in this study, several integrated Artificial Neural Networks (ANNs) were presented to estimate monthly river flow and the models include the semi-distribute forms of ANNs which can explore spatial variation in hydrological process (such as rainfall distribution and evaporation distribution) and no requirement of physical characteristic parameters of the catchments. An arid inland basin of Northwest as a case, integrated ANNs were developed using hydrological and agricultural data and its performance were compared with that of lumped ANN and local linear regression model (LLR). Results showed that the integrated ANNs perform well to estimate the monthly streamflow at outlet of mountain with Root Mean Square Error (RMSE) of 0.36 × 10³ m³ and Relative Error (RE) of 9%. Similarly, the integrated ANNs can also accurately estimate the monthly river flow in down-stream of the basin with RMSE of 0.35–0.38 × 10³ m³ and RE of 22–27%. Comparing to integrated ANNs, the lumped ANN and LLR models have lower precision to simulate monthly streamflow in arid inland basin. Presented integrated ANNs models retain advantages of the semi-distributed models considering the heterogeneity and spatial variation of hydrological factors and nature character in the catchment, while taking advantage of the potential of ANNs as an effective tool in nonlinear mapping or functional relationship establishment. In contrast to traditional models either in the lumped ANN or in empirical regression forms, the new approach of integration of Artificial Neural Networks has shown great potential in streamflow modeling.

1. Introduction

Streamflow model including rainfall–runoff and river flow models play an important role in water resources management. Especially in arid regions where water resources is scarce, streamflow simulations are useful to water resources temporal and spatial plan and distributions. To address this, different types of models with various degrees of complexity have been developed. Recently, hydrologists have endeavored to better understand the streamflow transformation process and many conceptual model had been developed, such as the Xinanjiang Model (Zhao and Liu, 1995), the Soil Moisture Accounting and Routing (SMAR) Model (Tan and Connor, 1996) and the Tank Model (Sugawara, 1995). However, the rainfall–runoff transformation is one of the most complex hydrological phenomena to comprehend, as it usually involves a number of interconnected elements, such as evapotranspiration, infiltration, surface and subsurface runoff generation and routing.

It is hard to accurately describe rainfall–runoff in a catchment. In fact, the streamflow process is further complicated as heterogeneity of the catchment geomorphological characteristics (such as soil type, and vegetation cover) and the spatial and temporal variations of model’s inputs (such as rainfall patterns). For further improving the performance of rainfall–runoff, a lot of recent researches focus on the distributed hydrological model (Schumann et al., 2000), such as Soil and Water Assessment Tool (SWAT) model. However, the distributed hydrological model need a number of catchment’s parameters, such as soil type, vegetation cover and generally these data are hard to be observed. Although some optimize techniques, such as genetic algorithm (GA), fuzzy optimal model (FOM), were used to calibrate the model (Cheng et al., 2002), and web-based flood forecasting system have been attempted (Li et al., 2006) the distributed hydrological model is not convenient to use widely.

Artificial Neural Networks (ANNs) are flexible mathematical structures, which are capable of identifying complex non-linear
relationships between input and output data. A comparison between model performances was made by Hsu et al. (1995) using daily time steps. They concluded that ANN could better simulate the rainfall–runoff relationship on a river basin in Mississippi, USA, if compared to a conceptual model and a linear autoregressive moving average with exogenous inputs (ARMAX) model. ANNs have been compared to other methods including genetic programming (GA), support vector machine (SVM), fuzzy logic (FL) and linear transfer function (LTF) methods for river flow simulation and obtained better performance (Wang et al., 2009; Lohani et al., 2011; Lin et al., 2006). The recent decade has seen a tremendous growth in the interest of application of ANNs in streamflow modeling (Kumar and Minocha, 2001; Tokar and Markus, 2000; Sajikumar and Thandaveswara, 1999; Zhang and Govindaraju, 2003). Some researches had been conducted to improve ANN’s performance, such as the data-preprocessing techniques of singular spectrum analysis (SSA) and moving average (MA) (Wu et al., 2009), particle swarm optimization techniques (PSO) for ANN’s training (Chau, 2006). ANNs had also been used to predict further long term streamflows (Gao et al., 2010). However, most of the ANN models for streamflow process reported in literature have used a total rainfall value over the catchments in the input vector, i.e. a single ANN were used to simulate hydrological processes for a catchments. Similar to traditional conceptual hydrological, present ANN models cannot reflect effect of heterogeneity of the catchment geomorphological characteristics on hydrological processes.

Furthermore, the ANN and conceptual models have been combined to estimate the river flow (Ashu and Sanaga, 2006; Corzo et al., 2009; Chen and Adams, 2006; Kamp and Savenije, 2007; Jeong and Kim, 2005; Nilsson et al., 2006). These models of combining conceptual hydrological models and ANNs model usually include two parts, one is conceptual model for streamflow of every sub-catchment and another is the ANN model to ensemble the streamflow from each catchment. In fact, these combining distributed hydrological models have not avoided the requirement of parameters for conceptual hydrological model for every sub-catchment. In addition, overall, traditional conceptual models have disadvantage of requirement of spatial variations parameters about physical characteristics of the catchments and the single ANNs cannot reflect the spatial variations of hydro meteorological factors and geomorphological characteristics. Thus, a kind of integrated ANNs model is better method to overcome these faults for hydrological process simulation over a catchment. The integrated ANN model will model flow for every sub-catchments and no requirement of physical characteristic parameters of the catchments.

The objectives of present study are (i) to propose an integrated ANNs model to estimate streamflow; (ii) to perform a case study and compare the performance of the integrated ANNs with that single ANN and local linear regression (LLR) models to estimate monthly streamflow.

2. Materials and methods

2.1. Study area

The Shiyang River basin, one of three continental rivers in the Hexi corridor, located in the eastern portion of the corridor in Gansu province of Northwest China was selected as the study area. The basin encompasses an area of $4.16 \times 10^5$ km$^2$ with a population of 2.2 million and covers the area between $101^1-104^1$ E and $36^2-39^2$ N (Fig. 1). The Shiyang River basin includes three climate zones (Kang et al., 2004). The Qilian Mountain in the south of the basin comprises a very frigid, semiarid humid area. The middle part of the basin is the Wuwei sub-basin, cool and arid. The northern part of the basin, also called the Minqin sub-basin, is warmer and more arid. The Shiyang River starts from north of the Qilian Mountains and includes eight tributaries, but only five tributaries (the Zamu, Gulang, Huangyang, Jinta and Xiying) converge as the Shiyang River in the outlet of the Qilian Mountains, and then flow into the Hongyashan reservoir in the Minqin oasis, the largest desert reservoir in Asia (Fig. 1). Characteristics of five catchments in the Shiyang River basin and proportion of major land use in the five catchments of the Shiyang River basin in 2000 were presented in Tables 1 and 2 respectively. The five tributaries are mainly fed by
rainfall, snowmelt, and glacier melt from the Qilian Mountain. In summary, all streamflows have steadily decreased, particularly the inflow into the Hongyashan reservoir, as climate changes and water-related human activities such as irrigation using river flow have increased in recent years.

2.2. Data sets

As the climate differences are significant over space within the Shiyang River basin, data including monthly total precipitation, monthly average maximum air temperature and minimum air temperature, relative humidity, sunshine hours, wind speed for the period of 1956–2003 from 15 weather stations located within the basin and the surrounding areas were selected. Potential evapotranspiration (ET) were calculated using the Penman–Monteith equation recommended by Food and Agriculture Organization (FAO) (Allen et al., 1998). Linear regression relationship between monthly precipitation and catchments’ characteristics such as elevation, latitude, and longitude were developed. Similar relationships were also developed for monthly potential evapotranspiration. A digital elevation model (DEM) with grid resolution 100 m × 100 m supplied by Western Eco-environmental Data Center of National Natural Science Foundation of China (WEDC-NSFC) was used to interpolate monthly precipitation and ET according to elevation, latitude, and longitude. Then average monthly precipitation and ET for every tributaries and down-stream of the basin can be calculated in Geographic Information System (GIS) (Ma et al., 2008). Previous researches have showed that average annual precipitation varied between 513 and 660 mm in 1950–1975 and decreased to 441 and 557 mm in 1975–2005. Average potential evapotranspiration showed an increasing trend over the two periods (Ma et al., 2008; Huo et al., 2008). It is clear that these changes in precipitation and potential evapotranspiration would lead to reduction in streamflow.

Monthly streamflow time-series from 1956 to 2003 for five tributaries and downstream of the basin were used in this study. The streamflow data for the five tributaries is from observation stations at mountain outlets. Flow data for the downstream of Shiyang River were measured at the Caiqi station (Fig. 1). Flows for both the tributaries and the Shiyang River exhibit decreasing tendencies. The total flow in mountain outlets varied from 12.1 × 10^8 m^3 in 1950s to 9.2 × 10^8 m^3 in 1970s and 8.2 × 10^8 m^3 in 1990s. Similarly, observation data show that annual streamflow at Caiqi station has decreased from 5.4 × 10^8 m^3 in 1950s to 3.2 × 10^8 m^3 in 1970s and 1.1 × 10^8 m^3 in 1990s (Fig. 2). In addition, irrigation area and irrigation water ration for unit area were collected to estimate the effect of agricultural activities on streamflow.

2.3. ANN technology

The ANNs are mathematical models, which attempt to exploit the massively parallel local processing and the distributed storage properties believed to exist in the human brain. In recent decades, the ANN technique, also called parallel distributed processing, has received a great deal of attention as a tool of computation by many researchers and scientists. There have many kinds of ANNs and the most common learning rule for ANNs is the back propagation algorithm. Back propagation involves two phases, a feed-forward phase in which the external input information at the input nodes is propagated forward to compute the output information signal at the output unit, and a backward phase in which modifications to the connection strengths are made based on the differences between the computed and observed information signals at the output units (Rumelhart et al., 1986).

There are several parameters including numbers of hidden layers and hidden nodes, learning rate for ANN architecture and training. Theoretically, the numbers of hidden layers and hidden nodes in a neural network can be unlimited. However, as pointed out by Funahashi (1989) and Hornik et al. (1989), an ANN with a single hidden layer containing a sufficient number of nodes can approximate any functional relationships to any degree of accuracy. Therefore, ANNs designed with three layers, including only one hidden layer are usually preferred in practical applications. So, the neural network structure in this study possessed a three-layer learning network consisting of an input layer, a hidden layer and an output layer. Furthermore, experiments of trail and error can be performed to determine the optimal nodes of hidden layer by starting with a few hidden layer nodes and comparing validation error.

### Table 1
Characteristics of five catchments in the Shiyang River basin.

<table>
<thead>
<tr>
<th>Catchment</th>
<th>Area (km²)</th>
<th>Streamflow (10⁸ m³)</th>
<th>Precipitation (mm)</th>
<th>ET (mm)</th>
<th>Elevation (m)</th>
<th>Slope (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Xiying</td>
<td>1455</td>
<td>3.6</td>
<td>520</td>
<td>800</td>
<td>3335</td>
<td>32</td>
</tr>
<tr>
<td>Jinta</td>
<td>841</td>
<td>1.3</td>
<td>460</td>
<td>860</td>
<td>2982</td>
<td>22</td>
</tr>
<tr>
<td>Zamu</td>
<td>851</td>
<td>2.3</td>
<td>559</td>
<td>781</td>
<td>3482</td>
<td>31.6</td>
</tr>
<tr>
<td>Huangyang</td>
<td>828</td>
<td>1.3</td>
<td>482</td>
<td>843</td>
<td>2997</td>
<td>22</td>
</tr>
<tr>
<td>Gulang</td>
<td>878</td>
<td>0.6</td>
<td>470</td>
<td>856</td>
<td>2876</td>
<td>18.1</td>
</tr>
</tbody>
</table>

### Table 2
Proportion of major land use in the eight catchments of the Shiyang River basin in 2000 (Ma et al., 2008).

<table>
<thead>
<tr>
<th>Catchments</th>
<th>Crop (%)</th>
<th>Forest (%)</th>
<th>Pasture (%)</th>
<th>Residential area (%)</th>
<th>Bare soil (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Xiying</td>
<td>1.61</td>
<td>26.24</td>
<td>53.78</td>
<td>0.15</td>
<td>17.32</td>
</tr>
<tr>
<td>Jinta</td>
<td>14.11</td>
<td>15.25</td>
<td>56.83</td>
<td>0.07</td>
<td>13.68</td>
</tr>
<tr>
<td>Zamu</td>
<td>1.20</td>
<td>33.65</td>
<td>47.74</td>
<td>0.04</td>
<td>17.36</td>
</tr>
<tr>
<td>Huangyang</td>
<td>25.83</td>
<td>28.39</td>
<td>35.98</td>
<td>0.86</td>
<td>7.64</td>
</tr>
<tr>
<td>Gulang</td>
<td>35.69</td>
<td>33.82</td>
<td>27.72</td>
<td>1.06</td>
<td>1.61</td>
</tr>
</tbody>
</table>

Fig. 2. Total streamflow of five tributaries and river flow at Caiqi station in down-stream of the Shiyang River from 1956 to 2003.
when nodes number of hidden layer is gradually increased. The procedure of adding hidden nodes is repeated and network training is restarted until the validation error is observed to bottom out and start increasing.

Usually, every input and output of ANN is not belong to same dimension, and all inputs and output need be normalized to same dimension, which mean that all input and output values are within same scope. In this study, the input and output data were normalized in the range from 0.1 to 0.9. From the input layer to the hidden layer, the log sigmoid function has been commonly used in hydrologic ANN models. From the hidden layer to the output layer, a linear function was employed as the transfer function as other studies.

In the present study, the scaled conjugate gradient method (SCGM) proposed by Moler (1993) and had been used to training ANNs for river flow model (Turan and Yurdusev, 2009). The scaled conjugate gradient method, an efficient second-order learning algorithm, is somewhat intermediate between the steepest descent method and Newton’s method. It accelerates the typically slow convergence associated to the steepest descent, while maintaining calculation simplicity by avoiding the requirements associated to the evaluation, the storage, and the inversion of the Hessian matrix in the Newton’s method (Liu et al., 2005). Its advantages are the increased learning speed (since it avoids the line search) and the fact that it eliminates the dependence on critical user-selected parameters (Learning rate, Momentum Coefficient) (Falas and Stafylopatis, 2005). The detailed calculating process of the SCGM can be found in literature Moler (1993).

2.4. Local linear regression (LLR) model

The local linear regression model is a popular nonparametric regression technique which has been widely used in many low dimensional forecasting and smoothing problems (Remesan et al., 2009). Reliable modeling even on a small amount of sample data and accurate predictions in regions of high data density in the input space are considered as the major advantages of LLR models. The LLR procedure requires only three data points to obtain an initial prediction and then uses all newly updated data in the order they becomes available to make further predictions. Deciding the size of \( p_{\text{max}} \) (the number of near neighbors to be included for the local linear modeling) is the tricky part in LLR modeling.

Given a neighborhood of \( p_{\text{max}} \) points, we must solve a linear matrix equation,

\[
X_m = y
\]

where \( X \) is a \( p_{\text{max}} \times d \) matrix of the \( p_{\text{max}} \) input points in \( d \)-dimensions, \( x_i \ (1 \leq i \leq p_{\text{max}}) \) are the nearest neighbour points, \( y \) is a column vector of length \( p_{\text{max}} \) of the corresponding outputs, and \( m \) is a column vector of parameters that must be determined to provide the optimal mapping from \( X \) to \( y \). If the matrix \( X \) is square and nonsingular then a unique solution to equation is \( m = X^{-1}y \). If \( X \) is not square or singular, we should find a vector \( m \) which minimizes

\[
|Xm - y|^2
\]

where the unique solution to this problem is provided by \( m = Xy \)

where \( X \) is a pseudo-inverse matrix.

3. Integrated ANNs model for monthly streamflow

3.1. Schematic diagram of the integration of ANNs

In the development of the lumped ANN models, the spatial variations of model parameters and model inputs are not explicitly considered in the modeling process. However, spatial variations in rainfall and catchment heterogeneity are common in nature and can be significant factors affecting the overall model performance. Traditionally, the river flow for an inland basin can be estimated by combining two ANNs, namely lumped ANN (Fig. 3). One ANN is to estimate total streamflow at outlet of mountain using weather data in upstream of the basin and another is to estimate the river flow at downstream of the basin using output of first ANN, weather data and human activities data. In this lumped ANN, precipitation and evaporation for every tributaries are respectively averaged to one value and as the inputs of first ANN. In other words, the heterogeneity and spatial variation of the rainfall, evaporation and land cover are not considered in the lumped ANN.

To overcome this deficiency, two integrated form of the ANNs models is proposed in this study. These integrated forms of ANNs retains advantages of the semi-distributed models considering the heterogeneity and spatial variation of the rainfall in the catchment, while taking advantage of the potential of ANNs as an effective tool in nonlinear mapping or functional relationship establishment. Flow charts of the two integrated ANNs are illustrated in Figs. 4 and 5. As shown in the figures, similar to the lumped ANN, the integrated ANNs contain two parts. The first part is the distributed form with several ANNs for sub-catchments and the second part is single ANN for middle stream. The development of a distributed form of the ANNs is intended to reflect the spatial variations of rainfall, evapotranspiration and the heterogeneity of the catchment characteristics across the catchment. As indicated in Figs. 4 and 5, the entire catchment is divided into five sub-catchments based on the characteristics of the catchment as illustrated in Fig. 1 and the five ANNs were developed to simulate streamflow from the five sub-catchments respectively.

There are two methods to develop the single ANN for streamflow for down stream of the basin. For first model (IANN1), the outputs of five ANNs were added up as the inputs of ANN for flow in down stream (Fig. 4). For another (IANN2), the outputs of five ANNs for streamflow of tributaries were used respectively as the inputs of ANN for streamflow in down stream (Fig. 5). Similar to the lumped ANN, the inputs of ANN in the second part include...
weather and water-related human activities data beside streamflow from tributaries.

3.2. Training and testing integrated ANNs model for monthly streamflow

An important issue in the ANN modeling is the choice of input variables, but there is no general theory yet to solve this issue, and it is still a problem. According to the hydrological processes in sub-catchments, the five tributaries are mainly fed by rainfall, snowmelt, and glacier melt from the Qilian Mountain. Snowmelt and glacier are determined by some meteorological factors such as temperature, and wind speed. In addition, soil moisture over the catchment also affects the rainfall–runoff processes and correlative with evapotranspiration. So, input variables used for these monthly streamflow models are the previous and current month’s precipitation and evapotranspiration calculated by Peman–Motith equation, and using the current month’s streamflow as the target variable. However, in the middle stream of the catchments, the Wuwei basin, river flows were affected by human activities, especially agricultural production activities, beside climate conditions. As a result, input variables used for monthly streamflow model are current monthly streamflow from tributaries, the previous and current month’s precipitation and evaporation, irrigation area, irrigation ratio of unit area.

Cross-correlation analysis between the target streamflow \( Q(t) \) and different lag time series of precipitation and ET data (viz \( P(t), P(t-1), P(t-2), P(t-3), P(t-4), ET(t), ET(t-1), ET(t-2), ET(t-3), ET(t-4) \)) were performed to obtain the important factors for streamflow estimation. The analysis results are shown in Tables 3 and 4 respectively for five tributaries and Caiqi station. As observed in Tables 3 and 4, up to a time lag of 2 months, the cross-correlations are higher for precipitation and ET information. It indicated that the two hydrological factors time series after a time lag of 2 months would not possess any significant effect on the target streamflow data, \( Q(t) \), as the cross-correlation values are close to zero. For the application of the model, rainfall (\( P(t) \)) can be obtained from public weather forecast information in several stations. Similarly, some meteorological variables such as temperature, humidity, wind speed can be also obtained from weather forecast information. Then potential evapotranspiration (\( ET(t) \)) can be calculated using P–M equation.

The training and testing patterns should be representative of similar physical systems for development of ANN models. For this study, the physical process of streamflow change is typical agreement over period of 1956 to 2003. So, the observed precipitation, ET, irrigation data and streamflow data from 1956 to 1991 were used for training ANNs for monthly streamflow, and the recent 12 years data from 1992 to 2003 were used testing the performance of the trained ANN models. Furthermore, scope of rainfall, evaporation and streamflow from testing sample are within scope of training sample. In this study, each member model of the integrated ANNs models was developed using the same procedure as the single modeling. For example, the SCGM algorithm, the log sigmoid, the linear transfer functions and the early stopping method were also employed for the each ANN.

The capacity of each ANN to estimate monthly streamflow was checked by applying the calibrated or generated model to the testing data. Results were compared by means of the Root Mean Square Error (RMSE), the mean relative error (MRE) and coefficient of determination \( R^2 \). RMSE and MRE provided different types of information about the predictive capabilities of the model. The RMSE measured the goodness of fit relevant to high streamflow, whereas the RE yielded a more balanced perspective of the goodness of fit at moderate groundwater levels. The \( R^2 \) measures the degree to which two variables were linearly related. The RMSE and RE were respectively defined as:

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{m}(y_i - \hat{y}_i)^2}{m}}
\]

(3)

\[
MRE = \frac{1}{m} \sum_{i=1}^{m} \left( \frac{|y_i - \hat{y}_i|}{\hat{y}_i} \right) \times 100\%
\]

(4)

\[
R^2 = \frac{\sum (y_i - \bar{y})(\hat{y}_i - \bar{y})^2}{\sum (y_i - \bar{y})^2 \sum (\hat{y}_i - \bar{y})^2}
\]

(5)

where \( m \) is the number of observations, and \( \hat{y}_i \) and \( y_i \) are the ith observed and predicted data, respectively, (using the ANN procedures).
Table 3
Cross-correlations of \(Q(t)\) with different time lags of precipitation \((P(t-\delta))\) and evaporation \((ET(t-\delta))\) for the five sub-catchments.

<table>
<thead>
<tr>
<th>Time lags</th>
<th>Xiying</th>
<th>Jingta</th>
<th>Huangyang</th>
<th>Zamu</th>
<th>Gulang</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zero-month</td>
<td>0.56</td>
<td>0.38</td>
<td>0.53</td>
<td>0.29</td>
<td>0.48</td>
</tr>
<tr>
<td></td>
<td>0.48</td>
<td>0.33</td>
<td>0.50</td>
<td>0.25</td>
<td>0.61</td>
</tr>
<tr>
<td>One-month</td>
<td>0.43</td>
<td>0.21</td>
<td>0.40</td>
<td>0.18</td>
<td>0.35</td>
</tr>
<tr>
<td></td>
<td>0.32</td>
<td>0.2</td>
<td>0.12</td>
<td>0.05</td>
<td>0.13</td>
</tr>
<tr>
<td>Two-month</td>
<td>0.2</td>
<td>0.11</td>
<td>0.13</td>
<td>0.10</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>0.12</td>
<td>0.05</td>
<td>0.05</td>
<td>0.01</td>
<td>0.04</td>
</tr>
<tr>
<td>Three-month</td>
<td>0.08</td>
<td>0.09</td>
<td>0.11</td>
<td>0.06</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>0.08</td>
<td>0.04</td>
<td>0.05</td>
<td>0.01</td>
<td>0.04</td>
</tr>
<tr>
<td>Four-month</td>
<td>0.11</td>
<td>0.03</td>
<td>0.08</td>
<td>0.02</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>0.02</td>
<td>0.01</td>
<td>0.02</td>
<td>0.01</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Table 4
Cross-correlations of \(Q(t)\) with different time lags of precipitation \((P(t-\delta))\) and evaporation \((ET(t-\delta))\) for the down-stream of the basin.

<table>
<thead>
<tr>
<th>Time lags</th>
<th>Q(t) vs. P(t-\delta)</th>
<th>Q(t) vs. ET(t-\delta)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zero-month</td>
<td>0.21</td>
<td>0.13</td>
</tr>
<tr>
<td>One-month</td>
<td>0.18</td>
<td>0.09</td>
</tr>
<tr>
<td>Two-month</td>
<td>0.07</td>
<td>0.03</td>
</tr>
<tr>
<td>Three-month</td>
<td>0.04</td>
<td>0.02</td>
</tr>
<tr>
<td>Four-month</td>
<td>0.01</td>
<td>0.01</td>
</tr>
</tbody>
</table>

4. Result analysis and discussion

4.1. Performance of ANNs for five tributaries

The optimized hidden node architecture and performances of ANNs for streamflows of five tributaries are evaluated using the three criteria namely \(RMSE\), \(RE\) and \(R^2\) presented in Table 5. Results showed that three are consistent trend for monthly streamflow between observed and simulated from ANNs data for five tributaries (Fig. 6). According to the evaluated criteria, all ANNs models have higher precision with \(RMSE\) of 0.08–0.33 \(\times 10^7\) m³, MRE of 13–19%, \(R^2\) of 0.89–0.93 for training data and \(RMSE\) of 0.18–0.53 \(\times 10^7\) m³, MRE of 18–37%, \(R^2\) of 0.88–0.91 for testing data. It was also observed that the higher monthly stream values, the higher \(RMSE\) of the model. For example, \(RMSE\) of Xiying and Zamu tributaries are 0.33 \(\times 10^7\) m³, 0.25 \(\times 10^7\) m³ and 0.53 \(\times 10^7\) m³, respectively for training and testing data. \(RMSE\) of ANNs for other three tributaries is comparably lower than that of Xiying and Zamu tributaries both for training and testing data. At the same time, a residuals statistic analysis results were presented in Table 6 and showed there are some various among ANNs for five tributaries.

However, MRE of ANN models is higher for tributaries where agricultural activities are comparably intensive. For example, MRE of ANN models are 19% and 37% respectively for training and testing data in Gulang tributary where the planted area makes up 35.8% of total land area. Similarly, \(RE\) of ANN models are 17% and 32% respectively for training and testing data in Huangyang tributary where the planted area makes up 25.83% of total land area. For other three tributaries, agricultural activities are comparably few and proportion of planted area is lower than 15%. As results, MRE of ANN models are within the scope of 13–16% and 18–22% which is obviously lower than that of ANN models for Gulang and Huangyang tributaries. It can be concluded that agricultural activities affect the hydrological process of land surface and the rain–runoff process become complex in these tributaries. ANNs are more difficult to model streamflow in catchments where agricultural activities are intensive.

4.2. Comparison of integrated ANNs with lumped ANN for streamflow at outlet of mountain

For assessing the overall performance of integrated ANNs to simulate monthly streamflow at outlet of mountain, monthly streamflow of the five tributaries estimated by ANNs were summed as the total monthly streamflow at outlet of mountain. Fig. 7 present the time series plot of observed and estimated with integrated ANNs monthly streamflow at outlet of mountain. This resulted in the overall \(RMSE\) value of 0.25 \(\times 10^7\) m³ and
0.36 × 10^7 m^3 respectively for training and testing data. The MRE are 7% and 9% respectively for training and testing data comparing to observed streamflow. Furthermore, R^2 are 0.91 and 0.9 respectively for training and testing data. Compared with that of single ANNs respectively for the five tributaries, errors of ANN for outlet of mountain are lower significantly. The RMSE of integrated ANNs had same scope with that of single ANNs for every tributary and this can be contributed to the offset of errors of every single ANNs when estimated streamflow of five tributaries were summed as the streamflow at outlet of mountain. However, the MRE of the integrated ANNs to estimate monthly streamflow at outlet of mountain are markedly lower than that of single ANNs for every tributaries.
as the notable increase of total streamflow at outlet of mountain comparing to streamflow of single tributaries.

At the same time, a lumped ANN for monthly streamflow at outlet of the mountain was developed to compare its performance with that of integrated ANNs. As pointed in the former sections, precipitations and ET of the five sub-catchments were averaged as the inputs of the lumped ANN and the lag of precipitation, evaporation also was two months. The output of the lumped ANN was total monthly streamflow of the five tributaries. The same technology was used to develop the single ANN and the training and testing data were consistent with that of integrated ANNs. The time series of observed and estimated monthly streamflow at outlet of mountain were presented in Fig. 7. The different between observed and estimated value is evident when streamflow value are relatively high. The optimized hidden node architecture and errors statistics for the two ANN models (integrated ANN and lumped ANN) were listed in Table 7. It can be observed that errors of the lumped ANN are obviously higher than that of the integrated ANNs to estimate monthly streamflow at outlet of mountain. The RMSE of the lumped ANN are $1.64 \times 10^7$ m$^3$ and $2.43 \times 10^7$ m$^3$ respectively for training and testing data and increased by about five times comparing to that of the integrated ANNs. Similarly, the MRE and $R^2$ of the lumped ANN are $42\%$ and $0.79$ and 0.75 respectively for training and testing data and increase remarkably comparing to that of the integrated ANNs.

Different of precision of the two models to estimate streamflow at outlet of mountain can be explained by the structure of models. The integrated ANNs include several single ANNs for tributaries and consider the spatial variation of precipitation and ET. In other word, the integrated ANNs are similar to semi-distributed model which represent the change of parameters affecting hydrological processes. However, the lumped ANN assumed that the rainfall and ET are uniformly distributed over the catchments and can be understood as a lumped non-linear ‘total-response’ model. As a result, precision of the integrated ANNs is higher significantly than the lumped ANN.

### 4.3. Comparison of integrated ANNs with lumped ANN for monthly streamflow in down-stream

Two integrated ANNs (IANN1 and IANN2) and one lumped ANN (LANN) were used to estimate monthly streamflow at Caiqi station in down-stream of the study area and the time series of observed and estimated monthly streamflow are presented in Fig. 8. It is

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**Table 6**

<table>
<thead>
<tr>
<th>Training data</th>
<th>Testing data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max</td>
<td>Min</td>
</tr>
<tr>
<td>Xiying</td>
<td>6.38</td>
</tr>
<tr>
<td>Jingta</td>
<td>3.19</td>
</tr>
<tr>
<td>Zamu</td>
<td>5.04</td>
</tr>
<tr>
<td>Huangyang</td>
<td>2.97</td>
</tr>
<tr>
<td>Gulang</td>
<td>1.39</td>
</tr>
<tr>
<td>Outlet of mountain</td>
<td>5.83</td>
</tr>
<tr>
<td>Caiqi-IANN1</td>
<td>5.93</td>
</tr>
<tr>
<td>Caiqi-IANN2</td>
<td>6.01</td>
</tr>
</tbody>
</table>

Note: Max, Min mean maximum and minimum residual from ANN. Var mean the variance of residual from ANN.

---

**Table 7**

<table>
<thead>
<tr>
<th>Optimized ANN structure</th>
<th>Training data</th>
<th>Testing data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RMSE (10^7 m^3)</td>
<td>MRE (%)</td>
</tr>
<tr>
<td>Integrated ANNs</td>
<td>–</td>
<td>0.25</td>
</tr>
<tr>
<td>Lumped ANN</td>
<td>4:7:1</td>
<td>1.64</td>
</tr>
</tbody>
</table>

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Fig. 7. Observed and estimated t by ANN total monthly streamflow at outlet of mountain ((a) lumped ANN; (b) integrated ANNs).

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**Table 7**

Errors statistic of integrated ANNs and lumped ANN for total streamflow of outlet of mountain.

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obvious that results of IANN1 model and IANN2 models are better than that of LANN because the former estimate the streamflow at outlet of mountain using semi-distributed method while latter estimate using lumped method.

The optimized hidden node architecture. Errors of the three combined ANNs models for monthly streamflow in down-stream are listed in Table 8 and results indicated that IANN1 and IANN2 perform significantly better than LANN. For training data, two IANN models have same precision with RMSE of 0.28–0.29 × 10^7 m^3, MRE of 13% and R^2 of 0.91–0.92. However, the LANN obviously have higher error with RMSE of 0.58 × 10^7 m^3, MRE of 27% and R^2 of 0.78 for training data. Similarly, errors of two IANN models are lower with RMSE of 0.35–0.38 × 10^7 m^3, MRE of 22–27%, R^2 of 0.88–0.90 for testing data, but RMSE, MRE and R^2 of LANN increased respectively to 0.71 × 10^7 m^3, 46% and 0.7 for testing data. Overall, the LANN have about twice errors than IANN to estimate monthly streamflow at outlet of mountain. In fact, the different between the two kinds of combining ANN models to estimate streamflow in down-stream are from their different precision to estimate streamflow at outlet of mountain.

As for the two IANN models, IANN1 have higher precision than IANN2 and this can be explained with structure of ANN. There are seven inputs for IANN1 and 11 inputs for IANN2 which is relatively complex. For ANN, the increase of inputs factors can make ANN more complex and the parameters (weights and thresholds) become more and more. It is difficult to train a more complex ANN, especially when excess inputs factors do not include further useful information to output. In this study, streamflow from five tributaries at outlet of mountain were summed as an input of ANN in IANN1, but they were respectively different in IANN2. In fact, inputs of IANN1 contain the information of inputs of IANN2. As a result, IANN2 can be over trained and its ability had been declined.

Furthermore, another ANN model for monthly streamflow of down-stream was developed to test the capability of different ANN model to simulate streamflow of arid-inland area. In this ANN, P and ET in every tributary were directly arranged as inputs.
It is noticeable that the precision of the model is lower than the two IANN and the RMSE, MRE, $R^2$ is respectively $0.60 \times 10^7$ m$^3$, 30% and 0.77 for testing sample. This error is almost equivalent to that of LANN. This can be attributed to change cause of streamflow in upper reach of basin is different that in down reach in arid region. Again, usually there are hydrological stations in every outlet of tributary and ANNs for river flow at outlet of mountain and down reach can be easily developed and used.

### 4.4. Comparison of ANNs models with LLR models for monthly streamflow

Several LLR models were developed to further assess the performance of ANNs to estimate monthly streamflow. The hydrological data used to develop LLRs are same to that of ANNs. For the LLRs in down-stream of the basin, estimated monthly streamflow by a lumped LLR model were arranged as inputs. The observed and estimated scatter plot of using LLR and ANN monthly streamflow for the five tributaries are shown in the Fig. 9. Similarly, the observed and estimated scatter plot of using two methods monthly streamflow at outlet of mountain and Caiqi station in down-stream are shown in Fig. 10.

**Fig. 9.** Scatter plot of observed and estimated by ANN and LLR monthly streamflow for tributaries.

**Fig. 10.** Scatter plot of observed and estimated by ANN and LLR monthly streamflow at outlet of mountain.
presented in Figs. 10 and 11 respectively. The performance of LLRs in terms of the two model evaluation criteria namely RMSE and RE are presented in Table 9.

Results imply that errors of LLRs to estimate monthly streamflow of five tributaries, outlet-mountain and down-stream of the basin are higher than corresponding ANNs. For the five tributaries, LLRs have errors with RMSE of 0.14–0.47 \( \times 10^3 \) m\(^3\), MRE of 19–33\%, \( R^2 \) of 0.78–0.83 and RMSE of 0.32–0.64 \( \times 10^3 \) m\(^3\), MRE of 27–57\%, \( R^2 \) of 0.66–0.77 respectively for training and testing data. Overall, the errors of LLRs are significantly higher than that of ANNs and especially at the period in which the streamflow values are low (Fig. 9). For the total monthly streamflow of an outlet of mountain, the LLR have errors with RMSE of 1.91 \( \times 10^3 \) m\(^3\), MRE of 50\% and \( R^2 \) of 0.71 in training period and RMSE of 2.62 \( \times 10^3 \) m\(^3\), MRE of 61\% and \( R^2 \) of 0.63 in testing period. Although error of the LLR is near to that of the lumped ANN, it is obviously higher than that of the integrated ANNs with RMSE of 0.36 \( \times 10^3 \) m\(^3\) and RE of 61\%. Also, it can be observed from Fig. 10 that the observed and estimated scatter plot of using the integrated ANN is near to 1:1 line very much, but the plots for the LLR and the lumped ANN are dispersive. Similarly, integrated ANNs performed remarkably well in both training and testing data than LLR in down-stream (Fig. 11). According to the two evaluation criteria, LLR have errors with RMSE of 0.64–10^3 m^3, MRE of 30\% and \( R^2 \) of 0.77 for training data and RMSE of 0.85 \( \times 10^3 \) m\(^3\), MRE of 56\% and \( R^2 \) of 0.65 for testing data which is more than twice that of integrated ANNs.

As pointed out in former sections, hydrological process is a complex and nonlinear system and LLRs have not enough ability to capture the relationship between runoff and rainfall, evaporation, etc. However, ANN can statistically simulate the hydrological process as its nonlinear feature. Especially in this study, the integrated ANNs considered variates of rainfall and evaporation among the five sub-catchments and can simulate total monthly streamflow at outlet of mountain well than lumped ANN and LLR. In down-stream of the basin, a number of agricultural activities impact the hydrological process and change the streamflow. Although the streamflow estimate is more difficult using LLRs, integrated ANNs have higher precision to estimate monthly streamflow in down-stream of the basin.

5. Conclusions

The new approach of integration of Artificial Neural Networks (integrated ANNs model) for streamflow estimation have been developed and used in an arid inland basin. The integrated ANNs model has shown great potential in streamflow modeling comparing with traditional models either in the lumped. By developing the semi-distributed form of ANNs to explore the spatial variation in hydrological process, such as rainfall distribution and evaporation distribution, streamflow generated from individual subcatchments can be summed as the streamflow at the outlet of mountain. Furthermore, rive flow estimation in down-stream of the basin can be improved by the application of the semi-distributed form of ANNs in upper-stream. The integrated ANNs models in this study retains advantages of the semi-distributed models considering the heterogeneity and spatial variation of hydrological factors and nature character in the catchment, while taking advantage of the potential of ANNs as an effective tool in nonlinear mapping or functional relationship establishment. As demonstrated in this study, the integrated form of ANNs offer the most promising results compared to single ANN and LLR models. However, it need be pointed out that use of the integrated ANNs is limited in some regions where long-term hydrological and meteorological data are lackage. Moreover, As the limitation of soil and other parameters, the distribution physics model have not be further used to assess the ability of integrated ANNs and this will be performed in future study.

Acknowledgements

The authors are grateful for support from National Nature Science Foundation of China (No. 50909094). Two anonymous reviewers are appreciated as some good suggestions improved the quality of the paper.

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