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A new hybrid algorithm for rainfall–runoff process modeling based on the wavelet transform and genetic fuzzy system

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ABSTRACT

In this paper, two hybrid artificial intelligence (AI) based models were introduced for rainfall–runoff modeling. In the first model, a genetic fuzzy system (GFS) was developed and evolved for the prediction of watersheds' runoff one time step ahead. In the second model, the wavelet-GFS (WGFS) model, wavelet transform was also used as a data pre-processing method prior to GFS modeling and in this way the main time series of two variables (rainfall and runoff) were decomposed into some multi-frequency time series by the wavelet transform. Then, the GFS was trained using the transformed time series, and finally the runoff discharge was predicted one time step ahead. In addition, to specify the capability and reliability of the proposed WGFS model, multi-step ahead runoff forecasting was also implemented for the watersheds. The obtained results through the application of the models for rainfall–runoff modeling of two distinct watersheds, located in Azerbaijan, Iran showed that the runoff could be better forecasted through the proposed WGFS model than other AI-based models in terms of determination coefficient and root mean squared error criteria in both training and verifying steps.

Key words | genetic fuzzy system, rainfall–runoff modeling, wavelet transform

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INTRODUCTION

Over the past decades, the data-driven models such as artificial neural network (ANN), adaptive neuro fuzzy inference system (ANFIS) and genetic algorithms (GAs) have been appropriately applied in modeling and forecasting non-linear hydrological time series (e.g. Cheng & Chau 2001; Jain *et al.* 2004; Nayak *et al.* 2004; Chau *et al.* 2005; Chau 2006; Muttil & Chau 2006; Wu *et al.* 2008; Rajaee *et al.* 2009; Sudheer *et al.* 2010; Taormina *et al.* 2012; Asadi *et al.* 2013). In the modeling of hydrological process, particularly in the field of rainfall–runoff process, sometimes there can be a shortfall when time series fluctuations are highly non-stationary and the physical hydrologic process operates under a large range of scales varying from 1 day to several decades. This can mean the data-driven models may not be able to cope with non-stationary data (Cannas *et al.* 2006; Nourani *et al.* 2011, 2013). In these situations, the combination of artificial intelligence (AI) based models with other data pre-processing approaches as hybrid models may be an appropriate choice. The basic idea of model combination in forecasting is to use each model's unique features to capture different patterns in the data. Both theoretical and empirical findings suggest that combining different methods can be an efficient way to improve forecasting (Zhang 2003). Hence, wavelet-ANN (WANN) and wavelet-ANFIS (WANFIS) have been recently generated as efficient hybrid models for hydrological time series forecasting. Wavelet analysis can effectively detect and diagnose the signal's main frequency components and abstract local

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information of the time series (Wang & Ding 2003). In recent years, the wavelet technique has been successfully applied to hydrology in general as well as rainfall–runoff modeling (Partal & Kis 2007; Nourani *et al.* 2009, 2011; Adamowski & Sun 2010).

In some hydrological processes, the use of ANFIS model has led to promising results. Most of the learning algorithms for ANFIS are based on gradient descent. The calculation of gradients in each step is difficult and the use of the chain rule may cause a local minimum, which can definitely affect modeling accuracy. To cope with this deficiency, in the current research, a hybridization of fuzzy logic and GAs as genetic fuzzy systems (GFSs) (Cordón *et al.* 2001) is used. A GFS is basically a fuzzy system that is augmented by a learning process based on evolutionary computation, which includes GAs and other evolutionary algorithms (Cordón & Herrera 1995). In recent years some articles have been published in favor of using GFS for time series forecasting (Shahrabi *et al.* 2013). They reported satisfactory results and concluded that GFS is a promising approach for forecasting issues because the ability to obtain better accuracy in modeling complex and chaotic systems, in comparison with other models such as statistical and intelligent models.

In this paper, two new multivariate black box models based on AI techniques are proposed for the rainfall–runoff modeling of two watersheds located in Azerbaijan, Iran with different climatologic characteristics. In the first model, considering the existence of highly nonlinear dependence between model inputs and output, the authors focus on a new nonlinear approximator, called GFS model, in order to forecast watershed runoff one and several time steps ahead. A multivariate wavelet-GFS (WGFS) model is then introduced as the second model which combines the discrete wavelet transform (DWT) and GFS algorithm to capture the periodic and seasonal characteristics of the process. To the best of the authors' knowledge, the presented study is the first application of the hybrid WGFS not only in hydrological studies but also in any engineering field.

PROPOSED HYBRID MODELS

The current research presents two new hybrid AI based models as GFS and WGFS in order to predict watershed runoff. Also in the modeling process, the data set was divided into two parts: the first 75% of total data were used as a training set and the second 25% were used for verifying the models.

The first model presented in this paper is GFS. There are three main stages in this research to construct the GFS model. Variable selection is the first stage in which a stepwise regression analysis (SRA) is used to choose the key variables that are to be considered as the model inputs. In the second stage, GFS is constructed for prediction of the target runoff 1 month ahead. Finally, the proposed GFS is tested in the third stage using test data set by reporting the determination coefficient and root mean squared error.

In the second model, by applying wavelet transform, the main time series of two variables (rainfall and runoff) are decomposed into some multi-frequency time series. Then, these time series (transformed data) are imposed as input data into the GFS model. Finally, the proposed WGFS model is verified using a test data set. In order to evaluate the efficiency of the proposed hybrid models, the obtained results are also compared with the results of ANN, ANFIS, WANN, and WANFIS models presented by Nourani *et al.* (2011). It should be noted that for WGFS model, after obtaining the wavelet-based sub-series, the GFS should be calibrated using theses sub-series which may lead to different GFS parameters in comparison to the first GFS model.

The schematic of the proposed GFS model is shown in Figure 1. The GFS type used in this article consists of two general stages: stage 1 derives the rule base (RB) of the Fuzzy Rule Base System (FRBS) and stage 2 tunes the database of FRBS. Details of each stage are described below.

Input selection by SRA

Input selection is the process of selecting an optimum subset of input variables from the set of potentially useful variables which may be available in a given problem. Different researchers have applied a variety of feature selection methods such as GA (ElAlami 2009), principal component analysis and SRA to select key factors in their prediction systems (Zhang 2007). Linear regression portrays a fundamental relationship between inputs and output variables in a system. In recent years, many researchers have used SRA

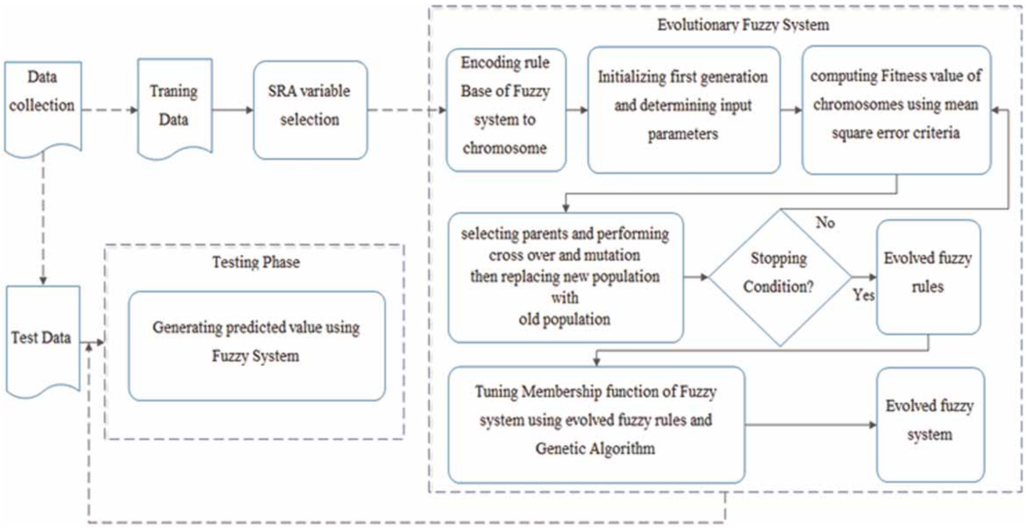

Figure 1 | The framework of proposed GFS model.

for input variable selection for a nonlinear system and have obtained promising results (Hadavandi *et al*. 2010; Fazel Zarandi *et al*. 2012; Asadi *et al*. 2012a, b). In the same way, an autoregressive structure was chosen in order to develop the GFS model. The use of SRA is a suitable method for choosing the significant lagged variables. In this study, five lags for each variable were assumed and by the use of SRA, the meaningful number of lagged variables was chosen.

The criterion for adding or removing is determined by *F*-test statistic value and decreasing the sum of squared error. After the entrance of first variable to the model, the variable number is increased step by step; once it is removed from this model, it will never enter the model again. Before selecting variables, the critical point, level of significant and the values of F_e (*F*-to-enter) and F_r (*F*-to-remove) have to be determined first. Then the partial *F* value of each step has to be calculated and compared to F_e and F_r; If $F > F_e$, it is considered to add variables to the model; otherwise, if $F < F_r$, the variables are removed from model (for more detail see Asadi *et al*. 2012a).

The proposed GFS

The FRBS can be classified into three broad types, namely the linguistic (Mamdani-type), the relational equation, and the Takagi–Sugeno–Kang (TSK). In linguistic models, both the antecedent and the consequence are fuzzy sets, while in the TSK model the antecedent consists of fuzzy sets but the consequence is made up of linear equations. Fuzzy relational equation models aim at building the fuzzy relation matrices according to the input–output data set (Wang 1997).

The Mamdani-type FRBS was used in this study because it has the following advantages (Hamam & Georganas 2008): expressive power; easy formalization and interpretability; reasonable results with relatively simple structure; intuitive and interpretable nature of the RB. For this reason Mamdani-type FRBS is widely used in particular for decision support application. It can be used for both multiple-input and single-output, and multiple-input and multiple-output systems, and finally output can be either fuzzy or crisp.

The difficulty presented by human experts in expressing their knowledge in the form of fuzzy rules has forced researchers to develop automatic techniques. In this sense, several methods have been proposed to automatically generate fuzzy rules from numerical data. Usually, they use complex rule generation mechanisms such as ANNs (Nauck *et al*. 1997) or GAs (Cordón *et al*. 2001; Hadavandi *et al*. 2010).

Using the GAs, each individual in the population needs to be described in a chromosome representation. A chromosome is made up of a sequence of genes from a certain alphabet. An alphabet could consist of binary digits, continuous values, integers, symbols, matrices, etc. The representation method determines how the problem is structured in the GA and determines the genetic operators to be used. In this work, a chromosome is represented by a vector of continuous values, as it has been shown that natural representations are more efficient and produce better solutions. In this case, the chromosome length is the vector length of the solution which comprises coefficients of the proposed model.

GAs have been demonstrated to be a modeling tool for automating the definition of the knowledge base (KB), since adaptive control, learning, and self-organization may be considered in many cases as optimization or search processes (Cordón & Herrera 1995). In this paper we use a Mamdani-type FRBS to deal with the prediction of target. The process we use in this paper for evolving the KB of FRBS consists of two general stages: stage 1 learns the RB of FRBS and stage 2 tunes the database of FRBS, which are briefly described in the following sub-sections.

Genetic learning of the rule base

The most common types for the membership functions (in FRBSs) are triangular, trapezoidal or Gaussian functions. Among them, the triangular membership functions are computationally simpler and there are some well established methods for tuning them available in the literature (Cordón *et al.* 2001).

Uniform fuzzy partitions with triangular membership functions crossing at height 0.5 is considered in constructing of the model. The number of linguistic terms forming each of them can be specified by the GFS designer, and then the Pittsburgh approach (Smith 1980) is used for learning the RB. Each chromosome encodes a whole fuzzy rule set and the learned RB is the best individual of the last population. The Pittsburgh approach is described below. A uniform partitioning with 4 triangular membership functions is also shown in Figure 2.

Many GFSs employ the decision table proposed by Thrift (1991) as the common classical representation for the RB of an FRBS. A fuzzy decision table represents a special case of a crisp relation (the ordinary type of relations we are familiar with) defined over the collections of fuzzy sets corresponding to the input and output variables. A fuzzy rule in the Mamdani-type FRBS and for a first order TSK-type FRBS is presented by following way.

A chromosome is obtained from the decision table by going row-wise and coding each output fuzzy set as an integer number starting from 1 to the number of output variable linguistic terms (Hadavandi *et al.* 2011).

Fuzzy decision table for an FRBS with two inputs (X_1, X_2) (in our case study, the inputs could be runoff at time steps t–1(Q_{t-1}) and rainfall at time step t–1(I_{t-1})) and one output (Y) variable that is runoff at time step $t(Q_t)$, with three fuzzy sets (A_{11}, A_{12}, A_{13}, A_{21}, A_{22}, A_{23}) related to each input variable, and three fuzzy sets (B_1, B_2, B_3) related to the runoff at time step t (Q_t). Application of this code to the fuzzy decision table is presented in Figure 3.

Initial chromosomes (N_{pop}) are randomly generated, while the alleles are in the set $\{1, 2, \dots, N_B\}$ (N_B is the number of Q_t linguistic terms). All consequent labels have the same probability of being assigned to each gene.

Regarding the fitness function, it is based on an application-specific measure usually employed in the

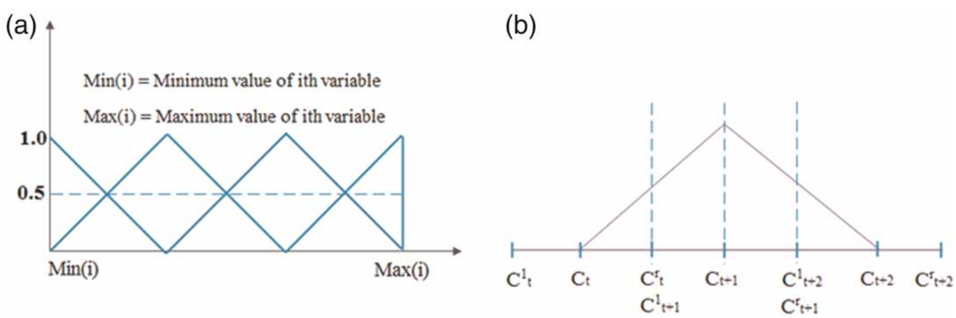

Figure 2 | (a) A uniform partitioning with four triangular membership functions. (b) Interval of performance of membership function.

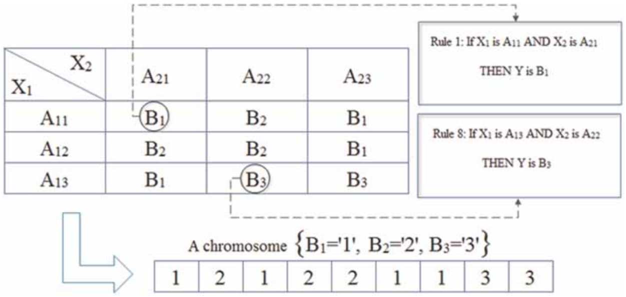

Figure 3 | Coding rule set of fuzzy rainfall–runoff prediction system as a chromosome.

design of GFSs, the mean-squared error (MSE) over the rainfall–runoff training data set. A binary tournament selection scheme is used. The best rule set is added to the current population in the newly generated (N_{pop}–1) chromosome to form the next population.

Genetic tuning of the database

After generation of the RB, the genetic tuning process proposed by Cordón & Herrera (1997) is utilized. This tuning process slightly adjusts the shape of the membership functions of a preliminary defined database (DB) for rainfall–runoff variables. This approach can be performed in the following way. Each chromosome encodes a different DB definition. Triangular membership functions are used for input and output variables' linguistic terms. Each triangular membership function is encoded by three real values, a primary fuzzy partition is represented as an array composed of $3N$ real values, with N being the number of linguistic terms for each variable (we take the same number of linguistic terms for each input and output linguistic variable). The complete DB for a problem, in which M linguistic variables are involved, is encoded into a fixed-length real coded chromosome C_j built by joining the partial representations of each of variable fuzzy partitions as shown in Equation (1):

$$C_i^j = \left(a_{i1}^j, b_{i1}^j, c_{i1}^j, a_{i2}^j, b_{i2}^j, c_{i2}^j, \ldots, a_{iN}^j, b_{iN}^j, c_{iN}^j\right) \tag{1}$$

$$C_j = C_1^j C_2^j C_3^j \ldots C_{M-1}^j C_M^j \tag{2}$$

A sample coded database with one input variable (runoff at time step t–1(Q_{t-1})) as well as one output variable (runoff at time step t (Q_t) is shown in Figure 4. Each variable is defined by a fuzzy linguistic term such as small, medium, and large.

The initial population (N_{pop}) is created using the initial DB definition. The first chromosome (C_1) is encoded directly from initial DB definition. The remaining individuals (N_{pop}–1) are generated by associating an interval of performance, $[c_h^l, c_h^r]$ to every gene c_h in C_1, $h = 1, 2, \ldots, 3NM$. Each interval of performance will be the interval of adjustment for the corresponding variable, $c_h \in [c_h^l, c_h^r]$.

If $t \bmod 3 = 1$, then c_t is the left value of the support of a triangular fuzzy number. The triangular fuzzy number is defined by the three parameters (c_t, c_{t+1}, c_{t+2}) and the intervals of performance as Equations (3)–(5) (Figure 2):

$$c_t \in \left[c_t^l, c_t^r\right] = \left[c_t - \frac{c_{t+1} - c_t}{2}, c_t + \frac{c_{t+1} - c_t}{2}\right] \tag{3}$$

$$c_{t+1} \in \left[c_{t+1}^l, c_{t+1}^r\right] = \left[c_{t+1} - \frac{c_{t+1} - c_t}{2}, c_{t+1} + \frac{c_{t+2} - c_{t+1}}{2}\right] \tag{4}$$

$$c_{t+2} \in \left[c_{t+2}^l, c_{t+2}^r\right] = \left[c_{t+2} - \frac{c_{t+2} - c_{t+1}}{2}, c_{t+2} + \frac{c_{t+3} - c_{t+2}}{2}\right] \tag{5}$$

MSE over a training data set is used as the fitness function. The best ten percent of the population are copied without changes in the elitism set. The elitism set ensures

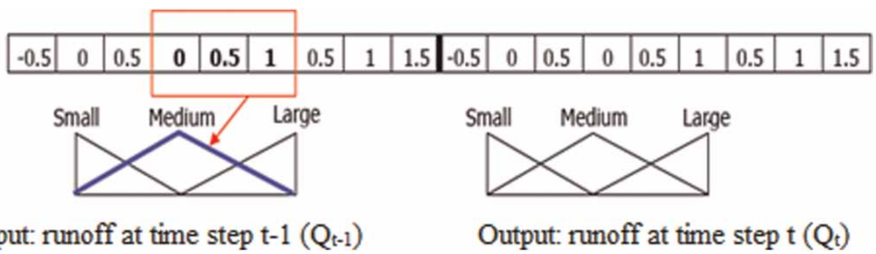

Figure 4 | Coding database of fuzzy rainfall–runoff prediction system as a chromosome.

that the best chromosomes will not be destroyed during crossover and mutation. The selection process is then implemented. A binary tournament selection scheme is used to select chromosomes for the mating pool. The size of the mating pool equals ninety percent of the population size.

BLX–0.1 crossover (the blend crossover, BLX-a) (Eshelman & Schaffer 1993) and uniform mutation are used in the proposed genetic tuning process. The current population is replaced by the newly generated offsprings, which forms the next generation by integrating the elitism set.

Proposed hybrid WGFS model

Wavelet transform

The wavelet transform is a strong mathematical tool that provides a time–frequency representation of an analyzed signal in the time domain. The time-scale wavelet transform of a continuous time signal, $x(t)$, is defined as (Mallat 1998)

$$T(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} g*\left(\frac{t-b}{a}\right) x(t).dt \tag{6}$$

where g^* corresponds to the complex conjugate and $g(t)$ is the wavelet function or mother wavelet. The parameter a acts as a dilation factor, while b corresponds to a temporal translation of the function $g(t)$, which allows the study of the signal around b. For practical applications in hydrology, discrete time signals are usually available, rather than continuous time signal processes. A discretization of Equation (6) based on the trapezoidal rule is the simplest discretization of the continuous wavelet transform (Addison et al. 2001). A discrete mother wavelet has the form

$$g_{m,n}(t) = \frac{1}{\sqrt{a_0^m}} g\left(\frac{t - nb_0 a_0^m}{a_0^m}\right) \tag{7}$$

where m and n are integers that control the wavelet dilation and translation, respectively, a_0 is a specified dilation step greater than 1, and b_0 is the location parameter, which must be greater than zero. The most common and simplest choice for parameters are $a_0 = 2$ and $b_0 = 1$.

This power of two logarithmic scaling of the translation and dilation is known as the dyadic grid arrangement. The dyadic wavelet can be written in more compact notation as (Mallat 1998)

$$g_{m,n}(t) = 2^{-m/2} g(2^{-m}t - n) \tag{8}$$

Since both rainfall and runoff time series are measured points and in a discrete form, in this study dyadic DWT was used rather than a continuous wavelet.

For a discrete time series, x_i, the dyadic wavelet transform becomes (Mallat 1998)

$$T_{m,n} = 2^{-m/2} \sum_{i=0}^{N-1} g(2^{-m}i - n)x_i \tag{9}$$

where $T_{m,\,n}$ is the wavelet coefficient for the discrete wavelet of scale $a = 2^m$ and location $b = 2^m n$. Equation (9) considers a finite time series, x_i, $i = 0, 1, 2, \ldots, N–1$, and N is an integer power of 2, $N = 2^M$. This gives the ranges of m and n as $0 < n < 2^{M-m} - 1$ and $1 < m < M$, respectively. The inverse discrete transform is given by (Mallat 1998)

$$x_i = \bar{T} + \sum_{m=1}^{M} \sum_{n=0}^{2^{M-m}} T_{m,n} 2^{-m/2} g(2^{-m}i - n) \tag{10}$$

or in a simple format as (Mallat 1998)

$$x_i = \bar{T}(t) + \sum_{m=1}^{M} W_m(t) \tag{11}$$

where $\bar{T}(t)$ is the approximation sub-signal at level M and $W_m(t)$ are detail sub-signals at levels $m = 1, 2, \ldots, M$. The wavelet coefficients, $W_m(t)$ $(m = 1, 2, \ldots, M)$, provide the detail signals, which can capture small features of interpretational value in the data. The residual term $\bar{T}(t)$ represents the background information of data.

Structure of WGFS

One of the advantages of the AI based-wavelet conjunction model compared with the AI method is its ability to identify data components in a time series such as irregular components with multi-level wavelet decomposition (Adamowski & Chan 2011). For this purpose, each of the rainfall and runoff signals (I_t, Q_t) were separated into different temporal scales (levels) by DWT. The schematic diagram of the developed model is shown in Figure 5. In this way, each of the mentioned parameters was considered as input signals to wavelet operator. As can be seen in Figure 5, I_a and Q_a denote rainfall and runoff approximation sub-signals, respectively, and also I_{di} and Q_{di} show detail sub-signals (i refers to the decomposition level). Hence, all of the obtained sub-signals were used as inputs to the GFS model in order to forecast runoff 1 month ahead. Some of the most popular wavelet families such as (1) Haar wavelet, a simple wavelet, (2) Daubechies-4(db4) wavelet and (3) coiflets-1(Coif1) were considered to develop the hybrid WGFS model.

EFFICIENCY CRITERIA

The following measures of evaluation have been used to compare the performance of the different models (Nourani et al. 2009)

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (Y_i - P_i)^2}{\sum_{i=1}^{N} (Y_i - \bar{Y}_i)^2} \tag{12}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (Y_i - P_i)^2} \tag{13}$$

where R^2, RMSE, N, Y_i, P_i and $\bar{Y}_i$ are determination coefficient, root mean squared error, number of observations, observed data, computed values and mean of observed data, respectively. Likewise, Legates & McCabe (1999) indicated that a hydrological model can be sufficiently evaluated by these two statistics. Moreover, due to the uppermost importance of the extreme values in the rainfall runoff modeling, Equation (14) can be used to compare the ability of different models in capturing the peak values in runoff time series, similar to Equation (12) for the total data

$$R^2_{\mathrm{Peak}} = 1 - \frac{\sum_{i=1}^{n} (Q_{\mathrm{PC}_i} - Q_{\mathrm{PO}_i})^2}{\sum_{i=1}^{n} (Q_{\mathrm{PO}_i} - \bar{Q}_{\mathrm{PO}})^2} \tag{14}$$

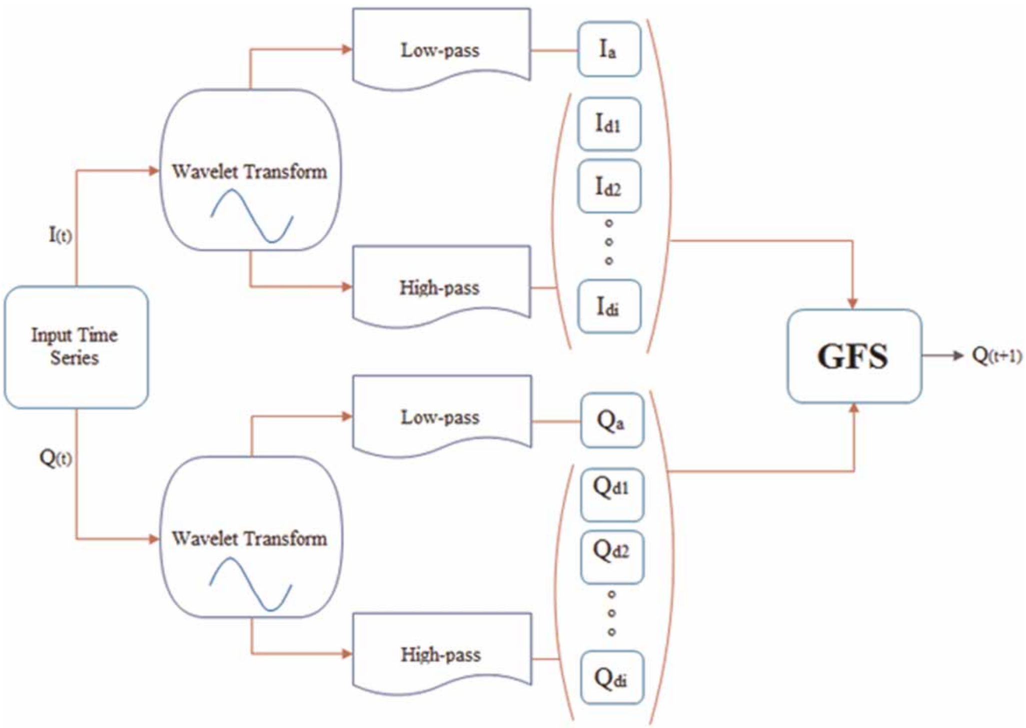

Figure 5 | The schematic flowchart for WGFS.

where R^2_{Peak} determination coefficient for peak values, n number of peak values, Q_{PO_i}, Q_{PC_i} and $\bar{Q}_{\text{PO}}$ are observed data, computed values and mean of observed data for peak values, respectively.

STUDY AREA DESCRIPTION

The data used in this paper are from the Aghchai and Lighvanchai watersheds, located in northwest Iran at Azerbaijan province. The time series data for 12 (from 1995 to 2007) and 17 (from 1990 to 2007) years were used for rainfall–runoff modeling of the Aghchai and Lighvanchi watersheds, respectively. Due to the data limitation in the current research, monthly data were adopted for examining the proposed model. This issue has always been one of the major drawbacks in data gathering for hydrological modeling. The first 75% of total data were used as training set and the second 25% were used for verifying the models. Therefore, for the Aghchai watershed, the data series were divided into a training set from 1995 to 2004 and a testing set from 2004 to 2007, and also for the Lighvanchai watershed the data were split into a training set from 1990 to 2003 and a testing set from 2003 to 2007. The statistics of rainfall and runoff for both watersheds in monthly time scale are tabulated in Table 1. The time series data before going through the network were normalized between 0 and 1. A brief description about other characteristics of the watersheds is presented below.

Case (1): The Aghchai watershed is located between 38°40′ and 39°30′ North latitude and 44°10′ and 44°57′ East longitude. The watershed area is 1,440 km^2. Watershed elevation varies between 1,168 meters and about 3,280 meters above sea level and its longest waterway is 64.88 km in length (Figure 6). The topography is steep with an average slope of 25%.

Case (2): The Lighvanchai watershed is located between 37°45′ and 37°50′ North latitude and 46°25′ and 46°26′ East longitude. The watershed area is 75 km^2 (Figure 6). Watershed elevation varies from 2,140 m to 3,620 m above sea level and its longest waterway is 17 km in length.

Likewise, in spite of similarities between the two watersheds from the standpoint of climatological and geological criteria (due to the fact that both watersheds are adjacent), there are significant differences in terms of runoff, slope, and area. By comparison of the mentioned characteristics of both watersheds, it is concluded that the Aghchai watershed can be categorized as a wild watershed with respect to the Lighvanchai watershed. For instance, the average slope ratio (25:11) for Aghchai watershed is twice that of the Lighvanchai watershed. This characteristic causes the Aghchai watershed to have a quicker response than the Lighvanchai watershed for an event of precipitation. The prevailing climate of the study areas is rainy and sub-humid having four well defined seasons, viz. spring, summer, autumn and winter. During the wet season, the area is under the influence of middle latitude westerlies, and most of the rain that occurs over the region during this period is caused by depressions moving over the area, after forming in the Mediterranean Sea on a branch of the polar jet stream in the upper troposphere. The mean daily temperatures vary from −22 °C in January up to 40 °C in July with a yearly average of 9 °C. The mean annual temperature over the two watersheds is quite mild at 11.9 °C. Average monthly temperatures have a range of 29.2 °C which is a moderate range. July is the warmest month (hot) with a mean temperature of 26 °C and January is the coolest month (slightly cold) having a mean temperature of −3.2 °C.

Table 1 | Statistic characteristics of rainfall and runoff data for case studies

	Rainfall time series (mm)				Runoff time series (m^3 /s)			
Case study	**Max**	**Min**	**Mean**	**Standard deviation**	**Max**	**Min**	**Mean**	**Standard deviation**
Calibration data set								
Aghchai	133.5	0	21.12	22.05	762.5	9.96	122.64	132.70
Lighvanchi	89	0	22.92	19.20	157	0	21.88	30.09
Verification data set								
Aghchai	117	0	27.81	25.71	610.2	27.5	143.51	137.06
Lighvanchi	151	0	18.21	23.75	99	0	13.41	22.02

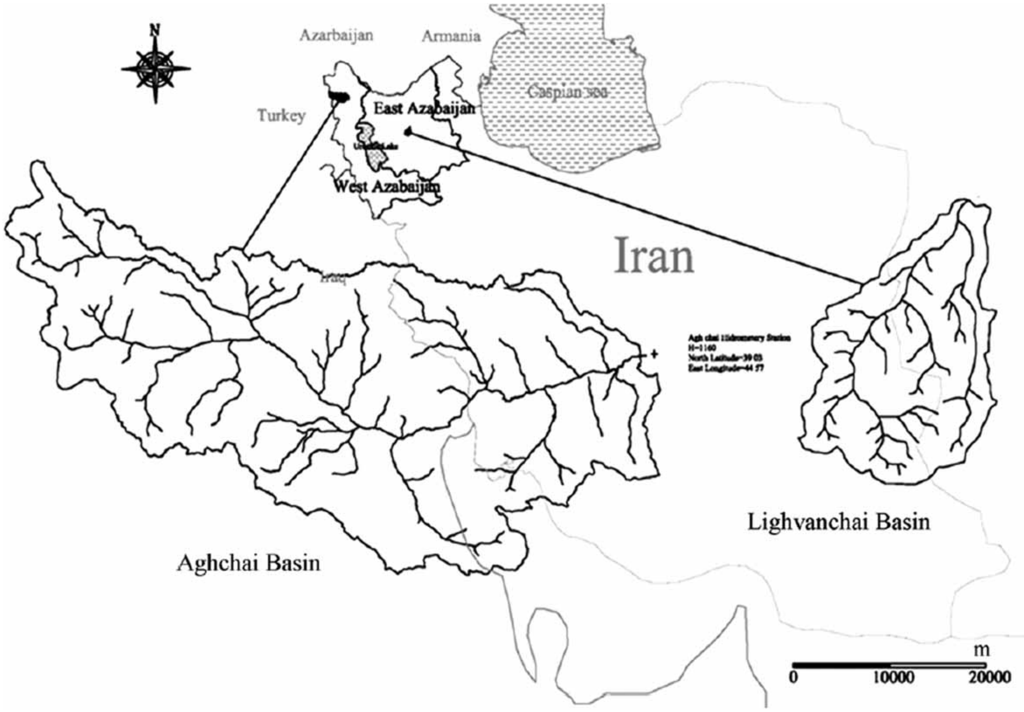

Figure 6 | Location of the study areas.

Table 2 shows the seasonal behavior of the rainfall and runoff time series in both case studies. Moreover, according to the evaluation and comparison of a linear model and a non-linear model presented by Nourani *et al.* (2011), the rainfall–runoff process of both watersheds are characterized by high non-linearity and non-stationary behavior.

RESULTS AND DISCUSSION

Results of proposed GFS model

In this section, the proposed GFS model is examined for the rainfall–runoff modeling of the watersheds. To this end, first the relationship between input and output variables is to be scrutinized; subsequently the results based on correlation coefficients analysis showed there is poor linear relationship between input and output data (Table 3) which approved a need for utilization of non-linear modeling. In the current research, the best input combination was selected according to the SRA in which both pervious rainfall and runoff time series that are more related to output, ($Q(t+1)$), were considered as inputs of the proposed model. Then SRA was used to eliminate low impact inputs and choose the most influential ones out of the mentioned inputs. The statistical software SPSS 17.0 (Ho 2006) was used to apply the SRA in this research considering $F_e = 3.84$ and $F_r = 2.71$. These parameters gain the best-fit regression model with highest R-square. The outcomes of this stage for the Aghchai watershed were runoff at time steps t–1(Q_{t-1}), t–2 (Q_{t-2}) and rainfall at time step t–1(I_{t-1}),

Table 2 | Average seasonal values of both watersheds

	Rainfall time series (mm)				Runoff time series (m³/s)			
Case study	**Spring**	**Summer**	**Autumn**	**Winter**	**Spring**	**Summer**	**Autumn**	**Winter**
Aghchai	18.05	13.28	20.42	26.81	76.23	65.78	95.45	154.66
Lighvanchi	16.14	11.32	19.74	24.03	43.45	28.33	51.12	60.01

Table 3 | The correlation coefficients between input and output data in both watersheds

Time series	Aghchai	Lighvanchai
The correlation coefficients between observed Q_t and I in both watersheds		
I_t	0.46	0.36
I_{t-1}	0.40	0.21
I_{t-2}	0.13	0.05
I_{t-3}	0.031	0.012
I_{t-4}	−0.066	−0.058
The correlation coefficients between observed Q_t and its lags in both watersheds		
Q_{t-1}	0.51	0.48
Q_{t-2}	0.19	0.18
Q_{t-3}	0.038	0.08
Q_{t-4}	−0.24	−0.26

and for the Lighvanchai watershed were runoff at time step t–1 (Q_{t-1}) and rainfall at time step t–1(I_{t-1}) which were considered as inputs to the GFS model. In the second stage, GFS was built using training data. Finally, the prediction was verified by means of the test data.

Fine-tuning the parameters of a learning algorithm is always a difficult task and the parameter values may have a strong effect on the results of the learning for each problem (Eiben *et al.* 1999; Alsinet *et al.* 2008). The modeling process was initiated using the parameters set; it is recommended to start with the values which are known to be good for a number of numeric tests (Eiben *et al.* 1999), accordingly the architecture of the model was improved by sampling the parameter space, considering a stream of instances, sequentially evaluating candidates by comparing number of hit rates, discarding statistically worse candidates and selecting the winning architecture.

Regarding the above explanations, in order to meet the best architecture (i.e. best parameter values) yielding least error, different feature of parameters (i.e. different numeric values) were examined for each learning model and suitable values were obtained. For both watersheds, the suitable features of GFS after examination of different parameters are shown in Table 4.

Therefore, for the first case study (Aghchai), the determination coefficient and RMSE for the calibration stage were obtained by the GFS model as 0.92 and 12.20 m^3/s, respectively. The same metrics as above for the verification stage were also acquired: 0.90 and 13.72 m^3/s, respectively. The GFS model shows a higher determination coefficient and lower RMSE as compared with the ANN ($R^2 = 0.70$, RMSE = 32.02 m^3/s) and the ANFIS ($R^2 = 0.86$, RMSE = 27.45 m^3/s) methods. In the second case study (Lighvanchai), for the calibration stage the determination coefficient and RMSE could be reported as 0.93 and 2.35 m^3/s, respectively. Also in verification of the model the same metrics were derived to be 0.91 and 3.14 m^3/s, respectively. With regard to the ANN ($R^2 = 0.77$, RMSE = 5.65 m^3/s) and ANFIS ($R^2 =$ 0.89, RMSE = 3.45 m^3/s) models, it was elicited that the GFS model is superior to the others. For both watersheds the GFS-estimated time series significantly approximate the general behavior of the observed data. In particular, the observed runoff peaks in the testing period were closely estimated by the GFS model. It is worth mentioning that the results based on the GFS model are quite significant since the ANN and ANFIS models face difficulties in forecasting the extreme values of the observed runoff series.

A model which has been over-fitted generally has poor predictive performance and exaggerates minor fluctuations in data. In this study, as mentioned, the evolved GFS capability in performing predictions on test data set (which was not fed to GFS model at the evolving stage) was acceptable and better than ANFIS and ANN models, so it can be concluded that the GFS model was not over-fitted. Testing with data not seen before can be done while training to see how

Table 4 | Suitable features of GFS

	Parameters				
Case study	Number of labels	Population size	Number of generation	Crossover probability	Mutation rate
Aghchai	3	80	500	0.78	0.05
Lighvanchi	3	90	250	0.85	0.08

much training is required in order to perform well without over-fitting.

The experimental results show that the proposed GFS model is better than ANN and ANFIS in terms of determination coefficient and RMSE criteria. It also has the following characteristics: GAs have been demonstrated to be a modeling tool for automating the definition of the fuzzy rule-based systems, the proposed GFS uses GAs for extracting the RB of the fuzzy expert system. To improve the forecasting accuracy, the proposed GFS tunes the database of the fuzzy system using a GA.

Results of proposed WGFS model

This paper proposes a new hybrid model of GFS and wavelet transform for runoff prediction of the Aghchai and Lighvanchai watersheds. In this work, when wavelet transform is combined with the GFS model, the effects of various decomposition levels and mother wavelet type on the model efficiency should be examined which makes the modeling process time consuming.

In order to overcome this problem, in the current research, decomposition level was determined based on other studies which offer the following formula (Wang & Ding 2003; Nourani *et al*. 2009):

$$L = \text{int}[\log N] \tag{15}$$

where L and N are the decomposition level and time series length, respectively. For the first case study at hand, $N = 144$, so $L = 2$ and also for the second case study the mentioned parameters were specified as 204 and 2, respectively. Hence, several WGFS models were developed using different input scenarios extracted by decomposition levels at levels 1 and 2. For instance, the level 2 decomposition of rainfall time series for the Lighvanchai watershed which yields three sub-series (one approximation and two details at levels 1, 2) by db4 wavelet is shown in Figure 7.

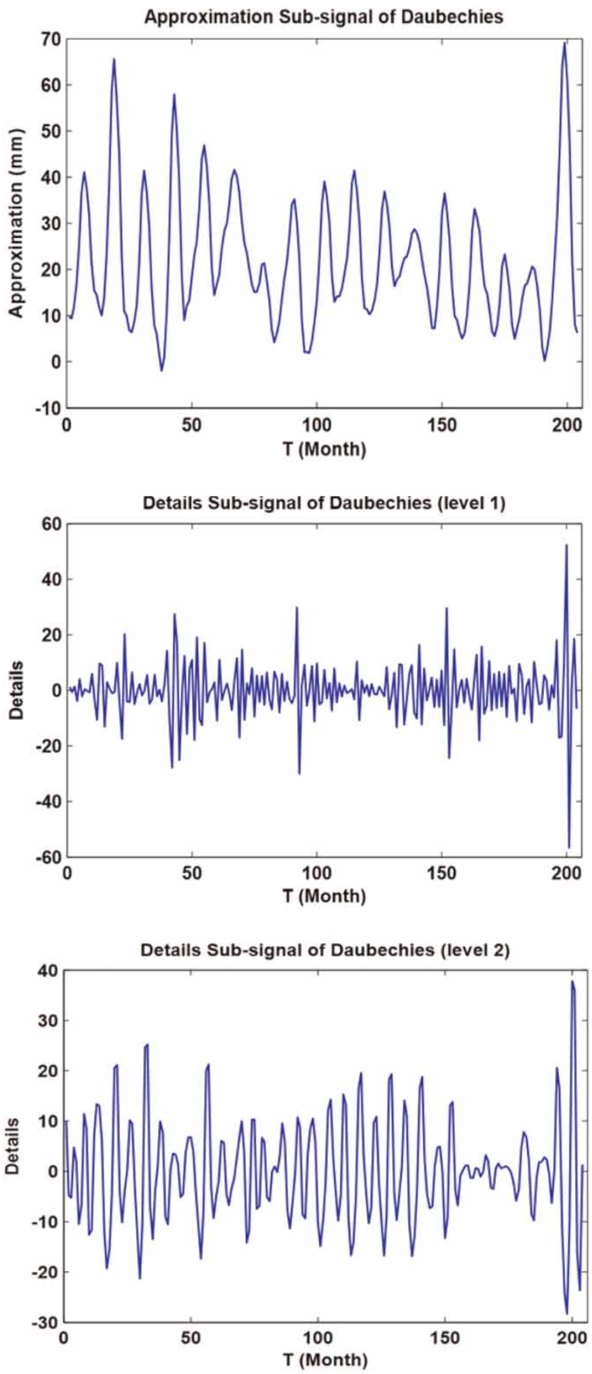

Figure 7 | Approximation and details of sub-signals of db4 Wavelet (level 2).

The detail sub-series can take several negative values (as well as positive values) but approximation may take only a few small negative values when the rainfall values of the original time series are zero, due to the applied mother wavelet. It does not matter that we see the negative values for the sub-series, because according to Equation (11) the summation of these sub-series (e.g., summation of three sub-series of Figure 7) should be the original time series (for rainfall all values of this summation will be positive or zero). So, these sub-series even with some negative values are imposed into the GFS as inputs where the GFS applies weights to these inputs, and finally in the output unit, the model will sum all to get the output (runoff).

To continue, the calibration data set of rainfall and runoff signals were decomposed by passing through high-pass and low pass wavelet filters which were then considered as inputs to the GFS model. Predictive capability of the model was then validated by the test data set. The results of the modeling have been presented based on R^2 and RMSE criteria in Table 5. It should be noted that in Table 5 the rainfall and runoff decomposition levels (i.e., i and j) can be substituted by different values but considering the direct relation between rainfall and runoff amounts, it is expected that both rainfall and runoff time series have the same seasonal levels. Hence, the decomposition levels for the rainfall (i) and runoff (j) time series were considered equal in the current study.

Based on the results (Table 5), there is an increasing trend in the model's performance from low decomposition level towards higher decomposition level. The obtained results for both watersheds show that the db4 mother wavelet decomposed at level 2 could provide a good match between observed and predicted runoff time series in both calibration and verification steps. For both watersheds optimum features of WGFS after examination of different parameters for decomposing by db4 at level 2 are shown in Table 6.

For the first case study (Aghchai), the tuned membership functions of input and output variables in the best proposed WGFS (db4 at level 2-GFS) and their RB are shown in Figures 8 and 9, respectively. These membership functions represent the linguistic terms characterized by fuzzy sets rather than quantity terms. For example, the exposure level of input and output variables is regularly expressed linguistically as MF1 = 'low', MF2 = 'moderate', and MF3 = 'high'. These linguistic variables with non-crisp information are consistent with the imprecise and uncertain nature. Comparing the WGFS model results with those of individual ANN, ANFIS and GFS models, the WGFS is more efficient (Table 7). The reason for such an outcome may be related to the wavelet used in the WGFS model; thus, by decomposing the main time series into multi-scale sub-signals, each sub-signal represents a separate seasonal scale and therefore, the multi-seasonality features of the time series can be handled. Therefore, the results of the WGFS model are more satisfactory when compared with those of other models (i.e., ANN, ANFIS, GFS, WANN, and WANFIS) in terms of prediction accuracy by considering uncertainty and multi-resolution features of the process. More details about the implementation of these models are shown in Table 8. Although the WGFS model

Table 5 | Results of WGFS model

		Calibration		Verification	
Mother wavelet type	Decomposition level ($i = j$)	R^2	RMSE (m^3/s)	R^2	RMSE (m^3/s)
Aghchai					
Coif1	1	0.95	12.20	0.93	12.96
Coif1	2	0.96	11.43	0.95	12.20
Haar	1	0.95	13.72	0.93	13.72
Haar	2	0.95	12.96	0.94	12.20
Db4	1	0.96	11.43	0.94	12.20
Db4	2	0.98	10.67	0.97	11.43
Lighvanchi					
Coif1	1	0.93	2.82	0.92	3.14
Coif1	2	0.94	2.66	0.93	2.82
Haar	1	0.92	3.14	0.91	3.29
Haar	2	0.93	2.82	0.92	2.98
Db4	1	0.95	2.51	0.94	2.66
Db4	2	0.97	2.35	0.96	2.51

Table 6 | Suitable features of WGFS (mother wavelet is db4 at level 2)

	Parameters				
Case study	Number of labels	Population size	Number of generation	Crossover probability	Mutation rate
Aghchai	2	90	1,200	0.85	0.08
Lighvanchi	2	90	850	0.8	0.08

has a costly structure, this is unavoidable when you consider it catches all uncertain and multi-scale seasonality effects in a modeling process.

To sum up, the GFS model was first developed employing meaningful lagged data of rainfall and runoff time series and in this way, SRA was used to select dominant inputs. However, for the WGFS model, rainfall and runoff sub-signals at different scales (levels) obtained via the wavelet transform were considered as inputs in which each sub-signal represents a specific scale of l (as 2^l-mode) and

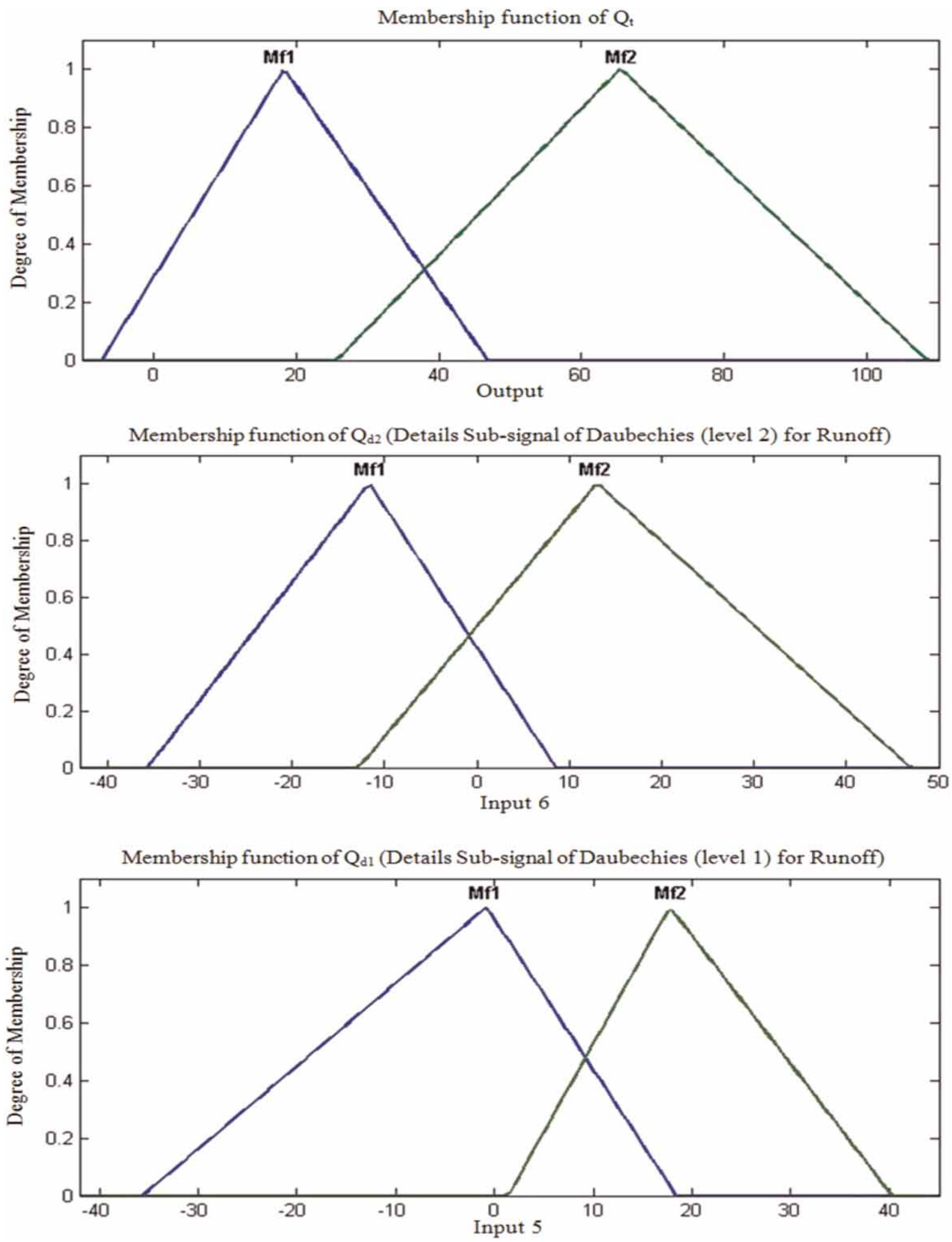

Figure 8 | Membership functions of input and output variables in WGFS model. *(continued)*

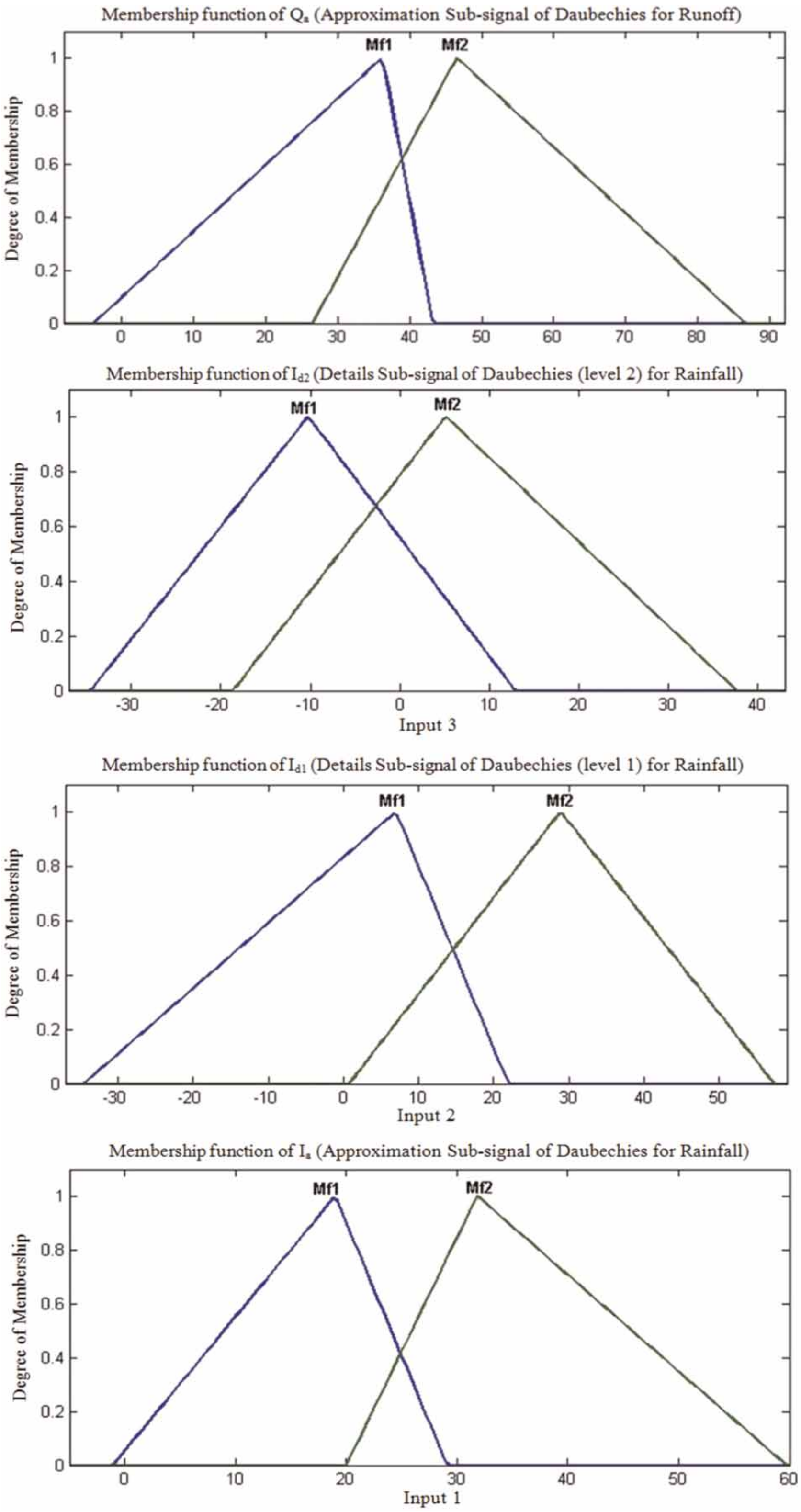

Figure 8 | Continued.

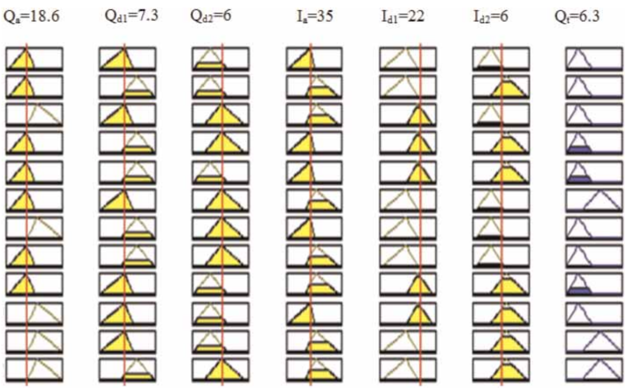

Figure 9 | Fuzzy RB in WGFS model.

these input sub-signals can play the same role of lagged data in the GFS or classic ANN models.

Comparison of models

Finally, in order to evaluate the performance of the proposed hybrid models (i.e., GFS and WGFS), the obtained results were also compared with results of ANN, ANFIS, WANN and WANFIS models which have already been presented by Nourani *et al.* (2011) (it should be noted that all of these methods are applied to the same data sets with the same portion of training and test data). The time series of observed and forecasted runoff through mentioned models for the Aghchai and Lighvanchai watersheds are plotted in Figures 10 and 11. Whereas multi-step ahead forecasting is essential to show whether the proposed model is properly tested or not, the potential of WGFS model for 2 and 3 months ahead flow forecasting was also investigated in the current research for both watersheds. The WGFS model was compared to the WANFIS model for 2 and 3 months ahead flow forecasting. It is worth mentioning that the correlation coefficients between sub-signals and original data provide information about the selection of the conjunction model inputs. Therefore, the input combinations were obtained after the examination of the correlation coefficients between each of sub-time series and original data. db4 wavelet transformation at level 2, which was known

Table 7 | Comparison of different rainfall–runoff models

Case study	Aghchai			Lighvanchai		
Model	**Calibration (R^2)**	**Verification (R^2)**	[b] (R^2_{peak})	**Calibration (R^2)**	**Verification (R^2)**	[b] (R^2_{peak})
ANN[a]	0.78	0.70	0.41	0.77	0.69	0.53
ANFIS[a]	0.89	0.86	0.71	0.89	0.84	0.79
WANN[a]	0.91	0.88	0.85	0.92	0.90	0.91
WANFIS[a]	0.94	0.93	0.96	0.96	0.93	0.96
GFS	0.92	0.90	0.93	0.93	0.91	0.92
WGFS	0.98	0.97	0.97	0.97	0.96	0.97

[a]Nourani *et al*. (2011).
[b]Determination coefficient for peak values.

Table 8 | Structures of the ANN and ANFIS models

Case study	Network structure	Input variables	epoch
ANN			
Aghchai	(8,10,1)	$Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}, I_t, I_{t-1}, I_{t-2}, I_{t-3}$	150
Lighvanchai	(8,5,1)	$Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}, I_t, I_{t-1}, I_{t-2}, I_{t-3}$	150
ANFIS			
Aghchai	gbellmf-2[a]	$Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}, I_t, I_{t-1}, I_{t-2}, I_{t-3}$	200
Lighvanchai	gbellmf-2[a]	$Q_t, Q_{t-1}, I_t, I_{t-1}$	200

[a]Bell function as the membership function and two MFs.

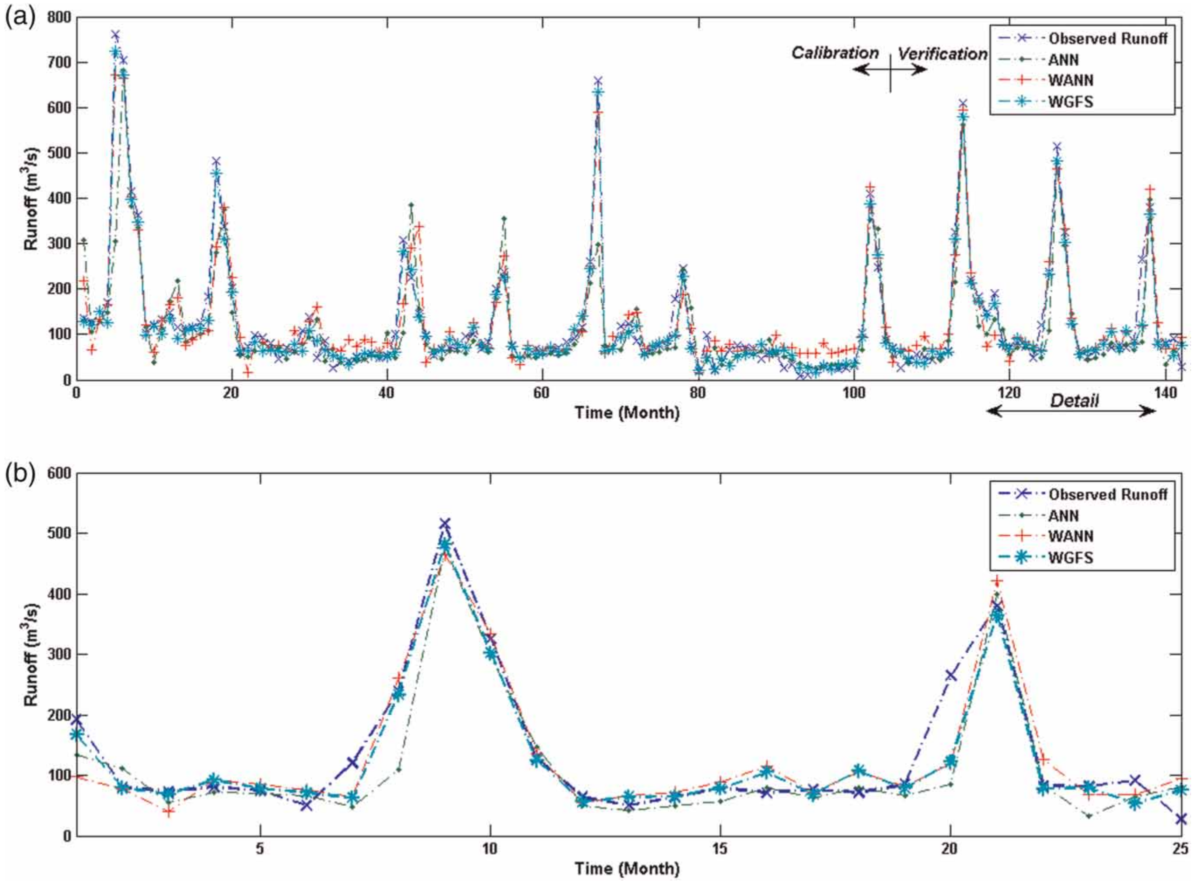

Figure 10 | The results of different models for (a) Aghchai watershed with (b) detail of first 25 months.

as an appropriate wavelet function in the previous section, was also considered for decomposition purposes. Table 9 shows the dominant combinations of input data for both watersheds. After the implementation of the two models for multi-step ahead flow forecasting, it was determined that for both 2 and 3 months ahead forecasting, the WGFS model could provide more accurate results than the WANFIS model. The superiority of the WGFS model in multi-step ahead forecasting is shown in Figures 12 and 13. The forecasting performances of the WGFS and WANFIS models during the testing period are presented in Table 9 in terms of RMSE and R^2. Table 9 shows that WGFS model has a positive effect on multi-step ahead runoff forecasting.

The main aim of this paper is to develop a hybrid fuzzy system and wavelet transform for the runoff discharge prediction in which most of the characteristics of the process could be taken into consideration. According to the obtained results, it is clear that the GFS model is more efficient than the ANN and ANFIS models in forecasting both watersheds runoff. The reason for this fact may be related to the use of a tuning method in the developed model. Thus, in spite of the uncertainty of the process which is captured using a GFS model similar to the ANFIS model, in the GFS, the GA as a global search method has been employed to escape the local optimum and finding the best parameters of the fuzzy system. In this way, the proposed model can find the appropriate parameters of the fuzzy system under the complex and chaotic conditions of the rainfall–runoff process. Therefore, with regard to the mentioned models, it is expected that the GFS model would be more appropriate to simulate the non-linear behavior of the phenomenon. What is more, there are remarkable weaknesses in capturing peak values through ANN and ANFIS models and to cope

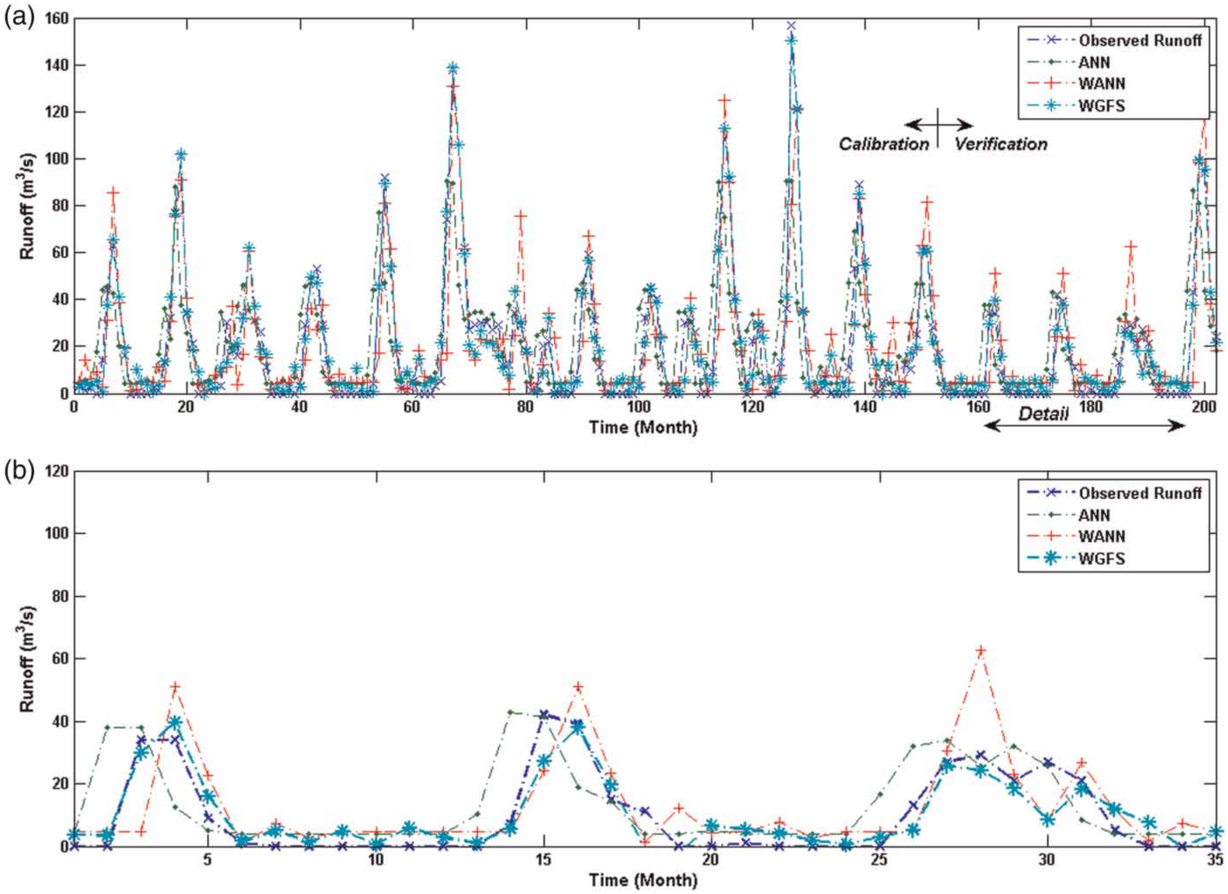

Figure 11 | The results of different models for (a) Lighvanchai watershed with (b) details of first 35 months.

Table 9 | Results of 2 and 3 months ahead forecasting for WGFS and WANFIS models during the testing period

Case study	Input	Output	R^2	RMSE (m³/s)
WANFIS				
Aghchai	I_t, Q_t, I_{t-1} and Q_{t-1} in level 2	Q_{t+2}	0.91	16.77
	I_t, Q_t, I_{t-1} and Q_{t-1} in level 2	Q_{t+3}	0.89	20.58
Lighvanchai	I_t, Q_t, I_{t-1}, Q_{t-1}, I_{t-2} and Q_{t-2}, in level 2	Q_{t+2}	0.90	3.61
	I_t, Q_t, I_{t-1}, Q_{t-1}, I_{t-2} and Q_{t-2}, in level 2	Q_{t+3}	0.87	4.55
WGFS				
Aghchai	I_t, Q_t, I_{t-1} and Q_{t-1} in level 2	Q_{t+2}	0.94	15.25
	I_t, Q_t, I_{t-1} and Q_{t-1} in level 2	Q_{t+3}	0.92	16.77
Lighvanchai	I_t, Q_t, I_{t-1}, Q_{t-1}, I_{t-2} and Q_{t-2}, in level 2	Q_{t+2}	0.93	3.29
	I_t, Q_t, I_{t-1}, Q_{t-1}, I_{t-2} and Q_{t-2}, in level 2	Q_{t+3}	0.91	3.45

with this deficiency the GFS model considering the aforementioned benefits was implemented. In the same vein, this model has significant advantages under some critical hydrological conditions, such as in the case of severe storm when extreme values are created by the sudden imposition of extreme inputs on the hydrological system, and so is able to estimate such peak values better than other autoregressive black box models such as ANN and ANFIS.

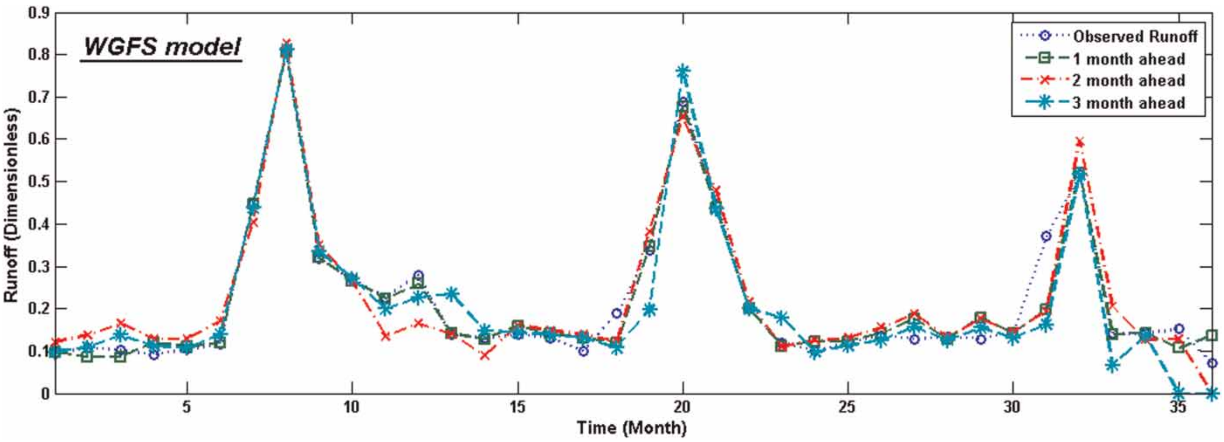

Figure 12 | The results of WGFS model in multi-step ahead forecasting for the Aghchai watershed.

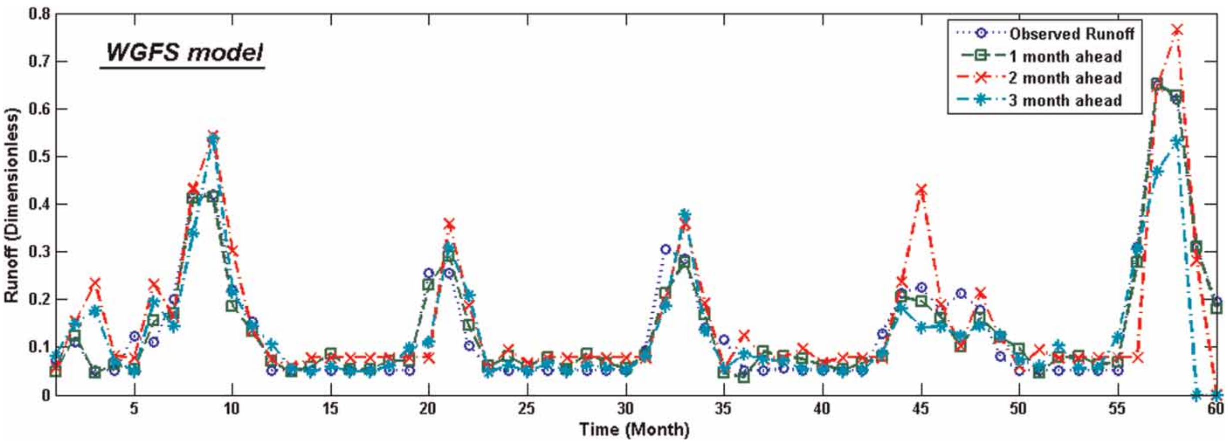

Figure 13 | The results of WGFS model in multi-step ahead forecasting for the Lighvanchai watershed.

One of the most significant characteristics of the hydrological time series is seasonality pattern. The seasonality feature is the dominant factor in monthly modeling. Therefore, as core to the paper, we developed a novel hydrologic process model called WGFS, which could lead to more reliable results than other seasonal models (i.e., WANN and WANFIS); by applying multi-scale time series as inputs to the GFS model. In spite of conclusive evidence, according to the R^2 and RMSE, about the superiority of the proposed method to other techniques, in order to ensure the superiority of the WGFS model over the WANFIS model – which has been recently known as vigorous tool in perdition of the rainfall–runoff process – the hypothesis was tested.

The best fit model out of WGFS and WANFIS (Nourani *et al.* 2011) would be chosen by hypothesis testing. To meet this purpose following hypothesis was proposed:

H0: There is no difference between prediction accuracy of WGFS and WANFIS.

H1: There is a difference between the prediction accuracy of the two models.

Since the data used for prediction in both models are the same, paired *t*-test (two samples for mean) on prediction accuracy (relative error percentage) was carried out.

As has been shown, since the *P*-value (0:0014) is <0.002 so H_0 was rejected in level of confidence $\alpha = 0.002$. The results of the paired *t*-test in terms of mean deviation, standard deviation and *t*-test value are −2.61, 4.856 and −3.356, respectively.

The evidence indicates that the average prediction error (μ) of WGFS is significantly lower than that of WANFIS. Thus, again, the WGFS model was concluded to be a rigorous method for constructing watershed's runoff response.

Since the feasible estimation of peak values is usually the most important factor in any flood mitigation program, another key point when comparing different models is the capability of the models in estimating peak values. For this purpose, peak values were sampled by considering the threshold of the top 5% of the data from the original runoff time series contractually. The performances of the various models in this respect were evaluated using Equation (14) and are presented in Table 6. By comparing the results, it is found that the capability of the WGFS model for predicting extreme values is better than ANN, ANFIS, GFS and WANN models. Also, the efficiency of the WGFS model is 0.97 compared with 0.96 for WANFIS. There is an identical high capability of the two models in predicting peak flows. But as mentioned above, WGFS has promising results, especially in the low-flow context. Therefore, not only is the proposed model appropriate in monitoring peak values, but it can also be considered as a promising streamflow forecasting tool which is necessary in the water resources systems management where it is directly influenced by streamflow forecasting. Furthermore, one of the main traits that distinguishes the WGFS model over the WANFIS model is its capability in multi-step ahead forecasting, one of the significant concerns of hydrologists.

In spite of the issue that by a combination of wavelet transform and AI models watershed runoff can be predicted precisely and that under such circumstances the seasonality feature of the process can be captured remarkably well, through hybridization of wavelet transform and AI models (in the current research is GFS) the capability of the model in predicting extreme values is considerably increased due to the essence of the wavelet transform. The GFS as the main structure of the WGFS model plays a key role not only in estimating high values but also more so in the low-flow context. As can be seen, all WGFS models have led to satisfactory results in terms of R^2 and RMSE, but in this research the db4 wavelet transform at level 2 yielded the highest capability in forecasting watershed runoff. Such an outcome was obtained using the available 12 and 17 year monthly data but it is clear, as with any data-driven model, the proposed model may lead to much more promising results if a longer data set is used (if available) in the modeling. Due to the climatological conditions, for both case study watersheds, there may have been some snowy days every year and this snowmelt water may impact on the runoff. This impact is more remarkable in the daily modeling than the presented monthly modeling. In the freezing days, it may take a few days for the snow to melt and change the runoff, and as a result, the current day snow may impact on the outlet runoff a few days later. However, this condition is much less significant in the monthly modeling since in the monthly time scale there is enough time (1 month) to see the impact of snowmelt on the outlet.

CONCLUDING REMARKS

The purpose of this study was to investigate the effect of a hybrid GFS model and wavelet transform on improving the accuracy of monthly runoff forecasting by considering dominant hydrological characteristics of the rainfall–runoff process, simultaneously. To this end, the Lighvanchai and Aghchai basins were used as case studies, in which rainfall and runoff time series of both watersheds are characterized by high non-linearity, non-stationary and seasonality behavior.

Based on previous research (Nourani *et al.* 2011) implementing ANN and ANFIS models, the non-linear relationship of input and output data could not be determined thoroughly and these models also face difficulties in estimating peak runoff values. Therefore, in order to cope with these weaknesses, in the current research the GFS model was introduced. The use of GA in the framework of the GFS model invigorates it to escape the local optimum and consequently acquire the appropriate parameters of the fuzzy system. The obtained results showed a good improvement in the runoff forecasting for both watersheds through the hybrid GFS model in comparison with those of individual autoregressive ANN and ANFIS models.

The next task was to capture the seasonality feature of the rainfall–runoff process. Therefore, the second hybrid model called WGFS was also proposed, in which the wavelet transform, which can capture the multi-scale features of a signal, was used to decompose the Lighvanchai and Aghchai rainfall and runoff time series. The sub-signals were then used as inputs to the GFS model to predict the runoff discharge 1 month ahead. In this research, in order to overcome the time-consuming issue of the modeling process, the wavelet decomposition level was selected according to signal length. It is worth noting that the wavelet transform type plays a pivotal role on the performance of the WGFS model. Thus, different kinds of wavelet transforms (i.e., Coif1, Haar and db4) were evaluated on how they enhanced the capability of the proposed model in runoff forecasting. In this paper, for both watersheds Daubechies wavelet order-4 (db4) at level 2, considering the shape similarity with main time series, provided a good match between observed and predicted runoff time series. The comparison of the results showed that the WGFS model is able to forecast watershed runoff better than both autoregressive (i.e., ANN, ANFIS and GFS) and seasonal models (i.e., WANN and WANFIS). Moreover, this claim was proven with respect to the superiority of the WGFS model in estimating extreme values and in the field of multi-step ahead forecasting.

For future work, it is recommended to use the presented methodology to forecast the runoff in daily scale and also to model the rainfall–runoff process of a watershed by adding other hydrological time series and variables (e.g., temperature or/and evapotranspiration) to the input layer of the model.

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